Analysis

The economics of global light pollution

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ABSTRACT

This paper is the first analysis of the economic factors of global light pollution. Light pollution commonly refers to excessive or obtrusive artificial light caused by bad lighting design. Light pollution generates significant costs including negative impacts on wildlife, health, astronomy, and wasted energy—which in the U.S. amounts to nearly 7 billion dollars annually. Current scientific models of light pollution are purely population based. The current paper utilizes unique remote sensing data and economic data from the World Bank to quantify the economic causes of light pollution globally. Fractional logit models show that, similar to other types of pollution, both population and GDP are significant explanatory variables.

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1. Introduction

This paper examines light pollution, an issue that has been largely neglected in economics. Light pollution has been described as "One of the most rapidly increasing alterations to the natural environment;" a problem whereby "mankind is proceeding to envelop itself in a luminous fog" (Cinzano et al., 2001, 689). Light pollution is a broad term referring to excessive or obtrusive artificial light caused by bad lighting design. It includes such things as glare, sky glow, and light trespass. Excessive and misdirected light from streetlights, homes, and towns not only interferes with wildlife, stargazing, sleep habits, and professional astronomy, but it also wastes a vast amount of energy. Many people assume artificial light provides safety and improves visibility. However, a large portion of lighting does neither. Lighting that is overused, misdirected, or otherwise obtrusive is simply pollution.

For example, many cities produce a glow in the night sky that can be seen for 100 miles away. Consequently, 66% of the United States and 50% of the European population can no longer see the Milky Way at night (Cinzano et al., 2001). Additionally, approximately 40% of the United States and almost 20% of the European Union population has lost the ability to view the night sky with an eye that can adapt to the darkness of the night sky—in other words, it is as if they never really experience nighttime (Cinzano et al., 2001, 689).

This paper is meant to address a major shortcoming in the current modeling and understanding of light pollution. Current models ignore economic factors contributing to light pollution and focus almost entirely on population being the key determinate. We correct for this shortcoming by combining a broad spectrum of World Bank data with satellite data measuring the amount of artificial sky brightness (as distinct from the utilization of useful lighting) in 184 different countries. Using fractional logit models to analyze these data, we are able to determine the key factors which contribute to global light pollution. Not surprisingly, we find strong evidence that economic activity and urban density are correlated with the existence of light pollution.

This paper is divided up into the following sections. Section 2 begins with a brief overview of light pollution and how it fits into the externality literature. Section 3 provides an explanation of how various levels of light pollution were measured and quantified. Section 4 discusses our models and their results. Section 5 offers some conclusions and discusses areas of future research.

2. Externalities and light pollution

While most people have a sense that artificial lighting can interfere with birds and insects, the effects are far more common, widespread, and serious than commonly realized. Light pollution does substantial damage to wildlife, aesthetics, and even to human health. Mammals, birds, amphibians, insects, fish and even plants are all affected by light pollution. Light pollution disrupts feeding, reproduction, sleeping and migration. Indeed, problems from light pollution are so pervasive that "unless we consider protection of the night, our best-laid conservation plans will be inadequate" (Rich and Longcore, 2006, 2). Until very recently, darkness has been an inescapable part of the environment and natural history or our planet. Accordingly, life has evolved and

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adapted to daily, monthly, and annual cycles in the level of ambient light. We should not be surprised that the radical transformation of the environment, made possible by artificial lights, has substantial, if inadequately understood, deleterious consequences.

Light pollution exhibits many of the characteristics of a negative externality and has been studied by biologists and astronomers for many years. For example, light pollution disrupts the migration patterns of nocturnal birds and can cause hatchling sea turtles to head inland, away from the sea, and be eaten by predators or run over by cars (Verheijen, 1985; Witherington and Bjorndal, 1991; Salmon and Witherington, 1995; Salmon et al., 1995). Human physiology is not immune to the problem of light pollution. Davis et al. (2001) have concluded that there is an increased risk of breast cancer in women due to lower levels of melatonin production that results from light pollution. Ostensibly, light pollution keeps people from falling into a deep sleep, which causes their bodies to decrease the production of melatonin (Kerenyi et al., 1990).

Light pollution also interferes with both professional and amateur astronomy by reducing the visibility of galaxies, nebulae, and other celestial objects. As a related matter, light pollution does tremendous damage to a unique scenic resource—the night sky (Gallaway, in press). Economic studies quantifying this damage are only now beginning. However, the night sky has been a part of art, science, and culture for as long as these things have existed. When one considers that this cultural resource is no longer visible to the majority of people living in developed countries, and that few places on the globe are unaffected by sky glow, then it is not unreasonable to suspect that aesthetic damages may be exceptionally large (Gallaway, in press). Indeed, light pollution is starting to encroach into areas previously noted for their dark skies. Such damage to an area's natural amenities likely reduces willingness to pay by visitors to the area (Murdock, 2006; Font, 2000). This could be especially acute for state and national parks and other rural areas.[1] Recent studies have shown that a majority of visitors to specific National Parks in the American west have a positive willingness to pay to preserve dark skies in those locations.

Light pollution also wastes energy. Accordingly, poor lighting design contributes to increased carbon dioxide emissions and global warming. In the United States, roughly 6% of the 4.054 million megawatt hours (mwh) of electricity produced are used for outdoor lighting and an estimated 30% of this is wasted as light pollution (California Energy Commission 2005). This translates into 72.9 million mwh of electricity needlessly being generated at a cost of $6.9 billion a year. Furthermore, this unnecessary electricity usage generated an additional 66 million metric tons of CO_2 (Ristinen and Kraushaar, 2006; DOE, 2006). Eliminating light pollution would be the CO_2 equivalent of removing over 9.5 million cars from of the road (EPA, 2006; DOT, 2001).[2]

Viewing excessive artificial light as a form of pollution is made difficult by the fact that, other than being unwanted, light as a pollutant is no different than light as a good. With many negative externalities, the good and the pollutant are distinct. Gas and coal provide services key to the propulsion of vehicles or the generation of electricity. It is easy to distinguish these services from undesirable byproducts such as CO_2, SO_2, or NO_x. Light pollution does not lend itself to such easy categorization. However, other negative external-

ities share this trait. Non-point pollutants such as fertilizers or pesticides come to mind. With all of these, it is very often the case that the good in question becomes problematic when it is found in the wrong location or in the wrong amount, or when it affects the wrong population. We might argue that the good becomes a pollutant when its effects are something other than its intended purpose. Fertilizer that increases crop yield is a good; runoff that leads to reduced levels of dissolved oxygen in a stream is a pollutant. Similarly, light that improves visibility (for humans) is a good. However when lighting causes glare, or deepens shadows, or washes out the stars, this reduces visibility. Such light is light pollution. Neon lights might improve the visibility of a sign or a storefront. However, a thousand such displays merely add to the clutter and reduce the visibility of any individual sign. This positional externality could also be classified as pollution.[3]

Interestingly, light pollution has some characteristics of a local, a regional and a global externality. Often, nuisance problems, such as homeowners being bothered by lights from ball parks, car lots, or prisons, are local. Sky glow might be characterized as a regional issue, in as much as the glow from large cities can wash out part of the heavens from even 200 miles away.[4] On the other hand, if one was more concerned with light pollution's deleterious impact on migratory wildlife or scientific research, or if one were examining the wasted energy and global warming implications, then it might be best to view light pollution as a global externality. Naturally, local problems are easier to address. Indeed, many communities have lighting ordinances designed variously to mitigate nuisance lighting, reduce municipal lighting expenses, or, more commonly in the desert southwest, to protect an area's dark skies for cultural, aesthetic, or scientific purposes.

In many ways, light pollution is similar to other pollutants and environmental problems that have been carefully studied by economists over the years (Baumol, and Oates, 1971; Wirl, 2007; Sobotta et al., 2007; Picazo-Tadeo and Reig-Martinez, 2007; Shimshack et al., 2007). It is easier to identify light pollution than to measure its 'damage' or create politically palatable solutions. Certainly, one can imagine additional negative, as well as positive, externalities associated with artificial lighting. We do not attempt to measure damages or make policy recommendations in this paper. The point is simply that there are important, widespread problems associated with artificial lighting. In this paper, we identify economic factors that contribute to the problem. In particular, we accept a definition of light pollution, by Cinzano et al. (2001) as "the alteration of the ambient light levels in the night environment produced by man-made light." We also rely on the light-pollution data they generated by using satellite measurements to model this artificial sky brightness at zenith.

3. Light pollution data

The light pollution data used in this paper are remote sensing data from satellite observations. The raw data are from the Defense Meteorological Satellite Program (DMSP) Operational Linescan System (OLS). Data from the DMSP-OLS were, for example, previously used to create a widely published cloud-free composite image of the "Earth at Night" (Elvidge, et al., 1997, 2001; Mayhew and Simmon, 2000). This striking image did help illustrate the scope of artificial

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[1] In Chaco Culture National Historical Park, for example, the night sky is officially one of the assets the park tries to preserve for the public. Even though the park is in a remote and relatively unpopulated part of New Mexico, it is increasingly affected by light pollution.

[2] These are rough estimates based on data from stated references. The figures are simply meant to provide "ballpark" figures for the scope of the problem. Additional technologies which would turn off lights when not in use, or which, in addition to eliminating uplighting, would reduce glare and allow improved visibility with lower wattage fixtures would increase energy savings estimates. Alternatively, a significant percentage of recently installed outdoor lighting is already well designed and efficient. Accounting for this newer lighting would reduce estimates. The lack of good data is one of the challenges to mitigating light pollution. The methodology used here is available upon request.

[3] Noise pollution is widely recognized, complained about, and regulated; yet it is similar to light pollution in many respects. While some noises are a byproduct, others such as radios, sirens, alarms, shouts, and the thousands of conversations of a throng, are the goods themselves. We accept that one person's loud music is pollution in another's ears.

[4] Astronomers have a law, known as Walkers Law, which estimates the reduced visibility from a city based on its size and distance from the viewer. The model estimates the increase in the sky's natural glow when looking at the sky 45° above the horizon in the direction of the pollution's source. Looking towards a metropolitan area of 1.5 million people could increase sky glow by 25% for a location over 50 miles away.

lighting but it was not sufficiently refined to accurately model light pollution and allow comparisons across different times or locations.

Researchers used DMSP-OLS data to create the first "quantitative and accurate depiction of the artificial brightness of the night sky" to be "available to the scientific community and governments" (Cinzano et al., 2001, 689). Their data is particularly valuable because of the singular lack of data on light pollution. Other direct measures of light pollution are *ad hoc*, ground-based measures (Cinzano et al., 2001). Such data are sporadic and limited to only a few locations, including data collected near observatories, data gathered by amateur astronomers, and data collected by the National Park Service in a number of national parks in the western United States.

This lack of direct data has forced researchers to rely almost exclusively on population-based models of light pollution (e.g., Walker, 1977). Indeed, there is a very strong connection between population and light pollution. Nevertheless, "the apparent proportionality between population and sky glow breaks down going from large scales to smaller scales and looking in more detail" (Cinzano et al., 2001, 690). Additionally, light pollution is affected by such things as the level and composition of economic development, and local ordinances (e.g. Bertiau et al., 1973). Of course, population-based models also depend upon the reliability of the population data. Even when accurate data are available, they often give the total population for some relatively large area, say a province or a metropolitan area, but offer no details about how the population is distributed within those areas. Accordingly, this new empirical data on light pollution opens up new possibilities for analysis.

Satellite observations were collected for "the darkest nights of the lunar cycles" for nearly 30 nights in 1996 and 1997. (Cinzano et al., 2000, 642). The data "covers the range for primary emissions from the most widely used lamps for external lighting: mercury vapor (545 and 575 nm), high-pressure sodium (from 540 to 630 nm), and low-pressure sodium (589 nm)" (Cinzano et al., 2000, 642).[5]

Lights that did not reoccur in the same place at least three times were eliminated from the data. Crucially, earth-based measurements were used to ensure that these data were translated into an accurate measure of a key type of light pollution—artificial sky brightness—rather than simply measuring lights (Cinzano et al., 2000, 649, 652).[6] Modeling techniques, taking into account light scattering and diffraction, were then used to compute the propagation of light pollution. Simplifying assumptions generated results that emphasize the distribution of light pollution rather than show how local sky brightness is affected by atmospheric conditions and elevation (Cinzano et al., 2001, 691).The minimum detectable luminance, of a light with and effective wavelength of 550 nm, corresponded to what one might expect from two 250-w high-pressure sodium lamps placed every square kilometer. (Cinzano et al., 2000, 643).

The resulting map demarks areas by the level of light pollution present. These levels corresponded to various ratios of artificial sky brightness to average natural night sky brightness (Cinzano et al., 2001, 691–692). Finally, the light pollution atlas was compared to a population atlas using the same grid size.[7] The two data sets were superimposed and statistics were extracted for 201 countries by tallying the percent of the populations living within each of the light pollution tiers (Cinzano et al., 2001, 696).

In addition to population figures, data were collected showing the percentage of land area that was affected by various levels of light pollution for each country. For example, in 1996/1997, 85.3% of the EU's land mass and 61.8% of the US's land mass were covered by a night sky where artificial light added at least 11% to the natural brightness of the sky at zenith (Cinzano et al., 2001, 704). The percent of landmass affected drops sharply for higher levels of light pollution so that only 0.1% of the EU and 0.6% of the US were severely polluted with artificial nighttime brightness more than 27 times the natural levels (Cinzano et al., 2001, 704). Nevertheless, most of the developed world lacks pristinely dark areas and most of the world's population encounters some light pollution. Light pollution is concentrated precisely because populations are concentrated. Moreover, this concentration tends to be along coastal areas, which can often be ecologically important. To use a previous example, light pollution from coastal cities and resorts can interfere with the way sea turtle hatchlings use positive phototaxis to find the ocean.

In this paper we have chosen to focus on three different tiers of light pollution. The first of these is the percent of the population affected by the minimum level of artificial brightness required for an area to be considered polluted, which we have called *POP3*. These criteria consider the night sky polluted when the artificial brightness of the sky is greater than 10% of the natural sky brightness above 45° of elevation (Cinzano et al., 2001, 697; Smith, 1979).[8] We also considered two more severe categories of light pollution, with total sky brightness, from natural and artificial sources, at double and quadruple natural levels. We examine both the percent of population, *POP1* and *POP2* respectively, and the percent of landmass affected by these high levels of light pollution, *SURFACE1* and *SURFACE2* respectively.[9]

For example, in Table 2, we can see that almost 99% of the population in North American countries live in an area where light pollution has reached the threshold level, 94% of the population lives with sky glow that is at least double its natural level while 70% of the population experiences sky glow that is 4 times higher than the natural level of light at night. In addition, in North American countries an average of 41.4 and 9.93% of the land has a night sky glow that is, respectively, at least twice, or 4 times the natural level.[10]

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[5] Ordinarily, these data are collected at a gain setting of 60 dB. For this project, some observations were gathered at a setting of 24 dB to avoid saturation, while other observations were acquired at settings of 40 and 50 db to permit detection of suburbs and small towns (Cinzano et al., 2000, 642).

[6] The methodology for gathering and processing the data used in the atlas are described at length in Cinzano, et al., 2001 and especially in Cinzano et al., 2000. We have provided a brief discussion in this paper. Cinzano et al. provided a summary outline of their data processing. "The primary processing steps include: (i) establishment of a reference grid with finer spatial resolution than the input imagery using the 1-km equal-area Interrupted Homolosine Projection (Goode, 1925; Steinwand, 1993) developed for the NASA-USGS Global 1-km Advanced Very High Resolution Radiometer (AVHRR) project; (ii) identification of the cloud-free section of each orbit based on OLS-TIR data; (iii) identification of lights, removal of noise and solar glare, cleaning of defective scan lines and cosmic rays; (iv) projection of the lights from cloud-free areas from each orbit into the reference grid; (v) calibration to radiance units using prior-to-launch calibration of digital number for given input telescope illuminance and VDGA gain settings in simulated space conditions; (vi) tallying of the total number of light detections in each grid cell and calculation of the average radiance value and (vii) filtering of images based on frequency of detection to remove ephemeral events" (Cinzano, et al., 2001, 643).

[7] The Landscan 2000 DOE global population density database.

[8] For those not living in urban areas, light pollution is often seen as sky glow above neighboring towns or cities. This sky glow can be seen from as far as 200 miles away and is much worse closer to the horizon in the direction of its source. The observed light pollution is a function of the angle altitude above the horizon as well as the brightness and distance from the source. A location meeting the minimum threshold for pollution might have darker skies at zenith and much brighter skies closer to the horizon.

[9] That is, an artificial sky brightness equal to natural level will double the *total* sky brightness, and artificial levels are three times natural levels, quadruple the total levels. Pop1 measures the percent of the population living where the total light level is at least twice the natural level. Similarly Pop2 measures the percentage of the population living under skies where the total light level is at least four times the natural level. Surface1 and Surface2 have a similar interpretation.

[10] Our aggregate statistics do not compare directly to those reported by Cinzano. For example, Cinzano provides data for 204 countries. Only 186 of these matched countries for which we had World Bank data. Moreover, Cinzano's aggregate statistics are weighted averages, while we are only able to report un-weighted averages.

Table 1
Variable definitions.

Variable	Definition
POP1	Percentage of the population living under skies whose artificial glow is greater than the natural level
POP2	Percentage of the population living under skies whose artificial glow is 3 times the natural level
POP3	Percentage of the population living under skies above the threshold pollution level
SURFACE1	Percentage of the surface area with skies whose artificial glow is greater than the natural level
SURFACE2	Percentage of the surface area with skies whose artificial glow is 3 times the natural level
GDP Per Capita	Real GDP per capita in 1996, 1995 U.S. dollars
Urban	Percentage of total population living in urban areas
Arable	Percentage of total land area that is arable
Energy	Energy (oil, natural gas, and coal) depletion/extraction as percentage of Gross National Income
Foreign Investment	Net inflows of foreign direct investment as a percentage of GDP
Roads	Percent of total roads paved

Sources: Light pollution data is from Cinzano et al. (2001). All other data is from the World Bank (2002).
Note: All data unless otherwise noted is from 1996.

4. Fractional logit regression results and discussion

Table 1 presents variable definitions both for the light pollution variables discussed above and for the explanatory variables used in the regressions discussed in this section. Table 2 presents the percentage of the population or surface area in a light polluted state in various geographic regions in the world. Table 3 includes summary statistics for the variables included in the regression analysis. Finally, Tables 4 and 5 present coefficient estimates and marginal effects from light pollution fractional logit regressions. Estimates are provided for the five measures of light pollution presented in the previous section (Table 2)—three measures of the percentage of the population living in a light polluted tier in a given country and two measures of the percentage of the surface area of a given country that lies within a light polluted tier. Recall that we begin with a lower threshold level of pollution, one where the artificial glow equals the normal night glow (POP1 and SURFACE1) and go up to an artificial glow that is three times the normal night glow (POP2 and SURFACE2). Finally, we also include the percentage of the population living above the scientific

Table 2
Percentage of the population or the surface area in light polluted state by geographic region or income level.

	POP1	POP2	POP3	SURFACE1	SURFACE2	Number of countries
The World	50.71	36.16	63.40	16.97	8.08	184
North America	94.33	70	98.67	41.4	9.93	3
South Asia	17	7	41.43	2.66	0.33	7
East Asia and Pacific	43.68	35	53.59	17.2	12.42	22
European Union	90	72	99.00	36.7	11.5	N.A.
Europe and Central Asia	72.83	47.33	91.23	29.48	11.42	52
Latin America and Caribbean	56.51	42.97	71.60	13.09	6.24	35
Middle East and North America	77	63.52	86.95	28.17	17.32	21
Sub-Saharan African	13.32	7.41	18.75	0.43	0.14	44
Low income	20.18	9.88	31.33	1.17	0.22	60
Low middle income	45.96	29.83	64.87	5.99	2.51	47
Upper middle income	62.61	44.97	76.45	19.55	7.26	33
High income OECD	86.86	71.55	96.55	38.71	16.1	22
High income non-OECD	90.14	72.77	95.00	57.95	34.67	22

Geographic regions and income levels are defined by the World Bank (2002) except for European Union, which is as defined by Cinzano et al. (2001).

Table 3
Summary statistics for the world.

	Number of countries	Mean	Standard deviation	Minimum	Maximum
POP1	184	0.507	0.336	0	1
POP1	184	0.362	0.316	0	1
POP3	184	0.634	0.347	0	1
SURFACE1	184	0.170	0.288	0	1
SURFACE2	184	0.081	0.201	0	1
GDP Per Capita	162	$6,155	$9,723	$110	$45,223
Urban	173	53.386	23.460	5.800	100.000
Arable	174	14.300	13.393	0.075	60.383
Energy	164	4.701	11.786	0.000	73.018
Foreign Investment	151	3.541	12.268	−8.520	145.132
Roads	155	48.723	33.724	0.800	100.000

minimum standard for light pollution (see Cinzano et al., 2001). Fractional logit models are presented because the dependent variables are percentages.

A fractional logit model assumes that the model is given by:

$$Pop1 = 1 / (1 + \exp(-X\beta)) \tag{1}$$

A logit transformation of Eq. (1) yields:

$$\ln(Pop1 / (1 - Pop1)) = X\beta \tag{2}$$

The original dependent variable, which is a fraction and bounded by 0 and 1 is now transformed into a continuous variable on the real line. Papke and Wooldridge (1996) note that one method of estimation is to simply drop observations where the dependent variable equals 0 or 1 (because the transformation cannot be performed on these observations) and estimate using OLS. The current paper uses a superior alternative to estimating the fractional logit model suggested by Papke and Wooldridge (1996), which does not require dropping observations.[11]

As noted above, standard scientific models of light pollution focus on population as the major and often only explanatory variable for the existence of light pollution. The main point of this paper is to also examine the impact of economic variables upon the existence and extent of light pollution worldwide. Similar to earlier economic researchers (e.g., Grossman and Krueger, 1995; Harbaugh et al., 2002), Table 4 begins with three classes of explanatory variable: (1) the common scientific explanation of light pollution—population as measured by the percentage of the total population living in urban areas, (2) a measure of economic activity, GDP per capita, and (3) arable land as a percentage of total land area.

Following earlier researchers (Grossman and Krueger, 1995; Harbaugh, et al., 2002), we allow for the possibility that the relationship between GDP and light pollution may have an inverted u-shape. For a number of other pollutants, economic development tends to first increase pollution then eventually decrease it as economic growth continues. Because of its similarity to economic inequality functions first pointed out by Kuznets (1955), the inverted u-shape is often referred to as an "environmental Kuznets curve" (EKC). That is, while economic activity initially increases pollution, it may eventually lead to improved environmental quality.[12] There may be both supply-side factors (such as full-cutoff light fixtures that reduce glare and prevent uplighting) and demand-side factors (such as less crime, a concern for wildlife, or a

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[11] As suggested by Papke and Wooldridge (1996), we estimate using STATA's GLM procedure with family (binomial), link(logit), and robust. When the article was published, STATA's GLM procedure could not estimate fractional logit models but has since been updated to allow such estimation.

[12] Testing the relevancy of the environmental Kuznets curve for light pollution is not the main point of the current paper. However, GDP is one of the most important economic variables and is included as a result. For more information regarding testing for the environmental Kuznets curve see Merlevede et al. (2006).

Table 4
Fractional logit light pollution coefficient estimates and marginal effects by the percentage of the population or the surface area in light polluted state.

	POP1	POP2	POP3	SURFACE1	SURFACE2
Intercept	−3.1860*	−3.9540*	−2.9416*	−6.7324*	−9.8732*
	(−15.60)	(−16.70)	(−12.22)	(−12.11)	(−9.40)
GDP per capita	0.0002*	0.0002*	0.0003*	0.0005*	0.0004*
	4.92E-05	**3.94E-05**	**5.84E-05**	**2.21E-05**	**3.31E-06**
	(2.96)	(3.92)	(2.01)	(4.84)	(3.03)
GDP Per Capita Squared	−9.20E-09**	−8.57E-09*	−2.04E-08	−2.35E-08*	−2.01E-08**
	−2.30E-09	**−1.77E-09**	**−3.97E-09**	**−1.06E-09**	**−1.54E-10**
	(−2.20)	(−2.93)	(−1.45)	(−3.94)	(−2.41)
GDP Per Capita Cubed	1.39E-13**	1.13E-13**	4.53E-13	3.27E-13*	2.67E-13**
	3.47E-14	**2.33E-14**	**8.82E-14**	**1.48E-14**	**2.05E-15**
	(2.06)	(2.51)	(1.33)	(3.66)	(2.15)
Urban	0.0449*	0.0490*	0.0470*	0.0359*	0.0700*
	0.0112	**0.0101**	**0.0092**	**0.0016**	**0.0005**
	(10.79)	(11.34)	(8.48)	(3.66)	(4.18)
Arable	0.0199*	0.0019	0.0440*	0.0462*	0.0216
	0.0050	**0.0004**	**0.0086**	**0.0021**	**0.0002**
	(4.25)	(0.41)	(5.82)	(4.95)	(1.51)
Number of observations	157	157	157	157	157
Log PseudoLikelihood	−57.4963	−53.2835	−53.8001	−32.9362	−18.2491
First Turning Point	$18,153.51	$16,516.45	$12,905.47	$15,375.99	$15,616.07
Total Effect	0.3428	0.2729	0.2821	0.1430	0.0219
Second Turning Point	$26,034.77	$34,127.32	$17,102.08	$32,371.76	$34,465.23
Total Effect	0.3343	0.2093	0.2788	0.1067	0.0151
Percentage Decrease	−2.48%	−23.32%	−1.16%	−25.40%	−31.29%

Asymptotic *t*-statistics in parentheses; marginal effects are in bold and are calculated at variable mean values.
*Indicates significance at the 1% level, **indicates significance at the 5% level; and ^indicates significance at the 10% level.
Total effect shows the impact of GDP, via a cubic function, on the dependent measure of light pollution, at the turning point. Percentage decrease measures the change in light pollution between the two turning points and equals (TE2/TE1)-1.
NA indicates that no turning point exists (i.e., an inflection point exists in the cubic function but the function is otherwise monotonically increasing).

desire to protect the historic legacy of the night sky) that would explain this effect.

In short, our model adds economic activity to the well-established population-based light pollution models. We focus on GDP and allow for a possible Kuznets-type relationship. Unfortunately, the lack of comparable economic data across many countries greatly limits our possible explanatory variables. However, we are able to include some basic variables that are indicative of a country's resources and economic structure. These variables include arable land, energy production, foreign direct investment (FDI), and roads.

We use the percentage of arable land to capture the impact of a country's geography. For example, a country with lots of desert or mountainous areas (less arable land) would tend to have less light pollution. Abundant energy may allow for cheaper lighting. Moreover, gas flares at wells and refineries add to light pollution directly, such flares burn at least 150 billion cubic meters of natural gas annually (World Bank, 2009). FDI is considered to be an important factor in shaping the way many economies evolve. For instance, FDI can accommodate projects on a larger scale with more advanced technology than would otherwise be possible. Researchers have shown, for example, that FDI increases air pollution in China, via scale and technology effects (He, 2008). The percentage of roads that are paved is a rough indicator of the level of infrastructure development. We would expect this to have a positive impact on light pollution, including the surface measures since paved roads promote economic development of the hinterland.

Tables 4 and 5 include fractional logit regression coefficients of individual explanatory variables. Marginal effects calculated at independent variable means are also presented in Tables 4 and 5. The main focus of the discussion in this section will be on the signs of the coefficient estimates and their statistical significance. Table 4 illustrates that population does have the expected impact on light pollution, as the percent of the population living in urban areas increases then so does the level of light pollution. This result is present whether using a population-based measure of light pollution or a surface-area measure. Similar fractional logit regressions were run using alternative measures of population, including population

density and the percent of the population living in rural areas, and were found to have similar effects on light pollution.

Notice also, though, that measures of economic activity, real per capita GDP, also tend to have statistically significant impacts on levels of light pollution that first increase the percentages of the population living in light pollution in a country although at a decreasing rate. A similar result is found in Table 4 when measuring light pollution as the surface area affected. This result suggests, unsurprisingly, that light pollution is concentrated in areas with high levels of population and that surface area measures of light pollution are also affected by economic development.

Tables 4 and 5 also include calculations testing for the existence of an EKC. First, as noted above, the regressions estimate the impact of GDP assuming a cubic function. The results from Table 4 illustrate the possibility of an EKC with an estimated positive impact of GDP per capita on light pollution, a negative impact of GDP per capita squared, and a positive impact of GDP per capita cubed. Although these results are consistent with an EKC they still allow for the possibility that the impact of GDP per capita on light pollution is monotonically increasing.[13] As a result, the actual estimates must be tested to see whether or not the cubic function does or does not provide evidence to support an EKC (Merlevede et al., 2006).

Tables 4 and 5 perform this test by presenting GDP per capita at the first and second turning points of the cubic function. For example, the impact of GDP per capita on *POP1* is positive until GDP per capita reaches the first turning point, which occurs at GDP per capita of $18,153. The overall effect of GDP per capita on *POP1* at this level is .3428. That is, 34.28% of the population falls within the *POP1* tier at the

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[13] Essentially, a cubic function may have two turning points. In this case, the impact of GDP per capita on light pollution would at first be positive then, when reaching a turning point, its impact would be negative. Finally, after reaching the second turning point the function would again exhibit a positive relationship between GDP per capita and light pollution. However, cubic functions may instead have one inflection point rather than two turning points which implies that the function is monotonically increasing aside from the inflection point.

Table 5

Fractional logit light pollution coefficient estimates and marginal effects by the percentage of the population or the surface area in light polluted state.

	POP1	POP2	POP3	SURFACE1	SURFACE2
Intercept	−3.3815*	−3.8766*	−3.4071*	−7.2732*	−10.5663*
	(−16.41)	(−15.08)	(−14.67)	(−11.63)	(−10.32)
GDP per capita	0.0001	0.0002*	0.0001	0.0004*	0.0004*
	2.80E-05	**3.63E-05**	**2.23E-05**	**1.58E-05**	**2.21E-06**
	(1.41)	(2.82)	(0.71)	(3.77)	(2.86)
GDP Per Capita Squared	−4.67E-09	−7.82E-09**	−9.56E-09	−1.84E-08*	−1.59E-08**
	−1.17E-09	**−1.62E-09**	**−1.85E-09**	**−7.39E-10**	**−9.88E-11**
	(−0.99)	(−2.19)	(−0.67)	(−3.17)	(−2.29)
GDP Per Capita Cubed	6.83E-14	1.04E-13^	2.69E-13	2.55E-13*	2.14E-13**
	1.71E-14	**2.15E-14**	**5.21E-14**	**1.02E-14**	**1.33E-15**
	(0.90)	(1.85)	(0.78)	(2.98)	(2.07)
Urban	0.0411*	0.0431*	0.0444*	0.0275*	0.0582*
	0.0103	**0.0089**	**0.0086**	**0.0011**	**0.0004**
	(8.99)	(8.80)	(7.26)	(2.64)	(3.70)
Arable	0.0134**	0.0005	0.0355*	0.0385*	0.0186
	0.0033	**0.0001**	**0.0069**	**0.0015**	**0.0001**
	(2.28)	(0.08)	(4.98)	(4.02)	(1.31)
Energy	0.0119**	0.0154*	0.0115	0.0137	0.0068
	0.0030	**0.0032**	**0.0022**	**0.0006**	**0.0000**
	(2.09)	(2.90)	(1.42)	(1.13)	(0.57)
Foreign Investment	−0.0059	−0.0131	0.0164	0.0693^	0.1563*
	−0.0015	**−0.0027**	**0.0032**	**0.0028**	**0.0010**
	(−0.32)	(−0.59)	(0.89)	(1.75)	(3.79)
Roads	0.0124*	0.0052	0.0211*	0.0189*	0.0169**
	0.0031	**0.0011**	**0.0041**	**0.0008**	**0.0001**
	(3.85)	(1.57)	(5.32)	(3.71)	(2.35)
Number of observations	133	133	133	133	133
Log pseudolikelihood	−48.0544	−46.0003	−42.4396	−25.9593	−13.3809
First turning point	NA	$16,867.84	NA	$15,971.18	$17,063.38
Total effect	NA	0.2546	NA	0.1054	0.0156
Second turning point	NA	$33,364.72	NA	$32,329.47	$32,460.43
Total effect	NA	0.2063	NA	0.0831	0.0131
Percentage decrease	NA	−18.96%	NA	−21.18%	−15.61%

Asymptotic *t*-statistics in parentheses; marginal effects are in bold and are calculated at variable mean values.

*Indicates significance at the 1% level, **indicates significance at the 5% level; and ^indicates significance at the 10% level.

Total effect shows the impact of GDP, via a cubic function, on the dependent measure of light pollution at the turning point. Percentage decrease measures the change in light pollution between the two turning points and equals (TE2/TE1)-1.

NA indicates that no turning point exists (i.e., an inflection point exists in the cubic function but the function is otherwise monotonically increasing).

first turning point. Thereafter, the impact of GDP per capita on *POP1* is negative until GDP per capita reaches the second turning point at $26,035. The bottom of the table shows how much light pollution would be reduced between these levels of income. Notice that the negative impact of GDP per capita between the first and second turning points is relatively slight, having only a negative 2.48% impact on *POP1*. The decline in light pollution, between turning points, is much larger for *POP2* and the two surface variables.

Although Table 4 illustrates the existence of an EKC for all five measures of light pollution, the negative impact between the first and second turning points is noteworthy only for 3 of the 5 measures of light pollution, *POP2*, and *SURFACE1* and *SURFACE2*. For these light pollution measures, sharply increasing GDP per capita between the first and second turning points reduces light pollution by between 23 and 31%. Further, the tests of the EKC provided in Tables 4 and 5 are only relevant around mean values for per capita GDP, given that marginal effects vary as GDP per capita varies.

Table 4 also shows that, as expected, the percentage of land that is arable has a positive impact on light pollution. That is, less desert and the like tends to be associated with more light pollution. These results are statistically significant for 3 out of the 5 measures of light pollution. The expanded models in Table 5 show similar results, with the same positive relationships and statistical significance for the same three measures of light pollution.

One of the main problems with using the cross-sectional country-level economic data with the light pollution atlas data, is that many countries have missing values for the economic data. Different economic variables have more or fewer numbers of missing values. For example, a total of 184 countries have both light pollution atlas data and at least some economic data. However, increasing the number of economic variables in the

fractional logit regressions has the impact of reducing the number of observations. The fractional logit regression coefficients presented in Table 4 are based on 157 of the original 184 countries. Thus, the most parsimonious models have the advantage of increased numbers of observations.

Table 5 presents fractional logit regression estimates with three additional economic explanatory variables and, hence, a decreased number of observations, now only 133 countries. The additional economic variables included in Table 5 are energy resources extracted during the year and FDI, both as a percent of gross national income. Finally, the percentage of total roads in the country that are paved is included as an additional measure of economic development.

Along with the reasons outlined above, energy extraction is likely to increase levels of pollution, including light pollution, simply because it is activity that occurs in the country. Table 5 illustrates that this expectation is met in the fractional logit regression estimates with energy extraction being positively associated with light pollution. In general, the impact of energy extraction has a statistically significant impact in the models where light pollution is population based but not when light pollution is surface area based. Moreover, the impact of energy extraction is relatively large with a marginal effect of approximately .003 for the population measures of light pollution. In other words a 10% increase in energy extraction yields a 3% increase in the percentage of the population living in a light polluted state.[14] Thus, referring to the statistics in Table 3 for energy extraction, if we compared

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[14] As Table 3 illustrates, the five measures of light pollution are fractions that vary between 0 and 1. However, all the other variables that are percentages are measured in percentage terms and vary between 0 and 100.

a country with the minimum, zero percent of its gross national income, to a country with the maximum 73% then the percent of the population living in a light polluted state would rise by 21.9%.[15]

Foreign direct investment affects the nature, scope, and scale of capital projects. Table 5 shows that FDI generally decreases the percentage of the population affected by light pollution, though this effect is statistically insignificant. In contrast, increased FDI tends to increase the surface area affected by light pollution, and these estimates are statistically significant. While the impact on the population variables is statistically insignificant, their contradiction with the positive impact on the surface variables is interesting and may warrant further investigation. It suggests that FDI helps push development into the hinterland. One can readily imagine examples, such as projects involving mining or logging, where this might be the case.

Likewise, Table 5 illustrates that a more developed infrastructure as measured by the percentage of roads paved within the country also tends to increase light pollution. The coefficient estimates for Roads is positive for all measures of light pollution, and statistically significant in four of the five models.

Table 5 shows that adding the three additional explanatory variables, FDI, energy depletion, and percent of roads paved have little impact on the estimated impact of any of the other explanatory variables. For example, adding these additional measures of economic activity change none of the signs on the coefficient estimates for GDP per capita although in a few cases these coefficient estimates do become statistically insignificant. These results are consistent with Harbaugh et al. (2002) who found that the existence of an EKC was sensitive to functional form and the other economic explanatory variables in the regression results. Table 5 does still find the existence of an EKC, however, for the same three measures of light pollution as in Table 4, POP2, SURFACE1, and SURFACE2.

Taken together the fractional logit regression results presented in Tables 4 and 5 are a unique contribution to the environmental literature, not the least because they provide the first evidence regarding the importance of economic activity to global light pollution. In general, the regression results provide consistent evidence that both population and economic activity are important explanatory variables when it comes to light pollution. The regression results provide evidence that GDP and light pollution have a nonlinear relationship consistent with various supply-side and demand-side factors that can yield an EKC.

5. Conclusion

Light pollution is a serious problem with implications for wildlife, human health, scientific research, energy consumption, global warming, and the ageless pastime of observing the night sky. Pristinely dark skies are very scarce in the developed world and most of the world's population—and nearly all of those living in the EU or the US—live under skies with at least some light pollution. Economists have largely ignored this issue, and existing models of light pollution emphasize population as the determining factor. We have combined unique remote sensing data on light pollution with economic data from the World Bank to estimate fractional logit regression light pollution models.

These models show that population, as measured by the percent of the population living in urban areas, remains an important explanation for the existence of light pollution. However, real per capita GDP also tends to be a highly significant variable in explaining the percent of a country's population affected by different levels of light pollution. The relationship between income and light pollution is non-linear as

might be expected from an EKC. Other economic factors such as foreign investment and land use patterns also tend to be significant.

Quantifying the link between real GDP and various levels of light pollution across the globe is a significant first step in correcting economists' neglect of this important environmental issue. However, much remains to be done. For example, it would be useful to know what types of industries, if any, are most closely tied to light pollution. This question, and many others, remained unanswered in no small part because of the absence of uniform data, especially in developing countries. More progress can be expected as more and better data become available. Astronomers and others continue efforts to collect satellite data and refine their modeling techniques. Our future research will focus on regions, such as the United States, where light pollution is very common and better economic data is available. Continued research in this area is needed and will help illuminate the economic aspects of light pollution.

Acknowledgements

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[15] Of course, the marginal effects vary along the distribution of energy extraction.

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