Can India Tunnel Through? Energy Use in a Services Boom

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Introduction

[*] During the last twelve years, several authors in development and environmental economics have written about the existence of an "Environmental Kuznets Curve" – a posited ∩-shaped relationship between, as the dependent variable, pollution or environmental degradation, and as the independent variable, per-capita income in a country. The name is derived from the "Kuznets Curve," a stylized empirical fact showing that inequality follows a ∩-shaped curve when plotted against economic growth, either cross-sectionally or over time within one country. Beginning with seminal papers written by Shafik (1994), Selden and Song (1994) and Grossman and Krueger (1995), empirical studies of the Environmental Kuznets Curve (EKC) have used various panel data samples to assess the long-term relationship between pollution and output. Most EKC studies run a reduced-form single-equation regression, using as RHS regressors a quadratic or cubic polynomial of income, along with other relevant explanators including population density, sectoral shares of GDP, and trade openness. The theoretical underpinnings of the EKC relationship have mostly lagged rather than led the empirical findings. The ∩-shaped curve has been implied by several theoretical models including Stokey (1998), John and Pecchenino (1994), Jones and Manuelli (2000), Andreoni and Levinson (2001) and Pfaff, Chaudhuri and Nye (2004).

On the other hand, a related literature, energy economics, has shown more sophisticated and theoretically sound econometric approaches than the EKC literature. Considering the possibility that the time series of energy and output may be integrated, authors have typically looked first for a cointegrating relationship between energy and output, and then used a VAR or VECM model to simultaneously estimate the relationship between the two series. Authors in the literature speak explicitly of causality, or at least Granger causality.

Surprisingly, few authors have explicitly related energy-GDP analyses to EKC analyses; that is, few authors have applied the econometric tools from the energy literature to pollution, or recognized that energy-use patterns (per capita) may follow an inverted parabola like pollution patterns. This is unexpected because energy use and pollution are obviously closely related; most

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fuel sources are organic and linearly produce greenhouse gas (GHG) emissions including carbon dioxide (CO_2) and sulfur dioxide (SO_2). Indeed, the simple correlation coefficient between commercial energy use and CO_2 emissions for India over the last 40 years is 0.998. Stern (1998, 2002, 2003 with Perman) has extensively discussed many econometric problems inherent in EKC studies. As many authors, notably Grossman and Krueger (1995) have noted, reduced-form regressions that find a ∩ relationship between pollution and income are interesting, but merely descriptive: they do not indicate much about the causal or structural relationships driving the process. A moment's thought indicates that pollution depends on a large set of factors, including technology, regulation, prices, and broad macroeconomic conditions. Suggested structural avenues for the EKC effect include sectoral change away from industry; increasing environmental awareness; progress on clean technology; strengthening of open political institutions, and increased public fiscal resources for environmental protection. If these effects are strong enough at early stages of development, a country may be able to "tunnel through" the EKC hill without significant increase of emissions per capita.

Energy use is especially important today vis-à-vis pollution because of the threat of global warming from greenhouse gases. The Intergovernmental Panel on Climate Change (IPCC) has found that the global average surface temperature increased by 0.6°C over the 20th century, largely due to anthropogenic emissions of carbon and other GHG. The IPCC forecasts an increase of between 1.4C and 5.8C by the end of the 21st century, considering current projections of energy use and GHG emission. Potential impacts include rising sea levels, melting ice caps, habitat destruction, species extinction, lower crop yields, and more "extreme weather" events such as flash floods, heat waves, and hurricanes. UK Prime Minister Tony Blair has called climate change "the bigg[est] long-term question facing the global community."[2] Many authors, like Asuategi and Escapa (2002) point out that amelioration of CO_2 emissions is even more difficult than for other pollutants because the effects of local emission are globally dissipated. Additionally, harms from climate change are not yet palpable in most parts of the world, or obviously attributable to CO_2. Thus, CO_2 concentration is unlikely to show a ∩-shaped curve.

According to the International Energy Agency, two-thirds of the increase in global energy demand until 2020 will come from developing countries.[3] In light of empirical and theoretical findings that a high-services economy may be less damaging to the environment, it may be valuable to test this relationship in the developing country with one of the most robust service sectors: India. A relatively new state-level panel data set enables energy or EKC analysis within

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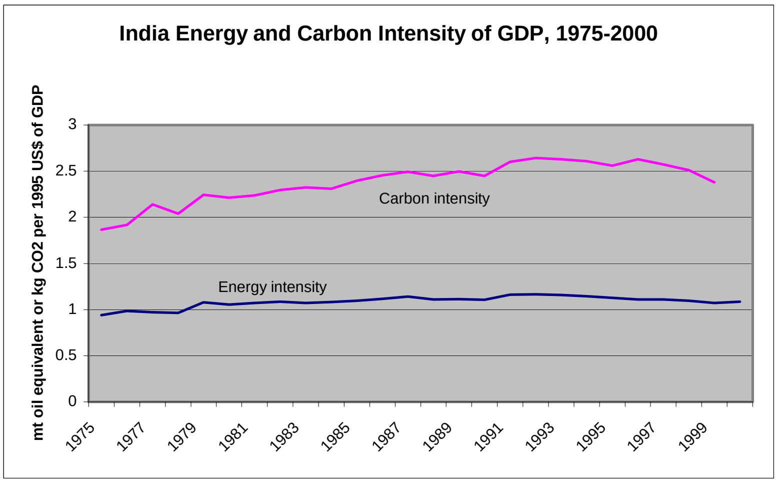
[2] "Climate issue 'critical' to Blair." BBC News Online, April 27th 2004. Available online at http://news.bbc.co.uk/1/hi/uk/3662303.stm.

[3] "Power to the Poor." *The Economist*, Feb.8th 2001.

one country, with less economic, technological, and cultural heterogeneity than the global sample of countries typically used in other studies.

The Case of India

India is one of the poorest countries in the world, with average per-capita income of US$460 for 2002. (By this measure, India ranked 43rd out of over 200 countries; its per-capita income was almost 100 times smaller than that of the United States.) Surprisingly, India's services sector contributed 51% of GDP for 2002, against about 23% for agriculture and 26% for industry. In China, with per-capita income of $960, services comprised 33% of GDP in the same year. Medlock and Soligo (2001) show using a cross-sectional regression that the average low-income country has 41% of GDP in services, 38% in agriculture and 21% in industry, while the average high-income country has 65% in services, 3% in agriculture, and 31% in industry. As Gordon and Gupta (2003) observe in an IMF working paper, "the sectoral composition of output in India has come to resemble a middle-income country, even though its per capita income remains that of a low-income country."[4] Using sectoral and aggregate growth rates from 1996-2000, they forecast that services in India will increase to 58% of GDP by 2010, "closer to that of an upper middle income country, while still belonging to the low income group."[5]



Since the 1991 liberalization reforms in India, the services sector has grown over 8% annually, while the industrial sector grew at just over 6% annually and the agricultural sector grew at about 3%. The growth gap between services and industry was greatest during the "Ninth Plan" period of 1997-2002, when industry grew at only 4.5% annually. Services growth has also been more stable and less cyclical than growth in industry and agriculture.[6] The highest-growth service subsectors in the last 12 years were telecoms, information technology (IT), financial services, and "business process outsourcing" (such as call centers and data management) and, to a lesser extent, hospitality and social services.

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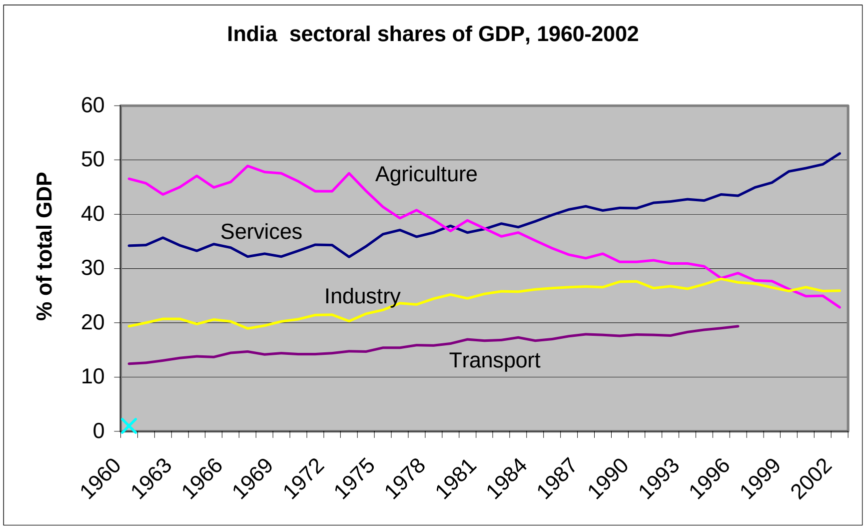
[4] Gordon and Gupta 2003, p.3.
[5] Ibid, p.7.
[6] Gordon and Gupta 2003, p.2.

These fast-growing sectors were responsible for the post-1991 boom in services growth over the relatively flat 5% annual services growth rate from 1947-1991. Despite the trend of the last decade and significant attention in popular media, the high-growth service subsectors remain a small component of the total services sector – together they comprise only about 10% of GDP, whereas all services, including transport, personal services, public administration, and distribution, comprise about 50% of GDP. IT alone makes up less than 1% of GDP.

Gordon and Gupta propose several explanations for India's services boom, including "splintering" of industrial activity (a process by which industrial organizations begin to outsource their internal service functions); high income elasticity of services demand; increased foreign demand; increased productivity through technology progress; and political liberalization. Their empirical analysis indicates that the first three factors are significant in explaining slow-growth service subsectors, and the latter two factors are significant in explaining high-growth subsectors.

The opening to foreign investment and liberalization of competition laws has helped greatly. Services exports increased from 3.6% to 7.4% of GDP over the 10 years after the 1991 reforms; according to Prime Minister Vajpayee's economic adviser, the volume of services exports grew by about 14% annually from 1999-2003.[7] European companies including Deutsche Bank, Société Générale, British Airways, and Lufthansa own call centres and customer-service operations in India.[8] US-based organizations including General Electric, FedEx, and even the World Bank have "offshored" support, accounting, and data-management functions to India.



I wish to investigate the relationship between GDP, services, and per-capita energy use in India to determine what predictions we can make, if any, about India's future contribution to GHG emissions. Of course, there are many non-economic determinants of energy efficiency, such as political institutions. In 1995, India's public expenditure for environmental protection

[7] S.Narayan, lecture at Imperial College, London UK, Nov.18th 2003.
[8] "Job Exports: Europe's Turn." *Business Week*, April 19th 2004.

totaled 0.035% of GDP, according to the Asian Development Bank. In the United States, the budget for the federal Environmental Protection Agency alone (not counting state- and local-level environmental spending) in that year was over twice that as a proportion of GDP. Still, I wish to isolate the effect of services growth on energy use.

Previous Studies

<u>Energy</u>

The early literature on energy vs. output combined relatively advanced econometric techniques with simple models; most researchers focused on finding significant empirical relationships between energy and income without looking for deep causal links. Brookes (1972) shows that the output elasticity of energy consumption declines with increasing output, using a panel data set for rich and poor countries over 1950-65. Yu and Hwang (1984) examine US energy consumption data for 1947-79 and find no causality between GNP and energy, confirming earlier work of Akarca and Long (1980). Ang (1987) uses cross-sectional data from 1975 for 100 countries and finds that income elasticity of energy consumption increases from about 1 for low-income developing countries to about 1.8 for middle-income countries, and then decreases for rich countries. He also finds energy intensity monotonically increasing with income.

There is a rich literature on energy use in Asia. Masih and Masih (1996) examine cointegration between energy consumption and GDP for six Asian countries including India. Using a dynamic vector error-correction model, they find causality running from energy to GDP for India; from GDP to energy for Pakistan; and in both directions for Indonesia. Soytas and Sari (2003) perform a similar analysis for the G-7 countries and 10 emerging economies. They find causality running from energy to GDP for Turkey, France, Japan, and West Germany, and vice-versa for Italy and Korea. The Argentina time series displays bidirectional causality. Shiu and Lam (2004) do a similar analysis for China over 1971-2000 and find causality running from electricity consumption to GDP. Ghosh (2002) examines the relationship between electricity consumption and per-capita GDP for India from 1950-1996. Unlike the Masih and Masih study's India result, Ghosh cannot reject a null hypothesis of no cointegration between energy and GDP. Using an unrestricted VAR, Ghosh finds Granger causality[9] running from GDP to energy consumption, but not in the other direction.

Zhang (2003) provides something approaching a structural model of energy use. He notes that energy intensity has fallen by almost 75% in China over the 1980-2000 period and seeks to explain the decline. He calculates China's elasticity of energy consumption at 0.41, in contrast to India's income elasticity of 1.21. Zhang analyzes energy consumption change according to the formula: $\Delta E_{tot} = \Delta E_{out} + \Delta E_{str} + \Delta E_{int}$

In words, total change in energy consumption can be decomposed into change from aggregate output growth, change due to sectoral shifts in the economy, and change due to subsectoral energy intensity changes.) Based on this methodology, using a data set of 29 industrial subsectors, Zhang concludes that 88% of the energy savings in the industrial sector (savings compared to the base case with no structural shifts or intensity changes) are attributable to improvements in energy intensity at the subsectoral level.

de Nooij *et al.* (2003) use a similar structural decomposition analysis to determine the factors causing per-capita energy use to differ across countries. Looking at a 1990 cross-sectional sample of eight OECD countries, they conclude that inter-country differences in energy consumption arise from differences in sectoral energy intensity *and* differences in GDP. Differences in production technology and composition of final demand are less important determinants.

Medlock and Soligo (2001) introduce an explicit accounting of the sectoral composition of an economy. They use a panel data set for 28 rich and poor countries from Asia, Europe, and the Americas over 1978-1995. Their dependent variable, energy demand, is disaggregated by sector. They estimate an equation with RHS regressors including country- and sector-specific fixed effects, a vector of country- and sector-specific prices, a lagged term of energy demand, and a quadratic polynomial of per-capita income. (They use a 2SLS approach to deal with the lagged endogenous regressor.) Unlike earlier authors who were concerned with two-way causality, Medlock and Soligo explicitly claim that they are treating income as exogenous. All variables enter in logs. Their estimated curves have a turning point of $16,000/person for the industrial sector, $34,000 for the residential and commercial sector, and $533,000 for the

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[9] As economic analysis cannot "prove" causality, Granger causality is a technical characterization of relationships in which changes in one variable appear to drive changes in another. Specifically, we can say that X "Granger causes" Y if, in the model

$$\Delta Y_t = \alpha + \sum_{i=1}^{m} \beta_i \Delta Y_{t-i} + \sum_{j=1}^{n} \gamma_j \Delta X_{t-j} + \varepsilon_t$$

we can find at least one γ_j significantly different from zero. If X and Y are cointegrated, we add an error-correction term to the RHS and also check for a nonzero coefficient on that term. The optimal m and n are calculated by minimizing the Akaike Information Criterion or Schwarz Bayesian Information Criterion.

transport sector. Using their estimated coefficients, they calculate that the industrial sector dominates total energy demand at very low income levels – comprising 60% of total energy use – but at high income levels, the transport and residential/commercial sectors each take over one-third of energy demand, and industrial energy demand drops to one-quarter of the total. Their results also show a ∩-shaped curve for energy *intensity*, peaking at $2600/person.

Environmental Kuznets Curve

The first major paper addressing the EKC was Shafik and Bandyopadhyay (1992; also published as Shafik 1994), a background paper to the 1992 *World Development Report* issued by the United Nations. Using a panel data set for 130 countries from 1960-1990, the authors regress 10 different metrics of environmental damage on linear, quadratic, and cubic functions of per-capita income. They posit four determinants of environmental quality: natural endowments; available technology; per-capita income; and abatement policies. To capture the first two factors, they use country dummies and a time trend, respectively. (They admit that they are unable to effectively proxy for the last factor.) Their results include some monotonically increasing pollution metrics (municipal solid waste and CO_2 emissions) and some monotonically decreasing variables (lack of safe water and lack of urban sanitation), but they do find a ∩-shaped relationship for ambient concentrations of SO_x (sulfur oxides including SO_2) and SPM, with turning points between $3,000 and $4,000. The authors also calculate income elasticities based on the best-fitting functional forms and find that elasticity for CO_2 emissions, 1.62, is the highest for any pollutant besides fecal coliform.

Grossman and Krueger (1995), in perhaps the most-quoted EKC paper, use a global panel data set of air quality and water quality indicators to estimate a reduced-form relationship between income and environmental quality. Their RHS regressors include third-order polynomials of current and of lagged GDP, and other relevant explanators like population density and geography. For most of their environmental indicators, they find a significant ∩ relationship, with a per-capita "turning point" less than $8,000. They also include a time trend; the coefficient on time shows steadily improving air quality but steadily worsening water quality. Grossman and Krueger also point out that reduced-form models, in which pollution is taken as a function of income, fail to capture the causal relationship driving the EKC pattern. They suggest that the ∩ curve may occur as an "induced policy response"[10] because wealthier people are better able to devote their resources to pollution abatement and political lobbying for abatement.

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[10] Grossman and Krueger, p.372.

Several authors have examined CO_2 emissions specifically. Holtz-Eakin and Selden (1995) use a reduced-form model of GHG emissions vs. per-capita income. They use a panel of data for the years 1951-86 for 130 countries, which together comprise over 70% of total global CO_2 emissions. Using a quadratic-in-levels specification with a time trend and country fixed effects, they estimate an EKC turning point of $38,000, although this exceeds the maximum of their sample. They also find that poorer countries have a greater "marginal propensity to emit," i.e. these countries are at an earlier and steeper point in their ∩-shaped curve. They predict that middle- and low-income countries will take the greatest share of CO_2 emissions by the late 21st century. Cole, Rayner and Bates (1997) also examine CO_2 emissions in an EKC context; using OECD and UNEP panel data from 1970-1990, they find that CO_2 emissions increase monotonically throughout the observed income range, with an EKC turning point far greater than the observed income maximum. However, Dijkgraaf and Vollebergh (1998) estimate the relationship between CO_2 and income using an OECD panel data set, and they find a ∩-shaped relationship with a turning point within the observed range.

Westbrook (1995) represents one of the first authors to incorporate data on the sectoral composition of the economy. She uses data on CO2 emissions from a panel of 56 developing countries between 1971 and 1991. On the RHS she includes a quadratic function of per-capita income and the sectoral shares of agriculture and services. Westbrook notes that including the sectoral shares of agriculture, services, *and* manufacturing would cause multicollinearity problems, as those three variables would sum to 1. Her estimates on income predict a ∩-shaped curve, with a turning point around $17,000. The coefficients on agriculture and services are significant and negative, although agriculture has a greater effect than services.

Hilton and Levinson (1998) begin to complicate the EKC literature by introducing a decomposition model. They examine a panel data set of automotive lead emissions in 48 countries over 20 years. They make the useful observation that pollution from economic activity is the product of two factors: pollution intensity of the activity, and scale of the activity. Their results show that in this case, gasoline consumption increases monotonically with income but the proportionate lead content of gasoline decreases with income, leading to a ∩ relationship for total lead exposure against per-capita income. They find a negative and significant time trend in their regression, indicating consistent technological change in favor of cleaner gasoline.

Along the same lines, Stern (2002) uses a global panel data set of SO_2 emissions from 1973-1990 for 23 OECD and 41 non-OECD countries. He breaks down emissions into four proximate causes: scale, output mix, input mix, and technology. All four of the posited explanators are significant in the regression. However, the impact of scale and of technical change is far greater than the impact of changes in input mix or output mix. Although input mix and output mix have a large impact on determining emissions in some countries, the average effect across all countries is close to zero. For the decomposition model, Stern finds that (controlling for all other factors) each sector of the economy has a positive output elasticity for emissions, except manufacturing, surprisingly.

EKC analyses tend to suffer from the problem of imposing a single model on the pollution-income relationship for every country in the world. Intuitively, this sort of homogeneity seems unlikely, as preferences and endowments differ across countries. Perman and Stern (2003) reject the null hypothesis that the EKC curve for SO_2 emissions has the same coefficients for every country in their panel, concluding that the concept of an EKC is misguided.[11] Anticipating the problem of potential heterogeneity across countries, List and Gallet (1999) use a panel of SO_2 and NO_x emissions data for US states over 1929-1994, expecting that the EKC relationship will be more homogeneous within the United States than among a global sample of countries. They estimate an EKC model in levels using a quadratic or cubic polynomial of income, and a time trend. They allow for potentially heterogeneous intercept, slope, and time trends across states. Despite the expectation of homogeneity among US states, their results show significant evidence of heterogeneous EKC relationships. They analyze state characteristics to explain this; for example, they find that states with higher population densities or warmer climates show earlier EKC peaks. List and Gallet do not, however, incorporate econometric critiques given by, e.g. Stern and Common (2001) by testing their data for unit roots or cointegration.

My economic models

I will analyze energy use in India using both an EKC framework and a structural decomposition model. The most useful decomposition model that I have found comes from Stern (2002) who specifies:

$$E_{i,t} = \gamma_i A_t \cdot [\prod_{j=1}^{J} y_{jit}^{\alpha_j}] \cdot [\sum_{k=1}^{K} \beta_k x_{kit}] \cdot \epsilon_{i,t}$$

where E is emissions, γ is an individual-specific efficiency parameter, A is a time-varying panel-wide technology parameter, y is sectoral output, indexed by j (there are J sectors) and the x values are production inputs. Individuals and years are indexed by i and t. Stern specifies that the sub-function of sectoral outputs should be homogeneous of degree zero, so the α coefficients should sum to zero. This implies that if every sector doubles its output using the same amount of inputs, total emissions is unchanged, ceteris paribus.

[11] Perman and Stern, p.4.

Dividing both sides by population (P) and taking logs, we get

$$\ln(\tfrac{E_{i,t}}{P_{i,t}}) = \ln(P_{i,t})^{-1} + \ln(\gamma_i) + \ln(A_t) + [\sum_{j=1}^{J} \alpha_j \ln(y_{jit})] + \ln[\sum_{k=1}^{K} \beta_k x_{kit}] + \ln(\varepsilon_{i,t})$$

Unfortunately, whereas Stern uses various energy types as his measures of production inputs and SO_2 as his LHS emissions measure, my data set lacks measures of inputs. Thus, I use total energy not as a regressor but as my LHS dependent variable, which can be interpreted as a proxy for CO_2 emissions. To cope with the lack of input data on the RHS, I use Y_{it} as a proxy for the linear combination of inputs, $\Sigma\beta_k x_{kit}$. This is reasonable as $\Sigma\beta_k x_{kit}$ could be seen as a production function, although perfect substitutability of inputs is not the most realistic assumption.

This leads to the convenient form

$$\ln(\tfrac{E_{i,t}}{P_{i,t}}) = \ln(\tfrac{Y_{i,t}}{P_{i,t}}) + \ln(\gamma_i) + \ln(A_t) + [\sum_{j=1}^{J} \alpha_j \ln(y_{jit})] + \ln(\varepsilon_{i,t})$$

As my income data is provided in the dataset in terms of real money per capita, this specification is particularly convenient. Note that the coefficient on the per-capita income variable is restricted to be 1.

Now, the usual EKC model takes the form

$$\ln(\tfrac{E_{i,t}}{P_{i,t}}) = \ln(\gamma_i) + \delta_0 \ln(t) + \delta_1 \ln(\tfrac{Y_{i,t}}{P_{i,t}}) + \delta_2[\ln(\tfrac{Y_{i,t}}{P_{i,t}})]^2 + \ln(\varepsilon_{i,t})$$

Following the suggestion of Stern (2002), I construct a maintained hypothesis that nests both the decomposition and EKC models:

$$\ln(\tfrac{E_{i,t}}{P_{i,t}}) = \ln(\gamma_i) + \ln(A_t) + \delta_0 \ln(t) + \delta_1 \ln(\tfrac{Y_{i,t}}{P_{i,t}}) + \delta_2[\ln(\tfrac{Y_{i,t}}{P_{i,t}})]^2 + [\sum_{j=1}^{J} \alpha_j \ln(y_{jit})] + \ln(\varepsilon_{i,t})$$

For the EKC model, I impose the restriction that all the α coefficients on the sectoral shares are zero, and there are no time dummies. For the decomposition model, I impose the restrictions that $\delta_1 = 1$ and $\delta_0 = \delta_2 = 0$; thus the only RHS variables in the regression are the sectoral shares. (This is a slight modification of Stern's formulation.)

After estimating an EKC model, we can calculate the "turning point" or peak of the $\cap$-shaped curve by taking a derivative of the polynomial. If the (simplified) function is

$$\tfrac{E}{P} = \delta_1 \ln(\tfrac{Y}{P}) + \delta_2[\ln(\tfrac{Y}{P})]^2$$

then the first-order condition with respect to (Y/P) is: $0 = \delta_1 + 2\,\delta_2[\ln(\tfrac{Y}{P})]$

leading to the peak at: $\tfrac{Y}{P} = e^{(-\delta_1/2\delta_2)}$

Econometric Methods

The first step in analyzing time-series or panel data is to check the variables for integration or stationarity. It is generally believed that a stationarity test in a panel has more power than a stationarity test in a single-member time series; the power of the test increases with the number of cross-sections.[12] Quah (1994) finds that when testing a variable for a unit root in panel data, the simple Dickey-Fuller statistic approaches a normal distribution as the number of periods and number of members increases. I will use the procedure of Im, Pesaran and Shin (2003) who show that in order to test a given variable for a unit root in panel data, we can apply an augmented Dickey-Fuller (ADF) test for each individual member of the panel and average the results over all individuals. The ADF test takes the form

$$\Delta y_t = \alpha + \rho y_{t-1} + \sum_{j=1}^{m} \gamma_j \Delta y_{t-j} + v_t$$

where y is the variable of interest and m is some positive amount of lags and v_t is an i.i.d., mean-zero error term. McCoskey and Kao (1999) advocate including a time trend:

$$\Delta y_t = \alpha + +\delta t + \rho y_{t-1} + \sum_{j=1}^{m} \gamma_j \Delta y_{t-j} + v_t$$

and computing the ADF test both with and without the trend term, allowing for the possibility that the variables may be trend stationary.

The ADF test includes the hypotheses

$H_0 : \rho = 0 \Leftrightarrow y_t$ is an I(1) process vs. $H_a : \rho < 0 \Leftrightarrow y_t$ is an I(0) process

The optimal number of lags for an ADF test is determined by minimizing the Akaike Information Criterion and/or the Schwarz Bayesian Information Criterion. The "varsoc" command in Stata indicates that generally the optimal number of lags is 1 for the (logged) income and sectoral variables and 2 for the (logged) energy variable. As the alternative hypothesis is one-sided, we look for a test statistic far enough below zero to reject the null. To complete the IPS test, we estimate the ADF equation for every individual state and get a t-statistic for the value of ρ. We then take the arithmetic mean over all N individuals:

$$\bar{t}_\rho = \frac{1}{N} \sum_{i=1}^{N} t_{\rho i}$$

Im, Pesaran, and Shin use Monte Carlo estimation methods to tabulate critical values for this statistic for various values of T, N, and a trend term. The table is available in their paper.

[12] Hadri 2000, p.149.

Next, I estimate the EKC and decomposition models both individually for each state and also using the pooled panel. The EKC model is straightforward, and I compute the pooled panel estimates using both fixed effects and random effects. The decomposition model includes time effects. One method of accounting for this is to explicitly include year dummies in the regression. An equivalent approach, as Pedroni (1999) discusses, would be to subtract the cross-country time mean from each observation:

$$\tilde{y}_{it} = y_{it} - \bar{y}_t = y_{it} - \frac{1}{N}\sum_{i=1}^{N} y_{it}$$

I choose to use time dummies, for simplicity and also to easily see the value of each year dummy. However, when I estimate the decomposition model for each state, I omit the time effects, as including the time dummies would remove all the degrees of freedom from the model. When I estimate the decomposition model for the panel, I do the four possible cases of combining fixed effects vs. random effects and time dummies vs. no time dummies.

A Hausman test can indicate whether a random-effects specification is appropriate in a pooled panel regression; that is, whether unobserved state effects are uncorrelated with the explanators. If Hausman rejects the null hypothesis of independent state effects, then a fixed-effects specification, which relies on variance over time *within each state*, is more appropriate.

The "xttest1" command in Stata, available as an auxiliary download, implements several diagnostic tests for random-effects panel data regressions, including the Breusch-Pagan LM test for random effects and the Baltagi-Li test for first-order serial correlation in the residuals.

I also wish to test whether the panel data really should be pooled. Baltagi (2001) shows that the null hypothesis of a common set of coefficients for all the individuals in a panel can be tested with a Chow test:

$$F = \frac{(RSS_{pooled} - \sum_{N} RSS_N)/(N-1)K}{(\sum_{N} RSS_N)/(T-K)N} \sim F([N-1]K, [T-K]N)$$

where K is the number of regressors, T is the number of observations, N is the number of states, RSS_{pooled} is the residual sum of squares from the pooled fixed-effects regression, and RSS_N is the residual sum of squares from an ordinary time-series regression for state N alone.

Finally, it is important to test for cointegration between all variables in the model. If all variables have a unit root, OLS might generate a "spurious regression" in which the variables appear to fit into a linear model, but they are not moving together over the long run. By contrast, cointegration is a relationship in which a linear combination of integrated (of equal order) variables produces a stationary series. To test cointegration, the easiest procedure is to get the residuals from an OLS regression of the basic model, and test the null hypothesis that these residuals contain a unit root; i.e. that the model is *not* cointegrated. Engle and Granger (1987) note that a Dickey-Fuller test will "reject the null too often" if the cointegrating vector is not known *a priori,* i.e. it comes from OLS estimates.[13] Based on power considerations, they recommend using an ADF test rather than DF or Durbin-Watson test. If we obtain an ADF test statistic from the residuals, we can use the critical values documented by MacKinnon (1991). The structure of the ADF test, i.e. the number of lags, is determined as above by the AIC or SBIC. This strategy can be extended to a panel data set using a pooled regression. Authors including McCoskey and Kao (1998) and Pedroni (1999) present more complex tests for cointegration in panels, allowing for heterogeneous autoregressive relationships in the residuals, but I will follow the simplest strategy here. McCoskey and Kao (1999) suggest that a pooled ADF test on the panel residuals or an ADF test for each individual is satisfactory.

Data

My India state-level data set was helpfully given to me by Professor Robin Burgess and Berta Esteve-Volart of STICERD at the London School of Economics. The data are extracted from a large set of variables covering 16 major states of India over the years 1960-2000. The relevant data for this study is an unbalanced panel, in the sense that the per-capita real output data for each state run from 1960 until 1992, while the energy data run from 1959 to 1989 (with a few missing observations) and the sectoral output data run from 1960 to 1997 (for manufacturing subsectors) and from 1980 to 1997 (for services subsectors).

State aggregate and sectoral output figures come from the Department of Statistics, Ministry of Planning, Government of India. As best as I can tell, the figures are expressed in real 1974 rupees. I have not been able to determine the precise governmental source of the energy figures. The energy figures are given in crores (1 crore = 10 million) of kilowatt-hours. The population figures come from the Census of India decennial surveys of 1951, 1961, 1971, 1981, 1991, and 2001. Values between these years are interpolated using a constant exponential growth rate.

[13] Engle and Granger, p.265.

Table 1. **Summary of data**

State	Variable	Obs	Mean	Std.Dev.	Min	Max
India-wide	Income	508	10393.35	3600.045	3993.128	26369.77
	Energy	360	439.226	459.283	1.2	3455.1
	Services share	287	.328	.047	.237	.476
Andhra Pradesh	Income	33	9979.639	2488.608	7396.627	16159.26
	Energy	31	530.748	452.124	70.1	1506.4
	Services share	18	.354	.015	.326	.379
Assam	Income	27	9119.522	2063.008	6544.146	12693.08
	Energy	31	46.100	35.098	3.1	114.7
	Services share	18	.324	.025	.288	.381
Bihar	Income	33	6326.347	1093.243	3993.128	8416.854
	Energy	31	188.322	108.808	14.7	392.4
	Services share	18	.268	.016	.245	.303
Gujarat	Income	33	11844.36	2870.841	7725.746	18033.86
	Energy	31	643.270	501.457	109.1	1973.3
	Services share	18	.292	.016	.265	.325
Haryana	Income	28	14716.44	3765	8881.522	22159.38
	Energy	23	332.662	193.2438	1.2	649.7
	Services share	18	.278	.018	.238	.314
Jammu & Kashmir	Income	28	10269.67	2308.954	6158.178	13367.28
	Energy	29	41.955	36.355	4.2	105.3
	Services share	17	.425	.028	.385	.476
Karnataka	Income	33	10330.74	2123.838	7468.731	15258.56
	Energy	31	462.326	289.953	100	1111
	Services share	18	.342	.024	.304	.391
Kerala	Income	33	8641.61	1816.068	6352.22	12639.43
	Energy	31	279.6	180.374	48.8	553.3
	Services share	18	.339	.0134	.312	.362
Madhya Pradesh	Income	33	8401.098	1841.905	5222.511	12819.95
	Energy	31	432.465	367.478	35.4	1264.5
	Services share	18	.263	.014	.237	.288
Maharashtra	Income	33	12955.95	3451.284	8950.021	20581.24
	Energy	31	1287.365	865.351	292	3455.1
	Services share	18	.377	.029	.333	.427
Orissa	Income	33	8729.456	1867.117	6100.593	12769.83
	Energy	31	222.678	133.181	50.2	487
	Services share	18	.310	.025	.268	.356
Punjab	Income	29	17416.13	4342.227	9914.349	26369.77
	Energy	31	504.783	349.195	19	1450.8
	Services share	18	.306	.008	.294	.323
Rajasthan	Income	33	7864.355	1384.629	5415.495	11228.89
	Energy	31	210.474	198.515	8	649.3
	Services share	18	.310	.032	.246	.360
Tamil Nadu	Income	33	10136.62	2692.846	5976.627	16325.98
	Energy	31	582.413	247.177	189.8	1186
	Services share	18	.379	.018	.349	.411
Uttar Pradesh	Income	33	8772.787	1456.563	6355.484	11584.65
	Energy	31	736.026	476.452	118.3	1888.8
	Services share	18	.332	.012	.303	.352
West Bengal	Income	33	12044.8	2120.535	8588.629	15834.84
	Energy	31	476.717	174.894	210.9	873.6
	Services share	18	.356	.015	.336	.398

The data set provides *sub*-sectoral output, so I add together various subsectors to get the sectoral totals. I add the output for forestry, fisheries, mining, and agriculture to get what I call the extractive sector. I add the output for communications, banking/insurance, hospitality, real estate, business services, public administration, and "other services" to get a total for the services sector. I add registered manufacturing and unregistered manufacturing to get a total for the manufacturing sector.

I have a few concerns with the integrity of the data. The current state borders of India have not been constant since 1949. In 1956, the States Reorganization Commission ordered a large reorganization of states along ethnic and linguistic lines. Later, in 1960, Bombay state was dissolved and apportioned among Maharashtra, Gujarat, and Karnataka. In 1966, a large section of Punjab was partitioned off and renamed Haryana. Thus, the constancy of the data-gathering methods and relevant populations over the 54 years of the sample is uncertain. There was also one very anomalous energy observation in Madhya Pradesh for 1981, which I dropped.

Results and Discussion

Table 2. **Unit Root Tests for variables of interest**
Following Im/Pesaran/Shin (2003) ADF method

	t-bar without trend	t-bar with trend
Log(energy per capita)	-1.402	-2.404
	(2 lags)	(2 lags)
Log(income per capita)	-.296	-2.385
	(1 lag)	(2 lags)
[Log(income per capita)]^2	-.645	-2.801
	(1 lag)	(2 lags)
Log(services share)	-1.180	-2.217
	(1 lag)	(2 lags)
Log(manufacturing share)	-1.639	-2.632
	(1 lag)	(2 lags)
Log(extractive share)	-.604	-2.536
	(1 lag)	(2 lags)

For all variables except manufacturing share with trend, I fail to reject the null hypothesis of a unit root.
After taking first differences, all variables were stationary, i.e. the t-bar statistic was less than the relevant Im/Pesaran/Shin 5% critical value.

Table 3. **EKC Panel Regression**
Dependent variable: log(energy per capita)

	Fixed effects	Random effects
Log(income per capita)	4.461	4.497
	(.266)	(.280)
[Log(income per capita)]^2	-.251	-.220
	(.249)	(.331)
Year	.069	.058
	(.000)	(.000)
R^2 (within)	.625	.615
R^2 (between)	.181	.426
Turning point	7123	27755
Hausman		Reject H_0: random effects; $Prob(\chi^2(3) \geqslant 84.57) = 0$
Chow test for poolability	$Prob(F(45,416) \geqslant 7.776)=0$	$Prob(F(45,416) \geqslant 8.425)=0$
ADF test on residuals	Did not perform for pooled sample because Chow test rejects H_0 of poolability.	Did not perform for pooled sample because Chow test rejects H_0 of poolability.

Figures in parentheses below coefficient estimates are P-values.

Table 4. **Decomposition Panel Regression**
Dependent variable: [log(energy per capita) – log(income per capita)]

	Time dummies		No time dummies	
	Fixed effects	Random effects	Fixed effects	Random effects
Log(services share)	-.363 (.440)	-.434 (.341)	-.418 (.352)	-.472 (.278)
Log(manufacturing share)	-.288 (.057)	-.257 (.082)	-.293 (.041)	-.267 (.057)
Log(extractive share)	-.703 (.069)	-.778 (.034)	-1.028 (.002)	-1.046 (.001)
1980	-.081 (.191)	-.073 (.231)		
1981	-.100 (.106)	-.092 (.131)		
1982	-.008 (.887)	-.003 (.956)		
1983	.040 (.506)	-.035 (.563)		
1984	-.021 (.715)	-.018 (.760)		
1985	-.014 (.795)	-.014 (.799)		
1986	-.007 (.902)	-.006 (.915)		
1987	.035 (.539)	.033 (.552)		
1988	(dropped)	(dropped)		
1989	-.022 (.693)	-.024 (.668)		
R^2 (within)	.151	.150	.114	.113
R^2 (between)	.007	.038	.050	.065
Hausman		Do not reject H_0: random effects; $Prob(\chi^2(11) \geqslant 0.80) = 1$		Do not reject H_0: random effects; $Prob(\chi^2(3) \geqslant 1.37) = .712$
Chow test for poolability	Did not perform because time dummies make it impossible to compare with state-by-state regressions.	Did not perform because time dummies make it impossible to compare with state-by-state regressions.	$Prob(F(45,112) \geqslant 2.657)=0$	$Prob(F(45,112) \geqslant 2.666)=0$
Breusch-Pagan LM test for random effects		Reject H_0 of no random effects; $Prob(\chi^2(1) \geqslant 559) = 0$		Reject H_0 of no random effects; $Prob(\chi^2(1) \geqslant 555) = 0$
Baltagi-Li test for serial correlation		Do not reject H_0 of no serial correlation; $Prob(\chi^2(1) \geqslant .35)=.552$		Do not reject H_0 of no serial correlation; $Prob(\chi^2(1) \geqslant .36)=.549$
ADF test on residuals			Did not perform for pooled sample because Chow test rejects H_0 of poolability.	Did not perform for pooled sample because Chow test rejects H_0 of poolability.

Figures in parentheses next to coefficient estimates are P-values.

According to Table 2, all the variables (except manufacturing share with trend) show a unit root in levels and are stationary in first differences, which suggests that I should be concerned about a spurious regression *and* should search for a cointegrating relationship. When I examined the variables on a state-by-state basis (results not shown), the presence of unit roots was less certain; anywhere from four to ten states were stationary in levels for any given variable.

Table 3 summarizes the EKC panel regression. A Hausman test guides us to choose the fixed-effects estimator. The within-groups R^2 was over 0.6 for the fixed-effects model, although the between-groups R^2 was only 0.18, suggesting a relatively poor fit across states. The estimated turning point is 7123 rupees. However, a Chow test suggests that the null hypothesis of a single vector of coefficients for every state is wrong. I also ran EKC regressions for each of the individual state time series (results not shown)[14]. The R^2 for these regressions was above 0.7 for all states but two. Five states – Bihar, Jammu & Kashmir, Madhya Pradesh, Orissa, and Tamil

[14] In fact, this was necessary in order to compute the Chow tests for poolability.

Nadu – had EKC turning points at income levels below the pooled panel fixed-effects estimated turning point of 7123. All five of these states had negative fixed effects (not shown) in the fixed-effects panel regression. All five of these states had mean per-capita incomes (averaged over the whole time period) less than the India-wide income mean of 10393. Three of these states had mean services shares below the India-wide mean services share of .328. When I ran EKC regressions for the individual states with non-stationary variables and then tested the residuals with an ADF test (results not shown), the results had estimates beyond the MacKinnon critical values, allowing me to reject the null of no cointegration.

For the decomposition panel regression, the diagnostics tell us to choose the random effects model. Surprisingly, the only non-significant sectoral variable is services. Manufacturing and extraction are significant at a 10% or 5% confidence level in various models. Services and manufacturing have the expected (negative) sign, but manufacturing is positive. This is very surprising. The time dummies reduced the effect of the significant variables.

The within-groups R^2 was far lower in these models than in the EKC model, and the between-groups R^2 was also far lower than in the EKC model. The within-R^2 was still larger than the between-R^2, suggested that no single relationship exists. The R^2 values (not shown) for the individual decomposition state regressions are much higher. As the Chow test rejected the idea of a single cointegrating vector, I did not attempt to check for cointegration in the panel. In contrast to the EKC models, when I ran decomposition regressions on individual state time series (results not shown) and then tested the residuals, I was unable to reject the null of no cointegration in most cases. The poor performance of the decomposition model may be due to the low number of observations: although the sample runs from 1960-2000, the only years for which the income, energy, and sectoral output variables are *all* available are 1980-1989.

Conclusion

The EKC model proved to be a better country-wide fit for this data than the decomposition model. I expected the decomposition model, which represents a tighter causal accounting of energy use, to be a better fit. It is true that as I lacked measures of energy inputs, I was not able to fully execute the decomposition analysis proposed by authors like Zhang, de Nooij *et al.* and Stern. The decomposition model might perform better with better data.

It is very surprising that services does not play a significant role in driving energy use in the decomposition model. This may be due to incomplete data, however. If I had better data on inputs and fuller observations over the whole time period, the negative coefficient might become significant. The biggest effect on energy use clearly comes (negatively) from the extractive sector, including agriculture. This may be worrisome, as agriculture is projected to continue a steady decline in India in the coming decades.

There is much potential for India to ameliorate its dirty energy use. For example, Kroeze *et al.* (2004) try to quantify the technical potential of GHG emissions abatement technologies for the electricity sectors of India and China. They compare "Best Practice Technology" (BPT) scenarios to "Business As Usual" (BAU) scenarios. For India, they predict that available technology can reduce 2020 GHG emissions by up to 45% from the BAU scenario, which includes 50% population growth and six-fold increase in GDP by 2020. Possible technologies include: end-use efficiency improvement; replacement of coal by renewable energy, natural gas, or nuclear power; closing small power plants; cogeneration; reducing electricity losses during transmission; and efficiency improvement of power plants. Also, Anderson and Cavendish (2001) use a numerical simulation of a large, India-like developing country to show that early anti-pollution policies (such as Pigouvian taxes, tradable permits, or technology subsidies) can lead to an EKC peak at one-half the pollution level (per capita) and several decades earlier than in the empirical record of previous EKC patterns.

Fuller data and more sophisticated econometric models could tell us more about the energy-income-sectoral relationship in India. The research potential is promising.

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