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Economic Growth and the Diffusion of Clean Technologies: Explaining Environmental Kuznets Curves*

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Production often causes pollution as a by-product. Once environmental degradation becomes too severe, regulation is introduced by which society forces the economy to make a transition to cleaner production processes. We model this transition as a change in "general purpose technology" and investigate how it interferes with economic growth driven by quality-improvements. The model gives an explanation for the inverted U-shaped pollution-income relation found in empirical research for many pollutants (Environmental Kuznets Curve). We provide an analytical foundation for the claim that the rise and decline of pollution can be explained by policy-induced technology shifts and intrasectoral changes.

Keywords: Environmental Kuznets curve, general purpose technology, growth, intrasectoral shifts
JEL classification: O41, Q20

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1 Introduction

An old, classical and recurring theme in economics is the relationship between economic growth and concern for environmental problems. It ranges from the physiocrats' focus on land, Jevons's coal question and the Club of Rome's doomsday scenarios, to the current greenhouse gas problem. The Environmental Kuznets Curve (EKC) is one of the most-used concepts to analyse the pollution-income relation and has recently attracted considerable attention. Empirical EKC studies find evidence for an inverted U-shaped pollution-income relation for many pollutants, in particular for short-lived air and water pollutants that have local and immediate effects.[1] The theoretical EKC literature explains the hump-shaped pollution-income relation from, among others, scale economies, income-induced policy changes and exogenous shifts in the nature of growth.

In the paper at hand, we study the relationship between endogenous economic growth and pollution in a model in which pollution problems first gradually build up with the introduction of new technologies, new materials and new energy sources. Environmental degradation attracts the public's attention and triggers a regulatory response in the form of a pollution tax. Finally, firms adopt cleaner technologies to minimise costs. We use the model, first, to give an integrated explanation for the EKC, second, to analyse how technological change may drive pollution reductions when the economy grows and, third, to show how intrasectoral – rather than intersectoral – shifts accompany the adoption of pollution-reducing technologies.

We differ from the existing theoretical literature on the EKC since we treat changes in technology as endogenous. In particular, innovation opportunities and incentives not only determine the growth rate of income, but also whether technological change is pollution-using or pollution-saving. Usually, the theoretical EKC literature assumes either exogenous income (Lieb 2002, Andreoni and Levinson 2001), exogenously given factor endowments that determine income (Copeland and Taylor 2003, chapter 3) or exogenous technological change (Brock and Taylor 2004). Previous results, however, have pointed out that the source of growth and the nature of technology determines whether economic growth and pollution are linked or delinked. What is missing in the theoretical EKC literature is an explanation of why and how the sources of growth change and how they are related to pollution problems. To make both income and technology endogenous, we use a Schumpeterian endogenous growth model. Other endogenous growth models have studied the link between income and pollution, but have neglected temporal shifts in the direction of technological change as resulting from profit incentives.[2] For example, Stokey (1998) generates the EKC in a model with exogenous technology. Aghion and Howitt

[1]For example sulphur dioxide, nitrogen oxides or suspended particulate matter. For a survey of the empirical evidence see e.g. the special issues of *Environment and Development Economics* 1997 and *Ecological Economics* 1998, or the recent review articles by Stern (2004) and Lieb (2003).

[2]See Smulders (1995, 2000) for surveys on environmental growth models and Bretschger (1999) for the integration of natural resource use into modern growth theory.

(1998) have extended her model by introducing endogenous technology, but focus on balanced growth only and do not distinguish between pollution-using and pollution-saving technological change. Finally, de Groot (1999) models an EKC with technological change as a learning-by-doing process.

Besides the shifts towards cleaner production technologies a second mechanism is often stressed in explaining the decoupling of environmental degradation from economic growth: changes in the composition of production.[3] Shifts between agriculture, manufacturing and services as well as intersectoral shifts within manufacturing have been relatively small in recent decades in developed countries, see Torvanger (1991) and de Bruyn (1997). An exception is the US, where dramatic shifts towards cleaner industries have been observed at the end of the last century (Ederington et al., 2004). Hence, such composition effects can account for at most a small part of the EKC. But, there is strong evidence for the importance of intrasectoral change. For example, Jänicke et al. (1997) report that in 1989 the industrial final energy consumption of Germany was 30.4% lower than it would have been without intrasectoral change since 1970. The corresponding figures for Japan and Sweden are 58.6% and 27.6%.[4] Moreover, in empirical decomposition analyses, intrasectoral changes are mostly subsumed under the label "technique effect", which usually accounts for the major part of emission reductions. This effect, however, contains more than purely technological changes. It also incorporates changes in the spectrum of goods produced in a sector, i.e. intrasectoral shifts, as well as substitution of inputs and the application of end-of-pipe technologies, see de Bruyn (2000).

While the literature has often used a decomposition of changes in pollution in terms of a scale, technology and composition effect, this decomposition has been purely descriptive, or as a decomposition of the effects of a shock (notably trade liberalisation shocks, see Copeland and Taylor 2004). What is missing is an explanation of how and why the interaction of the composition, scale and technology effects can generate the EKC pattern. Our contribution to the theoretical literature on the EKC is an attempt to provide elements of these missing links. In particular, first we model how incentives arise to invest in pollution-intensive technologies before incentives become in favour of pollution-saving technologies, and, second, we sort out how over the technology lifecycle the balance between (intrasectoral) composition and technique effects changes so that the EKC arises. To do so, we carefully analyse firm behaviour under the different technology conditions.

The remainder of the paper is organised as follows. Section 2 provides an informal overview of the model and presents the general mechanisms producing EKCs. In Section 3, the formal model is introduced. The development of innovation and pollution in four different phases are analysed in Section 4. In Section 5, it is examined to what extend the model accounts for empirical observations. Finally, Section 6 summarises and concludes.

[3] See Copeland and Taylor (1994) for the distinction between scale, composition and technique effects.

[4] By contrast, intersectoral change reduced energy consumption by only 13% in Germany and Japan and by 2.1% in Sweden.

2 An Informal Overview of the Model

This section gives an informal overview of the model. In particular, we describe how technology changes, how firms determine investments in new technologies and how pollution evolves over time.

Technology changes along two dimensions. First, firms improve the quality of their products incrementally. Second, pollution-saving an pollution-using inventions arise in clusters at discrete times. They can be interpreted as *general purpose technologies* (GPT), defined by Bresnahan and Trajtenberg (1995) as technologies that have a potential to affect a large part of the economy. For example, we can think of energy systems: the use of horsepower, fossil fuels or nuclear power as source of energy constitute milestones in energy production. Such technology changes had and have a large impact on pollution, e.g. in the context of the regional pollution of air and water.[5]

Both types of innovation, i.e. quality improvements and the adoption of a new GPT, are costly and require R&D expenditures. Firms choose the type of innovation that yields highest profits. Since it is costly to adopt new technologies, diffusion is slow and producers using old technologies may coexist with producers using new ones. Thus, firms are heterogeneous in terms of pollution output ratios, prices and output levels. Changes in pollution result not only from changes in the scale of activity and the technique used within firms, but also from the process of creative destruction in which producers of one type are gradually replaced by producers of another type.

As our model has to include several technologies, different types of producers and different types of product qualities, the framework runs the risk of becoming very complex. To reduce complexity, we make two simplifying assumptions. First, we set up the model such that only one type of innovation is being undertaken at a certain moment in time, either quality improvements or new GPT adoption. Second, at most two types of firms are active at any point in time. That is, after the occurrence of an new GPT no quality improvements are undertaken until all sectors have adopted the new GPT.

In the model, we distinguish four phases, of which the main characteristics are summarised in Figure 1. In the first phase, the so-called "green phase", only one GPT is available, which causes no pollution. In the second phase, a new GPT becomes available and is gradually adopted; this defines the "adoption subphase". Firms invest in the adoption of the new GPT since it saves on their labour costs. Once all sectors in the economy have adopted the new GPT, firms again invest in product quality improvements; this defines the "improvement subphase". Yet, to operate the new GPT, pollution cannot be avoided. As a result, pollution rises, first, with adoption and, subsequently, with rising output. The latter is due to the fact that firms, which have improved their product quality, charge a lower price and produce more than their predecessors. However, pollution is not yet recognised as a problem. Accordingly, we call the

[5]GPTs have been studied in endogenous growth literature in the context of Romer's variety expanding model (Helpman and Trajtenberg 1998) or models of growth based on inhouse R&D (Nahuis 2003). We contribute to this literature by modelling GPTs in the quality ladder framework (Grossman and Helpman 1991, chapter 4).

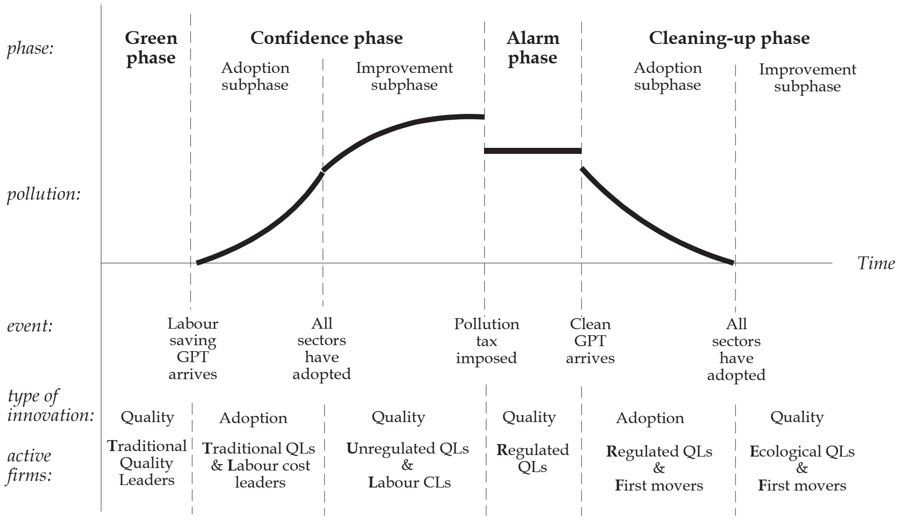


Figure 1: Overview of the model

second phase the "confidence phase". The third phase starts once it becomes clear that the new technology is harmful and once public concern has become widespread. Correspondingly, the third phase is labelled "alarm phase". The government responds to the public's concern by taxing emissions. As a result, firms cut back production and pollution decreases. As soon as a new, clean GPT becomes available, a new phase of adoption starts. We assume that this third GPT allows firms to reduce costs since it saves on pollution tax expenditures. With its invention, the "cleaning-up phase" starts. The clean GPT is gradually introduced in the different sectors of the economy and pollution decreases in the course of time (during the adoption subphase). Ultimately, all firms have adopted the new, clean GPT and, therefore, pollution is absent and firms again invest to improve their product quality (improvement subphase).

Over time, technological change not only affects the level of pollution, but also market structure. Firms that improve quality drive producers with lower quality levels out of the market. Similarly, firms that adopt a new GPT drive producers exploiting the old technology out of the market. The bottom part of Figure 1 indicates the different types of firms that are active in each phase. In the green phase, all incumbent firms use and improve the first GPT; we refer to "traditional quality leaders". The next GPT entails lower labour costs. Hence, firms that have adopted this GPT are called "labour-cost leaders" and gradually replace traditional firms. As soon as all traditional firms are replaced by labour-cost leaders, researchers start inventing blueprints to upgrade goods qualities. Firms buying these blueprints replace in turn the initial cost leaders. As there is no environmental regulation, we call this firms "unregulated quality leaders". In the alarm phase, unregulated quality leaders suddenly become "regulated quality leaders" as they are now taxed for their emissions. Once a new clean GPT has arrived, firms that have adopted this GPT enter the market and replace regulated quality leaders. We call these firms "first movers". Once all sectors have switched to the clean technology, sectors start investing in quality upgrading. As a consequence, "ecological quality leaders" gradually penetrate the market.

3 The Model

There is a continuum of sectors, indexed i, each producing a good that enters the households' utility function as an imperfect substitute. Each good can be produced in a number of varieties. Varieties differ in two dimensions. First, different qualities, indexed m, of the same good can be produced. A new generation of the product is of higher quality. Second, the labour input requirements and pollution output ratios for a given quality level may differ according to the general technology, indexed j, used.

Pollution hurts households' utility. Whether a new technology causes pollution or not is unknown at the time of its introduction. Only when exposure to the pollutant has been long enough, damages, if any, can be established and an emission tax is implemented. This increase in production costs makes it attractive to switch to new production processes with lower pollution output ratios.

Households

The representative consumer maximises intertemporal utility given by:[6]

$$U_0 = \int_0^\infty [\ln (C_t) - H_t] e^{-\rho t} dt \tag{1}$$

where ρ is the utility discount rate, C is the index of consumption, H is harm from emissions, which consumers take as given, and t is a time index. Consumers have Cobb Douglas preferences over a continuum of goods indexed i on the unit interval. Differentiated products of a given good i substitute perfectly for one another, once the appropriate adjustment is made for quality differences:

$$\ln(C_t) = \int_0^1 \ln \left(\sum_m q_{im} x_{imt} \right) di \tag{2}$$

where q_{im} is the quality of the mth product generation in industry i and x_{imt} is the associated production at time t. Maximisation of utility subject to the usual budget constraints implies that only the good with the lowest price per unit of quality is consumed in each industry i. We denote this good by $\tilde{m}_i$. Static utility maximisation implies:

$$\begin{aligned} x_{imt} &= Y_t / p_{imt} \quad \text{for} \quad m = \tilde{m}_i \\ x_{imt} &= 0 \qquad\qquad \text{otherwise} \end{aligned} \tag{3}$$

[6] Households are modelled exactly as in Grossman and Helpman (1991), but for the inclusion of damages in the utility function.

where $Y_t \equiv \int_0^1 \left(\sum_m p_{imt} x_{imt}\right) di$ denotes total consumption expenditure and p_{imt} is the price of good i of quality m at time t.

Utility maximisation also implies that consumption expenditure Y grows at a rate equal to the difference between the (nominal) interest rate r and the utility discount rate:

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

Production

Each producer holds a unique blueprint (patent) for production such that the market form is monopolistic competition. The blueprint allows the holder to produce good i at quality m, using technology j.

Unit production costs vary with technology but not with sector or quality. Production of one unit of output x requires a_{Lj} units of labour and emits a_{Zj} units of pollution if technology j is used. Unit costs c for technology j at time t are thus given by:

$$c_{jt} = a_{Lj} w_t + a_{Zj} \tau_t \tag{5}$$

where w and τ denote the wage and pollution tax respectively. Output in each sector is given by:

$$x_i = Y/p_i, \tag{6}$$

that is spending per sector, Y (which equals aggregate spending because the total mass of sectors is normalised to one), divided by the price set by the incumbent in the sector, p_i.

Within a sector, firms engage in Bertrand competition. The leading firm sets the limit price that equals the cost level of its closest rival corrected for quality differences. It is useful to distinguish between two (broad) types of firms: cost leaders and quality leaders. Cost leaders are the first producers in the sector that have introduced a new general purpose technology. They have a cost advantage over their closest rival (but produce the same quality level). Cost leaders using technology j set a price equal to their rival's cost level c_{j-1}. Quality leaders are the producers that supply the highest quality level in the sector. They have a cost advantage over their closest rival in terms of costs corrected for the quality lead (but use the same technology). A quality leader using technology j sets the limit price λc_j, where $\lambda > 1$ represents the quality difference. Since new blueprints for higher quality levels become available as a result of the innovation process (with the newest quality level being λ times the previous quality level developed), quality leaders are always λ ahead. This implies that we may write for the price set in sector i:

$$\begin{aligned} p_i &= \lambda c_j \quad \text{if in } i \text{ a quality leader is active that employs technology } j, \\ p_i &= c_{j-1} \quad \text{if in } i \text{ a cost leader is active that employs technology } j. \end{aligned} \tag{7}$$

Corresponding profit levels are then given by:

$$\begin{aligned} \pi_i &= \left(1 - \frac{1}{\lambda}\right) Y && \text{if in } i \text{ a quality leader is active,} \\ \pi_i &= \left(1 - \frac{c_j}{c_{j-1}}\right) Y && \text{if in } i \text{ a cost leader is active that employs technology } j. \end{aligned} \tag{8}$$

Let us now be more specific and distinguish between the three GPTs and six types of producers already described above. The three GPTs appearing in the model are indexed $j = 1, 2, 3$ for the "traditional", "labour-saving" and "clean" technology respectively. GPT 1 requires one unit of labour per unit of output and emissions are zero. GPT 2 requires $\eta < 1$ units of labour, but emits one unit of the pollutant per unit of output. GPT 3 is again a zero-emissions technology and requires γ units of labour per unit of output. We assume that GPT 3 improves upon GPT 1, i.e. $\gamma < 1$. Hence we may write:

$$a_{L1} = 1, a_{L2} = \eta < 1, a_{L3} = \gamma < 1, a_{Z1} = a_{Z3} = 0, a_{Z2} = 1. \tag{9}$$

In the green phase and in the confidence phase, there is no tax on pollution, that is $\tau = 0$, but from the alarm phase onward, emissions are taxed. The tax is assumed to be constant in terms of the wage, and we then have $\tau/w > 0$.

The six types of producers described in Section 2 and the bottom part of Figure 1 are index by $k \in \{T, L, U, R, F, E\}$, where T denotes "traditional quality leaders", L "labour cost leaders", U "unregulated quality leaders", R "regulated quality leaders", F "first movers" and E "ecological quality leaders".

Using equations (7) and (8) it is now straightforward to determine prices and profits of each type of producer. Table 1 gives the results for producers of type k.

Table 1: Prices and profits for the six types of producers

k	T	L	U	R	F	E
p_k	λw	w	$\lambda\eta w$	$\lambda(\eta w + \tau)$	$\eta w + \tau$	$\lambda\gamma w$
π_k	$\left(1 - \frac{1}{\lambda}\right) Y$	$(1 - \eta) Y$	$\left(1 - \frac{1}{\lambda}\right) Y$	$\left(1 - \frac{1}{\lambda}\right) Y$	$\left(1 - \frac{\gamma}{\eta + \tau/w}\right) Y$	$\left(1 - \frac{1}{\lambda}\right) Y$

Total employment in manufacturing, denoted by L_x, can be written as:

$$L_x = n_T \frac{Y}{\lambda w} + n_L \frac{Y}{w}\eta + n_U \frac{Y}{\lambda\eta w}\eta + n_R \frac{Y}{\lambda(\eta w + \tau)}\eta + n_F \frac{Y}{\eta w + \tau}\gamma + n_E \frac{Y}{\lambda\gamma w}\gamma \tag{10}$$

where n_k is the number of sectors with firms of type k.

Total emissions are given by the sum of emissions of cost leaders, unregulated quality leaders, and regulated quality leaders. Hence, aggregate pollution Z can be calculated as:

$$Z = n_L \frac{Y}{w} + n_U \frac{Y}{\lambda\eta w} + n_R \frac{Y}{\lambda(\eta w + \tau)} \tag{11}$$

Innovation

R&D aims at developing blueprints for improving the quality of a certain product or blueprints for adopting the latest technology in a certain sector. The development of a blueprint requires a units of labour, so that the cost of a blueprint is aw. There are six types of blueprints corresponding to the six firm types. For example, there are blueprints for higher quality using the traditional technology (denoted by T) or blueprints for adopting the labour-saving GPT 2, denoted by L. We denote these blueprints as type $k \in \{T, L, U, R, F, E\}$. The total amount of blueprints developed per period, or the research intensity ι, is:[7]

$$\iota = \frac{1}{a} \sum_k L_{gk}, \tag{12}$$

where L_{gk} is the amount of labour engaged in developing blueprints of type k.

The value of a blueprint equals the stock market value of a firm that exploits the blueprint. Free entry in research guarantees that, whenever research activity is targeted at developing blueprints of type k, the value of a firm of type k, i.e. v_k, equals the cost of the blueprint:

$$v_k \leq aw \qquad \text{with equality whenever } L_{gk} > 0. \tag{13}$$

The value of a firm is determined by the no arbitrage equation which states that the expected rate of return on stock must equal the return in an equal size investment in a riskless bond:

$$\pi_k + \dot{v}_k - s_k = r v_k \tag{14}$$

where s_k is the expected value of the capital loss that occurs because of shocks – technological innovation – to the sector. This capital loss crucially depends on what type of innovation is going on in the economy: whether it is quality improvement or adoption and which sectors innovation is aimed at. To solve the model, we only need to know the risk term for the type of firm for which new blueprints are developed. In the present model setup, only one type of blueprints is developed at a certain point in time. Whenever quality improvements are developed, quality leaders face the risk of being replaced by a new quality leader. They lose total value of the firm with a probability equal to the number of blueprints being developed; hence, $s_k = \iota v_k$. However, when researchers develop blueprints to adopt the newest technology, cost leaders – firms that already have adopted the new technology – face no risk until all firms have adopted the new GPT, such that $s_k = 0$.

Labour market

Labour is supplied inelastically and equals L. Labour demand consists of employment in manufacturing and total employment in R&D. Clearing of the

[7] Since the number of sectors is normalised to one, the number of blueprints developed equals the fraction of sectors in which innovation occurs.

labour market requires:

$$L = L_x + \sum_k L_{gk} \tag{15}$$

4 Innovation and Pollution in Four Stages

We now discuss the different stages of growth that the economy goes through. Each stage can be characterised by a state variable, which is the number of firms of one particular type. This number is inherited from the previous stage and endogenously changes over time in each stage.

4.1 Innovation and pollution in the "green phase"

In the first phase, the green phase, all active enterprises are traditional firms, i.e. quality leaders using GPT 1. Innovation is exclusively aimed at improving product qualities. This reduces the model to the Grossman/Helpman model (1991, chapter 4). Since the clean GPT is used, there is no pollution at all. The rate of innovation is given below in equation (28).

4.2 Innovation and pollution in the "confidence phase"

General equilibrium dynamics

In the adoption subphase GPT 2 is available for adoption, but has not yet been implemented in all sectors. Since adoption is costly, i.e. a sector-specific blueprint must be developed, it takes place only if the returns to this research investment are large enough. If research were targeted not only at adoption but also at quality improvement in traditional sectors, we would require $\pi_L = \pi_T$ for this to be an equilibrium, which only happens by coincidence. If $\pi_L < \pi_T$, no adoption would take place ($L_{gL} = 0$), the confidence phase would not start and the economy would remain in the green phase. Therefore, we focus on the more interesting case in which $\pi_L > \pi_T$ so that adoption takes place without simultaneous quality improvements in traditional sectors. Accordingly, we assume:

$$\eta < 1/\lambda.$$

Hence, once the new GPT becomes available, in the beginning all labour in R&D develops blueprints for adoption so that $L_{gk} = 0$ for all $k \neq L$, $a\iota = L_{gL}$, and $L_{gL} + L_x = L$. The relevant state variable in this phase is the number of labour-cost leaders n_L, which starts at zero. It increases with the number of patents developed:

$$\dot{n}_L = \iota = \frac{1}{a}(L - L_x) \tag{16}$$

As noted above, with adoption only, cost leaders face no risk of being replaced, i.e. $s_L = 0$. Using equations (8), (13) and (14), we find the following no-arbitrage equation for adoption:

$$\left(1-\frac{c_j}{c_{j-1}}\right)\frac{Y}{aw}+\frac{\dot{w}}{w}=r \tag{17}$$

Substituting (4) into (17) to eliminate r, substituting (10) into (16) to eliminate L_x and taking into account $c_j/c_{j-1}=\eta$, $n_T+n_L=1$ and $n_U=n_R=n_F=n_E=0$, we find:

$$\frac{\dot{y}}{y}=(1-\eta)\left(\frac{1}{a}\right)y-\rho \tag{18}$$

$$\dot{n}_L=\frac{L}{a}-y\left(\frac{1}{a}\right)\left(\frac{1}{\lambda}-\mu n_L\right) \tag{19}$$

where $\mu=(1/\lambda)-\eta>0$ and $y=Y/w$. Note that y is not per capita income but spending per wage income. This system of differential equations in n_L and y characterises the dynamics of the first period of the confidence phase. The resulting phase diagram is depicted in Figure 2 by the $\iota=\dot{n}_L=0$ locus, the lower d$y=0$ locus and the curved path to the North East. The area above the $\iota=0$ locus is infeasible since it represents negative employment in R&D. For any point below this locus, innovation takes place, causing the number of quality leaders n_L to increase. The area to the right of the line $n_L=1$ is also infeasible since n_L represents a fraction of sectors, which cannot exceed unity. Adoption comes necessarily to an end if all sectors have adopted the new GPT. It is clear from (18) and (19) that this will happen in finite time. In the diagram, it happens when the $n_L=1$ line or the $\iota=0$ locus is hit. What exactly happens depends on the value y initially takes at the time that GPT 2 becomes available. At this time, the confidence phase starts at $n_L=0$. Variable y has to jump initially such that the boundary conditions are satisfied. Since consumption is proportional to L_x and L_x is proportional to y [see (10)], consumption smoothing by households rules out a jump in y in the absence of unexpected shocks. Hence, the end condition for y in the adoption subphase is given by the initial value for y in the subsequent improvement subphase, which is determined below.

In the second period of the confidence phase, the improvement subphase, all sectors have switched to the new GPT. As there is no further possibility to invent blueprints for adoption and because research is still economically attractive, inventions are now directed at improving product qualities so that $L_{gk}=0$ for all $k\neq U$ and $L_{gU}+L_x=L$. The rate of innovation can be again expressed as:

$$\iota=\frac{1}{a}(L-L_x) \tag{20}$$

The rate of innovation now reflects the fraction of sectors in which a new quality leader replaces an incumbent. Since an innovator is indifferent between replacing a quality leader (firm of type U) or a cost leader (L-firm) – in both cases, profits equal $(1-1/\lambda)Y$ – she spreads innovation effort equally over all

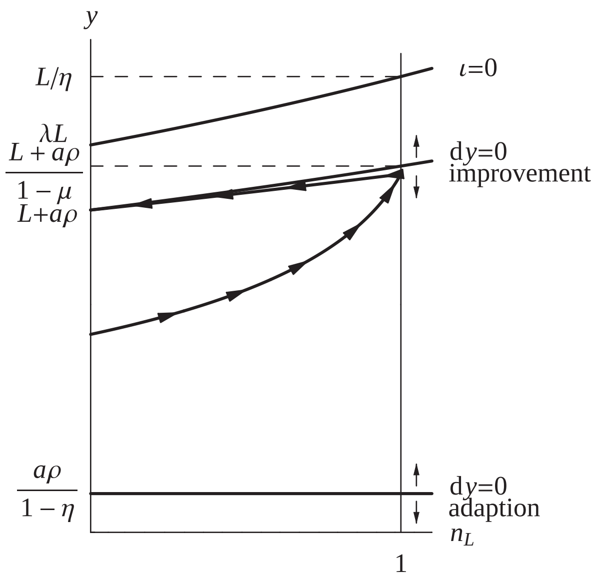


Figure 2: Dynamics confidence phase in the n_L, y plane

sectors. As a result, a fraction n_L of the total number blueprints developed (ι) hits L-firms, which are then replaced by quality leaders. Hence we have:

$$\dot{n}_L = -n_L \iota \tag{21}$$

At the same time, ι is the probability for an individual quality leader that he will be replaced and will experience a complete capital loss. Hence, we have $s_U = \iota v_U$. Using (8), (13) and (14), we find the following no-arbitrage equation for quality improvements:

$$\left(1 - \frac{1}{\lambda}\right)\frac{Y}{aw} + \frac{\dot{w}}{w} - \iota = r \tag{22}$$

Substituting (4) into (22) to eliminate r, substituting (10) into (20) to eliminate L_x and taking into account $n_L + n_U = 1$, $n_T = n_R = n_F = n_E = 0$, we find:

$$\frac{\dot{y}}{y} = (1 - \mu n_L)\left(\frac{1}{a}\right) y - \left(\frac{L}{a} + \rho\right) \tag{23}$$

$$\frac{\dot{n}_L}{n_L} = \left(\frac{1}{\lambda} - \mu n_L\right)\left(\frac{1}{a}\right) y - \frac{L}{a} \tag{24}$$

This dynamic system in the n_L, y plane characterises the second period of the confidence phase. It is saddlepoint stable. Hence, starting at $n_L = 1$, y jumps to the saddlepath and asymptotically converges to $n_L = 0$ and $y = L + a\rho$. The path to the South West in Figure 2 depicts the dynamic adjustment. As a result of the determination of the starting- and endpoint of the improvement subphase, also the starting-point of the adoption subphase can be identified.

Pollution and innovation

During the confidence phase, untaxed emissions rise. This rise in pollution can be decomposed in a scale effect, technique effect and composition effect. In the adoption subphase, pollution can be derived from (11) as:

$$Z = n_L y \tag{25}$$

Since both n_L and y gradually increase during the adoption subphase, we see immediately from (25) that the same holds for pollution. We argue that this happens because changes in scale, composition and technique all tend to increase pollution. First, the technique effect is positive, i.e. pollution enhancing, since GPT 2 is polluting. Second, when a sector adopts the new GPT, it not only starts to pollute but also reduces prices and produces more. The gradual adoption of the new GPT (n_L rises) changes the composition of total output. This corresponds to intrasectoral changes from clean to dirty firms. Finally, total production affects pollution. Defining total production as the sum of sectoral production levels, we find the following expression for the confidence adoption subphase [from (6) and Table 1]:

$$X \equiv \sum_k n_k x_k = y \left[\frac{1}{\lambda} + \left(1 - \frac{1}{\lambda} \right) n_L \right] \tag{26}$$

Because n_L and y gradually increase during the adoption subphase, we see immediately from (26) that total production gradually rises, so that the scale effect also contributes to rising pollution levels.

To describe the development of the innovation rate, we need to determine how L_x changes over time [see (16)]. Appendix A shows that L_x increases (decreases) and innovation falls (rises) over time if η is large (small). The intuition is as follows. On the one hand, the rate of innovation tends to fall over time. This reflects the fact that the more sectors have switched, the fewer opportunities are left for further adoption and the sooner innovation has to be redirected to quality improvements, which yields a lower rate of return. Forward-looking behaviour of investors ensures that the rate of return is smoothed and research efforts are gradually reduced. With lower research efforts, labour becomes available to expand the scale of production. On the other hand, if production with the new GPT saves a lot of labour, i.e. if η is small, the opposite happens and labour becomes available for research. With a small η, the process of adoption is relatively fast and the scale of production as measured by L_x declines. Nevertheless, pollution increases over time since fast adoption allows the technique and composition effect to dominate the (pollution-saving) scale effect. The rise in pollution and the decreasing innovation rate (for a sufficient high η) during the confidence adoption subphase is illustrated in Figure 3 by the curve segments from $n_L = 0$ to $n_L = 1$.

In the improvement subphase, pollution increases as well over time, although at a decreasing pace. Since all sectors are using GPT 2 with a fixed emission output ratio, changes in pollution can be explained entirely by changes in total output (X) or labour in production (L_x). There are no intrasectoral changes

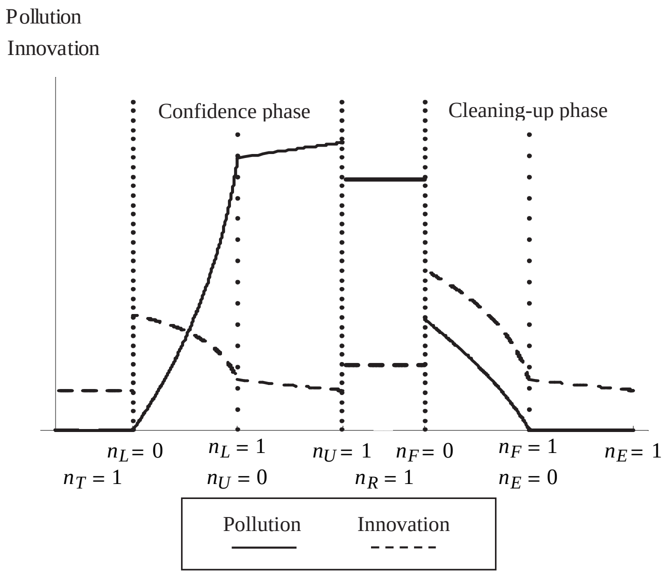


Figure 3: Pollution and innovation in all phases

or technological effects. From (10) and (11) we find:

$$Z = X = \frac{1}{\eta} L_x \tag{27}$$

Appendix A shows that L_x rises over time. This implies a gradual increase in pollution and a gradual fall in innovation. The underlying cause is a fall in the rate of return to innovation. As the proportion of low-price firms increases, more labour is allocated to incumbents and less is available per quality leader that replaces a cost-leader. As a result, profits for entrants fall and innovation becomes less profitable. The paths of pollution and of the innovation rate are again depicted in Figure 3 (curve segments from $n_U = 0$ to $n_U = 1$).

The innovation intensity at the end of the confidence phase (when n_L approaches zero) can be solved by first substituting (21) and (23) into (24) to eliminate $\dot{n}_L/n_L$ and y respectively, and then setting $n_L = \dot{y} = 0$. This yields:

$$\iota = \frac{\lambda - 1}{\lambda} \frac{L}{a} - \frac{1}{\lambda} \rho \equiv \iota_{GH} \tag{28}$$

When only quality improvement is possible and the mass of cost leaders approaches zero, the model structure is the same as in Grossman and Helpman (1991, chapter 4). Hence, the innovation rate in (28) equals the innovation rate of their model (denoted by ι_{GH}).

4.3 Innovation and pollution in the "alarm phase"

The economy enters the alarm phase once it starts taxing pollution. Society is aware of or alarmed about the polluting effects of using GPT 2. To mitigate the adverse effects, firms are charged a pollution tax. Provided that all sectors are at least hit once during the second period of the confidence phase, all active firms at the beginning of the alarm phase are regulated quality leaders (R-firms). To simplify matters, we assume that the alarm phase starts not until labour-cost leaders have disappeared, i.e. $n_L = 0$.

In addition, we rule out the case that it is profitable for firms to switch back to the old traditional technology. This requires that the profits from readopting GPT 1 fall short of those from further quality improvements still using GPT 2. From (8), we see that this requires $1 - a_{L1}w/(a_{L2}w + \tau) < 1 - 1/\lambda$, or after substitution of (9):[8]

$$\tau/w < \lambda - \eta$$

Firms still make profits and research is still profitable. Innovators develop new quality generations of the regulated products. Successful innovators become new quality leaders and set prices $p_R = \lambda(\eta w + \tau)$. No other types of innovation are undertaken, so that $L_{gk} = 0$ for $k \neq R$ and $L_{gR} + L_x = L$. The value of a blueprint is determined by v_R, and we have $aw = v_R$ if $L_{gR} > 0$.

The dynamics of the alarm phase can be determined in analogy to the dynamics of the improvement subphase of the confidence phase. Substituting (4) into (22) to eliminate r, substituting (10) into (20) to eliminate L_x, and taking into account n_R= 1, n_k= 0 for $k \neq R$, we find:

$$\frac{\dot{y}}{y} = y\frac{1}{a}\left(\frac{\lambda - 1}{\lambda} + \frac{\eta}{\lambda\left(\eta + \tau/w\right)}\right) - \left(\frac{L}{a} + \rho\right) \tag{29}$$

If firms expect no shocks, i.e. they do not anticipate the arrival of a new GPT or a change in taxation, equation (29) can only hold forever if y remains constant over time.[9] Hence, we can set (29) equal to zero to obtain the following expression for the steady state expenditures per wage income:

$$y = \frac{L + a\rho}{1 - \theta_{Z2}/\lambda} \tag{30}$$

where $\theta_{Z2} = (\tau/w)/(\eta + \tau/w)$ is the share of pollution in total cost for GPT 2. In addition, from equations (10), (20) and (30) the steady state innovation growth rate in the alarm phase, $\iota_{SSAlarm}$, is readily calculated as:

$$\iota_{SSAlarm} = \frac{\lambda}{\lambda - \theta_{Z2}}\left[\frac{L}{a}\left(\frac{\lambda - 1}{\lambda}\right) - \frac{\rho}{\lambda} + \frac{\theta_{Z2}}{\lambda}\rho\right] \tag{31}$$

or, equivalently as:

$$\iota_{SSAlarm} = \frac{\lambda}{\lambda - \theta_{Z2}}\left[\iota_{GH} + \frac{\theta_{Z2}}{\lambda}\rho\right] \tag{32}$$

[8]If $\tau/w > \lambda - \eta$, the alarm phase as described in the text does not arise and the economy enters immediately a "reswitching phase" once the tax is imposed. This phase is very similar to the cleaning-up phase analysed in the text (see section 4.4). The only modification needed is setting γ equal to one. When GPT 3 arrives, a adoption phase starts in which GPT 1 is replaced by GPT 3. The analysis of this phase is more complex than the one in the text since with "reswitching" there are potentially three GPTs in the market.

[9]Otherwise y would grow or shrink at an increasing rate, both of which is not feasible.

Note that spending per wage income and the rate of innovation increase in the pollution tax; for $\tau > 0$ we have $\iota_{SSAlarm} > \iota_{GH}$ and $(L + a\rho)/(1 - (\theta_{Z2}/\lambda)) > L + a\rho$. The intuition behind this remarkable result for growth is that a pollution tax increases the cost of production relative to that of R&D, which is a non-polluting activity. Thus, the policy intervention causes a reallocation of labour from manufacturing to the development of blueprints. As a result, in the alarm phase, the rate of innovation jumps up and total emissions jump down compared to the values at the end of the confidence phase as shown in Figure 3 (curve segments at $n_R = 1$). But both variables remain constant during the alarm phase.

4.4 Innovation and pollution in the "cleaning-up phase"

General equilibrium dynamics

From the point of view of GPTs, the cleaning-up phase is similar to the confidence phase. A new unregulated technology is available for adoption, but its diffusion takes time, since adoption is costly. Adoption takes place only if the returns to the development of a blueprint for adopting GPT 3 are large enough. To guarantee sufficient incentives to adopt GPT 3 we assume:

$$\gamma < \frac{\tau/w + \eta}{\lambda}, \tag{33}$$

which implies $\pi_R < \pi_F$ (see Table 1). Regulated quality leaders stay active as long as no rival in their sector has incurred the cost to adopt GPT 3. Innovators that produce with the new GPT are first movers (F-Firms).

We can use expressions derived for the confidence phase to describe the dynamics of the cleaning-up phase. For the adoption subphase, we need to replace n_L by n_F in (16). Substituting (4) into (17) to eliminate r, substituting (10) into (16) to eliminate L_x, and taking into account $c_j/c_{j-1} = \gamma/(\eta + \tau/w)$, $n_R + n_F = 1$ and $n_T = n_L = n_U = n_E = 0$, we find:

$$\frac{\dot{y}}{y} = \left(1 - \frac{\gamma}{\eta + \tau/w}\right)\left(\frac{1}{a}\right) y - \rho \tag{34}$$

$$\dot{n}_F = \frac{L}{a} - y\left(\frac{1}{a}\right)\theta_{L2}\left[\left(\frac{\gamma}{\eta} - \frac{1}{\lambda}\right) n_F + \frac{1}{\lambda}\right] \tag{35}$$

where $\theta_{L2} = 1 - \theta_{Z2} = \eta/(\eta + \tau/w)$ is the labour cost share for GPT 2.

For the improvements subphase, we need to replace n_L by n_F in (21). Substituting (4) into (22) to eliminate r, substituting (10) into (20) to eliminate L_x, and taking into account $n_F + n_E = 1$, $n_T = n_L = n_U = n_R = 0$, we get:

$$\frac{\dot{y}}{y} = (1 - \mu_F n_F)\left(\frac{1}{a}\right) y - \left(\frac{L}{a} + \rho\right) \tag{36}$$

$$\frac{\dot{n}_F}{n_F} = \left(\frac{1}{\lambda} - \mu_F n_F\right)\left(\frac{1}{a}\right) y - \frac{L}{a} \tag{37}$$

where $\mu_F = (1/\lambda) - \gamma/(\eta + \tau/w)$.

The two dynamic systems in (34)-(37) can be depicted in a n_F, y plane similar to Figure 2. The equilibrium dynamics can again be characterised by a rise in n_F from 0 to 1, while y increases. After a finite time there is an endogenous switch to the improvement subphase in which both n_F and y fall over time.

Pollution and innovation

Pollution is obviously absent in the improvement subphase. Moreover, innovation falls similar to innovation in the improvement subphase of the confidence regime. Hence, we focus on what happens to pollution and innovation in the adoption subphase. Pollution is given by [see (11)]:

$$Z = y\left(\frac{1-n_F}{\lambda(\eta+\tau/w)}\right) \tag{38}$$

It turns out that pollution continuously falls over time (see Appendix B). More and more sectors switch to the clean technology (n_F increases), which reduces pollution. The upward pressure on pollution from increases in spending y is dominated by intrasectoral shifts from dirty to clean firms. The clean F-firms are for the most part responsible for rising y, since they charge a lower price and produce more than regulated quality leaders. In this case, the composition and technique effect outweigh the pollution-using scale effect.

Labour allocated to production can be written from (10) as:

$$L_x = y\left(\frac{(\lambda\gamma-\eta)n_F+\eta}{\lambda(\eta+\tau/w)}\right) \tag{39}$$

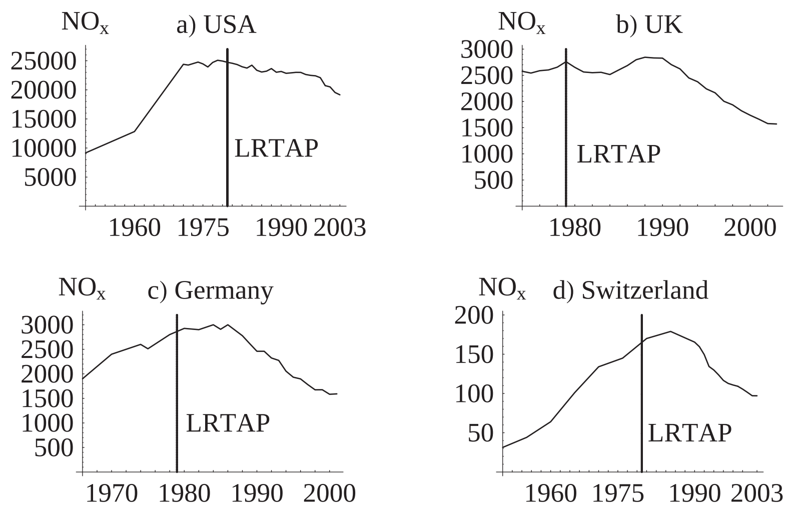
Since y and n_F increase over time, the amount of labour in production also gradually increases if $\lambda\gamma \geq \eta$. Since the rate of innovation is negatively related to L_x, as in (16), innovation falls over time. This seems to be the most realistic case. It seems natural to assume that the superiority of GPT 3 over GPT 2 in terms of pollution ($a_{Z3} = 0 < a_{Z2} = 1$) comes at the cost of a higher labour requirement, that is $a_{L3} = \gamma > a_{L2} = \eta$. Since $\lambda > 1$ we have $\lambda\gamma > \eta$.[10]

The progression of both pollution and the innovation rate during the cleaning-up phase is shown in Figure 3 (curve segments form $n_F = 0$ to $n_F = 1$ for the adoption subphase and from $n_E = 0$ to $n_E = 1$ for the improvement subphase). At the beginning of the adoption subphase pollution jumps down and the innovations rate jumps up compared to the values during the alarm phase. The reason for these jumps is a reallocation of labour from manufacturing to R&D. Developing blueprints for adopting GPT 3 yields a higher rate of return than developing blueprints for quality improvements.

[10] In case $\lambda\gamma < \eta$ innovation may first rise and then fall over time. In this case (39) is isomorphic to (A.8) so that the analyses of appendix A can be repeated and the pattern of innovation found there emerges.

5 Empirical Validation

In the model analysed above, the rise in pollution is primarily caused by the availability of a new GPT, which entails lower labour costs but causes higher pollution, and an increase in aggregate production. Likewise, the downturn in pollution is based on two main mechanisms: first, the imposition of a pollution tax due to the awakening of the public's attention to environmental degradation and, second, the intrasectoral adjustments towards cleaner production technologies. These results fit fairly well with real-world observations. As an example, consider the nitrogen oxide emissions in the last decades for the USA, UK, Germany and Switzerland, as shown in Figure 4. It was not until the eighties of the last century that the NO_X emissions stopped increasing, and then started to decline significantly. Similar emission patterns can also be observed for other air pollutants, e.g. sulphur dioxide.



Note: NO_X emissions in Gg.

Source: USA: EPA (2000 and 2005); UK: DEFRA (2005),
Germany: DESTATIS (1966 - 2004), Switzerland: SAEFL (1995 and 2005).

Figure 4: NO_X for the USA, UK, Germany and Switzerland

The rise in nitrogen oxide emissions was mainly caused by scale effects. For example, increasing mobility and globalisation led to drastic growth in road traffic in all four countries. Environmental degradation attracted broad public attention in the late nineteen seventies. In 1979, the countries considered signed the *Convention on Long-Range Transboundary Air Pollution* (LRTAP) of the United Nations Economic Commission for Europe. In 1988 the convention was extended by a protocol concerning the control of nitrogen oxides or their transboundary fluxes.[11] The vertical lines labelled "LRTAP" in Figure 4 depict

[11] Up until 1999, the convention was extended by eight protocols aiming at the reduction of specific pollutants.

the signing of the LRTAP convention.

In the subsequent years the governments enacted a number of laws to achieve the agreed emission reductions. The regulations were mainly geared to the major sources of nitrogen oxide: road transport and combustion plants. In the USA and particularly in California, catalytic converters became mandatory in the late nineteen seventies; Switzerland followed in 1987 and the European Union in 1993. This regulation has led to a gradual displacement of old motor vehicles by less exhaust-intensive vehicles with catalytic converters. In addition, the exhaust gas regulations were and are still tightened continuously. Moreover, Germany and Switzerland recently established a performance-based heavy vehicles fee, inter alia in order to confine heavy vehicle traffic. Concerning combustion plants, tightened emission restrictions led to the installation of so-called low nitrogen oxides burners, which can reduce emissions by up to 30%. Summarising, the NO_x emission reductions can be traced back to the interaction of governmental regulation, intrasectoral substitution processes and the adoption of new, cleaner technologies.

6 Conclusions

To analyse the relationship between economic growth, environmental degradation and technology changes, we have set up a Schumpeterian endogenous growth model with pollution. The model contributes to the literature by, first, treating the direction of technological change as endogenous, i.e. innovation opportunities and incentives determine whether technological change is pollution-using or pollution saving. Second, the model stresses the importance of intrasectoral – rather than intersectoral – shifts as a leading cause for the resulting pollution-income relation.

At first, a technological breakthrough in the form of a new general purpose technology gives rise to the gradual adoption of this new technology by profit maximising firms. As a side-effect, pollution rises. Once pollution taxes are imposed to address the pollution externality, the pattern of technological change and innovation is affected. Due to the emission taxation it becomes profitable for firms to adopt a new, clean GPT. This results in a gradual decrease of pollution associated with the use of the previous GPT.

We have shown that the gradual adoption of new general purpose technologies, which leads to intrasectoral shifts from clean to dirty firms or vice versa, predicts a pattern of pollution over time that is consistent with the EKC hypothesis. New technologies sometimes increase pollution, and decrease pollution at other times, depending on the characteristics of the general purpose technology that opens up opportunities for innovation and on the environmental policies that are in place. Our investigation of the relationship between innovation and pollution shows that we cannot expect an unambiguous correlation between changes in pollution and innovation, since both variables are endogenous and determined by several forces that act simultaneously. When pollution is not taxed (during the confidence phase), pollution rises while innovation falls over time; but during adoption of the clean technology (cleaning-up phase), both pollution and innovation decline over time. Hence, the relationship between environmental policy and economic growth varies with the different stages of growth.

The model set up above does not necessarily predict an EKC for all pollutants. In empirical research, the EKC is found only for specific pollutants, i.e. for pollutants with local and immediate effects. In our model, the downward sloping part of the EKC emerges only if the polluting GPT is eventually replaced by a cleaner GPT. The adoption of the cleaner GPT requires sufficient incentives, i.e. a high pollution tax or low enough labour costs associated with the clean GPT. Otherwise, no technology shift takes place and the pollution tax only has the conventional static (level) effect. In this case, the economy would remain in the alarm phase.

Our model provides a natural framework for the examination of the idea of overlapping EKCs. Booth (1998) has argued quite strongly that one pollutant can only be phased out because it is replaced by another pollutant. Put more moderately, it could be that seemingly clean GPTs turn out to be polluting in the end. If this is the case, additional GPTs have to be developed in a row until finally, hopefully, one GPT really turns out to be clean. In the model, the substitution of a pollutant for another would result in an overlapping of the cleaning-up phase with a second confidence phase.

An obvious extension of the model would be the possible ability of individuals to expect the arrival of new GPTs. For example, we could assume that the occurrence of new GPTs follows a Poisson process. It is conceivable that, for certain pollutants, technical solutions in the future can be anticipated to a certain degree. In other cases, however, it seems reasonable to assume that the arrival of a technological breakthrough is highly uncertain and arrives, if ever, unexpectedly. In addition, the sequencing of the different phases can be more complex than modelled in this approach. Arrival dates of profitable GPTs and/or the introduction of taxes can be assumed to occur at different points in time so that more types of producers are active in the markets when a new phase begins. Finally, one could elaborate more on optimal taxation. This requires the analysis of instruments to correct pollution, to correct R&D, and to correct output levels in order to remove the distortionary pricing effects. All these issues are left for future research.

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Appendix

A Pollution and Innovation in the Confidence Phase

To find out the development of aggregate pollution and the rate of innovation in the confidence phase, we transform the phase diagram from Figure 2 and equations (18), (19), (23) and (24) into a phase diagram in the L_x, n_L plane.

Adoption subphase

L_x may either fall or rise during the adoption subphase, depending on whether η is small or large respectively. From (10) we find the following expression for L_x in the confidence adoption subphase:

$$L_x = y\left(\frac{1-(1-\lambda\eta)n_L}{\lambda}\right) \tag{A.1}$$

We use (A.1) to replace y in (18) and (19) by L_x and find the following dynamic system for the adoption subphase:

$$\begin{aligned}\frac{\dot{L}_x}{L_x} &= \frac{1}{a[1-(1-\lambda\eta)n_L]} \\ &\quad \cdot\{[\lambda(1-\eta)+1-\lambda\eta]L_x-(1-\lambda\eta)L-[1-(1-\lambda\eta)n_L]a\rho\}\end{aligned} \tag{A.2}$$

$$\dot{n}_L = \frac{1}{a}(L-L_x) \tag{A.3}$$

The $\dot{L}_x = 0$ locus is downward sloping as long as $1/\lambda > \eta$ which is the case due to our assumption that $\mu \equiv 1/\lambda - \eta > 0$ (to ensure that $\pi_L > \pi_T$). The initial jump in L_x is determined in the same way as that of y, see main text: the endvalue of L_x is determined by its initial value in the subsequent improvement subphase. However, we can also use the endvalue of y to determine the end value of L_x by using the relation between these two variables given by (A.1). Hence, we can infer some useful properties of the endvalue of L_x from the endvalue of y. From Figure 1 or (18) we see that when $n_L = 1$, y is bounded as follows:

$$y < \frac{1}{1-\mu}(L+a\rho) \tag{A.4}$$

Thus, from (A.1) we see that when $n_L = 1$, L_x is bounded as follows:

$$L_x < \frac{\eta}{1-\mu}(L+a\rho) \tag{A.5}$$

From (A.2) we see that when $n_L = 1$,we have

$$\dot{L}_x \leq 0 \quad \text{if} \quad L_x \leq \frac{\mu L + \eta a\rho}{\mu+1-\eta} \tag{A.6}$$

Now consider the following condition:

$$\frac{\eta}{1-\mu}(L+a\rho) \leq \frac{\mu L+\eta a\rho}{\mu+1-\eta} \tag{A.7}$$

If condition (A.7) holds, L_x has to reach a value at the end of the adoption phase that turns out to be so small [namely smaller than the expression at the LHS of (A.7), see (A.5)] that it can only be reached by a declining L_x [as is revealed by (A.6)]. Note that for sufficiently low values of η this condition is satisfied. Figure 5 c) depicts this situation.

Let us now consider the opposite case in which η takes its maximal value, that is $\eta = 1/\lambda$ so that $\mu = 0$. The $\mathrm{d}y = 0$ locus and the $\mathrm{d}L_x = 0$ locus are horizontal. Moreover, y and L_x have to reach the values $L + a\rho$ and $(L + a\rho)/\lambda$ respectively at the end of the adoption subphase. Under our assumption that $\iota_{GH} > 0$, see (28), this endpoint lies above the $\mathrm{d}L_x = 0$ locus, see (A.2), and L_x has to increase over the entire adoption subphase. Figure 5 a) depicts this situation.

For intermediate values of η we get the dynamics as depicted in Figure 5 b). The larger η, the more likely a rising pattern for L_x becomes. Note that L_x may first fall and then rise (but never the other way around) in the adoption subphase.

Improvement subphase

We show that L_x unambiguously falls during the improvement subphase. For this subphase, we find from (10):

$$L_x = \left(\frac{1}{\lambda} - \mu n_L\right) y \tag{A.8}$$

We use (A.8) to replace y in (23) and (24) by L_x and find the following dynamic system for the improvement subphase:

$$\begin{aligned} \frac{\dot{L}_x}{L_x} &= \frac{1}{a(1/\lambda - \mu n_L)} \\ &\quad \cdot \{[1 - 2\mu n_L]L_x - [1/\lambda - 2\mu n_L]L - [1/\lambda - \mu n_L]a\rho\} \end{aligned} \tag{A.9}$$

$$\frac{\dot{n}_L}{n_L} = -\frac{1}{a}(L - L_x) \tag{A.10}$$

The $\dot{L}_x = 0$ locus is downward sloping. Since the improvement subphase starts at $n_L = 1$ and has to converge to a constant value for L_x and $n_L = 0$, L_x has to start at a value above the $\mathrm{d}L_x = 0$ locus and will increase over time. Figure 5 combines the two subphases.

The development of pollution in the improvement subphase directly follows from (27) and the notion that L_x rises over time. The development of the rate of innovation is the mirror image of that of L_x, since $\iota = (L - L_x)/a$.

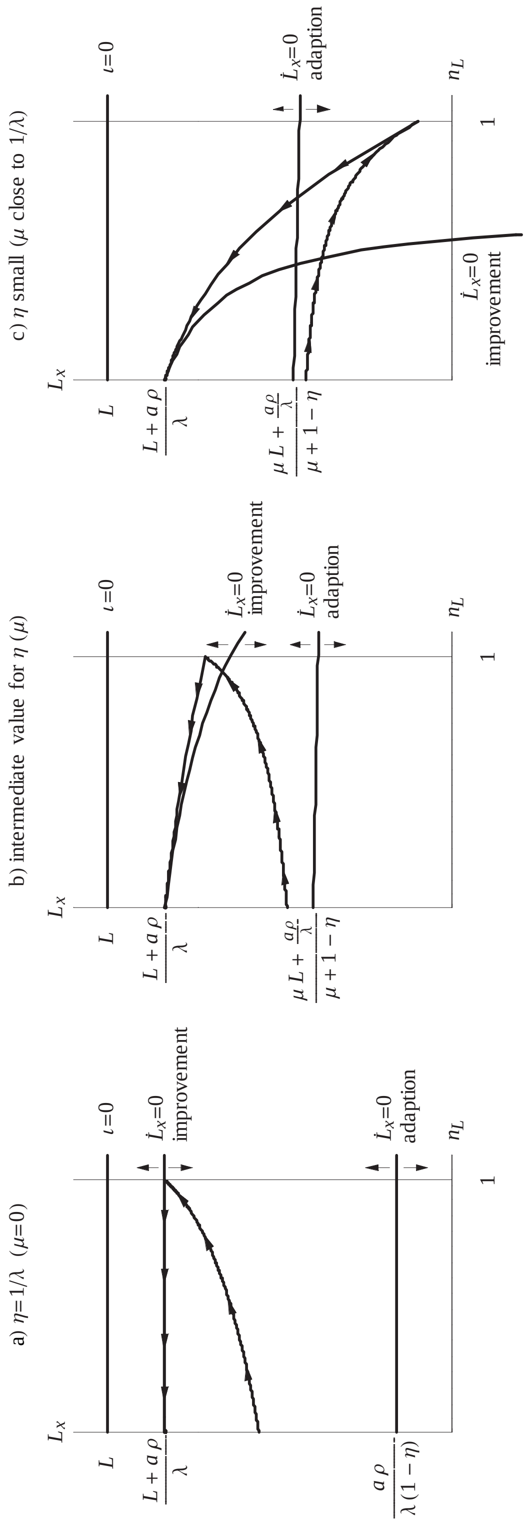

Figure 5: Dynamics confidence phase in the n_L, L_x plane

B Pollution in the Cleaning-up phase

We transform the dynamic system in (34)-(35) into a dynamic system in terms of Z and n_R. Substituting (38) in these equations to eliminate y, and replacing n_F by $1 - n_R$, we find:

$$\frac{\dot{Z}}{Z} = \frac{(\xi + \lambda\gamma/n_R)Z - L - a\rho n_R}{a n_R} \tag{B.1}$$

$$\frac{\dot{n}_R}{n_R} = -\frac{L - [\lambda\gamma/n_R - (\lambda\gamma - \eta)]Z}{a n_R} \tag{B.2}$$

where $\xi = \eta + (\lambda - 1)(\tau/w + \eta) + [\tau/w + \eta - \lambda\gamma] - \lambda\gamma$. Note that $\xi > -\lambda\gamma$ from our assumptions made above to ensure adoption of the clean GPT [the term in square brackets is positive, see (33)].

We now have two situations, depending on whether ξ is positive or negative. First, if it is positive, the d$Z = 0$ locus slopes positive in the feasible region (for $0 < n_R < 1$) and the saddlepath slopes downward so that pollution unambiguously falls with the fall in n_R. Figure 6 shows the phase diagram for this case. Second, if ξ is negative, the d$Z = 0$ locus has a vertical asymptote at $n_R = -\lambda\gamma/\xi > 1$ and slopes downward in the feasible range (for $0 < n_R < 1$). However, the saddlepath slopes downward so that again pollution unambiguously falls with the fall in n_R. The corresponding phase diagram would resemble the one shown in Figure 6.

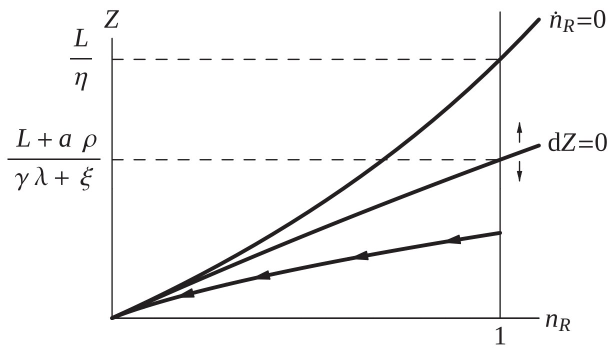

Figure 6: Dynamics cleaning-up phase in the n_R, Z plane

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