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Pollution, Endogenous Capital Depreciation, and Growth Dynamics*

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Abstract

This paper documents a positive and significant relationship between carbon dioxide emissions and capital depreciation rate for a large sample covering more than 80 countries in recent decades. Using this result, we develop a simple Solow model with an AK production function in which a pollution externality, viewed as a stock, increases the capital depreciation rate. In the long run, it appears that whatever the magnitude of the pollution effect on capital depreciation, there is no room for endogenous growth despite the AK technology. Moreover, we observe that a sufficiently sensitive capital depreciation rate to pollution can lead to the emergence of a limit cycle near the steady state (i.e., a Hopf bifurcation), indicating that the relationship empirically documented within this paper acts as a destabilizing force for the economy.

JEL Codes: E22, O41, O44, Q56

Keywords: Endogenous Capital Depreciation, Growth Model, Pollution

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1 Introduction

The links between pollution, capital depreciation, and growth have become extremely important in the context of today's global challenges.

First, there is the question of environmental sustainability. Pollution poses significant threats to environmental sustainability. The degradation of air, water, and land resources adversely affects ecosystems, biodiversity, and the overall health of the planet.[1] Second, pollution-related damages impose substantial cost on economies. These costs can manifest as increased healthcare expenses (Xia et al. (2022), Giaccherini et al. (2021)) or diminished workers productivity (Chang et al. (2019), Graff Zivin and Neidell (2012)), which can reduce competitiveness. Exploring the linkages between pollution, capital depreciation, and growth can inform policy decisions aimed at minimizing economic disruptions, promoting sustainable economic development, and fostering long-term ecological balance.

To the best of our knowledge, the first attempts to consider pollution in a dynamic general equilibrium model date back to Keeler et al. (1972) and Forster (1973). These two studies focus on the central planner solution of a Ramsey-Cass-Koopmans model wherein pollution enters the utility function as a separable argument. They both point out that the optimal path leads to a steady state where the capital level is lower than the one obtained without pollution. Meanwhile, Heal (1982) studies the market solution rather than the centralized one and considers a non-separable utility function between consumption and pollution. Interestingly, he points out that the economy can converge towards a limit cycle (i.e., a Hopf bifurcation) if and only if pollution sufficiently increases the marginal utility of consumption. Such a positive pollution effect on consumption demand is later designated as a *compensation effect* by Michel and Rotillon (1995). A similar conclusion is drawn more recently by Bosi

[1] See for instance Paoletti et al. (2010), Lovett et al. (2009), Vörösmarty et al. (2010), Keeler et al. (2012) and Chapter 4 in Montanarella et al. (2018).

et al. (2019). In their model, pollution affects both consumption demand and labor supply, but the necessary condition for a Hopf bifurcation still rests on the existence of a compensation effect.

The question of the existence and optimality of endogenous growth in an economy with pollution is challenging. Indeed, it is well-known that endogenous growth appears in economies with positive externalities (learning-by-doing, human capital accumulation) while pollution acts as a negative externality and then stands in stark contrast to what is needed to ensure sustained economic growth. Considering a growth model *à la* Romer (1986) with an AK technology, Michel and Rotillon (1995) show that without pollution abatement expenditures, endogenous growth is possible if and only if preferences are depicted by a sufficiently strong compensation effect. In any other cases, there is no room for endogenous growth, that is, the economy converges towards a steady state. A similar conclusion is obtained by Stokey (1998). In her paper, she considers a very similar framework to the one proposed by Michel and Rotillon (1995) and points out that there is no room for endogenous growth by considering a separable utility function. Interestingly, this separability allows a characterization of the shape of the optimal path. It displays an inverted U-shape relationship between per capita income and pollution, that is, the optimal path is a so-called Environmental Kuznets Curve and leads to a steady state.

More recently, Heutel (2012) examines how environmental policies should react to economic fluctuations caused by productivity shocks. Using a dynamic stochastic general equilibrium model, he suggests that optimal policy should allow carbon emissions to rise during economic expansions and fall during recessions. From an econometric perspective, Heutel (2012) assesses the link between the cyclical elements of carbon dioxide emissions and US gross domestic product (GDP) and finds it to be inelastic. Kahn et al. (2021) study the long-term impact of climate change on economic activity across countries and find that persistent deviations in temperature from its historical norm negatively impact the growth of real per-capita output. However, to the best of our knowledge, none of these studies have considered the effects of pollution through the capital depreciation rate channel.

The aim of this paper is to fill this research gap. We hypothesize that pollution affects capital depreciation rate in several ways. A direct one is through physical damage. Air pollution and chemical pollution can cause physical damage to capital goods and infrastructure. For example, pollution can react with oxygen in air and water vapor and produce acid rain, which, in turn, can corrode metal structures. Air pollutants can erode buildings and machinery; chemical pollutants can degrade equipment as well (see Okochi et al. (2000) and, more recently, Sharma et al. (2023)). This physical damage reduces the useful life of capital assets, leading to accelerated depreciation. Another way is through maintenance costs. Pollution can clog machinery and equipment, necessitating more frequent cleaning and maintenance. As a consequence, pollution can increase the frequency and intensity of maintenance and repair activities required to keep capital assets functioning optimally. The additional maintenance costs incurred to combat pollution can contribute to higher depreciation rates. An indirect way in which pollution may affect depreciation rates is through pollution-related regulations and policies. Stricter environmental standards may require firms to invest in pollution control measures or adopt cleaner technologies. Compliance with regulations may necessitate early retirement or replacement of polluting capital assets, leading to accelerated depreciation. If this hypothesis proves genuine, it is also important to understand how pollution affects economic dynamics through the capital depreciation channel.

Therefore, the aim of this paper is twofold: (a) to measure by how much pollution affects the capital depreciation rate, and (b) to describe the mechanism through which a variable depreciation rate depending on pollution influences economic growth.

We tackle the first question by estimating the relationship between pollution, measured through carbon dioxide emissions, and the rate of capital depreciation on a panel of 87 countries. Our estimates suggest that a positive and significant relationship exists between the cyclical components of these two variables. Using annual data over the period 1970–2016, we document that a one percent increase in CO_2 emissions produces an increase in capital depreciation rate between 0.20–0.33 percentage point. This effect is estimated quite precisely and it is robust to a number of empirical specifications. Interestingly, the relationship between pollution and the capital depreciation rate also seems stronger in developed countries.

Having shown that pollution does affect depreciation rates, we tackle the second question by developing a growth model in which pollution increases the capital depreciation rate. To keep things as simple as possible, we consider an economy *à la* Solow (1956) with an AK production function and where pollution is viewed as a stock coming from production. In the long run, similar to Stokey (1998), there is no room for endogenous growth since pollution affects the economy. Moreover, after analyzing the dynamics around the steady state, it follows that a sufficiently sensitive capital depreciation rate to pollution can lead to the emergence of a limit cycle through a Hopf bifurcation, a dynamic very close to the one pointed out by Heal (1982) or Bosi et al. (2019) but without any pollution effects on preferences. That is, the pollution effect on capital depreciation acts as a destabilizing force for the economy.

This paper is structured as follows. Section 2 presents the econometrics analysis and its results. Section 3 describes the theoretical model and studies the economic dynamics in our framework. Section 4 simulates the theoretical model using an ad-hoc calibration and discusses its implications. Finally, Section 5 concludes the paper.

2 Empirical evidence

In this section, we provide empirical evidence on the effects of pollution on the capital depreciation rate using a panel annual data analysis. Before presenting our results, let us briefly discuss the dataset utilized. Our sample contains annual observations and consists of a panel of 87 countries. The criteria for a country to be included in our study are to have at least 30 consecutive annual observations on the two main variables of interest, i.e., consumption of fixed capital and carbon dioxide emissions, together with a population size greater than one million inhabitants. The period is from 1970 to 2016. While drafting this paper, the World Bank shifted its CO_2 database from 1970–2016 to 1990–2020. Despite this update, we chose to stick with the former to maintain a more extended time span of data. It is noteworthy that the correlation between these two series is exceptionally high, standing at 0.99 over the overlapping period. In Appendix A, we detail the source and the construction of time series for capital depreciation rate and pollution.

In the econometric analysis, carbon dioxide (CO_{2t}) emissions (in kilotons) per capita is used as a proxy for the flow of pollution. As explained in Hoffmann et al. (2005), although not flawless, CO_2 serves as a valid proxy for pollution because of its status as the primary greenhouse gas responsible for global warming, the ready availability of reliable time series data on CO_2 emissions, and the notable high correlation between CO_2 and other pollutants such as NO and SO_2. The critical variable for our analysis is a time-varying depreciation rate. As we conjecture that CO_2 emissions flow affects the capital depreciation rate through direct physical damage of capital and higher frequency of capital maintenance, we cannot assume a constant depreciation rate over time, as is usually done in the literature. Instead, we construct a time series of capital depreciation rates for each country as follows. We use the perpetual inventory method to construct an initial capital stock series, given data on investment and an initial constant depreciation rate, δ, that we set to 0.1. We construct the initial capital stock series using the law of motion for capital in the model:

$$K_{t+1} = gfcf_t + (1 - \delta)K_t, \tag{1}$$

where $gfcf_t$ is gross fixed capital formation (in real terms and per capita) at date t. Capital stock at the beginning of series K_0 is given by:

$$K_0 = \frac{gfcf_0}{g + \delta}, \tag{2}$$

where g is the compound annual growth rate of the (per capita) real gross capital formation series from 1970 to 2016. Then, the time-varying capital depreciation rate series (δ_t) is constructed as the ratio of consumption of fixed capital (i.e., the decline in the value of fixed capital due to tear, damage, obsolescence and aging) to the capital stock:

$$\delta_t = \frac{cfc_t}{K_t}, \tag{3}$$

where cfc_t is the consumption of fixed capital (in real terms and per capita) at date t. For the 87 countries in our sample, the time average of capital depreciation rate averages 5.9% (the median is 6.2%) and ranges from 1.1% in Nigeria to 17.2% in Burundi. Furthermore, as our objective is to analyze the cyclical relation between both variables of interest, we apply the Hodrick and Prescott (1997) filter (with a smoothing parameter of $\lambda = 100$ as we use annual data) to detrend the (logged) time series of CO_{2t} and δ_t. The cyclical component of these two variables are denoted by CO_{2t}^{HP} and δ_t^{HP} respectively.

We estimate the following equation in panel format:

$$\delta_{it}^{HP} = \alpha_i + \alpha_t + \beta CO_{2it}^{HP} + \epsilon_{it}, \tag{4}$$

where α_i are country fixed effects and α_t are time dummies. Our parameter of interest is β, which measures how depreciation responds to cyclical fluctuations in CO_2. The baseline regression (4) is enriched by adding a set of control variables whose influence is allowed to vary over time. These variables control for the change in the structure of the economy that accompanies the process of growth and include the value-added share of services, the share of investment expenditures in GDP and the share of tangible capital assets in total capital assets (to proxy any change in the composition of the capital stock). All controls, denoted $Services_{it}$, $Investment_{it}$ and $Tangibles_{it}$ respectively, are entered in the regression in log. Depreciation rates are potentially larger in countries with a high share of services in GDP. Intuitively, services are more intensive than manufacturing industries in capital assets depreciating at a more rapid rate (i.e., computers and software). We thus expect a positive coefficient associated with $\log(Services_{it})$. By contrast, because tangible capital goods, such as structures, have long asset lives and, thus, low depreciation rates, one may expect a negative coefficient on the variable $\log(Tangibles_{it})$. In addition, to the extent that countries with a high investment rate may experience larger damage and maintenance capital costs, they are more likely to exhibit higher depreciation rates. Therefore, we expect a positive coefficient associated with the variable $\log(Investment_{it})$.[2]

Table 1 shows the results for the baseline specification (see Equation (4)) along with its variants to identify the magnitude of the cyclical relationship between the capital depreciation rate and CO_2 emissions. The dependent variable in each case is the cyclical component of the capital depreciation rate. The regressors are the cyclical component of CO_2 emissions (CO_{2t}^{HP}), country fixed effects, and time dummies. Robust standard errors are reported in parentheses.

Column (1) gives the baseline result. The estimated coefficient of 0.041 is signif-

[2] Heutel (2012) finds that CO_2 emissions in the US are pro-cyclical, exhibiting an elasticity ranging between 0.5 and 0.9. As consumption of fixed capital (cfc) is a component of the gross national income, it has the potential to generate CO_2 emissions, introducing an endogeneity concern in regression (4). However, given that in our sample, cfc represents only about 10% of GDP, CO_2 emissions stemming from the depreciation of capital goods may not significantly compromise the consistency of our econometric estimates.

Table 1: Regression results of the capital depreciation rate and CO_2

Dependent variable	δ_{it}^{HP}					δ_{it}^{loop}	δ_{it}^{PWT}
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CO_{2it}^{HP}	0.041***	0.042***	0.034**	0.035**	0.051*	0.056***	0.024***
	(0.016)	(0.016)	(0.015)	(0.015)	(0.028)	(0.018)	(0.005)
$\log(Services_{it})$		0.030**		0.025			
		(0.015)		(0.015)			
$\log(Investment_{it})$			0.044***	0.041***			
			(0.008)	(0.008)			
$\log(Tangibles_{it})$					-0.136		
					(0.104)		
Observations	3878	3846	3878	3807	699	3097	3878
R-squared	0.037	0.043	0.050	0.055	0.182	0.035	0.126

Notes: ***, **, and * denote significance at the 1%, 5% and 10% levels. Robust standard errors are reported in parentheses. All regressions include country fixed effects and time dummies.

icant at the 99% confidence level, with a t-statistic of 2.61.[3] This result highlights that pollution, measured through CO_2 emissions, significantly impacts the rate at which capital is depreciated over time. Quantitatively, the estimated coefficient implies that a one percent increase in CO_2 emissions produces an increase of capital depreciation rate by 0.242 percentage point.[4] Columns (2) to (5) extend the baseline regression by adding our set of control variables. Column (2) controls for the share of services in domestic value-added, while in Column (3), we include the share of investment in GDP as a control variable. Column (4) displays the results when both variables are included simultaneously in the baseline regression. Finally, Column (5) adds as a control variable the share of tangible capital assets in total capital assets. As this variable is available only for Organisation for Economic Co-operation and Development (OECD) countries, the sample is considerably reduced in Column (5). Remarkably, the estimates remain highly significant across all these tests. They vary

[3] Running the same regression with the updated CO_2 database over the 1990–2016 period, we obtain $\hat{\beta} = 0.045$.

[4] Given the estimation $\hat{\beta} = 0.041$ and an average depreciation capital rate of 5.9%, an increase of CO_{2t}^{HP} by 1% gives rise to an increase in the depreciation rate by $0.041 \times 5.9\% = 0.242$ ppt.

from a low of 0.034 when the share of investment in GDP is included in the regression (Column (3)) to a high of 0.051 when the share of tangible capital assets is controlled for (Column (5)). The results thus become stronger when only OECD countries are considered and we control for the share of tangible capital assets, with the estimated coefficient rising from 0.041 to 0.051, and a greater explanatory power as the R-squared is now 18%, as compared with 3.7% in the benchmark specification. For the control variables, their estimated coefficients have the expected signs. Indeed, a high share of investment or services in GDP contributes to speeding up capital depreciation. The coefficient associated with $\log(Investment_{it})$ in Column (3) and (4) is 0.04 and is clearly statistically significant. In Columns (2) and (4), the size of the coefficient associated with $\log(Services_{it})$ varies from 0.03 to 0.025. However, the significance of this variable varies across the different regressions. As expected, we find that increases in tangible capital goods relative to total capital goods are associated with lower depreciation rates, with an estimated coefficient of -0.136 (see Column (5)). However, this effect is not statistically significant at a conventional level.

Columns (6) and (7) of Table 1 present two robustness tests with respect to the construction of the time-varying depreciation rate. Given that the construction of our capital depreciation rate series may be controversial, we tested two alternative series. The first is obtained by using an iterative method as in Imbs (1999) and Levchenko and Pandalai-Nayar (2020). In this algorithm procedure, our baseline variable δ_{it} is used as a starting series. Then an iterative procedure is used to construct a time-varying depreciation rate and capital stock consistent with the observed investment in the data by iterating the method described in Equations (1) and (2) until the square difference of the last two generated series converges to zero. We denote the final series δ_{it}^{loop}.[5] The second series we use for robustness purposes is the

[5] For 18 countries, the iterative procedure ends up with negative values for δ_{it}. We thus exclude these countries when running Equation (4). This group is composed essentially of developing or

one provided by the Penn World Table (Feenstra et al. (2015)), which we denote by δ_{it}^{PWT}. In the Penn World Table, investments are cumulated into capital stocks using asset-specific geometric depreciation rates and the perpetual inventory method. Accordingly, the average depreciation rate δ_{it}^{PWT} varies across countries and over time, as countries differ in the asset composition of their capital stock and depreciation differs across assets. A full description of the construction of δ_{it}^{loop} and δ_{it}^{PWT} is provided in Appendixes A and B. As our benchmark δ_{it}^{HP} variable, the variables δ_{it}^{loop} and δ_{it}^{PWT} are included into the baseline regression as deviations from the trend (the latter being obtained with a Hodrick and Prescott (1997) filter where the smoothing parameter λ is set to 100). In these two runs displayed in Columns (6) and (7), the results remain highly significant and our baseline estimate (0.041) is halfway between the estimates obtained with δ_{it}^{PWT} (0.024) and δ_{it}^{loop} (0.056).

3 An AK model with endogenous capital depreciation and pollution

The previous section puts forward a statistical relationship between CO_2 and capital depreciation rate. In this section, we will describe how the dynamics of production should be affected when we take this relationship into account.

To address this question, we use the AK model developed by Romer (1986) and Rebelo (1991), to which we add a pollution stock as in Jouvet et al. (2010). The next subsections describe the economic and pollution components of the model, their interactions, and, finally, the analysis of the dynamics induced.

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poor economies for which obtaining reliable macro data is still a challenge. After excluding these countries, the correlation between the cyclical component of δ_{it}^{loop} and our benchmark δ_{it}^{HP} is 0.968.

3.1 The economic part

Similar to Romer (1986) and Rebelo (1991), we assume that production Y is made using only physical capital K, such that:

$$Y_t = AK_t, \tag{5}$$

where $A > 0$ captures the capital productivity. Following Solow (1956), we assume the following law of motion for capital accumulation:

$$K_{t+1} = sY_t + (1 - \delta) K_t, \tag{6}$$

where $s \in (0, 1)$ and $\delta \in (0, 1)$ represent the saving rate and capital depreciation rate, respectively. Given the AK formulation for Y, Equation (6) becomes:

$$K_{t+1} = [sA + (1 - \delta)] K_t. \tag{7}$$

From (7), the growth rate of the economy is given by:

$$\frac{K_{t+1} - K_t}{K_t} = sA - \delta. \tag{8}$$

It follows that endogenous growth appears if the propensity to save is not too low (i.e., $s > \delta/A$). Departing from this well-known result, we propose to discuss the case where δ is affected by a pollution externality.

3.2 The environmental part

To keep things as simple as possible, let us assume, as in Jouvet et al. (2010), that the stock of pollution P evolves according to a linear process defined by

$$P_{t+1} = (1 - m) P_t + bY_t, \tag{9}$$

where $m \in (0, 1)$ and $b \in (0, 1)$ represent the natural rate of pollution absorption and the environmental impact of production, respectively. Contrary to what we have done in the econometric part, we assume here that pollution is a stock variable instead of a pure flow. Equation (9) is more general since it encompasses the pure flow case that corresponds to $m = 1$.

By combining Equations (5) and (9), the pollution process is rewritten as:

$$P_{t+1} = (1 - m) P_t + bAK_t. \tag{10}$$

In accordance with our empirical evidence presented in Section 2, we assume that pollution increases the capital depreciation rate:

$$\delta \equiv \delta (P_t). \tag{11}$$

The properties of this function are summarized within the following assumption.

Assumption 1 *$\delta : \mathbb{R}_+ \to \mathbb{R}_+$, is $\mathcal{C}^2$ with $\delta' (P) > 0$, $\lim_{P\to 0} \delta (P) = 0$ and $\lim_{P\to +\infty} \delta (P) = 1$.*

For further reference, we denote by γ the elasticity of the depreciation rate with respect to pollution. This elasticity is given by:

$$\gamma \equiv \frac{P\delta' (P)}{\delta (P)} > 0, \quad \delta(P) \neq 0. \tag{12}$$

As we will see later, γ has an important impact on the transitional dynamics.[6]

3.3 Equilibrium and steady state

An inter-temporal equilibrium is a non-negative sequence $(K_t, P_t)_{t=0}^{+\infty}$ satisfying the dynamic system:

$$K_{t+1} = [sA + (1 - \delta(P_t))] K_t, \tag{13a}$$

$$P_{t+1} = (1 - m) P_t + bAK_t. \tag{13b}$$

Different from the case without pollution, the dynamic system (13a)-(13b) allows for the existence of a non-trivial steady state. Indeed, at the steady state, $K_{t+1} = K_t = K^*$ and $P_{t+1} = P_t = P^*$. In this context, the system (13a)-(13b) gives:

$$P^* = \delta^{-1}(sA) > 0, \tag{14a}$$

$$K^* = \frac{m}{bA} P^* > 0. \tag{14b}$$

Interestingly, the economy can reach a steady state when pollution affects capital depreciation rate while the economy reaches a balanced growth path when there is no pollution (Cf. Section 3.1). Stokey (1998) reaches the same conclusion in an AK model where a pollution externality negatively affects a household's utility. She shows that there is no room for endogenous growth. The same result appears in our model, in which pollution affects the capital depreciation rate when saving is exogenous.

[6] It is important to note that although strongly related, the estimated coefficient β in the empirical section is not strictly equal to the parameter γ presented here. The difference stems from the treatment of pollution as a stock or flow variable. As noted previously, when $m = 1$, β and γ are conceptually the same objects.

3.4 Local dynamics

To study the local dynamics of the system, we linearize Equations (13a)-(13b) around its unique positive steady state:

$$\begin{bmatrix} \frac{dK_{t+1}}{K} \\ \frac{dP_{t+1}}{P} \end{bmatrix} = J \begin{bmatrix} \frac{dK_t}{K} \\ \frac{dP_t}{P} \end{bmatrix}, \tag{15}$$

where J is the Jacobian matrix evaluated at the steady state:

$$J \equiv \begin{bmatrix} 1 & -\gamma s A \\ m & 1-m \end{bmatrix}. \tag{16}$$

The parameter of interest in our case is γ. In the following, we will study how the magnitude of γ affects the transitional dynamics of our modeled economy. However, it is important to note that J is fully parametric, and any variation of γ has no effect on s, A, or m. The trace T and the determinant D of matrix J are given by the sum and the product of the eigenvalues of J, respectively. Then:

$$D = sAm\gamma + 1 - m \equiv D(\gamma), \tag{17a}$$

$$T = 2 - m. \tag{17b}$$

The characteristic polynomial of J writes $\psi(\lambda) \equiv \lambda^2 - T\lambda + D$. The eigenvalues of J are given by the roots of ψ. Those roots are real (complex) if and only if:

$$D < (>) \frac{T^2}{4}. \tag{18}$$

To discuss the dynamics, we proceed as in Grandmont et al. (1998) by considering the (T, D)-plane (see Figure 1). In Figure 1, numbers in brackets give the dimension of the stable manifold.

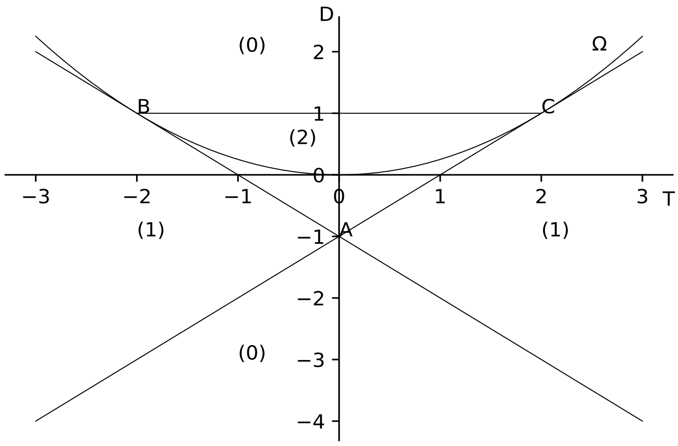


Figure 1: The (T, D)-plane

The curve $D = T^2/4$ is represented by Ω in Figure 1. Along the line (AC), one eigenvalue is equal to 1, namely $\psi(1) = 1 - T + D = 0$. Along the line (AB), one eigenvalue is equal to -1, namely $\psi(-1) = 1 + T + D = 0$.

Finally, along the segment $[BC]$, J possesses two complex conjugate eigenvalues with a unit modulus, namely, $D = 1$ with $|T| < 2$. Inside the ABC triangle, the two eigenvalues are located inside the unit cycle. At the right of (AC) and at the left of (AB), J possesses one eigenvalue inside the unit cycle and another one outside of the unit cycle. Elsewhere, J possesses two eigenvalues outside of the unit cycle.

When (T, D) cuts (AC), (AB), or $[BC]$, a local bifurcation takes place. More precisely, when (T, D) cuts (AC), a saddle-node bifurcation generically occurs. This implies that two steady states collide and disappear. When (T, D) cuts (AB), a flip bifurcation occurs, giving rise to a periodic cycle of order two around the steady state. Finally, when (T, D) cuts $[BC]$, a limit cycle arises around the steady state through a Hopf bifurcation.

Furthermore, since $m \in (0, 1)$, $D > 0$ while $1 < T < 2$. We also obtain the following:

$$\begin{aligned} T'(\gamma) &= 0, & \text{(19a)} \\ D'(\gamma) &= sAm > 0. & \text{(19b)} \end{aligned}$$

That is, a continuous variation of γ from 0 to $+\infty$ generates a vertical half-line (Δ) in the (T, D)-plane with $(T, D(0))$ as an initial point, such that:

$$D(0) = 1 - m = T - 1 > 0. \tag{20}$$

This setup results in the disappearance of the steady state (saddle-node bifurcation). This outcome stems from the fact that when $\gamma = 0$, pollution exerts no influence on capital accumulation. Consequently, the framework coincides with the standard Solow model characterized by an AK technology, leading to the manifestation of endogenous growth.

Hence, as shown in Figure 2, the initial point of (Δ) lies on (AC), such that $D(0) > 0$. Progressively raising γ from this starting point results in a vertical line (Δ) in the (T, D)-plane, such that (Δ) cuts Ω for $\gamma = \gamma_\Omega$. Moreover, (Δ) cuts $[BC]$ when $\gamma = \gamma_H$. Finally, we get $\lim_{\gamma \to +\infty} D(\gamma) = +\infty$.

The values of γ_Ω and γ_H are given by:

$$\begin{aligned} \gamma_\Omega &= \frac{1}{4}\frac{m}{sA}, & \text{(21a)} \\ \gamma_H &= \frac{1}{sA}. & \text{(21b)} \end{aligned}$$

The following proposition summarizes the previous discussion.

Proposition 1. *The dynamics are the following:*

- If $\gamma < \gamma_\Omega$, J possesses two real stable eigenvalues; the steady state (K^*, P^*) is locally stable, and the convergence is monotonic.

- If $\gamma_\Omega < \gamma < \gamma_H$, J possesses two complex stable eigenvalues; the steady state (K^*, P^*) is locally stable, and the convergence happens through damped oscillations.

- If $\gamma > \gamma_H$, J possesses two complex unstable eigenvalues; the steady state (K^*, P^*) is locally unstable, and the trajectory displays diverging oscillations.

- If $\gamma = \gamma_H$, a limit cycle arises around the steady state through a Hopf bifurcation.

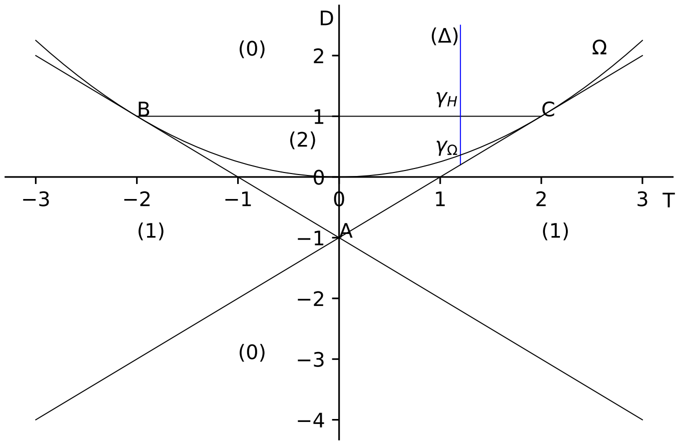


Figure 2: (Δ) in the (T, D)-plane

The existence of a Hopf bifurcation deserves an economic interpretation. Assume that the economy is at the steady state at time t and assume an exogenous rise of the pollution level P_t. According to Assumption 1, this implies a rise of the capital depreciation rate, which reduces the capital level and increases the next period pollution stock (13b). That is, the fact that pollution accelerates the capital depreciation rate implies that a rise of the pollution level at time t is followed by a drop at time $t+1$, giving rise to endogenous cycles. Our paper is not the first to show the possible existence of endogenous cycles in a neoclassical growth model with pollution. In particular Day (1982) considers a Solow model where a pollution flow coming from capital accumulation reduces total factor productivity. In this very simple framework, he shows that the economy can follow a chaotic trajectory. The present paper shows another type of instability, namely, the occurrence of a limit cycle when pollution is viewed as a stock affecting the capital depreciation rate.

4 Numerical simulations

Our empirical findings have demonstrated that pollution expedites the rate of capital depreciation. Subsequently, we present a straightforward growth model to delve into its long-term ramifications. Our key outcomes are twofold: first, the economy can attain a steady state instead of a balanced growth path and, second, oscillations may emerge, exhibiting characteristics of being damped, stable, or diverging. The following section aims to illustrate these oscillations through numerical simulations.

Let us consider the following functional form for the depreciation rate:

$$\delta(P_t) = \omega P_t^{\gamma}, \tag{22}$$

where ω corresponds to the value of δ for which pollution has no impact on the depreciation of capital (i.e., when $\gamma = 0$).

The calibrated parameters are as follows: the savings rate is set at 0.22, reflecting the average annual investment rate observed in our sample from 1970 to 2016. Similarly, A is fixed at 0.38, representing the average annual ratio of GDP over physical capital. The parameter ω is assigned a value of 0.06, corresponding to the average annual capital depreciation rate obtained from our constructed series. Following the approach of Heutel (2012), we calibrate m to 0.003. The parameter b is established at 0.5, indicating that half of the production is converted into pollution each period. Lastly, the initial conditions are defined as $K_0 = 0.01$ and $P_0 = 1$.

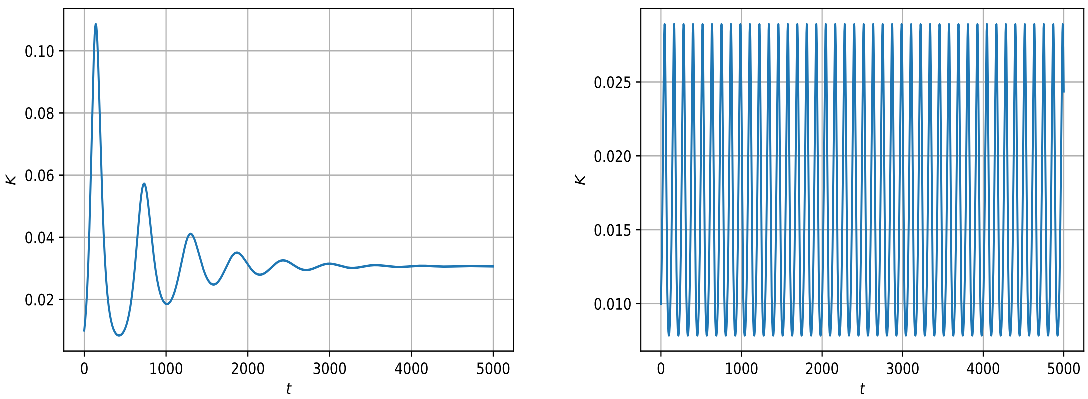
Considering (22), the steady state (14a)–(14b) is written as:

$$P^* = \left(\frac{sA}{\omega}\right)^{\frac{1}{\gamma}}, \tag{23a}$$

$$K^* = \frac{m}{bA}P^*. \tag{23b}$$

For the benchmark calibration, we pin down γ_Ω and γ_H according to Equations (21a) and (21b). This gives $\gamma_\Omega \approx 0.0089713$ and $\gamma_H \approx 11.962$. To illustrate damped oscillations, we choose $\gamma_\Omega < \gamma = 0.5 < \gamma_H$, while we set $\gamma = \gamma_H$ to generate stable oscillations (limit cycle). In the first case, the steady state values of capital and pollution are $K^* = 0.031$ and $P^* = 1.941$. In the second exercise, the corresponding values are 0.016 and 1.028, respectively.

Figure 3 depicts the capital dynamics obtained in each scenario:



(a) $\gamma = 0.5$, (b) $\gamma = 11.962$,

Figure 3: Physical capital dynamics

Given our calibration, our model gives rise to cycles even for a relatively small value of γ. That is, for any value of $\gamma \in (\gamma_\Omega, \gamma_H)$, the economy enters a regime where capital increases then decreases over time. As displayed in Figure 3(a), the cycle gets smaller each period of time, implying that the economy converges towards its steady state.

This convergence is no longer obtained when $\gamma \geq \gamma_H$. Figure 3(b) illustrates the loss of stability arising when $\gamma = \gamma_H$. In this case, a limit cycle emerges near the steady state and, as shown by Figure 3(b), we observe stable oscillations of capital occurring along the limit cycle.

The absence of a convergence characteristic could be better observed in a plane (K, P). As shown in Figure 4, when $\gamma = \gamma_H$, pollution and capital will turn around the steady state.

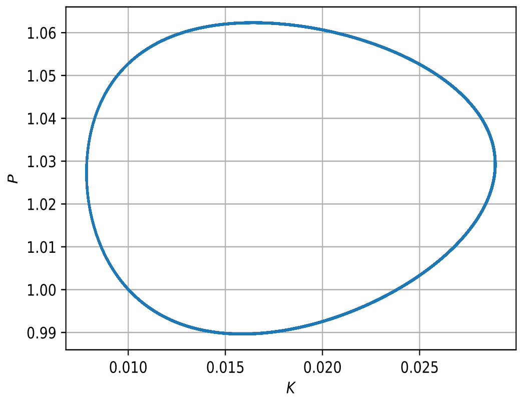


Figure 4: The limit cycle ($\gamma = 11.962$)

While our developed model significantly simplifies reality, our findings indicate that even a marginal influence of pollution on the depreciation rate can trigger the economy to enter a cyclic phase. Our simulations demonstrate that a mere 1% rise in pollution, causing a 0.053 ppt increase in depreciation, is enough to generate oscillations. Though not directly comparable, our empirical estimates suggest a 1% pollution increase results in a rise of 0.242 ppt in the capital depreciation rate. However, achieving a limit cycle state or divergent oscillations seems challenging for the economy under our calibration. This outcome would only arise if a 1% increase in pollution caused the depreciation rate to increase by more than 64.9 ppt.

Within our framework, sustained economic growth appears unattainable. Yet, it is crucial to note that the extent of oscillations diminishes as pollution exerts a lesser impact on the depreciation rate. Consequently, we can infer that a government aiming for economic stability should actively pursue environmental protection to mitigate pollution, thereby limiting capital depreciation. Furthermore, our findings underscore the importance of adapting physical capital to be less susceptible to pollution. This adaptation might involve investing in more resilient infrastructure. In essence, our findings provide a compelling basis for governments to engage in both mitigation and adaptation initiatives.

5 Conclusion

This paper underscores the critical relevance of exploring the intricate connections between pollution, capital depreciation, and economic growth, particularly in the face of contemporary global challenges. Investigating these linkages is imperative for informed policy decisions that aim to mitigate economic disruptions, foster sustainable development, and maintain ecological balance.

The study contributes to the existing literature by introducing a novel perspective: the impact of pollution on capital depreciation rates. While prior research has delved into environmental policy responses and the long-term effects of climate change, our focus on pollution's influence on capital depreciation provides a unique angle. The hypothesis that pollution affects depreciation rates is supported by empirical evidence, revealing a positive and significant relationship between carbon dioxide emissions and the rate of capital depreciation across a panel of 87 countries.

The paper also ventures into the realm of economic modeling, positing a neoclassical growth model where pollution intensifies the capital depreciation rate. The findings suggest that, in the long run, pollution acts as a destabilizing force, potentially leading to the emergence of a limit cycle through a Hopf bifurcation. This dynamical perspective aligns with earlier studies but adds a new dimension by focusing on the destabilizing role of pollution through depreciation rate and not via pollution effects on preferences.

In light of these outcomes, it is evident that pollution plays a pivotal role in shaping economic dynamics. The results not only confirm the tangible impact of pollution on capital depreciation rates but also highlight its potential to induce cyclicality in the economy. This dual contribution, supported by empirical and theoretical insights, emphasizes the need for a comprehensive understanding of the interplay between pollution, capital depreciation, and economic growth.

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A Data construction

Coverage. Our sample consists of a panel of 87 countries: Albania, Algeria, Argentina, Australia, Austria, Bangladesh, Belgium, Benin, Bolivia, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cameroon, Canada, Central African Republic, Chile, China, Colombia, Congo Republic, Costa Rica, Cote d'Ivoire, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Finland, France, Gabon, Gambia, Greece, Guatemala, Guinea, Honduras, Hong Kong, India, Indonesia, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kenya, South Korea, Malawi, Malaysia, Mauritania, Mauritius, Mexico, Mongolia, Morocco, Mozambique, Nepal, Netherlands, New Zealand, Niger, Nigeria, Norway, Pakistan, Panama, Paraguay, Peru, Philippines, Portugal, Rwanda, Saudi Arabia, Senegal, Singapore, South Africa, Spain, Sri Lanka, Sudan, Sweden, Switzerland, Thailand, Togo, Tunisia, Turkey, Uganda, United Kingdom, United States, Uruguay, Venezuela and Zimbabwe.

The criteria for a country to be included in the panel is to have at least 30 consecutive annual observations on the two main variables of interest, i.e., consumption of fixed capital and carbon dioxide emissions, and to have a population size greater than one million inhabitants.

Construction of variables. We describe below the construction of the data employed in the empirical analysis.

- **Capital depreciation rate**: Our baseline measure for the capital depreciation rate is denoted as δ_t and constructed as follows. First, we collect data on the consumption of fixed capital cfc_t (at current prices) and gross fixed capital formation $gfcf_t$ (at current prices). Both series are then expressed in real terms using the GDP deflator and scaled by the total population. Data for cfc_t, $gfcf_t$, GDP deflator and population are taken from the World Bank World Development Indicators database. Second, we construct a time series for the aggregate capital stock K_t for each country in our sample. To do so, we adopt the perpetual inventory approach. The inputs necessary to construct the capital stock series are *i*) capital stock at the beginning of the investment series, K_{1970}, *ii*) an initial value for the depreciation rate δ_0, which we set to 0.1, and *iii*) real gross capital formation series. We then construct the series for the capital stock using the law of motion for capital in the model:

$$K_t = gfcf_{t-1} + (1-\delta_0)K_{t-1}, \text{ for } t = 1971, ..., 2016.$$

For the initial value of the capital stock, we chose $K_{1970} = I_{1970}/(\delta_0 + g)$ where I_{1970} corresponds to the real gross capital formation in the base year 1970 and g is the compound annual growth rate of the real gross capital formation series from 1970 to 2016. Finally, δ_t is obtained as the ratio of consumption of fixed capital (in real and per capita terms) to the real stock of capital obtained in the previous step. We tested our results with other choices for the initial depreciation rate δ_0 and found no substantive difference.

As robustness checks, we use two alternative measures of the capital depreciation rate. The first, denoted by δ_t^{loop}, is based on an algorithm procedure developed by Imbs (1999) and Levchenko and Pandalai-Nayar (2020). We briefly describe the steps of the algorithm in Section B. As a second alternative measure, we use the capital depreciation rate provided by the Penn World Table (Feenstra et al. (2015)). This rate is denoted δ_t^{PWT} and is based on PWT on the assumption that investments are cumulated into capital stocks using asset-specific geometric depreciation rates and the perpetual inventory method. Accordingly, the average depreciation rate δ_t^{PWT} varies across countries and over time, as countries differ in the asset composition of their capital stock and depreciation differs across assets.

- **Carbon dioxide emissions (CO_{2t})**: These are expressed in per capita terms by dividing carbon dioxide emissions by the population. Carbon dioxide emissions (in kilotons) stem from the burning of fossil fuels and the manufacture of cement. They include carbon dioxide produced during consumption of solid, liquid, and gas fuels and gas flaring (Source: World Bank World Development Indicators database).

- **Share of services in total GDP ($Services_t$)**: This is the ratio of the valued-added in services (at current prices) to the total GDP (at current prices). The services sector comprises Wholesale, Retail Trade, Restaurants and Hotels (code ISIC G-H), Transport, Storage and Communication (code ISIC I) and Other Activities (code ISIC J-P). The remaining industries, namely, Agriculture, Hunting, Forestry, Fishing (code ISIC A-B), Mining, Manufacturing, Utilities (code ISIC C-E), Manufacturing (code ISIC D) and Construction (code ISIC F) are treated as the goods sector (Source: United Nations).

- **Share of investment in total GDP ($Investment_t$)**: This is the ratio of gross capital formation (in current US dollars) to the gross domestic product (in current US dollars). (Source: World Bank World Development Indicators database).

- **Share of tangibles assets in total investment ($Tangible_t$)**: This is the ratio of tangible assets (at current prices) in total gross fixed capital formation (at current prices). Construction, Machinery and Equipment, Weapon System, and Cultivated Biological Resources are treated as tangible assets. Intangible assets consist of Intellectual Property Product Assets. (Source: OECD National Accounts database).

B Iterative depreciation rate series construction

We now describe the algorithm procedure used to construct a series for δ_t^{loop}. We provide the steps of the algorithm using commonly seen relationships from the perpetual investment method. For a detailed presentation of the steps, see Imbs (1999) and Levchenko and Pandalai-Nayar (2020).

1. Construct a starting capital stock series using the perpetual inventory method from investment series I_t and an initial annual depreciation rate of 0.10. For the initial value of the capital stock, we chose $K_{1970} = I_{1970}/(\delta_0 + g)$ where I_{1970} corresponds to the real gross capital formation in the year 1970, and g is the compound annual growth rate of the real gross capital formation series from 1970 to 2016.

2. Use the capital stock series K_t, the consumption of fixed capital series cfc_t and the relationship $\delta_t = cfc_t/K_t$ to construct an initial time-varying series for δ_t.

3. Together with the series for real investment I_t and the time-varying δ_t, construct a new capital stock using the accumulation equation $K_t = I_{t-1} + (1 - \delta_t)K_{t-1}$.

4. Using the new δ_t and the new capital stock, return to step 1 and construct a new series for δ_t and K_t.

5. Iterate until the capital stock and δ_t converge. Then, construct the final implied series for the capital depreciation rate δ_t^{loop}.

C Capital depreciation rate series

The series for the capital depreciation rate obtained with the three methods we use in the paper and its first momentum can be found in Table A-1 below.

Table A-1: Capital depreciation rate series (average over the period 1970–2016)

Country name	δ	δ^{loop}	δ^{PWT}	Country name	δ	δ^{loop}	δ^{PWT}
Albania	0.034	0.004	0.030	Jordan	0.036	0.001	0.038
Algeria	0.027	0.005	0.041	Kenya	0.079	0.029	0.042
Argentina	0.043		0.031	South Korea	0.069	0.044	0.044
Australia	0.069	0.015	0.027	Malawi	0.066		0.055
Austria	0.075	0.026	0.038	Malaysia	0.078	0.050	0.046
Bangladesh	0.057	0.037	0.044	Mauritania	0.045	0.012	0.038
Belgium	0.083	0.025	0.040	Mauritius	0.047	0.013	0.046
Benin	0.066	0.004	0.043	Mexico	0.058	0.015	0.034
Bolivia	0.055	0.014	0.051	Mongolia	0.029		0.038
Botswana	0.076	0.049	0.047	Morocco	0.054	0.028	0.042
Brazil	0.065	0.018	0.048	Mozambique	0.109		0.039
Bulgaria	0.071	0.016	0.050	Nepal	0.030	0.011	0.034
Burkina Faso	0.050	0.019	0.042	Netherlands	0.076	0.011	0.036
Burundi	0.172		0.033	New Zealand	0.071		0.030
Cameroon	0.044	0.012	0.049	Niger	0.032		0.031
Canada	0.083	0.040	0.035	Nigeria	0.011		0.034
Central African Rep.	0.075		0.040	Norway	0.078	0.033	0.044
Chile	0.079	0.042	0.029	Pakistan	0.060	0.042	0.070
China	0.051	0.031	0.054	Panama	0.040	0.013	0.045
Colombia	0.071	0.035	0.032	Paraguay	0.053	0.021	0.039
Congo, Rep.	0.071	0.005	0.048	Peru	0.044	0.012	0.052
Costa Rica	0.039	0.012	0.051	Philippines	0.050	0.020	0.047
Cote d'Ivoire	0.026		0.045	Portugal	0.075	0.028	0.028
Denmark	0.084	0.019	0.036	Rwanda	0.066	0.031	0.054
Dominican Rep.	0.028	0.010	0.053	Saudi Arabia	0.024		0.052
Ecuador	0.057	0.021	0.039	Senegal	0.040	0.011	0.037
Egypt	0.034	0.014	0.068	Singapore	0.058	0.027	0.046
El Salvador	0.036	0.006	0.061	South Africa	0.064		0.045
Finland	0.084	0.026	0.038	Spain	0.067	0.015	0.034
France	0.079	0.019	0.031	Sri Lanka	0.034	0.015	0.074
Gabon	0.047	0.007	0.046	Sudan	0.048	0.007	0.036
Gambia	0.087	0.002	0.034	Sweden	0.067	0.013	0.034
Greece	0.060		0.026	Switzerland	0.082	0.009	0.045
Guatemala	0.065	0.012	0.041	Thailand	0.062	0.031	0.059
Guinea	0.031	0.012	0.045	Togo	0.027		0.038
Honduras	0.024	0.004	0.055	Tunisia	0.065	0.024	0.044
Hong Kong	0.060	0.029	0.027	Turkey	0.096	0.072	0.047
India	0.059	0.033	0.041	Uganda	0.062	0.044	0.056
Indonesia	0.064	0.039	0.045	United Kingdom	0.079	0.018	0.035
Ireland	0.076	0.042	0.040	United States	0.080	0.032	0.037
Israel	0.067	0.012	0.037	Uruguay	0.093		0.031
Italy	0.076	0.010	0.034	Venezuela	0.027		0.041
Jamaica	0.034		0.034	Zimbabwe	0.019		0.037
Japan	0.078	0.016	0.039				
				Mean	0.059	0.021	0.042
				Median	0.062	0.018	0.041
				Min	0.011	0.001	0.026
				Max	0.172	0.072	0.074
				Countries	87	69	87