

**Economic Growth and the Environment:
Theory and Facts***

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Abstract

Several recent papers propose competing theoretical explanations for the empirical observation of an inverted U-shape relationship between environmental degradation and per-capita income. We propose the following test of the theory: calibrate a theoretical model to an already developed economy using information unrelated to the pollution-income curve. Then simulate the model starting from a less developed initial condition and compare the predicted pollution-income relationship with that in the data. Our results are mixed. Some support exists for the theory that the inverted U-shape results from a corner solution in which less developed countries do not abate pollution. However, because we find abatement is relatively inexpensive, the model predicts pollution peaks at a level of per capita income much lower than that observed in our U.S. data. For some pollutants, we find evidence of a structural break in preferences in the early 1970s. When the structural break is added, the model performs better for two of three pollutants.

1 Introduction

A large literature investigates the relationship between environmental degradation and economic development. For some pollutants, a number of empirical papers (surveys include Copeland and Taylor, 2004; Dasputa, Laplante, Wang, and Wheeler, 2002; Dinda, 2004) find evidence of an inverted U-shape: pollution levels rise and then fall as income increases. This result, popularly known as the Environmental Kuznets Curve (EKC), has been called into question by a number of authors (see for example Stern, 2004). These authors show the EKC result is not robust to various changes in the specification of the econometric model. A large number of theoretical explanations also exist (see Dinda, 2004, for a survey), but none of these theoretical models have been tested. Thus no bridge between the theoretical and empirical models exists. This research uses calibration and simulation to test a growth model with emissions as a factor of production and environmental quality as a normal good. We also test the idea that the EKC results from a corner solution in which pollution initially rises with economic development because no pollution is abated, then falls with development as abatement grows.

Our results are mixed. Some support exists for the theory that the inverted U-shape results from a corner solution in which less developed countries do not abate pollution. However, because we find abatement is relatively inexpensive, the model predicts pollution peaks at a level of per capita income much lower than that observed in our U.S. data: 10-16% of the steady state capital stock, depending on the pollutant, versus 77-87% in our U.S. data. For two pollutants, particulates and sulfur dioxides, we find some evidence for a structural break in preferences in the early 1970s. Our estimate of the parameter governing preferences for environmental quality is larger when the data is split between pre and post 1973. When the structural break is added to the model, emissions peak much later, although still not as late as in the data for particulates. Our results also provide guidance to the

empirical literature by showing how particular theoretical models imply testable restrictions on the functional form of the time trend in empirical models. Finally, our results are of independent interest as we develop a new methodology for testing theoretical environmental economics models based on calibration.

The use of calibration to analyze the pollution-income relationship has some advantages. In particular, calibration requires only data from a developed economy. Thus we avoid missing or low quality data in developing countries, and do not have to worry about country specific effects that might be present if the model were instead estimated using data from a panel of countries. Further, our calibration exercise is a direct test of a theoretical model, as well as a test of the idea that the inverted U-shape pollution-income curve arises because countries initially choose a corner solution with no pollution abatement. Therefore, unlike most empirical papers we directly test a model without using reduced-form equations, which obscure exactly how and why the inverted U-shape occurs. Also, our results provide some guidance to empirical research.

The calibration to the developed U.S. economy finds some surprising parameter values. In particular, the data indicates that controlling pollution is relatively inexpensive. For example, for lead emissions the data indicates up to 96% of emissions were controlled for less than 0.015% of GDP. In turn, because abatement is inexpensive, the model predicts positive abatement and thus a peak in emissions early in development. However, in the U.S. data, emissions for most pollutants did not peak until the early 1970s, relatively late in development.

In fact, four of five pollutants peaked in the early 1970s, a time of significant changes, such as the first oil crisis, the Clean Air Act, and growth in the environmental movement. Were such events and the emissions peak a consequence of economic growth, or were they exogenous shocks that caused emissions to peak apart from economic growth? We split the data into subsamples before and after 1973 and find that for particulates and sulfur

oxides the parameter governing preferences for environmental quality is higher after 1973, indicating a structural break in preferences. On the other hand, we find no such break for nitrous oxides and carbon monoxide. After including the structural break in preferences, particulates peak at 38% of the steady state capital stock and sulfur oxides peak at the time of the structural break, as in the data. Thus for sulfur and particulates, the model performs better with the structural break.

Finally, this paper is of general interest in that we provide one of the few rigorous calibrations of a model of growth and the environment. All parameters are calibrated so that the model matches a variety of long run average features of the data. Thus the theory is consistent with the data in a way that simple numerical examples of theoretical models generally are not.¹ We hence provide a framework for a more rigorous test of theoretical environmental economics models at the national level. Rather than ask if a numerical example exists that is analytically consistent with observed facts (for some parameters, the model has an inverted U-shape), the test we propose asks if a numerical example consistent with a variety of features of the data generates also the observed fact in question (for a particular set of parameters, the model has an inverted U-shape which peaks at a point reasonably close to that in the data).

The structure of this paper is as follows. First, we provide a list of existing empirical regularities and theoretical explanations. Next, we develop our model. We calibrate the model with U.S. emissions data for five pollutants. The time series data indicate that emissions of all pollutants in our sample peak late, after the U.S. was nearly completely developed. We then computationally examine the shape of the pollution-income curve predicted by the model for each pollutant. The model predicts an inverted U-shape, but pollution peaks at an income level lower than that in the U.S. data. We then conclude, noting that the U.S.

¹A few theoretical models give numerical examples. For example, Stokey (1998) has a numerical example in which pollution peaks at about 50% of the steady state capital stock.

data appears more consistent with the idea that some sort of preference or technology shock occurred in the 1970s.

2 Empirical Regularities

We examine five pollutant categories: sulfur dioxide (SO_2), carbon monoxide (CO) and nitrogen oxide (NO_2 and NO, collectively NO_x), particulates (PM_{10} and $\text{PM}_{2.5}$, collectively PM), volatile organic compounds (VOC), and airborne lead. We choose these pollutants based on the availability of compliance cost data.

The existing empirical literature, which mostly uses data from a panel of countries, show pollutant-specific results for a variety of ambient, water and soil pollutants. In general, most research in this area entails using fixed effects and random effects estimation of quadratic, log-linear, log-quadratic and/or cubic-polynomial pollution-income relationships. Emissions or pollutant concentrations (either urban or national) are regressed on GDP per capita as well as other variables such as a time trend, population density and site-related variables. The reduced-form equation adopted by most of the empirical studies is assumed to capture the structural model in which income influences technology, the composition of GDP and environmental policy, and how changes in these factors in turn affect environmental pressure. An important issue in the empirical literature is the estimation of the location of the turning point; i.e., the income level at which emissions peak. Dozens of studies exist; here we present a few standard ones.²

Grossman and Krueger (1995) estimate a cubic reduced-form relationship between per capita income and various environmental indicators. They use Global Environmental Monitoring System (GEMS) pollution concentration data on SO_2 , heavy particulates, and smoke (their classification for smaller particulates). For most pollutants, they find an inverted-U result, where pollution peaks at a relatively low GDP per capita. Bandopadhyay and Shafik

²See Dinda (2004) for a survey.

(1992), using a polynomial with log income and ambient levels of SO_2 and suspended particulate matter (SPM), also find an inverted U-shape, where pollution peaks at a relatively low GDP per capita. Selden and Song (1994), employing a quadratic pollution-income relationship, utilize a panel of national emissions data on SPM, SO_2 , NO_x , and CO. They estimate slightly higher turning point income levels. They speculate this is because ambient pollution concentrations likely decline before aggregate emissions, due to the population concentrations in cities, the ability to install higher smokestacks, etc. Panayotou (1993) also measures pollutants in terms of emissions per capita on a national basis. They obtain inverted U-shape results for SPM, SO_2 , and NO_x . Hilton and Levinson (1998) estimate the relationship between lead emissions and income. They find an inverted U-shape pollution-income relationship with a turning point that is sensitive to both functional form (polynomial and log-quadratic) and time period (pre and post 1983). For post 1983, they find a statistically significant peak. Table 1 gives the turning points for all studies in constant U.S. dollars.³

More recently, Stern and Common (2001) use a larger and more globally representative SO_2 sample (31 annual observations on each of 73 countries) than previous EKC studies. They estimate a logarithmic quadratic pollution-income curve for world, OECD and non-OECD samples. They find that the turning point for SO_2 depends on the sample employed; for the OECD countries, \$11,250, and for the world, \$123,188.

Harbaugh, Levinson, and Wilson (2002) also question the specification of the basic econometric model. They update up the data employed by Grossman and Krueger (1995); i.e., their results benefit from 10 years of additional observations, more cities, and revisions of some of the original observations. In addition, the authors test the sensitivity of the pollution-income relationship to alternative functional forms, additional covariates and changes in the nations, cities and years sampled. They include variables describing national income, po-

³All dollar figures in this paper are in year 2000 constant U.S. dollars.

litical structure, investment, trade and population density, as well as control variables that account for location of monitoring stations. They find the results to be highly sensitive to these changes and conclude that the jury is still out on whether sufficient empirical support exists for an inverted U-shaped relationship. By adding 10 years and 25 cities to Grossman and Krueger's data set, Harbaugh et al. find SO_2 emissions peak at \$29,587. Depending on the length of the GDP time-lag, explanatory variables, year dummies, structural form, and outlier removal, estimated SO_2 peaks range from \$27,700 to \$96,507. Due to smaller sample sizes the results are generally less statistically significant for NO_x and airborne lead. Yet, NO_x appears to peak at \$7,956 and airborne lead at \$21,070.

Citing the data availability and accuracy problems with GEMS data, List and Gallet (1999) and Millimet, List, and Stengos (2003) utilize pooled U.S. state-level data from the Environmental Protection Agency (2000b).⁴ List and Gallet (1999) use quadratic and cubic specifications popular in previous EKC studies, as well as a semiparametric model that allows for state-level EKC heterogeneity. For parametric models, they estimate NO_x peak emissions at incomes from \$13,071 to \$16,275, and for semiparametric models, incomes from \$19,224 to \$26,541. For SO_2 , they estimate peak emissions at incomes from \$30,408 to \$34,055 (parametric) and at \$19,920 to \$29,415 (semiparametric). Millimet, List, and Stengos (2003) test the parametric model against a more flexible semiparametric approach. Millimet, et al., using a parametric cubic specification, estimate peak NO_x emissions at \$13,072 for the full data set and \$15,961 for the 1985-94 data. For SO_2 , they find statistically insignificant results for the full data set and a peak at \$24,790 for the 1985-94 data set. Utilizing the semiparametric approach, they find peaks at \$18,120 (NO_x) and \$12,080 (SO_2). They also test the validity of the parametric specification and determine they can statistically reject parametric models in favor of the semiparametric approach. Specifically, they note that the

⁴A problem with this data is that the EPA changed its state level measurement methods in 1985, so emissions estimations fall into two major regimes: 1929-1984 and 1985-1994.

estimated parametric peak for SO_2 is very sensitive to modeling assumptions.

Figure 1 plots the U.S. time series pollution data. We use U.S. national emissions data from 1947-1998 from Environmental Protection Agency (2000b). We aggregate CO and NO_x emissions since the cost data is not disaggregated between these two pollutants. Some additional modifications are also made prior to 1985 to account for changing collection methods (See Appendix B.3 for a detailed discussion). All pollutants show some evidence of an inverted U-shape over time, although particulates and lead are mostly decreasing. When emissions are plotted against per capita income, lead is even less clearly inverted U-shaped.

Table 1 gives the level of per-capita income at which pollution peaks. All economic data is described in Appendix B. As detailed in Appendix B, changes to income data were made so that the data is consistent with the theoretical model developed below. Table 1 shows that emissions peaked late in development for the U.S., ranging from an income of \$20,983 per capita for particulates to \$35,091 for SO_2 . As seen in Table 1, these values are more consistent with the later empirical literature, which predicts emissions peak at a relatively high income. These results are also broadly consistent with Brock and Taylor (2003), who note pollution in the U.S. peaks in the 1970s for most pollutants.⁵ The peaks are somewhat higher than U.S. state level studies, but as Selden and Song (1994) note, the emissions peak using national data tends to be higher than the emissions peak using more disaggregated data. In addition, our modifications to the income data include adding imputed services from government capital and durable goods, which increases income by as much as 18%. Table 1 shows that all categories except particulates peaked between 1970 and 1973. Particulates peaked in 1950. Therefore, we conclude that the stylized fact in the U.S. data is that the pollution-income curve has an inverted U-shape, and that emissions peak at a relatively late stage of development.

⁵The results are also broadly consistent with Portney (1990). Further, Deacon and Norman (2006) show that SO_2 was decreasing since the 1970s for a variety of wealthy countries.

An alternative way of looking at the data is to estimate emissions as a non-linear function of output per capita and a time trend. Similar to Harbaugh, Levinson, and Wilson (2002), here the peak is sensitive to the functional form. For example, Table 2 indicates that for SO₂ emissions peaks range from \$31,866 to \$72,045 depending on if emissions are a quadratic, cubic, or log quadratic function of output and a linear, quadratic, or not a function of time. For some econometric models, the quadratic term is positive or not significant. Nevertheless, it remains true that emissions peak at a relatively late stage of development. We show in Section 6 that our model implies a restriction on the functional form of the time trend. When this restriction is included, a statistically significant emissions peak occurs late in development for all five pollutants.

3 Development and the Environment: Theory

Dinda (2004) divides the large number of theoretical explanations into five broad categories. Here we review only three categories and formally test one.⁶

Andreoni and Levinson (2001) and Kelly (2003) focus on the cost of abatement. According to Kelly (2003), simple convexity in costs of abatement is sufficient for the marginal cost of abatement to rise along the growth path. By modeling environmental quality as a normal good, marginal damages rise with income. The trade-off between these two effects determines the shape of the pollution-income curve. Andreoni and Levinson (2001) suppose that abatement has increasing returns to scale. They show that after the economy achieves a certain minimum size, it is worthwhile to pay the initial or fixed costs and begin abatement.

Cropper and Griffiths (1994), Jones and Manuelli (2001) and others focus on institutional explanations. Countries with strong property rights and institutions typically are more wealthy and are better able to regulate emissions. Hence, a panel of countries with varying degrees of institutional strength could produce an inverted U-shape: pollution increases with

⁶In Section 8 we discuss how the other two explanations could be tested.

growth among poor countries with weak institutions and decreases with growth in wealthy countries with strong institutions.

Stokey (1998) and John and Pecchenino (1994) provide models with pollution-income curves that are inverted U-shaped, peaking when the optimum switches from a corner solution with zero abatement to an interior optimum with positive environmental investment. Low income countries use the dirtiest possible technology, so that pollution increases with income (Stokey, 1998) or consumption (John and Pecchenino, 1994). As income and consumption increases, the marginal utility of consumption falls, eventually to a point where cleaner technologies are optimal. Emissions then fall if preferences for environmental quality are strong enough.

Levinson and Israel (2004) provide an indirect test of the theory. Using largely qualitative survey data, Levinson and Israel investigate whether the patterns of marginal willingness to pay (MWTP) are consistent with the above theories. They do not find evidence that MWTP increases with income, which is not consistent with the institutional or corner solution ideas (the increasing returns argument does not have a specific prediction for MWTP). However, their analysis is limited by low-quality survey data.

An alternative is to see if reasonable preferences (and technology) are such that the model produces an inverted U-shape with emissions peaking late in development, as is the case in the U.S. data. The remainder of the paper examines this question.

4 Model

The model is a generalization of Kelly (2003), which allows for exogenous labor-augmenting and pollution-reducing technological change. The model does not have increasing returns to abatement, and implicitly assumes institutions exist that can regulate pollution. The model does have a constraint that abatement is non-negative. Thus we will test whether the non-negativity constraint explains the shape and the timing of the pollution-income curve

in the U.S. data.

The population of L_t identical households have preferences over end-of-the-period environmental quality N_{t+1} , consumption $\frac{C_t}{L_t}$, and leisure, equal to one less hours worked h_t , in each period. Capital letters denote aggregate quantities. Preferences are given by the utility function:

$$U \left[\frac{C_t}{L_t}, N_{t+1}, h_t \right] = \alpha \log \left(\frac{C_t}{L_t} \right) + (1 - \alpha) \log (N_{t+1}) - \gamma h_t. \quad (1)$$

We use the Hansen (1985) indivisible labor assumption, which implies linear aggregate disutility of labor. A particular issue is the assumption that utility is separable in consumption, leisure and environmental quality. Strong complementarity between consumption and environmental quality would tend to make environmental quality more appealing at high incomes, when consumption and leisure are highest, and less appealing at low incomes.⁷

A constant returns to scale technology exists that produces output, Q_t , from capital, K_t , and productivity-augmented total hours, $h_t L_t A_t$. Here A_t is the level of technology, which grows exogenously at rate ϕ . Population grows at rate η . The production technology is such that:

$$Q_t = K_t^\psi (h_t L_t A_t)^{1-\psi}. \quad (2)$$

Unabated pollution is an exogenous proportion $\frac{1}{B_t}$ of output. Let u_t denote the fraction of emissions abated, then $\frac{1-u_t}{B_t}$ is the emissions intensity of output and emissions, E_t , is:

$$E_t = (1 - u_t) \frac{Q_t}{B_t}. \quad (3)$$

The cost of emissions abatement is $C(u_t) Q_t$. Hence output net of abatement costs, Y_t , is:

$$Y_t = (1 - C(u_t)) Q_t. \quad (4)$$

⁷Given that utility is separable, the pollution-income curve is not very sensitive to labor supply. We have endogenous labor supply in the model to make the calibration easier.

We assume a convex cost function:

$$C(u_t) = 1 - (1 - u_t)^\varepsilon. \quad (5)$$

Using equations (2), (3), (4), and (5) to substitute out for Q_t and u_t implies output net of abatement costs is Cobb-Douglas:

$$Y_t = F(K_t, B_t E_t, h_t L_t A_t) = K_t^\theta (B_t E_t)^\varepsilon (h_t L_t A_t)^{1-\theta-\varepsilon}. \quad (6)$$

Here $\theta = \psi(1 - \varepsilon)$ is the capital share and ε can thus be interpreted as the emissions share.⁸

The economy converges to a balanced growth path, or steady state, where aggregate capital, output, and consumption all grow at the same constant rate $\eta + \phi(1 + \eta)$, and where hours and leisure are constant. We also assume the control rate and emissions, E_t , are constant in the steady state. Therefore, the exogenous growth rate of B_t must equal the growth rate of output.⁹ Exogenous growth of B_t is assumed to capture technological change in abatement and compositional changes in output.

Let capital depreciate at rate δ_k . The resource constraint then sets consumption plus net investment equal to production net of abatement costs:

$$C_t = Y_t + (1 - \delta_k) K_t - K_{t+1}. \quad (7)$$

Environmental quality is a decreasing function of the stock of pollution, M_{t+1} :

$$N_{t+1} = \widehat{M} - M_{t+1}. \quad (8)$$

Here \widehat{M} is the maximum sustainable pollution stock.¹⁰ We assume the pollution concentration decays at a constant rate δ_m . Therefore the stock of pollution accumulates according

⁸The total cost of emissions equals $Q_t - Y_t$, which is decreasing in B_t from equation (6). Thus B_t can be viewed as cost-reducing technical change.

⁹Writing a model for which emissions are decreasing along the balanced growth path poses theoretical problems. In particular, such a model requires exogenous emissions intensity to fall faster than exogenous labor productivity rises. Thus, emissions saving technological change would continue at a constant rate, despite having marginal benefits that approach zero.

¹⁰See Appendix D for a derivation.

to:

$$M_{t+1} = E_t + (1 - \delta_m) M_t. \quad (9)$$

The objective function of the social planner is to maximize lifetime utility of all households:

$$V = \max_{C_t, K_t, E_t, h_t} \left\{ \sum_{t=0}^{\infty} \beta^t L_t \left[U \left(\frac{C_t}{L_t}, N_{t+1}, h_t \right) \right] \right\}. \quad (10)$$

The problem can be normalized with economic variables written in per productivity unit terms. Let the units of emissions be such that $A_0 L_0 = B_0$, let $k_t = \frac{K_t}{L_t A_t}$ and similarly for c_t and y_t and assume $\beta(1 + \eta) < 1$. Then the social planning problem is:

$$v = \max_{C_t, K_t, E_t, h_t} \sum_{t=0}^{\infty} (\beta(1 + \eta))^t [U(c_t, N_{t+1}, h_t)], \quad (11)$$

subject to:

$$c_t = F(k_t, E_t, h_t) + (1 - \delta_k) k_t - (1 + \eta)(1 + \phi) k_{t+1} \quad (12)$$

$$N_{t+1} = \widehat{M} - M_{t+1} \quad (13)$$

$$M_{t+1} = E_t + (1 - \delta_m) M_t. \quad (14)$$

In addition, maximum and minimum emissions exist corresponding to $u = 0$ and $u = 1$:

$$0 \leq E_t \leq k_t^{\frac{\theta}{1-\varepsilon}} h_t^{\frac{1-\theta-\varepsilon}{1-\varepsilon}}. \quad (15)$$

If $u = 0$, we have a corner solution with no abatement, maximum emissions $E_t = k_t^{\frac{\theta}{1-\varepsilon}} h_t^{\frac{1-\theta-\varepsilon}{1-\varepsilon}}$, and the non-negativity constraint on abatement given by equation (15) is binding. The recursive version of the problem is:

$$v(k, M) = \max_{k', h, M'} \left\{ U \left[F(k, E, h) + (1 - \delta_k) k - (1 + \eta)(1 + \phi) k', \widehat{M} - M', h \right] + \beta(1 + \eta) v(k', M') \right\}.$$

The maximization is subject to (14) and (15).

5 Calibration

In contrast to the panel studies, we focus solely on U.S. data. Our “out-of-sample” strategy is to calibrate using recent (steady state) U.S. data, then compare the predicted and actual pollution-income curves along the transition path. All data are described in Appendix B.

5.1 Assignment of Model Parameters

Most of the economic parameters are calibrated in an identical manner to the previous literature (see for example Cooley and Prescott, 1995). In general, we choose the parameters to match certain long run average features of the data. We do not use the observed dynamic relationship between emissions and income in the data to calibrate any of the parameters, since we are testing this aspect of the model.

We calibrate the rate of growth in population so that the rate of growth in population in the model economy matches the average rate of growth in population in the data over the sample period. Similarly, the rate of growth of technology is chosen so that the steady state rate of growth in per capita output, ϕ , in the model economy matches the average rate of growth in per capita output in the data. We define investment, X , as:

$$X_t = K_{t+1} - (1 - \delta_k)K_t. \tag{16}$$

Since in the steady state investment, output, and capital all grow at the same rate, the steady state investment to capital ratio, $\frac{X}{K}$, is:

$$\frac{X}{K} = (1 + \eta)(1 + \phi) - (1 - \delta_k). \tag{17}$$

Using (17), we choose δ_k so that the model economy matches the investment to capital ratio of the data.

Let $\rho = \frac{1-\beta}{\beta}$ be the pure rate of time preference. The first order condition for optimal

investment at the steady state is then:

$$[(1 + \rho)(1 + \phi) - (1 - \delta_k)]k = \theta y. \quad (18)$$

Equation (18) implies θ is the share of income accruing to capital owners since the left hand side is the return on capital. Let I_t denote capital income, then we choose $\theta = \frac{I}{Y}$, so that the share of income accruing to capital owners in the model matches the average share of income accruing to capital owners in the data.¹¹ Then using (18), ρ is chosen so that the steady state capital to output net of abatement costs ratio in the model economy matches the data. We thus assign the parameters ρ , ϕ , η , δ_k , and θ using the standard technique of Cooley and Prescott (1995). Table 3 gives the calibrated values of the economic parameters.¹²

We use scientific studies to calculate the rate of decay of the stock of pollution, δ_m . We classify pollutants that survive in the atmosphere for less than a year as flows ($\delta_m = 1$). Particulates, SO₂, NO_x, lead and VOCs all last in the atmosphere for less than a week. CO has an atmospheric residence time of one to three months. One type of VOC, hydrocarbons, has a residence time of 16 years. Since we cannot separate the spending on hydrocarbons from other VOCs, we use an average residence time of eight years ($\delta_m = 0.125$).¹³

We explore three alternatives for the calibration of the emissions share, ε . Ideally, the emissions share may be computed using observed tax rates or permit prices if the government uses a market-based regulation instrument. The planning problem of Section 4 can be decentralized into a competitive equilibrium in which the marginal product of emissions equals the tax rate per unit of emissions (or the price of a tradeable permit that allows one

¹¹The capital share depends on y , output net of compliance spending, rather than total output, q . Since y is pollutant specific, the capital share is pollutant specific. This is an artifact of running the model separately for each pollutant, rather than considering all pollutants together, an assumption we make for computational simplicity. In practice, because compliance spending is a small fraction of GDP, the capital share and most other economic parameters are nearly identical across pollutants.

¹²Differences between Table 3 and Cooley and Prescott (1995) arise due to NIPA data revisions and because we use a different time period.

¹³The Environmental Protection Agency (2000b) estimates 43-50% of VOC emissions are hydrocarbons.

unit of emissions). Thus, with τ denoting the tax rate (or permit price), we have:

$$\tau = \varepsilon BzK^\theta (BE)^{\varepsilon-1} H^{1-\varepsilon-\theta}. \quad (19)$$

Equation (19) then implies:

$$\frac{\tau E}{Y} = \varepsilon. \quad (20)$$

Hence we choose ε so that the share of income spent on emissions taxes (or permits) equals the average share of income spent on permits or taxes in the data. It is important to note we only use data from a developed economy at the steady state to calculate ε . In the transitional dynamics, changes in the marginal product of emissions as a country develops are important for the shape of the pollution-income curve (see Kelly, 2003). However, we reiterate that our calibration only utilizes data from a fully developed economy, so ε is not chosen to match the peak of the pollution-income curve in any way.

Unfortunately among the pollutants in the data only SO₂ regulation is market-based. For the remaining pollutants (and SO₂, for comparison) we use EPA environmental compliance cost data to calibrate the emissions share. From equation (5):

$$\varepsilon = \frac{\log(1 - C(u_t))}{\log(1 - u_t)}. \quad (21)$$

We thus set ε so that the elasticity governing the sensitivity of compliance costs to the control rate matches the average elasticity in the data. Unfortunately, the EPA provides control rate data only for the period 1984-1988, so this method of calibration relies on a small data set.

A third method involves combining equations (3) and (5):

$$\frac{BE}{Q} = (1 - C(u_t))^{\frac{1}{\varepsilon}}.$$

Hence ε equals:

$$\varepsilon = \frac{\log(1 - C(u_t))}{\log\left(\frac{B_0[(1+\phi)(1+\eta)]^t E}{Q}\right)}. \quad (22)$$

Note that since B grows at the same rate as output and emissions is constant along the balanced growth path, BE/Q is also constant along the balanced growth path and equals $1 - u$. Thus we can set ε to match the cost/control rate elasticity, but use BE/Q data rather than control rate data.

We have then three calibration strategies, each with some advantages and disadvantages. Choosing ε to match spending on pollution permits has the advantage of relying on higher-quality market data. However, permit data is available only for SO_2 . Calibrating ε using BE/Q requires construction of an estimate of exogenous improvements emissions intensity, which is highly variable. Calibrating ε to match control rate data does not require information on emissions intensity improvements, but data is available only for five years. All methods yield reasonably similar results (see Tables 4 and 5). Section 7 shows that a large change in ε is needed to affect the results, so for the remainder of the paper we employ the control rate calibration.

An example may help the reader understand the calibration. Consider that in 1986 lead emissions dropped from 22.9 to 7.3 million short tons. In that year, compliance spending was nearly unchanged at 0.007% of output, and the control rate increased from 91% to 96%. Using the second method, the 1986 observation indicates almost all lead emissions were controlled at little cost, and therefore the technology for controlling lead emissions appears very efficient, and thus ε is small. Given that lead emissions fell dramatically without any increase in costs, it is clear that the exogenous part of emissions intensity $1/B_{1996}$ fell dramatically. However, the model assumes a constant rate of growth in exogenous emissions intensity. Given an average improvement in emissions intensity and a large decline in emissions, the denominator in (22) falls and ε needs to be larger to match the 1986 cost data.¹⁴ Thus in 1986 the cost strategy overestimates ε because it does not account for the unusual fall in emissions intensity. Relying on the control rate data avoids this problem, but,

¹⁴That regulations changed is not relevant, since ε measures only technological cost of reducing emissions.

again, that data is only available for five years.

Let subscripts on functions denote derivatives. The first order condition for optimal emissions at the steady state is:

$$((1 + \rho) - (1 + \eta)(1 - \delta_m)) U_c(c, \widehat{M} - M, h) F_E(k, E, h) = U_N(c, \widehat{M} - M, h) (1 + \rho). \quad (23)$$

Hence:

$$((1 + \rho) - (1 + \eta)(1 - \delta_m)) \varepsilon \frac{Y}{C} \alpha = (1 + \rho) \frac{E}{\widehat{M} - M} (1 - \alpha). \quad (24)$$

Equation (24) equates the marginal benefits and marginal costs of emissions at the steady state. We therefore set α so that steady state emissions in the model matches long run average emissions in the data.

The first order condition for optimal hours worked at the steady state is:

$$\gamma = U_c(c, \widehat{M} - M, h) F_h(k, E, h). \quad (25)$$

Hence:

$$\gamma = \frac{Y}{C} \frac{\alpha(1 - \theta - \varepsilon)}{h}. \quad (26)$$

Given the ratio Y/C implied by the model, we calibrate γ so that the steady state fraction of time spent working in the model matches the data.

It is typical to assume the U.S. economy is fluctuating around a deterministic balanced growth path, or steady state. Hence, variables and ratios which are constant in the steady state can be taken as the long run average of U.S. data. Since the model generates constant steady state emissions, we expect that in the data emissions are also fluctuating around a constant value. Emissions of most pollutants, however, are either trending downward or appear to be fluctuating around a constant value only recently. Therefore, we must choose a suitable time period during which emissions of each pollutant is assumed to be fluctuating around a constant value. Particulates have been roughly constant since 1980 and lead since

1986. Thus we use 1980-1998 and 1986-1998 data to calculate the steady state emissions and abatement costs for particulates and lead, respectively. However, SO_2 , NO_x/CO , and VOCs have only leveled off recently, if at all. SO_2 and NO_x/CO are roughly constant over the period 1995-1998, while VOCs are roughly constant over the period of 1996-1998. For all pollutants, a time series forecast indicates a steady state very close to current levels. We therefore use 1995-1998 data to calculate the steady state emissions and abatement costs for SO_2 and NO_x/CO and 1996-1998 data for VOCs. The model then implicitly assumes the U.S. is transitioning to a balanced growth path over the period 1952 to the period where emissions are fluctuating around their steady state value, with k , y , and abatement spending increasing and E decreasing. This matches the data, with k and y increasing 10-20% over the transition period.¹⁵ An alternative is to calibrate without assuming the economy is in a steady state. We explore this possibility in Section 7.

We have thus chosen nine parameters to match various features of the U.S. economy. Five economic parameters depend only on the environmental data in that y differs from q , which makes no difference up to two significant digits. One parameter is chosen from scientific studies. The remaining three parameters are derived using only data from a developed economy (1980 and after) and are in fact chosen to match the hours, emissions, and environmental compliance cost elasticity of the recent U.S. economy. An interesting question is the prediction of the model for transition economies, which we turn to next.

6 Results

The model was solved using the method of Kelly and Kolstad (1999), which computes non-linear approximations of the value function and decision rules $E(k, M)$, $k'(k, M)$, and $h(k, M)$. Since $q = k^\psi h^{1-\psi}$, the decision rule may be written as $E(q^{\frac{1}{\psi}} h^{\frac{\psi-1}{\psi}}, M)$. For the flow pollutant categories (particulates, SO_2 , NO_x/CO , and lead), the decisions are independent

¹⁵Most of the increase in k and y occur prior to 1980. We therefore use the period 1980-1998 to calculate the economic ratios.

of M ; therefore the pollution-income curve $E(q)$ shares a similar shape with $E(k)$,¹⁶ and thus also with the pollution-income curve generated from time series data starting from a less-developed initial condition (k_0 equal to a small positive number). For the stock pollutant category, VOCs, the effect of an increase in income on emissions (or the end of the period pollution stock M') varies with M , so we report several versions of the pollution-income curve.

The model exhibits an inverted U-shape pollution-income curve for all flow pollutants (see Figures 2-5). Specifically, for sufficiently low incomes (low capital stocks), our model displays a corner solution. When income is low, no abatement exists. The planner prefers to set abatement equal to zero in order to increase output and thus increase consumption. Hence, the constraint that emissions cannot exceed emissions with zero abatement (equation 15) binds. Then, as the capital stock increases past a certain level, abatement rises above zero and emissions decline.

For the stock pollutant VOCs, the shape of the pollution-income curve varies according to how pollution is measured. No matter the value of M , emissions have an inverted U-shape as a function of income. If we generate a time series starting from a sufficiently small k_0 and M_0 and plot emissions as a function of q , the result is again an inverted U-shape (see Figure 6). However, if we use the same time series, but plot M as a function of q , then the pollution-income curve is increasing. The current stock of pollution is a function of all previous emissions decisions and thus all previous incomes. Therefore, the stock will tend to increase with income even if emissions are a decreasing or inverted U-shaped function of current income.¹⁷

Analytically, for flow pollutants, the optimal emissions are determined from the trade-off between the marginal benefit of emissions, equal to the marginal product of emissions

¹⁶Section 7 shows that h has little effect on E .

¹⁷Kelly (2003) show this result is a possibility in numerical examples.

times the marginal utility of consumption, and the marginal cost of emissions, equal to the marginal utility of environmental quality. For our calibrated values, the marginal utility of consumption falls with income whereas the marginal utility of environmental quality is relatively constant in income. Hence the unconstrained pollution-income curve is decreasing. Further, the emissions constraint is concave in capital. Together, these facts imply that the pollution-income curve will be inverted U-shaped or increasing and the constraint that emissions cannot be negative will be binding for sufficiently low incomes (see Figure 7). Indeed, we prove this theoretically in Appendix C. For the stock pollutant VOCs, it turns out that emissions continue to increase for a short income interval after the constraint is no longer binding (the slope of the unconstrained pollution-income curve becomes less than the slope of the constraint, but still is positive). Emissions then decline once income exceeds this interval. Thus the nature of the cost function, rather than the non-negative abatement constraint, explains the inverted U-shape for VOCs.¹⁸

Although we garner an inverted U-shape, the downward turn occurs very early in development. Table 1 shows that the peak emissions occur between 10 and 13 percent of the steady state capital stock, whereas in the data the peak occurs between 77 and 90 percent of the steady state capital stock. Why does the model predict emissions peak so early in development? In the steady state U.S. economy, compliance spending is small relative to output. Steady state abatement for all pollutants is 70-74% of uncontrolled emissions. Yet, steady state compliance spending is well under 1% of output for each pollutant. Therefore the calibration chooses a small ε to reflect that abatement is relatively inexpensive in the data. But if pollution is inexpensive to abate, then countries can afford to abate at a relatively low income. Indeed, it is apparent from the calibration that the puzzle in the data is why the U.S. waited until 1970 to begin significant abatement, given that abatement is so

¹⁸Kelly (2003) shows the non-negativity constraint is not necessary for an inverted-U in a simpler version of this model.

inexpensive. This is most striking for lead emissions. The U.S. reduced lead emissions from 255 million short tons in 1972 to 4.5 million short tons in 1992, but compliance spending rose from essentially zero to only 0.015% of output. Given that lead emissions could be reduced so inexpensively, why was compliance spending still essentially zero in 1972, when the U.S. output per capita was \$32,396? We explore possible answers in Sections 7 and 8.

Emissions would also peak later in development if the parameter governing household preferences for environmental quality, $1 - \alpha$, were lower. However, the calibration requires households have some preference for environmental quality, otherwise emissions would decline little and end up at a higher steady state than observed in the U.S. data.

Alternative parameter values exist that can generate an emissions peak identical to the data (see Section 7), but these parameter values are unrealistic. They imply emissions reduction is more costly, or that households have weaker preferences for environmental quality, than is apparent in the U.S. data.

Turning now to the empirical studies, our U.S. data is more consistent with the later empirical studies, which predict emissions peak at a relatively high income, if at all. According to our model, emissions peak early in development, which is more consistent with the earlier empirical studies that predict emissions peak for middle income countries. Still, comparisons are difficult because the literature focuses on output per capita as the state variable rather than output per productivity unit, which is the state variable of our model. If the data is cross sectional and all countries have the same technology, then our model maps one-to-one into the empirical literature by simply multiplying output per productivity unit by A_t . However, most empirical studies use panel data, so two data points with nearly the same income per capita but different years could represent significantly different places on the transition path.

Our results thus provide some guidance to the empirical literature. Our state variable is output per productivity unit rather than output per capita. In the empirical literature, the

regression is of the form:

$$E_t = \beta_0 + g\left(\frac{Y_t}{L_t}; \beta_1\right) + h(t; \beta_2) + \zeta_t \quad (27)$$

Thus the time trend may pick up a mixture of time-related effects: productivity advances, compositional changes, emission efficiency innovations, and any structural breaks that may have occurred (e.g. a shift in preferences in the 1970s). In contrast, our model allows only one explanation for the EKC, and so the relationship between emissions and time is more restrictive:

$$E_t = g\left(\frac{1}{A_t} \cdot \frac{Y_t}{L_t}; \beta_1\right) + \zeta_t. \quad (28)$$

Or if productivity data is not available:

$$E_t = g\left(\frac{1}{A_0(1+\phi)^t} \cdot \frac{Y_t}{L_t}; \beta_1\right) + \zeta_t. \quad (29)$$

Figures 2-6 show the results of estimating a quadratic version of equation (28).¹⁹ Thus, the corner solution idea points toward using income per productivity unit without a time trend as a regressor in reduced form regressions.

7 Sensitivity Analysis

Here we perform sensitivity analysis to check robustness of the results and to gain insight as to what parameters most affect the peak emissions. Each row of Table 6 is a simulation that holds all parameters constant at the values determined by the particulates calibration except for the given parameter. The critical value is the value of the given parameter that results in an emissions peak equal to the emissions peak in the U.S. data, about 77.25% of the steady state capital stock for particulates. Most of the parameters have little effect on the emissions peak. The consumption share α and emissions share ε are clearly the most

¹⁹The quadratic term is negative and significant at the 5% level for all pollutants. In contrast, if equation (27) is estimated, with g quadratic, then the quadratic term is negative and significant for two pollutants if h is linear, for one pollutant if h is cubic, and for no pollutants if h is quadratic.

important parameters, since these affect the central trade-off between environmental quality and consumption. A higher α means the marginal utility of consumption is higher, and thus optimal unconstrained emissions rise across the development path. Higher unconstrained emissions in turn implies that the abatement non-negativity constraint becomes non-binding at a later stage of development (a larger k). Graphically, this corresponds to a shift to the right of the optimal emissions curve in Figure 7. A higher ε means the marginal product of emissions is greater, increasing the incentive to emit regardless of development and causing the unconstrained optimal emissions curve to shift to the right. However, it is important to note that increasing α and ε also cause steady state emissions to rise. If we change α or ε so that the model predicts an emissions peak of 77.25% of the steady state capital stock, then the model predicts steady state emissions that are about three times the levels observed in the U.S. data.

The most important economic parameter is γ . Increasing preferences for leisure (increasing γ) decreases hours and thus income. Lowering income increases the marginal utility of consumption, which in turn increases incentives to emit and hence causes emissions to peak later. Decreasing hours also tightens the constraint that requires abatement to be positive (see equation 15). This also causes emissions to peak later. However, to get emissions to peak as in the U.S. data requires increasing γ to a point such that steady state hours are 27% below that in the U.S. data.

Increasing δ_k , η , and ϕ lower income per-productivity unit available for consumption and abatement. The marginal utility of consumption thus falls and optimal emissions rise, which causes emissions to peak later. Increasing ρ or decreasing θ reduces investment, freeing up income to be spent on consumption and abatement. This causes optimal emissions to fall and emissions to peak earlier. However, reducing investment also reduces the steady state capital stock. For an increase in ρ the second effect dominates: emissions peak at a lower capital stock, but at a higher percentage of the steady state capital stock. The first effect

dominates for low values of θ , the second effect for high values of θ .

Table 6 shows that economic parameter values *exist* for which the model replicates the U.S. experience, where emissions peaked late in development. However, these parameter values are *unrealistic*: they are contrary to intuition and imply the model will not perform well in a variety of other standard dimensions.

To examine interaction effects among the parameters, we randomly select a sample of parameter vectors from an assumed distribution, solve the model for each parameter vector, and calculate the emissions peak. We then compute statistics from the resulting emissions peak data. To keep the computations manageable, we allow only the two parameters that are most uncertain and most strongly affect the emissions peak, α and ε , to vary. We assign a very conservative distribution for each parameter. We assume α and ε are uniformly distributed, with lower bound equal to the baseline value and upper bound equal to the value that results in steady state emissions that are twice that of the U.S. data when all other parameters are held at their baseline values.²⁰ Thus:

$$\begin{bmatrix} \alpha \\ \varepsilon \end{bmatrix} \sim \text{UNIFORM} \begin{bmatrix} 0.9238, 0.9612 \\ 0.0014, 0.0028 \end{bmatrix}.$$

We ran 100 simulations, the results of which are summarized in Table 7. We reject the hypothesis that the emissions peak is greater than or equal to 50% of the steady state capital stock given the assumed parameter uncertainty with 95% confidence. We therefore conclude that the results of the model are robust to reasonable joint parameter uncertainty.

An additional test of the robustness of the model is to repeat the calibration exercise without assuming the economy is in a steady state. Following the steps in Section 5.1, we

²⁰Since we lack a statistical distribution for α and ε , we simply assume a conservative distribution. The resulting distribution of emissions peak should not be taken as providing a confidence interval for the emissions peak, but rather as an indication that no strong interaction effects exist: a small increase in α and ε do not produce a large increase in the emissions peak.

solve equation (16) for δ_k , which gives the analog of equation (17):

$$\delta_k = 1 - \frac{K_{t+1}}{K_t} + \frac{X_t}{K_t}. \quad (30)$$

We thus take δ_k to be the sample average of the right hand side of equation (30). The equations which determine η , θ , ε , and δ_m do not assume the economy is in a steady state, so η , θ , ε , and δ_m are calibrated as in Section 5.1. We then compute ϕ as a ratio of the growth in output to the growth in inputs:

$$\begin{aligned} \frac{Q_{t+1}}{Q_t} &= \frac{K_{t+1}^\psi (A_{t+1} L_{t+1} h_{t+1})^{1-\psi}}{K_t^\psi (A_t L_t h_t)^{1-\psi}} = \left(\frac{K_{t+1}}{K_t}\right)^\psi (1 + \phi)^{1-\psi} \left(\frac{L_{t+1}}{L_t}\right)^{1-\psi} \left(\frac{h_{t+1}}{h_t}\right)^{1-\psi}, \\ \phi &= \left(\frac{Q_{t+1}}{Q_t}\right)^{\frac{1}{1-\psi}} \left(\frac{K_{t+1}}{K_t}\right)^{\frac{-\psi}{1-\psi}} \left(\frac{L_{t+1}}{L_t}\right)^{-1} \left(\frac{h_{t+1}}{h_t}\right)^{-1} - 1. \end{aligned} \quad (31)$$

Hence ϕ is the sample average of the right hand side of equation (31). The capital share equation is Euler equation evaluated at the steady state. Here we solve the Euler equation for ρ without imposing the steady state:

$$\begin{aligned} \frac{(1 + \phi)}{c_t} &= \frac{\beta}{c_{t+1}} \left(\frac{\theta y_{t+1}}{k_{t+1}} + 1 - \delta_k \right), \\ \rho &= \frac{1}{1 + \phi} \left(\frac{c_t}{c_{t+1}} \right) \left(\frac{\theta y_{t+1}}{k_{t+1}} + 1 - \delta_k \right) - 1 = (1 + \eta) \left(\frac{C_t}{C_{t+1}} \right) \left(\frac{\theta Y_{t+1}}{K_{t+1}} + 1 - \delta_k \right) - 1. \end{aligned} \quad (32)$$

Thus ρ is set to match the sample average of the right hand side of equation (32), so that on average the intertemporal marginal rate of substitution equals the interest rate. The equation which determines α is the Euler equation for optimal emissions:

$$\varepsilon \alpha \frac{Y_t}{C_t} = (1 - \delta_m) \frac{(1 - \alpha) E_t}{\widehat{M} - (1 - \delta_m) M_t - E_t} + \beta \alpha \varepsilon (1 - \delta_m) \frac{Y_{t+1}}{C_{t+1}} \frac{E_t}{E_{t+1}}. \quad (33)$$

Since we have only data on emissions, not concentrations, equation (33) can only be used to compute α for flow pollutants. Imposing $\delta_m = 1$ and solving for α gives:

$$\alpha = \left(1 + \varepsilon \frac{Y_t}{C_t} \left(\frac{\widehat{M} - E_t}{E_t} \right) \right)^{-1}. \quad (34)$$

So we set α to match the sample average of the right hand side of equation (34). The equation for γ is identical to equation (26):

$$\gamma = \frac{Y_t}{C_t} \frac{\alpha(1 - \theta - \varepsilon)}{h_t}.$$

Calibration of α and γ change in that the output-consumption ratio now comes from the data, rather than the steady state output-consumption ratio implied by the model.

It remains to choose a suitable time period to use for determining the parameter values. In principle, all data is available over the period 1965-1998, except for the cost and control rate data, which we need only to calibrate ε . Typically, the literature calibrates using data prior to the event the model is trying to explain and then tests the model on the event. For example Bergoeing, Kehoe, Kehoe, and Soto (2002) seek to explain the slow recovery of the Mexican economy following a shock which occurred in 1980. They therefore calibrate using 20 years of data, 1960-80, and then test the model on the recovery period 1980-90. However, in our model peak emissions are endogenous. No exogenous shock exists to differentiate the calibration period from the test period. One strategy is to simply use the entire data set. On the other hand, using emissions data near or prior to the peak emissions means the test is no longer out of sample. We therefore also try calibration over the period 1978-1998.

Table 8 shows the parameter values. All economic parameters are very similar except ϕ . This is because most economic ratios fluctuate around a relatively constant value over the 1965-1998 period, indicating the steady state assumption is reasonable. An exception is ϕ which is lower due to the well known productivity slowdown in the 1970s. The calibration of ε is unchanged since that calibration relies on cost data which is only available for a small number of years. The calibration of α will generally rise since we are now including data with higher emissions, indicating a stronger preference for consumption. A higher α in turn causes the calibrated value of γ to rise. On the other hand, the calibration outside the steady state uses the output to consumption ratio in the data of about 1.6, whereas the steady state calibration uses the model steady state output consumption ratio of 1.3. This

tends to lower α , but increase γ .

The only parameters for which the results display even a limited amount of sensitivity to are α and ε . So the results will change only if the data, which has higher emissions, increases α enough. Table 8 indicates that α actually falls slightly for PM, NO_x/CO , and lead due to the higher output to consumption ratio. Emissions thus peak even earlier than in the previous calibration, with the exception of PM using the full data set, in which case changes in other parameters cause the emissions peak to rise slightly. For SO_2 , α is quite a bit higher and emissions peak later. In particular, Table 8 indicates that SO_2 emissions peak at 43.8% and 50.0% of the steady state capital stock depending on if 20 years or the entire data set is used. In the data, emissions peak at 90.2% of the steady state capital stock. As noted above, the model with a larger α predicts higher steady state emissions (and thus a smaller downturn in emissions) than that in the data. Further, using the 1965-98 data set means the test is no longer out of sample. Nonetheless, the timing of the emissions peak is closer to the data if the entire data set is used for SO_2 .

Another interesting check is to look for structural breaks in the parameter values. In particular, a number of unusual events coincide with the peak emissions for four of five pollutants during the period of 1970-1973, such as the first oil crisis, passage of the Clean Air Act, and significant growth of the environmental movement. Were such events a consequence of growth, implying we should observe no change in the parameter values, or were these events exogenous shocks to technology and/or preferences that altered parameter values? Our data begins in 1965 for flow pollutants PM, SO_2 , and NO_x/CO , and so we can calculate the value of α using data from 1965-73 and then from 1974-98, both without assuming the economy is in a steady state. For PM and SO_2 , α is quite different across the two sub samples. For PM, α equals 0.951 using the 1965-73 data set and 0.913 using the 1974-98 data set. For SO_2 , α equals 0.917 using the 1965-73 data set and 0.853 using the 1974-98 data set. The values of α for the whole data set, given in Table 8 of 0.923 for PM and 0.870 for SO_2 are

thus intermediate values. However, for NO_x/CO , α is essentially unchanged. To see the effect on the emissions peak, we solved the model for PM and SO_2 for both the high and low value of α . We then simulated the model assuming the structural break occurred when k equaled 88% of the steady state capital stock, as was the case in 1973. For PM, the peak in the model occurs prior to the structural break, so the value of α generated from the 1965-73 data now determines the peak, at 38% of the steady state capital stock. The rate of decline in emissions simply increases after 1973 (see Figure 8). Still, the capital stock at which emissions peak is about three times greater than the peak generated from the entire data set. For SO_2 , the peak using the 1965-73 data set occurs after the structural break, while the peak using the 1974-98 data set occurs prior to the structural break. Combining these facts means that the model predicts a peak at the time of the structural break, nearly identical to the data (Figure 9). Thus, allowing a structural break in preferences improves the results for PM and SO_2 .

A final robustness check is to consider a more general specification for the cost function, equation (5). Let:

$$C(u_t) = 1 - \left((1 - \lambda) + \lambda(1 - u_t)^\nu \right)^{\frac{1}{\nu}}, \quad (35)$$

then the production net of abatement costs now has constant elasticity of substitution between emissions and q_t :

$$y = \left((1 - \lambda) \left(k_t^\psi h_t^{1-\psi} \right)^\nu + \lambda E^\nu \right)^{\frac{1}{\nu}}. \quad (36)$$

Equation (36) reduces to the previous cost and production function for the special case of $\nu = 0$ and $\lambda = \varepsilon$. It is straightforward to show that $C(u_t)$ satisfies our maintained assumptions if and only if $\nu < 1$ and $0 < \lambda \leq 1$.

Repeating the calibration exercise of Section 5.1, the calibration equations for δ_k , δ_m , η , and ϕ do not change. The remaining calibration equations are now:

$$\lambda = \frac{1 - (1 - C(u))^\nu}{1 - (1 - u)^\nu}, \quad (37)$$

$$\psi = \left(\frac{I}{Y} \right) \frac{(1 - C(u))^\nu}{(1 - \lambda)}, \quad (38)$$

$$\rho = \left(\frac{1}{1 + \phi} \right) \left(\psi (1 - \lambda) (1 - C(u))^{-\nu} \left(\frac{Y}{K} \right) + 1 - \delta_k \right) - 1, \quad (39)$$

$$\alpha = \left(1 + \left(\frac{Y}{C} \right) \left(1 - \frac{(1 - \lambda)}{(1 - C(u))^\nu} \right) \left(\frac{\widehat{M} - M}{E} \right) \left(1 - \frac{(1 + \eta)(1 - \delta_m)}{(1 + \rho)} \right) \right)^{-1}, \quad (40)$$

$$\gamma = \alpha \left(\frac{Y}{C} \right) \frac{(1 - \lambda)(1 - \psi)}{(1 - C(u))^\nu h}. \quad (41)$$

The calibration equations are identical to the previous calibration equations for $\nu = 0$ and $\lambda = \varepsilon$. Given an assumed value for ν , equations (37)-(41) form a system of 5 nonlinear equations for unknowns λ , ψ , ρ , α , and γ , using the steady state values of $C(u)$ and Y/C implied by the model. The parameters are chosen jointly to match the long run average values of u , I/Y , Y/K , E , and h in the data.

Table 9 gives the calibrated parameter values for several values of ν for the particulates case. Most calibrated parameter values change little from the previous calibration, but the peak emissions tend to rise as ν approaches one. If abatement costs are nearly proportional to control rates ($\nu = 0.9$), emissions peak at 65.6% of the steady state capital stock, close to the 77.25% peak in the data.²¹ The results are thus robust to some changes in the production function, but if abatement costs are nearly proportional to control rates, the model can replicate the late emissions peak observed in the data.

8 Conclusions/Implications

Our results show increasing and then decreasing pollution emissions as income rises. At first, abatement is equal to zero. People are more interested in eating than environmental quality. Then, preferences for environmental quality come into play and the abatement constraint ceases to bind. Indeed, if we remove the requirement that abatement must be non-negative, we find a decidedly negative relationship between income and emissions.

²¹As ν approaches one, emissions decrease more and more sharply after the peak. Thus it becomes more computationally difficult to precisely compute both the parameter values and the optimal decision rules. Thus we report results only up to $\nu = 0.9$.

The fact that abatement is initially equal to zero (a corner solution) is in accord with Stokey (1998) and others. However, the model predicts that emissions peak early in development, largely because abatement is inexpensive relative to output, according to U.S. emissions and compliance spending data. The results are robust across pollutants and alternative calibrations, with the possible exception of SO_2 , or if abatement costs are nearly proportional to control rates. Thus the results imply an interesting puzzle: why did the U.S. wait until the 1950s to begin significant abatement for particulates and until the 1970s for all other pollutants?

Although we test only one theoretical explanation, the corner solution, other standard theories are not likely to fare better. Consider the institutional explanation of Jones and Manuelli (1995). The U.S. clearly had many functioning institutions common to developed countries prior to 1970 (justice system, etc.). Why did the EPA not arise until 1970? Or consider the theory of Andreoni and Levinson (2001) that increasing returns to abatement exist. Since total compliance costs, including fixed costs, are small, why the U.S. require such a high income to make it optimal to pay the fixed costs and begin abatement?

Less standard explanations may hold some promise. Adding uncertainty either over the cost of abatement or the damage from pollution could explain some of the delays. Similarly, a significant technological innovation could have reduced the cost of abatement in the 1970s. The peak could be linked to increases in the price of energy during the 1970s. Or perhaps a shift in preferences for environmental quality in the 1970s caused the observed increase in abatement. Indeed, we have shown α does fall when estimated over the period 1965-73 versus 1974-1998 for PM and SO_2 . Thus, the model performs better when a structural break is added. Apparently, both structural breaks and economic growth contribute to the shape of the EKC, and the contribution varies by pollutant.²²

²²Empirically, it is difficult to differentiate between structural breaks and other hypotheses and structural breaks do not alone imply an inverted U-shape pollution-income curve. Deacon and Norman (2006) look at time series data for a variety of countries and find a similar empirical result to ours for the U.S. They

Another possibility is that the corner solution is the correct idea, but some modifications of the model are needed. For example, the functional form of the cost or utility functions could be incorrect. The modified cost or utility function would have to raise emissions only for low and middle income stages of development, however.

Empirical work of late has called into question whether the relationship between growth and pollution is a simple inverted U-shape. Our results show that existing theory may need substantial modifications to explain the U.S. experience with growth and pollution. The relationship between economic growth and the environment is apparently considerably more complicated than once thought. Nonetheless, the effect of economic growth on the environment is an important problem and is therefore deserving of continued research.

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speculate that the downward trend in emissions since the 1970s may be a result of a shift in preferences, but note that other explanations may be observationally equivalent.

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Appendix A Tables

Empirical Studies	Pollutant				
	PM	SO ₂	NO _x /CO	Pb	VOCs
GK	\$9,011	\$5,967			
SS	\$15,221	\$12,786	\$8,767-\$16,560		
SC		\$123,188			
HL				\$12,420	
HLW		\$27,700-\$96,507	\$7,956	\$21,070	
U.S. Empirical Studies					
LG		\$19,920-\$34,055	\$13,071-\$26,541		
MLS		\$12,080-\$24,790	\$13,072-\$18,120		
Our Data (US\$)	\$20,983	\$35,091	\$34,296	\$34,296	\$32,396
Our Data (% \bar{k})	77.25%	90.22%	86.75%	83.53%	83.53%
Our Results	12.6%	12.7%	12.5%	10.0%	15.5%

Table 1: Emissions peaks for selected empirical studies, for our U.S. data, and for our model. All dollar values are in constant year 2000 dollars. Empirical studies are GK, Grossman and Krueger (1995), SS, Selden and Song (1994), SC, Stern and Common (2001), HL, Hilton and Levinson (1998), LG, List and Gallet (1999), MLS, Millimet, et al. (2003), and HLW, Harbaugh, Levinson, and Wilson (2002). Our U.S. GNP data is modified by adding imputed services from government capital and durable goods. The percentages are capital levels at which emissions peak divided by the steady state capital, \bar{k} .

Econometric Model		Pollutant				
Y/L	t	PM	SO ₂	NO _x	VOC	Pb
Log-Quad.	None	\$8,391 (110-∞)	\$31,866 (30,662-32,976)	\$34,322 (33,518-35,277)	\$31,124 (30,606-31,797)	∞
Log-Quad.	Linear	∞	\$57,974 (39,680-116,511)	\$35,278 (29,032-42,956)	\$39,553 (33,350-46,617)	∞
Log-Quad.	Quad.	∞	∞	∞	∞	\$43,917 (39,413-502,779)
Log-Cubic	None	\$21,620 (21,052-23,707)	\$35,048 (32,911-35,878)	\$36,659 (35,877-37,228)	\$32,574 (31,336-33,324)	\$50,769 (1,271-∞)
Log-Cubic	Linear	∞	\$48,293 (44,882-52,011)	\$42,310 (39,602-44,618)	\$42,876 (39,015-46,147)	\$99,520 (2,230-∞)
Log-Cubic	Quad.	∞	\$72,045 (53,279-126,829)	\$61,671 (47,429-99,762)	\$131,278 (120-∞)	\$39,304 (38,016-41,976)

Table 2: Econometric estimates of the output per capita at which emissions peak. An infinite result indicates the critical value is a minimum if the econometric model is quadratic, and indicates the estimated relationship is strictly increasing if the econometric model is cubic. 95% confidence intervals calculated via the bootstrap method are in parenthesis.

Parameter	ρ	θ	δ_k	η	ϕ
Value	0.071	0.402	0.046	0.011	0.018-0.019

Table 3: Economic parameter values. Small differences (less than 0.001 for ϕ , less than 0.0001 for all other economic parameters) exist in the economic parameters across pollutants.

	PM	SO ₂	NO _x /CO	Lead	VOCs
Emissions	0.0434	0.0194	0.1179	0.0052	0.0199
Compliance Spending	0.1511	0.1812	0.0221	0.0154	0.0622
Abatement	66.34	29.61	68.76	99.87	39.62
Steady State Period	1980-1998	1995-1998	1995-1998	1986-1998	1996-1998

Table 4: Average yearly emissions (short gigatons) and compliance spending (% of output) in steady state time period. Average abatement (% of unabated emissions) over the period 1985-1989.

Control Rate Calibration					Cost Calibration				Permit Calibration			
	ε	α	γ	δ_m	ε	α	γ	δ_m	ε	α	γ	δ_m
PM	0.00139	0.924	3.640	1	0.00091	0.949	3.741	1				
SO ₂	0.00516	0.756	2.960	1	0.00145	0.918	3.615	1	0.00033	0.980	3.867	1
NO _x /CO	0.00019	0.989	3.905	1	0.00017	0.989	3.908	1				
Pb	0.00002	0.998	3.945	1	0.00015	0.990	3.911	1				
VOCs	0.00123	0.894	3.525	0.125	0.00046	0.958	3.780	0.125				

Table 5: Environmental Parameter values.

Parameter	Base Value	Critical Value	Error	E-peak(parameter)
ε	0.00139	0.004	E : +302%	increasing
α	0.924	0.974	E : +300%	increasing
γ	3.640	9.392	h : -27.2%	decreasing
ρ	0.071	0.753	r : +867%	increasing
θ	0.402	none		inverted-U
δ_k	0.046	0.144	X/K : +228%	increasing
η	0.011	none		increasing
ϕ	0.018	0.109	g_y : +589%	increasing

Table 6: The critical value is the parameter value where emissions peak at 77.25 percent of the steady state capital stock. The error is the difference between the model steady state value and the average of steady state U.S. data which the parameter was calibrated to. The last column indicates how the emissions peak varies with the parameter.

Statistic	Value			95% Confidence Interval	
				lower bound	upper bound
number	100	Hypothesis	Result		
mean	46.0%	peak=77.25	reject	44.4%	52.1%
standard deviation	19.5%	peak >=50	reject	$-\infty$	49.2%
median	43.9%				
maximum	106.4%				
minimum	17.6%				

Table 7: Statistics are from a data set of emissions peaks as a percentage of the steady state capital stock.

Parameters	1978-98 Data					Full Data Set				
Economic	θ	η	δ_k	ρ	ϕ	θ	η	δ_k	ρ	ϕ
	0.402	0.012	0.049	0.066	0.013	0.405	0.015	0.048	0.074	0.012
Environmental	δ_m	ε	α	γ	E Peak	δ_m	ε	α	γ	E Peak
PM	1	0.00139	0.905	4.430	10.0%	1	0.00139	0.923	4.640	16.3%
SO ₂	1	0.00516	0.853	4.146	43.8%	1	0.00516	0.870	4.344	50.0%
NO _x /CO	1	0.00019	0.987	4.694	13.8%	1	0.00019	0.987	4.948	12.8%
Pb	1	0.00002	0.996	4.738	2.5%	1	0.00002	0.996	4.987	2.5%

Table 8: Sensitivity Analysis. Calibrated parameter values and results without assuming emissions and the economy are in a steady state.

Parameter	Calibration						
	ν	ρ	ψ	λ	δ_k	δ_m	γ
ν	0.05	0.10	0.20	0.40	0.60	0.80	0.90
ρ	0.073	0.073	0.073	0.073	0.073	0.090	0.094
ψ	0.405	0.405	0.405	0.405	0.405	0.404	0.404
λ	0.0015	0.0014	0.0014	0.0015	0.0015	0.0030	0.0039
δ_k	0.046	0.046	0.046	0.046	0.046	0.046	0.046
δ_m	1	1	1	1	1	1	1
γ	3.672	3.682	3.681	3.672	3.699	3.648	3.648
α	0.931	0.933	0.933	0.931	0.938	0.923	0.923
η	0.011	0.011	0.011	0.011	0.011	0.011	0.011
ϕ	0.019	0.019	0.019	0.019	0.019	0.019	0.019
E Peak	19.5%	18.2%	18.2%	18.2%	19.5%	45.9%	65.6%

Table 9: Sensitivity Analysis. Calibration with CES production. Each column contains calibrated parameter values and an emissions peak for a given elasticity of substitution ν .

Appendix B Data

B.1 Economic Data

Data manipulations for our economic calibration closely follow the methods used in Cooley and Prescott (1995), to which the reader should refer for a detailed discussion. Economic data is from the National Income and Product Accounts (NIPA), Bureau of Economic Analysis (2005), the Board of Governors of the Federal Reserve (2005), the Bureau of Labor Statistics (2005), and the Survey of Current Business (US Dept. of Commerce, 2000). Our model falls under the umbrella of neoclassical growth, which emphasizes the role of capital accumulation in determining long-run growth in output. Indeed, we are concerned with the transition path of emissions as capital accumulates in an economy. We do not model government, foreign, or household production sectors, nor do we provide explicit treatment of inventories. Yet both our economic and environmental data do include these sectors. Consider an example of automobiles. One way to think of emissions from automobiles is as a consumption externality. However, this idea is not consistent with our model because the automobile is not consumed (and because our model has only production externalities). A more consistent way to model automobiles is as a piece of capital, which along with labor produces a consumption good “driving services,” and causes a “production” externality of

emissions. This is consistent with the model.²³ Thus we should add the stock of durable goods to the capital stock and add an estimate of service flows from durable goods to output, since emissions includes automobile emissions. Similarly, we should add government-owned capital to the capital stock and an estimate of service flows from government capital to output. These service flows likely result in little emissions, but we add them to output anyway just like we add non-emissions intensive private services to output, so that our model has the correct economy-wide average emissions intensity.

Thus, the private capital stock is the sum of fixed nonresidential capital (from the Survey of Current Business), real estate, land value, and private inventories (all from the Balance Sheet of the U.S.). The aggregate capital stock is the private capital stock plus government capital and the stock of durable goods (both from the Survey of Current Business).

Investment spending that corresponds to the aggregate capital stock is the sum of private investment (equal to fixed investment plus the change in inventories and net exports), net government investment, and consumption of consumer durables (all NIPA data). Similarly, we deduct consumption of consumer durables from NIPA consumption to get private consumption. Aggregate consumption spending is then private consumption plus government consumption (NIPA).

Next, we compute capital income corresponding to the aggregate capital stock. Reported gross private capital income equals rental income, corporate profits, net interest and depreciation (all NIPA data). NIPA income from proprietors (PI) as well as income paid as indirect business taxes (e.g. sales taxes, hereafter IBT) presumably have a capital income component but only the total incomes are reported. Assuming the capital share is the same for these incomes as the rest of the economy (0.3), we can calculate an estimate of gross private capital income as the sum of reported gross capital income and 30% of PI and

²³The data is also more consistent. Suppose as a country develops, it uses less taxis and more cars. Driving services appear to fall and thus output is underestimated, so emissions appear to peak earlier.

IBT. Gross government and durable capital income are not reported, but may be computed as follows. Net capital income is the interest rate times the capital stock. We assume the interest rate is identical across private, durable, and government sectors. Hence the interest rate is net private capital income divided by the private capital stock. We obtain an interest rate of 8.1%. Hence net government and durable capital income are 8.1% of the government and durable capital stocks, respectively. We use equation (16) to estimate the depreciation rate of 0.04 for government capital and 0.25 for durables. Government and durable depreciation are then 4% of the government capital stock and 25% of the stock of durables, respectively. Aggregate capital income is then the sum of gross private, government, and durable capital incomes.

Next, private output corresponding to the private capital stock is NIPA GNP. Aggregate capital income includes service flows of government and consumer durables as well as private capital income. Because these flows are construed as income, they are also added to GNP as service flows to get aggregate output.

Finally, our results for the aforementioned constructed variables will be slightly different than those from a model without the environment. NIPA's GNP includes spending on environmental compliance; we subtract compliance costs from aggregate output as Y in our model is equal to aggregate output *minus* compliance spending. More on compliance costs can be found in the following section.

We use the Bureau of Labor Statistics (BLS) Current Employment Statistics (CES), an establishment survey, for data on average weekly hours worked and the fraction of the population employed. We assume the amount of hours per week available for work or leisure (after accounting for personal time) is 94.5 hours, as estimated by Hill (1985). Since we use the indivisible labor assumption, the model h represents the fraction of the population employed times the time spent working, conditional on being employed (Hansen, 1985). We therefore multiply average hours by the employment-to-population ratio. Thus, we

calculate an average fraction of time spent working as average weekly hours multiplied by the employment to population ratio divided by 94.5.²⁴ The total population is the CES civilian non-institutional population. The ‘actual data’ series in Figures 2-5 require hours data from 1952 to 1998, but the standard CES data begins in 1964. Therefore, for these figures we use Gabor, Houlder, and Carpio (2001). This survey uses primarily establishment data (CES), but likely gets information from other sources prior to 1964, when hours data for services was not available. This data is used only to compare the predicted results of our calibrated model to the actual U.S. experience (i.e. not the data used for the calibration).

B.2 Environmental Data: Compliance Costs and Control Rates

To calibrate the environmental parameters, we require data on compliance costs and control rates. Here, our biggest limitation is the availability of compliance cost data. We don’t use commonly cited surveys such as the Pollution Abatement Cost and Expenditure Survey (PACE), as they generally don’t disaggregate emissions spending by pollutant. We instead use *Environmental Investments: The Cost of a Clean Environment* (Environmental Protection Agency, 1990), hereafter CCE, which provides pollutant-specific compliance spending.²⁵ Specifically, for air and radiation pollution compliance costs, the categories include: PM, SO₂, VOCs, NO_x/CO,²⁶ and ambient lead. CCE provides capital and operation and maintenance expenditures. CCE estimates from 1972 through 1987 are from surveys of firms. The authors estimate figures for 1987 on the basis of historical shares within total manufacturing.

Due to discontinuation of the program, CCE uses costs projections from 1989 through

²⁴This methodology is fairly standard. For example, McGrattan (1994) gets $h = 0.27$ using the same methodology except that she uses the household survey, whereas we use the establishment survey and get $h = 0.2$. The establishment survey reports lower hours (and thus higher productivity) especially in the 1990s.

²⁵The method of disaggregation into pollutant category is available in Appendix B of the report, which acknowledges that many assumptions are required to break down pollutants by category, and thus the data have a high degree of uncertainty.

²⁶The report aggregates nitrogen oxides and carbon monoxide, so we treat nitrogen oxides and carbon monoxide as a single category.

2000. The authors attempt to predict how much government and private sectors will spend to maintain compliance with existing pollution control requirements. CCE linearly regresses historical pollution control expenditures against time; the resulting parameter estimates are used to predict costs for future years. Use of this method makes a very strong assumption that trends in population growth, economic growth, compliance levels, and other factors that may affect pollution control costs will continue as in the recent past and will have similar influences on expenditures.

CCE reports both capital and flow cost data, but our model has only flow costs. CCE does provide a section with amortized capital expenditures, but the authors pick an interest rate of 7 percent. We instead use the interest rate corresponding to our economic data, estimated in Appendix B.1, of 8.1%. Annualized costs for any given year are equal to operating expenditures plus amortized capital costs (i.e., depreciation plus interest costs associated with the pre-existing capital stock for that year). Stationary source air pollution control costs are amortized over 20 years; mobile source air pollution control costs are amortized over 10 years. Capital costs are amortized using the formula for an annuity; that is $\frac{r}{1-(1+r)^{-t}}$, where r is the rate of interest and t is the amortization period. Multiplying the capital cost by the appropriate annuity factor gives a constant annual cost to be incurred for t years, the present value of which is equal to the capital cost.²⁷

Cost estimates for 1972-1990 are shown in 1986 dollars. The price deflators used in CCE include indices developed by the BEA for air compliance costs and the GNP implicit price index. We multiply by the given EPA deflator to convert the sequence to current dollars. CCE gives deflators up to 1990, so we use these deflators from 1972-90. After 1990, the data is in 1986 dollars but was never converted using an actual deflator. We therefore use the standard BEA GNP deflator from 1990 on.

²⁷An issue with the report is that the cost data begins in 1972. Our model therefore assumes that no capital compliance spending exists prior to 1972. If not, then we would need data on capital spending from 1952 onward since in a 20-year amortization 1952 capital costs would not be paid off until 1972.

CCE also provides control rate data for the period 1984-1988, which we use this for calibration of ϵ . Since we cannot disaggregate cost data for CO and NO_x, we construct a weighted average control rate for the two pollutants. If we define uncontrolled emissions as $E^u = \frac{E}{1-u}$, we can construct:

$$E_{co}^u = \frac{E_{co}}{1 - u_{co}} \quad (42)$$

and

$$E_{nox}^u = \frac{E_{nox}}{1 - u_{nox}}. \quad (43)$$

Then:

$$1 - u_{co+nox} = \frac{E_{co} + E_{nox}}{E_{co}^u + E_{nox}^u}. \quad (44)$$

We also calibrate using SO₂ permit price data, gleaned from Environmental Protection Agency (2000a). Finally, atmospheric depreciation rates are from air pollution textbooks (Stern, 1976; Stern, Boubel, Turner, and Fox, 1984).

B.3 Environmental Data: Emissions Data

Emissions data is from Environmental Protection Agency (2000b) (*National Air Pollutant Trends 1900-1998*). For our purposes, two problems exist. First, evolving collection methods have led to new emissions sources over time; hence some sources are missing for years prior to adoption of new sources. The second is that the emissions data broken down by source is decadal (total emissions are annual). Thus we extrapolate to fill in the missing data. Sources are missing only for data *prior to 1985*. Thus, with the exception of PM from 1980-1985, extrapolated data is not part of the data used for calibration. However, ‘actual data’ series in Figures 2-5 use emissions data from 1952 to 1998, and Figure 1 uses emissions data from 1947-1998. Therefore, the figures use some extrapolated data to compare the predicted results of our calibrated model to the actual U.S. experience.

Our extrapolation is best illustrated with the example of the particulate category fugitive dust (particulates from roads and construction). Data on fugitive dust was not collected until 1985. We could simply omit this data for the missing years. However, this is quite an omission: fugitive dust accounted for more than 60 percent of particulate emissions in 1990 and for 56 percent in 1996.²⁸ Instead, we fill in the missing years for fugitive dust by extrapolating backwards. Our method is to assume that if a new source is added in period t , the change in emissions for that source from $t - 1$ to t equals the average change from all other known sources (e.g. we assume fugitive dust grows approximately at the same rate as other sources, such as emissions from onroad vehicles). Since data by known sources is decadal, we divide decadal growth rates by 10 and then employ a constant growth rate. We can then estimate emissions in period $t - 1$ and so on back to the initial year. For all pollutants except particulates, new sources are relatively small. Thus, the results are not sensitive to how and if we modify the data to deal with new sources.

Indeed, although we have made many modifications of the emissions, cost, and economic data, the results are remarkably robust: it remains true that emissions peaked late in development and that compliance costs are relatively small, regardless of how the problems with the data are resolved.

Appendix C Theoretical Pollution-Income Relationship

In this appendix, we show theoretically that, for the flow case, unconstrained emissions are decreasing in the capital stock, and hence that unconstrained pollution decreases as a country develops. We then establish how the constraint changes with the capital stock to establish the theoretical pollution-income curve. The results use the supermodularity results of Milgrom and Shannon (1994).

²⁸Excluding new sources would also introduce a downward bias on national emissions and bias some parameters (for example, lower national emissions would cause an upward bias in the parameter which measures preferences for environmental quality).

First, let $s' = -(1 + \eta)(1 + \phi)k'$, then the optimization problem is to maximize:

$$H(k, E, h, s') \equiv U \left[F(k, E, h) + (1 - \delta)k + s', \widehat{M} - E \right] - \gamma h + \beta(1 + \eta)v \left(\frac{s'}{-(1 + \eta)(1 + \phi)} \right).$$

Let k^m and E^m denote the maximum sustainable capital and emissions, and let $x = [E, h, s']$.

Define $T = [0, k^m]$ as the set of all sustainable capital stocks, and a set Ω as:

$$\Omega = \{x | 0 \leq h \leq 1, 0 \leq E \leq E^m, -(1 + \eta)(1 + \phi)k^m \leq s' \leq 0\}.$$

Then T is a partially ordered set and Ω is a lattice under the component-wise ordering \geq .

Notice that we are considering the unconstrained problem only and thus do not consider constraints on maximum and minimum emissions, other than sustainability.

The next step is to show the optimization problem is submodular. Milgrom and Shannon (1994) establish that H is submodular as a function of x if and only if the cross partial derivatives are all negative. We have:

$$H_{Es'}(k, E, h, s') = U_{cc}(\cdot, \cdot)F_E(k, E, h) < 0,$$

$$H_{hs'}(k, E, h, s') = U_{cc}(\cdot, \cdot)F_h(k, E, h) < 0,$$

$$\begin{aligned} H_{Eh}(k, E, h, s') &= U_c(\cdot, \cdot)F_{Eh}(k, E, h) + U_{cc}(\cdot, \cdot)F_E(k, E, h)F_h(k, E, h) \\ &= U_c(\cdot, \cdot) \left[\varepsilon(1 - \theta - \varepsilon) \frac{y}{Eh} - \frac{-U_{cc}(\cdot, \cdot)c\varepsilon(1 - \theta - \varepsilon)y^2}{U_c(\cdot, \cdot)cEh} \right] \\ &= \varepsilon(1 - \theta - \varepsilon)U_c(\cdot, \cdot) \frac{y}{Eh} \left[1 - \frac{y}{c} \right] < 0. \end{aligned}$$

The above inequality holds since consumption is less than income. Hence H is sub modular.

It remains to show that H has decreasing differences in k . Milgrom and Shannon (1994) show that H has decreasing differences if and only if the cross partial derivatives with respect to the decision variables and k are negative. We have:

$$H_{ks'}(k, E, h, s') = U_{cc}(\cdot, \cdot)(F_k(k, E, h) + 1 - \delta_k) < 0,$$

$$\begin{aligned}
H_{Ek}(k, E, h, s') &= U_c(\cdot, \cdot)F_{Ek}(k, E, h) + U_{cc}(\cdot, \cdot)F_E(k, E, h) (F_k(k, E, h) + 1 - \delta_k) \\
&= U_c(\cdot, \cdot) \left[\varepsilon \theta \frac{y}{Ek} - \frac{-U_{cc}(\cdot, \cdot)c \varepsilon y}{U_c(\cdot, \cdot) Ec} \left(\frac{\theta y}{k} + 1 - \delta_k \right) \right] \\
&= U_c(\cdot, \cdot) \frac{y\varepsilon}{Ek} \left[\theta - \frac{(\theta y + (1 - \delta_k) k)}{c} \right] \\
&= U_c(\cdot, \cdot) \frac{y\varepsilon}{Ek} \left[\theta \left(1 - \frac{y + (1 - \delta_k) k}{c} \right) - \frac{(1 - \theta)(1 - \delta_k) k}{c} \right] < 0.
\end{aligned}$$

Here the above inequality holds since consumption is less than wealth. Finally,

$$\begin{aligned}
H_{kh}(k, E, h, s') &= U_c(\cdot, \cdot)F_{kh}(k, E, h) + U_{cc}(\cdot, \cdot)F_h(k, E, h) (F_k(k, E, h) + 1 - \delta_k) \\
&= U_c(\cdot, \cdot) \left[(1 - \theta - \varepsilon) \theta \frac{y}{hk} - \frac{-U_{cc}(\cdot, \cdot)c (1 - \theta - \varepsilon)y}{U_c(\cdot, \cdot) hc} \left(\frac{\theta y}{k} + 1 - \delta_k \right) \right] \\
&= U_c(\cdot, \cdot) \frac{(1 - \theta - \varepsilon)y}{hk} \left[\theta \left(1 - \frac{y + (1 - \delta_k) k}{c} \right) - \frac{(1 - \theta)(1 - \delta_k) k}{c} \right] < 0.
\end{aligned}$$

Hence H has decreasing differences. Therefore, E , h , and s' are all decreasing functions of k .

Equation (15) implies:

$$E \leq k^\psi h(k)^{1-\psi} \equiv ub(k).$$

Since h is a decreasing function of k , the emissions bound may be increasing or decreasing for a given k . However, $ub(0) = 0$ and $F_h(k, E, 0) = \infty$ implies $ub(k) > 0$ for $k > 0$. Since the upper bound is a continuous function, it follows that there exists a $\tilde{k} > 0$ such that $ub(k)$ is increasing in k over the interval $[0, \tilde{k}]$.

Unconstrained emissions are decreasing and non-negative, and the upper bound on emissions is increasing for k sufficiently small and satisfies $ub(0) = 0$. Hence the constrained optimal pollution-capital curve cannot be strictly decreasing. If unconstrained emissions are everywhere greater than the upper bound, the pollution-capital curve is increasing over the interval $[0, \tilde{k}]$. If unconstrained emissions drop below the upper bound, then the pollution-capital curve will be an inverted U-shape with abatement equal to zero over some interval of capital stocks $[0, k > \tilde{k}]$. Figure 9 depicts these results for the particulates case. The upper

bound is increasing and concave, and the unconstrained emissions eventually drop below the upper bound, creating the inverted U-shape.

Appendix D Maximum Sustainable Pollution Stock

The maximum sustainable value of M , \widehat{M} , is calculated as follows. First, we calculate the maximum sustainable capital stock, k^m , by assuming $h = 1$, $u = 0$, and $c = 0$. Then, according to the resource constraint, capital will accumulate until the total production just equals total depreciation. At this point, the capital stock cannot further accumulate. From the resource constraint:

$$0 = (k^m)^\psi + (1 - \delta_k)k^m - (1 + \eta)(1 + \theta)k^m, \quad (45)$$

$$k^m = ((1 + \eta)(1 + \theta) - (1 - \delta_k))^{-\frac{1}{1-\psi}}. \quad (46)$$

Next, we calculate the maximum sustainable emissions, E^m , from equation (3). Emissions are maximized when $u = 0$, $h = 1$, and $k = k^m$:

$$E^m = (k^m)^\psi. \quad (47)$$

Finally, from equation (9), if $E = E^m$, the pollution stock will increase until emissions just equals total decay. At this point, the pollution stock cannot accumulate further and the pollution stock is at its maximum sustainable value:

$$\widehat{M} = E^m / \delta_m. \quad (48)$$

Setting $N_{t+1} = \widehat{M} - M_{t+1}$ ensures that environmental quality cannot be negative and, along with the Inada conditions, ensures that the planner will not chose a path that leads to $N = 0$.

Appendix E Figures

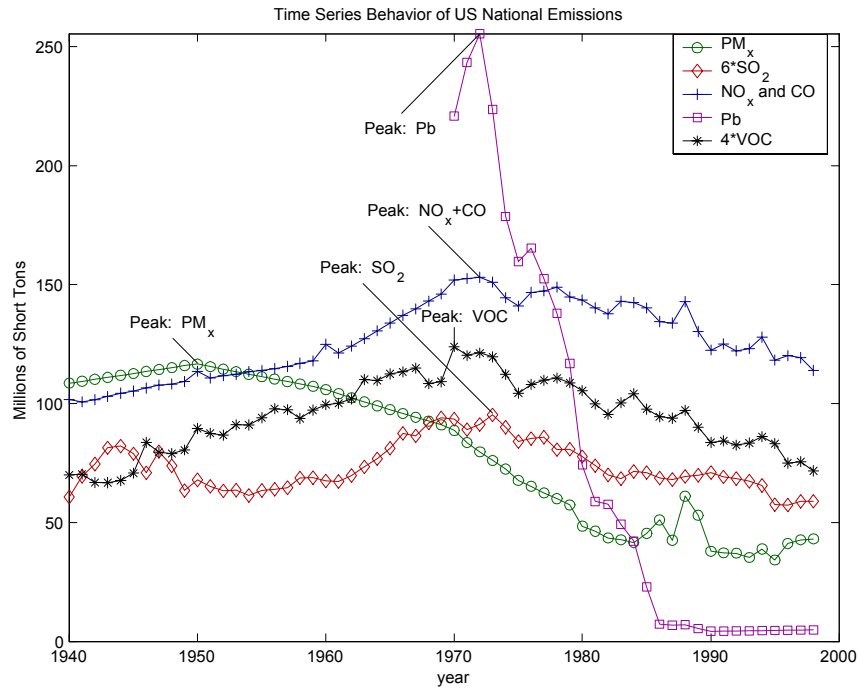


Figure 1: Time series of U.S. national emissions data.

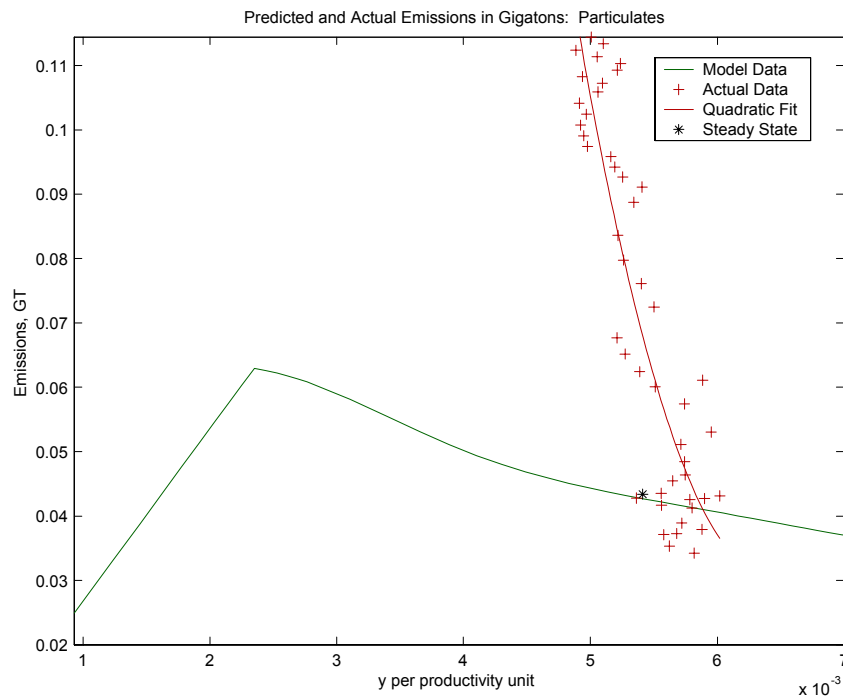


Figure 2: Predicted and actual pollution-income curve for particulates.

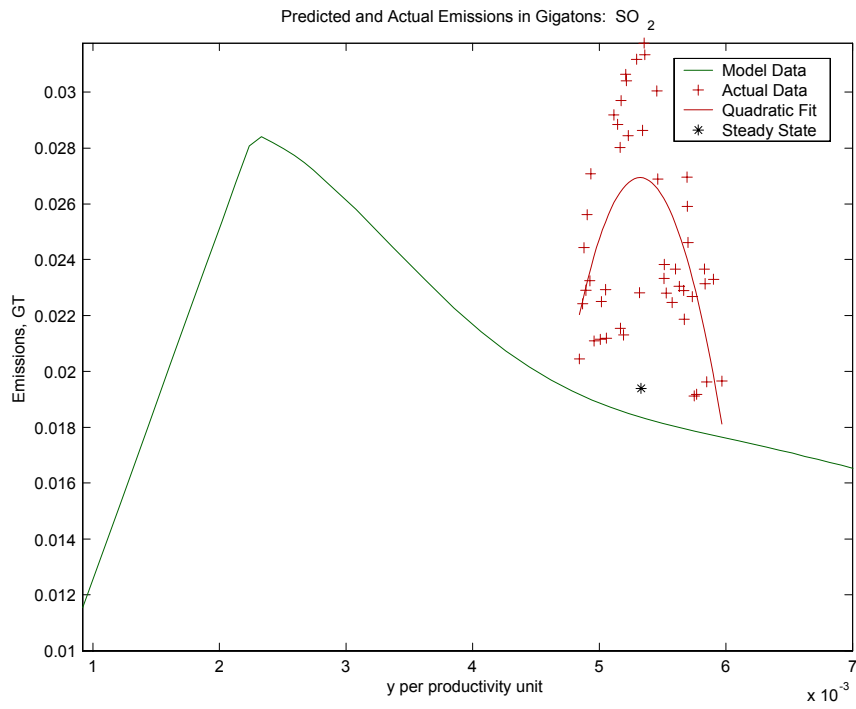


Figure 3: Predicted and actual pollution-income curve: SO_2 .

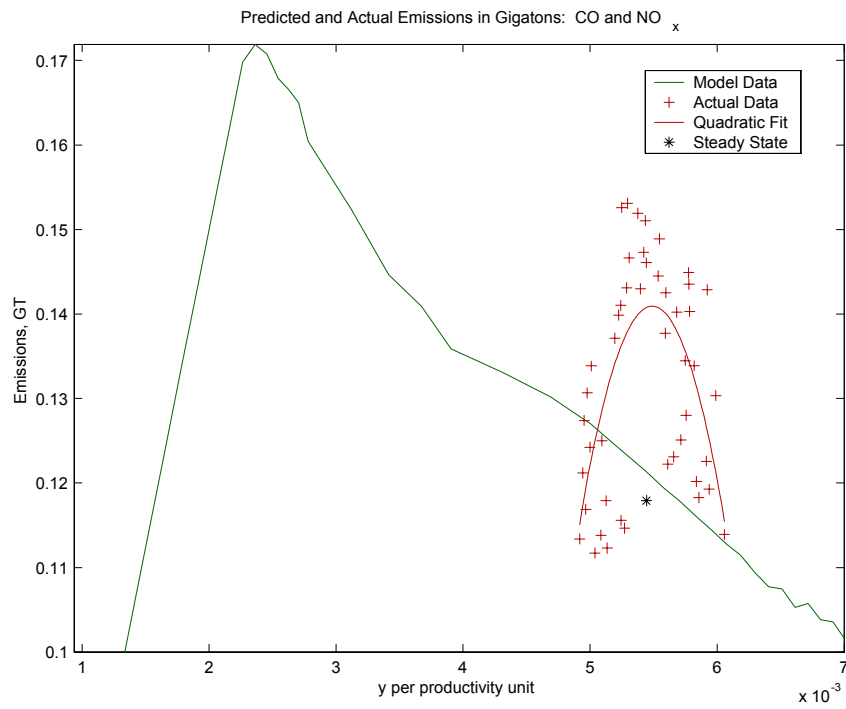


Figure 4: Predicted and actual pollution-income curve: NO_x and CO.

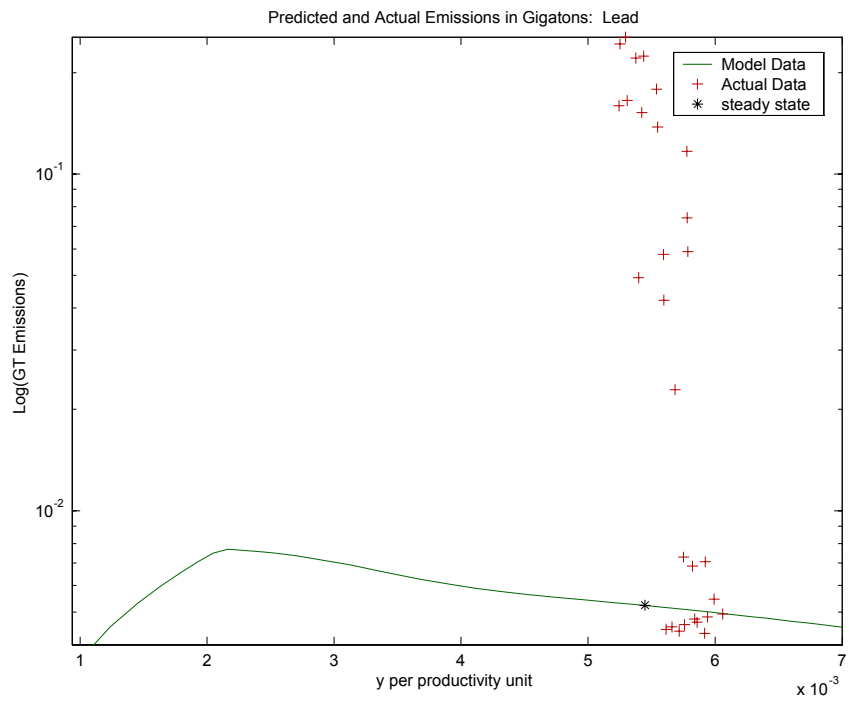


Figure 5: Predicted and actual pollution-income curve: Airborne Lead.

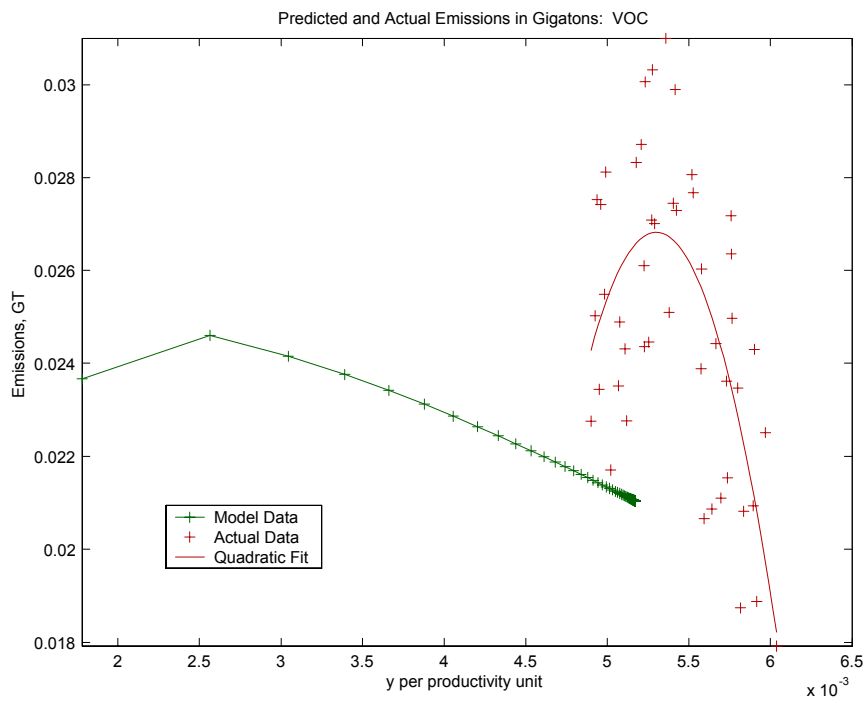


Figure 6: Predicted and actual pollution-income curve: VOC.

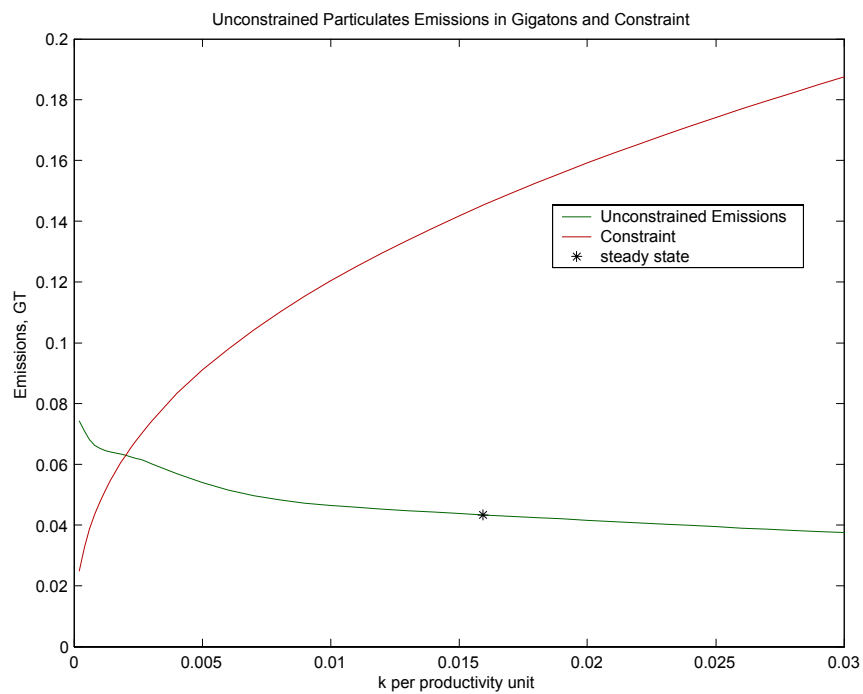


Figure 7: Predicted Pollution-Income Curve: Unconstrained Particulates.

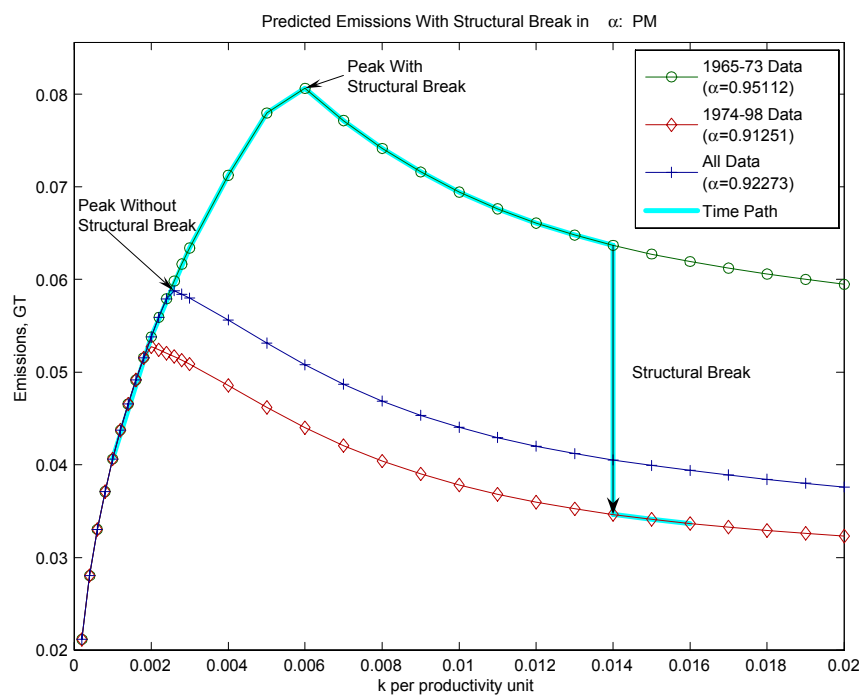


Figure 8: Predicted Pollution Income Curve With Structural Break in α : Particulates.

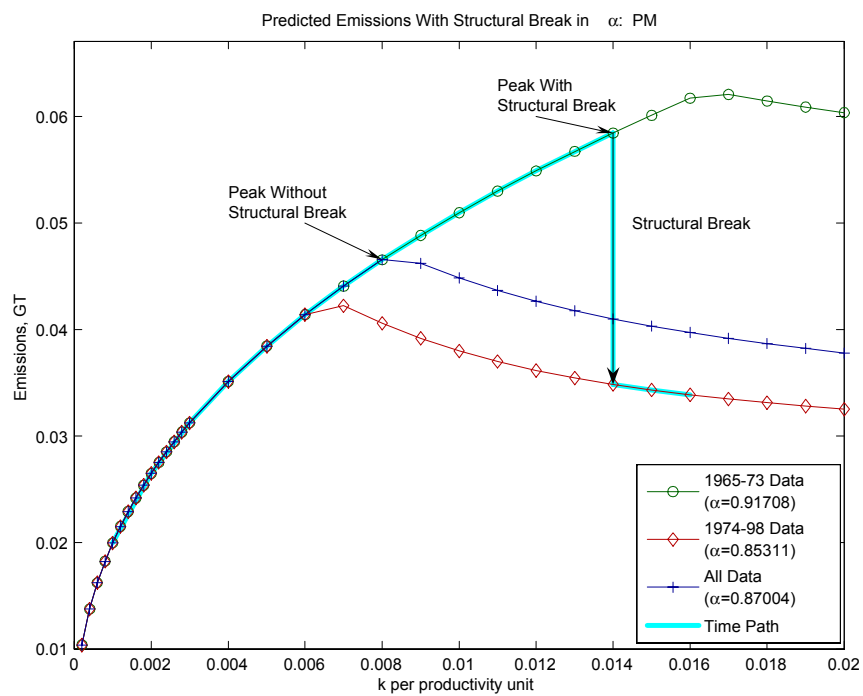


Figure 9: Predicted Pollution Income Curve With Structural Break in α : SO_2 .