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On the use of disequilibrium models in applied microeconomic research and the value of sample separation information

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The use of disequilibrium models in applied microeconomic research is evaluated. A disequilibrium or switching regime model is used to explain sales levels of individual retail stores. It is investigated whether substantial differences are found if an equilibrium approach is followed instead. Disequilibrium models are known to suffer from the fact that sample separation is unknown. Usually this information is not available. Our sample contains explicit information with respect to the regime to which an observation belongs. Therefore, the value of sample separation information in estimating the disequilibrium model is investigated. Finally, Monte Carlo experiments are conducted to get more insight into these matters.

I. INTRODUCTION

Economists typically model the world as determined by the interplay of supply and demand. Usually equilibrium is assumed. There are situations, however, where the classical equilibrium hypothesis is not appropriate. In empirical work one has to decide whether the outcomes of the model are supply determined, demand determined or that both opportunities are feasible. In the last case knowledge per observation is required as to which *regime*[1] prevails. If this knowledge is not available and if the assumption of the dominance of either supply or demand is not appropriate, switching models with endogenous regime choice are used. Typically, they are applied to analyse markets in disequilibrium where outcomes result from the minimum of supply and demand. Notable examples of such analyses are the labour, the housing and the credit markets (Rosen and Quandt, 1978; Fair and Jaffee, 1972 and Laffont and Garcia, 1977). Aggregate time series are used to estimate these models. Regime switches are unlikely to be discrete at an aggregate level. Therefore several smoothed versions of the switching model have been proposed (Muellbauer, 1978; Kooiman and Kloek, 1979; Malinvaud, 1982; Lambert, 1984; Kooiman, 1984). On the whole their assumption is that the minimum condition of supply and demand is more likely to apply to the micro level than to the aggregate. The straightforward use of microdata is the obvious alternative: the discrete minimum condition can be maintained and no smoothing is required (Kooiman *et al.*, 1985). In the present paper we will report some experiments applying the switching model to a cross-section of observations of individual retail establishments.

The economic problem we want to address in the present paper is that of the explanation of sales levels of individual retail stores and the measurement of store marketing mix effects. Obviously, sales levels of retail stores are determined by the interplay of store supply capacity and the store specific demand characteristics (Kooiman *et al.*, 1985). In the cross-section situation we study it is likely that some stores are capacity determined (i.e., demand is large enough), whereas other stores are demand determined (i.e., demand is smaller than store capacity). This implies, for

[1] I.e., excess supply or excess demand.

0003–6846

example, that the use of a classical equilibrium approach for estimating the important effect of advertising expenses on sales may lead to biased estimation results (Bode *et al.*, 1988). A disequilibrium model is then proposed to estimate the marketing mix effects. In such a model sales are either supply determined or demand determined. In the present paper the gains of such a switching model are discussed *vis-a-vis* the classical equilibrium concept. This will be done in the setting of a sample of 137 retail stores.

Another point of enquiry in the present paper is the value of sample separation information. Usually, information regarding the regime to which each individual observation belongs is not available (Kooiman *et al.*, 1985; Bode *et al.*, 1988). Both possibilities then have to be included in the model, and it is up to the data to decide on the most likely regime distribution. Such endogenous regime choice models have not proved to be very succesful. According to Maddala (1983, p. 299) one of the problems with disequilibrium models with unknown sample separation is that we 'are asking too much from the data when we do not know which observations are on the demand function and which are on the supply function.' Some authors have studied this problem. Goldfeld and Quandt (1975) analysed the value of prior information regarding the regime to which each observation belongs by Monte Carlo methods, and Kiefer (1979) analysed the value of such information in an analytical way by considering the problem as a comparison between the precisions of estimates based on a joint density and those based on a marginal density. According to these studies there may be considerable loss of information if sample separation is not known.

In the present paper we want to analyse the value of sample separation information once more. There are three reasons. First, the analysis of Goldfeld and Quandt is based on Suits' (1955) model of the watermelon market. In the applied section of their paper the authors use the original data set of 33 observations, and these data provide the basis of the analysis also in the experimental section. The results reported by Goldfeld and Quandt should be considered as *small* sample results. *A priori*, it is less likely that the information loss is still substantial when a *larger* sample is used. Secondly, although Kiefer (1979) also deals with the question of information loss in large samples, in his paper use is made of a very *simplified* switching model. Comparing his results with the Goldfeld–Quandt study, Kiefer notes that they seem to indicate '. . . that the information loss in a more complicated model is greater than that in the simple model, as seems plausible (although this must be qualified since the Goldfeld–Quandt results are for small samples)', see Kiefer (1979, p. 1002). An analysis using a relatively large sample in combination with a *less simplified* model may shed more light on this matter. Thirdly, Suits' model was originally estimated using *aggregate time-series* data, whereas our current model is estimated using *cross-section* data from *individual* stores. As far as we know the value of prior information has not yet been analysed in the context of individual cross-section data. Hence, its seems worthwhile to consider the value of sample separation information once more in the situation where a relatively *large* sample of *individual cross-section* data is used to estimate a disequilibrium model which is *not unjustifiedly simple.*

The outline of our study is as follows: Section II deals with the conceptual framework of the disequilibrium model. In Section III the data are discussed and the empirical specification of the model equations is given. Section IV deals with the empirical results. In Section V some caveats are discussed. In Section VI the results of some Monte Carlo experiments are discussed. The paper ends with some conclusions in Section VII.

II. CONCEPTUAL FRAMEWORK OF DISEQUILIBRIUM MODEL

In this section the disequilibrium model in its basic form will be discussed. As mentioned in the introduction, we believe that the sales level in retail stores is determined by an interplay of store supply capacity and store demand. Therefore, first of all we need an equation describing store demand and an equation describing store supply capacity:

$$q^d = f^d(X^d) \tag{1a}$$

$$q^s = f^s(X^s) \tag{1b}$$

In these equations q^d stands for the volume of store demand; q^s is the volume of store supply capacity; X^d are explanatory variables affecting store demand; and X^s are explanatory variables affecting store supply capacity. The variables X^d and X^s will be further specified in the next section.

Once a store is established, store supply capacity is more or less *fixed*, at least in the short run. This does not imply, however, that the store always operates *at* this capacity.[2] *Actual* supply (volume of sales) varies at or below store supply capacity depending on the level of demand. Consider, for example, an entrepreneur who wants to open up a new store. It is not always easy to find a suitable establishment, both in terms of location and in terms of space. Sometimes supply capacity will be too large to meet demand; there is a situation of excess capacity[3] and the store operates below capacity. But it is also possible that the capacity of the store is too small to meet demand. Then the store operates at capacity and a situation of excess demand

[2]In retailing the initiative for the use of capacity lies on the side of the consumer (see also Nooteboom, 1986, p. 234).

[3]In view of the difference made between 'actual supply' and 'supply capacity', it might be confusing to use here the term 'excess supply'. Therefore, the term 'excess capacity' will be used.

exists. Even if at the beginning the situation is such that store demand equals store supply capacity, this equilibrium may be disturbed in time as a result of a changing environment. For example, an excess capacity situation may arise from a decreasing population size or from an increasing number of competitors.

As a result of this we expect a considerable number of stores to be in a situation of disequilibrium between store demand and store supply capacity at the moment of sample observation. This is also supported empirically by our survey held among confectioners' stores (see Section III). The results of this survey indicate that stores may operate under different economic regimes, viz., excess capacity or excess demand.[4] Adding the equation $q^d = q^s$ to Equation 1a and b (in accordance with the classical economic equilibrium hypothesis) would not be appropriate in our situation. Such an approach is based on the idea that the storekeeper is always in a position to 'clear the market' by a suitable choice of his marketing instruments. We believe that, in general, this is not true for an entrepreneur in the retail trade. Suppose, for example, that in a specific store the level of demand is smaller than supply capacity. The storekeeper will then try to stimulate demand in order to diminish excess capacity. One way to achieve this is by lowering the product prices. Of course, other store marketing instruments like advertising or assortment composition might also be used for this purpose. However, we believe that in many stores the disequilibrium between store demand and store supply capacity will continue to exist, despite the lower price level. This can be explained as follows: first, it is possible that profit margins are so low that prices can only slightly be reduced. Such a minor reduction will not be enough to bridge the gap between store demand and store supply capacity. But even if in a specific store prices can considerably be reduced before creating negative margins, it may be unwise to do so in view of the fact that competitors might follow. Secondly, there are many opportunities for product differentiation in retailing. The 'product' offered in retail stores is in fact a 'bundle of services'[5] with several dimensions, such as price level, proximity, accessibility (parking space), availability of other products, and other aspects of service (helpfulness, opening time, spaciousness, atmosphere, etc.). Price level is one of these dimensions, but nonprice competition also plays a role in retail stores. Price is not the only competing instrument. Therefore, a lower price level does not necessarily attract many new customers. The situation is analogous in case of an excess demand regime: now the storekeeper is in a position to increase the prices of his products. As long as prices are not increased too much, most customers will continue to visit the store. Here the argument of Nooteboom (1980, pp. 17–18) also applies. According to him retailing 'does not provide a physical product (utility of form) to be shipped to points of sale, but a utility of time and place at a point of sale. In the provision of the utility of place, the numerous retailers serve not one market but a cluster of geographically fragmented markets. In other words: there may be partial spatial monopolies'. But if prices are further increased in order to achieve an equilibrium situation, demand may drop at once below store capacity. As a consequence, we believe that excess demand causes, for example, store prices to become higher,[6] but this does not necessarily imply that equilibrium is restored: demand may still be larger than supply capacity.

This brings us to define actual (realized) volume of store sales, q, as the minimum of store demand and store supply capacity:

$$q = \min(q^d, q^s) \tag{1c}$$

This equation should be interpreted as follows: the storekeeper tries to meet store demand given his store supply capacity. Therefore, the realized volume of sales q is the minimum of q^d and q^s.

This equation is added to Equations 1a and b and completes our disequilibrium model. The endogenous variables in model (1) are q^d, q^s and q. Only q is observable; q^d and q^s are so-called *latent* variables.

III. DATA AND EMPIRICAL SPECIFICATION

Data

We have at our disposal a cross-section sample of Dutch confectioners' stores. The number of observations is 137 and the year of collection is 1985. The reason for choosing confectioners' stores is primarily because this particular sample contains prior information with respect to the regime to which an individual store belongs. The survey contained the following question: 'Was your business in 1985 in a situation of *excess capacity* (i.e., you could have produced more at given capacity, but demand was insufficient), or was there an *excess demand* situation (i.e., you could have sold more, but you were at your maximum production capacity)?' In 85 cases the storekeeper answered to be in a situation of excess capacity; 42 confectioners said to be in an excess demand regime; and 10 said to be in a situation of equilibrium between store demand and store supply capacity. We decided to consider the equilibrium

[4]Apart from possible exceptional cases, every store will have excess capacity during some periods of opening time, and shortage of capacity during some other periods. But our regime concept should be interpreted as describing the 'average situation' during a longer period of time, say, one year. In Section V this point will be further dealt with.
[5]Cf. Hall *et al.* (1961), and Arndt and Olson (1975).
[6]See also Bode *et al.* (1990).

observations as excess demand observations.[7] So, our sample consists of 85 excess capacity observations and 52 excess demand observations.

Total value of annual sales varies from 60 thousand to 1305 thousand Dutch guilders, with an average value of 488 thousand Dutch guilders.[8] Total floorspace varies from 41 to 530 m^2 with an average value of about 150 m^2. This area is partitioned into selling area, with an average value of about 50 m^2, and remaining space (i.e., bakery room, storehouse and office), with an average value of about 100 m^2. In Appendix A more information on the data is given.

Empirical specification

In our specific situation where confectioners' stores are analysed, we decided to measure the *theoretical variable q* in model (1) by total *value* of annual store sales of *home-made*[9] products, Q_{hm}, divided by some appropriate store price index for home-made products, p_{hm}:

$$q_{hm} = Q_{hm}/p_{hm} \tag{2}$$

The variable q_{hm} can be described as the realized *volume* of annual store sales of home-made products.

The *demand equation* (1a) is empirically specified as[10]

$$q^d_{hm} = \exp(\delta_0)A^{\delta_1}(S_c)^{\delta_2}(C - TL)^{\delta_3}\exp(\delta_4 F)(p_{hm})^{\delta_5} \times \exp\{\delta_6(Q_{nhm}/Q) + \delta_7 Dtl\} \tag{3a}$$

where q^d_{hm} is value of annual store demand for home-made products, divided by p_{hm}; A is annual advertising expenses; S_c is selling service, measured as number of weekly working hours of selling personnel (including the storekeeper's wife) per square metre of selling area; C is selling area (room for customers); TL is part of selling area used for tearoom and/or lunchroom; F is share of the assortment groups '*nat gebak*' (i.e., products like cream confections and chocolate éclairs) and '*droog gebak*' (i.e., products like sweet biscuits and butter-cake) in total value of home-made products sales; p_{hm} is store price index for home-made products; the exact definition is given below; Q_{nhm} is total value of annual sales of products that are not home-made; Q is total value of annual sales; and Dtl is dummy tearoom/lunchroom: equals one for stores having a tearoom and/or lunchroom, zero otherwise.

Volume of annual store demand for home-made products is made a function of advertising expenses, service level, selling space, assortment composition, price level, share of products that are not home-made and presence of a tearoom and/or lunchroom. The exp(·) function is used in Equation 3a to avoid that the right-hand side becomes zero when F, Q_{nhm}/Q or Dtl is zero.

This specification is comparable to earlier demand equations that we used in disequilibrium models. Cf. Bode *et al.* (1988, Equation 2 on p. 109) and especially Bode *et al.* (1990, Equation 6 on p. 47). We made some alterations to take into account specific aspects of confectioner's stores operations. Both the share of specific assortment groups among the home-made products sales, F, and the share of products that are not home-made in total value of annual sales, Q_{nhm}/Q, may influence the volume of demand in confectioner's stores. In addition, the presence of a tearoom and/or lunchroom is explicitly considered. This is reflected in the dummy variable Dtl, while the space used for tearoom and/or lunchroom, TL, is subtracted from the total room for customers, C.

The *supply capacity equation* reads:

$$q^s_{hm} = \exp(\beta_0 + \beta_1 F)H^{\beta_2}C^{\pi\varepsilon}(W - C)^{(1-\pi)\varepsilon}\exp\{\beta_3(Q_{nhm}/Q) + \beta_4 Dsib\} \tag{3b}$$

where q^s_{hm} is value of annual store supply capacity of home-made products, divided by p_{hm}; H is annual occupancy costs per square metre of total floorspace; W is total floorspace, i.e., selling area, C, plus remaining space for production, storage and office; $Dsib$ equals one for confectioners who also sell products to other stores and/or institutions and businesses, minus one for confectioners who do not, and zero if information is not available from the questionnaire.

Volume of annual store supply capacity of home-made products is specified as a function of assortment composition, occupancy costs per unit of floorspace, selling area, remaining space, share of products that are not home-made and a variable indicating whether a confectioner also sells products to other stores and/or institutions and businesses.

See again our earlier papers for comparable supply capacity equations: Bode *et al.* (1988, Equation 3 on p. 110) and Bode *et al.* (1990, Equation 7 on p. 48), respectively. In the supply capacity equation above TL is not subtracted from

[7] Other possibilities could have been to exclude them from the data set, or to distribute them among the two regimes according to some probabilistic procedure.

[8] One US dollar was about 3.32 Dutch guilders in 1985.

[9] By 'home-made' products we mean products made on a premises. There are two reasons for restricting ourselves to home-made products sales: first, the majority of the confectioners' products sold are home-made. The average sample share in total value of annual sales is about 83%. This is what distinguishes confectioners from bakers. Secondly, the prior information question in the survey implicitly refers to home-made products.

[10] This demand equation was chosen as the 'best' one in terms of plausibility and fit after estimating several specifications using the 85 excess capacity observations. An analogous procedure was followed with respect to the supply capacity equation (cf. Equation 3b) using the 52 excess demand observations.

C. We assume that total floorspace, W, and the partitioning into selling area, C, and remaining space, $W - C$, determine supply capacity to a large extent[11] and that the presence of a tearoom and/or lunchroom does not play an important explicit role. We take into account that confectioners' stores which also sell products to other stores and/or institutions and businesses, produce more efficiently through anticipation and suppressing fluctuating demand. This should be reflected in a positive value for β_4.

The *minimum condition* Equation 1c now becomes:

$$q_{hm} = \min(q^d_{hm}, q^s_{hm}) \tag{3c}$$

The *store price index* for home-made products, p_{hm}, is defined as follows:

$$p_{hm} = \{1 - (Q_{sib}/Q)\}p^*_{hm} + (Q_{sib}/Q)(1 - \alpha_{sib})p^*_{hm} \tag{4}$$

where Q_{sib} is total value of annual sales to other stores and/or institutions and businesses; p^*_{hm} is a weighted average of product prices of some typical confectioners' stores products;[12] α_{sib} is the average discount rate for other stores and/or institutions and businesses; in our analysis we assume $\alpha_{sib} = 0.25$ after consultation with the '*Bedrijfschap Banketbakkersbedrijf*'[13] in Zeist, The Netherlands. This definition reflects the fact that other stores, institutions and businesses pay a lower price than individual customers.

IV. EMPIRICAL RESULTS

Estimation method

Equations 3a–3c are written in logarithm form,[14] disturbances are added to the demand equation and the supply capacity equation,[15] and observations are indexed by i. We then get the following model to be used for estimation:

$$\begin{aligned}\ln(q^d_{hm})_i = {} & \delta_0 + \delta_1 \ln A_i + \delta_2 \ln(S_c)_i + \delta_3 \ln(C_i - TL_i) \\ & + \delta_4 F_i + \delta_5 \ln(p_{hm})_i + \delta_6 (Q_{nhm})_i/Q_i \\ & + \delta_7 Dtl_i + U^d_i \end{aligned} \tag{5a}$$

$$\begin{aligned}\ln(q^s_{hm})_i = {} & \beta_0 + \beta_1 F_i + \beta_2 \ln H_i + \pi\varepsilon \ln C_i \\ & + (1 - \pi)\varepsilon \ln(W_i - C_i) + \beta_3 (Q_{nhm})_i/Q_i \\ & + \beta_4 Dsib_i + U^s_i \end{aligned} \tag{5b}$$

$$\ln(q_{hm})_i = \min\{\ln(q^d_{hm})_i, \ln(q^s_{hm})_i\} \tag{5c}$$

The method of maximum likelihood is applied to find parameter estimates. We assume that the disturbances U^d_i and U^s_i are independently normally distributed with zero mean and variance σ^2_d and σ^2_s, respectively. The likelihood function L to be maximized with respect to the parameter vector θ, depends on whether sample separation information is present or not:

Sample separation unknown (SSU). In this case only $(q_{hm})_i$ is observed. Denoting the right-hand sides of Equations 5a and b by $R^d(X^d_i) + U^d_i$ and $R^s(X^s_i) + U^s_i$, respectively, it is shown in Appendix B that the likelihood function equals

$$\begin{aligned} L = \prod_{i=1}^{N} & (n(\ln(q_{hm})_i - R^d(X^d_i); \sigma_d)\{1 - N([\ln(q_{hm})_i \\ & - R^s(X^s_i)]/\sigma_s)\} + n(\ln(q_{hm})_i - R^s(X^s_i); \sigma_s) \\ & \times \{1 - N([\ln(q_{hm})_i - R^d(X^d_i)]/\sigma_d)\}) \end{aligned} \tag{6a}$$

where N denotes the sample size, $n(.;\sigma)$ is the normal density function with zero mean and variance σ^2, and $N(.)$ is the cumulative standardized normal distribution function.

Sample separation known (SSK). In this situation both $(q_{hm})_i$ and the corresponding regime is observed. We can use the regime information to classify the observations into excess capacity observations and excess demand observations. Let us denote the set of indices for which $(q^d_{hm})_i < (q^s_{hm})_i$ by I_d and the set for which $(q^d_{hm})_i \geq (q^s_{hm})_i$ by I_s. The likelihood function now becomes

$$\begin{aligned} L = \prod_{i \in I_d} & (n(\ln(q_{hm})_i - R^d(X^d_i); \sigma_d)\{1 - N([\ln(q_{hm})_i \\ & - R^s(X^s_i)]/\sigma_s)\}) \prod_{i \in I_s} (n(\ln(q_{hm})_i - R^s(X^s_i); \sigma_s) \\ & \times \{1 - N([\ln(q_{hm})_i - R^d(X^d_i)]/\sigma_d)\}) \end{aligned} \tag{6b}$$

[11]See Thurik (1984) and Thurik and Koerts (1984a; 1984b) for an extensive study of this relationship.

[12]In the survey total sales value of home-made products was partitioned into four specific assortment groups $(Q_{hm})_1$ through $(Q_{hm})_4$ and one remaining group $(Q_{hm})_5$. For each specific assortment group storekeepers were asked to give the 1985 usual product prices of some typical products belonging to that group. For each observation these product prices were averaged per assortment group, yielding $\overline{p_1}$ through $\overline{p_4}$, and then the variable p^*_{hm} was defined as

$$p^*_{hm} = \sum_{k=1}^{4} \overline{p_k}(Q_{hm})_k \Big/ \sum_{k=1}^{4} (Q_{hm})_k.$$

[13]The trade organization of the Dutch confectioners.

[14]We aim at a multiplicative disturbance structure in Equations 3a and b. Therefore, the equations are written in logarithm form before disturbances are added.

[15]No disturbance term is added to Equation 3c because the minimum condition is considered as a definition equation. Kooiman *et al.* (1985, p. 127) use a different argument, but employ the same stochastic specification.

See again Appendix B for the derivation. This likelihood function contains the same parts as likelihood function Equation 6a, but now L is of the form

$$L = \prod_{i \in I_d} (expression)_{1i} \times \prod_{i \in I_s} (expression)_{2i} \quad (7b)$$

instead of

$$L = \prod_{i=1} \{(expression)_{1i} + (expression)_{2i}\} \quad (7a)$$

Numerical maximization of $\ln L$ with respect to the parameter vector θ yields an estimate $\hat{\theta}_{ML}$ of θ. The asymptotic distribution of the maximum likelihood estimator $\hat{\theta}_{ML}$ is multivariate with mean θ and covariance matrix Σ. A consistent estimate of Σ is given by $\hat{\Sigma}$, where $\hat{\Sigma} = (\partial^2 \ln L/\partial\theta\partial\theta^T)^{-1}_{\theta=\hat{\theta}_{ML}}$.

Estimation results: disequilibrium model

The estimation results of disequilibrium model (5) are presented in columns 1 and 2 of Table 1: column 1 shows the results in case sample separation is unknown (using likelihood function Equation 6a)[16] and column 2 contains the parameter estimates in case sample separation is known (using likelihood function Equation 6b). First of all, we discuss the results in column 2 where use is made of the regime information.[17]

Looking at the *demand equation* we conclude:

δ_1 (advertising): the volume of annual demand for home-made products in confectioners' stores is significantly influenced by the store's annual advertising expenses. The advertising elasticity is 0.18.

δ_2 (selling service): the selling service has a significant effect on demand. When the number of working hours of selling personnel per unit of selling space increases, the volume of demand also increases.

δ_3 ($C - TL$): the size of the room where products are sold also has a significant effect on demand. The higher $C - TL$, the higher volume of demand.

δ_4 (assortment): stores with a relatively large share of '*hat gebak*' and '*droog gebak*' in total value of home-made products sales, are confronted with a demand volume that is somewhat lower than average, although the effect is not significant.

δ_5 (price): there is no significant effect of price level on the volume of demand. It is possible that p_{hm} not only measures prices, but also the quality of the products sold. If this is the case, the sign of δ_5 is not known in advance.

δ_6 (Q_{nhm}/Q): the higher the share of products that are not home-made, the lower the volume of demand for home-made products.

δ_7 (dummy tearoom/lunchroom): the presence of a tearoom and/or lunchroom influences demand significantly.

With respect to the *supply capacity equation* we conclude:

β_1 (assortment): the share of '*nat gebak*' and '*droog gebak*' in total value of home-made products sales has a negative effect on store supply capacity, although the effect is not significant.

β_2 (occupancy costs): the higher the occupancy costs per unit of floorspace, the larger the store supply capacity. If stores are located in an expensive area, floorspace is used more efficiently.

β_3 (Q_{nhm}/Q): supply capacity of home-made products is smaller than average in stores which sell relatively few home-made products (i.e., Q_{nhm}/Q is high).

β_4 (*Dsib*): stores which also sell products to other stores and/or institutions and businesses seem to use their floorspace more efficiently than stores which do not sell to these customer groups.

π (distribution parameter): $\hat{\pi}$ is about 0.48. This indicates that selling area and remaining space are about equally important in determining store supply capacity of home-made products. This contradicts the results found in Thurik (1984, p. 103), where a comparable specification is estimated on a sample that contains both excess capacity and excess demand observations. In that study $\hat{\pi}$ was found to be 0.24.

ε (homogeneity parameter): the value 0.68 for $\hat{\varepsilon}$ indicates that there are no economies of scale in confectioners' stores. This value is somewhat lower than the value 0.92 found in Thurik (1984).

Next, the results in column 1 and column 2 are compared with each other. It appears that all corresponding parameter estimates have the same sign, except for $\hat{\beta}_0$ which is negative in column 2 and positive (but not significant) in column 1. Apart from the intercepts $\hat{\delta}_0$ and $\hat{\beta}_0$ there are two parameter estimates that are significant in column 2 but not significant in column 1, viz., $\hat{\beta}_3$ and $\hat{\varepsilon}$,[18] and two parameter estimates that are significant in column 1 but not in column 2, viz., $\hat{\delta}_5$ and $\hat{\beta}_1$. Comparing the parameter estimates in terms of their corresponding 90% confidence intervals, we

[16]Trying several combinations of starting values for the optimization process, we found three *local* extremes of ln L. The results in column 1 correspond to the *global* extreme found. Of course, theoretically it is possible that this is also a local extreme. If so, this may explain why the estimate for the distribution parameter π is at its lower bound of zero.

[17]*Given correct model specification*, either set of estimates (SSU and SSK) should be *consistent*, but in the case of SSK the estimates should be more *efficient*. Therefore, the SSK results are expected to be most accurate.

[18]We do not trust the estimate zero (lower bound) for π in column 1. As mentioned in Footnote 16 three local extremes of ln L were found. In one of these situations $\hat{\pi}$ was found to be 0.60, which seems more realistic. The fact the $\hat{\pi}$ is zero in column 1 may also explain why $\hat{\varepsilon}$ is very small and not significant. (The local extreme with $\hat{\pi} = 0.60$ gave $\hat{\varepsilon} = 1.10$.)

Table 1. *Estimation results of disequilibrium model (5) and single Equations 8a and b*

Parameter	Model 5 SSU	Model 5 SSK	Equation 8a $N = N_d$	Equation 8b $N = N_s$	Equation 8a $N = N_t$	Equation 8b $N = N_t$
Demand equation						
δ_0 Intercept	3.484	0.949	− 0.266		2.147	
	(1.850)	(1.893)*	(1.906)*		(1.344)*	
δ_1 Advertising	0.191	0.178	0.155		0.166	
	(0.047)	(0.043)	(0.038)		(0.031)	
δ_2 Selling service	0.953	0.446	0.343		0.446	
	(0.161)	(0.111)	(0.112)		(0.080)	
δ_3 *C-TL*	1.053	0.468	0.531		0.500	
	(0.204)	(0.143)	(0.126)		(0.104)	
δ_4 Assortment	− 0.043	− 0.228	− 0.203		− 0.213	
	(0.335)*	(0.231)*	(0.205)*		(0.170)*	
δ_5 Price	− 1.363	− 0.404	− 0.253		− 0.690	
	(0.390)	(0.379)*	(0.379)*		(0.267)	
δ_6 Q_{nhm}/Q	− 1.966	− 1.466	− 1.398		− 1.391	
	(0.397)	(0.362)	(0.323)		(0.267)	
δ_7 Dummy tea /lunchroom	2.771	0.570	0.525		0.558	
	(0.710)	(0.168)	(0.154)		(0.120)	
σ_d	0.420	0.535	0.408		0.423	
	(0.047)	(0.043)	(0.031)		(0.026)	
Supply capacity equation						
β_0 Intercept	0.122	− 1.831		− 1.245		− 2.394
	(0.695)*	(0.677)		(0.817)*		(0.464)
β_1 Assortment	− 0.444	− 0.336		− 0.679		− 0.181
	(0.260)	(0.249)*		(0.313)		(0.177)*
β_2 Occupancy costs	0.113	0.108		0.131		0.125
	(0.054)	(0.052)		(0.065)		(0.038)
β_3 Q_{nhm}/Q	− 0.496	− 0.993		− 0.966		− 1.595
	(0.516)*	(0.438)		(0.550)		(0.293)
β_4 *Dsib*	0.146	0.153		0.258		0.124
	(0.062)	(0.058)		(0.067)		(0.042)
π Distribution parameter	0	0.483		0.561		0.512
	(.)	(0.124)		(0.180)		(0.096)
ε Homogeneity parameter	0.169	0.677		0.515		0.683
	(0.113) *	(0.134)		(0.158)		(0.091)
σ_s	0.440	0.486		0.448		0.463
	(0.050)	(0.046)		(0.044)		(0.028)
Number of observations	137	137	85	52	137	137
ln *L* log-likelihood	− 63.670	− 166.644	− 44.486	− 32.020	− 76.450	− 89.014
r^2	0.622	0.548	0.601	0.451	0.571	0.485

Note: SSU stands for 'sample separation unknown', SSK for 'sample separation known'. N denotes the number of observations used: N_d is the number of excess capacity observation, i.e. 85; N_s is the number of excess demand observations, i.e. 52; N_t is total number of observations, i.e. 137. Estimated standard errors are printed in parentheses under the estimated parameters. An asterisk (*) is printed next to the estimated standard error $\hat{\sigma}(\hat{\theta})$ of parameter estimate $\hat{\theta}$ if $|\hat{\theta}| < 1.645\,\hat{\sigma}(\hat{\theta})$, i.e., if $\hat{\theta}$ does not differ significantly from zero at a 10% level of significance. r^2 denotes squared correlation coefficient of the dependent variable (ln (q_{hm})) and its fitted value. In case of SSU fitted value can be determined in two ways (cf. Gersovitz, 1980): first, fitted value equals $\min(\hat{R}^d(X^d), \hat{R}^s(X^s))$, where $\hat{R}^d(X^d)$ and $\hat{R}^s(X^s)$ stand for fitted values from Equation 5a and b, respectively. Secondly, fitted value equals $\hat{R}^d(X^d)$ if $\hat{P}_{ec} > 0.5$, and $\hat{R}^s(X^s)$ if $\hat{P}_{ec} < 0.5$, where $\hat{P}_{ec}$ is the estimated value of the *conditional regime probability* P_{ec} (see Appendix B). In our analysis both approaches resulted in the same value (0.622) of r^2 (up to the third decimal place). In case of SSK fitted value equals $\hat{R}^d(X^d)$ if an excess capacity regime applies, and $\hat{R}^s(X^s)$ if an excess demand regime applies. In columns 3 and 5 the fitted values used are $\hat{R}^d(X^d)$ and in columns 4 and 6 the fitted values are $\hat{R}^s(X^s)$.

find that in 5 out of 17 cases the confidence intervals do not overlap,[19] viz., in cases of $\hat{\delta}_2$, $\hat{\delta}_3$, $\hat{\delta}_7$, $\hat{\pi}$ and $\hat{\varepsilon}$. Hence, although there are some differences between the parameter estimates in column 1 and column 2, these differences are 'not significant' in 12 out of 17 cases. In terms of fit the SSU results seem to be slightly better: $r^2_{SSU} = 0.622$ and $r^2_{SSK} = 0.548$.

[19] I.e., $|\hat{\theta}_1 - \hat{\theta}_2| > 1.645(\hat{\sigma}(\hat{\theta}_1) + \hat{\sigma}(\hat{\theta}_2))$, where $\hat{\theta}_1$ refers to the estimate in column 1 and $\hat{\theta}_2$ to the estimate in column 2.

Estimation results: disequilibrium model versus single equation approach

Notwithstanding the theoretical objections against the use of a classical equilibrium model in our situation (as made clear in Section II), one still might use such an approach as a first approximation to a more complex model. It is interesting to see whether this approach in our specific example yields parameter estimates that are quite different from those using the disequilibrium model.

First of all, given the fact that we are in a position to classify our sample into excess capacity observations and excess demand observations (based on the regime information from the survey), we could estimate the demand Equation 5a on the set of observations for which $(q^d_{hm})_i < (q^s_{hm})_i$ (denoted by I_d) and the supply capacity Equation 5b on the the set for which $(q^d_{hm})_i \geqslant (q^s_{hm})_i$ (denoted by I_s).[20] Using $(q^d_{hm})_i = (q_{hm})_i$ under excess capacity and $(q^s_{hm})_i = (q_{hm})_i$ under excess demand, Equations 5a and b are rewritten as

$$\begin{aligned}\ln(q_{hm})_i = {} & \delta_0 + \delta_1 \ln A_i + \delta_2 \ln(S_c)_i + \delta_3 \ln(C_i - TL_i) \\ & + \delta_4 F_i + \delta_5 \ln(p_{hm})_i \\ & + \delta_6 (Q_{nhm})_i/Q_i + \delta_7 Dtl_i + U^d_i \end{aligned} \tag{8a}$$

for $i \in I_d$, and

$$\begin{aligned}\ln(q_{hm})_i = {} & \beta_0 + \beta_1 F_i + \beta_2 \ln H_i + \pi\varepsilon \ln C_i \\ & + (1 - \pi)\varepsilon \ln(W_i - C_i) \\ & + \beta_3 (Q_{nhm})_i/Q_i + \beta_4 Dsib_i + U^s_i \end{aligned} \tag{8b}$$

for $i \in I_s$, respectively. These equations are also estimated by means of the maximum likelihood method. The likelihood functions now boil down to[21]

$$L = \prod_{i \in I_d} n(\ln(q_{hm})_i - R^d(X^d_i); \sigma_d) \tag{9a}$$

for Equation 8a and

$$L = \prod_{i \in I_s} n(\ln(q_{hm})_i - R^s(X^s_i); \sigma_s) \tag{9b}$$

for Equation 8b. The estimation results are given in column 3 and column 4 of Table 1.[22]

Another approach, which does *not* make use of the sample separation information at all, would be to assume that Equations 8a and b hold for *all* observations in the sample, based on the assumption that $\ln(q^d_{hm})_i = \ln(q^s_{hm})_i = \ln(q_{hm})_i$. Next, let us estimate these equations separately by means of the maximum likelihood method. The likelihood functions now become

$$L = \prod_{i=1}^{N} n(\ln(q_{hm})_i - R^d(X^d_i); \sigma_d) \tag{10a}$$

for Equation 8a estimated on *all* observations, and

$$L = \prod_{i=1}^{N} n(\ln(q_{hm})_i - R^s(X^s_i); \sigma_s) \tag{10b}$$

for Equation 8b estimated on *all* observations. The estimation results are given in column 5 and column 6 of Table 1, respectively.

Comparing the single equation estimates in columns 3 and 4 with the disequilibrium estimates in column 2, it appears that they are generally more in line with the SSK results than the SSU estimates are. On the one hand, this is more or less a predictable outcome since both the estimates in column 2 and the estimates in columns 3 and 4 are based on the regime information from the survey, whereas the results in column 1 are not. On the other hand, as mentioned in Footnotes 17 and 20, *given* the fact that both model (5) and the regime information from the survey are correct, the estimates in column 1 should be *consistent* (although *less efficient*[23] than the estimates in column 2), whereas the parameter estimates in columns 3 and 4 should be *inconsistent*. Therefore, the SSU estimates might also have been closer to the SSK estimates than the single equation estimates are.

Looking at the estimates in columns 5 and 6, the same conclusions can be drawn: the parameter estimates in columns 5 and 6 are generally closer to the SSK results than the SSU results are. In addition, comparing the parameter estimates in column 2 with all remaining parameter estimates in Table 1, in 11 out of 17 cases the estimates in columns 5 and 6 are closest to the SSK estimates although the sample separation information is *not* used *at all*[24] in estimating the parameters in columns 5 and 6.[25] This result is even more surprising: we would have expected

[20]It should be noted that using the sample separation information in this way, produces *inconsistent* parameter estimates of disequilibrium model (5). Cf. Maddala (1983, pp. 293–4) and Fair and Jaffee (1972, pp. 503–4). But we are interested in the *extent* to which these estimates in our specific situation differ from the disequilibrium estimates. We will come back on this point in Section VI.

[21]Of course, maximizing the normal likelihoods (Equations 9a and b) just amounts to nonlinear least squares.

[22]These are in fact the final results of the model building procedure mentioned in Footnote 10. We followed this procedure to minimize specification errors in constructing the disequilibrium model.

[23]Note that in nearly all cases the *estimated* standard errors of the parameter estimates in column 1 are higher than the corresponding ones in column 2.

[24]Apart form the procedure followed to *develop* Equations 3a and b as described in Footnote 10.

[25]In three cases the estimates in columns 3 and 4 are closest, viz., in case of δ_5, δ_6 and β_3 and in three cases the estimates in column 1 (SSU) are closest to those in column 2, viz., in case of β_1, β_2 and β_4.

that the results in columns 3 and 4 would be closer to those in column 2 than the estimates in columns 5 and 6 would be.

Comparing the parameter estimates in terms of their 90% confidence intervals, we find that all intervals calculated from column 2 (SSK) and the corresponding intervals calculated from columns 5 and 6 overlap. The same holds true when we compare column 2 with columns 3 and 4 (except for $\hat{\sigma}_d$). On the other hand, comparing the confidence intervals based on the results of column 1 (SSU) with the intervals based on the single equation estimates of columns 3–6, we find more nonoverlapping intervals: with respect to the parameter estimates $\hat{\delta}_2$, $\hat{\delta}_7$ and $\hat{\pi}$ there are 'significant' differences between column 1 and columns 3 and 4, and with respect to the parameter estimates $\hat{\delta}_2$, $\hat{\delta}_3$, $\hat{\delta}_7$, $\hat{\beta}_0$, $\hat{\pi}$ and $\hat{\varepsilon}$ there are 'significant' differences between column 1 and columns 5 and 6.

In order to compare the single equation approach with the disequilibrium estimates *in terms of fit* we combined the results in columns 3 and 4 and in columns 5 and 6, respectively: with respect to columns 3 and 4 for each observation i the fitted value of $\ln(q_{hm})_i$ was determined either by $\hat{R}^d(X_i^d)$ or by $\hat{R}^s(X_i^s)$ depending on which regime applied according to the regime information. With respect to columns 5 and 6 the fitted value was defined as the minimum of $\hat{R}^d(X_i^d)$ and $\hat{R}^s(X_i^s)$. Next, the squared correlation coefficient of $\ln(q_{hm})$ and its corresponding fitted value (based on all $N_t = 137$ observations) was determined, yielding $r^2 = 0.569$ for columns 3 and 4 and $r^2 = 0.528$ for columns 5 and 6. The single equations approach in columns 3 and 4 apparently results in a fit that is slightly better than the disequilibrium approach with sample separation known. But differences are not very large.

Summarizing, there are some differences between the various models/equations used in this section, but these differences *in a certain sense* are not large: most corresponding 90% confidence intervals overlap. With respect to the disequilibrium estimates this might imply that the information loss is not substantial in our situation if sample separation is not known. On the other hand, given the fact that the single equation estimates (in particular the results in columns 5 and 6) are generally (much) more in line with the SSK (disequilibrium) estimates than the SSU estimates are, we might conclude as well that the information loss is indeed substantial if we move from SSK to SSU. The fact that the single equation estimates in columns 5 and 6 closely resemble the SSK disequilibrium estimates, also seems to imply that the (theoretically incorrect) single equation estimates *practically* still are of interest in our situation as a first approximation to a more complex (disequilibrium) model. However, it is hard to draw definite conclusions based on this single concrete example. Such conclusions would directly depend on the quality of the data, the correctness of the regime information, the appropriateness of the functional specifications Equations 3a and b, etc. In order to correct for the type of shortcomings that are always present in a real world situation, in the next section some Monte Carlo experiments are conducted that will hopefully shed more light on the matter.

V. SOME CAVEATS

Of course, the results obtained in the empirical section depend on:

1. the appropriateness of the assumption of *disequilibrium*;
2. the correctness of the *regime information*;
3. the quality of the *data*; and
4. the suitability of the functional *specifications* Equations 3a and b.

ad 1. We started from the assumption that the annual volume of home-made products sales in confectioner's stores is determined by the interplay of supply capacity variables and demand factors. This does not necessarily imply that a disequilibrium model like Equation 1 is appropriate. In Bode *et al.* (1988, Footnote 2) we referred to Kiefer (1980) who argues that, given that q in Equation 1c does not represent an equilibrium, there is no reason to think it will be the minimum of q^d and q^s. However, as mentioned in Section II, the minimum condition Equation 1c should be interpreted as the result of the storekeeper's trying to meet demand given his supply capacity. We consider the supply side of our model as a technical restriction on the storekeeper's supply capabilities. Therefore, model (1) seems to be appropriate.

But there is another point worth mentioning. Stores are faced with strong demand fluctuations with daily, weekly, monthly and yearly components. A store may have excess capacity during *some* periods of opening time and excess demand during *other* periods. Then the minimum condition only holds *within* such periods of opening time, whereas we have $q < \min(q^d, q^s)$ on *annual* basis. This can be seen as follows: writing $q_{ij} = \min(q_{ij}^d, q_{ij}^s)$, where q_{ij} is realized volume of sales in store i during period j; q_{ij}^d is volume of demand in store i during period j; and q_{ij}^s is volume of supply capacity in store i during period j, it follows that

$$q_i = \sum_j q_{ij} \leqslant \sum_j q_{ij}^d = q_i^d \tag{11}$$

and

$$q_i = \sum_j q_{ij} \leqslant \sum_j q_{ij}^s = q_i^s \tag{12}$$

Therefore,

$$q_i \leqslant \min(q_i^d, q_i^s), \tag{13}$$

where strict inequality holds in case store i is in an excess capacity situation during *some* periods and in an excess demand situation during *other* periods.[26] However, our concepts of excess capacity and excess demand should be interpreted as describing the 'average situation' during a year. In that case model (1) is still appropriate.

ad 2. Assuming that the concept of disequilibrium is appropriate in our context, storekeepers may still have no clear idea about the regime that applies to their situation. It may not be easy to describe the 'average situation' during a year. Therefore, it is possible that our sample separation information is biased. This point will be further dealt with in the next section.

ad 3. Our sample consists of 137 Dutch confectioners' stores. A questionnaire was sent to all confectioners' stores operating in The Netherlands at the moment of observation (about 800). The number of respondents was 257. Both the number of observations and the number of variables that could be used for analysis had to be limited drastically due to missing values. In a number of cases we had to correct for inconsistencies in the data. We even sometimes had to estimate the missing values of specific variables ourselves in order not to get a too small sample. Therefore, some distrust exists with respect to the quality of the data.

ad 4. The procedure followed to develop Equations 3a and b was described in Footnote 10. These equations closely resemble demand equations and supply capacity equations used in earlier disequilibrium models. These earlier models were estimated on four largely differing types of stores in the Dutch retail trade and the results obtained were satisfactory.[27] This supports the suitability of Equations 3a and b. On the other hand we feel that the appropriateness of the specification used is crucial in the present analysis. There are several store characteristics and environmental factors that might be important variables in explaining store demand and store supply capacity. Some of these are competition, consumer characteristics and variables like image or atmosphere. These variables may very well improve the quality of Equations 3a and b, but they could not be used because of the data problems mentioned above.

VI. MONTE CARLO EXPERIMENTS

Following Goldfeld and Quandt (1975) a Monte Carlo experiment is conducted in order to remove the effects that the caveats 2, 3 and 4 may have on the results found in the empirical section.

Design of experiments

Two adjustments are made to Equations 5a and b to restrict the number of parameters to be estimated: the variable 'assortment' is removed both from the demand equation and from the supply capacity equation. The parameter estimate $\hat{\delta}_4$ did not differ significantly from zero in all models/equations in Table 1. The same holds true for $\hat{\beta}_1$ in 2 out of 4 cases. Hence, the following model equations are used in the simulation analysis:

$$\ln(q^d_{hm})_i = \delta_0 + \delta_1 \ln A_i + \delta_2 \ln(S_c)_i + \delta_3 \ln(C_i - TL_i) + \delta_5 \ln(p_{hm})_i + \delta_6 (Q_{nhm})_i/Q_i + \delta_7 Dtl_i + U^d_i \quad (14a)$$

$$\ln(q^s_{hm})_i = \beta_0 + \beta_2 \ln H_i + \pi\varepsilon \ln C_i + (1-\pi)\varepsilon \ln(W_i - C_i) + \beta_3 (Q_{nhm})_i/Q_i + \beta_4 Dsib_i + U^s_i \quad (14b)$$

$$\ln(q_{hm})_i = \min\{\ln(q^d_{hm})_i, \ln(q^s_{hm})_i\} \quad (14c)$$

First of all, the model is estimated on the sample of 137 observations using the original regime information from the survey. The results are shown in Table 2. As a result of the adjustments made the value of ln L has decreased from − 166.64 in Table 1 to − 168.03 and the value of r^2 declines from 0.548 to 0.535. The parameter estimates are (of course) very close to the SSK results in column 2 of Table 1. Next, the estimated parameter values in Table 2 are taken as true parameter values. Observations on the endogenous variables $\ln(q^d_{hm})_i$ and $\ln(q^s_{hm})_i$ are generated from Equations 14a and b using independently normally distributed disturbances with variances σ^2_d and σ^2_s equal to the (squared) estimated values from Table 2. Observations on $\ln(q_{hm})_i$ are determined from definition (14c). Each experiment is replicated 50 times. Regime information is now directly available from the individual observations on $\ln(q^d_{hm})_i$ and $\ln(q^s_{hm})_i$.

We varied the values of σ_d and σ_s in order to study the effect of differences in quality of the specifications of the model equations: case 1 refers to the basic situation where $\sigma_d = 0.538$ and $\sigma_s = 0.495$; case 4 corresponds with the situation where $\sigma_d = 0.0538$ and $\sigma_s = 0.0495$, i.e. the standard deviations of the disturbances have decreased with a factor 10; in case 3 $\sigma_d = 0.2690$ and $\sigma_s = 0.2475$, i.e. the standard

[26]Modelling this situation becomes very complicated if only annual sales data are available. We have tried to estimate a model which has the same structure as the model presented in Kooiman (1986, Ch. 3). He formulated a model for *aggregate* employment where at the level of *micro* labour markets transactions equal the minimum of supply and demand. Our situation, where store sales volume instead of total employment in The Netherlands is explained, is similar if 'periods' are considered as micro markets and a 'year' is considered as the aggregate level. But we had computational problems in finding the parameter estimates. More research is still necessary to get more definite conclusions with respect to this complicated disequilibrium model, but we feel that here Maddala's (1983) concern that we are asking too much from the data might indeed be a serious point.
[27]See Bode *et al.* (1988, Table 1; 1990, Table VI).

Table 2. *Estimation results of disequilibrium model (14) using the sample separation information from the survey*

Demand equation			Supply capacity equation		
δ_0	Intercept	1.441 (1.809)*	β_0	Intercept	− 2.139 (0.650)
δ_1	Advertising	0.178 (0.043)	β_2	Occupancy costs	0.098 (0.053)
δ_2	Selling service	0.445 (0.112)	β_3	Q_{nhm}/Q	− 1.030 (0.439)
δ_3	$C - TL$	0.471 (0.144)	β_4	*Dsib*	0.146 (0.058)
δ_5	Price	− 0.532 (0.352)*	π	Distribution parameter	0.461 (0.121)
δ_6	Q_{nhm}/Q	− 1.483 (0.365)	ε	Homogeneity parameter	0.700 (0.135)
δ_7	Dummy tea/lunchroom	0.573 (0.169)			
σ_d		0.538 (0.043)	σ_s		0.495 (0.047)
Number of observations		137			
ln L log-likelihood		− 168.033			
r^2		0.535			

Note: See note Table 1.

deviations have decreased with a factor 2; case 2, finally, corresponds with $\sigma_d = 0.41$ and $\sigma_s = 0.41$.[28]

In accordance with the analysis in the empirical Section IV, in the simulation analysis again four types of models c.q. equations are estimated on the generated data:

1. model (14) is estimated using all N_t ($=137$) observations, making *no* use of the information on the (generated) regimes (SSU);
2. model (14) is estimated using all N_t ($=137$) observations making use of the (generated) regime information (SSK);
3. Equation 15a below (which is similar to Equation 8a in the empirical section) is estimated using the N_d (generated) excess capacity observations and Equation 15b (similar to Equation 8b) is estimated using the N_s (generated) excess demand observations;[29]
4. Equations 15a and b are estimated separately using all N_t ($=137$) observations.

In view of model (14) the single equations to be used in the simulation analysis now become

$$\ln(q_{hm})_i = \delta_0 + \delta_1 \ln A_i + \delta_2 \ln(S_c)_i + \delta_3 \ln(C_i - TL_i) + \delta_5 \ln(p_{hm})_i + \delta_6 (Q_{nhm})_i/Q_i + \delta_7 Dtl_i + U_i^d \quad (15a)$$

$$\ln(q_{hm})_i = \beta_0 + \beta_2 \ln H_i + \pi\varepsilon \ln C_i + (1-\pi)\varepsilon \times \ln(W_i - C_i) + \beta_3 (Q_{nhm})_i/Q_i + \beta_4 Dsib_i + U_i^s, \quad (15b)$$

respectively (cf. Equations 8a and b).

Results of experiments

Table 3 shows the mean biases[30] of the parameter estimates for all models and cases. The root mean-square errors (RMSEs)[31] are presented in Table 4. In addition, the ratios of the RMSEs of the SSK estimates to the corresponding RMSEs of the SSU estimates (of model (14)) are given in Table 5. The following conclusions can be drawn:

Basic set of experiments. Inspecting the SSK results for case 1 in terms of the *mean biases* it appears that the results are

[28]These latter values were chosen such that the proportion of variation in the dependent variable (i.e. $\ln(q_{hm})$) could expected to be about 0.60 (which is quite satisfactory in a cross-section context). The value of 0.41 was determined *very roughly* by solving the equation $R^2 = 0.60 = 1 - \sigma^2/S^2_{\ln(qhm)}$ in terms of σ^2, where $S^2_{\ln(qhm)}$ stands for the sample variance of $\ln(q_{hm})$ *in the survey* (i.e. 0.65^2).
[29]In the basic set of experiments (i.e. $\sigma_d = 0.538$ and $\sigma_s = 0.495$) N_d varied from 74 to 97, with an average value of 87.3 which is comparable with the value $N_d = 85$ in the survey. (Hence, N_s varied from 40 to 63 with an average value of 49.7.) As a result of changing the values of σ_d and σ_s in the cases 2 through 4, the values of N_d and N_s also change: in case 2 N_d varied from 77 to 100 with an average value of 89.2; in case 3 N_d varied from 87 to 111 with an average value of 98.3; in case 4 N_d varied from 107 to 115 with an average value of 111.3.
[30]I.e., $1/50\sum_{r=1}^{50}(\hat{\theta}_r - \theta_0)$, where r is a replication index and θ_0 is the true parameter value from Table 2.
[31]I.e., $(1/50\sum_{r=1}^{50}(\hat{\theta}_r - \theta_0)^2)^{1/2}$.

Table 3. *Mean biases of parameter estimates*

		Case 1 ($\sigma_d = 0.538$ $\sigma_s = 0.495$)				Case 2 ($\sigma_d = 0.41$ $\sigma_s = 0.41$)				Case 3 ($\sigma_d = 0.2690$ $\sigma_s = 0.2475$)				Case 4 ($\sigma_d = 0.0538$ $\sigma_s = 0.0495$)			
	True value	model (14) SSU	model (14) SSK	eq. (15a) & (15b) $N = N_d$ & $N = N_s$	eq. (15a) & (15b) $N = N_t$	model (14) SSU	model (14) SSK	eq. (15a) & (15b) $N = N_d$ & $N = N_s$	eq. (15a) & (15b) $N = N_t$	model (14) SSU	model (14) SSK	eq. (15a) & (15b) $N = N_d$ & $N = N_s$	eq. (15a) & (15b) $N = N_t$	model (14) SSU	model (14) SSK	eq. (15a) & (15b) $N = N_d$ & $N = N_s$	eq. (15a) & (15b) $N = N_t$
Demand equation																	
δ_0	(1.441)	0.8516	0.2915	− 0.6488	− 0.9260	− 0.1422	− 0.1602	− 0.7376	− 1.2514	0.1130	− 0.0251	− 0.4090	− 1.0177	0.0164	0.0207	− 0.0128	− 0.9364
δ_1	(0.178)	0.0155	− 0.0011	− 0.0213	− 0.0365	0.0046	0.0039	− 0.0204	− 0.0363	0.0048	0.0034	− 0.0146	− 0.0290	0.0007	0.0006	− 0.0004	− 0.0247
δ_2	(0.445)	0.0936	0.0141	− 0.0667	− 0.0974	0.0341	0.0127	− 0.0660	− 0.1135	0.0147	0.0047	− 0.0553	− 0.0860	0.0014	0.0013	− 0.0010	− 0.0678
δ_3	(0.471)	0.0512	0.0193	0.0419	0.0286	0.0277	− 0.0029	− 0.0031	0.0072	0.0040	− 0.0030	0.0060	0.0048	0.0002	0.0010	0.0019	0.0120
δ_5	(− 0.532)	− 0.2140	− 0.0710	0.0637	0.1414	0.0026	0.0294	0.1261	0.2300	− 0.0271	0.0044	0.0689	0.1937	− 0.0035	− 0.0049	0.0008	0.1810
δ_6	(− 1.483)	0.2505	0.0361	0.1664	0.0981	0.1122	0.0206	0.0879	0.0539	− 0.0106	0.0102	0.0662	0.0293	− 0.0031	− 0.0016	0.0037	− 0.0426
δ_7	(0.573)	0.2070	0.0347	− 0.0584	− 0.1057	0.0911	0.0292	− 0.0533	− 0.1224	0.0305	0.0070	− 0.0575	− 0.1100	0.0022	0.0022	− 0.0005	− 0.1006
σ_d		− 0.0515	− 0.0180	− 0.0970	− 0.0945	− 0.0399	− 0.0137	− 0.0666	− 0.0570	− 0.0142	− 0.0100	− 0.0336	− 0.0236	− 0.0014	− 0.0013	− 0.0018	0.0486
Supply capacity equation																	
β_0	(− 2.139)	− 0.5060	− 0.1081	− 0.0685	0.0043	− 0.1225	0.1012	0.0819	0.0969	− 0.0242	0.0198	0.0865	0.2158	− 0.0212	− 0.0138	− 0.0336	0.3098
β_2	(0.098)	0.0277	− 0.0035	0.0007	− 0.0029	− 0.0365	− 0.0036	− 0.0146	− 0.0047	− 0.0149	− 0.0085	− 0.0031	− 0.0062	0.0000	0.0010	0.0020	− 0.0052
β_3	(− 1.030)	− 0.1281	0.0424	− 0.2786	− 0.5263	− 0.0718	− 0.0491	− 0.2434	− 0.5719	0.3112	0.0589	− 0.1091	− 0.6238	0.0054	0.0098	0.0278	− 0.7241
β_4	(0.146)	0.0588	− 0.0019	− 0.0287	− 0.0425	0.0900	0.0160	− 0.0088	− 0.0377	0.0270	0.0010	− 0.0142	− 0.0402	− 0.0001	− 0.0008	− 0.0013	− 0.0468
π	(0.461)	− 0.0249	− 0.0149	0.0401	0.0545	0.0045	0.0239	0.0923	0.0611	− 0.0254	− 0.0050	0.0131	0.0502	0.0033	0.0003	0.0029	0.0620
ε	(0.700)	0.1629	0.0312	− 0.0461	− 0.0844	0.1180	− 0.0177	− 0.0487	− 0.0915	0.0233	0.0037	− 0.0495	− 0.1031	0.0048	0.0014	0.0029	− 0.1103
σ_s		− 0.1775	− 0.0186	− 0.1019	− 0.0183	− 0.1010	− 0.0317	− 0.0944	− 0.0205	− 0.0427	− 0.0124	− 0.0461	0.0631	− 0.0069	− 0.0063	− 0.0064	0.1851

Table 4. *Root mean-square errors (RMSEs) of parameter estimates*

True value		Case 1 ($\sigma_d = 0.538$ $\sigma_s = 0.495$)				Case 2 ($\sigma_d = 0.41$ $\sigma_s = 0.41$)			
		model (14) SSU	model (14) SSK	eq. (15a) & (15b) $N = N_d$ & $N = N_s$	eq. (15a) & (15b) $N = N_t$	model (14) SSU	model (14) SSK	eq. (15a) & (15b) $N = N_d$ & $N = N_s$	eq. (15a) & (15b) $N = N_t$
Demand equation									
δ_0	(1.441)	3.6450	2.0584	2.0971	1.6755	2.4547	1.3420	1.9041	1.6962
δ_1	(0.178)	0.0876	0.0370	0.0478	0.0479	0.0699	0.0302	0.0379	0.0454
δ_2	(0.445)	0.3234	0.1217	0.1342	0.1300	0.2071	0.1001	0.1204	0.1365
δ_3	(0.471)	0.2087	0.1452	0.1452	0.1090	0.1668	0.1037	0.0952	0.0840
δ_5	(− 0.532)	0.7009	0.3953	0.3835	0.2963	0.4812	0.2600	0.3588	0.3174
δ_6	(− 1.483)	0.9237	0.3630	0.4011	0.2602	0.5214	0.2562	0.2752	0.2311
δ_7	(0.573)	0.5939	0.1790	0.2070	0.1521	0.3024	0.1496	0.1821	0.1662
σ_d		0.1097	0.0523	0.1054	0.1001	0.0784	0.0315	0.0721	0.0613
Supply capacity equation									
β_0	(− 2.139)	1.6653	0.5829	0.6784	0.4566	1.4795	0.5059	0.6003	0.3839
β_2	(0.098)	0.1831	0.0607	0.0666	0.0413	0.1338	0.0342	0.0436	0.0295
β_3	(− 1.030)	1.3260	0.3648	0.5635	0.5814	1.0335	0.3632	0.5663	0.6083
β_4	(0.146)	0.2540	0.0651	0.0748	0.0563	0.2903	0.0517	0.0562	0.0478
π	(0.461)	0.2902	0.1127	0.1578	0.1295	0.2140	0.1008	0.1366	0.0938
ε	(0.700)	0.5234	0.1192	0.1344	0.1259	0.3809	0.1061	0.1304	0.1141
σ_s		0.2342	0.0485	0.1098	0.0377	0.1686	0.0535	0.1009	0.0351

True value		Case 3 ($\sigma_d = 0.2690$ $\sigma_s = 0.2475$)				Case 4 ($\sigma_d = 0.0538$ $\sigma_s = 0.0495$)			
		model (14) SSU	model (14) SSK	eq. (15a) & (15b) $N = N_d$ & $N = N_s$	eq. (15a) & (15b) $N = N_t$	model (14) SSU	model (14) SSK	eq. (15a) & (15b) $N = N_d$ & $N = N_s$	eq. (15a) & (15b) $N = N_t$
Demand equation									
δ_0	(1.441)	1.1447	0.8846	1.0377	1.2439	0.1925	0.1792	0.1893	0.9499
δ_1	(0.178)	0.0266	0.0198	0.0245	0.0336	0.0039	0.0037	0.0039	0.0250
δ_2	(0.445)	0.0794	0.0556	0.0770	0.0983	0.0139	0.0132	0.0132	0.0686
δ_3	(0.471)	0.0835	0.0647	0.0650	0.0533	0.0172	0.0167	0.0163	0.0180
δ_5	(− 0.532)	0.2094	0.1599	0.1800	0.2314	0.0408	0.0380	0.0397	0.1841
δ_6	(− 1.483)	0.2026	0.1808	0.1764	0.1617	0.0325	0.0303	0.0314	0.0508
δ_7	(0.573)	0.1295	0.0979	0.1119	0.1304	0.0184	0.0178	0.0174	0.1014
σ_d		0.0230	0.0179	0.0364	0.0270	0.0040	0.0042	0.0041	0.0487
Supply capacity equation									
β_0	(− 2.139)	0.8533	0.3083	0.4197	0.3144	0.1242	0.1007	0.1214	0.3135
β_2	(0.098)	0.0737	0.0336	0.0315	0.0195	0.0099	0.0085	0.0093	0.0069
β_3	(− 1.030)	1.7772	0.2913	0.3544	0.6443	0.1005	0.0874	0.0968	0.7247
β_4	(0.146)	0.1157	0.0329	0.0430	0.0444	0.0132	0.0105	0.0112	0.0470
π	(0.461)	0.1358	0.0763	0.0873	0.0698	0.0197	0.0216	0.0231	0.0634
ε	(0.700)	0.1854	0.0668	0.1093	0.1131	0.0283	0.0245	0.0272	0.1109
σ_s		0.0687	0.0276	0.0529	0.0662	0.0109	0.0096	0.0101	0.1852

Table 5. *Ratios of RMSEs* (*model* (*14*): *SSK*/*SSU*)

Parameter	Case 1	Case 2	Case 3	Case 4
Demand equation				
δ_0	0.5647	0.5467	0.7728	0.9309
δ_1	0.4225	0.4313	0.7462	0.9547
δ_2	0.3763	0.4834	0.6997	0.9559
δ_3	0.6958	0.6217	0.7749	0.9718
δ_5	0.5641	0.5403	0.7634	0.9303
δ_6	0.3930	0.4914	0.8923	0.9319
δ_7	0.3013	0.4945	0.7558	0.9710
σ_d	0.4771	0.4021	0.7762	1.0369
Supply capacity equation				
β_0	0.3501	0.3420	0.3613	0.8107
β_2	0.3314	0.2558	0.4561	0.8619
β_3	0.2751	0.3514	0.2474	0.8696
β_4	0.2562	0.1781	0.2845	0.7941
π	0.3884	0.4712	0.5622	1.0977
ε	0.2277	0.2787	0.3601	0.8666
σ_s	0.2070	0.3173	0.4014	0.8811

quite satisfactory: the mean biases of the parameter estimates are relatively small compared with their true values. Apart from δ_0, which has a ratio of mean bias to true value of 0.20, the maximum (absolute) values for these ratios are 0.13 (δ_5) and 0.06 (δ_7). The average of the 15 ratios is 0.0525. The SSU results for case 1, on the other hand, are much worse: the maximum (absolute) values for the ratios of mean bias to true value are 0.59 (δ_0), 0.40 (β_4), 0.40 (δ_5), 0.36 (δ_7) and 0.36 (σ_s). The average of the 15 (absolute) ratios equals to 0.2478.

Looking at the SSK and the SSU results for case 1 in terms of the RMSEs we find again that the results for SSK are much better: the ratios of the RMSEs for SSK to the corresponding RMSEs for SSU (Table 5, column 1) are all substantially lower than 1, indicating that the regime information improves the estimation results considerably. The average ratio in this column is about 0.39, implying a more than 60% improvement 'on the average'.

We also computed the *ratio of the average* (*over replications*) *estimated asymptotic standard error to the RMSE* for each parameter. The results are given in Table 6 (for SSK and SSU only). Under general conditions these ratios converge to 1 as N tends to infinity. For case 1 these ratios are satisfactory for SSK[32] (although there is no rigorous test to determine when the ratios are 'close enough' to unity). In case of SSU, however, the RMSEs are about twice as large as the average estimated asymptotic standard errors.

Comparing cases 1–4 we find that in estimating the disequilibrium model, knowledge of the regime to which each individual observation belongs becomes less important. It appears that both the SSK results and (in particular) the SSU results become better when σ_d and σ_s decrease (as was to be expected). The (absolute) values of the *mean biases* (generally) decrease as we move from case 1 to case 4. For SSK the average (over 15 parameters) (absolute) ratios of mean bias to true value move from 0.0525 for case 1 via 0.0478 for case 2 and 0.0228 for case 3 to 0.0149 for case 4. Looking at SSU we can compute the following results for these averages: 0.2478 for case 1, 0.1425 for case 2, 0.0815 for case 3 and 0.0151 for case 4.

Inspecting the RMSEs again we see an improvement of the results as we move from case 1 to case 4. The decline in RMSEs for SSK is more or less proportional to the decline in the values of σ_d and σ_s. For example, the RMSEs in case 3 are about one half of the corresponding values in case 1. For SSU the decline is more than proportional: the ratios in Table 5 generally become better as we move to case 4. The average values of these ratios are: 0.39 for case 1, 0.41 for case 2, 0.59 for case 3 and 0.92 for case 4. Hence, in the situation where the standard deviations are about 0.05, on the average there are nearly no differences between estimating the disequilibrium model *with* and *without* the regime information (both in terms of mean biases and RMSEs).

Looking at Table 6 it appears that the *ratios of average estimated asymptotic standard errors to RMSEs* are sensitive to changes in σ_d and σ_s *in the case of SSU*: the ratios more closely approach unity as we move to case 4. For SSK no significant improvement can be found as σ_d and σ_s decrease. Apparently if sample separation is *not* known the *rate* of convergence of these ratios to unity depends on the quality

[32]Note that the RMSEs for SSK in case 1 are comparable with the estimated standard errors in Table 2, where the estimation results of model (14) using both the survey data and the regime information from the survey, were given.

Table 6. *Ratios of average (over replications) estimated asymptotic standard errors to RMSEs (model (14): SSU and SSK)*

	Case 1		Case 2		Case 3		Case 4	
Parameter	SSU	SSK	SSU	SSK	SSU	SSK	SSU	SSK
Demand equation								
δ_0	0.6173	0.8708	0.6521	1.0248	0.9108	1.0072	0.9787	1.0238
δ_1	0.5736	1.1360	0.5580	1.0601	0.9179	1.0393	1.0998	1.1349
δ_2	0.4600	0.8885	0.5362	0.8296	0.8680	0.9688	0.8633	0.8843
δ_3	0.7985	0.9722	0.7759	1.0370	0.9607	1.0758	0.8467	0.8574
δ_5	0.6129	0.8700	0.6342	1.0128	0.9472	1.0643	0.8763	0.9170
δ_6	0.5272	0.9827	0.6614	1.0600	0.9856	0.9633	1.1216	1.1926
δ_7	0.4590	0.9594	0.6145	0.8876	0.8810	0.8827	1.1045	1.1073
σ_d	0.4752	0.7654	0.4683	0.9533	0.9388	1.0403	0.8842	0.8393
Supply capacity equation								
β_0	0.4397	1.0368	1.3062	0.9695	0.6466	1.1130	0.8343	0.9069
β_2	0.3632	0.8438	0.4948	1.1848	0.5896	0.8383	0.8269	0.8173
β_3	0.4566	1.2228	0.5823	1.0141	0.4008	0.9664	0.9253	0.9471
β_4	0.4247	0.8963	4.3968	0.9211	0.5273	1.0068	0.8053	0.8841
π	0.4949	1.0887	0.6584	1.0376	0.7806	0.9118	1.0047	0.8204
ε	0.3151	1.0686	0.4412	0.9785	0.6938	1.1199	0.8399	0.8543
σ_s	0.2318	0.9708	0.3402	0.7063	0.5311	0.9294	0.5887	0.5823

Table 7. *Number of parameters in single equation approach having lower (absolute) value of mean bias and RMSE than in disequilibrium approach*

	Eq. (15a) & (15b) $[N = N_d \; \& \; N = N_s]$ vs model (14) [SSK]		Eq. (15a) & (15b) $[N = N_t]$ vs model (14) [SSK]		Eq. (15a) & (15b) $[N = N_d \; \& \; N = N_s]$ vs model (14) [SSU]		Eq. (15a) & (15b) $[N = N_t]$ vs model (14) [SSU]	
case	demand eq.	supply cap. eq.	demand eq.	supply cap. eq.	demand eq.	supply cap. eq.	demand eq.	supply cap. eq.
case 1								
RMSE	1	0	5	4	8	7	8	7
mean bias	1	2	0	3	6	5	4	5
case 2								
RMSE	1	0	2	5	8	7	8	7
mean bias	0	2	0	2	3	5	2	5
case 3								
RMSE	1	1	2	2	7	7	2	7
mean bias	0	1	0	1	0	4	0	1
case 4								
RMSE	4	0	0	1	7	6	0	1
mean bias	5	0	0	0	5	3	0	0

of the model equations (as expressed by the values of σ_d and σ_s).

In order to *compare the single equation approach with the disequilibrium estimates*, first of all (based on the results in Tables 3 and 4) for each case and model/equation we counted the number of parameters for which the single equation estimates yield better results than the disequilibrium estimates. The numbers are shown in Table 7. We conclude that both in terms of *mean bias* and in terms of RMSEs most of the time estimating model (14) using the regime information performs better than using the regime information to partition the data into excess capacity observations and excess demand observations and estimating Equations 15a and b separately (cf. column 1 of Table 7). Only in case 4, where σ_d and σ_s are very small, there are some parameters that are better[33] estimated using the single equation approach. We conclude from these exercises that if

[33]However, looking at Table 4 we can see that RMSE differences occur only in the fourth decimal place (see δ_2, δ_3, δ_7 and σ_d)

regime information is available, the disequilibrium approach (SSK) should be used instead of estimating two single equations on two separate subsamples.

It is remarkable that in cases 1 and 2, where the standard deviations are largest, the single equation estimates that do *not* use the regime information *at all* are comparable with the SSK estimates *in terms of the RMSEs*: 9 out of 15 parameter estimates have a smaller RMSE in case 1 and 7 out of 15 parameter estimates in case 2!

Looking at columns 3 and 4 of Table 7, we find that most of the time the single equation estimates are better than the SSU estimates: only in case 4 the SSU results are better (both in terms of mean biases and in terms of RMSEs) than the single equation estimates that do not use the regime information, and in case 3 the results for SSU are generally better both in column 3 and column 4 *in terms of the mean biases*. It is remarkable that in terms of RMSEs the single equation results that do *not* use the regime information *at all* are better than the SSU results in cases 1 and 2, and most of the time in case 3. The single equation SSU estimates that are *based on* the regime information, on the other hand, are nearly always better than the estimates (in terms of RMSEs; cf. column 3 of Table 7).

Two conclusions can be drawn from these results: first, if the fit of the model equations is moderate, as measured by the relatively large standard deviations σ_d and σ_s, a single equation approach (without regime information) performs better than a disequilibrium approach without regime information (SSU), although the disequilibrium model is *theoretically correct.* In this situation the single equation estimates even approach the quality of the SSK estimates (in terms of the RMSEs). Secondly, with respect to Footnote 20 we conclude that the *inconsistent* single equation approach that uses the regime information to partition the sample, produces nearly always lower RMSEs (and sometimes lower mean biases) than the *consistent* but *inefficient*[34] (SSU) disequilibrium approach.

Finally, for completeness sake we also computed *average (over replications) squared correlation coefficients* r^2 of generated $\ln(q_{hm})$ and its corresponding fitted value depending on the model used. The results are given in Table 8. For the SSU estimates both definitions of r^2 mentioned in the note to Table 1 were applied: r_A^2 refers to the definition where fitted value equals $\min(\hat{R}^d(X_i^d), \hat{R}^s(X_i^s))$ and r_B^2 corresponds with the definition based on the conditional regime probabilities. The squared correlation coefficient for SSK is denoted by r_C^2. With respect to the single equation estimates the definition for SSK (r_C^2) was applied if the regime information was used to partition the sample, whereas the definition of r_A^2 was applied if the regime information was not used at all (see also Section IV).

Several conclusions can be drawn: first, the average values for *case 1* (basic set of experiments) are of the same order of magnitude as the corresponding values in Table 1[35] (as could be expected). Only the squared correlation coefficients for SSU in Table 1 are somewhat higher than the corresponding average values of r_A^2 and r_B^2 in Table 8. Secondly, for each case the various models used do not differ dramatically from each other with respect to their degree of fit (as measured by r^2). Thirdly, regarding the degree of fit of the disequilibrium models it appears that on the average the fit of SSU is always slightly better than the fit of SSK. In addition, r_B^2 is always somewhat higher than r_A^2.[36] Hence, we consistently find (on the average) $r_B^2 > r_A^2 > r_C^2$ for the disequilibrium estimates, with more or less identical (perfect) r^2 values appearing in case 4. Fourthly, it is remarkable that the average fit of the single equation approach that uses the regime information to partition the sample is slightly better than the average fit of SSK *in case 1.*

VII. CONCLUSIONS

We evaluate the use of disequilibrium models in applied microeconomic research. A model is applied for explaining sales levels of individual retail stores. The model assumes that sales levels in retail stores are determined by the interplay of supply capacity and demand. Some stores are demand determined, whereas other stores are capacity determined. The realized sales level is the minimum of store demand and store supply capacity. A cross-section sample of individual confectioner's stores is used for testing. This is done because the usually unknown information regarding the regime to which each individual store belongs is explicitly available. In our situation of confectioners' stores the variable to be explained is the level of home-made products sales. Store demand for home-made products is made a function of advertising expenses, service level, selling space, assortment composition, price level, share of products that are not home-made and presence of a tearoom and/or lunchroom. Store supply capacity of home-made products, on the other hand, is supposed to depend on assortment composition, occupancy costs per unit of floorspace, selling area, remaining space, share of products that are not home-made and a variable indicating whether a confectioner also sells products to other stores and/or institutions and businesses. In this last section we will not reiterate on the economic findings of our model nor on its use for comparative applied research. We will deal primarily with

[34] Cf. Footnote 17.

[35] Remember that the 'combined' r^2 values for columns 3 and 4, and 5 and 6 were found to be $r_C^2 = 0.569$ and $r_A^2 = 0.528$, respectively.

[36] In the absence of sample separation information Gersovitz (1980) prefers the procedure underlying the definition of r_B^2 over the procedure underlying the definition of r_A^2 to partition the sample *a posteriori* into excess capacity observations and excess demand observations. It is interesting to see that in our Monte Carlo experiments the values of r_B^2 on the average are (slightly) higher than the r_A^2 values.

Table 8. *Average squared correlation coeffients r^2 of* $\ln(qhm)$ *and its fitted value*

r^2	Case 1				Case 2				Case 3				Case 4			
	model (14) SSU	model (14) SSK	eq.(15a) & (15b) $N = N_d$ & $N = N_s$	eq. (15a) & (15b) $N = N_t$	model (14) SSU	model (14) SSK	eq. (15a) & (15b) $N = N_d$ & $N = N_s$	eq. (15a) & (15b) $N = N_t$	model (14) SSU	model (14) SSK	eq. (15a) & (15b) $N = N_d$ & $N = N_s$	eq. (15a) & (15b) $N = N_t$	model (14) SSU	model (14) SSK	eq. (15a) & (15b) $N = N_d$ & $N = N_s$	eq. (15a) & (15b) $N = N_t$
r_A^2	0.5321			0.5035	0.6432			0.6115	0.8067			0.7635	0.9888			0.9309
r_B^2	0.5589				0.6545				0.8106				0.9888			
r_C^2		0.5148	0.5462			0.6280	0.5888			0.7947	0.7554			0.9886	0.9155	

Note: See Table 1 for the various definitions of squared correlation coefficients r^2. r_A^2 refers to the first definition mentioned for SSU and r_B^2 to the second. r_C^2 refers to the definition mentioned for SSK.

the two methodological questions which are central in the present paper. First, is the disequilibrium approach superior to the classical single equation one and second, to what extent is sample separation information indispensable?

Our disequilibrium model explaining home-made products sales in confectioners' stores is estimated both with and without regime information (denoted by SSK and SSU, respectively). In addition, the disequilibrium estimates are compared with parameter estimates based on two single equation approaches: first, the regime information from the survey is used to partition the sample into excess demand observations and excess capacity observations after which the demand equation is estimated on the excess capacity observations whereas the supply capacity equation is estimated on the excess demand observations. Secondly, both the demand equation and the supply capacity equation are estimated separately on all observations. Both single equation approaches result in parameter estimates that are generally more in line with the SSK estimates than the SSU estimates are. Two conclusions can be drawn from this for our specific situation: first, the ('complex') disequilibrium approach does not perform substantially better than the ('simple') single equation approach. Secondly, in estimating the disequilibrium model some information is lost if sample separation is not known. The resulting question is to what degree is this loss detrimental to a sound interpretation of our results?

In a real world context results will always be disturbed by data errors and specification errors. Therefore, Monte Carlo experiments are conducted to get more insight. Two main conclusions can be drawn from these experiments: first, in a situation where individual cross-section data are analysed and where the degree of fit is usually low to moderate, substantial loss of information is found if regime information is not available in estimating a disequilibrium model. Therefore, Maddala's (1983, p. 299) concern that we 'are asking too much from the data when we do not know which observations are on the demand function and which are on the supply function' seems to be grounded. In our basic set of experiments, where the average r^2 values are about 0.5 (which is comparable with the r^2 values found in the empirical section), the information loss is about 60% on the average (in terms of RMSEs). Even if the average values of r^2 are about 0.80, this loss of information is still 40% on the average. This is comparable with the *median* value found by Goldfeld and Quandt (1975, p. 338).[37] Hence, despite the fact that our sample size ($N_t = 137$) is relatively large as compared with Goldfeld and Quandt's study, the information loss is still substantial in most of our experiments. This also supports Kiefer's (1979, p. 1002) conclusion (when he compares his results with the Goldfeld–Quandt study)

[37]The degree of fit in Goldfeld and Quandt's study, where aggregate time-series data were used, may have been somewhat higher than 0.5 and possibly even close to 0.8.

'... that the information loss in a more complicated model is greater than that in a simple model, as seems plausible (although this must be qualified since the Goldfeld–Quandt results are for small samples)'. Our study shows that the information loss is still substantial in a *large* sample and in a situation where a relatively *complicated* model is used. Secondly, if regime information is not available and if the degree of fit is expected to be relatively low, it would be better to use a (formally wrong) single equation approach than a (theoretically correct) disequilibrium approach. On the other hand, if regime information is available, it is always better to use this information within a disequilibrium model than in combination with a (formally wrong) single equation approach.

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APPENDIX A: DATA

In this appendix we give a further description of the data used in this study. The sample consists of 137 cross-section observations on individual Dutch confectioner's stores. The year of collection is 1985. In the Tables A1–A3 the mean, the standard deviation, the minimum and the maximum of the variables used are given. Table A1 shows the results for the complete sample; Table A2 contains the results for the excess capacity observations; and Table A3 shows the results for the excess demand observations. In these tables total value of annual sales of home-made products (Q_{hm}) and advertising expenses (A) are measured in 1000 Dutch guilders of the year of collection; the price index (p_{hm}) is measured in cents; selling service (S_c) is measured in weekly working hours per square metre of floorspace; selling space (C), space for tearoom and/or lunchroom (TL) and total floorspace (W) are measured in square metres; the assortment variable (F) is measured as total value of annual sales of the assortment groups '*nat gebak*' and '*droog gebak*' divided by total value of home-made products sales; and the occupancy costs variable (H) is measured in guilders per square metre of floorspace.

APPENDIX B: DERIVATION OF THE LIKELIHOOD FUNCTIONS

Sample separation unknown

Let us rewrite Equations 5a through 5c as follows:

$$U_i^d = \ln(q_{hm})_i - R^d(X_i^d)$$

$$U_i^s = \ln(q_{hm})_i - R^s(X_i^s)$$

$$\ln(q_{hm})_i = \min\{\ln(q_{hm}^d)_i, \ln(q_{hm}^s)_i\} \quad \text{(B1)}$$

Table A1. *Complete sample (137 obs.)*

Variable	Mean	Standard deviation	Minimum	Maximum
Q_{hm}	408.71	227.70	36.00	1175.50
p_{hm}	197.30	28.33	106.00	267.00
q_{hm}	2.09	1.21	0.25	6.41
A	7.17	6.87	0.10	39.00
S_c	2.30	1.26	0.18	8.60
C	49.93	35.93	13.00	330.00
TL	7.39	23.77	0.00	150.00
F	0.77	0.23	0.07	1.00
Q_{nhm}/Q	0.17	0.14	0.00	0.75
Dtl	0.13	0.34	0.00	1.00
H	163.13	130.90	2.87	689.00
W	151.35	76.10	41.00	530.00
$Dsib$	− 0.23	0.95	− 1.00	1.00

Table A2. *Excess capacity observations (85 obs.)*

Variable	Mean	Standard deviation	Minimum	Maximum
Q_{hm}	369.12	215.54	36.00	1025.00
p_{hm}	194.92	26.21	135.00	265.00
q_{hm}	1.88	1.05	0.25	4.91
A	7.00	6.90	0.10	39.00
S_c	2.20	1.06	0.37	7.81
C	50.59	39.29	16.00	330.00
TL	7.53	23.75	0.00	140.00
F	0.77	0.23	0.07	1.00
Q_{nhm}/Q	0.18	0.15	0.00	0.75
Dtl	0.13	0.34	0.00	1.00
H	160.32	130.01	2.87	689.00
W	155.64	83.76	41.00	530.00
$Dsib$	− 0.26	0.94	− 1.00	1.00

Table A3. *Excess demand observations (52 obs.)*

Variable	Mean	Standard deviation	Minimum	Maximum
Q_{hm}	473.42	234.22	72.72	1175.50
p_{hm}	201.19	31.35	106.00	267.00
q_{hm}	2.44	1.37	0.33	6.41
A	7.45	6.88	0.10	34.90
S_c	2.47	1.53	0.18	8.60
C	48.85	29.95	13.00	175.00
TL	7.15	24.03	0.00	150.00
F	0.78	0.22	0.13	1.00
Q_{nhm}/Q	0.16	0.13	0.02	0.67
Dtl	0.13	0.34	0.00	1.00
H	167.73	133.48	3.89	623.00
W	144.35	61.70	50.00	330.00
$Dsib$	− 0.17	0.96	− 1.00	1.00

where $R^d(X_i^d)$ and $R^s(X_i^s)$ stand for the exogenous parts of the model equations. Let $f(U_i^d, U_i^s)$ be the joint density function of U_i^d and U_i^s, and $g(\ln(q_{hm}^d)_i, \ln(q_{hm}^s)_i)$ the joint density function of $\ln(q_{hm}^d)_i$ and $\ln(q_{hm}^s)_i$ derived from it. Then the marginal density of $\ln(q_{hm})_i$ reads:[38]

$$h(\ln(q_{hm})_i) = h^{ec}(\ln(q_{hm})_i) + h^{ed}(\ln(q_{hm})_i) \qquad \text{(B2)}$$

[38]See, for example, Maddala (1983, p. 297) or Kooiman *et al.* (1985, Appendix).

where

$$h^{ec}(\ln(q_{hm})_i) = \int_{\ln(q_{hm})_i}^{\infty} g(\ln(q_{hm})_i, \ln(q^s_{hm})_i)\, d\ln(q^s_{hm})_i \qquad \text{(B3a)}$$

and

$$h^{ed}(\ln(q_{hm})_i) = \int_{\ln(q_{hm})_i}^{\infty} g(\ln(q^d_{hm})_i, \ln(q_{hm})_i)\, d\ln(q^d_{hm})_i \qquad \text{(B3b)}$$

In our situation where U^d_i and U^s_i are independently normally distributed with zero mean and variance σ_d^2 and σ_s^2, respectively, $h^{ec}(\ln(q_{hm})_i)$ and $h^{ed}(\ln(q_{hm})_i)$ equal:

$$h^{ec}(\ln(q_{hm})_i) = n(\ln(q_{hm})_i - R^d(X^d_i); \sigma_d) \times \{1 - N([\ln(q_{hm})_i - R^s(X^s_i)]/\sigma_s)\} \qquad \text{(B4a)}$$

and

$$h^{ed}(\ln(q_{hm})_i) = n(\ln(q_{hm})_i - R^s(X^s_i); \sigma_s) \times \{1 - N([\ln(q_{hm})_i - R^d(X^d_i)]/\sigma_d)\} \qquad \text{(B4b)}$$

respectively, where $n(.; \sigma)$ stands for the normal density function with zero mean and variance σ^2, and $N(.)$ is the cumulative standardized normal distribution function. The likelihood function L then becomes

$$\begin{aligned} L &= \prod_{i=1}^{N} h(\ln(q_{hm})_i) = \prod_{i=1}^{N} (h^{ec}(\ln(q_{hm})_i) + h^{ed}(\ln(q_{hm})_i)) \\ &= \prod_{i=1}^{N} (n(\ln(q_{hm})_i - R^d(X^d_i); \sigma_d)\{1 - N([\ln(q_{hm})_i - R^s(X^s_i)]/\sigma_s)\} \\ &\quad + n(\ln(q_{hm})_i - R^s(X^s_i); \sigma_s) \\ &\quad \times \{1 - N([\ln(q_{hm})_i - R^d(X^d_i)]/\sigma_d)\} \end{aligned} \qquad \text{(B5)}$$

where N denotes the sample size.

The (conditional) *regime probabilities* according to Kiefer (1980) and Gersovitz (1980) can be derived as:[39]

$$\begin{aligned} (P_{ec})_i &= \Pr[(q^d_{hm})_i < (q^s_{hm})_i | (q_{hm})_i] \\ &= h^{ec}(\ln(q_{hm})_i)/(h^{ec}(\ln(q_{hm})_i) + h^{ed}(\ln(q_{hm})_i)) \end{aligned} \qquad \text{(B6a)}$$

and

$$\begin{aligned} (P_{ed})_i &= \Pr[(q^d_{hm})_i > (q^s_{hm})_i | (q_{hm})_i] \\ &= h^{ed}(\ln(q_{hm})_i)/(h^{ec}(\ln(q_{hm})_i) + h^{ed}(\ln(q_{hm})_i)) \end{aligned} \qquad \text{(B6b)}$$

respectively. The likelihood function (Equation B5) tends to go to infinity for certain parameter values. Maddala (1983) and Kooiman *et al.* (1985) deal quite extensively with this matter. In our study this problem is suppressed by restricting the *average* estimated P_{ec} to the interval [0.10, 0.90].

Sample separation known

Let us define the *regime* variable Z_i as follows:

$$\begin{aligned} Z_i &= 1 \text{ if } (q^d_{hm})_i < (q^s_{hm})_i \\ &= 0 \text{ if } (q^d_{hm})_i > (q^s_{hm})_i \end{aligned} \qquad \text{(B7)}$$

then the joint density of $\ln(q_{hm})_i$ and Z_i equals

$$h(\ln(q_{hm})_i, Z_i) = Z_i h^{ec}(\ln(q_{hm})_i) + (1 - Z_i)\, h^{ed}(\ln(q_{hm})_i) \qquad \text{(B8)}$$

Denoting the set of indices for which $(q^d_{hm})_i < (q^s_{hm})_i$ by I_d and the set for which $(q^d_{hm})_i \geqslant (q^s_{hm})_i$ by I_s, the likelihood function L now becomes

$$\begin{aligned} L &= \prod_{i=1}^{N} h(\ln(q_{hm})_i, Z_i) \\ &= \prod_{i=1}^{N} (Z_i h^{ec}(\ln(q_{hm})_i) + (1 - Z_i)\, h^{ed}(\ln(q_{hm})_i)) \\ &= \prod_{i \in I_d} h^{ec}(\ln(q_{hm})_i) \times \prod_{i \in I_s} h^{ed}(\ln(q_{hm})_i) \\ &= \prod_{i \in I_d} (n(\ln(q_{hm})_i - R^d(X^d_i); \sigma_d)\, \{1 - N([\ln(q_{hm})_i \\ &\quad - R^s(X^s_i)]/\sigma_s)\}) \times \prod_{i \in I_s} (n(\ln(q_{hm})_i \\ &\quad - R^s(X^s_i); \sigma_s)\, \{1 - N([\ln(q_{hm})_i - R^d(X^d_i)]/\sigma_d)\}) \end{aligned} \qquad \text{(B9)}$$

[39]See, for example, Kooiman *et al.* (1985, Appendix).