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How Market Structure Affects Food Product Proliferation: Theoretical Hypotheses and New Empirical Evidence for the U.S. and the German Food Industries*

by

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Contents

| | | Page |
|---|--------|---|
| 1 | Introd | uction1 |
| 2 | Linka | ges between Market Structure and Food Product Proliferation: A Literature Survey2 |
| | 2.1 | Studies on Market Structure and Innovation Activity |
| | 2.2 | Studies on Food Product Proliferation |
| 3 | Theor | etical Analysis: Determinants of New Food Product Introductions |
| 4 | Empir | ical Analysis: Determinants of Product Proliferation in the U.S. Food Industry12 |
| | 4.1 | Measurement of Product Proliferation |
| | 4.2 | The Empirical Model and Data |
| | 4.3. | Quantitative Analysis of Determinants of Product Proliferation in the U.S. Food In- |
| | | dustry: OLS versus Panel-Data Estimates |
| | 4.3.1 | Determinants of the Number of Product Innovations |
| | 4.3.2 | Determinants of Product Innovations per Company |
| 5 | An Ex | tension of the Empirical Analysis: A Comparison of the U.S. Results with Food Prod- |
| | uct Pr | oliferation in Germany |
| | 5.1 | Measurement of Product Proliferation in the German Food Industry |
| | 5.2 | Determinants of Product Proliferation in the German Food Industry: |
| | , | The Empirical Model and Results |
| 6 | Summ | nary and Conclusions |

1 Introduction

Product innovations are of crucial importance in a market economy. They are closely related to technical progress and, therefore, to the growth of an economy. As they may lead to a temporary monopoly position of the innovators in the SCHUMPETERian sense, incentives to innovate are strong and they are crucial for the effectiveness of a competitive system. Often, product innovations will be associated with a quality improvement. This means that products are developed which provide characteristics the consumers are willing to pay for. Improvements in product quality may raise consumers' and society's welfare. Product innovations may also cause reduced factor costs, when process innovations have reduced costs of input goods or added new valuable features to those goods.

These general features are characteristic for major product innovations and have been discussed in the economic literature in detail [TRAJTENBERG (1989), OI (1997)]. Most innovations in an economy, however, are incremental rather than radical. This is also a typical characteristic of innovations in the food industry [GALIZZI and VENTURINI (1996)], where product proliferation with a huge number of differentiated products dominates. There has been an intensive discussion on the optimal degree of product variety and on whether product differentiation is already too high from a societal point of view [SCHERER and ROSS (1990), pp.602 et seq.; SPENCE (1976); DIXIT and STIGLITZ (1977)]. The results of this discussion are still inconclusive. While it has been argued that additional product proliferation acts primarily as an entry barrier for newcomers [SCHMALENSEE (1978)], other authors have stressed the economic gains from even small changes in the characteristics of products [HAUS-MAN (1997)].

Apart from this important discussion on optimal product variety in an economy, innovations are important for the dynamics of a market structure [GEROSKI and POMROY (1990)]. Innovative firms will typically be those which are growing in the medium and long run. Theory suggests, too, that market structure variables influence technical change, growth and new product introductions [COHEN and LEVIN (1989)]. The major contribution of this paper lies in this latter area.

Based on a broad data set for new product introductions in various food industries, it is the objective of this contribution to elaborate how variables of market structure affect innovative activities in the food sector. The primary focus is on the U.S. food industry, but a comparative view with the German food sector will also be provided. From a methodological standpoint, the pooled cross-section and time-series data make it necessary to use fixed-effects and random-effects models. These approaches to panel-data analysis have not been applied in earlier studies on food product innovations.

The article is organized as follows. In Section 2, a short literature review will be given on the linkages between market structure and product proliferation in general and for food products

specifically. Section 3 formulates the theoretical hypotheses to be tested in the empirical model. Important determinants of new product introductions will be discussed, e.g. the influence of market concentration on innovative activity. An empirical analysis in the structure-conduct-performance (SCP) tradition is performed in Section 4 for the U.S. food industry. The data base on product innovations will be explained and surveyed as will be the measurement of the structural variables affecting innovation. The empirical model will be developed and the results of OLS, fixed-effects and random-effects models provided and discussed. A similar data set on new product introductions was constructed for Germany. Therefore, comparable empirical models will be estimated to explain product innovations in the German food industry in Section 5. A comparative analysis between the U.S. and Germany follows. It will be discussed in how far and to what extent the determinants of product innovations differ between the two countries. The findings are summarized in Section 6 where some conclusions for future research and policy are also outlined.

2 Linkages between Market Structure and Food Product Proliferation: A Literature Survey

In the process of new product introductions, it is distinguished between inventions, innovations and the dispersion or adoption of innovations. Inventions are the scientific ideas and innovations refer to the scaling-up from the invention to the commercial-sale stage. The focus in the following analysis is on innovations rather than inventions.

2.1 Studies on Market Structure and Innovation Activity

Innovations play a central role in the development of a market economy. Innovative activity can be viewed from two angles. The first one, arising more from the marketing profession, regards innovation as the detection and the fulfillment of yet unfulfilled consumer needs and wants. Companies with a strong market orientation which try to satisfy such needs are more likely to develop successful innovations [GRUNERT et al. (1997, p.11), SABISCH (1991)].

In the second view, associated with industrial economics, innovation is often closely linked to technological change and R&D activities. Innovative activity is addressed as one aspect of market performance in the industrial organization literature. At the same time the prevailing market structure is clearly connected to the degree of innovativeness.

There exists a large body of literature that discusses the links between market structure variables and innovative activity. The main variables which are discussed as determinants of innovative activity in theory are firm size and market concentration. The theoretical assessment of this relationship has often been tested empirically, leading to varying results.

SCHUMPETER (1947) first hypothesized a positive relationship between firm size and inno-

vation, a view also expressed by GALBRAITH (1956). The following arguments are in favour of this view: Absolute size is important as larger firms have more capital (or have better access to capital markets) and can therefore better afford R&D expenditures. In addition, there exist scale economies in innovation processes, especially if costly equipment or specialized researchers are required. Larger firms will most likely engage in a variety of research projects. As a consequence, risk, which is always entailed in R&D activities, also declines with added firm size due to risk diversification [WEIGAND (1996, p.38)].

This point of view was challenged by various authors. Firstly, not all innovation projects need to be costly. This provides opportunities for smaller firms. Moreover, as firms grow large, R&D efforts may no longer be very efficient as they become entangled in bureaucratization [SCHERER (1980)]. Finally, there exists some doubt whether larger firms which diversify their R&D projects will gain returns more than proportionate to the outlay [GREER (1992, p.660)].

Numerous empirical studies, many of which are summarized in COHEN and LEVIN (1989, pp. 1067 et seq.), examine the relationship between innovation and firm size. Some studies in the past, in particular in the 1980s, found a relationship between firm size and innovation in support of SCHUMPETER. More recent studies, however, do not uniformly confirm this result. This inconclusiveness might be partly attributed a) to the problem of an appropriate measure of innovation, b) to the selection of the data set which often is not a randomly drawn sample and c) to the degree to which studies control for characteristics of firms or differences in industry sectors in the empirical analyses [COHEN and LEVIN (1989, p.1069)]. The latter argument proves to be rather important in the study of ACS and AUDRETSCH (1990). They identify that under certain industry conditions, i.e. in less concentrated industries, smaller firms tend to be more innovative than larger firms. In contrast, large firms dominate innovations in capital- and research-intensive sectors and also in sectors with heavy advertising. FRISCH (1993) comes to the conclusion that small firms are often more creative in developing new ideas for innovations. In many cases, however, a lack of (financial) resources prevents them from further advancing the innovation to the stage of market commercialization. Therefore, large-scale production and marketing of innovations is often carried out by larger firms.

In the second SCHUMPETERian hypothesis, market power is considered to be an important factor enhancing innovative activity. If markets are structured in a way to allow monopolistic behaviour, firms will have more incentives to innovate. In this context it is useful to distinguish between anticipated and actual market power. Anticipated market power refers to the fact that firms will only engage in innovative activities if they expect alack of rivalry, i.e. imitation, to enjoy the full benefits of their research [GEROSKI (1990)]. Patent laws cover this principle. More controversial, however, is how far actual market power affects innovations. SCHUMPETER argued that an oligopolistic market structure made the competitors' behaviour more stable and predictable, thus reducing the uncertainty associated with more competitive

markets and therefore increasing the incentives to innovate. Returns from former innovations as well as other profits from the possession of monopoly power would give monopolistic firms the financial means to invest in future research activities.

As was the case with the first hypothesis, this view of the relationship between market power and innovation has been criticized. It is argued that monopolies may have the ability to innovate but they have only little incentive to do so. This is especially true for incumbent monopolists whose positions are based on previous innovations. Introducing another innovation would lower their net return as the monopolist 'replaces himself' if he innovates, whereas the competitive firm gets a monopoly [TIROLE (1988); see also ARROW (1962)].

ARROW (1962) argues that a competitive market structure creates higher incentives to innovate than a monopoly. The introduction of a (radical) innovation in a competitive environment leads to a temporary monopoly. The additional profit resulting from the monopoly situation is higher for firms in a competitive as opposed to a concentrated market due to a relatively higher reduction of marginal costs. Whereas incumbent monopolists are able to realize monopolistic profits even before/without introducing an innovation, firms in a competitive market will not be able to make profits in an equilibrium situation [WEIGAND (1996, pp. 49 et seq.)].

Again, COHEN and LEVIN (1989, pp. 1074 et seq.) provide a comprehensive discussion of empirical studies investigating the relationship between market power and innovation. Major results of these studies are the following:

- 1. The majority of the earlier studies find a positive relationship between concentration and R&D.
- 2. Some studies elaborated a nonlinear, inverted-U relationship. Theories which may explain such a relationship will be discussed in the next section.
- 3. Some empirical evidence favours a causality that runs from innovation to concentration, i.e. concentration can evolve as a consequence of innovation.
- 4. Because of the potential simultaneity between innovation and market structure some researchers modified their empirical model and worked, for example, with an instrumental variable approach.
- 5. Various studies also revealed that the effect of market concentration on innovative activity depends to a large extent on the industry sector under investigation. Studies on innovation behaviour across industries introduced sector-specific dummy-variables or fixed-effects models to control for these effects. As a consequence, the sector-specific variables are highly significant determinants of innovation, whereas concentration is no longer a strongly significant explanatory variable for innovation [see also WEIGAND (1996)]. Thus, empirical evidence seems to refute SCHUMPETER's hypothesis on market power and innovation [see, e.g., GEROSKI (1990)].

Finally, contestable market theory suggests that entry and exit barriers can also determine a firm's innovation activity [BAUMOL, PANZAR and WILLIG (1982)]. Truly contestable markets, i.e. without entry and exit barriers, imply an optimal market structure. Differing definitions of market barriers exist in the literature, however. Barriers to entry are often considered to be structural factors that permit potential entrants to compete successfully with the incumbents. Economies of scale, the degree of product differentiation or absolute cost barriers can restrain entry. Market entry barriers, including sunk costs, play an important role as determinants of innovation activity in empirical studies. This is shown for example by GEROSKI (1991). COMANOR's (1967) empirical results reveal that in industries with almost no market entry barriers there is hardly any incentive to innovate, since other competitors are likely to follow rapidly. Their market entry very soon leads to the erosion of the economic rents of the first innovator. But incentives to innovate are also lacking in industries with particularly high barriers to entry because the insulation from a threat of new competition could depress firms to constantly engage in innovative activities. WEIGAND (1996) argues that expenses which are irreversible and were made in the past by an incumbent (i.e. sunk costs) lead to a cost asymmetry with regard to new market entrants. New market entrants face an increased risk when entering the market, especially since incumbents might act strategically to deterentry. Thus, in addition to market structure variables market entry barriers can also be important factors that determine innovations.

2.2 Studies on Food Product Proliferation

Empirical studies of food product proliferation can be grouped into three important categories: (i) studies covering the welfare economics of product proliferation; (ii) case studies on the success and the determinants of new product introductions in individual branches of the food industry; (iii) cross-sectional analyses of product innovations and their determinants across food industries.

ad (i): The first literature segment on food product proliferation is related to the question whether product differentiation in the food industry is excessive from an economic point of view. This issue relates to the general economic question of optimal diversity on markets which has been discussed in various theoretical contributions on the welfare economics of product variety [LANCASTER (1975); SPENCE (1976); DIXIT and STIGLITZ (1977)]. Determinants of optimal diversity have been elaborated in this literature. However, there are few empirical demonstrations of whether product variety is excessive for individual industries.

Within the food industry, the question of an excessive product variety has been a competitionpolicy issue in the context of the U.S. breakfast-cereals industry. Important scientific contributions and methodological progress have also been made in studies on this industry. Product differentiation models have been developed which are suitable to draw antitrust implications on whether the product policy of firms on a market deter entry. The breakfast cereal industry is one of the most highly concentrated food industries in the U.S. [CONNOR (1999); CONNOR and SCHIEK (1997)]. The total number of companies in the industry is very small compared with other food industries. HAUSMAN (1997) reports that six firms realized 94% or more of total industry sales over the period 1982-92. These six firms were Kellogg's, General Mills, General Foods, Quaker, Ralston and Nabisco. Despite this strong concentration, the number of new product introductions as well as the degree of product differentiation has traditionally been high and the market shares of almost all brands have been rather low. Advertising intensity increased over time and reached a very high level in an interindustry comparison.

The ready-to-eat breakfast cereal industry became the objective of a major policy discussion in 1972 when the Federal Trade Commission filed a complaint against four leading manufactures of the industry – Kellogg's, General Mills, General Foods, and Quaker Oats. The complaint alleged that these firms collectively restrained competition in the industry, proliferating new product varieties and advertising intensely in order to create high entry barriers. This was a major antitrust case in U.S. competition policy which lasted nearly ten years. Because the FTC did not prevail, parallel actions by a few dominant suppliers which increase or maintain their market power have been "beyond the reach of U.S. antitrust law, as long as the companies make no overt agreements to act in concert" [CONNOR (1999), p.11].

There are two often-cited studies by SCHMALENSEE and SCHERER, which basically support the view of the Federal Trade Commission. SCHMALENSEE (1978) developed a spatial-competition framework for an analysis of the ready-to-eat cereal industry. The framework contains three major components: (i) increasing returns to scale in production and marketing at the brand level; (ii) localized rivalry among brands; and (iii) relative immobility in product space at the brand level. He derives the major result that "the industry's conduct, in which price competition is avoided and rivalry focuses on new brand introductions, tends to deter entry and protect profits" [SCHMALENSEE (1978), p. 305]. SCHERER (1979) applied the theory of optimal product variety to the U.S. ready-to-eat breakfast cereal industry. He posed the main question whether the industry's proliferation of product varieties was carried beyond the point at which economic welfare was maximized. SCHERER combined a demand function and consumer's surplus approach with a spatial economic model in order to evaluate the net benefit of new product varieties. He acknowledges that some innovations in the industry yielded gains in economic surplus which overcompensated the launching costs. For other innovations, however, a high substitutability, extensive cannibalization and substantial product launching costs negated the benefits. SCHERER (1979, p. 133) concludes his analysis with the view that "it appears probable that product proliferation has, at least at the margin, cost more than it was worth".

The dominating view that product proliferation acts mainly as an entry barrier, was challenged by HAUSMAN (1997). Based on a comprehensive econometric analysis of product demand at the brand level of the ready-to-eat breakfast cereal market, HAUSMAN argues against the view that the high rate of new-brand introductions is part of an anticompetitive strategy. His analysis stresses that consumers value the additional characteristics of new brands and he computes the additional consumers' surplus due to the introduction of Apple-Cinnemon Cheerios by General Mills in 1989. This evaluation is based on a three-stage econometric demand analysis at the brand level, which reveals high absolute values of own-price elasticities of demand for brands and rather low and often insignificant cross-price elasticities of demand between brands. HAUSMAN estimates in his perfect competition model a substantial annual consumers' gain due to this new product introduction of \$78.1 million for the U.S. Although some methodological issues are questionable [BRESNAHAN (1997)], HAUSMAN's analysis is probably the most challenging one on this issue and further careful empirical studies on the gains of new product introductions in the food industry are needed.

ad (ii): Some case studies on the success and the determinants of new product introductions in the food industry are related to individual products or firms in the food industry. Typically, success stories are covered in most cases. This part of the literature is mostly marketing-management oriented. Several examples of such case studies are reported in TRAILL and GRUNERT (1997), and conclusions on success factors and for marketing are drawn there.

Apart from this literature, there are several studies available which analyse new product introductions in selected branches of the food industry. TREMBLAY and TREMBLAY (1996) investigate motives for product line diversification by multiproduct firms in the U.S. brewing industry. They utilize data for 22 brewing companies over the period 1950-88 and estimate Poisson regression models to explain the absolute number of new product introductions. The authors conclude that industrial concentration, advertising, profits and economies of scope are not significant factors in explaining the number of new product introductions. However, they find evidence "that unsuccessful firms and large national firms are generally more likely to expand their product lines" [ibid., p.771].

ad (iii): CHRISTENSEN, RAMA and VON TUNZELMANN (1997), in a study for the European Commission, provide a very detailed statistical analysis of innovations in the European Food Products and Beverages Industry. The scope of this study is very broad as process and product innovation as well as many general trends in the food industry are covered, but some results are important in our context. The authors use data from the Community Innovation Survey (CIS) and patent statistics. They challenge the traditional view that the food industry is a "low-tech industry" by demonstrating that a substantial level of innovation activities is taking place. CHRISTENSEN, RAMA and VON TUNZELMANN show that "patented innovation tends to be produced predominantly by large firms" and "firms that produce a great number of patents tend to be profitable" [ibid., p.74]. With regard to innovation intensity, however, firm size is not seen as especially important. Innovation intensity is rather affected by home country effects: Across all firm sizes, European firms' innovation activities range behind that of

U.S. firms. Furthermore, innovation activities vary strongly by industry.

The first comparative study on product innovation across food industries was provided by CONNOR (1981). He examined the extent of product proliferation among manufactured food products and how it was related to the market structure of the food-manufacturing sector. With U.S. data for 102 product classes in the years 1977 and 1978, the author showed that new product introductions peaked when industry CR4 reached 65% and were significantly raised by an increase in advertising intensity and size of the product classes. A major conclusion by CONNOR was that "imperfect market structures do indeed generate high levels of food product proliferation" [ibid., p.615].

ZELLNER (1989) used 1977 data, partly based on CONNOR's analysis, and developed a fourequation model to explain the association among advertising intensity, concentration, profits, and new product introductions simultaneously. He extended a simultaneous-equation framework of PAGOULATOS and SORENSEN (1981) by introducing product innovations. In ZELLNER's analysis, new product introductions were affected positively by concentration, growth in value of shipments and the number of brands available in the respective product class. A significantly negative influence arose from the price-cost margin and advertising intensity. New product introductions on the other hand affected advertising intensity negatively and raised concentration. According to ZELLNER, his findings "support the view that advertising is a barrier to entry rather than a form of information which facilitates entry" and that "new product introduction is a substitute for intense advertising" [ibid., p.112].

The rising trend of food product introductions in the U.S. in the 1980s and 1990s has been reported in several contributions [GALLO (1995); CONNOR and SCHIEK (1997)]. However, there is no recent quantitative cross-section study of product innovations in the U.S. food industry which utilizes these data. Here is the starting point for our own empirical analysis in Section 4.

Individual recent studies refer, however, to the economic determinants of product innovations in the European food industry. Based on counts of product innovations in the German food industry for 1993 and 1994, HERRMANN (1997) presents regression analyses on the market-structure variables which determine those innovations. He concluded that there is definitely an influence of market structure on market performance. The existence of a strong product varie-ty in a sector, due to consumers' demand for variety, is shown to raise the number of product innovations significantly. Whereas this result is similar to one of ZELLNER for the U.S., two findings for Germany clearly differ from the U.S. studies:

 (i) In Germany, lower growth rates in an industry raise the number of product innovations. This is explained by the existing pressure on low-growth industries to react to unfavourable market conditions. In the U.S., the impact of growth on innovation was significantly positive in ZELLNER's and insignificant in CONNOR's analysis¹.

(ii) Both CONNOR and ZELLNER found a significant influence of concentration on new product introduction. There is no significant concentration-innovation linkage in Germany².

Based on new and more comprehensive data for Germany, we will provide a comparative analysis for Germany and the U.S. in Section 5. We will elaborate whether the differential results for the two countries remain with a more comprehensive data set than in earlier studies and by use of panel-data statistical methods which were not applied in the earlier work.

3 Theoretical Analysis: Determinants of New Food Product Introductions

The following chapters discuss the determinants of new product introductions that will be used in the empirical study to follow. The expected direction of influence will be specified on theoretical grounds. It should also be mentioned at this point, that in the remainder of the paper we refer to innovations as an output-oriented activity. In general, innovations can be captured through input- or output-related measures. Typical input-related measures are R&Dspending or the number of employees in R&D and typical output-related measures are the number of patents or the number of product innovations. Input-related measures are important indicators of innovative activity in research-intensive industry sectors. At first sight, the food industry does not seem to belong to this category as the innovations in the food sector are rather incremental than radical [GALIZZI and VENTURINI (1996)]. However, R&D is increasingly important in large food firms and, hence, in the food industry in general [CHRISTEN-SEN, RAMA and VON TUNZELMANN (1997)]. It can also not be generalized that input-related measures are necessarily inferior to output-related measures. In some studies of the food industry, structure-conduct-performance relationships were similar independent of the measurement approach. CONNOR et al. (1985, pp. 306-310), e.g., show that technological performance rises with concentration until four-firm concentration reaches 50 to 60 percent but declines with further concentration. This result held true for input-based R&D-measures of technological performance as well as for output-based indicators like patents or scientific publications. There are, however, some well-known shortcomings of R&D and patents as indicators of innovative activities [BROUWER and KLEINKNECHT (1996)]. In particular, there is no necessary linkage between these indicators and the number or success of new product introductions. The measure used in this study is the number of new products introduced in the various sectors of the food industry.

¹ The view that slow-growth industries tend to offer more new products than rapid-growth industries is, however, confirmed in a new study by CONNOR with U.S. data [CONNOR (1998)].

² This aspect will be reconsidered later in the empirical analysis. The linkage between concentration and innovations seems to be not very stable and depends on the methodology, too. CONNOR and ZELLNER found different functional forms for their significant concentration-innovation linkage. With regard to Germany, STÜHMEYER (1997) found in some model specifications with more recent data a significantly positive influence of concentration on innovative activity in the food industry.

According to theory and earlier empirical work, it can be expected that the following market structure variables have an influence on the innovative activities in the food industry:

- (i) the number of firms;
- (ii) concentration in an industry;
- (iii) size of an industry;
- (iv) growth of the market;
- (v) product differentiation.

Apart from these market structure variables, industry characteristics are introduced in the panel data models.

Most studies in the structure-conduct-performance (SCP) tradition, with the exception of contestable market theory, posit that an impact on innovative activities is caused by the number of firms on a market and by concentration. However, there are competing hypotheses on the direction of this relationship.

ad (i): There are plausible hypotheses on a positive as well as a negative impact of the number of firms on new product introductions.

ARROW (1962) showed for the case of process innovations, that the marginal revenue from this innovation is smaller in the monopoly case than under competition. One might conclude that the number of firms on a market affects innovations positively. On the other hand, monopolistic rather than polypolistic firms may have the financial basis for successful R&D activities and, thus, the introduction of new products. This is in line with SCHUMPETER's view that innovations increase with a declining number of firms and similar arguments in DASGUP-TA/STIGLITZ (1980).

Other authors stress the importance of oligopolistic market stuctures and argue that the relationship between concentration and innovations is not linear. An inverted U-shaped relationship between market power and innovations might exist. Innovations would then increase with a declining number of firms but, after reaching a maximum, fall with a further reduction in the number of firms [SCHERER (1992)]. KANTZENBACH (1967) argued that although the profits to be gained from an innovation might be high in a polypolistic market, the passive competitors' position is not seriously challenged. Introducing an innovation will only lead to small additional profits in the long run. The intensity of competition will increase with a declining number of market participants. The average profits gained from introducing an innovation will be higher and can therefore be invested in future innovative activities. KANTZENBACH claims that firms in a wide oligopoly are under competitive pressure to innovate. If the number of firms on a market diminishes more, the number of innovations is going to declineagain, as the intensity of competition is above the optimum.

ad (ii): Similar arguments are valid with regard to <u>concentration³</u>. Additionally to the number

³ The fact that similar theoretical arguments are utilized for the influence of the number of firms and concen-

of firms, concentration ratios capture the size distribution of firms on a market. With an increasing concentration, a rising average firm size goes along under ceteris-paribus conditions. Again, positive as well as negative hypotheses on the influence of concentration on innovative activities are possible in line with ARROW or SCHUMPETER. Combinations of a positive and negative influence in the form of an inverse U-type form, as sugested by KANTZENBACH, or a U-type function are possible, too. ALEXANDER (1997), who investigated the music recording industry, found that higher and lower levels of concentration result in lesser variety, i.e. fewer new product introductions. This result implies a U-shaped relationship between concentration and innovations. On the other hand, an inverted U-shaped relationship between concentration and product innovations was found in CONNOR (1981).

It can be summarized that the direction of the influence of the number of firms and concentration on new product introductions is a priori unclear. It is a major goal of the empirical analysis to elaborate this influence.

ad (iii): The <u>size of a market</u> gives an indication of the demand potential in a specific sector of the food industry. Market size, measured in absolute terms, can be expected to influence incentives to innovate positively. The larger a market, the more segments it will have and the higher is the expected potential for a successful product innovation [CONNOR (1981)]. Hence, the benefits gained by investing in the development of new products are increasing with the size of the market. Under ceteris-paribus conditions, one would expect a higher innovation activity in larger markets.

We do not further analyze here the possibility that the two explanatory variables size and concentration are interrelated. It is argued elsewhere that concentration diminishes with the size of a market, and this plays a role in SUTTON's analysis of exogenous and endogenous sunk costs [SUTTON (1991)].

ad (iv): In addition to the absolute size of a market, its dynamics are important for attracting innovators. The <u>growth of markets</u> is therefore expected to have an impact on innovation activity. Growth rates can differ between industries due to diverging income elasticities of demand. Changing trends in preferences might also be responsible for differing dynamics in industry development. Moreover, the growth potential differs between the various segments of the food industry. If a market segment is developing dynamically it can be expected that it will also attract product innovations. Growth may lower entry barriers. If markets of equal size are considered, a larger number of innovations would thus be expected in the markets that have the highest growth potential [COHEN and LEVIN (1989, p.1081)].

However, opposite hypotheses are also conceivable. If an industry sector is experiencing a recession the companies within this sector are forced to take action against the detrimental

tration has to do with empirical concepts. The HERFINDAHL-HIRSCHMAN Index (HHI), which is used as a measure of concentration, combines elements of both number of firms and market inequality [SCHERER and ROSS (1990)].

situation. Introducing new products to the market might be an important strategy to respond to a declining industry development [HERRMANN (1997); CONNOR (1998)].

In summarizing the above, it can be recorded that both a positive and a negative development of markets can affect new product introductions positively. Whereas a positive market growth is associated with incentives to innovate, a declining industry can put pressure on the market participants to maintain their position and therefore induce product innovations. It is a task of empirical analysis to elaborate the net effect.

ad (v): <u>Product differentiation</u> is believed to have a positive impact on product innovations, i.e. the higher the present product differentiation the more innovation activity can be expected in the future. It is conjectured that the consumers' demand for variety and the competitors' innovations in branches with high product heterogeneity put pressure on the individual firms to increase their innovative activities as well. Product differentiation can be measured with various concepts. In our analysis we work with the share of packaging costs in total marketing costs as a proxy of product differentiation and with the already existing variety of products in a product category. Following CONNOR (1981), packaging costs can be considered to indicate the opportunity to differentiate food products physically from each other. Moreover, product packaging is necessary for branding of foods and can be thought to reinforce advertising messages. The share of packaging costs in total costs of product is therefore considered to be positively related to product innovation.

Following the same rationale it is hypothesized that a large variety of products in an existing product category will also induce a higher number of new product introductions.

We further hypothesize that <u>industry-specific characteristics</u> matter, too. This can be justified as the sector-specific dummies will capture the innovative potential in the individual industries. Most likely, the reservoir of marketable innovations is very different across industries as technological knowledge or human capital may be very different. Not all of the relevant characteristics will be possible to quantify and are then captured in the sectoral dummies of the panel data models.

4 Empirical Analysis: Determinants of Product Proliferation in the U.S. Food Industry

The empirical analysis of product proliferation in the U.S. food industry will be provided in this section. The definition of product proliferation will be given first in Section 4.1 and the measurement approach will be clarified. We will then explain the method of the empirical analysis in Section 4.2. As pooled time-series and cross-sectional data are used, the relative advantages of fixed-effects or random-effects models compared to OLS estimates will be discussed. Moreover, the basic economic model and the data utilized are outlined. A detailed presentation and discussion of the economic findings follows in Section 4.3.

4.1 Measurement of Product Proliferation

The magnitude and structure of new product introductions and their distribution across U.S. food industries has been described, e.g., by CONNOR and SCHIEK (1997, pp. 386 et seq.) and GALLO (1995). They show that manufacturers have steadily increased the number of product innovations. It is important, however, to specify the way product innovations are measured. Different definitions of innovations exist in the literature, ranging from a totally new product for an industry to a new product or product variation from the individual supplier's point of view.

The data which will be used here are taken from the journal "New Product News". New products are defined there as any new brand, including products sold in test markets or regional markets. New packaging sizes, existing products with new ingredients, private-label products, hard liquors, products introduced in other countries or new promotions were not counted.

Table 1 gives an overview of the number of product innovations in 12 food categories from 1985 to 1994. According to "New Product News", new food product introductions have ranged above 10,000 annually since 1990. The most innovative categories were condiments with 21.7% and candy/gum/snacks with 16.1% of all innovations, followed by beverages (12.6%), bakery products (12.2%) and dairy products (11.5%). Annual introductions of new foods rose strongly, by more than 150% within the period 1985-94. Industry sectors which revealed the strongest increase in new product introductions were side dishes, followed by baking ingredients and beverages. With the exception of beverages the other two industry sectors are not among the industries which are most innovative when the number of new product introductions is considered.

New product introductions shown in Table 1 provide the data basis for measuring the dependent variable in the following quantitative analysis. As various independent variables are only available for a shorter period, the data basis has to be reduced to 1988-94, however.

4.2 The Empirical Model and Data

In the empirical analysis of the U.S. data, we utilize pooled cross-section and time-series data. Information on the total number of product innovations and on innovations per company in the period 1988-94 is utilized. The twelve sectors of the food industry included in Table 1 are covered.

In order to analyze the determinants of innovation activity across food industries and over time, OLS, fixed-effects and random-effects models are estimated and compared. All comparisons are carried out with TSP's PANEL procedure [HALL and CUMMINS (1997)]. The statistical procedures of panel data analysis are explained in great detail elsewhere [HSIAO (1989); BALTAGI (1995)] and have already been applied to innovation analyses outside the food sector [WEIGAND (1996); GEROSKI (1990)]. Therefore, only basic definitions are repeated here.

| FOOD CATEGORIES | 1985 | 1986 | 1987 | 1988 | 1989 | 1990 | 1991 | 1992 | 1993 | 1994 | Mean |
|---------------------|------|------|------|------|------|------|-------|-------|-------|-------|--------|
| | | | | | | | | | | | |
| Bakery products | 553 | 681 | 931 | 968 | 1155 | 1239 | 1631 | 1508 | 1420 | 1636 | 1172.2 |
| Baking ingredients | 142 | 137 | 157 | 212 | 233 | 307 | 335 | 346 | 383 | 544 | 279.6 |
| Beverages | 625 | 697 | 832 | 936 | 913 | 1143 | 1367 | 1538 | 1842 | 2250 | 1214.3 |
| Breakfast cereals | 56 | 62 | 92 | 97 | 118 | 123 | 108 | 122 | 99 | 110 | 98.7 |
| Candy/gum/snacks | 904 | 811 | 1145 | 1310 | 1355 | 1486 | 1885 | 2068 | 2043 | 2450 | 1545.7 |
| Condiments | 1146 | 1179 | 1367 | 1608 | 1701 | 2028 | 2787 | 2555 | 3147 | 3271 | 2078.9 |
| Dairy | 671 | 852 | 1132 | 854 | 1348 | 1327 | 1111 | 1320 | 1099 | 1323 | 1103.7 |
| Desserts | 62 | 101 | 56 | 39 | 69 | 49 | 124 | 93 | 158 | 215 | 96.6 |
| Entrees | 409 | 441 | 691 | 613 | 698 | 753 | 808 | 698 | 631 | 694 | 643.6 |
| Fruits & vegetables | 195 | 194 | 185 | 268 | 214 | 325 | 356 | 276 | 407 | 487 | 290.7 |
| Processed meat | 383 | 401 | 581 | 548 | 509 | 663 | 798 | 785 | 453 | 565 | 568.6 |
| Side dishes | 187 | 292 | 435 | 402 | 489 | 538 | 530 | 560 | 680 | 980 | 509.3 |
| TOTAL, FOOD | 5333 | 5848 | 7604 | 7855 | 8802 | 9981 | 11840 | 11869 | 12362 | 14525 | 9601.9 |
| Mean, pooled Sample | | | | | | | | | | | 800.2 |

| Table 1: | Product Innovations in the U.S. Food Industry, | 1985-94 ^{a)} |
|----------|--|-----------------------|

a) Data on the categories Baby Food, Pet Food and Soups are excluded here.

Source: New Product News, various issues. Own computations.

Suppose we have information on i = 1, ..., N sectors for each of t = 1, ..., T periods. The dependent variable is y_{it} and the independent variables are captured by the vector X_{it} . The most general model for pooled cross-section and time-series data would be

(1)
$$y_{it} = \alpha_{it} + \beta_{it}X_{it} + u_{it}$$

Equation (1) would allow for sector-specific and time-specific intercepts (α_{it}) as well as sector- and time-specific slope coefficients (β_{it}). The residual u_{it} is assumed to have a mean value $E(u_{it}) = 0$ and a constant variance $E(u_{it}^2) = \sigma^2$.

In the case of innovations, sector- and time-specific intercepts imply that the number of innovations could vary from sector to sector and from period to period – apart from the influence of the independent variables in the model. Sector- and time-specific slope coefficients imply in the case of innovations that the influence of concentration on innovations may be different from sector to sector and from period to period. In almost all applications in the literature, stronger assumptions than in (1) are imposed on the model.

The strictest assumptions are made in the basic pooled regression model

(2)
$$y_{it} = \alpha + \beta X_{it} + u_{it}$$
.

In this model, all regression coefficients are assumed constant over time and across sectors and all sectoral and time observations are utilized. The residuals u_{it} are again supposed to have a zero mean value and a constant variance σ_u^2 . The uniform intercept α in (2) implies for the case of innovations the following: The number of innovations as the dependent variable does not have sector-specific or time-specific characteristics apart from the influence of the independent variables, which are captured in the vector X_{it} . Uniform slope coefficients mean in the case of innovations that the marginal impact of concentration on product innovations can be measured in only one coefficient. This coefficient would be uniform in a cross-sectoral viewpoint and when variations from period to period are considered. This is a rather strong assumption. A considerable branch of the literature exists suggesting that cross-section data tend to capture long-run and time-series data short-run adjustments so that a uniform coefficient seems overly restrictive.

HSIAO (1989, pp.5-7) shows for several samples that this model, which is estimated by OLS, may lead to seriously biased estimates of coefficients. This possibility may be explained for the case in which either α or the β 's are different for various sectors, but constant over time. One example is illustrated in Figure 1. Suppose that we want to measure the effects of concentration on innovations and that pooled data are available. The true relationship shall be characterized by heterogeneous levels of innovation across sectors ($\alpha_i \neq \alpha_j$), but a homogeneous reaction to concentration across sectors ($\beta_i = \beta_j$). In Figure 1, all data points for sector 1 are in cloud 1, for sector 2 in cloud 2, etc. Regressions for the individual sectors would yield the broken lines with the same slope and, thus, would correctly indicate the influence of concentration on innovation. By pooling the data and ignoring the heterogeneous magnitude of innovations across sectors, the solid line would show the estimated regression curve and it would yield a biased estimate of the concentration's influence on innovations.

HSIAO shows in other examples that even the sign of the estimated relationship may be wrong when all time-series and cross-sectional data are simply pooled. Analogously, the assumptions of uniform slope coefficients in model (2) and of time-invariant intercepts may yield biased results.

The assumption of a uniform intercept for various sectors is relaxed in the two modelling frameworks which dominate the literature on panel-data analysis: (i) fixed-effects models and (ii) random-effects models. The basic fixed-effects model is:

 $(3) \quad y_{it} = \alpha_i + \beta X_{it} + u_{it}.$

Each sector in equation (3) is characterized by a sector-specific intercept (α_i). Apart from that, it is posited that the influence of the vector of explanatory variables is constant over time and across sectors.

Figure 1:Possible Bias in Regression Estimates when OLSIs Applied to Pooled Data without Sector-specific Coefficients



Source: Modification of HSIAO (1989), Fig.1.1.

The difference between the fixed-effects and the random-effects model lies in the way the α_i 's are computed. The difference can be clarified when the α_i in equation (3) is partitioned in two elements:

$$(4) \qquad \alpha_i = \alpha + z_i \, .$$

 $\overline{\alpha}$ is an average value for the intercept, when all sectors are taken into account, z_i is the deviation from this value for sector i. Introducing (4) in (3) yields the random-effects model

(3')
$$y_{it} = \overline{\alpha} + \beta X_{it} + v_{it}$$
.

The random-effects model is an error component model: In (3'), the error term v_{it} is the sum of two error components ($v_{it} = u_{it} + z_i$). In the fixed-effects model, the intercepts are regarded as fixed and are computed as dummy variables for each sector. The random-effects model, how-ever, assumes that the sector-specific intercepts (and the values of z_i) are randomly drawn from a statistical distribution with a given mean and variance. It is shown in the literature on the econometrics of panel-data models, that the fixed-effects model can be estimated efficient-ly by OLS. OLS is inefficient, however, for the random-effects model which has to be estimated by generalized least squares (GLS) [HSIAO (1989)].

In principle, there exist ex-ante arguments for either fixed- or random-effects models in certain cases [CAMERON (1998)]. Fixed-effects analysis, e.g., is a conditional analysis. The effects of the independent variables on the dependent variable are estimated after controlling for the effects of individual observations (here: sectors) in the sample. Out-of-sample applications of the estimates are generally not possible whereas they are in the random-effects models. This would be an argument for random effects. Although an out-of-sample application is intrinsically attractive, there is often the problem that the random effects are not uncorrelated with the regressors and yield biased results. As there are pros and cons to both approaches, we will show the effects of the fixed- and random effects models. Additionally, we show the OLS results. Figure 1 has shown that the panel estimates are principally superior to the OLS estimates. However, the computation of sector-specific dummies in the fixed-effects approach implies that less variation of the dependent variable than under OLS will be explained economically. Sector-specific differences in innovations, e.g., will typically explain a substantial share of variability in product innovations, but no further explanation of these dummies is provided in the panel data models.

The presentation of the OLS, fixed- and random-effects estimates allows to compare and to interpret differential results of the methodological approaches. It will be decided then on the basis of ex-post criteria which method yields the most satisfactory results. An F-test is used to test whether the classical OLS model with a uniform constant is equivalent to the fixed-effects model characterized by sector-specific constants. A second specification test, following HAUSMAN (1978), is utilized to compare the equivalence of the fixed-effects and randomeffects models⁴. A statistically significant HAUSMAN statistic indicates that the randomeffects models are not consistent due to correlations of the individual intercepts with the independent variables. The fixed-effects model is superior in that case.

⁴ For a comparison of HAUSMAN's test in this context with another test for misspecification suggested by MUNDLAK, see HSIAO (1989), pp. 48-49.

When the theoretical hypotheses on the determinants of product innovations (I) are introduced now, a typical OLS model to be estimated would be

(5) $I = \alpha + \beta_1 \cdot CONC + \beta_2 \cdot SIZE + \beta_3 \cdot PACKCOST + \beta_4 \cdot GROWTH + \beta_5 \cdot COMPANY + u$

and a typical fixed-effects model

 $\begin{array}{ll} (6) \ \ I \ = \alpha_1 \ \cdot D_1 + \alpha_2 \ \cdot D_2 + ... + \alpha_{N-1} \cdot D_{N-1} + \beta_1 \cdot CONC + \beta_2 \cdot SIZE + \ \beta_3 \cdot PACKCOST \\ & + \beta_4 \cdot GROWTH + \beta_5 \cdot COMPANY + u. \end{array}$

In (5) and (6), time subscripts are omitted for convenience. In general, the explanatory variables lag by one year in order to avoid simultaneity problems. In equation (6), D_1 to D_{N-1} are dummy variables for the sector-specific intercepts; one sector (N) is used as a reference. The regression coefficients of the dummy variables are usually suppressed in the output of fixed-effects models and they will also not been shown here⁵.

The independent variables contained in equation (5) and (6) are defined and measured as follows: **COMPANY** is the number of companies per food category. Data on the number of companies were taken from the Census of Manufactures (Subject Series: Concentration Ratios in Manufacturing) 1987 and 1992 and assigned to the respective food categories. Assuming constant growth rates for the period between censuses, the figures on the number of companies were interpolated, and a time series for the years 1987-93 was thus available.

The number of companies varies strongly by industry. The most companies exist in the processed meat sector, followed by the sector bakery products. The smallest number of companies was registered in the cereal industry.

The **SIZE** of the relevant food markets is measured by value of shipments. The Annual Surveys of Manufactures (Value of Product Shipments) 1991 and 1994 were used to collect the data on the value of shipments (1987-1993). The detailed data on product classes (SIC codes) were aggregated into the categories given by the innovation data. The industry sector with the highest value of shipment is the processed meat sector; the beverage industry and the dairy industry follow.

GROWTH of the respective food categories is measured with the percentage change in the value of shipments from year to year. The database is the same as for the SIZE variable. In the time period 1987-1993 the breakfast cereal industry grew the fastest (65%), followed by the side-dishes sector (48%) and entrees sector (42%).

CONC measures the concentration of sales in the respective food categories. The particular measure was CR4, the revenue share of the largest four firms in an industry. Data on concentration ratios were also taken from the Census of Manufactures. Similar to the number of companies, data on concentration ratios were only available for 1987 and 1992. The ratios

⁵ Sector-specific numbers of product innovations and of innovations per company were estimated but are not presented here.

between these years and for the year 1993 had to be interpolated assuming constant growth rates.

The cereal industry not only has the smallest number of companies but is also the most concentrated industry sector with a CR4 of 86%. The concentration within the food sector desserts is the lowest with a CR4 of 24%.

PACKCOST stands for packaging costs, expressed as a percentage of total marketing costs. The variable was chosen as an indicator of product differentiation. Packaging costs could not be identified for the twelve food categories but only for the food sector as a whole over time. They increased constantly over the time period under consideration.

Unfortunately, the advertising-to-sales ratio used by CONNOR (1981) and ZELLNER as a further indicator of product differentiation, was not available across industries as a time series. This variable affected new product introductions positively in CONNOR's and negatively in ZELLNER's study.

The data basis for the independent variables is shown in Appendix 1. Since the data on concentration ratios and the numbers of companies were only available for 1987-93, this period had to be chosen for the independent variables. Consequently, the data on product innovations explained in Section 4.2 could not be fully exploited and were utilized only for the period 1988-94. Compared with the earlier studies by CONNOR (1981) and ZELLNER (1989) yet, our data basis has the advantage that it is more recent and broader with regard to the number of years covered.

The quantitative analyses by CONNOR and ZELLNER had focused on the determinants of the number of new product introductions in the years 1977-78 and 1977 respectively. For 1988-94, we deal with the number of product innovations like CONNOR and ZELLNER. Additionally, we measure and try to explain innovations per company in the U.S. food industry. For that purpose, some independent variables are adjusted. The average size of the company (SIZECOMP = SIZE/COMPANY), e.g., is used as a determinant of innovative activities rather than the size of the market.

The quantitative analysis has included a rather comprehensive specification search. Apart from basic models, as indicated by (5) and (6), and additional estimations for product innovations per company, different functional forms were tested. Appendices 2 and 3 show loglinear models, e.g., as an alternative to the basic linear models. Additionally, squared terms for COMPANY and CONC were introduced in order to test for a possible nonlinear influence of

market structure variables. Some additional variables were also introduced in the analysis⁶. Selected results of the specification search are presented in Section 4.3.

4.3 Quantitative Analysis of Determinants of Product Proliferation in the U.S. Food Industry: OLS versus Panel-Data Estimates

4.3.1 Determinants of the Number of Product Innovations

Tables 2 and 3 show how market-structure variables affected the number of product innovations in the U.S. food industry in the period 1988-94. Table 2 captures the number of firms and Table 3 the concentration ratios in linear and squared form as explanatory variables of product innovations. Other independent variables are the value of shipments as an indicator of the size of the market, the share of packaging costs in total costs as indicator of product differentiation and (past) market growth.

The explanatory power of the selected models is rather high. The corrected coefficients of determination range between 0.34 and 0.64 in the plain OLS estimates and between 0.83 and 0.89 in the random-effects models for total product innovations. The corrected coefficients of determination range between 0.88 and 0.91 in the fixed-effects models. The major results can be summarized as follows:

1. The more sellers in a market, the higher is the total number of product innovations on that market (see equation (1) in Table 2). Equations (2) to (4) in Table 2 show, however, that the influence of the number of firms is clearly nonlinear. With a rising number of firms, the number of innovations rises less than proportionally and, as from a certain point, the number of innovations falls with the number of firms. The influence of the number of firms remains stable in the fixed-effects and random-effects models. Although the signs of the coefficients are identical to those in the plain OLS estimates and again statistically significant in the random-effects models. In the fixed-effects models, the linkage is linear: An increase by one firm in a sector raises the number of product innovations by 1.63 according to the fixed-effects model (5). However, the HAUSMAN test statistic is not statistically significant for equations (10) to (12) and this indicates no misspecification in the random-effects models. Those models clearly suggest a nonlinear influence of the number of the number of new product introductions in the food industry.

⁶ We experimented, e.g., with additional cost variables. Data on interest rates and the share of labour costs in total food marketing costs, however, were only available for the food sector as a whole over time and not across industries. These variables did not significantly contribute to the explanation of product innovations. For a cross-sectoral investigation, product variety was introduced as an explanatory variable. The variety of products per category that are already in the market was taken from "The Marketing Fact Book" 1993. It gives an approximate indication of the number of articles listed in supermarkets. The influence of product variety on product innovation was clearly positive in the cross-sectional analysis. Unfortunately, this information on product variety was not available as a time series.

- 2. The plain OLS estimates reveal a strong additional and positive influence of CR4 on the number of innovations. It can be concluded that industry concentration is positively associated with a higher number of innovations. The random-effects model (12) confirms this effect at the 95%-level of statistical significance and there is no indication of misspecification for this model as the HAUSMAN test statistic is insignificant.
- 3. The sensitivity of the results to the modelling approach is clearly visible in the influence of the variable SIZE. The size of the market, in terms of the value of shipments, has a differential impact on product innovations in the plain OLS as opposed to fixed-effects and random-effects models. According to equations (1) to (4) of Table 2, there is a negative and significant effect of SIZE on the number of innovations. The relationship is positive in the fixed-effects model (5), but statistically insignificant in all other fixed-effects models and in the random-effects models. The difference may be explained as follows: In the plain OLS estimates, the cross-sectoral effects seem to dominate. Smaller sectors, in terms of their value of shipments, tend to innovate more than larger sectors. If sector-specific differences in product innovations are taken into account, as is done in the fixed-effects and random-effects models, this effect is no longer significant. Model (5) even suggests that, after controlling for sector-specific innovations, an increase in the value of shipments raises the number of product innovations. Which result is valid in this case? The F-test shows significant values for the four model specifications and this means that systematic differences between the sectors in innovative activity are not captured in the classical OLS models. Hence, the panel-data models are superior as they account for these differences. Based on those estimates, we have to conclude that an increasing size of the market does not reduce product innovations.
- 4. The influence of the variable PACKCOST on the number of product innovations is positive and significant according to all three models. A trend towards a higher product differentiation, induced by a growing share of packaging costs in total costs of the food industry, causes more product innovations.
- 5. In general, the F-tests in Table 2 indicate that OLS and fixed-effects estimates are not equivalent. Except for packaging costs, sector-specific differences in product innovations matter. Across all model specifications, a strong improvement in the \overline{R}^2 values occurs due to a move from OLS to fixed-effects models. The fixed-effects models are in all cases superior. However, Table 2 also reveals that the signs of the regression coefficients are in most cases (COMPANY, (COMPANY)², PACKCOST, CR4) unaffected by a switch from OLS to panel-data models. It is more the magnitude of the coefficients and the statistical significance that change in several cases. Only in one case, SIZE, a statistically significant negative influence of an independent variable is rejected by all panel-data models.

| | | | | Indep | endent Variables | | | | | Test Statis | stics |
|-----------------------|--------------|------------------------|----------------------|---|--|----------------------|--------------------|---------------------|------------------|---|--|
| Method/ Equations | | Constant | COMPANY | (COMPANY) ² | SIZE | PACKCOST | GROWTH | CR 4 | \overline{R}^2 | F-Test: OLS=FE (DF) ^{b)} | Hausman's test statis- tic ^{c)} |
| OLS | (1) | 587.67*** (5.26) | 0.5557*** (5.26) | | -0.0135** (-3.06) | | | | 0.34 | | |
| | (2) | -2240.17*** (-3.54) | 1.7404*** (10.38) | -0.3813 · 10 ⁻³ *** (-7.82) | -0.8530 · 10 ⁻² * (-2.56) | 61.7937*** (3.56) | | | 0.60 | | |
| | (3) | -2338.79*** (-3.43) | 1.7526 (10.23) | -0.3845 · 10 ⁻³ *** (-7.74) | -0.8444 · 10 ⁻² * (-2.52) | 63.6681*** (3.52) | 4.9814 (0.40) | | 0.60 | | |
| | (4) | -2879.14*** (-4.57) | 1.9808*** (11.29) | -0.4216 · 10 ⁻³ *** (-8.82) | -0.9436 · 10 ⁻² ** (-2.98) | 61.5225*** (3.75) | | 10.3552** (3.21) | 0.64 | | |
| Fixed-effec models | cts (5) | | 1.6266** (3.06) | | 0.0368*** (3.76) | | | | 0.88 | 40.64*** (11; 70) | |
| | (6) | | 1.0611 (0.73) | -0.1805 · 10 ⁻⁴ (-0.05) | -0.2536 · 10 ⁻³ (-0.02) | 51.7034*** (4.12) | | | 0.90 | 23.24*** (11; 68) | |
| | (7) | | 1.0231 (0.70) | -0.2431 · 10 ⁻⁶ (-0.00) | -0.9463 · 10 ⁻³ (-0.07) | 50.2561*** (3.93) | -4.4149 (-0.68) | | 0.90 | 23.04*** (11; 67) | |
| | (8) | | 1.4131 (0.98) | -0.8509 · 10 ⁻⁴ (-0.25) | -0.0127 (-0.91) | 57.9365*** (4.54) | | 31.0447 (1.91) | 0.91 | 20.91*** (11; 67) | |
| Random-ef models | fects (9) | 333.992 (1.25) | 0.2827 (1.40) | | 0.9889 · 10 ⁻² (1.38) | | | | 0.83 | | 20.35*** |
| | (10) | -2202.57*** (-5.41) | 1.6182*** (4.28) | -0.3289 · 10 ⁻³ ** (-3.09) | -0.9606 · 10 ⁻² (-1.52) | 61.9686*** (6.65) | | | 0.88 | | 3.15 |
| | (11) | -2143.93*** (-5.01) | 1.6081*** (4.22) | -0.3247 · 10 ⁻³ ** (-3.02) | -0.9874 · 10 ⁻² (-1.55) | 60.9438*** (6.34) | -3.0140 (-0.47) | | 0.88 | | 4.15 |
| | (12) | -3101.42*** (-5.39) | 1.9638*** (5.05) | -0.3856 · 10 ⁻³ *** (-3.73) | -0.0117 (-1.92) | 62.1268*** (6.83) | | 14.4005* (2.13) | 0.89 | | 4.18 |

| | Fable 2 : Market Structure Determinants of Product Proliferation in the U.S. Food Industry. | 1988-94 (Dependent Variable: Innovations) | a) |
|--|--|---|----|
|--|--|---|----|

^{a)} For the definition of the variables, see the text. t-values in parentheses. - ^{b)} A statistically significant F-test implies that the null hypothesis of an equivalence of the OLS and the fixedeffects models is rejected. Sector-specific constants matter, which are not covered in the OLS model. DF stands for degrees of freedom. - ^{c)} A statistically significant Hausman test statistic implies that the null hypothesis of an equivalence of the fixed-effects and the random-effects model cannot be accepted. The fixed-effects model is preferable. - *** (**, *) Statistically significant at the 99.9% - (99% -, 95% -) level. Source: Own computations with the data shown in Appendix 1. 22

Table 3 specifies the concentration ratio rather than the number of companies in its original and squared form as explanatory variables of product innovations. Other independent variables are again the value of shipments as an indicator of the size of the market, the share of packaging costs in total costs as an indicator of product differentiation, the (past) market growth and the number of firms. The explanatory power of selected models is quite high. The "best" models explain 38% of the variation of product innovations in the plain OLS estimates and 93% in the fixed-effects models. The corrected coefficient of determination is slightly lower in the best random-effects model than in the best fixed-effects model.

Major economic results according to the plain OLS estimates are the following:

- 1. The number of product innovations peaks when CR4 reaches 57% and declines thereafter (see the OLS models (3) and (4) in Table 3).
- 2. The number of product innovations grows with a higher share of packaging in total costs. This variable is computed as an average across food industries over time. Hence, the significantly positive coefficient of PACKCOST in Table 3 suggests that the growing product differentiation over the period of analysis has also created incentives or pressure to innovate more frequently.
- 3. Apart from the nonlinear influence of the concentration ratio, an increasing number of firms on a market raises innovations. Furthermore, innovations are negatively affected by the size of a market as the OLS models (3) and (4) in Table 3 show.

Some results change if we use fixed-effects or random-effects models rather than plain OLS estimates. In general, the F-test for the fixed-effects models (5) to (8) in Table 3 suggests that sector-specific intercepts matter, i.e. innovations vary strongly across food industries. Compared to the plain OLS estimates, some of the measured influences of the market structure variables remain unaffected whereas others are not:

- 1. Equations (5) to (12) in Table 3 reveal again that the number of innovations rises with an increasing number of firms.
- 2. The fixed-effects estimates in model (6) and all random-effects models show that the number of innovations is fostered by a higher share of packaging costs in total costs. A rising product differentiation over time induces additional product proliferation.
- 3. The comparison between OLS and fixed-effects estimates in Table 3 reveals a striking difference in the impact of SIZE on the number of product innovations. The plain OLS estimates suggest that sectors with a high value of shipments are characterized by a lower number of product innovations as was the case for Table 2 already. However, if sectoral differences are taken into account, as is done in the fixed-effects models, Table 3 shows clearly that the number of innovations is significantly raised by a higher value of shipments. It seems that we can interpret this as follows: The size of an industry, measured by the value of shipments, is not favourable for the number of product innovations in a cross-sector comparison, but it is an incentive for product innovations over time in the respective food industries.

| | | | | | Independen | t Variables | | | | | Test Stat | tistics |
|------------------------|-------------|------------------------|------------------------|-----------------------|---------------------------------------|----------------------|---------------------|--------------------|-----------------------|------------------|---|--|
| Method/ Equations | | Constant | CR4 | (CR4) ² | SIZE | PACKCOST | COMPANY | GROWTH | SIZECOMP | \overline{R}^2 | F-Test: OLS=FE (DF) ^{b)} | Hausman's test statis- tic ^{c)} |
| OLS | (1) | 1186.90*** (4.45) | -7.0122 (-1.51) | | 0.2380 · 10 ⁻² (0.68) | | | | | 0.02 | | |
| | (2) | -2183.12 (-1.96) | 46.3546 (1.65) | -0.4227 (-1.55) | | 60.7229* (2.45) | | | -5.3185* (-2.01) | 0.18 | | |
| | (3) | -3699.12*** (-3.82) | 80.5227*** (3.60) | -0.7171*** (-3.53) | -0.0171*** (-4.19) | 65.4572** (3.04) | 0.6086*** (5.73) | | | 0.39 | | |
| | (4) | -3535.37*** (-3.48) | 79.9750*** (3.56) | -0.7087*** (-3.47) | -0.0172*** (-4.19) | 62.1627** (2.77) | 0.6087*** (5.70) | -8.6178 (-0.56) | | 0.38 | | |
| Fixed-effect models | s (5) | | 3.0275 (0.16) | | 0.0372** (3.25) | | | | | 0.87 | 47.73*** (11; 70) | |
| | (6) | | -167.215** (-3.22) | 1.8658*** (3.66) | | 55.4277*** (5.22) | | | -5.4672 (-0.67) | 0.92 | 68.15*** (11; 68) | |
| | (7) | | -292.412*** (-4.38) | 2.9504*** (4.95) | 0.0418* (2.57) | 17.0951 (1.26) | 1.0815* (2.53) | | | 0.93 | 57.32*** (11; 67) | |
| | (8) | | -310.252*** (-4.35) | 3.1063*** (4.89) | 0.0457** (2.67) | 16.1364 (1.18) | 1.0465* (2.43) | 4.2406 (0.73) | | 0.93 | 56.71*** (11; 66) | |
| Random-eff models | ects (9) | 318.067 (0.62) | 3.7940 (0.41) | | 0.0171* (2.61) | | | | | 0.83 | | 7.01* |
| | (10) | 687.701 (0.68) | -86.0300* (-2.22) | 0.9545* (2.62) | | 64.6041*** (7.75) | | | -13.6513** (-3.24) | 0.90 | | 8.33* |
| | (11) | -874.109 (-0.78) | -50.1331 (1.27) | 0.6014 (1.67) | -0.8268 · 10 ⁻² (-1.07) | 56.6564*** (6.52) | 0.6571** (3.21) | | | 0.89 | | 27.68*** |
| | (12) | -939.875 (-0.84) | -45.6357 (-1.13) | 0.5628 (1.53) | -0.9125 · 10 ⁻² (-1.16) | 55.8261*** (6.34) | 0.6737** (3.25) | -3.5504 (-0.64) | | 0.89 | | 27.64*** |

^{a)} For the definition of the variables, see the text. t - values in parentheses. - ^{b)} A statistically significant F-test implies that the null hypothesis of an equivalence of the OLS and the fixedeffects models is rejected. Sector-specific constants matter, which are not covered in the OLS model. DF stands for degrees of freedom. - ^{c)} A statistically significant Hausman test statistic implies that the null hypothesis of an equivalence of the fixed-effects and the random-effects model cannot be accepted. The fixed-effects model is preferable. - *** (**, *) Statistically significant at the 99.9% - (99% -, 95% -) level. **Source:** Own computations with the data shown in Appendix 1. 24 4. The implications of concentration for innovations are also dependent of the modelling framework. If fixed effects are accounted for, the impact of CR4 on innovations becomes U-shaped, with the minimum point at CR4 = 50%.

The value of HAUSMAN's test statistic for equations (9) to (12) in Table 3 show that fixedeffects models are superior to random-effects models in all four cases.

When all estimated equations of Tables 2 and 3 are compared, equations (7) and (8) in Table 3 perform best in terms of the corrected coefficient of determination. Equation (8), however, did not include significant new variables. Hence, we regard the more parsimonious equation (7) as the preferred estimate. By a more detailed analysis of equation (7), we can summarize now major results of this Section:

- 93% of the total variation in food product innovations across industries and over time in the U.S. in the period 1988-94 can be explained by the model. The level of concentration in the industries, the size of the industries in terms of their value of shipments, product differentiation as indicated by packaging costs, and the number of firms in an industry are important explanatory variables as well as fixed effects for sector-specific differences in innovation. This implies that market structure clearly affects market conduct and market performance.
- It is important to control for sector-specific differences in innovation in a pooled data set. This can be seen as the fixed-effects model raises the \overline{R}^2 compared to the similar OLS equation (3) from 0.39 to 0.93. The move to the fixed-effects model changes in some cases the sign of the measured impacts of individual explanatory variables (CR4, SIZE).
- The influence of concentration on innovations is of the U-type form. This means that an increase of concentration does not provide a uniform change in innovations across all possible values of CR4. Equation (7) indicates that a change in CR4 by one percentage point lowers product innovations by 115 (56) at a CR4 of 30% (40%), but raises innovation by 61 (121) at a CR4 of 60% (70%). The minimum number of innovations lies at a CR4 of 49.6%⁷. Consequently, the most positive influence of concentration on innovations occurs at lower and higher rates of concentration.
- Equation (7) of Table 3 shows additionally that an increase of the value of shipments in an industry by one billion dollars raises the number of product innovations by 42 per year.
- Moreover, an increase in the number of companies by one raises the number of product innovations by 1.08.

It is remarkable how the estimated concentration-innovation linkage is affected by the statistical estimation method. The results suggest the presence of bias of the type shown in Figure 1 in the food industries. When we compare the coefficients of equations (3) and (7) in Table 3, very different conclusions for the concentration-innovation linkage must be drawn on the basis of plain OLS as opposed to fixed-effects estimates, as Figure 2 illustrates.

⁷This can easily be derived from equation (7) as the first derivative of innovations (I) with regard to CR4 is $\partial I/\partial (CR4) = -292.412 + 2.9504 \cdot 2CR4 = 0$ or, after rearrangements, CR4 = 49.5546.





Source: Computed with equations (3) and (7) of Table 3.

As both equations consider a nonlinear influence of concentration on innovations, the marginal impact of a change in CR4 on product innovations is not constant for all levels of concentration. Under the fixed-effects model, the linkage is of the U-form type. The marginal impact of concentration on innovations is negative for CR4 < 49.6% and positive for CR4 > 49.6%. The effect is exactly opposite under the plain OLS estimates. Equation (3) of Table 3 reveals an inverse U-type relationship: A marginal increase in concentration raises the number of innovations until a maximum is reached at a CR4 of 56.1%. Above this level of concentration, a marginal increase of concentration lowers the number of product innovations.

Our interpretation of this result is that the plain OLS estimates yield biased results on the concentration-innovation linkage. When all data are pooled in a plain OLS estimate, some extreme observations seem to drive the overall regression: There are industries with a CR4 around 55% like beverages or candy/gum/snacks with a large number of product innovations on the one hand and highly-concentrated industries like side dishes and low-concentration industries like desserts with an especially low number of product innovations on the other hand. This may yield the inverse U-form linkage in the plain OLS estimates. When the sectorspecific intercepts for product innovations are taken into account, a U-type relationship bet-

26

ween concentration and innovations is revealed in the fixed-effects models.

How do the quantitative results for 1988-94 differ from the studies of CONNOR (1981) and ZELLNER (1989) which were based on data for 1977-78 and 1977 respectively? We can summarize that some findings of Table 3 confirm earlier results by CONNOR and ZELLNER, whereas some results are clearly different.

Consistent with CONNOR (1981) is the result that the number of new food product introductions is raised by a growing size of the markets of the respective industries. Furthermore, the share of packaging costs in total marketing costs had a clearly positive impact on product proliferation in CONNORS's analysis. Our findings in Table 3 show a positive regression coefficient of PACKCOST in all equations, and it is statistically significant in almost all equations. This suggests that physical differentiation and visual presentation remained an important determinant of new product introductions. Additionally, past growth does not significantly influence product proliferation in our more comprehensive data set as in CONNOR's analysis.

Different from CONNOR (1981) is the concentration-innovation linkage. His results indicate a positive influence of concentration on product proliferation, when CR4 is introduced only in unsquared form, and an inverse U-form when the squared coefficient is added. The latter result is confirmed in our plain OLS estimates, e.g. in equations (3) and (4) of Table 3, but a U-form influence is revealed when the sector-specific intercepts are taken into account, e.g. in equations (6) to (8) of Table 3. In this case, we regard the fixed-effects estimates as a superior methodological approach given the pooled data set and the theoretical argument for industry-specific differences illustrated in Figure 1. The result presented here differs also from ZELL-NER (1989), who found a linear and positive influence of concentration on new product introductions. Summing up, the earlier views on the concentration-innovation linkage have to be corrected when sector-specific differences in innovations are controlled for. The influence of the concentration ratio on the number of new food product introductions in the U.S. food industry is nonlinear and of the U-form.

ZELLNER's (1989) result of a positive impact of growth in value of shipments on new product introductions is not confirmed for our broader data set on the basis of all methodological approaches. However, ZELLNER's finding that the number of brands in an industry significantly stimulates the number of new product introductions, seems very consistent with the positive coefficient of PACKCOST in the earlier analysis of CONNOR (1981) and in our results. Again, this underlines the conclusion that new product introductions are especially important in food industries with an already substantial product differentiation.

Some additional computations have been performed with double-logarithmic models in order to check whether the results are sensitive to functional forms. These computations, which include the concentration ratio and the number of companies without a squared term, are presented in Appendix 2. It can be seen again that fixed-effects models outperform OLS and random-effects models. With fixed-effects models, a major share of variation in product innovations can be explained: The \overline{R}^2 values range between 0.95 and 0.97. Although these general results are similar to those in Table 4, some of the economic linkages are affected by the choice of the functional form. A significantly positive influence of product differentiation, measured by PACKCOST, on product innovations occurred. New product introductions increased significantly with a declining number of firms in the market as well as a falling CR4. Thus, the concentration-innovation linkage is affected by the functional specification of the model. The magnitude of the point estimates of the elasticities of product innovations is interesting: They range above unity in absolute terms with regard to CR4, PACKCOST and COM-PANY according to equations (5) and (6) in Appendix 2. A one-percent change in the independent variables changes the number of product innovations by more than one percent.

4.3.2 Determinants of Product Innovations per Company

Tables 4 and 5 show how market-structure variables affected the number of product innovations per company in the U.S. food industry in the period 1988-94. This topic had not been covered in earlier studies. The presentation of results is similar to the previous section. Table 4 captures the number of firms and Table 5 the concentration ratios in original and squared form as explanatory variables of product innovations per company. Other independent variables are the value of shipments as indicator of the size of the market or the value of shipments per company (SIZECOMP) as an indicator of the average firm size in the product class, the share of packaging costs in total costs as indicator of product differentiation and (past) market growth.

Table 4 shows that the models' results are very satisfactory given the pooled cross-section and time-series data. The corrected coefficients of determination in the "best" models are 0.60 for OLS estimates, 0.90 for fixed-effects and 0.88 for random-effects estimates. Striking results are the following:

1. Whereas product innovations increase with the number of firms, the reverse is true for innovations per company. A declining number of firms in a product class raises the innovation activity per firm, as equation (1) in Table 4 confirms. The OLS estimates (2) to (4) point at a nonlinear impact. With a declining number of firms, there is a less than proportionate increase in innovation activity. These OLS estimates have to be treated with caution, however. Neither the fixed-effects nor the random-effects model confirms a nonlinear influence and, as shown by statistically significant F-tests, systematic differences in innovation activities per firm exist and should not be ignored as in the OLS models. Fixed-effects and random-effects models differ with regard to the statistical significance of COMPANY. As the HAUSMAN test is insignificant for all model specifications, there is no indication of a misspecification of the random-effects models. Hence, we can conclude due to equations (10) and (11) in Table 4 that per-firm product innovations decline with a rising number of firms in a product class.

| | | | | I | ndependent Var | iables | | | | | Test Stat | istics |
|------------------------|-------------|----------------------|---|---|---------------------------------------|---------------------|-----------------------|---------------------|---------------------------------------|------------------|---|--|
| Method/ Equations | | Constant | COMPANY | (COMPANY) ² | SIZE | PACKCOST | GROWTH | CR 4 | SIZECOMP | \overline{R}^2 | F-Test: OLS=FE (DF) ^{b)} | Hausman's test statis- tic ^{c)} |
| OLS | (1) | 1.9868*** (12.85) | -0.5392 · 10 ⁻³ *** (-3.69) | | -0.2738 · 10 ⁻⁵ (-0.45) | | | | | 0.29 | | |
| | (2) | 0.5172 (0.46) | -0.1405 · 10 ⁻² *** (-4.72) | 0.2895 · 10 ⁻⁶ ** (3.34) | -0.8613 · 10 ⁻⁵ (-1.46) | 0.0539 (1.75) | | | | 0.39 | | |
| | (3) | 0.8838 (0.73) | -0.1451 · 10 ^{-2***} (-4.79) | $\begin{array}{c} 0.3014 \cdot 10^{-6} * * * \\ (3.43) \end{array}$ | -0.8930 · 10 ⁻⁵ (-1.51) | 0.0469 (1.47) | -0.0185 (-0.84) | | | 0.38 | | |
| | (4) | -1.4456 (-1.53) | -0.8457 · 10 ⁻³ ** (-3.02) | $0.1550 \cdot 10^{-6}$ * (2.07) | | 0.0487 (1.97) | | 0.0366*** (6.50) | -0.3205 · 10 ⁻² (-1.35) | 0.60 | | |
| Fixed-effect models | (5) | | $0.3665 \cdot 10^{-4}$ (1.63) | | $0.2453 \cdot 10^{-4}$ (1.63) | | | | | 0.86 | 31.75*** (11; 70) | |
| | (6) | | -0.2763 · 10 ⁻² (-1.20) | $0.4970 \cdot 10^{-6}$ (0.91) | -0.2380 · 10 ⁻⁴ (-1.20) | 0.0657** (3.31) | | | | 0.88 | 31.01*** (11; 68) | |
| | (7) | | -0.3081 · 10 ⁻² (-1.48) | $0.6505 \cdot 10^{-6}$ (1.31) | -0.2961 · 10 ⁻⁴ (-1.64) | 0.0535** (2.94) | -0.0371*** (-4.00) | | | 0.90 | 38.88*** (11; 67) | |
| | (8) | | -0.2582 · 10 ⁻² (-1.16) | 0.4096 · 10 ⁻⁶ (0.79) | | 0.0713*** (3.87) | | 0.0500* (2.27) | -0.0287* (-2.12) | 0.89 | 20.62*** (11; 67) | |
| Random-eff models | ects (9) | 1.8764*** (5.13) | -0.6795 · 10 ⁻³ * (-2.38) | | -0.8500 · 10 ⁻⁵ (-0.82) | | | | | 0.84 | | 2.70 |
| | (10) | 0.5362 (0.78) | -0.1450 · 10 ⁻² * (-2.13) | $0.3062 \cdot 10^{-6}$ (1.61) | -0.1123 · 10 ⁻⁴ (1.03) | 0.0555*** (3.71) | | | | 0.86 | | 0.93 |
| | (11) | 1.2431 (1.83) | -0.1594 · 10 ⁻² * (-2.33) | 0.3694 · 10 ⁻⁶ (1.94) | -0.1571 · 10 ⁻⁴ (-1.49) | 0.0439** (3.12) | -0.0361*** (-3.92) | | | 0.88 | | 2.48 |
| | (12) | -1.6576 (-1.97) | -0.1020 · 10 ⁻² (-1.66) | $0.2010 \cdot 10^{-6}$ (1.23) | | 0.0516*** (3.89) | | 0.0442*** (4.01) | -0.7502·10 ⁻² (-1.54) | 0.87 | | 3.76 |

Table 4: Market Structure Determinants of Product Proliferation in the U.S. Food Industry, 1988-94 (Dependent Variable: Innovations per Company)^{a)}

^{a)} For the definition of the variables, see the text. t - values in parentheses. - ^{b)} A statistically significant F-test implies that the null hypothesis of an equivalence of the OLS and the fixedeffects models is rejected. Sector-specific constants matter, which are not covered in the OLS model. DF stands for degrees of freedom. - ^{c)} A statistically significant Hausman test statistic implies that the null hypothesis of an equivalence of the fixed-effects and the random-effects model cannot be accepted. The fixed-effects model is preferable. - *** (**, *) Statistically significant at the 99.9% - (99% -, 95% -) level. Source: Own computations with the data shown in Appendix 1.

- 2. Besides the nonlinear impact of the number of firms, there is a positive effect of CR4 on product innovations per company. This is visible from the OLS model (4), the fixed-effects model (8) and the random-effects model (12) of Table 4. It can be concluded that a firm in a highly concentrated sector is more innovative than a firm in a less concentrated sector under ceteris-paribus conditions, and that innovations per company rise with an increasing concentration ratio.
- 3. When we consider industry-specific differences in innovations per company (models (5) to (12) in Table 4), it can be seen that PACKCOST affects ICOMP positively. A higher share of packaging costs in total costs over time signals more product differentiation, which itself puts an industry under pressure to continue to innovate.
- 4. The influence of GROWTH is significantly negative in the fixed-effects model (7) and the random-effects model (11) in Table 4. This suggests that low past growth may threaten an industry and forces companies to introduce more innovations in order to improve its future performance.
- 5. The variable SIZE is not an important variable in the explanation of product innovations per company. The regression coefficients are insignificant in all cases. The variable SIZE-COMP, however, is statistically significant at the 95%-level in model (8) of Table 4. We can conclude that firms in the food industry are more innovative on a per-firm basis when the average firm size lowers.

Table 5 presents the models where the concentration ratio entered in original and squared form. In general, the explanatory power of the models is high with an \overline{R}^2 of 0.57 to 0.62 in the plain OLS estimates, 0.87 to 0.95 in the fixed-effects estimates and 0.85 to 0.95 in the random-effects estimates. Industry-specific levels of product innovations per company matter as the F-test for equations (5) to (8) of Table 5 shows and fixed-effects models outperform random-effects models in three out of four cases. Major results are as follows:

- 1. Product innovations per company are higher the more concentrated an industry is (see equation (1) in Table 5). If nonlinearities are allowed for, there is a U-shaped influence of CR4 on ICOMP. This relationship is not significant in the OLS model, but statistically very significant in the fixed-effects and random-effects models, i.e. when industry-specific levels of product innovations per company are controlled for. Apart from the nonlinear impact of CR4, there is no significant effect of the number of firms in an industry on product innovations per company.
- 2. The signs of the SIZE coefficient are similar to those in the regressions of Table 3. In the OLS estimates, SIZE affects the number of product innovations per company negatively (see equations (1) and (2)), whereas the causality is positive and significant in one fixed-effects model (see model (6) in Table 5). Similar to the explanation of total product innovations, we can conclude that a negative influence of the size of the market does not exist when the industry-specific differences in innovations per company are controlled. Equation

| | | | | | Independent | Variables | | | | | Test Stati | stics |
|------------------------|--------------|---------------------|-------------------------------------|---------------------------------------|---|---------------------|-------------------------------------|-----------------------|---------------------------------------|------------------|---|--|
| Method/ Equations | | Constant | CR4 | (CR4) ² | SIZE | PACKCOST | COMPANY | GROWTH | SIZECOMP | \overline{R}^2 | F-Test: OLS=FE (DF) ^{b)} | Hausman's test sta- tistic ^{c)} |
| OLS | (1) | -0.2409 (-0.98) | 0.0387*** (8.99) | | -0.1175·10 ⁻⁴ ** (-3.64) | | | | | 0.59 | | |
| | (2) | 0.7012 (1.11) | -0.2440·10 ⁻² (-0.09) | 0.3801·10 ⁻³ (1.61) | -0.1077·10 ⁻⁴ ** (-3.31) | | | | | 0.60 | | |
| | (3) | -0.2379 (-0.20) | -0.0339 (-1.16) | 0.7683·10 ⁻³ ** (2.71) | | 0.0389 (1.45) | | -0.0212 (-1.12) | -0.4040 · 10 ⁻² (-1.43) | 0.57 | | |
| | (4) | -0.4269 (-0.38) | -0.4853·10 ⁻² (-0.19) | 0.3953·10 ⁻³ (1.73) | -0.8759·10 ⁻⁵ * (-1.91) | 0.0394 (1.57) | -0.1062·10 ⁻³ (-0.89) | -0.0308 (-1.79) | | 0.62 | | |
| Fixed-effect models | ts (5) | | 0.0610* (2.38) | | $\begin{array}{c} 0.8741 \cdot 10^{-5} \\ (0.55) \end{array}$ | | | | | 0.87 | 17.72*** (11; 70) | |
| | (6) | | -0.5374*** (-8.26) | 0.5735·10 ⁻² *** (9.52) | 0.4967·10 ⁻⁴ *** (4.37) | | | | | 0.94 | 46.94*** (11; 69) | |
| | (7) | | -0.3454*** (-5.80) | 0.4079·10 ⁻² *** (6.95) | | 0.0268* (2.26) | | -0.0274*** (-4.09) | -0.1668 · 10 ⁻² (-0.18) | 0.95 | 57.14*** (11; 67) | |
| | (8) | | -0.4235*** (-4.99) | 0.4730·10 ⁻² *** (6.25) | 0.2160·10 ⁻⁴ (1.06) | 0.0132 (0.81) | -0.3315·10 ⁻³ (-0.65) | -0.0243*** (-3.51) | | 0.95 | 49.05*** (11; 66) | |
| Random-eff models | fects (9) | -0.6599 (-1.32) | 0.0448*** (5.03) | | -0.6217·10 ⁻⁵ (-0.96) | | | | | 0.85 | | 3.04 |
| | (10) | 5.2333*** (4.89) | -0.2362*** (-5.26) | 0.2698·10 ⁻² *** (6.50) | 0.1156·10 ⁻⁴ (1.83) | | | | | 0.89 | | 53.37*** |
| | (11) | 3.8284*** (3.48) | -0.2115*** (-4.99) | 0.2604·10 ⁻² *** (6.53) | | 0.0398*** (4.17) | | -0.0314*** (-4.84) | -0.0147 (-3.26) | 0.93 | | 16.96** |
| | (12) | 3.0885* (2.40) | -0.1704*** (-3.70) | 0.2071·10 ⁻² *** (4.94) | -0.7054·10 ⁻⁵ (-0.79) | 0.0338** (3.27) | $0.3314 \cdot 10^{-4} \\ (0.14)$ | -0.0321*** (-4.90) | | 0.92 | | 30.26*** |

Table 5: Market Structure Determinants of Product Proliferation in the U.S. Food Industry, 1988-94 (Dependent Variable: Innovations per Company)^{a)}

^{a)} For the definition of the variables, see the text. t - values in parentheses. - ^{b)} A statistically significant F-test implies that the null hypothesis of an equivalence of the OLS and the fixedeffects models is rejected. Sector-specific constants matter, which are not covered in the OLS model. DF stands for degrees of freedom. - ^{c)} A statistically significant Hausman test statistic implies that the null hypothesis of an equivalence of the fixed-effects and the random-effects model cannot be accepted. The fixed-effects model is preferable. - *** (**, *) Statistically significant at the 99.9% - (99% -, 95%-) level. **Source:** Own computations with the data shown in Appendix 1. 31 (7) in Table 5 does not indicate a clear-cut picture of the influence of the average firm size on product proliferation, either.

3. A new and remarkable result of equations (7), (8), (11) and (12) in Table 5 is that the fixedeffects and random-effects models confirm a negative effect of past growth in an industry on product innovations per company. This result suggests that the pressure to innovate is particularly high after periods of low industry growth.

We can summarize the econometric results on the concentration-innovation linkage within Table 5, by saying that the modelling approach does not affect the results as severely as in the case of total innovations. The comparison between plain OLS estimates, e.g. equation (3), with the fixed-effects model (7) shows that the signs of the regression coefficients are the same for both models. The size of the coefficients differs, but the functional form does not change as for total innovations. The U-type form is stable across the different modelling approaches in explaining ICOMP.

A more precise interpretation of the determinants of innovations per company is possible on the basis of individual equations. Our preferred estimate is equation (7) of Table 5. Various explanatory variables are highly significant in that equation and the explanatory power is high. The comparison with equation (3) shows that the fixed effects for individual industries matter and equation (7) is superior to equation (3). The significant HAUSMAN statistic of equation (11) shows that (7) is also preferable to equation (11). Equation (7) can be interpreted as follows:

- 1. Apart from industry-specific levels of innovations per company, the industry's level of concentration (CR4), the product differentiation on the industry's markets as indicated by the share of packaging costs in total marketing costs, and the past growth in the individual industries affect innovations per company significantly.
- 2. The influence of concentration on innovations per company is nonlinear and of the U-type form. An increase in concentration does not lead to a uniform change in innovations for all possible values of CR4. A change in CR4 by one percentage point lowers product innovations in the U.S. food industry per company and year by 0.18 (0.10) at a CR4 of 20% (30%), by 0.02 at a CR4 of 40%, but raises innovations per company by 0.06 (0.14) at a CR4 of 50% (60%) and by 0.23 (0.31) at a CR4 of 70% (80%). The minimum number of innovations per company lies at a CR4 of 42.3%⁸. There are only a few industries with CR4 < 42%, and most of them serve small geographical markets. Consequently, concentration has a positive effect on innovations per company for most industries. This is consistent with the finding for the absolute number of innovations.</p>

⁸ This can be derived from equation (7) in Table 5 as the first derivative of innovations per company (ICOMP) with regard to CR4 is: δ ICOMP/ δ (CR4) = -0.3454 + (2.0.4079.10⁻²).(CR4). Hence, the first derivative is zero if CR4 = 42.3388.

- 3. Equation (7) of Table 5 shows additionally that an increase of the share of packaging costs in total marketing costs by one percentage point raises innovations per company by 0.03. More product differentiation fosters innovative activities.
- 4. A reduction of year-to-year growth of the value of shipment by one percentage point raises innovations per company and year in the U.S. food industry by 0.03.

As earlier quantitative studies on the determinants of product proliferation did not cover results on a per-company basis, the results of Table 5 cannot be compared with those of CON-NOR (1981) and ZELLNER (1989). Some interesting conclusions emerge, however, when one contrasts the determinants of the total number of innovations and of innovations per company. In both cases, market structure did significantly affect the introduction of new food products in the U.S. food industry in the period 1988-94. New product introductions in absolute numbers and per company are driven by industry-specific characteristics, i.e. the fixed effects. Beyond that, there is an influence of concentration on product innovations and innovations per company which is of the U-type form. The size of an industry does not affect innovations per company, but is positively associated with the absolute number of innovations. Product differentiation tends to have a positive impact on the absolute number of new product introductions and new product introductions per company, although the coefficients were not in all estimations statistically significant. Growth of an industry does not play a role for the total number of innovations in the U.S. food industry, but it negatively affects the number of product innovations per company. Hence, there are some common factors explaining product innovations as an absolute number and on a per-company basis, but other factors drive the two dependent variables very differently.

Additional computations have been carried out in order to test for the influence of functional form on the modelling results. They are shown in Appendix 3. The comparison of Table 6 and Appendix 3 shows that the presented economic linkages are in some cases changed by the functional form. The double-logarithmic specification of equation (5) in Appendix 3 indicates that the number of innovations per company rises with a declining size of the market and a lower number of companies in the market. When average firm sizes are computed as in equation (6) of Appendix 3, the number of innovations per company is significantly raised by a growing average firm size. This is different from the results in Table 3. However, the general result remains that sector-specific fixed effects are very important and more than 90% of the variation in innovations per company are explained by each of the fixed-effects models.

5 An Extension of the Empirical Analysis: A Comparison of the U.S. Results with Food Product Proliferation in Germany

For a comparative purpose, the amount and development of new product introductions in the German food industry will be outlined and analyzed in the following. Conclusions will then be drawn on how food product proliferation and its determinants differ between the U.S. and Germany.

This section continues recent work on product innovations in the German food industry, in which a detailed data basis on new product introductions has been developed by branch of the food industry [ZAHN (1995); STÜHMEYER (1997)]. Moreover, determinants of a differential activity across the branches of the food industry have been elaborated [HERRMANN, REIN-HARDT and ZAHN (1996); HERRMANN (1997)]. We extend this literature here in two respects:

- 1. The entire available data basis on new product introductions in the period 1992-95 is utilized, whereas the earlier analysis of HERRMANN (1997) concentrated on a shorter period.
- 2. We apply, consistent with the analysis for the U.S. food industry, panel-data models to elaborate on the determinants of product proliferation and compare those results with OLS estimates.

5.1 Measurement of Product Proliferation in the German Food Industry

Product proliferation is measured here with an output-oriented indicator. New products in the German food industry are counted and the numbers are attributed to individual branches of the industry. The source of data is the weekly published newspaper "Lebensmittelzeitung" which presents these product innovations. The data basis has been collected and provided by ZAHN (1995) and STÜHMEYER (1997). A new product is defined here in a very broad sense and covers three types of innovations: (i) <u>market innovations</u>, which are real novelties on a market; (ii) <u>quasi-new products</u>, i.e. innovations which improve the characteristics of existing products; (iii) me-too products which are only new for the individual firm but do not essentially differ from similar products of other firms.

Table 6 summarizes the number of new product introductions over the period 1993-96 in the German food and beverages industry. 3490 new product introductions are recorded over the four years. A substantial share of innovations is concentrated in a few industries. Five out of 20 industries account for 60.1% of all new products. The most innovative industries are the manufacture of condiments and seasonings, homogenized food preparations and dietetic food, with 517 new products and 14.8% of all innovations, and the manufacture of cocoa, chocolate and sugar confectionery, with 12.7%. Similar trends were observed for the U.S. food industry in Chapter 4.2.⁹ The operations of dairy and cheese making follow with 12.2%, the manufacture of other food products with 11.3% and the production, processing and preserving of meat and meat products with 9.1%. A large variety of products is produced by these industries and the consumers' demand for variety is very strong at the markets of these industries.

⁹ For two reasons it is difficult to compare U.S. and German data on product innovations on an absolute basis. Firstly, the categories in which food product innovations were recorded are not similar in the two countries. Secondly, due to data restrictions the data on new food product introductions in Germany are not as comprehensive as the U.S. data set. But although the absolute number of product innovations in Germany might be underestimated, data can be compared on a relative basis.

5.2 Determinants of Product Proliferation in the German Food Industry: The Empirical Model and Results

The empirical model described for the U.S. is also utilized for the analysis of the German data on innovations across food industries and over time. Similar to equation (6), we test the influence of concentration, the size and growth of the industries and the number of firms on the absolute number of innovations. In all panel-data models, the specific features of the industries in innovation activities are considered by fixed or random effects. Different from equation (6)

| Food Industries ^{b)} | 1993 | 1994 | 1995 | 1996 | 1993-96 |
|---|------|------|------|------|---------|
| Manufacture of grain mill products | 7 | 14 | 9 | 9 | 39 |
| Manufacture of macaroni, noodles, couscous and similar farinaceous products | 6 | 20 | 22 | 19 | 67 |
| Manufacture of condiments and seasonings, homogenized food preparations and dietetic food | 137 | 128 | 129 | 123 | 517 |
| Processing and preserving of potatoes | 10 | 9 | 14 | 11 | 44 |
| Manufacture of bread, manufacture of fresh pastry goods and cakes | 18 | 10 | 32 | 28 | 88 |
| Manufacture of rusks, pastry goods and cakes | 22 | 38 | 44 | 41 | 145 |
| Processing and preserving of fruit and vegetables | 45 | 80 | 45 | 56 | 226 |
| Manufacture of cocoa, chocolate and sugar confectionery | 115 | 112 | 130 | 85 | 442 |
| Operations of dairy and cheese making | 90 | 100 | 136 | 100 | 426 |
| Production of sterilized milk | 11 | 2 | 4 | 2 | 19 |
| Manufacture of crude and refined oils and fats | 1 | 4 | 9 | 0 | 14 |
| Manufacture of margarine and similar edible fats | 1 | 5 | 3 | 1 | 10 |
| Production, processing and preserving of meat and meat products | 71 | 74 | 78 | 94 | 317 |
| Production, processing and preserving of fish and fish products | 14 | 41 | 24 | 17 | 96 |
| Processing of tea and coffee | 27 | 31 | 43 | 36 | 137 |
| Manufacture of beer and malt | 12 | 14 | 8 | 16 | 50 |
| Manufacture of distilled potable alcoholic beverages | 34 | 58 | 41 | 48 | 181 |
| Manufacture of wines, fruit wines and other nondistilled fermented beverages | 20 | 42 | 33 | 33 | 128 |
| Production of mineral water and soft drinks | 25 | 39 | 55 | 31 | 150 |
| Manufacture of other food products | 51 | 125 | 99 | 119 | 394 |
| Total food industry | 717 | 946 | 958 | 869 | 3490 |

Table 6:Product Innovations in German Food Industry, 1993-96^{a)}

a) Data on the sugar industry and the manufacture of starch products are excluded here. b) The naming of the industries follows "NACE Rev. 1", the Eurostat classification [EUROSTAT (1993)].

Source: Data files from ZAHN (1995) and STÜHMEYER (1997).

is that the German data allow a more direct and sector-specific measure of the existing product differentiation on new product introductions. The variable VARIETY stands for the average number of products offered by an industry in German supermarkets. It captures product differentiation more directly than the variable PACKCOST in the U.S. database.

The determinants of innovations are measured as follows. COMPANY is defined, as for the U.S., as the number of firms in the individual branches of the food industry. Data were available for 1980-94 from STATISTISCHES BUNDESAMT(a) for the former West Germany and values for 1995-96 were forecast by linear trends from these data. It was experimented with two different SIZE measurements, namely gross-value added and sales. Gross-value added data were provided by STATISTISCHES BUNDESAMT(b) for 1980-94 in the former West Germany and the value for 1995 was estimated from a trend equation for 1980-94. Sales data are taken from BMELF. As the time series with sales data performed better in the econometric estimates, the SIZE coefficients are based on the sales data. CONC measures the concentration of sales in the respective food categories on the basis of the Herfindahl-Hirschman coefficient times 1000, following the statistical procedure in STATISTISCHES BUNDESAMT(c). Data on concentration were available from 1983-94 and the values for 1995 were forecast by linear or quadratic trend equations. VARIETY is quantified on the basis of EURO-HANDELSINSTITUT data. The average number of articles supplied for various food categories in supermarkets is presented there for individual years and were attributed to the branches of the food industry utilized here. Missing data were interpolated. The full data basis is shown in Appendix 4, and the empirical results are presented in Tables 7 to 10.

Tables 7 and 8 show how market structure variables affected the number of product innovations in the German food industry in the period 1993-96. Table 7 (8) captures the number of firms (the concentration coefficient) in original and squared form as an explanatory variable of product innovations.

The explanatory power of the models in Table 7 is rather high, with VARIETY responsible for much of the explanation. The corrected coefficients of determination range between 0.27 and 0.87 in the plain OLS and random-effects estimates and are 0.91 or 0.92 in the fixed-effects models. The major results are the following:

1. The fewer firms in a market, the higher is the total number of product innovations on that market (see equations (1) to (4) in Table 7 or the random-effects model (11)). The sign of the influence of COMPANY is thus different from the U.S. case. Also different is the fact that the estimates do not reveal any significant nonlinearity in the relationship. The coefficient of (COMPANY)² is statistically insignificant in all estimated models. The influence of the number of firms on innovations is negative in all estimates, but the coefficients are only statistically different from zero in the plain OLS models and in the random-effects model (11). In general, the F-test indicates that sector-specific differences in innovation matter

| | | | | Ind | ependent Variables | | | | | Test Statis | tics |
|-----------------------|--------------|--------------------|---------------------|---|---------------------------------------|----------------------|--------------------|--------------------|------------------|---|--|
| Method/ Equations | | Constant | COMPANY | (COMPANY) ² | SIZE | VARIETY | CONC | GROWTH | \overline{R}^2 | F-Test: OLS=FE (DF) ^{b)} | Hausman's test statis- tic ^{c)} |
| OLS | (1) | 15.9871* (2.38) | -0.0355* (-2.16) | | 0.4137·10 ⁻² *** (5.52) | | | | 0.27 | | |
| | (2) | -1.4827 (-0.49) | -0.0848* (-2.06) | 0.3094·10 ⁻⁴ (1.00) | 0.2825·10 ⁻² *** (5.30) | 0.1333*** (18.91) | | | 0.87 | | |
| | (3) | 6.5663 (1.13) | -0.1156* (-2.57) | 0.5159·10 ⁻⁴ (1.56) | 0.2756·10 ⁻² *** (5.21) | 0.1331*** (19.08) | -0.0384 (-1.62) | | 0.87 | | |
| | (4) | -0.7748 (-0.25) | -0.0904* (-2.16) | 0.3531·10 ⁻⁴ (1.12) | 0.2867·10 ⁻² *** (5.31) | 0.1330*** (18.68) | | -0.1062 (-0.54) | 0.87 | | |
| Fixed-effec models | ets (5) | | -0.0399 (-0.29) | | 0.4682·10 ⁻² * (2.38) | | | | 0.91 | 30.86*** (19; 58) | |
| | (6) | | -0.0828 (-0.29) | -0.0422·10 ⁻⁴ (-0.27) | $0.4522 \cdot 10^{-2} *$ (2.24) | 0.1358* (2.26) | | | 0.92 | 3.25*** (19; 59) | |
| | (7) | | -0.0903 (-0.31) | -0.3762·10 ⁻⁴ (-0.25) | 0.4514·10 ⁻² * (2.22) | 0.1368* (2.25) | -0.0532 (-0.38) | | 0.92 | 3.00*** (19; 55) | |
| | (8) | | -0.0893 (-0.31) | -0.2981·10 ⁻⁴ (-0.19) | 0.4835·10 ⁻² * (2.33) | 0.1330* (2.19) | | -0.1930 (-0.99) | 0.92 | 3.17*** (19; 54) | |
| Random-eff models | fects (9) | 14.7728 (1.26) | -0.0375 (-1.27) | | 0.4330·10 ⁻² *** (3.77) | | | | 0.27 | | 0.05 |
| | (10) | -1.7544 (-0.41) | -0.0886 (-1.63) | $\begin{array}{c} 0.3303 \cdot 10^{-4} \\ (0.81) \end{array}$ | 0.2936·10 ⁻² *** (4.17) | 0.1325*** (13.18) | | | 0.87 | | 1.72 |
| | (11) | 5.9792 (0.74) | -0.1165* (-1.97) | 0.5168·10 ⁻⁴ (1.19) | 0.2847·10 ⁻² *** (4.09) | 0.1323*** (13.51) | -0.0369 (-1.12) | | 0.87 | | 1.92 |
| | (12) | -1.0481 (-0.24) | -0.0957 (-1.73) | $\begin{array}{c} 0.3875 \cdot 10^{-4} \\ (0.93) \end{array}$ | 0.3002·10 ⁻² *** (4.20) | 0.1324*** (13.07) | | -0.1555 (-0.87) | 0.87 | | 1.90 |

Table 7: Market Structure Determinants of Product Proliferation in the German Food Industry, 1993-1996 (Dependent Variable: Innovations)^{a)}

^{a)} For the definition of the variables, see the text. t - values in parentheses. - ^{b)} A statistically significant F-test implies that the null hypothesis of an equivalence of the OLS and the fixedeffects models is rejected. Sector-specific constants matter, which are not covered in the OLS model. DF stands for degrees of freedom. - ^{c)} A statistically significant Hausman test statistic implies that the null hypothesis of an equivalence of the fixed-effects and the random-effects model cannot be accepted. The fixed-effects model is preferable. - *** (**, *) Statistically significant at the 99.9% - (99% -, 95% -) level. **Source:** Own computations with the data shown in Appendix 4. 37 and that the plain OLS models are inferior. The HAUSMAN test statistic is not significant, however, thus leading to the conclusion that the random-effects models are preferable to the fixed-effects models. The random-effects model (11) shows the negative impact of COMPANY at the 95%-level of significance and the models (10) and (12) at the 90%-level.

- 2. Apart from the number of firms, the concentration coefficient CONC does not affect the number of product innovations significantly. The variable GROWTH is not statistically significant either.
- 3. According to all modelling approaches, the impact of SIZE on the number of product innovations is positive for the German food industry. I.e., larger sectors in terms of sales earnings perform better with regard to innovative activities than smaller sectors.
- 4. As was already confirmed in earlier studies [HERRMANN (1997); STÜHMEYER (1997)], existing product differentiation is positively associated with the number of new product introductions in the food industry. This is confirmed by the positive coefficient of VARIETY which is statistically significant and ranges between 0.13 and 0.14 in all models. The random-effects model suggests that an increase by one unit in the average number of articles of an industry carried in supermarkets will raise the number of product innovations by 0.13 units. The rationale for this finding is that the consumers' demand for variety and the competitors' innovations in branches with high product heterogeneity put pressure on the individual firms in those branches to increase the innovative activities, too.

Table 8 considers a nonlinear effect of concentration rather than the number of companies. The explanatory power of selected models is quite high. The corrected coefficients of determination are 0.87 in the best plain OLS and random-effects models and 0.92 in the best fixed-effects models. Sector-specific differences matter and the random-effects and the fixed-effects models seem equivalent given the insignificant HAUSMAN tests. The empirical findings are, like in Table 8, that product innovations in the German food industry are fostered by SIZE and VARIETY, but diminished by an increasing number of companies. The latter effect is significant in the OLS and random-effects models.

Different from the U.S. case is that the concentration coefficient is not significantly changing the number of product innovations. A significant nonlinear effect of concentration on innovations is revealed by model 2. However, this result of the plain OLS model is not stable and disappears when the number of companies is introduced additionally as in model 3. Moreover, the OLS models seem inferior to the fixed-effects models given the F-test and none of the panel-data models confirm a significant impact of concentration on new food product introductions.

As for the U.S. data, we test now in Tables 9 and 10 which determinants drive the distribution of new product introductions per company across the branches of the German food industry. This topic has not been covered in earlier studies on food product innovations in Germany.

| | | | | Independ | lent Variables | | | | Test Statistic | cs |
|-----------------------|----------|----------------------|---|---|---------------------------------------|----------------------|-----------------------|------------------|---|--|
| Method/ Equations | | Constant | CONC | (CONC) ² | SIZE | VARIETY | COMPANY | \overline{R}^2 | F-Test: OLS=FE (DF) ^{b)} | Hausman's test statis- tic ^{c)} |
| OLS | (1) | 15.2809 (1.22) | $\begin{array}{c} 0.8502 \cdot 10^{-3} \\ (0.02) \end{array}$ | | 0.3483·10 ⁻² *** (3.84) | | | 0.22 | | |
| | (2) | -17.7902* (-2.09) | 0.1771* (2.25) | -0.4234·10 ⁻³ * (-2.13) | 0.2289·10 ⁻² *** (4.48) | 0.1303*** (15.34) | | 0.81 | | |
| | (3) | 4.1658 (0.52) | -0.0367 (-0.49) | $\begin{array}{c} 0.3205{\cdot}10^{-4} \\ (0.18) \end{array}$ | 0.2154·10 ⁻² *** (5.05) | 0.1330*** (18.76) | -0.0472*** (-5.85) | 0.87 | | |
| | (4) | -1.7886 (-0.60) | | | 0.2405·10 ⁻² *** (7.31) | 0.1332*** (18.90) | -0.0442*** (-6.38) | 0.87 | | |
| Fixed-effects models | (5) | | 0.0351 (-0.25) | | 0.4781·10 ⁻² * (2.46) | | | 0.91 | 32.91*** (19; 58) | |
| | (6) | | -0.0860 (-0.23) | $\begin{array}{c} 0.7610{\cdot}10^{-4} \\ (0.11) \end{array}$ | 0.4749·10 ⁻² * (2.47) | 0.1119* (2.00) | | 0.92 | 5.92*** (19; 56) | |
| | (7) | | -0.1295 (-0.34) | $0.1420 \cdot 10^{-3} \\ (0.21)$ | 0.4409·10 ⁻² * (2.26) | 0.1325* (2.24) | -0.1546 (-1.06) | 0.92 | 3.19** (19; 55) | |
| | (8) | | | | 0.4358·10 ⁻² * (2.29) | 0.1320* (2.28) | -0.1484 (-1.04) | 0.92 | 3.38*** (19; 57) | |
| Random-effec models (| ts 9) | 11.1735 (0.63) | 0.5654·10 ⁻² (0.07) | | 0.3930·10 ⁻² ** (3.14) | | | 0.22 | | 0.36 |
| (1 | 10) | -19.9217 (-1.58) | 0.1796 (1.59) | -0.4090 · 10 ⁻³ (-1.46) | 0.2534·10 ⁻² ** (3.35) | 0.1286*** (9.53) | | 0.81 | | 1.90 |
| (1 | 1) | 2.0695 (0.19) | -0.0208 (-0.21) | -0.1914·10 ⁻⁵ (-0.01) | 0.2322·10 ⁻² *** (3.96) | 0.1321*** (13.10) | -0.0475*** (-4.13) | 0.87 | | 2.25 |
| (1 | 2) | -2.2391 (-0.52) | | | 0.2514·10 ⁻² *** (5.38) | 0.1323*** (13.07) | -0.0455*** (-4.53) | 0.87 | | 1.93 |

| Table 8: Market Structure Determinants of Product Proliferation in the German For | od Industry, 1993-1996 (Dependent Variable: Innovations) ^{a)} |
|---|--|
|---|--|

^{a)} For the definition of the variables, see the text. t - values in parentheses. - ^{b)} A statistically significant F-test implies that the null hypothesis of an equivalence of the OLS and the fixed-effects model. DF stands for degrees of freedom. - ^{c)} A statistically significant Hausman test statistic implies that the null hypothesis of an equivalence of the fixed-effects and the random-effects model cannot be accepted. The fixed-effects model is preferable. - *** (**,*) Statistically significant at the 99.9% - (99% -, 95% -) level. Source: Own computations with the data shown in Appendix 4.

Table 9 captures the number of firms and Table 10 the concentration coefficients in original and squared form as explanatory variables of product innovations per company. As in the analysis for the U.S., SIZECOMP is used as a regressor rather than SIZE in some of the models. The corrected coefficients of determination are generally lower than for the absolute number of product innovations, but reach 0.94 in the best OLS model and 0.86 (0.63) in two fixed-effects (random-effects) models of Table 9 and similar values in Table 10.

Major results from Table 9 are the following:

- Innovations per company, as well as the absolute number of innovations, are inversely related to the number of firms. This is illustrated by the significantly negative sign of the COMPANY coefficients in all OLS and three random-effects models. The squared term shows, however, in the OLS models that this negative impact is a nonlinear one. Equations (2) to (4) of Table 9 suggest a U-type influence of the number of companies on innovations per company. The coefficient of the squared term is not significant at the 95%-level in the panel data models, although the signs of the relationship are generally confirmed and the coefficients of the random-effects models exceed the 90%-level. The statistical tests indicate that sector-specific intercepts matter but the fixed-effects estimates are not preferable to the random-effects models (except for equation (8) compared with equation (12)). It is striking that the direction of the influence of the number of firms on innovations per company is similar in the U.S. and German food industry (see Table 5).
- 2. Besides the (nonlinear) impact of the number of firms, the concentration coefficient, and the average size of the industry do not affect innovations per company.
- 3. As in the case of the absolute number of innovations, a positive and in almost all cases significant impact arises for VARIETY on product innovations per company: The higher the existing product differentiation in a branch of the food industry, the higher is the number of innovations per company in that industry. This is consistent with the positive impact of the variable PACKCOST in the U.S. case.

Table 10 basically confirms the results in Table 9, but gives more insight into the influence of the concentration coefficient on innovations per company:

- When the relative advantages of the approaches are compared, the F-test suggests that sector-specific differences in innovation per company matter. HAUSMAN's test statistics are insignificant and indicate that the fixed-effects models are not superior to random-effects estimates. The random-effects models, which are mainly interpreted here, are rather similar to the plain OLS estimates.
- 2. There is evidence for a nonlinear, inverse U-type influence of the concentration coefficient on product innovations per company in the German food industry (see equations (2) to (4) and the random-effects estimates (10) to (12)). When the concentration coefficient increases, product innovations per company rise but less than proportional. Apart from the nonlinear influence of CONC, the number of companies affects the dependent variable

| | | | | I | ndependent Var | iables | | | | Test Statist | tics |
|-----------------------|---------------|---------------------|---|--|---|--|---|-------------------------------------|------------------|---|--|
| Method/ Equation | | Constant | COMPANY | (COMPANY) ² | SIZE | VARIETY | CONC | SIZECOMP | \overline{R}^2 | F-Test: OLS=FE (DF) ^{b)} | Hausman's test statis- tic ^{c)} |
| OLS | (1) | 0.5951*** (7.03) | -0.5152·10 ⁻³ * (-2.49) | | -0.2349·10 ⁻⁵ (-0.25) | | | | 0.07 | | |
| | (2) | 0.4172*** (7.40) | -0.2189·10 ⁻² ** (-2.84) | $\begin{array}{c} 0.1206 \cdot 10^{-5} \ast \\ (2.08) \end{array}$ | -0.4478·10 ⁻⁵ (-0.45) | 0.1428·10 ⁻² *** (10.80) | | | 0.63 | | |
| | (3) | 0.3480** (3.15) | -0.1924·10 ⁻² * (-2.25) | $\begin{array}{c} 0.1028 \cdot 10^{-5} \\ (1.63) \end{array}$ | -0.3882·10 ⁻⁵ (-0.39) | 0.1430·10 ⁻² *** (10.78) | $\begin{array}{c} 0.3304 \cdot 10^{-3} \\ (0.73) \end{array}$ | | 0.63 | | |
| | (4) | 0.4258** (3.33) | -0.2353·10 ⁻² *** (-3.77) | 0.1312·10 ⁻⁵ ** (2.85) | | 0.1394·10 ⁻² *** (10.58) | 0.3613·10 ⁻³ (0.81) | -0.6396·10 ⁻³ (-1.23) | 0.64 | | |
| Fixed-effec models | cts (5) | | -0.6696 · 10 ⁻³ (-0.34) | | 0.5224·10 ⁻⁴ (1.87) | | | | 0.86 | 23.63*** (19; 58) | |
| | (6) | | -0.1653·10 ⁻² (-0.39) | 0.2969·10 ⁻⁶ (0.13) | 0.4953·10 ⁻⁴ (1.66) | 0.5802·10 ⁻³ (0.65) | | | 0.86 | 7.05*** (19; 56) | |
| | (7) | | -0.1813·10 ⁻² (-0.43) | 0.3524·10 ⁻⁶ (0.16) | 0.4935·10 ⁻⁴ (1.64) | 0.6016·10 ⁻³ * (0.67) | -0.1134·10 ⁻² (-0.55) | | 0.85 | 6.90*** (19; 55) | |
| | (8) | | -0.2439·10 ⁻² (-0.59) | 0.6298·10 ⁻⁶ (0.28) | | 0.7916·10 ⁻³ (0.88) | -0.8280·10 ⁻³ (-0.40) | $0.2587 \cdot 10^{-2} \\ (1.63)$ | 0.85 | 6.72*** (19; 55) | |
| Random-ef models | ffects (9) | 0.4949** (3.36) | -0.6704·10 ⁻³ (-1.81) | | 0.1340·10 ⁻⁴ (0.90) | | | | 0.05 | | 2.86 |
| | (10) | 0.4035*** (4.31) | -0.2632·10 ⁻² * (-2.48) | $\begin{array}{c} 0.1501 \cdot 10^{-5} \\ (1.88) \end{array}$ | $\begin{array}{c} 0.5568 \cdot 10^{-5} \\ (0.41) \end{array}$ | 0.1339·10 ⁻² *** (6.24) | | | 0.63 | | 4.89 |
| | (11) | 0.3486* (1.99) | -0.2439·10 ⁻² * (-2.06) | $\begin{array}{c} 0.1374 \cdot 10^{-5} \\ (1.58) \end{array}$ | 0.6159·10 ⁻⁵ (0.459) | 0.1342·10 ⁻² *** (6.24) | 0.2638·10 ⁻³ (0.37) | | 0.63 | | 5.20 |
| | (12) | 0.3541 (1.78) | -0.2091·10 ⁻² * (-2.16) | $\begin{array}{c} 0.1128 \cdot 10^{-5} \\ (1.59) \end{array}$ | | 0.1364·10 ⁻² *** (6.42) | $0.2256 \cdot 10^{-3} \\ (0.32)$ | 0.9611·10 ⁻⁴ (0.12) | 0.63 | | 6.03* |

Table 9: Market Structure Determinants of Product Proliferation in the German Food Industry, 1993-96 (Dependent Variable: Innovations per Company)^{a)}

a) For notes on the definition of variables and the statistical tests, see Table 2. **Source:** Own computations with the data shown in Appendix 4.

| - | | | | Ι | ndependent Var | iables | · • | | Â | Test Statist | ics |
|------------------------|-------------|----------------------|---|---|-------------------------------------|---|---------------------------------------|---|------------------|---|--|
| Method/ Equation | | Constant | CONC | (CONC) ² | SIZE | VARIETY | COMPANY | SIZECOMP | \overline{R}^2 | F-Test: OLS=FE (DF) ^{b)} | Hausman's test statis- tic ^{c)} |
| OLS | (1) | 0.4003* (2.55) | 0.9280·10 ⁻³ * (1.43) | | -0.1734·10 ⁻⁵ (-0.15) | | | | 0.02 | | |
| | (2) | -0.2042 (-1.55) | 0.6114 ·10 ⁻² *** (5.00) | -0.1331·10 ⁻⁴ *** (-4.33) | -0.4751·10 ⁻⁵ (-0.60) | 0.1395·10 ⁻² *** (10.59) | | | 0.64 | | |
| | (3) | 0.0348 (-0.24) | 0.4465·10 ⁻² ** (3.30) | -0.9801·10 ⁻⁵ ** (-2.98) | -0.5787·10 ⁻⁵ (-0.75) | 0.1415·10 ⁻² *** (11.09) | -0.3639·10 ⁻³ * (-2.50) | | 0.66 | | |
| | (4) | -0.2472** (-2.98) | 0.6781·10 ⁻² *** (6.46) | 0.1459·10 ⁻⁴ *** (5.11) | | 0.1360·10 ⁻² *** (11.36) | | -0.3472·10 ⁻³ (-0.69) | 0.64 | | |
| Fixed-effect models | .s (5) | | -0.1003·10 ⁻² (-0.49) | | 0.5398·10 ⁻⁴ (1.96) | | | | 0.86 | 25.10*** (19; 58) | |
| | (6) | | -0.4049 (-0.74) | $0.5709 \cdot 10^{-5}$ (0.59) | 0.5598·10 ⁻⁴ (1.99) | $\begin{array}{c} 0.4187 {\cdot} 10^{-3} \\ (0.51) \end{array}$ | | | 0.86 | 7.06*** (19; 56) | |
| | (7) | | -0.4433·10 ⁻² (-0.80) | $0.6292 \cdot 10^{-5}$ (0.64) | 0.5297·10 ⁻⁴ (1.87) | $\begin{array}{c} 0.6010 \cdot 10^{-3} \\ (0.69) \end{array}$ | -0.1367 · 10 ⁻² (-0.64) | | 0.85 | 6.23*** (19; 55) | |
| | (8) | | -0.5134·10 ⁻² (-0.92) | 0.8539·10 ⁻⁵ (0.86) | | $\begin{array}{c} 0.6321 \cdot 10^{-3} \\ (0.77) \end{array}$ | | 0.3195·10 ⁻² * (2.03) | 0.86 | 7.07*** (19; 56) | |
| Random-eff models | ects (9) | 0.2627 (1.14) | $\begin{array}{c} 0.1054 \cdot 10^{-2} \\ (1.06) \end{array}$ | | 0.1371·10 ⁻⁴ (0.83) | | | | 0.00 | | 3.92 |
| | (10) | -0.2239 (-1.13) | 0.5747·10 ⁻² ** (3.26) | -0.1183·10 ⁻⁴ ** (-2.73) | 0.1156·10 ⁻⁵ (0.98) | 0.1314·10 ⁻² *** (6.15) | | | 0.63 | | 7.88 |
| | (11) | -0.0454 (-0.21) | 0.4147·10 ⁻² * (2.15) | -0.8663 · 10 ⁻⁵ (-1.90) | $0.1447 \cdot 10^{-6}$ (0.01) | 0.1347·10 ⁻² *** (6.60) | -0.4252·10 ⁻³ (-1.82) | | 0.65 | | 7.11 |
| | (12) | -0.2090 (-1.73) | $\begin{array}{c} 0.5411 \cdot 10^{-2} * * \\ (3.41) \end{array}$ | -0.1117·10 ⁻⁴ ** (-2.69) | | 0.1336·10 ⁻² *** (6.27) | | $\begin{array}{c} 0.3407 \cdot 10^{-3} \\ (0.45) \end{array}$ | 0.62 | | 8.01 |

Table 10: Market Structure Determinants of Product Proliferation in the German Food Industry, 1993-96 (Dependent Variable: Innovations per Company)^{a)}

a) For notes on the definition of variables and the statistical tests, see Table 2. **Source:** Own computations with the data shown in Appendix 4.

negatively. This is shown by equation (11) in Table 10 and, at the 95%-level of statistical significance, by equation (3).

3. VARIETY affects product innovations per company again positively, as the OLS estimates and the random-effects models show at a high significance level. The existing degree of product differentiation clearly is a major determinant of future product innovations in the food industry.

6 Summary and Conclusions

The objective of this paper was to investigate how market structure variables influence innovative activities in the food sector. After a literature review on the linkages between market structure and innovation in general and for food products specifically, the determinants of new product introductions were discussed from a theoretical point of view. Hypotheses on the expected influence of market structure variables on innovative activity were developed. But not in all cases was it possible to formulate unidirectional hypotheses of the relationship between market structure and innovation.

In the empirical section the definition of new food product introductions used in the context of our study was followed by the development of the empirical model. As we were working with pooled cross-sectional and time-series data, it appeared to be important to control for sector-and/or time-specific influences in the model. OLS models might lead to biased results because they can omit some industry-specific characteristics. Therefore, we also fitted random- and fixed-effects models in order to allow a comparison of the results.

The empirical analysis was performed for the innovative activity within the U.S. and the German food industries. Although the data bases differed to some extent it is possible to compare the major results. In addition to the number of product innovations, which had been explained in earlier studies already, we also used innovations per company as dependent variable for both data sets.

In general, the coefficients of determination were higher in the fixed-effects and randomeffects models compared to the OLS estimates. The HAUSMAN test statistic permitted us to decide whether the fixed- or random-effects result were superior. With regard to the total number of innovations in the U.S. and the German food industry we were able to identify the following important relationships:

1. In the U.S. food industry, a nonlinear influence of the number of firms on new product introductions was identified. In both the OLS estimates and the random-effects models the number of innovations first rises with the number of firms but after reaching a maximum it declines again. In addition, the OLS estimates and the random-effects model reveal a strong positive influence of the CR4 concentration ratio on the number of product innovations. In the OLS estimates for the German food industry, on the other hand, we could not identify a nonlinear but a negative relationship between the number of companies and food product introductions. In the fixed- and random-effects estimates the number of companies was with only one exception not significant. Moreover, the concentration ratio, measured as the Herfindahl Index, was not a significant determinant of product innovations in Germany. Given this model specification, it can be concluded that there is a stronger relationship between market structure variables and innovative activity within the U.S. food industry in comparison to the German food industry.

2. With regard to the U.S. food industry, the modeling approach affected the significance of the SIZE variable. In the OLS estimates, where the cross-sectoral effects dominate, the effect of SIZE on product innovations was negative. Taking sector-specific differences into account, as it is the case for the fixed- and random-effects models, SIZE was no longer a significant determinant. The results differ for the German food industry. Independent of the empirical model, the size of a market always had a significantly positive influence on the number of product innovations. I.e., the hypothesis that larger markets lead to a higher innovation activity can be confirmed for the German food industry only.

3. The degree of product differentiation has a positive impact on the number of product introductions for both the U.S. and the German data set. This is true for all estimated models. The results therefore support the hypothesized relationship from Chapter 3.

4. When we substituted the concentration ratio in a nonlinear form for the number of firms, we could not identify uniform results for the U.S. and the German food industry. Moreover, the U.S. results differ between model specifications. Whereas in the OLS estimates the number of product innovations increases with rising concentration and then declines again, the impact of the concentration ratio changes to a U-shape in the fixed-effects models. The results suggest that positive relationships between the sector-specific intercepts are important, i.e. varystrongly among food industries in the U.S. The results reveal also that the number of innovations and the number of firms is independent of the model specification.

Assuming that the number of companies can be interpreted as an indicator of market concentration, these results are somewhat contradictory to the results reported under point 1. If the number-of-firms variable enters the model in linear and squared form we find the highest number of innovations at a medium number of firms. If this is contrasted to the model which includes the concentration ratio in nonlinear form, we would also expect the highest number of innovations at a medium range of concentration but in the fixed-effects models we identified the lowest innovation activity instead.

In Germany, in comparison, the concentration ratio does not significantly change the number of product innovations. The number of product innovations increases, however, with a declining number of firms. Again, this does not correspond to the U.S. results.

5. The impact of the SIZE variable on product innovations in the U.S. changes in sign when

sectoral differences are accounted for. The OLS estimates suggest that high values of shipments lead to fewer product innovations. Taking industry characteristics into account, the result changes and sectors with a high value of shipments are also characterized by a higher number of product innovations. The latter effect could also be identified for the German food industry regardless of the estimated model. The same effects were already reported under point 2 and can again be interpreted as a confirmation of the hypothesis that the number of innovations increases with the size of a market.

6. Similar to the model described first, product differentiation measured via the PACKCOST and VARIETY variables leads to a higher number of new product introductions, both in the U.S. and Germany.

Comparing these results to earlier studies [CONNOR (1981)], we can confirm a positive influence of the size of the market on product introductions for the U.S. but also for the German food sector. We can also confirm the positive impact of product differentiation variables on food product introductions for both countries. Our results differ somewhat, however, with regard to the influence of concentration on product innovations. CONNOR, who did not control for industry-specific characteristics, found an inverted U-shaped influence of concentration on innovations. In the OLS estimates we could identify the same inverted-U relationship, whereas we found a U-shaped influence when controlling for industry characteristics.

In the second part of our analysis we concentrated on the number of product innovations per company as a dependent variable. This aspect had not been covered in earlier analyses. Major results are the following:

7. While the OLS estimates point to a nonlinear, U-shaped influence of the number of firms on product innovations per firm, the random-effects models indicate a significantly negative influence of the number of firms on per-firm innovative activity. This result holds true for both countries under investigation. In addition, there is a significantly positive effect of the concentration ratio on product innovations per company in the U.S. This implies that firms surrounded by only a few incumbents and acting in highly concentrated (U.S.) sectors, respectively, are more innovative ceteris paribus. Thus, these results favour SCHUMPETER's notion of a positive relationship between oligopolistic market structure and innovative activity.

8. When industry-specific characteristics are accounted for, product differentiation in the U.S. food industry leads to an increased innovation activity. A similar effect could be found for the German food industry, where the effect prevails even if only the plain OLS estimates are considered. Similar to the estimations with the total number of product innovations as the dependent variable, the results confirm the hypothesis posited in Chapter 3 that product differentiation promotes new product introductions.

9. For the U.S. we could see that a low growth of an industry in the past puts the respective in-

dustries under pressure and induces innovative activity. The size of the market is not a significant determinant of the number of innovations neither in the U.S. nor in Germany. In contrast to the results for the number of product innovations in total, the hypothesized positive relationship between market size and innovations can no longer be confirmed when the innovation activity per firm is considered.

10. When the model specification was altered again and instead of the number of companies the concentration ratios entered in linear and squared form, we found a U-shaped relationship between concentration and the number of product innovations per firm in the fixed- and random-effects models for the U.S. The same result was found before, when we used the total number of product innovations as a dependent variable. In contrast to the U.S. results, there is evidence for a nonlinear inverted U-type influence of the concentration coefficient on product innovations per company in the German food industry. Additionally to the nonlinear influence of the concentration variable, the number of companies affects the dependent variable negatively if only the OLS estimates are considered.

11. Similar to the analyses of the determinants of the total number of product innovations in the U.S. we identified a negative influence of the size of the market on the number of product introductions per firm when the OLS estimates are considered. Moreover, the fixed- and random-effects models confirm a negative effect of past industry growth on innovations per company. In the German food industry the size of the market does not have a significant impact on innovative activity.

12. For both the U.S. and the German food industry a positive influence of product differentiation on food product introduction per firm existed. This indicates that the degree of product differentiation is clearly a major determinant of future product innovations.

In summary, it should be noted that not all independent variables have a similar influence on the number of product innovations in the two investigated countries. This is especially true for the influence of the number of firms and concentration.

It was shown that new product introductions in absolute numbers and per company are driven by industry-specific characteristics, i.e. the fixed effects. Consequently, we confirmed our hypothesis that industry-specific characteristics are important explanatory variables for innovative activity in the food industry apart from the market structure variables. Estimation results might therefore be biased if industry characteristics are not taken into account.

Results also differ with regard to the formulation of the dependent variable, i.e. the total number of innovations and of innovations per company. There is an influence of concentration on product innovations and innovations per company which is of the U-type form for the U.S. food industry. In Germany, however, a significant inverted U-shaped influence was identified but only for the number of innovations per company. The size of an industry does not affect innovations per company, but is positively associated with the absolute number of innovations. Product differentiation tends to have a positive impact on the absolute number of new product introductions and new product introductions per company, although the coefficients were not in all estimations statistically significant. Growth of an industry does not play a role for the total number of innovations in the U.S. food industry, but it negatively affects the number of product innovations per company.

For future investigations it is desirable to further adjust the German and the U.S. data set, e.g. by using similar definitions for product innovations, by including a variety variable in the U.S. data, etc. This would improve the comparability of the estimation results. But even with an improved data set a perfect homogeneity between the two data sets could not be reached due to the differing industry classifications and industry-data-recording methods in the two countries.

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| BRANCHES OF THE | | Time Period/Economic Variables | | | | | | | | | | |
|-----------------------|----------|--------------------------------|----------|--------------|----------|----------|----------|----------|--|--|--|--|
| FOOD INDUSTRY | 1987 | 1988 | 1989 | 1990 | 1991 | 1992 | 1993 | Ø1987-93 | | | | |
| | | | NUMBER C | F COMPANIES | S | | | | | | | |
| Bakery products | 2,367.0 | 2,436.4 | 2,505.8 | 2,575.2 | 2,644.6 | 2,714.0 | 2,783.0 | 2,575.1 | | | | |
| Baking ingredients | 472.0 | 478.0 | 484.0 | 490.0 | 496.0 | 502.0 | 508.0 | 490.0 | | | | |
| Beverages | 1,574.0 | 1,556.8 | 1,539.6 | 1,522.4 | 1,505.2 | 1,488.0 | 1,470.8 | 1,522.4 | | | | |
| Breakfast cereals | 33.0 | 34.8 | 36.6 | 38.4 | 40.2 | 42.0 | 43.8 | 38.4 | | | | |
| Candy/gum/snacks | 1,152.0 | 1,178.8 | 1,205.6 | 1,232.4 | 1,259.2 | 1,286.0 | 1,312.8 | 1,232.4 | | | | |
| Condiments | 1,854.0 | 1,878.4 | 1,902.8 | 1,927.2 | 1,951.6 | 1,976.0 | 2,000.4 | 1,927.2 | | | | |
| Dairy | 1,328.0 | 1,287.8 | 1,247.6 | 1,207.4 | 1,167.2 | 1,127.0 | 1,086.8 | 1,207.4 | | | | |
| Desserts | 469.0 | 457.4 | 445.8 | 434.2 | 422.6 | 411.0 | 399.4 | 434.2 | | | | |
| Entrees | 244.0 | 256.8 | 269.6 | 282.4 | 295.2 | 308.0 | 320.8 | 282.4 | | | | |
| Fruits & vegetables | 946.0 | 958.4 | 970.8 | 983.2 | 995.6 | 1,008.0 | 1,020.4 | 983.2 | | | | |
| Processed meat | 3,551.0 | 3,549.0 | 3,547.0 | 3,545.0 | 3,543.0 | 3,541.0 | 3,539.0 | 3,545.0 | | | | |
| Side dishes | 196.0 | 193.2 | 190.4 | 187.6 | 184.8 | 182.0 | 179.2 | 187.6 | | | | |
| TOTAL, FOOD | 14,186.0 | 14,265.8 | 14,345.6 | 14,425.4 | 14,505.2 | 14,585.0 | 14,664.4 | 14,425.3 | | | | |
| Mean, pooled sample | | | | | | | | 1,202.1 | | | | |
| | | | CONCENT | RATION RATIO |) | | | | | | | |
| Bakery products | 41.6 | 41.6 | 41.5 | 41.5 | 41.4 | 41.4 | 41.3 | 41.5 | | | | |
| Baking ingredients | 54.5 | 52.7 | 50.9 | 49.0 | 47.2 | 45.4 | 43.5 | 49.0 | | | | |
| Beverages | 53.5 | 54.6 | 55.8 | 57.0 | 58.1 | 59.3 | 60.4 | 57.0 | | | | |
| Breakfast cereals | 87.0 | 86.6 | 86.2 | 85.8 | 85.4 | 85.0 | 84.6 | 85.8 | | | | |
| Candy/gum/snacks | 50.7 | 51.9 | 53.0 | 54.1 | 55.3 | 56.4 | 57.5 | 54.1 | | | | |
| Condiments | 31.8 | 31.1 | 30.5 | 29.8 | 29.2 | 28.6 | 27.9 | 29.8 | | | | |
| Dairy | 32.1 | 32.3 | 32.6 | 32.8 | 33.1 | 33.3 | 33.6 | 32.8 | | | | |
| Desserts | 25.0 | 24.8 | 24.6 | 24.4 | 24.2 | 24.0 | 23.8 | 24.4 | | | | |
| Entrees | 43.0 | 42.4 | 41.8 | 41.2 | 40.6 | 40.0 | 39.4 | 41.2 | | | | |
| Fruits & vegetables | 36.5 | 36.6 | 36.7 | 36.8 | 36.9 | 37.0 | 37.1 | 36.8 | | | | |
| Processed meat | 26.6 | 27.8 | 29.1 | 30.4 | 31.6 | 32.9 | 34.2 | 30.4 | | | | |
| Side dishes | 73.0 | 74.0 | 75.0 | 76.0 | 77.0 | 78.0 | 79.0 | 76.0 | | | | |
| Median, pooled sample | | | | | | | | 41.5 | | | | |

Appendix 1: Data on Economic Determinants of Product Innovations in the U.S. Food Industry, 1987-93 a)

| BRANCHES OF THE | | Time Period/Economic Variables | | | | | | | | | |
|--|---|---|---|--|---|---|---|---|--|--|--|
| FOOD INDUSTRY | 1987 | 1988 | 1989 | 1990 | 1991 | 1992 | 1993 | Ø1987-93 | | | |
| | | | VALUE O | F SHIPMENTS | · | | | | | | |
| Bakery Products | 20,738.9 | 20,956.3 | 21,881.2 | 22,756.4 | 23,119.6 | 23,925.7 | 25,357.1 | 22,676.46 | | | |
| Baking ingredients | 14,201.9 | 15,971.8 | 17,477.5 | 17,445.4 | 17,136.2 | 18,112.4 | 19,671.6 | 17,145.26 | | | |
| Beverages | 51,973.0 | 54,522.8 | 55,060.2 | 58,318.9 | 59,890.5 | 62,372.5 | 62,263.6 | 57,771.64 | | | |
| Breakfast cereals | 5,081.1 | 5,666.9 | 6,382.6 | 6,678.9 | 7,007.5 | 7,733.6 | 8,392.3 | 6,706.13 | | | |
| Candy/gum/snacks | 17,917.3 | 18,956.9 | 19,534.6 | 20,422.6 | 21,945.6 | 23,357.2 | 24,420.5 | 20,936.39 | | | |
| Condiments | 7789.9 | 8,213.1 | 8,483.2 | 9,483.9 | 10,240.6 | 10,317.3 | 10,252.6 | 9,254.37 | | | |
| Dairy | 35,113.0 | 36,715.1 | 37,855.5 | 40,391.8 | 39,197.5 | 43,016.9 | 43559.3 | 39,407.01 | | | |
| Desserts | 4,859.0 | 5,334.5 | 5,258.9 | 5,784.6 | 5,774.8 | 5,986.8 | 6,155.5 | 5,593.44 | | | |
| Entrees | 9,425.0 | 9,645.1 | 10,818.7 | 11,592.5 | 12,412.7 | 12,711.9 | 13,424.5 | 11,432.91 | | | |
| Fruits & vegetables | 15,069.2 | 15,680.9 | 17,282.3 | 17,807.7 | 18,303.4 | 18,283.1 | 18,686.8 | 17,301.91 | | | |
| Processed meat | 75,394.0 | 79,928.2 | 83,275.8 | 90,338.8 | 89,826.2 | 94,708.4 | 99,784.2 | 87,607.94 | | | |
| Side dishes | 1,822.1 | 1,973.0 | 2,037.0 | 2,144.8 | 2,240.1 | 2,549.7 | 2,705.2 | 2,210.27 | | | |
| | | | | | | | | | | | |
| TOTAL, FOOD | 259,384.4 | 273,564.6 | 285,347.5 | 303,166.3 | 307,094.7 | 323,075.5 | 334,673.2 | 298,043.74 | | | |
| TOTAL, FOOD Mean, pooled sample | 259,384.4 | 273,564.6 | 285,347.5 | 303,166.3 | 307,094.7 | 323,075.5 | 334,673.2 | 298,043.74 24,836.98 | | | |
| TOTAL, FOOD Mean, pooled sample | 259,384.4 | 273,564.6 | 285,347.5 PACKAG | 303,166.3 GING COSTS | 307,094.7 | 323,075.5 | 334,673.2 | 298,043.74 24,836.98 | | | |
| TOTAL, FOOD Mean, pooled sample Bakery products | 259,384.4 31.0 | 273,564.6 | 285,347.5 PACKAC 35.2 | 303,166.3 GING COSTS 36.5 | 307,094.7 38.1 | 323,075.5 39.2 | 334,673.2 39.4 | 298,043.74 24,836.98 36.0 | | | |
| TOTAL, FOOD Mean, pooled sample Bakery products Baking ingredients | 259,384.4 31.0 31.0 | 273,564.6 32.6 32.6 | 285,347.5 PACKAC 35.2 35.2 | 303,166.3 GING COSTS 36.5 36.5 | 307,094.7 38.1 38.1 | 323,075.5 39.2 39.2 | 334,673.2 39.4 39.4 | 298,043.74 24,836.98 36.0 36.0 | | | |
| TOTAL, FOOD Mean, pooled sample Bakery products Baking ingredients Beverages | 259,384.4 31.0 31.0 31.0 | 273,564.6 32.6 32.6 32.6 | 285,347.5 PACKAC 35.2 35.2 35.2 | 303,166.3 GING COSTS 36.5 36.5 36.5 | 307,094.7 38.1 38.1 38.1 | 323,075.5 39.2 39.2 39.2 | 334,673.2 39.4 39.4 39.4 | 298,043.74 24,836.98 36.0 36.0 36.0 | | | |
| TOTAL, FOOD Mean, pooled sample Bakery products Baking ingredients Beverages Breakfast cereals | 259,384.4 31.0 31.0 31.0 31.0 31.0 | 273,564.6 32.6 32.6 32.6 32.6 | 285,347.5 PACKAC 35.2 35.2 35.2 35.2 35.2 | 303,166.3 GING COSTS 36.5 36.5 36.5 36.5 | 307,094.7 38.1 38.1 38.1 38.1 | 323,075.5 39.2 39.2 39.2 39.2 39.2 | 334,673.2 39.4 39.4 39.4 39.4 39.4 | 298,043.74 24,836.98 36.0 36.0 36.0 36.0 | | | |
| TOTAL, FOOD Mean, pooled sample Bakery products Baking ingredients Beverages Breakfast cereals Candy/gum/snacks | 259,384.4 31.0 31.0 31.0 31.0 31.0 31.0 | 273,564.6 32.6 32.6 32.6 32.6 32.6 32.6 | 285,347.5 PACKAC 35.2 35.2 35.2 35.2 35.2 35.2 | 303,166.3 GING COSTS 36.5 36.5 36.5 36.5 36.5 | 307,094.7 38.1 38.1 38.1 38.1 38.1 38.1 | 323,075.5 39.2 39.2 39.2 39.2 39.2 39.2 | 334,673.2 39.4 39.4 39.4 39.4 39.4 39.4 39.4 | 298,043.74 24,836.98 36.0 36.0 36.0 36.0 36.0 | | | |
| TOTAL, FOOD Mean, pooled sample Bakery products Baking ingredients Beverages Breakfast cereals Candy/gum/snacks Condiments | 259,384.4 31.0 31.0 31.0 31.0 31.0 31.0 31.0 | 273,564.6 32.6 32.6 32.6 32.6 32.6 32.6 32.6 32 | 285,347.5 PACKAC 35.2 35.2 35.2 35.2 35.2 35.2 35.2 35.2 | 303,166.3 GING COSTS 36.5 36.5 36.5 36.5 36.5 36.5 36.5 | 307,094.7 38.1 38.1 38.1 38.1 38.1 38.1 38.1 | 323,075.5 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 | 334,673.2 39.4 39.4 39.4 39.4 39.4 39.4 39.4 39.4 | 298,043.74 24,836.98 36.0 36.0 36.0 36.0 36.0 36.0 36.0 | | | |
| TOTAL, FOOD Mean, pooled sample Bakery products Baking ingredients Beverages Breakfast cereals Candy/gum/snacks Condiments Dairy | 259,384.4 31.0 31.0 31.0 31.0 31.0 31.0 31.0 31.0 | 273,564.6 32.6 32.6 32.6 32.6 32.6 32.6 32.6 32.6 32.6 32.6 | 285,347.5 PACKAC 35.2 35.2 35.2 35.2 35.2 35.2 35.2 35.2 | 303,166.3 GING COSTS 36.5 36.5 36.5 36.5 36.5 36.5 36.5 36.5 | 307,094.7 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 | 323,075.5 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 | 334,673.2 39.4 39.4 39.4 39.4 39.4 39.4 39.4 39.4 | 298,043.74 24,836.98 36.0 36.0 36.0 36.0 36.0 36.0 36.0 36.0 | | | |
| TOTAL, FOOD Mean, pooled sample Bakery products Baking ingredients Beverages Breakfast cereals Candy/gum/snacks Condiments Dairy Desserts | 259,384.4 31.0 31.0 31.0 31.0 31.0 31.0 31.0 31.0 | 273,564.6 32.6 32.6 32.6 32.6 32.6 32.6 32.6 32.6 32.6 32.6 32.6 32.6 32.6 | 285,347.5 PACKAC 35.2 35.2 35.2 35.2 35.2 35.2 35.2 35.2 | 303,166.3 GING COSTS 36.5 36.5 36.5 36.5 36.5 36.5 36.5 36.5 36.5 36.5 36.5 | 307,094.7 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 | 323,075.5 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 | 334,673.2 39.4 39.4 39.4 39.4 39.4 39.4 39.4 39.4 39.4 39.4 39.4 | 298,043.74 24,836.98 36.0 36.0 36.0 36.0 36.0 36.0 36.0 36.0 | | | |
| TOTAL, FOODMean, pooled sampleBakery productsBaking ingredientsBeveragesBreakfast cerealsCandy/gum/snacksCondimentsDairyDessertsEntrees | 259,384.4 31.0 31.0 31.0 31.0 31.0 31.0 31.0 31.0 | 273,564.6 32.6 32.6 32.6 32.6 32.6 32.6 32.6 32.6 32.6 32.6 32.6 32.6 32.6 32.6 32.6 32.6 | 285,347.5 PACKAC 35.2 35.2 35.2 35.2 35.2 35.2 35.2 35.2 | 303,166.3 GING COSTS 36.5 36.5 36.5 36.5 36.5 36.5 36.5 36.5 36.5 36.5 36.5 36.5 36.5 36.5 | 307,094.7 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 | 323,075.5 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 | 334,673.2 39.4 39.4 39.4 39.4 39.4 39.4 39.4 39.4 | 298,043.74 24,836.98 36.0 36.0 36.0 36.0 36.0 36.0 36.0 36.0 36.0 36.0 36.0 36.0 36.0 36.0 36.0 36.0 36.0 | | | |
| TOTAL, FOODMean, pooled sampleBakery productsBaking ingredientsBeveragesBreakfast cerealsCandy/gum/snacksCondimentsDairyDessertsEntreesFruits & vegetables | 259,384.4 31.0 31.0 31.0 31.0 31.0 31.0 31.0 31.0 31.0 31.0 31.0 31.0 31.0 31.0 31.0 31.0 | 273,564.6 32.6 | 285,347.5 PACKAC 35.2 35.2 35.2 35.2 35.2 35.2 35.2 35.2 | 303,166.3 GING COSTS 36.5 36.5 36.5 36.5 36.5 36.5 36.5 36.5 | 307,094.7 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 | 323,075.5 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 | 334,673.2 39.4 39.4 39.4 39.4 39.4 39.4 39.4 39.4 | 298,043.74 24,836.98 36.0 | | | |
| TOTAL, FOODMean, pooled sampleBakery productsBaking ingredientsBeveragesBreakfast cerealsCandy/gum/snacksCondimentsDairyDessertsEntreesFruits & vegetablesProcessed meat | 259,384.4 31.0 | 273,564.6 32.6 | 285,347.5 PACKAC 35.2 35.2 35.2 35.2 35.2 35.2 35.2 35.2 | 303,166.3 GING COSTS 36.5 37.5 37.5 37.5 37.5 37.5 37.5 37.5 3 | 307,094.7 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 38.1 | 323,075.5 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 39.2 | 334,673.2 39.4 39.4 39.4 39.4 39.4 39.4 39.4 39.4 39.4 39.4 39.4 39.4 39.4 39.4 39.4 39.4 39.4 39.4 | 298,043.74 24,836.98 36.0 | | | |

Appendix 1 continued: Data on Economic Determinants of Product Innovations in the U.S. Food Industry, 1987-93^{a)}

a) The variables used here are independent variables in the econometric estimates of determinants of product innovations.

Source: U.S. Department of Commerce, Census of Manufactures, various years; U.S. Department of Commerce, Annual Survey of Manufactures, various years; Food Review, various issues.

| | | | | Independe | ent Variables | | | | Test Statistic | 2S |
|-------------------------|-----------|------------------------|-----------------------|---------------------------------------|---------------------|-----------------------|---------------------------------------|------------------|---|--|
| Method/ Equations | | Constant | ln (CR4) | ln (SIZE) | ln (PACKCOST) | ln (COMPANY) | ln (GROWTH) | \overline{R}^2 | F-Test: OLS=FE (DF) ^{b)} | Hausman's test statis- tic ^{c)} |
| OLS | (1) | 1.5533 (0.88) | 0.1449 (0.49) | 0.4450*** (4.03) | | | | 0.15 | | |
| | (2) | -11.2003*** (-3.47) | 1.5227*** (6.07) | -0.2496** (-3.39) | 2.2195** (2.64) | 0.9634*** (9.50) | | 0.60 | | |
| | (3) | -10.6915** (-3.16) | 1.5258*** (6.06) | -0.2446* (-2.33) | 2.0912* (2.38) | 0.9531*** (9.20) | -0.9351 · 10 ⁻² (-0.53) | 0.60 | | |
| Fixed-effects models | (4) | | -0.6914 (-1.12) | 1.6448*** (6.63) | | | | 0.95 | 119.80*** (11; 70) | |
| | (5) | | -1.5656** (-2.93) | 0.5992 (1.04) | 1.9335** (2.97) | -2.0135*** (-4.20) | | 0.97 | 78.70*** (11; 68) | |
| | (6) | | -1.4621*** (-2.76) | -0.1268 (-0.18) | 2.5147*** (3.44) | -1.6452** (-3.15) | 0.0109 (-1.67) | 0.97 | 80.70*** (11; 67) | |
| Random-effect models | ts (7) | -3.6853 (-1.37) | -0.0897 (-0.19) | 1.0787*** (5.84) | | | | 0.93 | | 12.17** |
| | (8) | -2.4933 (-1.08) | -0.2429 (-0.59) | 0.1470 (0.62) | 1.9879*** (5.86) | 0.1937 (0.91) | | 0.94 | | 35.04*** |
| | (9) | -1.6866 (-0.73) | -0.1748 (-0.43) | -0.8208 · 10 ⁻² (-0.03) | 1.9550*** (5.79) | 0.2876 (1.32) | -0.0137* (-2.57) | 0.95 | | 32.08*** |

| | | | | | | | | ~ |
|----|-----------------------------------|-------------------------|--|------------------|--------------------------|--------------|--|----|
| A | | Determine of Determined | $\mathbf{D}_{1} = 1^{1} \mathbf{f}_{1} = \mathbf{f}_{1}^{1} = \mathbf{f}_{1}^{1} = \mathbf{f}_{1}^{1} = \mathbf{f}_{1}^{1} \mathbf{f}_{2}^{1} = \mathbf{f}_{1}^{1} \mathbf{f}_{2}^{1} = \mathbf{f}_{1}^{1} \mathbf{f}_{2}^{1} \mathbf{f}$ | | $1000 04 (D_{-1}1_{-1})$ | '(1 ' - C | $\mathbf{f} = \mathbf{f} \cdot $ | a) |
| Ar | Dendix 2: Market Structure | Determinants of Product | Proliferation in the U \mathbf{N} | Food industry | 1988-94 (Dollble-lo | garithmic Sr | Decification for innovations) | |
| r | | Determinants of Floadet | romeration in the c.b | · I ood maastij, | 1700 71 (Douole 10) | Sarranne St | centeution for mile (unons) | |

^{a)} For the definition of the variables, see the text. t - values in parentheses. - ^{b)} A statistically significant F-test implies that the null hypothesis of an equivalence of the OLS and the fixed-effects models is rejected. Sector-specific constants matter, which are not covered in the OLS model. DF stands for degrees of freedom. - ^{c)} A statistically significant Hausman test statistic implies that the null hypothesis of an equivalence of the fixed-effects and the ran-dom-effects model cannot be accepted. The fixed-effects model is preferable. *** (**, *) Statistically significant at the 99.9% - (99% -, 95% -)level.

Source: Own computations, with the data shown in Appendix 1.

| | | | | Ι | ndependent Varia | ables | | | | Test Statis | tics |
|-----------------------|-------------|------------------------|----------------------|--------------------------------------|---------------------|-----------------------|---|---------------------|------------------|---|--|
| Method/ Equations | | Constant | ln (CR4) | ln (SIZE) | ln (PACKCOST) | ln (COMPANY) | ln (GROWTH) | ln (SIZECOMP) | \overline{R}^2 | F-Test: OLS=FE (DF) ^{b)} | Hausman's test statis- tic ^{c)} |
| OLS | (1) | -3.7265** (-2.98) | 1.5973*** (7.62) | -0.2547** (-3.27) | | | | | 0.52 | | |
| | (2) | -10.6915** (-3.16) | 1.5258*** (6.06) | -0.2446* (-2.33) | 2.0912* (2.38) | -0.0469 (-0.45) | -0.9251 · 10 ⁻² (-0.53) | | 0.55 | | |
| | (3) | -14.2095*** (-4.11) | 1.9181*** (7.93) | | 1.9848* (2.11) | | -0.1787 · 10 ⁻² (-0.10) | -0.0922 (-0.90) | 0.48 | | |
| Fixed-effects models | ; (4) | | -0.3460 (-0.50) | 1.4213*** (5.11) | | | | | 0.93 | 43.39*** (11; 70) | |
| | (5) | | -1.4621** (-2.76) | -2.6452*** (-5.07) | 2.5147*** (3.44) | -2.6452*** (-5.07) | -0.0109 (-1.67) | | 0.96 | 80.70*** (11; 67) | |
| | (6) | | -1.1231 (-1.88) | | 0.0477 (0.09) | | -0.5093 · 10 ⁻³ (-0.0745) | 2.1576*** (3.72) | 0.95 | 71.96*** (11; 68) | |
| Random-effe models | ects (7) | -6.8967** (-2.90) | 1.2496** (3.03) | 0.2090 (1.33) | | | | | 0.89 | | 31.98*** |
| | (8) | -1.6865 (-0.73) | -0.1748 (-0.43) | 0.8208 · 10 ⁻² (-0.03) | 1.9550*** (5.79) | -0.7124** (03.28) | -0.0137* (-2.58) | | 0.94 | | 32.08*** |
| | (9) | -8.1281*** (-4.38) | 0.4182 (0.98) | | 1.4156*** (4.19) | | -0.0118 (-1.97) | 0.4425 (1.96) | 0.93 | | 20.66** |

Appendix 3: Market Structure Determinants of Product Proliferation in the U.S. Food Industry, 1988-94 (Double-logarithmic Specification for Innovations per Company)^{a)}

^{a)} For the definition of the variables, see the text. t-values in parentheses. - ^{b)} A statistically significant F-test implies that the null hypothesis of an equivalence of the OLS and the fixed-effects models is rejected. Sector-specific constants matter, which are not covered in the OLS model. DF stands for degrees of freedom. - ^{c)} A statistically significant Hausman test statistic implies that the null hypothesis of an equivalence of the fixed-effects and the random-effects model cannot be accepted. The fixed-effects model is preferable. *** (**, *) Statistically significant at the 99.9% - (99% -, 95% -) level.

Source: Own computations, with the data shown in Appendix 1.

Appendix 4:

Data on Economic Determinants of Product Innovations in the West German Food Industry, 1993-96^{a)}

| BRANCHES OF THE | Time Period/Economic Variables | | | | | | | |
|---|--------------------------------|--------|-------|---------------------------|---------------------------|----------|--|--|
| FOOD INDUSTRY ^{b)} | 1992 | 1993 | 1994 | 1995 ¹⁾ | 1996 ¹⁾ | Ø1992-96 | | |
| NUMB | ER OF C | COMPAN | IES | L | L | | | |
| Manufacture of grain mill products | 57 | 54 | 53 | 52 | 51 | 53.4 | | |
| Manufacture of macaroni, noodles, couscous and similar farinaceous products | 21 | 21 | 20 | 21 | 21 | 20.8 | | |
| Manufacture of condiments and seasonings, homogenized food preparations and dietetic food | 72 | 70 | 68 | 71 | 72 | 70.6 | | |
| Processing and preserving of potatoes | 42 | 43 | 40 | 43 | 43 | 42.2 | | |
| Manufacture of bread, manufacture of fresh pastry goods and cakes | 1,208 | 1,221 | 1,186 | 1,277 | 1,315 | 1,241.4 | | |
| Manufacture of rusks, pastry goods and cakes | 78 | 75 | 76 | 75 | 74 | 75.6 | | |
| Processing and preserving of fruit and vegetables | 171 | 167 | 166 | 158 | 151 | 162.6 | | |
| Manufacture of cocoa, chocolate and sugar confectionery | 163 | 164 | 153 | 150 | 142 | 154.4 | | |
| Operations of dairy and cheese making | 261 | 250 | 233 | 220 | 207 | 234.2 | | |
| Production of sterilized milk | 48 | 49 | 48 | 49 | 51 | 49.0 | | |
| Manufacture of crude and refined oils and fats | 15 | 14 | 14 | 14 | 14 | 14.2 | | |
| Manufacture of margarine and similar edible fats | 14 | 13 | 11 | 12 | 11 | 12.2 | | |
| Production, processing and preserving of meat and meat products | 273 | 275 | 276 | 282 | 286 | 278.4 | | |
| Production, processing and preserving of fish and fish products | 72 | 65 | 65 | 67 | 64 | 66.6 | | |
| Processing of tea and coffee | 41 | 40 | 40 | 40 | 40 | 40.2 | | |
| Manufacture of beer and malt | 420 | 414 | 398 | 380 | 367 | 395.8 | | |
| Manufacture of distilled potable alcoholic beverages | 64 | 70 | 64 | 65 | 58 | 64.2 | | |
| Manufacture of wines, fruit wines and other nondistilled fermented beverages | 36 | 36 | 36 | 35 | 33 | 35.2 | | |
| Production of mineral water and softdrinks | 202 | 189 | 178 | 169 | 157 | 179.0 | | |
| Manufacture of other food products | 113 | 109 | 104 | 103 | 102 | 106.2 | | |
| TOTAL, FOOD | 3,371 | 3,339 | 3,229 | 3,283 | 3,259 | 3,296.2 | | |
| Mean, pooled sample | | | | | | 3,340.8 | | |

Appendix 4 continued: Data on Economic Determinants of Product Innovations in the West German Food Industry, 1993-96 ^{a)}

| BRANCHES OF THE | Time Period/Economic Variabl | | | | | | |
|--|------------------------------|-----------|--------------|---------------------------|----------|--|--|
| FOOD INDUSTRY ^{b)} | 1992 | 1993 | 1994 | 1995 ¹⁾ | Ø1992-95 | | |
| CONCENTRATION RATIO (H | Ierfindahl | -Hirschma | an Coefficie | ent) ²⁾ | | | |
| Manufacture of grain mill products | 64.53 | 63.23 | 62.69 | 60.76 | 62.80 | | |
| Manufacture of macaroni, noodles, couscous and similar farinaceous products | 294.59 | 296.59 | 294.78 | 288.56 | 293.63 | | |
| Manufacture of condiments and seasonings, ho- mogenized food preparations and dietetic food | 235.66 | 218.99 | 216.14 | 270.60 | 235.35 | | |
| Processing and preserving of potatoes | 126.12 | 115.18 | 114.02 | 115.92 | 117.81 | | |
| Manufacture of bread, manufacture of fresh pastry goods and cakes | 7.22 | 7.29 | 7.23 | 7.74 | 7.37 | | |
| Manufacture of rusks, pastry goods and cakes | 86.76 | 106.48 | 76.22 | 85.31 | 88.69 | | |
| Processing and preserving of fruit and vegetables | 33.70 | 33.60 | 34.32 | 35.73 | 34.34 | | |
| Manufacture of cocoa, chocolate and sugar confectionery | 49.32 | 50.91 | 52.31 | 52.34 | 51.22 | | |
| Operations of dairy and cheese making | 18.36 | 22.24 | 23.47 | 26.13 | 22.55 | | |
| Production of sterilized milk | 87.49 | 88.01 | 91.99 | 92.07 | 89.89 | | |
| Manufacture of crude and refined oils and fats | 149.40 | 150.53 | 144.37 | 153.61 | 149.48 | | |
| Manufacture of margarine and similar edible fats ²⁾ | 409.28 | 384.98 | 360.68 | 336.39 | 372.83 | | |
| Production, processing and preserving of meat and meat products | 12.18 | 12.77 | 12.66 | 10.51 | 12.03 | | |
| Production, processing and preserving of fish and fish products | 148.80 | 128.24 | 129.70 | 130.46 | 134.30 | | |
| Processing of tea and coffee | 126.72 | 140.22 | 147.02 | 141.74 | 138.93 | | |
| Manufacture of beer and malt | 15.23 | 15.86 | 17.34 | 18.38 | 16.70 | | |
| Manufacture of distilled potable alcoholic beverages | 72.98 | 74.07 | 62.39 | 50.86 | 65.08 | | |
| Manufacture of wines, fruit wines and other nondistilled fermented beverages | 146.65 | 146.91 | 134.08 | 142.74 | 142.60 | | |
| Production of mineral water and soft drinks | 20.70 | 26.12 | 27.95 | 29.22 | 26.00 | | |
| Manufacture of other food products | 32.77 | 33.04 | 33.59 | 34.42 | 33.46 | | |

Appendix 4 continued: Data on Economic Determinants of Product Innovations in the West German Food Industry, 1993-96 ^{a)}

| BRANCHES OF THE | Time Period/Economic Variables | | | | | | | |
|--|--------------------------------|---------------------------|---------------------------|------------------------------|------------|--|--|--|
| FOOD INDUSTRY ^{b)} | 1992 ³⁾ | 1993 ⁴⁾ | 1994 ⁴⁾ | 1995 ^{4) 5)} | Ø1992-95 | | | |
| SALES | S (Million I | DM) | | | | | | |
| Manufacture of grain mill products | 2,713.8 | 2,984.1 | 2,759.6 | 3,722.5 | 3,045.00 | | | |
| Manufacture of macaroni, noodles, couscous and similar farinaceous products | 724.6 | 759.4 | 726.4 | 1108.8 | 829.80 | | | |
| Manufacture of condiments and seasonings, ho- mogenized food preparations and dietetic food | 6,354.5 | 6,713.8 | 6,521.9 | 5,460.8 | 6,262.75 | | | |
| Processing and preserving of potatoes | 1,610.8 | 1,558.9 | 1,540.7 | 1,633.8 | 1,586.05 | | | |
| Manufacture of bread, manufacture of fresh pastry goods and cakes | 9,533.3 | 11,053.0 | 11,239.7 | 11,327.1 | 10,788.28 | | | |
| Manufacture of rusks, pastry goods and cakes | 3,703.1 | 3,950.3 | 3,957.4 | 4,937.9 | 4,137.18 | | | |
| Processing and preserving of fruit and vegetables | 9,520.0 | 9,285.3 | 9,657.3 | 10,350.6 | 9,703.30 | | | |
| Manufacture of cocoa, chocolate and sugar confectionery | 14,337.8 | 14,812.8 | 16,359.5 | 16,275.3 | 15,466.35 | | | |
| Operations of dairy and cheese making | 21,644.8 | 23,751.3 | 23,496.6 | 24,329.95 | 23,305.57 | | | |
| Production of sterilized milk | 6,804.8 | 7,620.7 | 7,374.7 | 7,324.75 | 7,281.24 | | | |
| Manufacture of crude and refined oils and fats | 3,610.0 | 3,887.1 | 4,448.0 | 4,899.6 | 4,211.18 | | | |
| Manufacture of margarine and similar edible fats | 1,982.4 | 2,212.9 | 2,165.7 | 2,055.1 | 2,104.03 | | | |
| Production, processing and preserving of meat and meat products | 13,344.5 | 14,716.8 | 14,651.0 | 16,452.7 | 14,791.25 | | | |
| Production, processing and preserving of fish and fish products | 2,794.0 | 2,817.1 | 2,738.8 | 2,762.0 | 2,777.98 | | | |
| Processing of tea and coffee | 7,231.8 | 7,858.1 | 8,514.0 | 9,323.2 | 8,231.78 | | | |
| Manufacture of beer and malt | 15,558.7 | 16,986.8 | 17,090.6 | 16,923.7 | 16,639.95 | | | |
| Manufacture of distilled potable alcoholic beverages | 5,642.5 | 6,813.8 | 6,107.8 | 6,083.3 | 6,161.85 | | | |
| Manufacture of wines, fruit wines and other nondistilled fermented beverages | 2,428.1 | 2,395.7 | 2,383.8 | 2,032.6 | 2,310.05 | | | |
| Production of mineral water and soft drinks | 8,611.8 | 9,181.9 | 9,536.6 | 10,574.0 | 9,476.08 | | | |
| Manufacture of other food products | 5,968.7 | 5,987.1 | 6,160.3 | 5,209.2 | 5,831.33 | | | |
| TOTAL, FOOD | 144,210.0 | 155,436.0 | 157,524.0 | 163,088.0 | 155,064.50 | | | |
| Mean, pooled sample | | | | | 2,524.75 | | | |

Appendix 4 continued: Data on Economic Determinants of Product Innovations in the West German Food Industry, 1993-96^{a)}

| BRANCHES OF THE | Time Period/Economic Variables | | | | | | |
|--|--------------------------------|-------|-------|---------------------------|----------|--|--|
| FOOD INDUSTRY ^{b)} | 1992 | 1993 | 1994 | 1995 ⁶⁾ | Ø1992-95 | | |
| PRODU | J CT VARI | ЕТҮ | | L | | | |
| Manufacture of grain mill products | - | - | - | - | - | | |
| Manufacture of macaroni, noodles, couscous and similar farinaceous products | 82 | 84 | 86 | 88 | 85.0 | | |
| Manufacture of condiments and seasonings, ho- mogenized food preparations and dietetic food | 920 | 936 | 943 | 998 | 949.3 | | |
| Processing and preserving of potatoes | 34 | 35 | 33 | 32 | 33.5 | | |
| Manufacture of bread, manufacture of fresh pastry goods and cakes | 270 | 339 | 402 | 468 | 369.8 | | |
| Manufacture of rusks, pastry goods and cakes | 123 | 129 | 145 | 156 | 138.3 | | |
| Processing and preserving of fruit and vegetables | 452 | 458 | 467 | 474 | 462.8 | | |
| Manufacture of cocoa, chocolate and sugar confectionery | 478 | 475 | 472 | 469 | 473.5 | | |
| Operations of dairy and cheese making | 408 | 420 | 430 | 441 | 424.8 | | |
| Production of sterilized milk | 32 | 37 | 42 | 47 | 39.5 | | |
| Manufacture of crude and refined oils and fats | 34 | 34 | 33 | 33 | 33.5 | | |
| Manufacture of margarine and similar edible fats | 19 | 18 | 18 | 18 | 18.3 | | |
| Production, processing and preserving of meat and meat products | 423 | 450 | 477 | 504 | 463.5 | | |
| Production, processing and preserving of fish and fish products | 119 | 131 | 143 | 167 | 140.0 | | |
| Processing of tea and coffee | 138 | 116 | 95 | 75 | 106.0 | | |
| Manufacture of beer and malt | 53 | 51 | 50 | 49 | 50.8 | | |
| Manufacture of distilled potable alcoholic beverages | 158 | 160 | 163 | 165 | 161.5 | | |
| Manufacture of wines, fruit wines and other nondistilled fermented beverages | 219 | 218 | 218 | 218 | 218.3 | | |
| Production of mineral water and soft drinks | 151 | 123 | 96 | 68 | 109.5 | | |
| Manufacture of other food products | 605 | 638 | 685 | 725 | 663.3 | | |
| TOTAL, FOOD | 4,718 | 4,852 | 4,998 | 5,195 | 4,940.8 | | |
| Mean, pooled sample | | | | | 285.4 | | |

a) The variables used here are independent variables in the econometric estimates of determinants of product innovations. Product innovation data based on Table 6 of the text are used in the computations. As the independent variables are lagged, the period 1993-1996 is selected here.- b) Data on the sugar industry and the manufacture of starch products are excluded. The naming of the industries follows "NACE Rev. 1", the Eurostat classification [EUROSTAT (1993)].

Source: STATISTISCHES BUNDESAMT (a, b, c), various years.

¹⁾ Due to incomplete data the numbers were estimated with trend and forecasting methods respectively, using the time period 1980 -1994.- 2) All concentration ratios had to be estimated (data basis 1983 - 1991).- 3) West Germany.- 4) East and West Germany.- 5) In 1995 the aggregation of single food industries into branches was slightly changed.- 6) Data were estimated.