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

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

Keywords Environmental Kuznets curve · General purpose technology · Growth · Intrasectoral shifts

JEL Classification Q20 · O41 · Q56

1 Introduction

A classic and regularly recurring theme in economics is the relationship between economic growth and the concern for environmental problems. It ranges from the physiocrats' focus on land, Jevons' coal question and the Club of Rome's doomsday scenarios, to the greenhouse

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gas problem. The relevant question is whether we can expect our economies to "grow cleaner" in the future. Over the past years, this question has been approached using the concept of the Environmental Kuznets Curve (EKC). The basic idea is to link the rise and decline in pollution over time to the rise in income over time. Literature following this approach has generated a wealth of insights, providing evidence for the existence of the EKC, in particular for short-lived regional air and water pollutants.[1] However, more recent econometric analyses do not confirm the EKC patterns and question whether the EKC can be considered a stylized fact, see Perman and Stern (2003) and Deacon and Norman (2006).

Given the focus of the empirical research, theory has been developed that explicitly links "supply" and "demand" for pollution to income levels. It is assumed that pollution increases with production for given technologies and relative prices, which is called the scale effect. But the demand for a cleaner environment increases with income levels, which generates composition and technique effects, shifting the economy to cleaner sectors and production techniques. This line of reasoning can explain the EKC if green demand and regulative capacity increase strongly with income. But empirical evidence does not support this view. In particular, green product demand is income-inelastic, institutions and regulatory actions are persistent, and the history of environmental policy often shows a haphazard response to problems. The empirical research has gone back to the original question: can we expect pollution to first increase and then decrease over time, and what drives the process? By applying panel and time series econometrics, the role of income is proven to be smaller than originally assumed; however, the role of time, often seen as a proxy for technological change, appears to be more important than previously stated, see e.g. Stern (2004) and Wagner (2008).

In this paper, we aim at reconnecting theory to the recent empirical findings. In particular, we aim to explain why some pollutants first rise and then fall over time, while the turning point is not necessarily associated with a particular income level. We propose technological change and regulation as the main driving force behind the development of pollution over time. Firms have incentives to adopt dirty technologies in some periods, but find it more profitable to apply clean technologies in other periods. We use the model to check if technology, rather than income-driven demand for clean environment and income-driven regulation, can generate the EKC, and under which conditions technology gives rise to other pollution-income relationships.

The need for further theoretical foundations appears to be widely acknowledged in recent literature. Carson (2010, p. 19) suggests to think of the EKC "not in terms of its typical reduced-form representation, but in terms of a structural model". Harbaugh et al. (2002, p. 544) suggest that "because the reduced form relationships typically estimated in this literature are not driven by any particular model, there is little guidance for the correct specification." In a recent survey, Kijima et al. (2010, p. 1200) conclude that "in contrast to the vast empirical literature on EKC, there are only a few theoretical studies to explain why the EKC …appears, despite the importance of this issue." They propose to "examine the evolution of pollution as the aggregation of microeconomic behaviour" and that "pollution should be linked not only with a development path (…) but also with policy response."

This paper aims at filling this gap by providing a consistent theory of the income-pollution relationship with the help of a Schumpeterian endogenous growth model. Income, technology adoption, and pollution are endogenous. In this respect, we directly meet the requirements of Kijima et al. (2010). By construction, income is ruled out as a driving force, because in the steady state income grows through product quality improvement and pollution remains

[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 review articles by Smulders (2000), Stern (2004) and Lieb (2003).

constant. This allows us to isolate the effect of technology. In the model, pollution problems first gradually build up with the introduction of new technologies. Environmental degradation then attracts the public's attention and triggers a regulatory response in the form of a pollution tax. Finally, firms adopt cleaner technologies to reduce costs. Innovation opportunities not only determine the growth rate of income; we also model how incentives arise to invest in either pollution-intensive or pollution-saving technologies, which entails temporal shifts in the direction of technological change. In addition, we show how the balance between (intrasectoral) composition and technique effects change over the technology lifecycle.

We use our theoretical 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—changes accompany the adoption of pollution-reducing technologies.[2] In the second part of the paper we use the predictions of the theoretical model to explain the development of NOx emissions and to formulate guidelines for further empirical research on the pollution-income relationship.

The contribution is linked to the previous theoretical literature on pollution and development, in particular to Stokey (1998), Andreoni and Levinson (2001), Lieb (2002), Copeland and Taylor (2003, Chap. 3), and Brock and Taylor (2010). These contributions, however, model either income growth or technological change as an exogenous process, while we endogenize technological change. Aghion and Howitt (1998) introduce endogenous technology but focus on balanced growth and do not distinguish, as we do here, between pollution-using and pollution-saving innovations. De Groot (1999) models an EKC with technological change as a learning-by-doing process.

The remainder of the paper is organised as follows. Section 2 presents the formal model and introduces the equilibrium dynamics. In Sect. 3, the mechanisms generating EKCs are determined. Section 4 discusses the empirical implications of the theoretical model. Section 5 summarises and concludes.

2 The Model

2.1 Technology

We assume that technology changes along two dimensions. First, firms improve the quality of their products incrementally. Second, pollution-saving and 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 sources 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.[3]

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

[2] This corresponds to the empirical observation that, in developed countries, intrasectoral change has been by far more important than intersectoral shifts in recent decades.

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

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.

We distinguish between four different phases for the EKC pattern. In the first phase, the so-called 'green phase", only one GPT is available, which causes no or negligible pollution. The second phase starts as soon as a new GPT becomes available, which 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 recognized as a problem. Accordingly, we call the entire second phase the "confidence phase". The third phase starts once it becomes clear that the new technology is harmful and 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 (or cleaner) 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 (cleaner) 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 this new GPT and, therefore, pollution is absent (or lower) and firms again invest to improve their product quality (improvement subphase).

The next subsections explain the main model elements; the details are relegated to the appendix.

2.2 Production

The economy has a continuum of sectors, indexed i, each producing a good that enters the households' utility function. 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.

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:

$$c_{jt} = a_{Lj} w_t + a_{Zj} \tau_t \tag{1}$$

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

$$x_i = Y/p_i, \tag{2}$$

that is spending per sector Y divided by the price set by the incumbent in the sector p_i. Because we normalise the total mass of sectors to one, Y is equal to aggregate spending.

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:

$$\begin{aligned} p_i &= \lambda c_j \quad \text{if in } i \text{ a quality leader is active that employs technology } j, \\ p_i &= c_{j-1} \quad \text{if in } i \text{ a cost leader is active that employs technology } j. \end{aligned} \tag{3}$$

Corresponding profit levels are then given by:

$$\begin{aligned} \pi_i &= \left(1 - \frac{1}{\lambda}\right) Y \quad \text{if in } i \text{ a quality leader is active,} \\ \pi_i &= \left(1 - \frac{c_j}{c_{j-1}}\right) Y \quad \text{if in } i \text{ a cost leader is active that employs technology } j. \end{aligned} \tag{4}$$

Total employment in the production sector, denoted by L_x, can be derived as the sum of the labour demands of the different types of producers. By the assumption of limit pricing within a sector only one firm per sector is active and the labour demand of a sector is given by $a_{Lj} x_{ik}$. Thus, using (2), L_x can be written as:

$$L_x = \sum_k n_k a_{Lj} \frac{Y}{p_i} \tag{5}$$

where n_k is the fraction of sectors with firms of type k; k denotes quality or cost leaders in the different phases, see next section. Total emissions are given by the sum of emissions of the different types of producers. Hence, aggregate pollution Z can be calculated as:

$$Z = \sum_k n_k a_{Zj} \frac{Y}{p_i} \tag{6}$$

2.3 Innovation

R&D aims at developing blueprints for improving the quality of a certain product or blueprints for adopting the latest technology (GPT) in a certain sector. The development of a blueprint requires a units of labour, so that the cost of a blueprint is aw. The total amount of blueprints developed per period, or the research intensity ι, is:[4]

$$\iota = \frac{1}{a} \sum_k L_{gk}, \tag{7}$$

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

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

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:

$$v_k \leq aw \quad \text{with equality whenever} \quad L_{gk} > 0. \tag{8}$$

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:

$$\pi_k + \dot{v}_k - s_k = r v_k \tag{9}$$

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. 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 $s_k = 0$.

The model and in particular the specification of the R&D sector implicitly incorporates a spillover effect, which ensures ongoing growth. Spillovers arise since the development costs for a higher quality of a specific product are equal for all generations of this product. In other words, an inventor can develop a higher quality of a product without having himself taken all previous development steps of the product. Inventors rather gain the necessary information by scrutinising the latest product.

2.4 Dynamics

The development of the economy can be characterised by systems of differential equations; the appendix explains the corresponding equations. Each stage is characterised by a state variable, which is the fraction of firms of one particular type. This number in inherited from the previous stage and endogenously changes over time. For the differential equations we have to distinguish whether a new GPT is adopted (adoption subphases) or quality improvements take place (improvement subphases).

An *adoption subphase* starts if a new cost-reducing GPT is available. Since adoption itself 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. We focus on the case in which profits out of adoption strictly exceed profits out of improvement so that adoption takes place without simultaneous quality improvements.[5] Using (4), a new GPT is adopted if

$$\frac{c_{j-1}}{c_j \lambda} - 1 > 0 \tag{10}$$

i.e. it depends on the ratio between labour-input requirements and the pollution intensities and whether the economy is regulated or not.

[5] If research were targeted not only at adoption but also at quality improvement using the old GPT, we would require that profits out of adoptions equal profits out of quality improvements for this to be an equilibrium, which only happens by coincidence. If profits out of adoption fall short of those out of quality improvement, no adoption would take place, the adoption phase would not start and the economy would remain in an improvement phase.

Hence, once a new GPT is adopted, in the beginning all labour in R&D develops blueprints for adoption. The relevant state variable in these phases is the fraction of firms which have already adopted, which starts at zero. We summarise these firms as being of type B. The fraction increases with the number of patents developed:

$$\dot{n}_B = \iota = \frac{1}{a}(L - L_x) \tag{11}$$

With adoption only, cost leaders face no risk of being replaced, i.e. $s_B = 0$. Using Eqs. (4), (8) and (9), we find the following no-arbitrage equation for adoption:

$$\left(1 - \frac{c_j}{c_{j-1}}\right)\frac{Y}{aw} + \frac{\dot{w}}{w} = r \tag{12}$$

In the *improvement subphases* all sectors use the same GPT. We first analyse the case where all firms have just switched to the new GPT and then start improving product quality. Subsequently, we analyse the case where all firms are already quality leaders and further improve quality (which is relevant in the very first phase and after an eventual regulation). If the adoption of a new GPT is completed, inventions are directed at improving product qualities. The rate of innovation ι can be again expressed as:

$$\iota = \frac{1}{a}(L - L_x) \tag{13}$$

ι 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 or a cost leader—in both cases, profits equal $(1 - 1/\lambda)Y$—she spreads innovation effort equally over all sectors. As a result, a fraction n_B of the total number of blueprints developed (ι) hits B-firms, which are then replaced by quality leaders. Hence we have:

$$\dot{n}_B = -n_B \iota \tag{14}$$

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 $s_Q = \iota v_Q$. Using (4), (8) and (9), we find the following no-arbitrage equation for quality improvements:

$$\left(1 - \frac{1}{\lambda}\right)\frac{Y}{aw} + \frac{\dot{w}}{w} - \iota = r \tag{15}$$

3 EKC Pattern

We are now ready to derive the income-pollution relationship for the economy from these model elements.

3.1 Firm Types

The three GPTs appearing in the model are indexed $j = 1, 2, 3$ for the "traditional", "labour-saving" and "clean" technology respectively, see Fig. 1. In every GPT, we have quality and cost leaders, which leads us to six types of producers. Firms improving 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 Fig. 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 them as "traditional quality leaders". The

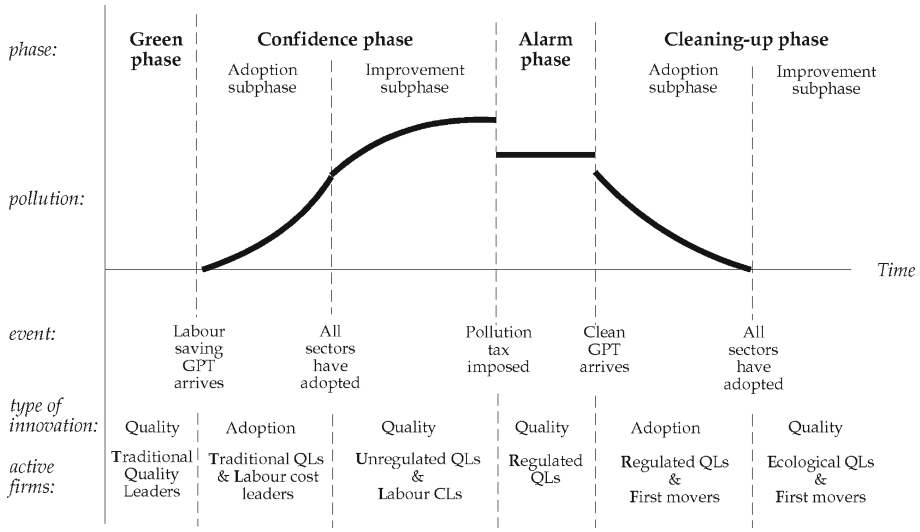

Fig. 1 The four phases

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 in turn replace the initial cost leaders. As there is no environmental regulation, we call these 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.

The different firm types are marked by the index $k \in \{T, L, U, R, F, E\}$, 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". 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. Since, by assumption, only two types of firms are active at any point in time, at most two out of the six n_k can be different from zero simultaneously.

3.2 GPT Characteristics

Without loss of generality we can normalize the labour requirement and emission intensity for one GPT. We choose $a_{Z2} = a_{L1} = 1$, so that GPT 1 requires one unit of labour per unit of output and GPT 2 emits one unit of the pollutant per unit of output. GPT 1 is assumed to be completely clean, so we have $a_{Z1} = 0$, and we simplify by assuming that GPT 3 is also completely clean, $a_{Z3} = 0$. Adoption decisions now depends on relative input prices τ/w and the labour requirements of the new GPTs, $a_{L2} \equiv \eta$ and $a_{L3} \equiv \gamma$. The pollution tax with rate τ—if implemented—is assumed to be constant in terms of the wage, and we then have

$\tau/w > 0$. We first explore the case that GPT 3 improves upon GPT 1 and that the superiority of GPT 3 over GPT 2 in terms of pollution comes at the costs of a higher labour requirement, i.e. $1 > \gamma > \eta$.[6] Hence we write:

$$a_{L1} = 1, a_{L2} = \eta < a_{L3} = \gamma < 1, a_{Z1} = a_{Z3} = 0, a_{Z2} = 1. \tag{16}$$

In the remainder of the section we analyze how these assumptions generate the EKC pattern in the model. Alternative assumptions on labour requirements, $a_{L2} \equiv \eta$ and $a_{L3} \equiv \gamma$, and on pollution intensity a_{Z3}, produce different (monotonic or N-shaped) pollution-income patterns and are discussed in a separate subsection below.

Evidently, the appearance and the adoption of GPTs have a major impact on the EKC pattern. Technological change not only affects the level of pollution, but also market structure. It is realistic to assume that the efforts to find new GPTs are continuous, but that their occurrence is random and unsteady. This reflects that some researchers are always concerned with big ideas and technologies, but that the market success is not predictable. We stress that a new technology is only adopted as a new GPT if it saves enough on production costs, which in our model include labour costs and tax payments. We view this as the decisive link between pollution and technology and thus focus on the adoption (rather than invention) of new GPTs in our framework. We now discuss the different phases in detail.

3.3 Green Phase

In the green phase, all active enterprises are traditional firms, i.e. quality leaders using GPT 1. There is no environmental regulation and innovation is exclusively aimed at improving product qualities. This reduces the model to the Grossman and Helpman (1991, Chap. 4). Since the clean GPT is used, there is no pollution at all. The rate of innovation is given below in Eq. (22).

3.4 Confidence Phase

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 (6) as:

$$Z = n_L y \tag{17}$$

where $y = Y/w$ is spending per wage income, a convenient way to reflect the level of economic activities, see the appendix. Since both n_L and y gradually increase during the adoption subphase, we see immediately from (17) 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 (1), (2) and (3)]:

[6] The last assumption assures that even if GPT 3 became available during the "confidence phase" it would not be adopted in the absence of a pollution tax.

$$X \equiv \sum_k n_k x_k = y\left[\frac{1}{\lambda} + \left(1 - \frac{1}{\lambda}\right) n_L\right] \tag{18}$$

Because n_L and y gradually increase during the adoption subphase, we see from (18) that total production gradually rises, so that the scale effect also contributes to rising pollution levels.

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). The intrasectoral changes from L-firms to U-firms have no effect on pollution, since both types of firms use the same production technology. From (5) and (6) we find:

$$Z = X = \frac{1}{\eta} L_x \tag{19}$$

The appendix 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.

3.5 Alarm Phase

Pollution hurts households' utility, the appendix shows the details. Whether a new technology causes pollution or not is unknown at the time of its introduction. Prominent examples for the increase in public awareness of damages over time are asbestos and CFC gas. When exposure to the pollutant has been long enough, damages, if any, can be officially established; then, an emission tax can be implemented via the political process. The tax-induced increase in production costs makes it attractive to switch to new production processes with lower pollution output ratios.

The economy enters the alarm phase once it starts taxing pollution. Society is 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. $n_L = 0$.[7] In addition, we do not explicitly consider the case where it is profitable for firms to switch back to the old traditional technology.[8] This requires that the profits from readopting GPT 1 fall short of those from further quality improvements still using GPT 2, i.e. $\pi_R > \pi_T$. From Eq. (4), we see that this requires $1 - a_{L1}w/(a_{L2}w + a_{Z2}\tau) < 1 - 1/\lambda$, or after substitution of (16) $\tau/w < \lambda - \eta$.[9]

[7] The "alarm phase" would vanish and the "cleaning-up phase" would start immediately after the implementation of a pollution tax, if GPT 3 were already available.

[8] When obsolete technologies are reintroduced, the EKC pattern does not emerge for obvious reasons; see also our discussion at the end of the section.

[9] 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 Sect. 3.6). 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.

3.6 Cleaning-Up Phase

In the adoption subphase, pollution is given by [see (6)]:

$$Z = y\left(\frac{1 - n_F}{\lambda(\eta + \tau/w)}\right) \tag{20}$$

It turns out that pollution continuously falls over time, see the appendix. More and more sectors switch to the clean technology (n_F increases), which reduces pollution. The upward pressure on pollution from increases in 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 (5) as:

$$L_x = y\left(\frac{(\lambda\gamma - \eta)n_F + \eta}{\lambda(\eta + \tau/w)}\right) \tag{21}$$

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 (11), innovation falls over time. The above condition is fulfilled by (16) and $\lambda > 1$.[10] In the improvement subphase, pollution is obviously absent. Moreover, innovation falls similar to innovation in the improvement subphase of the confidence regime.

3.7 Alternative Pollution-Income Scenarios

Concerning the pollution intensity of GPT 3 we can think also of an alternative scenario. Suppose GPT 3 is not absolutely clean, but pollutes on a lower level than GPT 2. In this case, pollution still falls during the adoption subphase since the newly adopted GPT is cleaner. However, pollution again rises during the improvement subphase due to a scale effect; firms, which have improved the product quality, charge a lower price and produce more than their predecessors. This results in a N-shaped EKC. Such a pollution path is not exceptional and has been found for a number of pollutants, see Lieb (2003).

Note that the general EKC pattern would also emerge if GPT 3 became available earlier, i.e. during the "confidence phase". As long as the labour requirements of the polluting technology are low enough, the clean GPT is not adopted in the absence of a pollution tax.[11] Alternatively, a second or a more polluting GPT with even lower labour requirements (say GPT 4 with $a_{L4} < a_{L2}$ and $a_{Z4} > 0$) could become available during the "confidence phase", resulting in new adoption subphases and a prolongation of the "confidence phase"; but this would not change the subsequent "alarm" and "cleaning-up phases", thus leaving the predicted EKC pattern unaffected.

A final possibility is that the cleaning up phase ends by the arrival of a new GPT that is profitable to adopt but is polluting. There might be two reasons for this. First, this new GPT could have very low labour cost so that labour saving outweighs the pollution cost. Second, this new GPT could introduce a new type of pollution that is not yet recognized as being harmful and hence not subject to regulation; this creates an artificial cost advantage that makes adoption profitable. It is important to note that the higher the tax rate on recognized

[10] In case $\lambda\gamma < \eta$ innovation may first rise and then fall over time. In this case (21) is isomorphic to (A.19) so that the analyses of appendix A can be repeated and the pattern of innovation found there emerges.

[11] In this case, however, the "alarm phase" would vanish, since the adoption of the third GPT and, herewith, the "cleaning-up phase" would start immediately after the implementation of a high enough pollution tax.

pollutants from existing technologies, the higher is the incentive to introduce technologies that rely on unknown pollutants. This scenario corresponds to the "new toxics scenario" in Dasgupta et al. (2002).

3.8 Innovation Behaviour

The driving force behind income and pollution dynamics is innovation, to which we turn now. To describe the development of the innovation rate in the confidence phase, we need to determine how L_x changes over time [see (11)]. The appendix shows that L_x increases (decreases) and innovation falls (rises) over time if labour requirement 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 innovation intensity at the end of the confidence phase (when n_L approaches zero) can be solved by first substituting (14) and $\dot{y}/y$ given by (A.8) into the expression for $\dot{n}_B/n_B$ according to (A.9) in the appendix to eliminate $\dot{n}_L/n_L$ and y respectively, and then setting $n_L = \dot{y} = 0$. This yields:

$$\iota = \frac{\lambda - 1}{\lambda}\frac{L}{a} - \frac{1}{\lambda}\rho \equiv \iota_{GH} \tag{22}$$

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, Chap. 4). Hence, the innovation rate in (22) equals the innovation rate of their model (denoted by ι_{GH}).

From Eqs. (5), (13) and y given by (A.11) in the appendix, the steady state innovation growth rate in the alarm phase, $\iota_{SSAlarm}$, is calculated as:

$$\iota_{SSAlarm} = \frac{\lambda}{\lambda - \theta_{Zj}}\left[\frac{L}{a}\left(\frac{\lambda - 1}{\lambda}\right) - \frac{\rho}{\lambda} + \frac{\theta_{Zj}}{\lambda}\rho\right] \tag{23}$$

or, equivalently as:

$$\iota_{SSAlarm} = \frac{\lambda}{\lambda - \theta_{Zj}}\left[\iota_{GH} + \frac{\theta_{Zj}}{\lambda}\rho\right] \tag{24}$$

Note that y [Eq. (A.11)] and the rate of innovation [Eq. (24)] increase in the pollution tax. The intuition behind this 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 the production sector 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. But both variables remain constant during the alarm phase.

In reality, the rate of innovation and total emissions are unlikely to jump after the introduction of a tax, since adjustment typically takes time and absorbs resources. Such steady

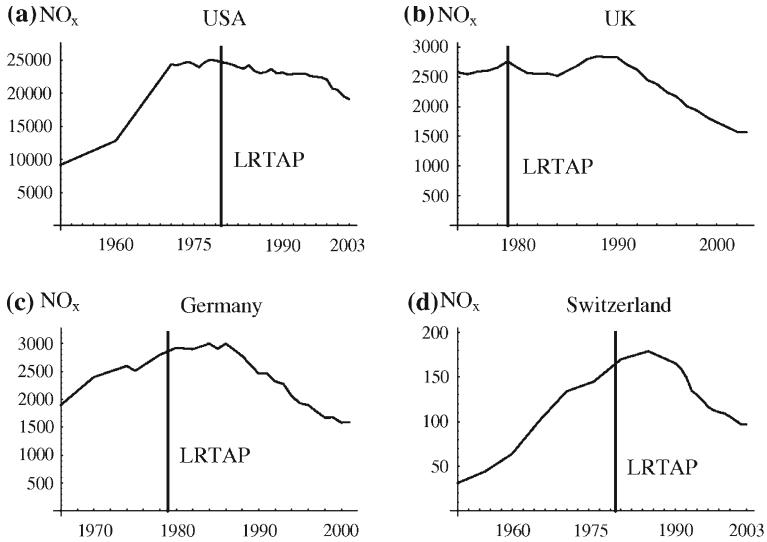

Fig. 2 NOx for the USA, UK, Germany and Switzerland. *Note* NO_X emissions in Gg. *Source* USA: EPA (2000 and 2005); UK: DEFRA (2005), Germany: DESTATIS (1966–2004), Switzerland: SAEFL (1995 and 2005)

adjustment processes could be added to our model by assuming e.g. appropriate adjustment costs. However, since our focus is on technology adoption and not on policy adjustment, we abstained from modelling such steady adjustment processes and consequently assumed that labour can be reallocated immediately and without any costs from the production sector to R&D or vice versa.[12]

4 Empirical Application

We now discuss the empirical relevance of the present approach. We first look at the case of NOx pollution and then derive conclusions for the further empirical testing of the underlying hypotheses.

4.1 NOx Emissions

The theoretical model explains several stylised facts on emissions, technologies, and policy adoption. In this subsection, we consider (total) nitrogen oxide emissions in the last decades for the USA, UK, Germany and Switzerland, as shown in Fig. 2. It was not until the 1980s that the NO_X emissions stopped increasing, and then started to decline significantly. The growth of nitrogen oxide emissions was mainly caused by scale effects. Increasing mobility and globalisation led to a drastic rise in road traffic. The induced environmental degradation started to attracted broad public attention in the late nineteen seventies. In 1979, the four countries above signed the *Convention on Long-Range Transboundary Air Pollution* of the United Nations Economic Commission for Europe (depicted by the vertical lines labelled

[12] It can be shown that, in these kind of models, adjustment costs due to a heterogeneous labor force affect the optimal speed of the transition, see Amigues et al. (2008).

LRTAP in Fig. 2. In 1988 the convention was extended by a protocol concerning the control of nitrogen oxides or their transboundary fluxes.[13]

In the subsequent years the governments enacted a number of laws to achieve the agreed emission reductions. The regulations were mainly geared towards 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. 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 case shows the main stylised facts of our theoretical approach: an initial increase in aggregate pollution until the public perception of pollution leads to environmental regulation and a subsequent decrease, which can be traced back to the interaction of governmental policy, intrasectoral substitution processes and the adoption of new, cleaner technologies.[14]

4.2 Implications for Empirical Studies

Most of the literature has studied income-driven EKCs and has only started to consider technology-driven EKCs. The latter is mainly done in a black-box way, by interpreting time trends or time effects as technology, see Perman and Stern (2003) and Lantz and Qu (2006). We have developed a model in which endogenous technology adoption drives pollution, income growth, and thus the pollution-income relationship. This suggests to scrutinise the role of technology more explicitly in the empirical applications, see also De Bruyn et al. (1998). In this regard, a more direct measurement of technology would be useful. A good starting point could be patent and diffusion studies, see Popp (2002, 2010). To connect this approach to the EKC hypothesis, we need to study how the development, adoption, and diffusion of dirty and clean technologies responds to earlier events of technology adoption and to regulation. Put differently, to test for sequences (and possibly cycles) in adoption phases appears to be fruitful. The model also suggests to test whether a sharp rise in pollution systematically creates an alarm phase and subsequent introduction of cleaner technologies.

In our model, it is the combination of broad technologies with incremental innovation which guides the dynamic process. In order to obtain an EKC pattern, a new GPT has to arise. But this is not sufficient, several GPTs might be around at a point in time. The model reveals that a new technology is only adopted as a new GPT if it saves enough on production costs, which in our model include labour costs and tax payments. We view this as the decisive link between pollution and technology. Thus, new technology in the form of GPTs becomes available exogenously but endogenous market conditions determine whether the new technology is adopted. Public awareness and the implementation of environmental policies are necessary for a decrease in pollution. This suggests that, in order to test the EKC hypothesis empirically, we have to use appropriate control variables for environmental policy. Taking the theoretical model seriously means to include a series of additional control variables into the regressions, e.g. measuring sectoral compositions and change, input

[13] The convention was extended until 1999 by eight protocols aiming at the reduction of specific pollutants.

[14] According to the model, we argue in terms of total pollution here rather than pollution related to another economic variable.

prices, and possibly—with regard to policy implementation—the quality of the institutions and regulatory capacity.

The model confirms that the EKC concerns a relationship between two highly endogenous variables, income and pollution, which has consequences for the empirical application. As technology adoption determines both income and pollution, we observe cross-equation disturbance correlations between the pollution and the income equation. Accordingly, the appropriate way of estimating the theoretical relationship is to depart from single-equation estimation and to apply a system estimation with the two endogenous variables income and pollution. The system approach is the procedure to obtain not only consistent but also efficient estimates.

In principle, the model is suited for both time-series analysis or panel estimation. As time series are often short and business cycle effects have to be filtered out carefully it seems a good option to include cross-country information, i.e. to use panel or pooled data. This is in close analogy to growth empirics. But in the context of the EKC, an important issue is to take care of international industry dislocation, in particular the shift of (polluting) manufacturing from rich to poor countries. The other econometric problems of growth empirics, such as simultaneity, parameter heterogeneity and missing variables, have also to be addressed, see Temple (1999) and Durlauf et al. (2005). The proposed system estimation can take care of these issues.

5 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 role of regulatory response to growing pollution.

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 does not necessarily predict an EKC for all pollutants. In empirical research, the EKC is mostly found for specific pollutants, i.e. for those with local and immediate effects.[15] 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.

Our model provides a natural framework for the examination of the idea of overlapping EKCs. Booth (1998) has convincingly argued 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, consistent with what Dasgupta et al. (2002) call the "new toxics scenario". If this is the case, additional GPTs—once available—have to be adopted 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.

The policy implications of the model partly confirm earlier analyses. First, regulation is needed to control pollution. Regulation was previously based on the argument that demand for environmental quality increases with income. In our model, the conclusion follows from the notion that a new technology with lower labour costs will be adopted whenever it becomes available. A technology with high pollution intensity is only abandoned when pollution is taxed at a sufficiently high rate. Second, regulation is unlikely to be immediate. It takes time to recognize pollution problems and design appropriate action. Policy makers need to be alert on new toxics and design dynamic preventive action systems or liability rules.

Our model deliberately left out some links between income and pollution, in order to isolate technology as driving the EKC. The model could be merged with the income-driven EKC model, at the cost of greater complexity. A scale effect would arise naturally when capital accumulation is introduced. Also, the level of the pollution tax could be dependent on income. Another obvious extension of the model would include the 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 research, and to correct output levels in order to remove the distortionary pricing effects. However, the important lesson from the model is that regulation requires information about the polluting consequences of new technologies and that this information might come late. A fruitful area for research would therefore be to study how and when information build up, disseminates, and affects policy. As regards the empirical application, the model could be used to implement a system estimation for pollution and income as proposed in the previous section. These issues are left for future research.

[15] An EKC pattern for non-local pollutants such as CO_2 is rarely found (e.g. Schmalensee et al. 1998). Furthermore, Aldy (2005) shows that the pollution-income relation for production-based CO_2 emissions does indeed follow a hump-shaped pattern, but the more relevant relation for consumption-based CO_2 emissions follows a "peak and plateau shape".

Appendix

Households: The representative consumer maximises intertemporal utility given by:[16]

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

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. The index of consumption C is given by:

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

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:[17]

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

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. Intertemporal utility maximisation implies that consumption expenditure Y grows at a rate equal to the difference between the (nominal) interest rate r and the utility discount rate:[18]

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

Labour is supplied inelastically and equals L. Labour demand consists of employment in the production sector and total employment in R&D. Clearing of the labour market requires:

$$L = L_x + \sum_k L_{gk} \tag{A.5}$$

Systems dynamics adoption periods: Let us first consider the dynamic behaviour of the economy during *adoption periods*. Substituting (A.4) into (12) to eliminate r, substituting (5) into (11) to eliminate L_x and taking into account that only firms of type B and their predecessors (T-firms or R-firms respectively) are active, i.e. $n_k + n_{k-1} = 1$, we find:

$$\frac{\dot{y}}{y} = \left(1 - \frac{c_j}{c_{j-1}}\right)\left(\frac{1}{a}\right)y - \rho \tag{A.6}$$

$$\dot{n}_B = \frac{L}{a} - y\left(\frac{1}{a}\right)\frac{a_{Lj-1}}{a_{Lj-1} + a_{Zj-1}\frac{\tau}{w}}\left(\frac{1}{\lambda} - \mu n_B\right) \tag{A.7}$$

[16] Households are modelled as in Grossman and Helpman (1991), except that we include damages in the utility function.

[17] Note that the optimisation problem of the households can be solved in two stages as in Grossman and Helpman (1991, Chaps. 3 and 4). First, households optimise the time path of spending. They then optimise instantaneous utility [Eq. (A.2)] for given levels of spending.

[18] To simplify notation, the time index is henceforth suppressed.

where $\mu = (1/\lambda) - \frac{a_{Lj}}{a_{Lj-1}}$ and $y = Y/w$. This system of differential equations in n_B and y characterises the dynamics during adoption subphases.

Systems dynamics improvement periods: For the dynamics during *improvement periods* we proceed as follows. Substituting (A.4) into (15) to eliminate r, substituting (5) into (13) to eliminate L_x and taking into account that only firms of type Q and their predecessors (L-firms or F-firms respectively) are active, i.e. $n_k + n_{k-1} = 1$, we find:

$$\frac{\dot{y}}{y} = y\frac{1}{a}\left(1 - \frac{a_{Zj}\frac{\tau}{w}}{\lambda\left(a_{Lj} + a_{Zj}\frac{\tau}{w}\right)} - n_B\varphi\right) - \left(\frac{L}{a} + \rho\right) \tag{A.8}$$

$$\frac{\dot{n}_B}{n_B} = y\frac{1}{a}\left(\frac{1}{\lambda}\frac{a_{Lj}}{a_{Lj} + a_{Zj}\frac{\tau}{w}} - n_B\varphi\right) - \frac{L}{a} \tag{A.9}$$

where $\varphi = \frac{a_{Lj}}{\lambda(a_{Lj}+a_{Zj}\frac{\tau}{w})} - \frac{a_{Lj}}{a_{Lj-1}+a_{Zj-1}\frac{\tau}{w}}$.

The dynamics for the case where all firms are quality leaders can be determined in close analogy. It is described by one differential equation only, since no switching between different types of firms takes place. Substituting (A.4) into (15) to replace r, substituting (5) into (13) to eliminate L_x and taking into account that only firms of type W, where $W \in \{T, R\}$ are active, i.e. $n_W = 1$ and $n_k = 0$ for $k \neq W$, we find:

$$\frac{\dot{y}}{y} = y\frac{1}{a}\left(\frac{\lambda - 1}{\lambda} - \frac{a_{Lj}}{\lambda(a_{Lj} + a_{Zj}\frac{\tau}{w})}\right) - \left(\frac{L}{a} + \rho\right) \tag{A.10}$$

If firms expect no shocks, i.e. they do not anticipate the arrival of a new GPT or a change in taxation, Eq. (A.10) can only hold forever if y remains constant over time.[19] Hence, we can set (A.10) equal to zero to obtain the following expression for the steady state expenditures per wage income:

$$y = \frac{L + a\rho}{1 - \theta_{Zj}/\lambda} \tag{A.11}$$

where $\theta_{Zj} = (a_{Zj}\tau/w)/(a_{Lj} + a_{Zj}\tau/w)$ is the share of pollution in total cost for GPT j.

System dynamics: confidence, alarm, and cleaning-up: The dynamics for the confidence phase is given by Eqs. (A.6), (A.7), (A.8) and (A.9) with $B = L$, $Q = U$ and $\tau = 0$. The dynamics for the alarm phase is given by Eq. (A.11) with $W = R$ and $\tau/w > 0$. The dynamics for the cleaning-up phase is given by Eqs. (A.6), (A.7), (A.8) and (A.9) with $B = F$, $Q = E$ and $\tau/w > 0$.

Production labour dynamics: Labour input L_x may either fall or rise during the adoption subphase, depending on whether η is small or large respectively. From (5) we find the following expression for L_x in the confidence adoption subphase:

$$L_x = y\left(\frac{1 - (1 - \lambda\eta)n_L}{\lambda}\right) \tag{A.12}$$

[19] Otherwise y would grow or shrink at an increasing rate, which is either infeasible or violates the transversality condition of the households, respectively.

We use (A.12) to replace y in (A.6) and (A.7) by L_x and find the following dynamic system for the adoption subphase:

$$\frac{\dot{L}_x}{L_x} = \frac{1}{a[1-(1-\lambda\eta)n_L]} \cdot \{[\lambda(1-\eta)+1-\lambda\eta]L_x - (1-\lambda\eta)L - [1-(1-\lambda\eta)n_L]a\rho\} \tag{A.13}$$

$$\dot{n}_L = \frac{1}{a}(L - L_x) \tag{A.14}$$

From (A.6) we see that, when $n_L = 1$, y is bounded as follows:

$$y < \frac{1}{1-\mu}(L + a\rho) \tag{A.15}$$

We then infer from (A.12) that, when $n_L = 1$, L_x is bounded as follows:

$$L_x < \frac{\eta}{1-\mu}(L + a\rho) \tag{A.16}$$

From (A.13) we see that, when $n_L = 1$,we have

$$\dot{L}_x \leq 0 \quad \text{if} \quad L_x \leq \frac{\mu L + \eta a\rho}{\mu + 1 - \eta} \tag{A.17}$$

Now consider the following condition:

$$\frac{\eta}{1-\mu}(L + a\rho) \leq \frac{\mu L + \eta a\rho}{\mu + 1 - \eta} \tag{A.18}$$

If condition (A.18) 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.18), see (A.16)] that it can only be reached by a declining L_x [as is revealed by (A.17)]. Note that for sufficiently low values of η this condition is satisfied. Let us now consider the opposite case in which η takes its maximal value, that is $\eta = 1/\lambda$ so that $\mu = 0$. Now, 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 (22) and considering (A.13) L_x has to increase over the entire adoption subphase. For intermediate values of η we get that the larger is η, the more likely becomes a rising pattern for L_x. Note that L_x may first fall and then rise (but never the other way around) in the adoption subphase. L_x unambiguously rises during the improvement subphase. For this subphase, we find from (5):

$$L_x = \left(\frac{1}{\lambda} - \mu n_L\right) y \tag{A.19}$$

We use (A.19) to replace y in (A.8) and (A.9) by L_x and find the following dynamic system for the improvement subphase:

$$\frac{\dot{L}_x}{L_x} = \frac{1}{a(1/\lambda - \mu n_L)} \cdot \{[1-2\mu n_L]L_x - [1/\lambda - 2\mu n_L]L - [1/\lambda - \mu n_L]a\rho\} \tag{A.20}$$

$$\frac{\dot{n}_L}{n_L} = -\frac{1}{a}(L - L_x) \tag{A.21}$$

Pollution dynamics: The development of pollution in the improvement subphase directly follows from (19) 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 $\iota = (L - L_x)/a$. To obtain pollution in

the cleaning-up phase we transform the dynamic system in (A.6)–(A.7) [with with $B = F$ and $Q = E$ and taking into account (16)] into a dynamic system in terms of Z and n_R. Substituting (20) in these equations to eliminate y, and replacing n_F by $1 - n_R$, we find:

$$\frac{\dot{Z}}{Z} = \frac{(\xi + \lambda\gamma/n_R)Z - L - a\rho n_R}{a n_R} \tag{A.22}$$

$$\frac{\dot{n}_R}{n_R} = -\frac{L - [\lambda\gamma/n_R - (\lambda\gamma - \eta)]Z}{a n_R} \tag{A.23}$$

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 (10) and (16)].

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