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Endogenous Growth and Structural Change in a Dynamic Input–Output Model

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ABSTRACT *This paper introduces a simple dynamic input–output model, in which some of the most important properties of recent endogenous growth theory are included: innovation, knowledge spillovers, constant returns to scale at the macro level, and full employment. The wish to keep the hybrid model as tractable as possible (despite the industry detail) caused some substantial simplifications: contrary to most endogenous growth models, the model lacks an explicit microeconomic foundation and disregards any opportunity for instantaneous substitution. After the constituent equations are presented, the long-run behavior of the model is studied by a number of computer simulations for a hypothetical economy. The paper concludes with some illustrations of the potential practical power of future interindustry endogenous growth models in integrating issues like technology, investment, trade and education.*

1. Objective and Set-up

Since the mid-1980s, input–output (IO) analysis has no longer been contained in the core of mainstream economics. Leading journals such as *Econometrica*, the *Review of Economics and Statistics* and the *Quarterly Journal of Economics* did not continue to publish IO papers and few top economists nowadays seem to show interest in developments in the field of IO analysis.[1] This is a sad state of affairs, since IO still could play the important role mentioned by its founding father,

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Editor's note: On the basis of this paper, Bart Los was awarded the first Leontief Memorial Prize at the 13th International Conference on Input–Output Techniques in Macerata (Italy). He received this prize for the best conference paper by authors younger than 40 years.

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Wassily Leontief, in his foreword to the very first issue of the journal *Economic Systems Research*:

> 'Input–output analysis is a general methodological approach designed to reduce the steadily widening gap between factual observation and deductive theoretical reasoning that threatens to compromise the integrity of economics as an empirical science.' (Leontief, 1989, p. 3)

Why did IO drift away from mainstream economics (or the other way round)? In my opinion, four major causes can be identified. First, from the mid-1970s onwards, faith in the ability of market mechanisms to yield 'socially optimal' solutions began to increase. Consequently, attention shifted away from government planning for which IO is seen as a useful instrument. Second, the belief grew stronger that macroeconomic theory should be rooted in microeconomic foundations. Since IO considers industries consisting of many firms as the smallest unit of analysis and the accompanying data material is also published at the industry level, IO did not fit into this development. Third, the vast majority of IO theories start from the (Post-Keynesian) notion that output and employment are mainly demand-constrained, whereas mainstream theory takes the opposite perspective that these variables are predominantly determined by supply-side factors. Fourth, and most important, mainstream economics got increasingly involved with explanations of long-run growth in which a major role is played by technological change, in particular after the emergence of the so-called endogenous growth theory. At the same time, IO is still generally judged to deal with situations in which production technologies are frozen. Hence, many hot topics in mainstream economics, such as changing trade patterns, changing skill compositions of workforces and changing environmental consequences of production could hardly be studied by IO methods, with the exception of pure *ex post* accounting techniques.

Of course, the above-mentioned causes and consequences are somewhat overstated. For instance, there have been some attempts to give IO analysis a microeconomic foundation (see, for example, Ten Raa & Mohnen, 1994, and Rose & Casler, 1996) and some work is going on to replace Ghosh's (1958) ultimately unsuccessful supply-side IO quantity model by more consistent methods to analyze the effects of supply restrictions, for instance concerning agricultural production (see for example Papadas & Dahl, 1999).[2] Despite these examples of progress in the direction of mainstream economics, it is clear that it would take IO economists much effort to regain the respect of the majority of mainstream economists.[3] Most importantly, they would have to monitor developments in mainstream economics quite closely, in order to note any opportunity for reducing the gap mentioned by Leontief in his above-cited remark. This contribution should be seen as a first result of explorations of what I think to be such an opportunity.

In this paper, I will try to indicate how the theory of endogenous growth in mainstream economics could be enriched by IO analysis. Since the publication of Paul Romer's (1986) article in the *Journal of Political Economy*, long-run growth and its potential determinants have become a paramount topic in mainstream economics. His ideas have been challenged, refined, and extended in numerous contributions to the literature. In most of these so-called endogenous growth models, Research & Development (R&D) and its accompanying positive externalities are the driving force of long-run productivity and output growth.[4] The externalities imply that governments could promote the long-run welfare of its citizens by pursuing active technology policies instead of laissez-faire.[5] This out-come naturally attracted a lot of attention from policy makers. Despite its impact, the practical usefulness of endogenous growth theory has been very limited until now, since it maintained the neoclassical assumption of economies consisting of perfectly identical, representative agents. In some contributions, distinctions were made between producers of capital goods, intermediates and consumption goods, but practically more relevant differences between, for example, buildings, computers, and transport equipment have not so far been introduced.

IO analysis explicitly focuses on differences between commodities themselves, as well as on the differences with respect to the inputs required for their production. However, in this strand of economics, issues of long-run economic growth and structural change have only scarcely been studied in a dynamic framework. After the construction and application of the well-known 'Leontief–Duchin–Szyld' model (Duchin & Szyld, 1985, and Leontief & Duchin, 1986) in the mid-1980s, the focus of the majority of empirical input–output studies seems to be on the prediction of short-run developments and *ex post* accounting for growth in a comparative statics framework (e.g. structural decomposition analyses).

As a first step towards a potentially fruitful bridge between endogenous growth theory and IO-analysis, I will introduce a very simple dynamic input–output model in which some of the most important properties of state-of-the-art endogenous growth theories are included: innovation, knowledge spillovers, constant returns to scale at the macro level and supply-side determination of production levels. From the IO perspective, the latter feature is clearly a deviation from standard practice. In exchange, the model lacks an explicit microeconomic foundation and assumes production functions with fixed coefficients in the short-run (no instantaneous substitution due to changes in relative prices) which is contrary to most endogenous growth models.

The paper is organized as follows. Section 2 is devoted to a brief review of the parts of endogenous growth theory that are relevant to the model. In Section 3, I will present and discuss the equations that, together, make up the model. The long-run behavior of the analytically complex model will be studied in Section 4 by a number of computer simulations for a hypothetical economy. In the presentation, I will put an emphasis on the identification of (industry-specific) 'optimal R&D investment levels', because it is the aspect of the endogenous growth theory that is most important for policy makers. Some illustrations of the potential power of future input–output endogenous growth models in integrating issues such as technology, investment, trade and education are given in the concluding Section 5.

2. A Brief Overview of Endogenous Growth Theory

In this section, I will survey some of the main results that have emerged from the endogenous growth theory. It is not my intention to provide a complete review, since a number of surveys have already been published (see for example Verspagen, 1992, Aghion & Howitt, 1998, and Los, 1999, Ch. 2). In particular, I will not engage in detailed discussions of the microeconomic aspects, because these do not play a substantial role in the remainder of the paper. Instead, I will focus on two issues that are characteristic of endogenous growth models and which are important from an industry-level perspective: technological spillovers and scale effects.

First of all, I should make clear which theories I would like to cover in this discussion of endogenous growth theory. For the present purpose, a theory or model should fulfil two criteria to be included: it should be 'Schumpeterian' and it has to assume that firms rationally optimize their profits. The first criterion implies that growth of output and productivity must be 'generated through the introduction of new goods or processes, as opposed to physical or human capital accumulation' (Dinopoulos & Thompson, 1999, p. 159). It thus excludes the traditional neoclassical model in which long-run productivity growth equals the exogenous rate of technological progress, as well as Post-Keynesian growth theories in which the rate of export growth determines the rate of output growth.[6] Further, it prevents me from discussing the models in which the long-run growth rate is endogenized by letting it depend on investment in human capital (education). The second criterion implies that I will not deal with contributions to the so-called evolutionary growth theory. Authors in this tradition also see a purposeful search for innovations (R&D) as the driving force of growth, but they argue that the intrinsic uncertainty with respect to the revenues of R&D prevents firms from maximizing their profits. Instead, they are modeled to follow routines that can be adopted in the course of time. I do not include evolutionary theories in this short survey simply because they do not belong to the mainstream I mentioned in the introduction. It should be borne in minds though, that the reduced form model that I will present in the next section can be brought in accordance both with models assuming rational optimization and with models assuming routine-based behavior.

2.1. Technology spillovers

The fundamental advantage of endogenous growth theories over the traditional exogenous neoclassical growth theory is that it provides explanations of why productivity levels have risen over time and why many firms devote substantial parts of their resources to the search for innovations. The notion that technology causes positive externalities (spillovers) has been crucial to the construction of all Schumpeterian endogenous growth theories.

In the famous paper leading to the first wave of endogenous growth theories (Romer, 1986), R&D variables entered the production function of firms as two additional inputs, next to labor and capital. First, the productivity of the rival inputs labor and capital could be increased by R&D paid for by the firm itself. Second, the public good characteristics of knowledge generated in R&D activities also enable firms to benefit from knowledge produced elsewhere. In the empirical literature, this variable is sometimes called 'the potential spillover pool' (Jaffe, 1986, p. 986). A fundamental problem connected with this class of models is their internal inconsistency with respect to incentives to invest in R&D. As technology is assumed to be completely public immediately, no firm would engage in R&D, because there are no opportunities to make a profit on its results.

In later new growth models, the traditional assumption of perfect competition was relaxed (see for example Grossman & Helpman, 1990, 1991, Romer, 1990, and Aghion & Howitt, 1992). Integrating insights from the field of industrial organization with the endogenous growth framework, these models assumed that technology is *not* completely public immediately and that markets in which firms sell their products are characterized by monopolistic competition. Given this market structure, firms have some freedom to set their own prices, due to the fact that they have some monopoly power in the segment of the market in which they sell their 'variety' of the product. By setting their prices appropriately, firms will, in principle, be able to earn enough to compensate for their R&D expenditures. In these second-wave new growth theories, at least two sectors are distinguished.[7] The R&D sector typically produces two goods, designs ('blueprints') for new goods, and general knowledge. The blueprints can be used in either the intermediate goods sector or the consumption goods sector, depending on the particular model. As blueprints provide 'recipes' for new products, positive profits can be secured for at least a short period by obtaining a patent or exploiting a time-lead. Consequently, specific blueprints are the driving force to engage in R&D projects, which yield general knowledge as a very important byproduct. Contrary to the blueprints, this general knowledge is assumed to be a public good: the entire research sector can use it too. The effects of these knowledge spillovers on the productivity of research have been modeled in several ways. Almost all recent endogenous models are constructed around either one of two broad classes of spillover mechanisms: 'increasing variety' and 'quality ladders'.

In Grossman & Helpman (1990) and Romer (1990) the output of the research sector (measured in blueprints) depends on its labor inputs and the availability of spilled general knowledge. The blueprints for new intermediate goods do not constitute quality increases. Instead, it is assumed that the expanding variety of intermediate inputs enhances productivity in the consumer goods sector, because more specialized inputs can be used. The positive knowledge spillovers in the 'increasing variety' models cause the equilibrium R&D expenditures to be lower than desirable from a social point of view: firms base their R&D decisions on the private returns to research which are lower than the social returns.

Aghion & Howitt (1992) assume that each new blueprint for each of a number of intermediate goods lowers the production costs of the unique consumption good. Knowledge spillovers are embodied in the previous blueprint, possibly invented by some other firm: when an innovation occurs the entire research sector is assumed to have obtained the underlying knowledge. Subsequently, all other firms can use their own R&D inputs to design new innovations that reduce production costs further. Grossman & Helpman (1991) exploit a similar idea, although they do not distinguish an intermediate goods producing sector. In their model, each innovation implies a step up the 'quality ladder' of one of various imperfectly substitutable consumer goods. Any R&D project is assumed to use the general knowledge associated with the consumer good with the highest quality so far. The length of the time period between two successive innovations (during which innovation rents can be earned) is a stochastic variable in both models, since innovations are assumed to arrive according to a Poisson process. The mean number of innovations per time period is assumed to be determined by the amount of labor (or human capital) employed in the R&D process. Although the 'quality ladder' models also contain positive knowledge spillovers, they do not yield conclusions identical to the 'increasing variety' models, due to the existence of a countervailing force. When a firm thinks of investing in an R&D project, it will calculate whether its expected revenues will exceed its costs, without taking into account that the stream of revenues of the current best blueprint is immediately ceased. So R&D projects cause a negative externality too, and it depends on the relative magnitudes of this negative 'creative destruction' effect and the positive knowledge spillover effect whether the social returns are smaller or larger than the private returns.

From this discussion of the second wave of Schumpeterian new growth theory, three issues arise that will be important from the perspective of the IO growth model to be presented in the next section. First, knowledge spillovers can be modeled in two ways. In the first specification, all R&D processes become more productive when the stock of general knowledge (which is a byproduct of the search for profitable innovations) increases. Alternatively, the knowledge contained in a cheaper production process or a qualitatively superior consumption product is immediately accessed by other firms, who start their continued search for innovations at the newly established level of technology. Second, innovators can earn supernormal profits for a limited time span, due to legal protection (patents) or the ability to build a time-lead. Third, it is more or less accepted to model the occurrence of innovations as a Poisson process, the parameter of which is determined by R&D efforts.

2.2. Scale Effects

Ever since the introduction of the endogenous growth models, the issue of scale effects has attracted much attention. Due to the above-mentioned positive externalities of R&D, returns to scale are no longer constant (as in the Solow, 1956, model), but increasing. This is exactly the reason why output growth can be sustained in endogenous growth models, even when population does not grow. The evidence presented by Jones (1995a, 1995b) against the implications of scale effects has evoked a new wave of Schumpeterian growth theories, the properties of which have some important consequences for my IO growth model.

To clarify the discussion, I borrow heavily from the review article by Dinopoulos & Thompson (1999). They present a simple two-sector model that can be conceived as a reduced form of the models discussed earlier. Labor is assumed to be the only rival production factor.[8]

$$X[t] = \Lambda[t]L^P[t] \tag{1}$$

$$\frac{\dot{\Lambda}[t]}{\Lambda[t]} = \gamma L^R[t] \tag{2}$$

The first equation states that output X of the commodity-producing sector depends on the prevailing labor productivity in production Λ and the amount of labor devoted to this sector L^P. Equation (2) implies that the proportional change of labor productivity is a linear function of the amount of labor allocated to R&D, L^R. The parameter γ is an indicator of labor productivity in the R&D sector. It should be noted that the specification of equation (2) implies that the research output $\dot{\Lambda}[t]$ of a given research labor force increases with the productivity level $\Lambda[t]$ already attained. The implications can be illustrated by interpreting the current productivity level as the upshot of 100 equally important 'ideas' (see Jones, 1998, for a similar exposition). Initially, the research labor force can manage a constant productivity increase of 3% per year by producing three new ideas per year. After 100 years of 3% productivity growth, however, the stock of ideas has grown to such an extent that about 58 new ideas per year are required to maintain an annual productivity growth rate of 3%! The assumption of a constant productivity of R&D in terms of proportional growth rates as reflected in equation (2) leads to an important but debatable model property, as will soon become clear.

The full employment condition, which the new growth literature assumes to be fulfilled automatically, ensures that labor supply L equals the sum of L^P and L^R. Combining equations (1) and (2), the growth rate of output per capita x (for a given ratio of R&D labor inputs to total labor inputs) can be shown to evolve in the long run according to

$$\frac{\dot{x}[t]}{x[t]} = \frac{\dot{\Lambda}[t]}{\Lambda[t]} = \gamma\left(\frac{L^R[t]}{L[t]}\right)L[t] \tag{3}$$

At least three important hypotheses concerning scale effects in the simple model can be extracted from equations (2) and (3). First, the output of an economy will grow twice as fast as the output of another economy with an identical R&D productivity (in terms of proportional growth rates) and an equal fraction of the workforce employed in the R&D sector, if its workforce is twice as large. Second, if an economy has a constant population and its productivity in R&D activities remains stable, its long-run productivity growth rate will remain equal only if the fraction of the labor force allocated to R&D remains stable. Third, if R&D productivity remains stable and the proportion of labor in R&D remains equal, population growth yields accelerating productivity growth.

The first hypothesis can be tested by confronting it with cross-country data. The most-cited study, which reports results of a related test, is Backus *et al.* (1992), who do not find a relation between per capita GDP growth and the logarithm of initial GDP for aggregate economies, but a significant positive link if only manufacturing output growth rates and initial levels are considered.[9] The second and third hypotheses are of a time series nature. Jones (1995a) presents evidence that the second hypothesis is untenable, at least when tested on data for the period 1950–1990: in four major industrialized countries, productivity growth did not change dramatically, while the numbers of scientists and engineers employed in R&D departments rose considerably. In fact, this is also evidence against the third hypothesis (since the population rose as well), but investigations on extremely long time series by Kremer (1993) yield results favorable to this hypothesis. All in all, the empirical evidence regarding scale effects is unclear, especially since all kinds of measurement problems emerge, short-run and long-run effects cannot be disentangled, or international effects of technology creation cannot be taken into account. Nevertheless, many authors feel very awkward about the scale effect results of models that are similar to the model of equations (1) and (2) and have constructed alternative Schumpeterian growth models in which scale effects are either absent or play a less prominent role. One of them will offer the basis for the most important equation in the IO growth model to be developed in the next section.

In fact, the theories that try to remove scale effects can be represented by a modified form of equation (3):

$$\frac{\dot{x}[t]}{x[t]} = \frac{\dot{\Lambda}[t]}{\Lambda[t]} = \frac{\gamma_0}{\gamma[t]}\left(\frac{L^R[t]}{L[t]}\right)L[t] \tag{4}$$

Now, the productivity of labor employed in R&D (in terms of proportional productivity growth rates) is no longer assumed to be constant, i.e. γ in equations (2) and (3) is replaced by $\gamma_0/\gamma[t]$. The equation shows that absence of scale effects in the time series dimension is ensured if and only if $\gamma[t]$ grows at a rate exactly equal to the long run growth rate of labor supply $L[t]$, when it is assumed that the fraction of total labor devoted to R&D activities remains constant. As Jones (1999) emphasizes, equation (4) offers the opportunity to classify models of R&D-driven

growth into three groups. First, if $\gamma[t]$ is constant or grows slower than $L[t]$ (as in the model discussed above), the model is an 'endogenous growth model with scale effects'. Second, if $\gamma[t]$ grows faster than $L[t]$, the model could be called a 'semi-endogenous growth model'. Finally, if $\gamma[t]$ grows exactly as fast as $L[t]$, the model could be called an 'endogenous growth model without scale effects'. In the final paragraphs of this section, I will discuss the most important properties of the 'semi-endogenous growth models' and 'endogenous growth models without scale effects' and will try to indicate why these group names are subject to debate.[10]

The first semi-endogenous model was formulated by Jones (1995b), followed by Kortum (1997) and Segerstrom (1998). The Jones (1995b) model is based on the conviction that it would be impossible to attain a constant proportional productivity growth rate with a given number of R&D workers, because these workers would be unable to develop the required ever-increasing number of ideas (see my discussion of equation (2)). This implies that more resources have to be allocated to R&D activities in order to maintain a constant productivity growth rate. The Jones (1995b) model and other semi-endogenous growth models boil down to equivalents of the following productivity growth equation:

$$\frac{\dot{x}[t]}{x[t]} = \frac{\dot{\Lambda}[t]}{\Lambda[t]} = \frac{\gamma_0}{\Lambda[t]^{(1-\varphi)}}\left(\frac{L^R[t]}{L[t]}\right)L[t] \tag{5}$$

Here, $1-\varphi$ is a measure of the speed at which R&D becomes less productive in the process of knowledge accumulation (note that the labor productivity *growth rate* $\dot{\Lambda}[t]/\Lambda[t]$ is negatively affected by a high labor productivity *level* $\Lambda[t]$). In the long run, productivity grows according to

$$\frac{\dot{\Lambda}}{\Lambda} = \frac{v}{1-\varphi} \tag{6}$$

where v indicates the population growth rate. The long run productivity growth rate is thus proportional to the population growth rate and is completely independent of the fraction of labor resources devoted to R&D.[11] This type of R&D-based models is similar to the traditional neoclassical growth model in the sense that long-run productivity growth is an exogenously determined phenomenon. Contrary to models of exogenous growth, however, the productivity and output *levels* that correspond to the growth path are positively related to the endogenously determined equilibrium fraction of labor devoted to R&D. These two properties lead many economists to label these models 'semi-endogenous growth models'.

Endogenous growth theories without scale effects (for example, Peretto & Smulders, 1998, Young, 1998, and Howitt, 1999) contain mechanisms that could save the conclusion of R&D-dependent long-run growth rates without running into scale effect problems. The central idea is that R&D is becoming less productive in an aggregate sense, because it is assumed to generate variety-specific knowledge and quality increases together with an ever-increasing number of varieties. So, in comparison to increasing variety models in the 'second wave' of endogenous growth theory (e.g. Romer, 1990), there are increasingly less useful knowledge spillovers between firms producing different varieties. Hence, each R&D worker produces less and less relevant (from a societal perspective) knowledge as the economy grows, although his productivity with respect to his 'own' variety does not change. Using standard profit maximization assumptions under monopolistic competition it can be shown that, in the long run, firms allocate their R&D workers in such a way that the number of varieties increases at the same pace as population.[12] Dinopoulos and Thompson (1999, p. 174) show that (at least some) 'endogenous growth models without scale effects' boil down to the productivity growth equation:

$$\frac{\dot{\Lambda}}{\Lambda} = \kappa\gamma_0 \frac{L^R[t]}{L[t]} \tag{7}$$

where κ is the constant ratio between the population size and the number of varieties. Hence, labor productivity growth can be written as a linear function of the proportion of the workforce devoted to R&D: aggregate productivity keeps growing at a steady pace when a constant fraction of an expanding population is devoted to R&D. Consequently, governmental policies which attempt to increase this fraction will be successful in promoting long-run growth, contrary to the prediction of the 'semi-endogenous' models. Further, scale effects do not apply to growth rates, but are only reflected in the result that larger economies produce more varieties than small countries (as long as they are technologically independent).

From this necessarily superficial overview of the scale effects issue in the endogenous growth theory, the main conclusion should be that the outcomes of these models are extremely sensitive to the specification of the equation linking output and productivity growth to one or more R&D variables. Of course, this will also apply with regard to my I0 growth model. In my personal view, the recent 'endogenous growth models without scale effects' do a good job in the sense that they explicitly consider the growth-inhibiting effects of the increasing complexity caused by the growth of R&D efforts. It should be realized that an important part of the results hinges on my choice for a specification that make the model belong to the class of 'endogenous growth models without scale effects'. The next section's discussion of the model equation will make clear how exactly I incorporated the above-discussed technology spillovers and scale effects issues into an interindustry context.

3. The Model

The IO growth model that I propose is a very simple example of a 'sequential' or 'two-stage dynamic' (Dervis *et al.*, 1982) model. At the beginning of each period, the industries have to decide on a number of issues, given a set of variables that are assumed to be beyond their range of influence at that stage. For example, industries decide on their current period R&D inputs on the basis of their previous sales levels, previous relative prices and the prevailing production functions in their R&D sector. The complete set of these short-run equations yields current output, R&D, employment and consumption levels. In fact, output determination just involves the solution of a kind of static input–output model in each period. The dynamics are introduced in the second stage, in which the consequences of the current decisions on the values that are assumed to be exogenous at the beginning of the next period(s) are modeled. For example, current decisions with respect to R&D expenditures shape future production functions. Consequently, new values of the variables, which are exogenous to the short-run decision process, can be fed to the system and long-run effects of parameter changes can be studied.[13]

Following the R&D-based growth models I reviewed in the previous section, the model deals with a closed economy. In this economy, n industries, each producing a single, homogeneous commodity, are specified. Each industry consists of two sectors, as in the endogenous growth models. In the production sector, the relation between output and inputs (labor and n intermediate inputs) is given by an industry-specific Leontief production function, the parameters of which indicate the requirements per unit of gross output.[14] In the R&D sector, inputs are used in fixed industry-specific proportions as well. The output of this sector consists of blueprints for new production processes. These blueprints are represented by industry-specific Leontief production functions with lower input coefficients than for the one currently in use. The allocation of inputs to the R&D process thus enlarges future output levels at the cost of decreasing the current capacity to produce commodities for consumption purposes.

Below, I will introduce the equations making up the model. For brevity, they are written in matrix notation whenever convenient. Bold capitals refer to matrices, bold lowercase symbols represent column vectors and italic symbols relate to scalars. Diagonal matrices are denoted by a hat and primes indicate transposed matrices or vectors. Further, superindices P and R relate to inputs for production and R&D, respectively. A subindex c indicates a coefficient matrix or vector, whereas a subindex s denotes a matrix or vector with stock or flow quantities. Tildes are used to indicate variables in money terms, and bars denote (weighted) sums or (weighted) averages.

3.1. R&D-driven Technological Progress

Since one of the main differences between recent dynamic input–output models (Duchin & Szyld, 1985, Leontief & Duchin, 1986, Kalmbach & Kurz, 1990, and Edler & Ribakova, 1993) and the present model is the explicit endogenous nature of technological progress, I will start the exposition of the equations with those describing the link between R&D and productivity growth. The specification of this equation is inspired by the aggregate models belonging to the 'endogenous growth without scale effects' category. Throughout the paper, I will denote the $(n \times 1)$-vector of labor quantities (required for production purposes) per unit of gross output as effective in the period starting at t and ending at $t+1$ by $\mathbf{l}_{\mathrm{c}}^{\mathrm{P}}[t+1]$. Its elements are assumed to change according to the difference equation

$$l_{c,j}^{P}[t+1] = \left(\frac{1}{1+\sigma Inn_j[t]}\right) l_{c,j}^{P}[t] \tag{8}$$

with Inn denoting the industry-specific number of process innovations occurring at t and σ indicating the fixed proportional increase in labor productivity implied by each innovation (their 'size').[15] Following Aghion & Howitt (1992), innovations arrive at stochastic intervals:

$$Inn_j[t] \sim \text{Poisson}(\lambda_j[t]) \tag{9}$$

in which λ_j is an industry-specific variable the value of which is given by

$$\lambda_j[t+1] = \gamma_j\left[(1+\eta_j^{\star}[t])\,\frac{l_{s,j}^{R}[t] + \sum_{k=1}^{n} z_{s,kj}^{R}[t]}{x_j[t]}\right]^{\alpha_j} \tag{10}$$

with

$$\eta_j^\star[t] = \sum_{i \neq j} \eta_{ij} \left(\frac{l_{s,i}^R[t] + \sum_{k=1}^n z_{s,ki}^R[t]}{\sqrt{x_i[t]\, x_j[t]}} \right)^{\alpha_i}$$

Although this equation (10) is less complicated than it seems, it does require a number of comments.

First, setting aside the factor $(1+\eta_j^\star[t])$, equation (10) almost resembles a multi-input version of equation (7): $\mathbf{l}_s^R$ denotes the R&D labor inputs, $\mathbf{z}_s^R$ indicates the inputs of materials in the R&D process and $\mathbf{x}$ reflects the total inputs, aggregated over the production and the R&D to sectors (all measured in constant prices). Thus, as in equation (7), the arrival rate of productivity-enhancing innovations is assumed to be dependent on the fraction of total inputs devoted to R&D. Further, the constant γ_j is the industry-specific equivalent of the constant $\kappa\gamma_0$ in equation (7). The main difference between equations (7) and (10) is in the exponent α $(0< \alpha< 1)$. If this parameter would equal 1 (as in equation (7)), it would yield serious problems in the specification of interindustry differences in innovation arrival rates. The empirical evidence shows that the ratio of R&D intensities in the 'average' low-tech industry and the 'average' high-tech industry is often roughly 1:20, whereas the corresponding labor productivity growth rates ratio is often of the order of 1:5.[16] This would imply that γ for low-tech industries should be about four times as high as for high-tech industries. The obvious drawback of that solution would be that the low-tech industry would produce four times as much innovations as the high-tech industry if it would spend the same fraction of its inputs on R&D! The specification of equation (10), however, reflects diminishing returns to R&D intensity. A given arrival rate λ can be attained for a given R&D intensity by an infinite number of (α, γ)-pairs. For pairs with relatively low γ-values, diminishing returns prevent the industry from gaining much more from allocating more of its inputs to R&D.

Second, it should be noted that the specification of equation (10) implicitly supposes that all firms *within* an industry have immediate access to the process technology related to the innovation and can direct their R&D towards further improvements, as in the quality ladder models discussed earlier. This kind of spillover does not occur *between* industries, however.

Third, the productivity effects of interindustry knowledge spillovers are accounted for by $\eta_j^\star[t]$. This specification is in line with the increasing variety models, i.e. a given R&D expenditure is assumed to be more productive if new ideas are brought forward by R&D undertaken in other industries. It should be borne in mind, however, that knowledge generated by other industries is very heterogeneous with respect to its relevance for a given industry's own R&D. Griliches (1979, p. 104), in his seminal contribution to the literature on technology spillover measurement, mentions that 'the photographic equipment industry and the scientific instruments industry (...) may be, in a sense, working on similar things and hence benefiting much from each other's research'. Nobody, though, would argue that such an argument would have empirical content for the photographic equipment industry and, for example, the leather products industry. To capture such differences in relevance, I included the non-negative parameters η_{ij}.[17]

To avoid systematic economy-wide scale effects on growth rates due to interindustry knowledge spillovers, I also express the spillover factor as a ratio of R&D inputs to total inputs. I decided to include not only the size of the 'sending' industry but also the size of the 'receiving' industry in the denominator, to reflect the notion that the spread of new knowledge may be limited to a diminishing fraction of the firms in both industries when they grow in size. As a consequence of this particular specification, spillover effects for the economy as a whole partly depend on changes in the industry structure in terms of output composition.

For simplicity, I assume that technological progress is purely labor-saving. This implies that the requirements (in quantities) of intermediate inputs per unit of gross output (also in quantities) remain constant over time. This assumption could easily be replaced by some other assumption for empirical reasons, but is in line with the well-known macroeconomic stylized facts of steadily increasing capital–labor ratios and virtually constant capital–output ratios.[18]

Finally, I assume that the materials requirements per unit of labor employed in R&D activities (indicated by the elements of $\mathbf{Z}_c^R$) change to the same extent as the intermediate input requirements per unit of labor employed in the production sector of the industry. This assumption, which reflects the empirical fact that R&D processes are also becoming more and more capital intensive, together with the assumption of constant intermediate input coefficients in the production sector, leads to

$$z_{c,ij}^{R}[t+1] = \left(\frac{l_{c,j}^{P}[t]}{l_{c,j}^{P}[t+1]}\right) z_{c,ij}^{R}[t] \tag{11}$$

Equations (8)–(11) distinguish the model from existing dynamic input–output models, in the sense that technological change is explicitly modeled as the result of the search for innovation. These equations do not indicate, however, how industries decide between allocating resources to the production sector and the R&D sector. This is the main topic of what follows in the next subsections, in which I try to relate the equations as much as possible to the endogenous growth models discussed in the previous section.

3.2. R&D Investment

In the endogenous growth literature, firms are assumed to base the size of their R&D budgets on a maximization of their profit streams. Roughly speaking, this implies that a higher chance of discovering a profit-increasing innovation given some R&D effort (i.e. more favorable technological opportunities) will lead to more resources being devoted to R&D activities. This relationship is empirically supported indeed, but it is also well-recognized in the more institutional theory on industrial innovation (e.g. Freeman, 1983) that R&D managers have to rely on relatively simple rules of thumb, since even the probabilities of innovational success and the magnitude of its possibly associated revenues are highly uncertain. In the model I will use a very simple rule of thumb, which says that each industry invests a fixed fraction θ_j of its sales (in current prices) of the previous period in R&D activities:

$$\tilde{\mathbf{i}}^{R}[t+1] = \hat{\boldsymbol{\theta}}\hat{\mathbf{p}}[t]\mathbf{x}[t] \tag{12}$$

Since I assume that R&D activities are characterized by industry-specific Leontief production functions (which change over time, due to innovations caused by R&D itself, see equation (11)), the relative prices of the inputs in these processes must be taken into account to determine how much of the various inputs are bought.[19]

Given the prices and the Leontief production functions (represented by $\mathbf{Z}_c^R$) that prevailed in the preceding period, the optimal allocation of research funds $\tilde{\mathbf{i}}^R$ can be specified as.[20]

$$\mathbf{l}_s^R[t+1] = (\hat{\bar{\mathbf{p}}}^R[t])^{-1}\tilde{\mathbf{i}}^R[t+1] \tag{13}$$

in which the diagonalized vector in the first right-hand side factor can be considered as a vector of 'R&D costs per unit of labor employed in the R&D processes':

$$\bar{\mathbf{p}}^R[t] = w[t]\mathbf{e} + (\mathbf{p}[t]'\mathbf{Z}_c^R[t])'$$

with $\mathbf{e}$ denoting the $(n \times 1)$-vector of ones. Now, the physical amounts of materials for R&D purposes are given by

$$\mathbf{Z}_s^R[t+1] = \mathbf{Z}_c^R[t]\hat{\mathbf{l}}_s^R[t+1] \tag{14}$$

3.3. *Wages and Prices*

In the IO literature, prices are often completely determined by supply-side factors. In models without capital goods, prices are assumed to be a function of the nominal wage rate (which is assumed to be equal across industries) and the set of input coefficients. I also adopt this procedure, but have to make an additional assumption with regard to the way in which R&D investment is financed. As discussed in Section 2, modern endogenous growth theories assume that innovation enables firms to earn back their R&D costs by imposing a positive mark-up over their production costs. In the price equation, I represent this micro-economic mechanism in a rough way, by simply assuming that industries include their R&D costs in their production costs. This implies that output prices are higher than would have been the case if no R&D costs had been incurred.[21] Introducing $\mathbf{A}$ as the matrix of input coefficients, commodity prices are then given by

$$\mathbf{p}'[t+1] = w[t](\mathbf{l}_c^P[t]' + \mathbf{l}_s'^R[t+1]\hat{\mathbf{x}}^{-1}[t])(\mathbf{E} - \mathbf{A}[t] - \mathbf{Z}_s^R[t+1]\hat{\mathbf{x}}^{-1}[t])^{-1} \tag{15}$$

in which it is implicitly supposed that industries are also backward-looking with respect to their expectations that their sales levels will remain unchanged (see Note 19). I will assume that the nominal wage rate is stable and treat it as a numéraire. Since prices fall over time (due to decreasing labor requirements in production per unit of output), the real wage rate increases at a pace which is about similar to the aggregate labor productivity growth rate. Generally, small deviations from this rate are due to differences in labor requirements between the production and the R&D sector, and changes in the composition of the consumption bundle, to which I turn now.

3.4. *Consumption and Output*

In most IO models, output levels are obtained as the product of the Leontief inverse (calculated from the intermediate input requirements per unit of output, $\mathbf{A}$) and the vector of final demands. For the closed economy I consider, final demand is the sum of materials demand for R&D purposes and consumption demand by households. Materials demand for R&D purposes has been dealt with in Section 3.2, so I will now turn to consumption demand.

Contrary to standard IO models, I will not let employment be dependent on total final demand, but the other way round. In order to stay as close as possible to endogenous growth theory, I will assume that output levels are determined by supply conditions. In the model, output levels are bound by a single condition: the aggregate labor supply is completely employed. Part of the labor supply is already employed in R&D activities or (directly and indirectly) occupied by the production of demands for R&D materials. My supply-side perspective in this paper implies that I assume that the remaining labor supply is used (directly and indirectly) to produce consumption demand. So, given labor supply conditions at the beginning of a period and the input requirements per unit of output, equation (12) involves a choice for a particular combination of investment in R&D and current consumption. This important trade-off also characterizes the endogenous growth theories discussed in Section 2, but is now extended to the industry-level.[22]

A major problem connected to this approach is the composition of the consumption vector. Many different consumption vectors fulfill the full-employment condition. In principle, one could adopt a linear programming approach (see for example Dervis *et al.*, 1982, Ch. 3), in which aggregate consumption is composed in such a way that the value of total consumption (measured either in constant prices or in current prices) is maximized. I do not choose this solution, however, mainly because this approach is likely to yield strongly discontinuous consumption compositions in periods in which many innovations take place in a few industries. Instead, I follow an approach recently put forward by Verspagen (1999) and extended in Los & Verspagen (1999), which starts from the assumption that the composition of consumption is given at the beginning of each period. For example, one can assume that the shares of the n commodities depend on the consumption level in the previous period, which allows for modeling commodity-specific Engel curves. Given that the composition of the consumption bundle is known, the full employment condition yields a unique consumption level $c[t+1]$, given by the equation

$$l^{sup}[t+1] - l_s^G[t+1] = \mathbf{l}_c^{\mathrm{P}}[t]'(\mathbf{E} - \mathbf{A}[t])^{-1}\mathbf{b}[t+1]c[t+1] \tag{16}$$

The left-hand side denotes the difference between labor supply (l^{sup}) and the part of this labor supply that is directly and indirectly 'absorbed' by the production of the materials for R&D and the labor employed in R&D. That is, $l_s^G[t+1] \equiv \mathbf{l}_c^{\mathrm{P}}[t]'(\mathbf{E} - \mathbf{A}[t+1])^{-1}\mathbf{Z}_s^{\mathrm{R}}[t+1]\mathbf{e} + \mathbf{e}'\mathbf{l}_s^{\mathrm{R}}[t+1]$.[23] For labor supply, a simple exponential growth pattern is modeled:

$$l^{sup}[t+1] = (1+v)l^{sup}[t] \tag{17}$$

where v denotes the exogenous rate of labor supply growth (cf. equation (6)). The evolution of consumption shares $\mathbf{b}$ (equation (16)) is governed by commodity-specific Engel curves, which were introduced in growth theory by Pasinetti (1981). To model these, I borrow an elegant specification from Verspagen (1993), which ensures that consumption shares always add up to one:

$$\mathbf{b}[t+1] = \mathbf{b}[t] + [\hat{\mathbf{b}}[t]\mathbf{T}(\mathbf{b}[t] - \mathbf{b}^\star) - (\hat{\mathbf{b}}[t] - \hat{\mathbf{b}}^\star)\mathbf{T}'\mathbf{b}[t]]\left(\frac{c[t]}{l^{sup}[t]} - \frac{c[t-1]}{l^{sup}[t-1]}\right) \tag{18}$$

In this specification, $\mathbf{b}^\star$ represents the consumption shares that prevail at infinitely high consumption per capita levels. The elements of matrix $\mathbf{T}$ indicate how quick current consumption shares adapt to $\mathbf{b}^\star$ in the presence of consumption growth. If $\mathbf{T}$ is chosen to have zeros on the main diagonal and sufficiently small non-negative values elsewhere, negative shares will not occur and actual shares will converge monotonically to their asymptotic values if the consumption per capita level grows (no overshooting).

Given the solution for $c[t+1]$ in equation (16), the vector of output levels $\mathbf{x}$ is determined using the standard static open Leontief model:

$$\mathbf{x}[t+1] = (\mathbf{E} - \mathbf{A}[t])^{-1}(\mathbf{b}[t+1]c[t+1] + \mathbf{Z}_{\mathrm{s}}^{\mathrm{R}}[t+1]\mathbf{e}) \tag{19}$$

Together, equations (8)–(19) constitute the IO model of R&D-driven growth. Given the solution for period t and the values of the parameters, it yields a new IO table for each period $t+1$. If expressed in constant prices, equality of the row and column sums of these tables requires more value added than can be accounted for by the inputs of labor and R&D materials. The 'excess' value added is created by the innovations. It is redistributed to the factor labor through lower prices (equation (15)). If expressed in current prices, the tables are nearly balanced. Small positive and negative 'excess' value added terms appear, due to the fact that the prices determined in equation (15) are not equilibrium prices. This is a consequence of the assumption that industries are not able to predict the actual labor requirements per unit of output correctly and use the labor requirements prevailing in the previous period.

Due to its industry detail and its stochastic nature it seems impossible to study the long-run behavior of the model by analytical means. Instead, the next section is devoted to a set of simulation experiments for a hypothetical economy.

4. Simulation Results

Having specified a model, and turning to simulation experiments to analyze its properties, it is often tempting to report as many experiments as possible. In this section, I have chosen to highlight just a few experiments, which either give basic insights into the interaction of the equations making up the model or provide indications of the potential policy-related value added of IO endogenous growth models relative to aggregate endogenous models.

With regard to the specification of the initial variable configuration and the calibration of the parameters, I could have chosen to let the economy resemble an actual economy as well as possible. I did not do this because it would have involved a very rich but intractable industry structure, and I would have had to adapt the empirical data to an unwarranted extent in order to get rid of international trade flows and capital goods stocks and flows. Instead, I present simulation results for a completely hypothetical economy with constant labor supply, which consists of only three homogeneous industries. The initial values of the variables and the parameters can be found in the Appendix. It should be noted that the initial values and the parameters are chosen such that they are nearly 'consistent'. For example, the initial labor supply level l^{sup} is chosen such that it approximately equals the labor required to produce the initial output levels $\mathbf{x}$ (given the initial labor requirements per unit of output $\mathbf{l}_{\mathrm{c}}^{\mathrm{P}}$) and to undertake the R&D activities implied by the R&D intensities $\boldsymbol{\theta}$ (given the initial materials to R&D labor ratios $\mathbf{Z}_{\mathrm{c}}^{\mathrm{R}}$). Sensitivity analysis in this section will show that the long-run behavior of the model is not affected qualitatively by 'non-consistent' initial values, as long as these are in a rather wide range around a set of 'consistent' values.

4.1. A Typical Simulation Run

A quick glance at the Appendix shows that the three specified industries are initially equally large in terms of gross output levels. The initial labor productivity levels do not deviate much (apart from the relatively small R&D materials costs, real value added levels initially equal labor inputs), but the industries mainly differ with respect to the average innovation arrival rates.

Industry 1 represents a high-tech industry, which is reflected in the mean productivity growth rate of more than 6%, which is implied by equations (8)–(10), the values for the R&D productivity parameters α_1, γ_1 and its high R&D intensity θ_1 of 10%. Further, its R&D yields relatively important knowledge spillovers to the other industries. Without spillover effects from industry 1 (the magnitude of which depends on the industry structure), industry 2's productivity growth rate would average slightly more than 3%, while spending 2% of its previous sales on R&D. Given this R&D intensity, this industry can be called a 'medium-tech' industry in terms of the often used OECD classification. Industry 3 has an R&D intensity of only 0.6%, but is assumed to benefit from knowledge spillovers from the two other industries. Setting aside these spillover effects, the average labor productivity growth rate of this low-tech industry amounts to 2.2%.

Figure 1 shows how R&D-driven productivity growth translates into consumption growth, expressed as $(c[t+1]/c[t]-1)$. It fluctuates to some extent, due to the specified random character of the innovation processes. The 'amplitude' of the fluctuations is, of course, affected by the exogenous size of the innovations. Clearly, the model yields long run consumption growth, although its average rate may be slowing down a bit over time. This is confirmed by analysis of 50 simulation runs for the same parameter configuration. Measured over the complete 100-period interval, the average annual consumption growth (averaged over the 50 runs) equals 2.75%, whereas the same statistic only amounts to 2.62% if measured over the last 20 periods of the simulation period. This could basically be due to two underlying sources: productivity growth slowdown at the industry level and/or a growth-hampering employment shift towards industries with lower productivity levels. Figures 2 and 3 show that the second explanation is the most likely.[24] In Figure 2 (with a logarithmic vertical axis), the almost straight lines indicate that industry-level labor productivity growth rates, in terms of real value added per worker, do not slow down.

Figure 3 shows that an increasing part of the labor force $(\mathbf{e}'(\mathbf{l}_s^P + \mathbf{l}_s^R))$ becomes active in the low-productivity growth industry 3. As such, the model results

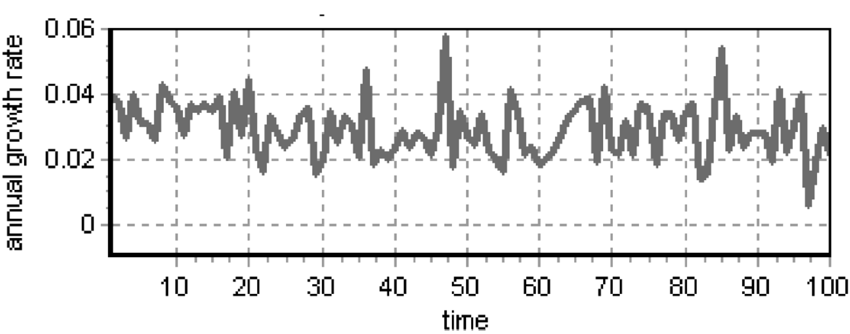

Figure 1. Consumption growth rates.

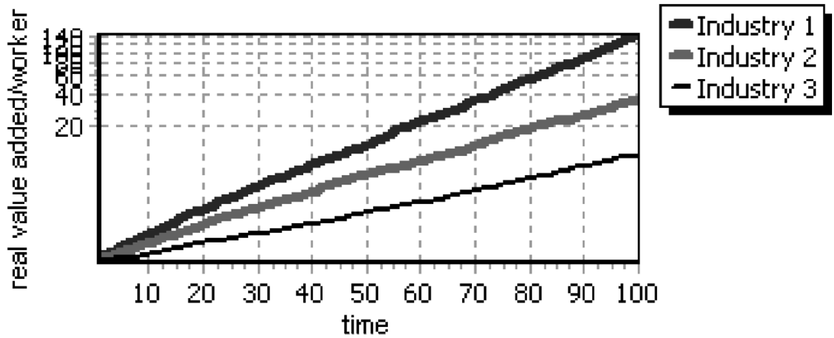

Figure 2. Labour productivity levels.

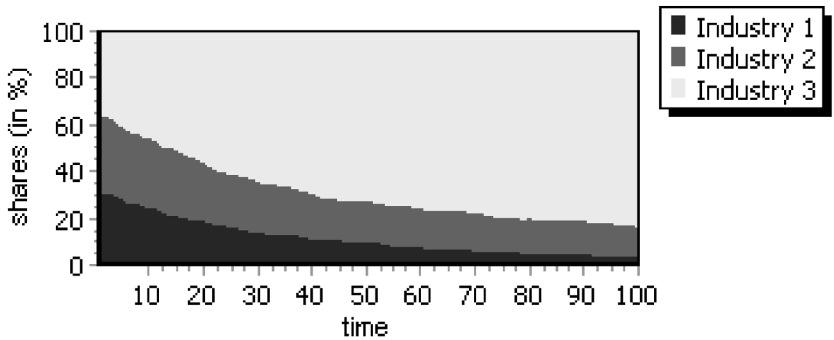

Figure 3. Workforce composition by industry.

are opposite to, but reconcilable with, the 'agricultural reserve army of labor'-explanation of growth proposed by some development economists (Lewis, 1954). This theory ascribes large parts of high productivity growth rates experienced by former underdeveloped countries to shifts from labor from low-productivity agriculture to high-productivity manufacturing.

The result that labor inputs in the high-tech and medium-tech industries 1 and 2 almost vanish is clearly not in line with observed facts. This is because the model regards all productivity increases as process innovations, whereas 'real' high-tech industries (e.g. 'computer manufacturing' and 'instruments manufacturing') are characterized by product innovations that lower labor requirements in downstream industries. The incorporation of product innovations should therefore be one of the first model improvements to be sought.

Figure 4 considers the composition of aggregate gross output ($\mathbf{e}'\mathbf{x}$), measured in constant prices. The differences between the initial consumption shares and the 'shares at infinite consumption levels' lead to an adjustment process of about 50 periods. During this period, the consumption shares of industries 1 and 2 decrease to the benefit of industry 3. This is translated in similar developments for output shares, through the effects of Leontief multipliers. It is interesting to note, however, that industry 1's output share seems to get reduced to a lesser extent than industry 2's. This has two causes. First, industry 1's initial consumption share b_1 is closer to its asymptotic level $b_1^\star$ than is the case for industry 2. Second, and probably more interesting, all R&D materials are assumed to be delivered by industry 1.

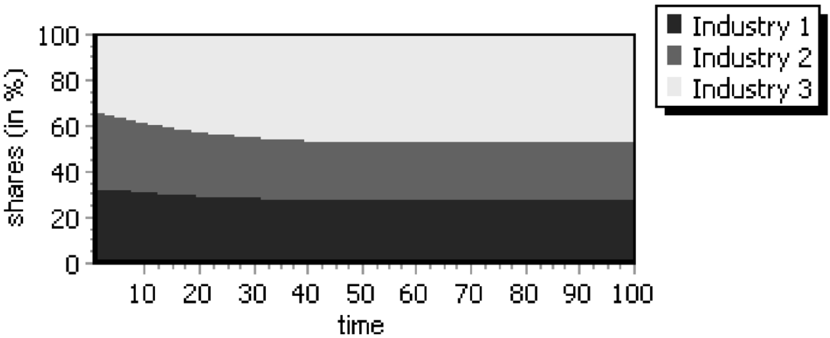

Figure 4. Output composition by industry.

Consequently, the increase of industry 3's output (induced by consumption share dynamics) causes an increase in its level of R&D activity, which induces demand for the R&D materials delivered by industry 1. This is a first result that indicates that interindustry linkages may be important for long-run growth and structural change.

4.2. Some Sensitivity Analysis

The simulation results presented so far sketch only a far from complete picture, in the sense that they do not give any clues to which variables or parameters cause the observed positive long-run growth rates. It might even be the case that these are not related to the choice of the R&D-intensities. Further, it remains to be seen whether similar results are found if different realizations of the stochastic process are considered. Before I turn to a discussion of some industry-specific simulation experiments, I will deal with some results that are obtained when R&D decisions and/or their consequences are assumed to vary in the entire economy to the same extent. In the presentation, I focus on two variables, which are generally seen as important measures of 'welfare in the long run', the net present value (NPV) of consumption and the average annual real GDP growth rate. The former was calculated according to $\Sigma(1-\delta)^t c[t]$, with δ the rate of time preference (discount rate), for a 100-period interval. The average real GDP growth rate was calculated over the periods 11 to 100, in order to exclude the short-run effects of 'non-consistent' initial variable configurations (see the introduction of this section). I ran 50 simulations for each of five scenarios. These scenarios do not differ with respect to the initial variable configuration, the changes are due to changes in the set of parameter values. The summary results, for $\delta = 0.05$, are given in Table 1.

Table 1. Economy-wide effects of economy-wide changes

	Mean NPV consumption*	std.dev.	Mean annual GDP growth	std.dev.
Benchmark configuration	48 788.2	1596.0	0.0280	0.00085
Permanent R&D increase	52 719.6	1803.0	0.0303	0.00094
Temporary R&D increase	51 453.5	1908.8	0.0278	0.00103
No spillovers	42 795.1	1226.2	0.0244	0.00078
No R&D investment	23 829.1	16.8	0.0000	0.00000

*NPV: net present value, in constant prices.

The first row ('benchmark configuration') is obtained for the parameter values given in the Appendix. Actually, the first of the 50 runs for this scenario was the one for which diagrams were presented in the previous subsection. The variation in GDP growth rates as evidenced by the standard deviation in the rightmost column appears to be relatively small.

The second scenario ('permanent R&D increase') supposes that each of the three industries increases its R&D intensity (θ) by 25% for the entire time span of 100 periods. Apparently, the initial sacrifice of consumption to release labor for additional R&D and the production of the required materials in order to attain a higher growth rate (approximately 0.23% per year) is worthwhile, since the NPV of consumption is higher than in the benchmark. With regard to this result and the simulation results to follow, it should be noted that the size of the emerging differences between scenarios is highly dependent on the parameter values chosen. Higher values for the 'diminishing returns to R&D' parameters α, for example, would increase the gap between the GDP growth rates found for the benchmark scenario and the 'permanent R&D increase' scenario. The most important conclusion, however, is that the model is a true endogenous growth model, since a permanent change in the fraction of resources devoted to R&D affects the long-run GDP growth rate.

The third scenario ('temporary R&D increase') is defined to see whether temporary changes in R&D intensities have permanent effects or not. This scenario is identical to the benchmark except for the first five periods, in which R&D efforts are doubled by every industry. From the reported mean annual growth rate, it can be concluded that a temporary change has no permanent effect on *growth*. Simultaneously, a permanent *level* effect is present, as in the 'endogenous growth models without scale effects' models I discussed in Section 2. This level effect (growth to a higher consumption level during the shock and equal growth rates afterwards) yields a NPV of consumption higher than in the benchmark case.[25]

Scenario four ('no spillovers') assumes that the industries invest as much in R&D as in the benchmark case and experience the same productivity effects of their own R&D, but cannot benefit from knowledge spillovers from other industries (all ηs are set to zero). This has a significant negative effect on the long-run growth rate. Further, the NPV of consumption is considerably lower. This does not come as a surprise as spillover-induced productivity growth does not require any sacrifice of current consumption.

The final scenario ('no R&D') simply assumes that no R&D is undertaken at all. The results are clear: the economy is caught in a stationary situation without growth. The very low NPV of future consumption is generated by a stable series of consumption levels.[26]

4.3. *Optimal R&D Intensities*

One of the most important issues emerging from endogenous growth theory is that R&D investment may be too low, due to the fact that profit-maximizing firms do not take the positive effects of spillovers into account (see Section 2). In the present model, industries are not maximizing their profits, but determine their R&D expenditures according to a very simple rule of thumb. This behavioral assumption creates the possibility that too many resources are devoted to R&D, irrespective of any creative destruction processes at the micro-economic level. In the framework of this IO growth model, overinvestment is reflected by too large a sacrifice of

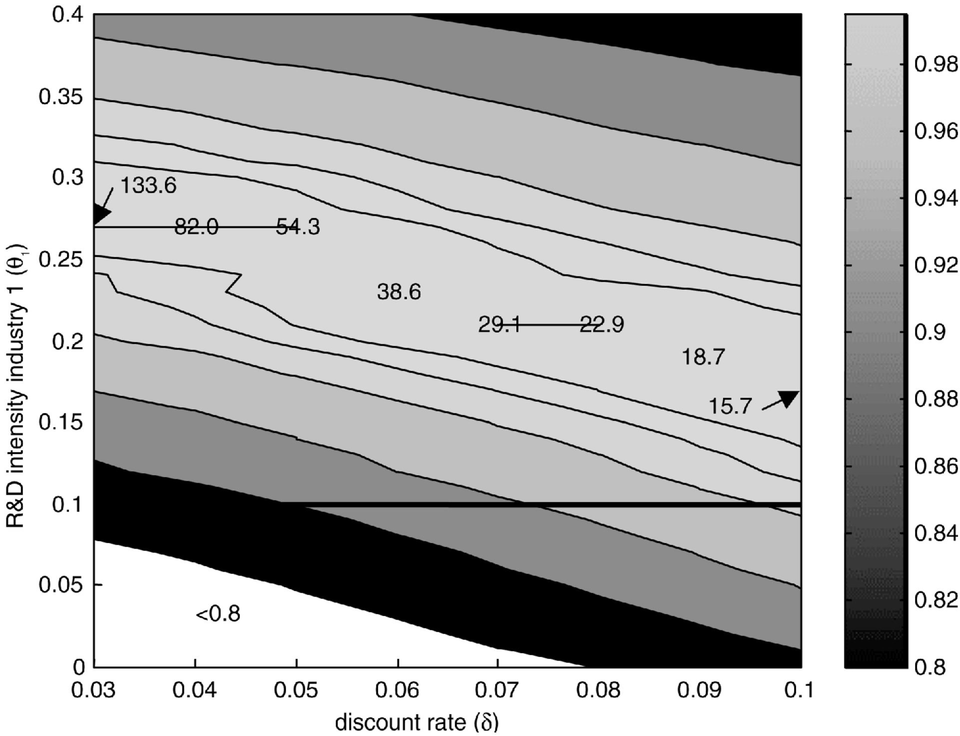

Figure 5. Optimal R&D intensities (industry 1), various discount rates.

current consumption. In this section, I want to stress the importance of both differences and linkages between industries for the issue of optimal investment in R&D. Along the way, the influence of chance on the outcomes will be pointed out.

In Figure 5, a large number of simulations are summarized. The benchmark parameter configuration was maintained, except for the R&D intensity of the high-tech industry 1. For each of the 41 values ranging from $\theta_1 = 0.0$ to $\theta_1 = 0.4$, 200 simulation runs were done for 100 periods. The resulting net present values of consumption were computed and averaged over the 200 runs for eight discount rates, ranging from $\delta = 0.03$ to $\delta = 0.10$. All average NPVs were divided by the maximum NPV found for the corresponding discount rate, to see which R&D intensity is optimal.

To indicate that the diagram is a projection of a three-dimensional graph on a two-dimensional plane, the maximum attainable NPVs are marked by their absolute values. It is no surprise that these values decrease with increasing discount rates, since a given future consumption level is valued less at higher discount rates. A first important conclusion is that the optimal R&D intensity is sensitive to the discount rate indeed. For low discount rates, the optimal θ_1 is about 0.27, for high discount rates it is reduced to about 0.17. This indicates that the hypothetical economy considered could improve on the benchmark configuration by keeping all parameters constant and increasing industry 1's R&D intensity from 0.10 (indicated in the figure by a horizontal line) to a higher value. The loss of sticking to the current intensity is highly dependent on the discount rate. At a discount rate of 0.1, the NPV corresponding to $\theta_1 = 0.1$ exceeds 98% of the maximum attainable level, but at a δ of 0.03 the loss rises to no less than 14% of the maximum NPV.

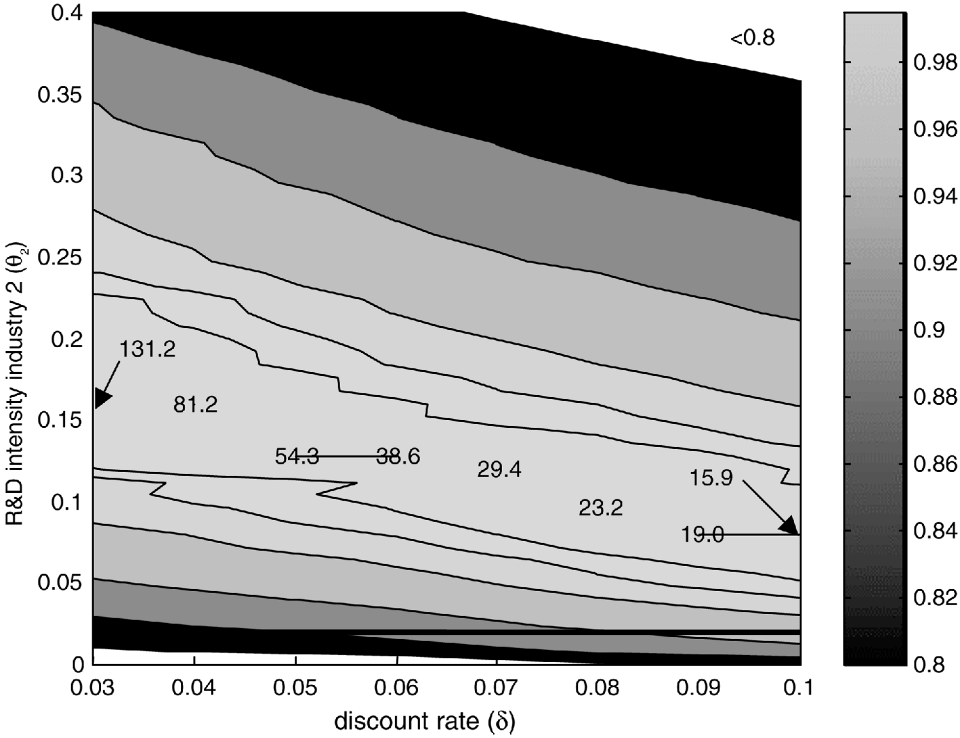

Figure 6. Optimal R&D intensities (industry 2), various discount rates.

To indicate the effects of differences between industries, I present a similar diagram for medium-tech industry 2 in Figure 6. The pattern of optimal R&D intensities diminishing with the discount rate is confirmed. The most important conclusion to be drawn from Figure 6, however, is that optimal R&D intensities are industry-specific indeed. Whereas Figure 5 indicated that industry 1's optimal intensities ranged from 0.17 to 0.27, Figure 6 shows that the corresponding values for industry 2 are much lower, between 0.09 and 0.18. Further, the loss of choosing (or inducing by policy measures) a suboptimal R&D intensity is smaller for industry 2 than for industry 1, in particular for low discount rates and for higher than optimal intensities. This is probably due to the fact that industry 3 (which becomes the largest in terms of employment and output, see Figures 3 and 4) benefits more from spillovers from industry 2 than from those generated by industry 1 ($\eta_{13} = 10.0$, $\eta_{23} = 15.0$). Hence, assigning too many labor resources to R&D in industry 2 is less costly than making a similarly wrong decision in industry 1, due to more compensation from future productivity gains in a third industry. At higher discount rates, this effect may even be reversed, because then the more even industrial distribution of employment and output at the beginning of the simulation interval gets more weight. Consequently, spillover effects from industry 1 to industry 2 gain in importance.

Another important observation is that the clear-cut pattern in the left part of Figure 6 does only appear after taking averages over many runs. For samples of less than 50 runs, the relative flatness of the 'NPV-landscape' causes the R&D intensities that are identified as 'optimal' to be fluctuating over quite a wide range of values. Since, in real life, the future consists of just one run, I would like to stress the result that the *ex ante* optimal R&D intensity will very often appear to be suboptimal *ex post*. In reality, this problem will be reinforced by the fact that even the probability distribution of the occurrence of an innovation given a certain R&D intensity (equations (8)–(10), and the parameters therein) will be unknown.

The IO growth model also provides opportunities to see how sensitive the optimal R&D intensities are to the productivity-enhancing effects of knowledge spillovers from one or more specific industries. It could be expected that stronger positive effects should lead to higher optimal intensities for the industry that generates the spillovers, since the rest of the economy would benefit more from a given sacrifice of current consumption. The effects for the optimal intensities of spillover receiving industries are less clear. To investigate these issues, I multiplied the productivity effects of the spillovers generated by high-tech industry 1 (η_{1j}, $j = 1..3$) by several values ρ ($\rho = 0.0$, 0.25, 0.5, 1, 2, 4 and 8) and again ran 200 simulations for varying R&D intensities. The NPVs of future consumption relative to their maximum value ($\delta = 0.05$) are plotted in Figures 7 (for the spillover-generating industry 1) and 8 (for a spillover receiver, industry 2).

Figure 7 shows that the simulation results confirm the expectations with regard to the optimal R&D intensity for the spillover-generating industry: at very low productivity effects (at least compared to the benchmark) θ_1 should take on a value of approximately 0.15, while very high productivity effects of spillovers (high ρs) would warrant a θ_1 of nearly 0.35. Further, the results for intermediate values of the ηs indicate that this relationship is of a monotonic nature.

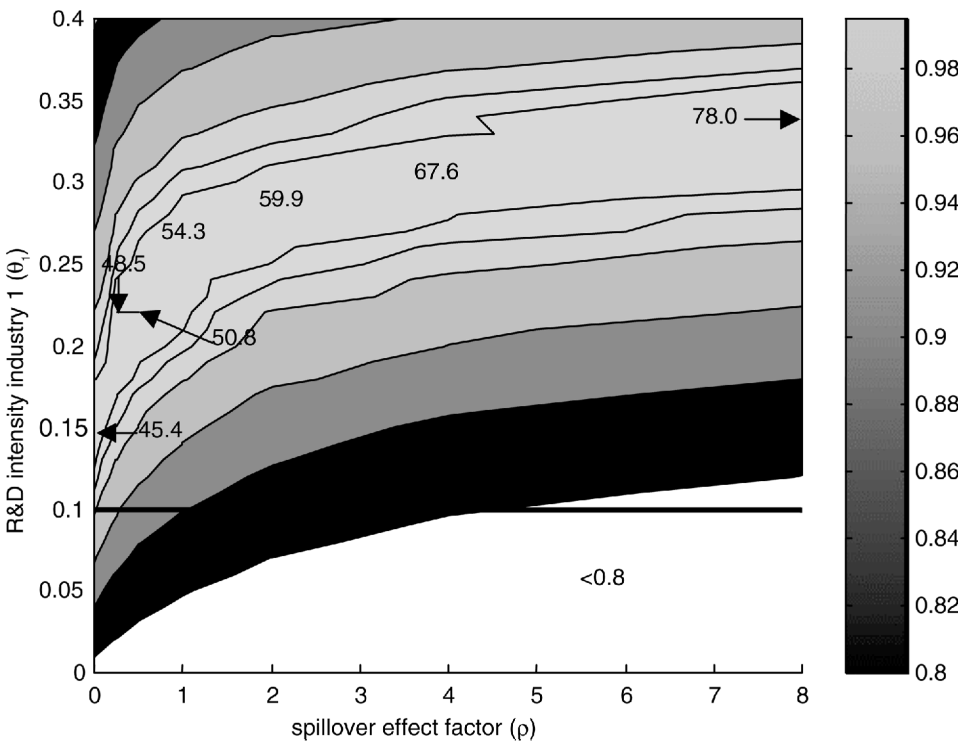

Figure 7. Optimal R&D intensities (industry 1), various spillover effects.

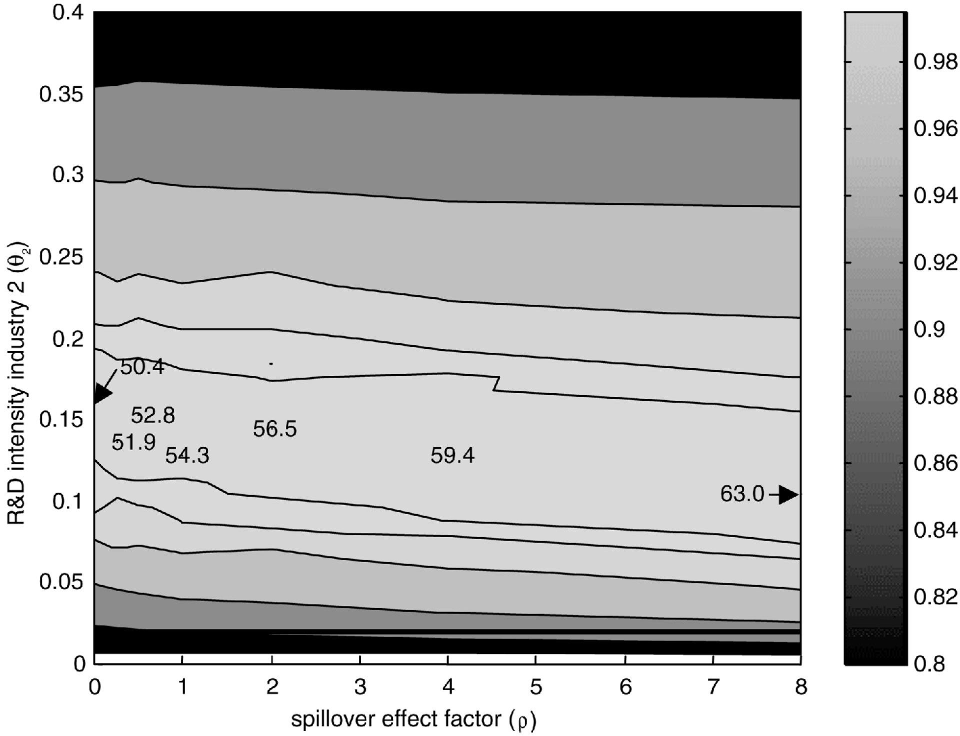

Figure 8. Optimal R&D intensities (industry 2), various spillover effects.

Figure 8 does not yield such a clear insight for a spillover-receiving industry. For low ρs, the optimal R&D intensity θ_2 jumps up and down, but the loss incurred as a consequence of not choosing the optimal intensity is, in general, smaller than for the spillover-generating industry. For high ρs, the optimal θ_2 seems to decrease somewhat. This possibly points towards a situation in which medium-tech industry 2 could best limit its R&D activities to a relatively modest level and rely on the positive productivity effects of knowledge spillovers from high-tech industry 1, if these exceed a certain threshold level. The NPV values plotted for the optimal R&D intensities show that such a strategy indeed yields higher NPVs for higher ρs.

The last issue I would like to discuss is the effect of consumption bundle dynamics on optimal R&D intensities and long-run growth rates. A shift towards consumption of the high-tech commodity is likely to yield higher real GDP growth, since a larger share of labor will be active in activities with high productivity growth. An interesting question is whether such a shift would also affect the optimal R&D intensity of this industry. According to equation (10), increasing the scale of the spillover-producing industry relative to the other industries would enhance the productivity effect of these spillovers. Consequently, one could expect that the optimal R&D intensity of the main spillover-producer would increase with its size, keeping the results for various spillover effects (Figure 7) in mind.

The results are shown in Figures 9 and 10. The horizontal axes of both figures represent the consumption share of the high-tech industry 1 at infinite consumption levels ($b_1^\star$). To satisfy the adding-up constraint of consumption shares, I assume that an increase of industry 1's asymptotic share leads to a decrease of the other

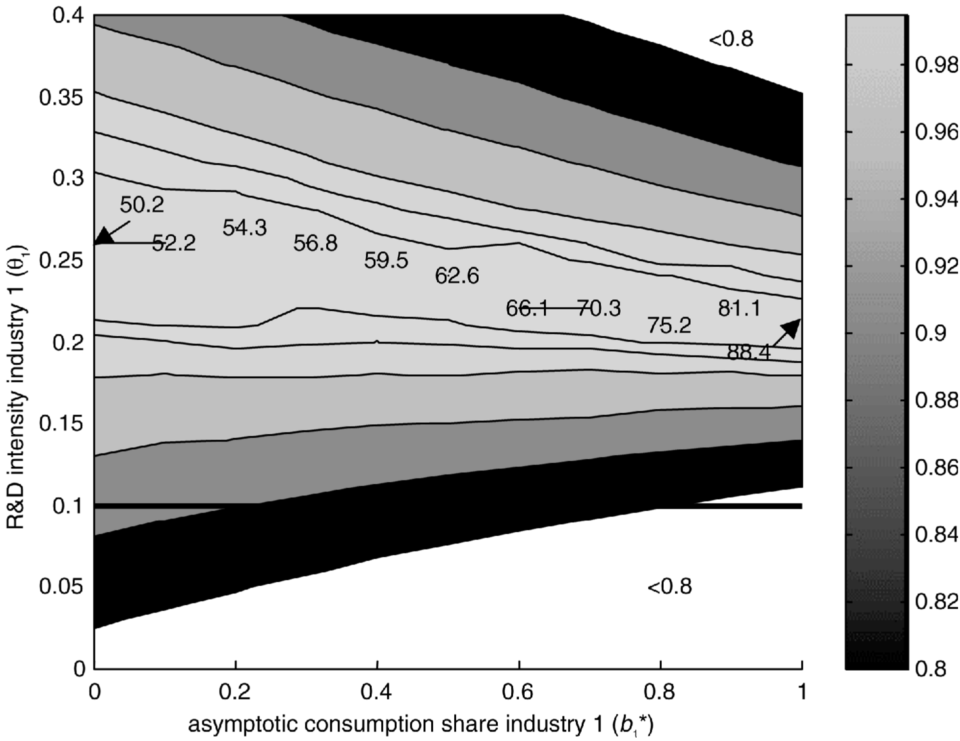

Figure 9. Optimal R&D intensities (industry 1), various consumption compositions.

two shares in proportion to their benchmark values. The results in Figure 9 are clear. The optimal R&D intensity (as found for a discount rate of 0.05) θ_1 is hardly affected by the consumption shares. If there is any effect, it is a negative effect, which is contrary to my above-formulated expectation. More in line with this expectation is the result that the loss incurred by investing too little in R&D clearly increases with the asymptotic consumption share of industry 1. The NPVs of future consumption at the optimal intensities increase with $b_1^\star$, which could be expected given the more favorable employment composition associated with high $b_1^\star$s.

Although the optimal R&D intensity does not appear to be very sensitive in the simulation results, Figure 10 shows that the long-run growth rate of real GDP (again measured over periods 11–100, see the discussion of Table 1) can be affected to a substantial extent. For high consumption shares of the high-productivity growth industry, relatively low R&D intensities suffice to attain a given growth rate.[27] Of course this result is not surprising, but it can have important policy implications, in particular when an economy is considered that competes for market share with other countries. In that case, extra export demand for high-tech commodities would be equivalent to a higher consumption share of these products. In the concluding section, I will deal with some possibly worthwhile extensions of the model, one of which is to incorporate international trade.

5. Conclusions

This paper started off with Leontief's (1989) statement that the main task of IO analysts should be to provide tools that could reduce the widening gap between

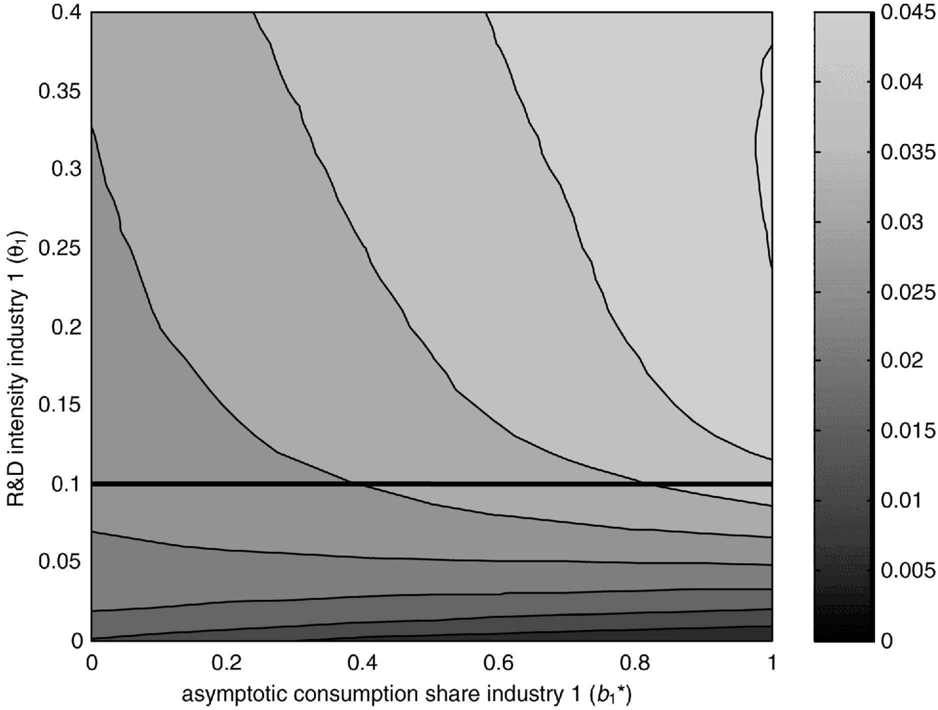

Figure 10. GDP growth rates, various R&D intensities (industry 1) and consumption compositions.

abstract economic theory and factual observation. In the previous sections I presented a dynamic IO model that preserves some of the characteristic elements of a relatively recent aspect of mainstream theory (endogenous growth theory) and showed that it yields intuitively plausible results in simulation experiments. The main message of the model is that differences between industries as well as their economic and technological linkages matter for R&D-driven long run growth rates. As such, one could say that endogenous growth theory gains from an explicit IO approach. It must be admitted, however, that the model itself has little to offer to policymakers who are faced with decision problems with regard to enhancing the innovativeness of particular industries or supporting threatened industries with a substantial contribution to national (or regional) economies in terms of output or employment. The model is too simplified, and results for hypothetical economies do not tell us too much about real economies. In this concluding section, I will therefore point out some opportunities for further research, of which I think that successful completion could increase the practical relevance of both endogenous growth theory and IO analysis.[28]

First, the model contains only two types of inputs, labor and intermediate inputs. This is clearly at odds with reality, in which many types of durable capital inputs are used in both production processes and R&D activities. Some preliminary experiments (which are not documented in this paper) indicate that inclusion of capital goods and associated profits should be possible in the framework of this model. One could, for example, think of a two-stage investment decision process in which an industry-specific fraction of profits from the previous period is retained for total investment.[29] Given the investment budget resulting from this first stage, industries spend a fixed fraction of this budget on R&D. This decision implies a choice between enlarging future productive capacity (by investing in physical capital goods) and lowering future labor requirements (by investing in the search for labor-saving innovations). In this case, the single constraint on output levels in the present model (labor demand equals exogenous labor supply), should be replaced by at least $n+1$ constraints. Total labor demand should not exceed exogenous labor supply and none of the n capital stock utilization rates (one for each industry) should exceed one. A mechanism in which the n profit rates are sensitive to the utilization rates of the n capital stocks and also to the aggregate unemployment rate should be expected to ensure a type of growth cycle. The preliminary experiments, however, suffered from 'fatal' short-term instabilities which occur when the model switches from a 'capacity of industry i-constrained' maximum consumption level to a 'capacity of industry j-constrained' maximum consumption level.

Modeling capital stocks does not only render the model more realistic, it is also a way to incorporate industry-specific constraints on production and consumption. A potentially worthwhile alternative with a more or less similar nature would be to introduce various types of labor, which are required in different industry-specific proportions. If one would, for instance, make the assumption that all R&D activities and high-tech production require relatively scarce high-skilled engineers, R&D decisions by medium-tech industries are likely to have much more impact than in the simulations I presented in this paper. The inclusion of several skill categories would also allow for IO-approaches to the class of non-Schumpeterian endogenous growth models where economies grow as a consequence of investment in human capital. The most straightforward way to take human capital formation into account seems to be to specify an education industry, which can be financed by taxes levied on production or consumption.

A final word on extensions of the model to make it more suitable for policy-making concerns the modeling of international trade. In particular, for most European and Asian countries, effects of newly created technology on export performance should be included, since their openness causes a strong relation between exports and growth. Incorporation of technology-exports links is likely to overturn the simulation result that the optimal R&D intensities are rather insensitive to the shares of industries in total production, since loss of world market share in high-value added industries could result. In my view, a natural way to proceed in this direction would be to integrate the R&D-driven model in this paper with a modified version of the two-country IO growth model recently proposed by Los & Verspagen (1999). In the latter model, market shares are dependent on differentials in technology, which are widened by (exogenous) innovation in the leading country and reduced due to intra-industry knowledge spillovers to the lagging country. Further, the feedback effects of technology on endogenous specialization patterns, balance-of-payments (dis)equilibria and exchange rate movements can be studied. Endogenizing the capabilities to innovate and to absorb knowledge spillovers by devoting part of the resources to R&D may prove a useful improvement.

I saved a brief discussion of the highest hurdle with regard to practical implementation of these models to the end. Widely published input–output tables, data on international trade by industry and data on R&D expenditures by industry may well be sufficient to prepare initial variable configurations that resemble actual economies reasonably well.[30] Nevertheless, the reliability of simulation results will be questionable as long as the parameters linking productivity growth to R&D efforts are not fixed at sensible values. The problem is that empirical studies come up with rates of return to 'own' R&D and R&D spillovers that vary across such a wide range that it is impossible to tell what values are sensible and which are not.[31] Therefore, continued research efforts and strong interactions between growth theorists, input–output researchers and applied econometricians seem indispensable to turn the theoretical advances in growth theory into a useful tool for policymakers.

Notes

1. This statement relates most strongly to 'traditional' IO analysis. Contributions on CGE-modeling and inter-industry technology flows sometimes feature in top journals with an empirical flavor.
2. Oosterhaven (1988) convincingly showed the flaws of Ghosh's supply-driven model. Dietzenbacher (1997) recently demonstrated that the Ghosh model should not be considered as a quantity model, but as a price model.
3. It should be questioned whether it is worthwhile to pursue acceptance by mainstream economists if this would require IO researchers to change their attitudes towards the nature of economic phenomena. I suppose that most IO researchers would like to be accepted more widely, as long as the 'core' of their methods can be left unchanged. Of course, this raises the question what belongs to the core of IO analysis and what does not.
4. The labels 'endogenous growth theory', 'new growth theory', 'R&D-driven growth theory' and 'Schumpeterian growth theory' are often used interchangeably in the literature. Each of these alternatives has its drawbacks. For convenience, I will stick as much as possible to the label 'endogenous growth theory'.
5. Note that this conclusion could induce a small shift from liberal free market policies to a very gentle form of planning', which would be a move opposite to the one mentioned as one of the causes of waning interest in IO economics.
6. In a very recent paper, Kurz & Salvadori (2000) argue why the standard dynamic input–output model should also belong to the broad class of endogenous growth models. Clearly, this model does not belong to the Schumpeterian models, because output growth is solely caused by capital accumulation.
7. In many contributions to the IO-literature, the words 'sector' and 'industry' are more or less synonyms. The difference between the notions of 'sectors' and 'industries' in this paper should therefore be noted. I use the term 'sector' for those parts of the economy that produce outputs that serve a common goal throughout the economy, such as blueprints and knowledge (the R&D sector) or consumption goods (the consumption goods sector). The term 'industry' refers to those parts of the economy that have certain similar intrinsic characteristics (or designs for such outputs), such as chemical products or business services. Given these 'definitions', parts of several sectors could well be present within one industry, and vice versa.
8. Note that my use of symbols is different from Dinopoulos & Thompson's (1999). The meanings of the symbols introduced here correspond as closely as possible to identical symbols in the interindustry model.
9. It should be noted, however, that Backus *et al.* (1992) offers only circumstantial evidence regarding the first hypothesis, since the *ceteris paribus* conditions (e.g. equal ratios of R&D labor to total labor) are certainly not fulfilled in their sample of 67 countries. Furthermore, GDP is not an ideal measure of scale for testing the simple model, because cross-country GDP differences could also be caused by different capital–labor ratios.
10. Dinopoulos & Thompson (1999), for example, prefer to denote models belonging to the second group by 'exogenous growth models'. Moreover, Jones (1999) argues that the phrase 'without scale effects' is mistaken with respect to the third group of models.
11. Note that endogenous growth models with scale effects assume $\varphi = 1$. This implies that these models do not have a constant long-run growth rate if population grows: more and more people can be allocated to R&D activities without diminishing returns.
12. This is due to the fact that the returns to developing a new variety depend on the extent of the market, which is partly determined by population size.
13. Note that this type of model is not dynamic in the sense that industries are assumed to solve some

kind of dynamic optimization process, as is the case in some recent Walrasian computable general equilibrium models. Instead, the dynamics are of a type similar to the dynamics of the 'Leontief–Duchin–Szyld' IO-model (Duchin & Szyld, 1985, Leontief & Duchin, 1986), where current decisions on investment in capital goods determine the capacity levels in future periods.
14. In a model aimed at providing a tool for policy evaluation, capital goods inputs might not be excluded. The inclusion of these goods, however, would yield short-run adjustment processes that would complicate the model to an unwarranted extent. I will return to this issue in the concluding section.
15. Labor productivity (in terms of real value added per unit of labor) is approximately inversely related to the labor requirements per unit of output, due to the assumption that intermediate input requirements per unit of output remain unaffected by innovations. The inverse relation is not exact, however, as a consequence of R&D costs, which may not be proportional to total inputs in constant prices (see Section 3.2 below).
16. See for example Los (1999, Ch. 1) for empirical comparisons of high-tech, med-tech and low-tech industries in OECD countries.
17. The measurement of the parameters η_{ij} has given rise to a whole literature, which I will not review here. In my opinion, the most original contributions are Terleckyj (1974), Griliches (1979), Scherer (1982), Jaffe (1986), Wolff & Nadiri (1993) and Verspagen (1997). See for example Van Meijl (1995, Ch. 6) or Los (1999, Ch. 3) for surveys. These studies estimate econometrically convenient specifications in which knowledge from 'own' R&D and knowledge obtained through spillovers are substitutes. In equation (10), these are treated as complements, which is more in line with endogenous growth theory and the empirical results reported in Cohen & Levinthal (1989).
18. Alternative assumptions concerning input coefficient change can be found in the models presented by Los (1999), Los & Verspagen (1999) and Verspagen (1999). The empirical studies by Leontief & Duchin (1986) and Kalmbach & Kurz (1990) explicitly aim to predict changes of particular input coefficients and their effects on the economy. See for example Sawyer (1992) for a study that specifically aims at investigating whether intermediate inputs requirements change systematically over time or not.
19. Note that the model cannot but involve important implicit assumptions with respect to the order in which several decisions are made. In general, I assume that decisions for period $t+1$ are based on the values of production function variables which prevailed during the last completed period, t. Furthermore, I assume that decisions concerning R&D expenditures are made before industries and consumers decide on prices, consumption levels and output levels. With regard to decisions on the latter variables, the outcomes of the R&D decisions for $t+1$ are assumed to be known and incorporated. In some equations to follow, these assumptions cause simultaneous inclusion of different time indices, which may seem inconsistent at first sight.
20. In most CGE-models, prices and quantities are determined simultaneously. In the present model, industries are assumed to be extremely backward-looking: most quantities are assumed to be set taking only previous prices into account, while prices are set according to previous technological standards. A model with more forward-looking expectations should be regarded as more realistic, but would introduce all kinds of complexities, which would probably not add to the understanding of the growth process in an interindustry context.
21. See Dietzenbacher & Los (2000) for an empirical account of the price effects of R&D expenditures.
22. Recently, Carter (1997) gave some indications of opportunities to include 'change costs' in input–output models. Obviously, R&D costs are part of these. As such, the proposed model can be seen as an elaboration of some of Carter's suggestions.
23. In theory, the left-hand side of equation (16) might become negative. If reasonable values are chosen for the R&D to output ratios $\boldsymbol{\theta}$ and the input coefficients in $\mathbf{A}$, this problem (yielding negative consumption levels) will not occur.
24. Inspection of simulation results for an extended period (not documented here) also shows that the consumption growth rate asymptotically settles at a constant value.
25. Of course, this welfare improvement is strongly dependent on the supposed discount rate. This issue will be dealt with below.
26. The very small but positive standard deviation in the second column of Table 1 is caused by innovations in the very first period. The positive R&D expenditures in the initial variable configuration generate innovations in some runs, due to the one-period lag in equation (10). This is a clear example of an initial variable configuration which is 'inconsistent' with the set of parameters.
27. Figure 10 shows that for the extreme cases of $b_1^{\star} > 0.9$, which imply that at high consumption per capita levels nearly all consumption demand is for the commodity produced by industry 1, a higher R&D intensity does not necessarily yield a higher GDP growth rate (see the results for $\theta_1 > 0.25$).

This counter-intuitive result is probably due to my choice to exclude periods 1–10 from the average annual growth rate calculations. Many innovations associated with very high θ_1s in these early periods cause relatively unfavorable employment compositions at the beginning of period 11.

28. The absence of product innovations was mentioned earlier and will not be discussed further here.
29. Alternatively, one could argue that households save a fixed fraction of non-wage income and allocate these funds to the industries in proportion to their share in aggregate profits. See Dervis *et al.* (1982, p. 177) for a more detailed discussion.
30. See for example the OECD IO, STAN, BTD and ANBERD databases which distinguish about 35 industries for a number of well-developed countries.
31. Surveys of estimation results can be found in Nadiri (1993) and Mohnen (1994).

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Appendix

This appendix contains the parameter values that were used in the benchmark run for which simulation results were presented in Section 4.1. Further, the initial variable configuration which was used throughout the entire simulation analysis is documented. Matrices are presented in the usual way: rows denote delivering industries, columns indicate using industries.

a. Parameter Values in Benchmark Configuration

0.05	δ {consumption discount rate}
0.00	v {labor supply growth rate}
0.005	σ {innovation size}
1.0	w {nominal wage rate}
80.0 30.0 12.0	$\boldsymbol{\gamma}$ {'productivity effects of own R&D'}
0.8 0.4 0.2	$\boldsymbol{\alpha}$ {'diminishing returns to R&D'}
0.0 12.0 10.0 0.0 0.0 15.0 0.0 0.0 0.0	$\boldsymbol{\eta}$ {'productivity effects of knowledge spillovers'}
0.100 0.020 0.006	$\boldsymbol{\theta}$ {R&D to sales ratios}
0.200 0.200 0.600	$\mathbf{b}^*$ {'asymptotic consumption shares'}
0.000 0.001 0.001 0.001 0.000 0.001 0.001 0.001 0.000	$\mathbf{T}$ {consumption share adjustment}

b. Initial Values for all Reported Simulation Runs

1137.0	l^{sup} {labor supply}
1137.0	c {consumption level}
0.300 0.380 0.394	$\mathbf{l}_c^P$ {labor requirements (for production) per unit of output}
0.4 0.1 0.1 0.1 0.4 0.1 0.1 0.1 0.4	$\mathbf{A}$ {intermediate input requirements (for production) per unit of output}
1.0 1.0 1.0 0.0 0.0 0.0 0.0 0.0 0.0	$\mathbf{Z}_c^R$ {materials requirements (for R&D) per unit of labor in R&D}
50.0 10.0 3.0 0.0 0.0 0.0 0.0 0.0 0.0	$\mathbf{Z}_s^R$ {materials used in R&D activities}
1.0 1.0 1.0	$\mathbf{p}$ {prices}

50.0	$\mathbf{l}_s^R$ {labor employed in R&D}
10.0	
3.0	
1000.0	$\mathbf{x}$ {output levels}
1000.0	
1000.0	
0.296	$\mathbf{b}$ {consumption shares}
0.352	
0.352	