Technological Progress and Market Growth: An Empirical Study Based on the Quality-Ladder Approach

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Abstract

This paper develops an extended version of the quality-ladder model by allowing for heterogeneous markets. Based on this model, it presents an empirical analysis of innovation-based growth at the market level using a technometric measurement concept. It can be shown that a growth-promoting effect due to technological progress in a particular, single year is observed after between two and up to seven years. This is true not only for highly innovative markets, but also for those in which fewer R&D resources are invested.

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1 Technological progress and growth: A fresh look

The Schumpeterian renaissance of recent decades can, to a great extent, be traced to a general feeling of inadequacy with regard to traditional growth theory that has existed for quite some time (see, e.g., Ramser/Stadler [1]). Models of growth in an all-inclusive sector – regardless of whether they are based on neoclassical or Keynesian schools of thought – contribute little to the understanding of actual progress of national economies because they fail to include the sectoral interactions between innovation and growth. The purpose of this article is to highlight both new innovation theories and new measurement opportunities at the market level.

Since the early nineties, endogenous growth theory has been enriched by the Schumpeterian growth models which build on horizontal and vertical product innovations developed through intentional R&D activities of private firms. In their quality-ladder version, introduced by Segerstrom/Anant/Dinopoulos [2], Grossman/Helpman [3, 4] and Aghion/Howitt [5, 6], these models attempt to formalize Schumpeter's vision of a continuing process of creative destruction due to the obsolescence of old products when new products with higher quality appear. The existing quality-ladder models are highly stylized and not suitable for an empirical assessment because they rely either on only one quality ladder in the whole economy or on a continuum of symmetric quality ladders in independent markets.

The present paper therefore aims to extend the standard quality-ladder model of Grossman/Helpman [3, 4] by allowing for technological heterogeneity and to derive some testable results about the determinants of innovative activities at the market level. According to the neo-Schumpeterian hypotheses, as summarized e.g. in Kamien/Schwartz [7], Cohen/Levin [8] and Cohen [9], the set of determinants should include at least market-power effects. The standard model includes expected market power as an essential determinant of the innovation process, but only within a symmetric treatment of all markets. The extended model presented in this paper captures market heterogeneity and is therefore able to describe the evolution of the structure of an economy as a result of market-specific innovation processes which themselves depend on technological market characteristics. Furthermore, even in this generalized quality-ladder model, an explicit aggregation over markets can be performed and, therefore, structural change at the macroeconomic level can be analyzed consistently and in line with the alternative fundamental models of endogenous growth (see, e.g. the systematic treatment in Barro/Sala-i-Martin [10], and Aghion/Howitt [6]).

The empirical part is organized to permit theory-based relationships to be derived and subjected to statistical inference. The characteristics approach of Lancaster [11 – 14] is seen as an adequate empirical concept for measuring quality ladders in product performance; one based on microeconomics and directly related to the properties of innovations. An operational variant, known as technometrics, offers aggregation rules for its application at the level of industries or markets, but the unsatisfactory state of data availability and the high cost of performing measurements at this level must be noted. Net production indices represent possible indicators for growth. The question is whether and, possibly, under what circumstances these indicators can be explained by the quality ladders in product performance. This task may appear to present a paradox, since production growth is traditionally an indicator for progress that has become commonplace in economic policy, while the technometric characteristics concept for product performance is a new one and therefore appears to require explanation. Regardless of any feelings of familiarity with the measurement concept, the task at hand is to determine whether production growth can be explained by the microeconomically determined yardstick to quality ladders, used to measure the multidimensional description of the characteristics of goods.

The paper is organized as follows. Section 2 presents an extended version of the quality-ladder model which allows for heterogeneous markets. It derives a testable equation of the markets' growth rates depending on market-specific innovation as technological explanation factors for market evolution. In Section 3 we explain our empirical concept for measuring product quality, in Section 4 the data used are discussed and in Section 5 the corresponding analysis is provided. In Section 6 we discuss the findings in view of the various roles of innovative sources and conclude.

2 An illustrative quality-ladder model with market-specific technological jumps

Following the lines suggested by Grossman/Helpman [3, 4], Helpman [15], Aghion/Howitt [5, 6] and others, we develop a modified version of the quality-ladder model with market-specific innovation-based growth rates. We consider an economy where a continuum of markets $j \in [0,1]$ exists. Consumers allocate spending to the time separable utility function

$$U = \int_0^\infty e^{-\rho t} \int_0^1 \ln Y(j)\,dj\,dt \qquad (1)$$

where ρ is the common rate of time preference and $Y(j)$ is the instantaneous production and consumption in market j. Households maximize their discounted utility subject to their intertemporal budget constraint

$$\int_0^\infty e^{-rt} E(t)\,dt \leq A(0) \qquad (2)$$

where r denotes the certain return on consumers' portfolio and A(0) is the present value of the stream of labor incomes plus the value of initial asset holdings at t = 0. The flow of spending is given by

$$E = \int_0^1 p\,(j)Y(j)dj$$

where p(j) is the price of product j. The maximization problem can be solved in two stages. In the second stage, consumers maximize instantaneous utility at time t subject to a given level of expenditures E. This yields the static market demand functions

$$Y(j) = E \,/\, p(j). \tag{3}$$

Substituting these demand functions into (1), the consumers' first-stage maximization problem is solved by choosing the dynamic time path subject to (2). Solving this intertemporal optimization problem yields the Keynes-Ramsey rule

$$\dot{E} \,/\, E = r - \rho. \tag{4}$$

Because of the homothetic preferences, the time path (4) applies not only to each representative consumer, but also to the whole economy when E denotes aggregated spending.

On the production side, the economy is endowed with the single input factor labor. At each point in time, the technologies for the producing firms are given by

$$Y(j) = \lambda(j)^{m(j)} L_Y(j) \tag{5}$$

where $L_Y(j)$ denotes labor input and the technological level is given by $\lambda(j)^{m(j)}$ where $\lambda(j)>1$ denotes innovation size and m(j) is the number of quality innovations realized up to the present.[1] The technological parameters λ(j) are assumed to be exogenous and fixed over time but may differ between markets. This allows us to account for different market structures and, hence, for market-specific quality ladders.[2] We already mentioned the convincing empirical evidence that the innovative behavior of firms varies across markets to a high degree. In each market, the technology level can be upgraded in a stochastic process of sequential

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1 In this formulation the quality-ladder model is designed to explain vertical product innovations of intermediate goods. However, as shown by Taylor [16], it can equivalently be interpreted as a model of cost-reducing process innovations.

2 The reasons why we prefer a sectoral classification by markets (product groups) rather than industries (branches) are discussed in Section 4.

improvements as a result of intentional innovative activities by firms employing labor in a separate R&D sector to be characterized below.

Any market leader whose technology is assumed to be perfectly protected by an infinitely lived patent, will set a price so that the closest follower cannot compete without realizing negative profit flows. It can be shown that market leaders undertake no R&D targeted to improve their own technology because the incremental gain of a two-step technology advantage to an incumbent is strictly smaller than the gain of a one-step technology advantage to an external innovator. The minimal unit cost of a follower one step behind equals $\lambda(j)^{-m(j)}w$, where w denotes the wage rate. Therefore, in each market the optimal pricing strategy of the incumbent firm is given by

$$p(j) = \lambda(j)^{-m(j)+1}w.$$

Thus, using (3) and (5), each industry leader can realize a corresponding profit stream

$$\pi(j) = p(j)Y(j)\text{-}wL(j) = (1 - 1 / \lambda(j))E \tag{6}$$

which depends on the aggregated spending of consumers as well as on the market-specific parameter $\lambda(j)$.

New technologies have to be developed by innovative firms in a separate R&D sector. The lure of monopoly rents drives potential entrants to engage in risky patent races to search for higher quality technologies. The prize for an innovation is the monopoly profit flow (6) that will last until the next success is achieved in the same market. There is free entry into each patent race for the next quality improvement. Each potential entrepreneur may target his research efforts at any of the (continuum of) markets. If the entrant firm undertakes R&D at intensity h(j) for a time interval of length dt, it will succeed in taking the next step up the quality ladder for the targeted product group with probability h(j)dt. This implies that the number of innovations in each market follows a Poisson process with the market-specific arrival rate h(j).

The technology discovered with any innovation opens up the opportunity for all R&D firms to search for the next innovation. This implies an external spillover effect of technological knowledge since even laggard firms can equally participate in each patent race without having taken all of the rungs of the quality ladder themselves.[3] It is only the patent protection which guarantees temporary appropriability of innovation rents. The innovation production function is

3 As Caballero/Jaffe [17] have noted, firms can achieve an innovation success by "standing on the shoulders of giants".

approximated by a linear specification where one unit of R&D intensity, h(j), requires μ units of labor $L_h(j)$ per unit of time. Thus, the number of realized innovations in each industry j follows a Poisson process whose arrival rate is given by

$$h(j) = L_h(j) / \mu, \tag{7}$$

where $L_h(j)$ is the labor input in the R&D sector devoted to a technology improvement in market j, and μ^{-1} denotes the labor productivity of R&D. The R&D projects in all markets are assumed to be equally difficult and there are no inter-market differences in the technological opportunities.[4] At a flow R&D cost of $wL_h(j)dt$ over the time interval of length dt, each firm participating in the present patent race can attain the stock value V(j) of a successful entrepreneur who becomes the technological leader in the industry j with probability h(j)dt. Maximization of $[V(j)L_h(j) / \mu]dt - wL_h(j)dt$ with respect to labor input would imply an infinite R&D investment if $V(j) > \mu w$, and no R&D activity at all if $V(j) < \mu w$. With free entry into the patent races the former case cannot occur. The latter case, which will be neglected in the following, implies for such markets a stationary equilibrium without any further technological evolution. The unique equilibrium with positive but finite R&D activities requires $V(j) = \mu w$. We choose labor as numéraire, i.e. w=1, so that the stock values of the incumbent firms are determined by

$$V(j) = \mu \tag{8}$$

in each market j.

Each firm participating in a patent race has no internal funds to finance its R&D activities and, therefore, needs to issue equity claims on a perfect capital market. These claims pay nothing if the firm's R&D effort fails but yield the profit stream (6), being paid out continuously as dividends, if the firm succeeds in winning the patent race and takes over the market leadership, until it will itself be replaced by the next entrepreneur. According to (8), the value of an incumbent firm remains constant as long as the R&D efforts targeted at the market of its goods fail. This event occurs with probability (1 – h(j)dt) in the time interval dt. With probability h(j)dt, however, one of the targeted innovation efforts will succeed, the leader will be replaced by an entrepreneur, and the equity owners will suffer a total capital loss of V(j). Taking the limit as the time length dt approaches zero, the no-arbitrage condition in each market j can be written as

$$\pi(j) - h(j)V(j) = rV(j). \tag{9}$$

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4 Stadler [18] presents a more generalized version of the quality-ladder model which also accounts for market-specific demand-pull and technology-push effects.

Arbitrage in the financial market ensures that the expected rate of return to the equity owners of an incumbent firm in market j equals the instantaneous interest rate r on a riskless bond which will turn out to be constant over time. Since R&D outcomes in the different markets are by assumption uncorrelated, the risks in all markets are idiosyncratic. Therefore, shareholders can earn a riskless return by holding a well-diversified portfolio of shares of firms in the continuum of markets, whereby the portfolio rate of return equals the expected market-specific rates of return.

Substituting (6) and (8) into the no-arbitrage equation (9) yields

$$(1 - 1 / \lambda(j))E - \mu h(j) = r\mu. \tag{10}$$

To close the model, we finally use the labor market clearing condition

$$L = \int_0^1 [E / \lambda(j)]dj + \int_0^1 \mu h(j)dj \tag{11}$$

where the first integral on the right hand side reflects employment in the manufacturing sector and the second integral reflects employment in the R&D sector. According to (11), the only stationary allocation of labor resources implies $\dot{E} = 0$ and thus from (4)

$$r = \rho\ , \tag{12}$$

i.e. the interest rate equals the rate of time preference and, hence, is constant over time.

Substituting (12) into (10), integrating the resulting expression over the continuum of markets j yields, using (11), the market-specific innovation rates

$$h^*(j) = (1-1 / \lambda(j))L / \mu - \rho/\lambda(j). \tag{13}$$

Finally, the expected market growth rate can be derived from (5) as

$$\dot{Y}(j) / Y(j) = h^*(j) \ln \lambda(j) = L\ [\ln \lambda(j)\ (1-1 / \lambda(j))]/\mu - \rho\ [\ln \lambda(j) / \lambda(j)]. \tag{14}$$

It is apparent from (13) and (14) that the pace of innovation and the rate of market growth are faster the larger is the endowment of the economy with (qualified) labor L, the greater is the productivity of labor in R&D μ^{-1}, the larger is the market-specific technological jump $\lambda(j)$, and the lower is the rate of time preference ρ.

While the innovation process in any particular market is erratic and stochastic, the macroeconomic development is smooth because of the continuum of markets.

Equation (14) will serve as the starting point for our empirical analysis of innovation-based growth at the market level. Note that we have two exogenous variables containing $\lambda(j)$ with the coefficients L/μ and ρ, respectively. The two variables are obviously dependent of each other, so that a careful check of multicollinearity will be required.

3 A new empirical concept for product quality

How do we measure "quality ladders" in product performance? Most of the established innovation indices, such as R&D expenditures, patents or data from innovation surveys do not contain information on product performance progress. For measuring the tacit, embodied knowledge included in innovative product features, measurement of technological characteristics is required.

At the beginning of the 1980s a series of "metrics" for evaluating and comparing technological sophistication and quality were proposed. What was coined "technometrics" in 1985 is a special procedure designed along Lancaster's [11, 14] consumer theory and is based on the observation that every innovative product or process has a set of key attributes that defines its performance, value or ability to satisfy customer wants. Each of these attributes has a different unit of measurement. Problems then arise in aggregating attributes to build a single quality index.

A solution to the problem is provided by an approach to product benchmarking known as "technometrics" [19, 20]. It is part of a huge literature in marketing on what are called "multi-attribute models" (for a review see [21]). Technometric benchmarking builds comparative metrics of product quality by implementing the following four stages for a given product, process or service:

1. Choose the fundamental characteristics or attributes that capture how the product, process or service creates value for customers. These attributes must be capable of being measured (though ordinal scales are acceptable).
2. Measure those attributes and do the same for competing products.

3. Normalize each of the product's attributes on a [0, 10] metric, where 0 represents the attribute's lowest value among all competing products, and 10 represents that attribute's highest value (the boundaries of this interval are arbitrary).
4. Graph, aggregate, and otherwise analyze the product's strengths and weaknesses across all attributes.

The i-th element of the characteristics of product (or service or process) j is the specification or attribute A(i, j). If market competition is assumed, one has to differentiate products k (or brands of the same firm) at time t_0. The measurement unit of this specification may differ from other specifications. The metric attribute M (for firm k') is obtained by

$$M(i,j,k',k,t) = 10[A(i,j,k',t) - A_{min}(i,j,k_{min},t_0)]/ [A_{max}(i,j,k_{max},t_0) - A_{min}(i,j,k_{min},t_0)], \tag{15}$$

whereby A_{max}, A_{min} being the maximum and minimum specifications within subset k. k_{min} and k_{max} denote those brands k for which A is minimum respective maximum with respect to the total subset. By this transformation, M(k') is no more dependent on specific physical units, but expressed as a defined point on an interval scale spanned by the specifications of all competing brands (products) in each dimension i. If the scale of the specification is inverse, that is, if the minimum value of A represents the most sophisticated technological level,[5] then an inverse formula holds

$$M_{inv}(i,j,k',k,t) = 1 - M(i,j,k',k,t). \tag{16}$$

From this micro-level, single-item definition, a quality profile may be aggregated at the level of all i specifications of product j if functional characteristics or (revealed) preferences F are defined:

$$M(j,k',t) = \Sigma_i [M(i,j,k',k,t) \cdot F(i,j)] / \Sigma_i F(i,j). \tag{17}$$

The preferences may be derived by introspective or market observation, from expert knowledge, by conjoint analysis or via hedonic prices.

Such profiles may be used for measuring the economic competence through the proxy firm-specific technological performance or quality level, one of the important determinants for the quality ladders which includes spillovers and tacit knowledge. Yet, the compilation of technometric data is time-consuming as the specifications are not accessible in data banks. The measure also does not differentiate between

5 Consider the fuel consumption of a car (compare also Figure 1).

the sources of know-how. It may be created within the firm, by a R&D sector, in the science system, by learning by doing or learning by using or by adoption of innovative solutions developed within other markets or firms and embodied in capital equipment and intermediate inputs. The latter variant is the one which corresponds best to our theoretical model.

The micro-macro bridge requires dissemination of knowledge within a market. In this broadly-based concept of progress in which spillover effects are spotlighted, an aggregate variable must be employed.[6] According to our theoretical model, we understand market development in terms of an established firm and the challengers competing constantly for an innovation; quality rises suddenly with every successive technological development at the end of a patent race by a constant factor $\lambda(j) > 1$. The market "climbs" up another rung on the vertical quality ladder with every product novelty.

Unfortunately, due to data scarcity (see Section 4), only cross-sectoral data for one particular year are available. We thus have to calculate $\lambda(j)$ from the "progress gap" of the leading firm towards a laggard firm with the understanding that the leading firm has already performed step $\lambda(j)^{m(j)}$ already, while the laggard firm arrived only at $\lambda(j)^{m(j)-1}$ on the quality ladder. In terms of measurement operationalisation this is tantamount to determining the metric assessment of the leading (k^l) and the backward firm (k^b):

$$M(j,k^l,t) = \sum_i[M(i,j,k^l,k,t) \cdot F(i,j)] / \sum_i F(i,j); \tag{18}$$

$$M(j,k^b,t) = \sum_i[M(i,j,k^b,k,t) \cdot F(i,j)] / \sum_i F(i,j); \tag{19}$$

$$\lambda(j) = M(j, k^l, t_0) - M(j, k^b, t_0). \tag{20}$$

If S is the union set for all suppliers (brands) in the country (or any other entity to be compared empirically), the progress distance of the leader l, $k^l \in S$, from the catching-up firm b, $k^b \in S$, must be determined. In other words: if the disparity in product quality in Germany between the incumbent and lagging firms is larger, then the innovation potential should be greater, giving rise to market growth. Here it does not matter that the M index is determined internationally, as the foreign patent races are not modelled endogenously.[7] To give an example, in Figure 1 such an aggregated bundle of characteristics is given. We took the passenger car, as this is

6 More on this issue in [22].

7 Note that the distance rather than the relation is required, as we deal with interval data (see Grupp [20], p. 117). Note further that the empirical values of (20) do not necessarily fulfill the theoretically required condition $\lambda(j)>1$. We therefore added 1 on the right-hand side and had the index run from 1 to 11.

the classic example of Lancaster [14]. Note that here – for confidentiality – we do not display single producers' data, but sectoral leaders as explained above.[8]

Note further that M(j) measures the "position on the quality ladder" reached internationally at a certain point in time, not exactly the constant, but tacit improvement steps of the past. For a statistical estimation, selected sectors j with possibly representative products must be prepared, and their aggregate technometric values compared with the world standard. In other words, a basket of commodities must be constructed, containing, for example, technology-intensive goods in a specific period of time. In doing this, it is permissible to initially let the time delay over which growth is to be observed remain variable, or to determine it from the regression, even though (14) does not anticipate a corresponding lag variable.

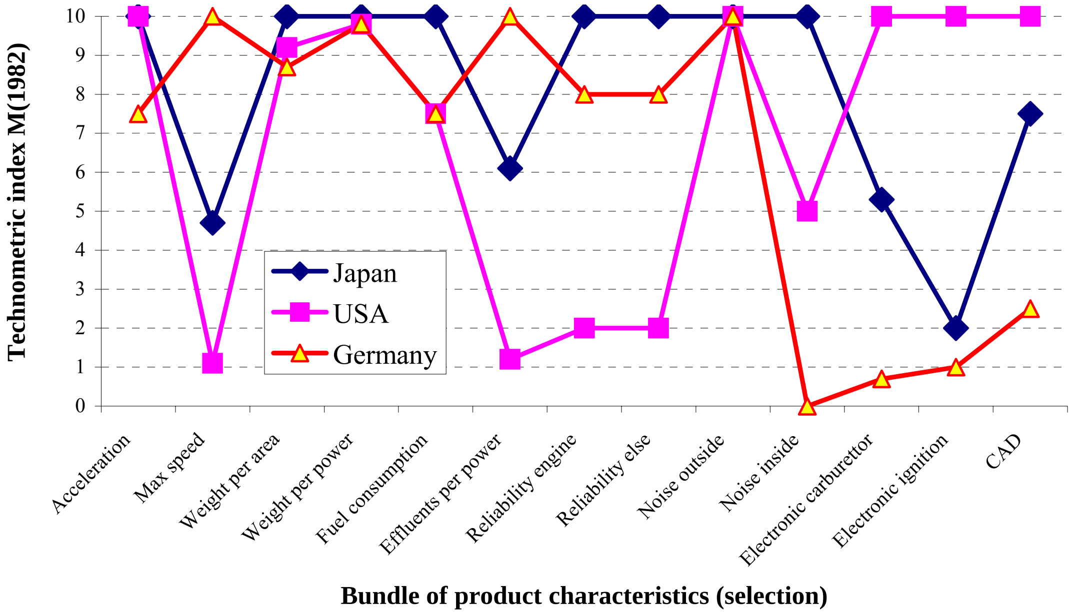

Figure 1: *Bundle of characteristics for a passenger car (for 1982 taken from Japanese data; see [23]).*

It must be noted that relationship (14) only exists under very restrictive assumptions. Without such assumptions, the so-called "micro–macro bridge" cannot be erected. In addition, with respect to the availability of data for the indicators, more complex relationships, even if they were suggestive, could possibly not be examined. To this extent, (14) represents an acceptable compromise between the reduction of theoretical complexity and the suitability for empirical examination. The concept strives for a two-component relationship between technological quality

8 Aggregated values in Table 2, position 12.

in product properties and the sectoral growth of the domestic economy's net production.

4 Product quality data: industries or markets?

In this Section, technometric data will be described to undertake the task described in the previous section. An innovative goods basket that covers various innovative markets and is representative for the early 1980s will be employed for a cross-sectional overview of the year 1982. The data are from a study carried out in 1982 at the request of the Japanese Agency of Industrial Science and Technology (AIST), a branch of Japan's Ministry of International Trade and Industry (MITI). The data set contains 984 technical specifications (properties) covering 42 markets and, in particular, distributions for the providers from the United States, Japan and selected European nations. In most cases, this European country is Germany, although in some markets British, Italian, French, Swiss, or Dutch products are examined in place of the German ones. Some markets are understood to be pan-European (civilian aircraft, communications satellites). Thus, the number of data sets available for an indicator comparison and the examination of growth effects in Germany is reduced to those goods in the basket for which comparative numbers are available for Germany. The set contains a total of 5,584 individual pieces of data. The reliability of the raw data can be classified as being good.[9] They were converted into a sectoral measure of progress, $\lambda(j)$, in accordance with (20).

It was intended to assign the available commodities in the goods basket for which technometric data are available to the individual branches of the economy in accordance with the German industry classification (SYPRO). Such an assignment to the manufacturing branches of the economy was successful at the subgroup level. Yet, it became readily apparent that the selected economic branches are far too inclusive and manufacture significantly more products than those in the basket. With regard to their weight in overall production, the selected economic branches represent a share of more than 38 per cent, thus including nearly half of all manufacturing activities (85 per cent). Since it is known that, in Germany, around two-fifths of all production activities and employment are in the total high-technology area,[10] this high proportion of high technology with regard to total production is the result of an insufficient degree of subdivision by branches.

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9 In the spring of 1985, one author (H. G.) carried out an in-depth interview with Katsuaki Marumo of the Japan Techno–Economics Society (JATES), the project leader in charge of gathering the data [23]. This source contains more detailed information about the data set.

10 Gehrke et al. ([24], p. 54 onwards).

But it is possible to go from economic branches to markets and, at the same time, to go to a six-digit subdivision. Using the German Goods Directory for Production Statistics (GP), nominal production values, Y(j), are available for a lower aggregation level.[11] This introduces two improvements to the synopsis between the compared quality properties and the growth indicator. On the one hand, markets are more homogeneous than industries (in fact, industrial providers as a rule serve several if not many commodity markets). On the other hand, the improvement reflects the inclusion of the six-digit subdivision. This low level is not defined by economic branches.

These improvements are not achieved without some disadvantages. Individual entries in the commodity production statistics are made as quantities (units, kg) or as production values (in €). Correction for inflation and the creation of net production indices is no longer possible since this level of subdivision contains no price indices. While it would be possible to perform a global correction with the aid of the deflationary price index for the gross domestic product, this would merely lead to a statistically irrelevant, constant factor in equation (14).

Table 1: Base data for the innovative goods basket and concordant markets.

Commodities in basket	Market demarcation	No.*	Type**	Weight in %	λ(j)
Cement	Portland cement	253151	HO, EI	0.186	3.66
Special steel	Precision tubular steel	273300	HO, EI	0.154	1.00
Common steel	Forged steels	274500	HO, EI	0.057	1.64
Powder metallurgy prod.	Products of sintered metals	302751	SG	0.031	5.43
Exhaust gas desulphurizer	Fume cupboards	315480	HO	0.021	8.86
Machining centres	Machining centres	321196	SG	0.084	4.43
Gas power turbines	Gas turbines	322400	SG	0.032	5.23
Injection moulding machines	Injection moulding machines	323545	SG	0.097	4.14
Construction machinery	Hydraulic dredgers	323662	SG	0.097	4.66
Spinners for polyester fibres	Spinning machines	326521	HO	0.041	8.88

Table 1 shows the comparison between the goods basket and the corresponding markets. This also includes the associated portion of production (weights) compared

11 Federal Statistical Office, Series 4, 3.1.

to total production. As the Table clearly shows, the concordance problem is solved much better than with industry data. For example, only the production values for motor vehicles with piston displacements over 1.5 litres are included, because the technometric data set for the property bundle includes motor vehicles in the 1.8 to 2.5 litre class. The chemical markets correspond precisely (antibiotics, PVC), as do the electronics products such as video recorders.

Table 1 continued

Commodities in basket	Market demarcation	No.*	Type**	Weight in %	λ(j)
Passenger cars	Passenger cars 1500 cm^3	331130	SG	3.744	5.71
Coaxial cables	Isolated communi–cation cables	362540	SG	0.037	3.27
Communication satellites	Radar navigation aerospace	365359	SG	0.036	4.01
Video recorders	Video recorders	366344	SG	0.169	4.36
Liquid chro-matography	Other photometric instruments	367411	SG	0.014	6.76
Polyvinyl chloride	Polyvinyl chloride	441452	SG, EI	0.163	3.52
Polyester filament	Polyester filament products	455515	SG, EI	0.177	5.42
Synthetic fibre dyestuff	Synthetic fibre dyestuff	461750	SG, EI	0.324	1.00
Antibiotics	Antibiotics	471700	SG	0.017	1.33
Surface-active agents	Surface-active products	492710	HO	0.096	11.00
Ceramics for electronics	Isolation and other ceramics	516100	SG	0.028	5.42
Total basket				5.603	
	Products of manufacturing industry			100	

Notes:

*) German production classification GP

**) SG: Schumpeter goods, HO: Heckscher–Ohlin products
EI: energy-intensive

A systematic process of examining the degree of representation indicates that the random sample now only contains just under 6 per cent of the total production value, compared with the 38 per cent acquired for industries. This value appears to be significantly more realistic, although stringent proof of representation is impossible because the aggregation problem on the goods basket side cannot be solved quantitatively.

The goods are classified by their R&D intensity into Schumpeter goods and Heckscher-Ohlin products [20]. Also included in Table 1 is an indication whether the product is produced energy-intensively. We want to control for possible growth restrictions from fluctuating energy prices.

5 Analysis of growth by products' quality improvement

Various growth rates can be calculated from the nominal production values, Y(j). On the one hand, the mean annual growth $\Delta Y(j,z)$ during a given year t(z), compared to the base year, $t_0 = 1982$, can be discounted and calculated as follows:

$$\Delta Y(j,z) = [Y(j,z) / Y(j,z)]^{1/z} - 1. \tag{21}$$

The actual growth rates during the intervening years are not included. If, on the other hand, one wishes to calculate the mean annual growth, $\Delta \acute{Y}(j,z)$, up to a given year t(z) and include all years t(g) where g = 1, ..., z, the following applies:

$$\Delta \acute{Y}(j,z) = [(\textstyle\sum_{g=1}^{z} Y\,(j,g)/(g\; Y(j,0)]^{1/z} - 1. \tag{22}$$

The mean annual growth rate $\Delta\acute{Y}(j,z)$ takes the nominal growth in each year into account and relates the discounted one to the base year. Another alternative would be to calculate the growth rate of each year over the production in the previous year. All three versions of the growth rate calculations were performed for all years between 1983 and 1992 in a heteroskedasticity-robust OLS regression calculation from equation (14). We have to note here that a time-series analysis would be preferable, of course. But as has been argued above, it is hard to get hold of product features. The data source used is a notable exception and contains high-quality data for 1982 only. Therefore we can only study the impact of the cross–section on later years as a proxy to the problem (two typical examples are given in Table 2).

We found no multicollinearity between the two λ(j)-dependent variables so that a proper estimation is possible. However, we found, when testing each variable separate of the other, that R^2_{adj} was almost the same so that we could explain the variances by each independent variable alone. For control of different cost influences per sector, we controlled for energy-intensive production and the fact whether a product is produced R&D-intensively (see footnote** to Table 1). The binary energy dummy turned out to be not significant. However, we monitored a difference from the binary dummy for Schumpeter- against Heckscher-Ohlin products. The mere fact of being produced R&D-intensively yields higher growth rates irrespective of product quality jumps. The use of average growth rates (equation 22) is superior to the use of discounted growth rates (in F and R^2). In Table 2, we provide the detailed results for two years.[12]

Table 2: A typical example of the OLS regression of average production growth from 1982 until 1986 (1987 resp.) (coefficients with standard deviation shown in brackets).

Variable	1986	1987
ln λ(j)[1 – 1 / λ(j)]	0.049 (0.020)**	0.043 (0.017)**
ln λ(j) / λ(j)	-0.122 (0.074)	-0.108 (0.060)*
Schumpeter goods	0.061 (0.022)**	0.050 (0.017)**
energy-intensive	-0.016 (0.030)	-0.020 (0.025)
Constant	0.007 (0.039)	0.011 (0.033)
R^2_{adj}	0.45	0.55
F	7.40***	9.27***

Notes:

* significant at the 10 % level; heteroskedasticity-robust errors throughout

** significant at the 5 % level

*** significant at the 1 % level

We now turn to a more detailed discussion of the influence of quality on growth. For the discussion of the results, a graph charting the probability of error is preferred in order to better discuss the temporal progression (lag structure) of the analytic results. Figure 2 shows that the average nominal growth in production, $\Delta\acute{Y}(j,z)$, in the selected markets during the years t_z = 1984 to t_z = 1989 is explained by the quality indicator ln λ(j) [1–1/λ(j)] with a probability of error of less than 5 per cent. The best equivalence is found for t_z = 1987 (see also Table 2). The other variable, ln λ(j) / λ(j), is less significant but is quite similar in the gap structure. It is also best for t_z = 1987.

12 Note that in equation (14) we expect a positive sign for the first term, but a negative one for the second. In our reporting of the regression results, for simplicity, we display the calculated signs for a positive regression.

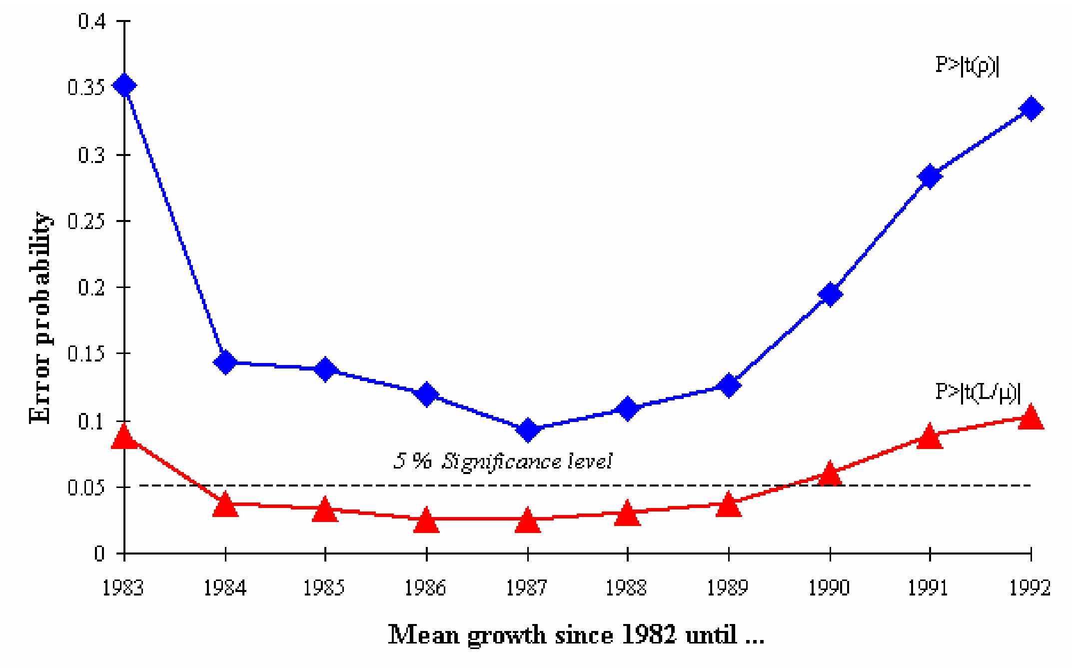

Figure 2: *Nominal production growth in selected markets, measured by the probability of error of an OLS correlation to the product quality indicators.*

This means that production growth can be derived from the position of product quality on an international quality ladder of the markets to which the innovative products belong. According to this analysis, the growth-enhancing effect of technological progress ceases after some seven years. It should, however, be noted that 1990 was characterized by special circumstances in Germany resulting from the economic and monetary union of the Federal Republic of Germany and the former German Democratic Republic that subsequently led to political reunion by the year's end. To this extent, the discontinuity in the probability of error between 1989 and 1990 can most likely be influenced by a unification effect and should not exclusively be regarded as technology-related.

As this is quite a long period, our interpretation should be the following: Quality levels of one particular year "impinge" on growth in future years, but are permanently replaced by more progressed ones (which we cannot observe as the data are missing). In one year this cohort effect is highly significant, in others too heavily mixed with "older" or "newer" unobserved product quality levels being traded on the markets.

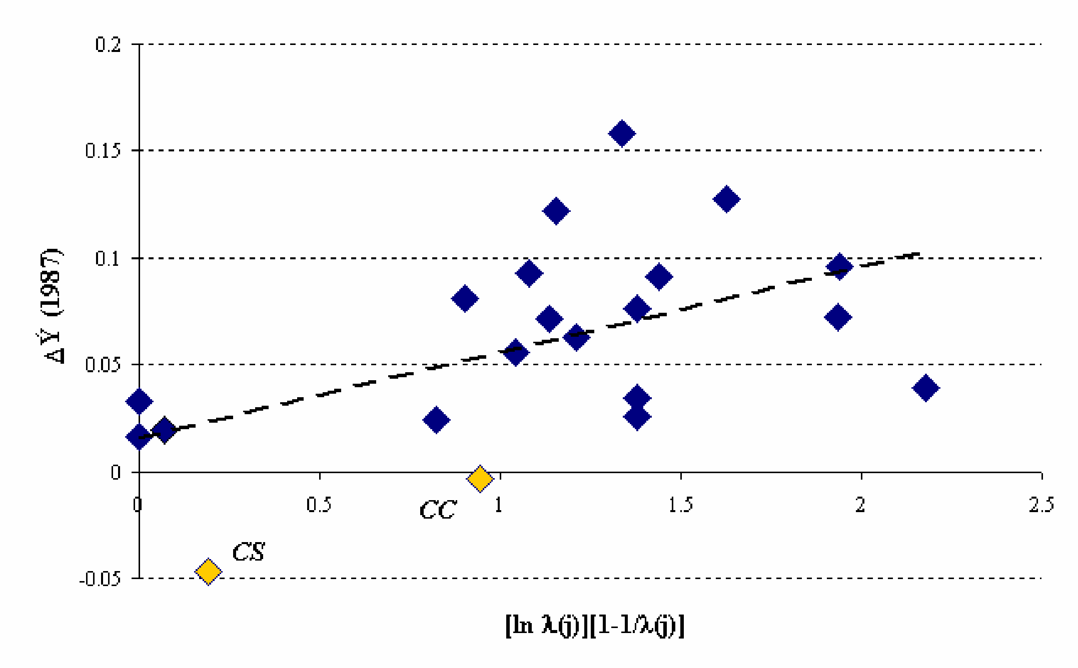

Figure 3: *Optimum fit for market growth in 1989 explained by relative product quality levels in 1982.*

In Figure 3, the regression result for the optimum year, 1987, is given. We note that two product groups which do not show any (nominal) growth or grow at a rate below zero are not of superior product quality (these data points are shaded in grey in Figure 3). These are the markets for common steel (CS) and concrete (CC). Three more products with negligible quality jumps did not grow much.

6 Discussion: What do we learn about the sources of innovation?

One of the most intriguing elements of Schumpeterian growth models is that they rely on non-competitive market structures which are, according to Schumpeter, necessary for firms to invest in risky R&D projects. The standard quality-ladder model uses the patent-race approach which is well established in the Industrial Organization literature, to describe the stochastic dynamic process of vertical product innovations. Due to the inter-market symmetry restrictions, however, the standard quality-ladder model is suitable to analyze macroeconomic growth, but not adequate to account for market-specific effects. The present paper has shown, however, that the standard model can consistently be extended by allowing for inter-market differences to derive some testable hypotheses about the determinants of growth at the market level.

The statistical results to test the relation of quality ladders and growth come, in their simplicity, as a surprise, as extensive data retrieval and handling has shown to be too difficult, and the analysis is based on a basket of goods with unproven, a fortiori, unprovable representation. What is shown is simply that Germany's growth is composed of faster and lesser growing markets which significantly mirror the relative jump German products took in a selected year with respect to the quality ladders. All the other factors meant to explain growth were not helpful. The heterogenous market-specific technological conditions seem to cover statistically all other explanation factors.

If we assume that at least the triad nations are open ones, there is no need to take separate account of who consumes these products, domestic purchasers or external ones. As the national position on the respective quality ladder is determined vis-à-vis the triad countries USA and Japan, this is just the right level of the comparison of product quality features and production growth – be it for domestic use or for satisfying foreign customers' preferences.[13]

While the progress measure explains the medium-term production growth in selected, representative German markets when Schumpeter markets and other markets are mixed, it might be expected that the reliability of the correlating growth indicator would improve still further if the examination were limited to Schumpeter markets alone (consider also the outliers in Figure 3). Indeed, regression results indicate that the discovered relationship is dependent of the R&D resources, whose intensity delineates high technology markets from others. Schumpeter markets show stronger growth.

Yet, the fact that low R&D-intensive markets also follow the quality-growth model can be explained by bearing in mind that, aside from the R&D expenditures that are fundamental for high technology goods, there are also other innovation resources, for example, investments in advanced goods. In fact, Pianta [26] found that two typical growth patterns can be observed in OECD nations between 1970 and 1990. One group of countries was able to initiate total economic growth primarily through its own R&D expenditures, while another group employed investment-linked progress as a growth engine. The product feature indicator is viewed as an ideal indicator for quality ladders precisely because the question of innovation resources no longer needs to be determined if increases in the quality of the innovative products' properties are determined. Two equally advanced goods may have been produced with different inputs. To this extent, the quality concept equalizes the diverse inputs calculated by Pianta by measuring the real outputs on the international quality ladder. The less R&D-intensive Heckscher-Ohlin markets may have initiated their characteristic progress by the application of technology through

[13] For a more detailed analysis of the openness of OECD markets see [25].

the formation of capital. This means that the distinction between process and product innovations is less important than normally assumed.

According to our theoretical model, we could have further studied the hazard rate that measures the intensity of competition.[14] More interesting than the intertemporal comparison of the hazard rate would be a comparison of countries like the US, Japan, United Kingdom and so forth. This appears possible, as each of these countries maintains detailed statistics on national goods that are, however, not internationally comparable. Internationally comparable statistical sources seem to be too highly aggregated for this purpose. An analogous examination of the validity of the market-related, finely subdivided, growth in production explained by quality ladders that fits very well for Germany should also be carried out for these countries.

14 Kamien and Schwartz [7], p. 105, Stadler [27], p. 161 and Schwitalla [28], p. 27.

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