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Outdoor light pollution and COVID-19: The Italian case

Amedeo Argentiero a, b, *, Roy Cerqueti b, c, Mario Maggi d

a Kore University of Enna, Faculty of Economics and Law, Italy
b Sapienza University of Rome, Department of Social and Economic Sciences, Italy
c London South Bank University, School of Business, United Kingdom
d University of Pavia, Department of Economics and Management, Italy

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ABSTRACT

There is a wide debate on the connections between pollution and COVID-19 propagation. This note faces this problem by exploring the peculiar case of the correlation between outdoor light pollution and the ratio between infected people and population. We discuss the empirical case of Italian provinces (NUTS-3 level), which represent an interesting context for the noticeable entity of contagions and for the relevant level of outdoor light pollution. The empirical results, based on a multivariate cross section model controlling for income, density, population ageing and environmental pollution, show that there is a positive relation between outdoor light pollution per capita and the strength of COVID-19 infection. This effect is statistically more robust in a non linear specification than in a linear one. We interpret our findings as a piece of evidence related to the impact of outdoor light pollution on human health, thus suggesting policies aimed at reducing this important source of pollution.

1. Introduction

Light pollution is the direct or indirect introduction of artificial light into the environment and is one of the most common forms of environmental alteration (Cinzano et al. 2001). “It includes such things as glare, sky glow, and light trespass” (Gallaway et al., 2010, 658).

Such a type of pollution is composed of indoor and outdoor light pollutions.

The World Atlas of Light Pollution (Falchi et al. 2016a, 2016b) brought the problem of outdoor light pollution to the fore.

According to the Atlas, the countries with the populations least affected by outdoor light pollution are Chad, the Central African Republic and Madagascar, where more than three quarters of the inhabitants live in conditions of pristine sky. On the other side, in Singapore, “the entire population lives under skies so bright that the eye cannot fully dark-adapt to night vision.” (Falchi et al. 2016a, 5).

Sorting countries by polluted areas, Italy and South Korea are the most polluted G20 countries, whereas Australia is the least polluted one.

According to the International Dark-Sky Association (2016), in one year in the United States, outdoor lighting uses about 120 terawatt-hours of energy, mostly to illuminate streets and parking lots. An amount of electricity that would be sufficient to satisfy the electricity demand of a city like New York for two years. About 50% of all this lighting is wasted. In terms of costs, these are figures that are around 3.3 billion dollars, with 21 million tons of CO2 emissions per year. To compensate for these emissions, we should plant 875 million trees every year. Hence, light pollution gives a negative contribution to climate change.

As discussed by Gallaway et al. (2010), light pollution causes many negative externalities, as it affects the life cycle of plants, the animal behavior and the human biorhythm. Moreover, outdoor light pollution also affects migration flows, mating rituals, hunting and many other processes essential for the life of plants, insects, animals and the human biorhythm.

This latter, under normal conditions, is programmed to alternate between day and night, the circadian rhythm. Depending on whether it is in light or dark conditions, the organism behaves differently. The pineal gland produces serotonin during the day and melatonin at night. A well synchronized circadian rhythm is essential for psychophysical balance, otherwise the risk of some diseases increases: depression, tumors,
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2.1. Data

Our sample concerns the 107 Italian provinces (NUTS-3 level). Different outdoor light pollution measures have appeared in the literature. Following Falchi et al. (2019), we here consider three types of measures: flux per capita (FC), flux per dollar (FD) and radiance (R). FC is the artificial light flux per capita (light flux divided by population and multiplied by $10^3$), FD is the artificial light flux per GDP unit and multiplied by $10^6$, with GDP measured in US$ using purchasing power parity; the measures of artificial light incorporated in FC and FD are related to R, but differ from it. The fluxes of artificial light (the numerators of FC and FD) are a metrics of how much outdoor light is produced in each pixel area from the Atlas, while R is a measure of artificial night sky brightness at the zenith from the center of each pixel. Data on FC, FD and R are provided by Falchi et al. (2019) and are referred to 2014. The range of variation of R is 0.0819 (Bolzano) - 3.63 (Monza Brianza) mcd/m² (millilambert per square meter), while those of FC and FD are 1.775 (Naples) - 23.9 (L’Aquila) and 0.156 (Bolzano) - 1.11 (Siracusa), respectively. As control variables for the multivariate analysis, we consider the population density of 2019 (ISTAT, 2020), the value added per capita of 2017 (ISTAT, 2020), the fraction of the population over 65 years old of 2019 (ISTAT, 2020), the number of motor vehicles per 1000 inhabitants in 2012, PIR associated to COVID-19 is given by the ratio between the stock of infected people and population; such a quantity is also computed at a provincial level. The website from which the data on infected people are taken is the one of the Italian Ministry of Health (2020).

The time span considered goes from 30th January 2020 to 21st June 2020. The population is the one of 2019 and it is retrieved from ISTAT (2020). For having a clear view of the data, PIR is multiplied by 1000.

2.2. Methods

To assess the relation between outdoor light pollution and PIR, we present both a univariate (Section 3.1) and a multivariate (Section 3.2) analysis.

A descriptive analysis introduces the univariate study. Then, pairwise relations between the PIR and outdoor light pollution variables are presented. Both raw and ranked data have been analyzed. Such a

1. The data are updated to 28 July 2020 (WHO, 2020).

2. “The two things are related, but not in a trivial way. As an example, the flux coming from the Upper Bay in New York is essentially zero (no light sources are on the water), while the night sky observed from the center of the bay is extremely light polluted, due to the lights coming from the surrounding sources. In fact, the Atlas radiance data for each pixel was computed taking into account the outdoor lights coming from a circle of 200 km radius.” (Falchi et al. 2019, 5).

3. We point out that 2014 is the last year in which the data at the provincial level (NUTS-3 level) are available. However, we are in the position of using such a dataset for describing the reality of the Italian provincial outdoor light pollution also for the year 2020, basically for two reasons. First, the data for the measurement of light pollution based on radiance both in absolute and per capita terms have shown for Italy a slight increase in light intensity, almost equal to 5.5%, between 2014 and 2020 (see https://www.lightpollutionmap.info/laPI_stats/country.html?country=Italy). Such an increase is of a rather small entity so that one can state that outdoor light pollution in Italy is substantially invariant from 2014 to 2020. Second, we have arguments for stating that also the distribution of light pollution at a provincial level is invariant over the last quinquennium. Indeed, light pollution is mainly due to human activities and can be reasonably linked to the urbanization level of a territory. In this respect, the proportion of the urban population in Italy moves from 69.27% in 2014 to 70.74% in 2019 – which is the last available year (see https://www.statistica.com/statistics/278471/urbanization-in-italy/). Thus, we have a very small increase of the urbanization level in the considered period of about 2.1%, hence pointing to a small variation of the distribution of the citizens in the Italian territory. To conclude: Italy shows small variations either in population density, income, population ageing and air pollution. Moreover, we find that a relevant improvement of the goodness of fit of the model is obtained using a nonlinear model.

4. The units used for calculation are somewhat arbitrary, simply obtained by multiplying the radiance of the VIIRS dataset (in nWcm⁻²sr⁻¹) by the pixel area measured in square kilometers, obtaining the dimensions of a radiant intensity in $10^{-7}\,\text{Wsr}^{-1}$.” (Falchi et al. 2019, 15).

5. The last data publicly available for the provincial value added per capita are referred to 2017 whereas those for private motor vehicles are updated to 2012.
The twofold approach is justified for two reasons. First, there are a few outliers that may affect the overall study. Second, the two studies offer the opportunity to observe different features of the relations. Indeed, in the former study, the average comovement of the considered quantities is strongly affected by clusters of extreme values and the presence of deviations within the samples; differently, the latter one focuses only on regularities and dissonances between the positions of the individual provinces in the overall rankings, so that the level of the ranked variables is not taken into consideration.

In the ranked data approach, provinces are ranked in increasing order according to the values of PIR, R, FC and FD, obtaining four series of ranks.

To deepen the analysis of the phenomenon, Section 3.2 presents a multivariate regression study. Various control variables are considered alongside the outdoor light pollution measures. These variables are the population density (Dens), the value added per capita (VAC), the fraction of the population over 65 years old (Over65), the number of motor vehicles per 1000 inhabitants (Vehicles). Dens may be relevant for the speed of spread of an outbreak due to the increasing chances of social interactions, the VAC is a measure of the wealth produced in each province, Over65 indicates the portion of the population more sensitive to the contagion, Vehicles is a proxy of air pollution.

Starting from the outdoor light pollution variables (R, FC, FD), a forward selection procedure is applied to select the most appropriate model. Differently from what the univariate analysis suggested, the variable R does not display a significant relation with respect to PIR. Both the other two measures of light pollution, FC and FD, result significant, with opposite effects: FC positively relates to PIR, while FD shows a negative relation with PIR. Moreover, a nonlinear transformation is proposed, obtaining a better fit and some additional insights, preserving the qualitative results obtained in the linear case.

3. Results and discussion

3.1. Univariate analysis

3.1.1. Descriptive

As a preliminary step, Table 1 presents a summary of the descriptive

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Table 1
Summary of the descriptive statistics of the PIR and the three measures of outdoor light pollution R, FC and FD, for the 107 Italian provinces. The correlation matrix between the PIR and all the considered variables is also reported. A star indicates correlations that are significant at 5% level.

| Variable | Mean   | Median | Minimum | Maximum |
|----------|--------|--------|---------|---------|
| PIRx1000 | 3.9875 | 2.5740 | 0.27085 | 18.354  |
| R        | 0.59964| 0.48500| 0.08190| 3.6300  |
| FC       | 16.262 | 16.200 | 7.7500  | 23.900  |
| FD       | 0.58713| 0.55600| 0.15600 | 1.1100  |

| Variable | Std. Dev. | C.V. | Skewness | Ex. kurtosis |
|----------|-----------|-----|----------|--------------|
| PIRx1000 | 3.7549    | 0.94167 | 1.3931  | 1.9205  |
| R        | 0.52998   | 0.88382 | 3.4713  | 15.189  |
| FC       | 3.5613    | 0.21900 | -0.11806 | -0.37358 |
| FD       | 0.22303   | 0.37986 | 0.37606 | -0.76405 |

| PIR | R  | FC | FD | VAC | Over65 | Dens | Veh. |
|-----|----|----|----|-----|--------|------|------|
| 1.0000 | 0.1973* | -0.0641 | -0.4473* | 0.3907* | 0.1754 | 0.0693 | -0.0259 |
| .   | 1.0000 | -0.3622* | -0.3819* | 0.1599 | -0.0482 | 0.9231* | -0.1638 |
| .   | .   | 1.0000 | -0.1480 | -0.0162 | -0.4738* | 0.0777 | FC    |
| .   | .   | .   | 1.0000 | -0.2850* | 0.0712 | -0.3856* | 0.1060 |
| .   | .   | .   | .   | 1.0000 | 0.8833* | 0.1258 | 0.1602 |
| .   | .   | .   | .   | .   | 1.0000 | -0.0394 | 0.1969* |
| .   | .   | .   | .   | .   | .   | 1.0000 | -0.1126 |
| .   | .   | .   | .   | .   | .   | .   | 1.0000 |

Fig. 1. Graphical representation of the relationship between the measures of outdoor light pollution R, FC and FD.

Our measure of environmental pollution differs from the one of Becchetti et al. (2020) based on PM10 and PM2.5. Nevertheless, particulate data are only available where the detection units are present (typically in the provincial capitals) and aggregated at province level by weighing observations by the population size of the municipality where the monitoring post is located. In our case, Vehicles is already available at a NUTS-3 level.

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statistics related to the considered datasets.

We can notice that, although of different magnitude, the variables share a moderate coefficient of variation. They are generally positively skewed, except FD which display a weak negative skewness. The extreme values produce a strong excess kurtosis for R. The variability in our sample is the consequence of the heterogeneity of the Italian provincial conditions, in many aspects. This feature may be desirable, since this single country analysis may be representative of different local frameworks. For what concerns the (significant) correlations, R is negatively correlated with FC and FD, and display a strong link with Dens. This latter relation follows from the fact that radiance increases with population density, whereas the negative correlation of R with FC and FD is in line with the inverse relation between outdoor light pollution in the big areas, such as the metropolitan areas, and outdoor light pollution per inhabitant or per unit of GDP. FC and FD are positively correlated. The negative correlation between FC and Dens can be explained because Dens is related with the denominator of FC. For the same reason, FD negatively correlates with VAC. The large correlation between VAC and Over65 deserves attention: the ageing of the population is related with the level of income, and in Italy the income gap between provinces is quite large. For a similar reason, we also notice that Over65 is positive correlated to Vehicle. The two high correlation coefficients help in explaining the collinearity issues presented in Section 3.2.

3.1.2. Relation between PIR and outdoor light pollution

Figs. 1 and 2 present the link between the three indicators for outdoor light pollution in our sample. For a better reading, the linear trend is juxtaposed, when the slope of the line is statistically significant. Notice the inverse relation between R and the other two indicators, FC and FD, while FC and FD show a clear positive relation.

Fig. 2 (left panels) presents the scatter plots of the relations between PIR and the measures of light pollution R, FC and FD: left panels raw data; right panels ranked data.

**Fig. 2.** Graphical representation of the relationship between the PIR and the measures of light pollution R, FC and FD: left panels raw data; right panels ranked data.
PIR – as expected. These results are confirmed once some PIR outliers are removed: we have considered outliers for PIR those values greater than $\mu + 2\sigma$. The behaviors observed with raw data are confirmed, once ranked data are considered (see Fig. 2, right panels). The analysis of ranked data allows to consider the observed relations more robust, because ranked data are less sensitive to concentrated and extreme values that can produce instability in the estimated relation. Due to the wide range of local conditions, this stability appears welcome.

### 3.2. Multivariate analysis

To obtain a complete picture of the phenomenon, we proceed to a multivariate analysis, setting as independent variable the PIR and using as regressors the measures of the outdoor light pollution (R, FC, FD) and some control variable (Dens, VAC, Over65, Vehicles). Table 2 presents the results of the estimates.\(^7\)

First of all, we estimate the univariate model M1, relating the PIR to the measure of radience R (as suggested by Fig. 2, first panel). From Table 2, R appears significant with a positive coefficient.

We proceed to model M2, by adding to R the other two light pollution measures, FC and FD. These added variables turn out to be significant with opposite sign coefficients. We exclude multicollinearity issues between R, FC and FD (VIFs lower than 2 for all variables).

The control variables Dens, VAC, Over65 and Vehicles are progressively introduced, following a stepwise procedure. At each step the control variable which is most correlated with the residuals of the previous model is added. Then, the multicollinearity is checked. If the additional variable introduces multicollinearity to the set of regressors, it is discarded and the procedure continues to the next variable most correlated with the residuals.

Following this method, the variable Over65 is added, obtaining model M3. From Table 2, we notice that Over65 is significant, with a positive coefficient, and the coefficients of FC and FD variables remain stable and significant. The next step, consists in adding Dens to the model, but this introduces collinearity (VIF\textsubscript{Dens}>8 and unstable coefficient of R). Therefore, we discard Dens and proceed including VAC. Also VAC introduces collinearity, even stronger than Dens (VIF\textsubscript{VAC}>14) and wide parameter instability. So the next variable to add remains Vehicles, obtaining model M4. The new variable turns out to have a non-significant coefficient, worsening the goodness of fit and information criteria. In conclusion, model M3 seems to be the most appropriate one to describe the phenomenon, with an adequate goodness of fit.

#### 3.2.1. Nonlinear model

Model M3 delivers an adequate description of the phenomenon. However, a nonlinear transformation can better describe the relation between the variables. For this reason, we report the estimation of the regression model M5, with the log of PIR as independent variable:

\[
\log(\text{PIR} \times 1000) = \alpha + \beta_1 R + \beta_2 FC + \beta_3 FD + \beta_4 Over65 + \beta_5 Vehicles + \epsilon
\]

(1)

For sake of interest and space, we do not report the entire stepwise procedure, but only the selected specification, i.e. model M5, M5 appears to be the best model among the presented ones: the $R^2$ and the information criteria attain their best values, with a considerable improvement over M3. The qualitative interpretation of the estimation results is consistent across all models. Moreover, the nonlinear specification (Becchetti et al., 2020) allows to interpret the estimated coefficient as semi-elasticities.

The empirical analysis presented above shows that outdoor light pollution measured in terms of flux per capita positively relates to the spread of infection. Territories that are more exposed to outdoor light pollution per inhabitant are more likely to develop COVID-19 contagions. This result supports the idea that the depression of the immune system induced by the outdoor light pollution makes the human body more vulnerable to attack from viruses such as Covid-19. The negative relation between FD and PIR, instead, captures the effects of the outdoor light pollution per inhabitant are more likely to develop COVID-19 contagions. Following Falchi et al. (2019), we consider three measures of light pollution: FC, FD and R. In the multivariate analysis, introducing some control variables, we find that FC positively affects the PIR associated to COVID-19, whereas FD has a negative effect on contagions and R does not exhibit any statistically significant relation with COVID-19 disease. We think that the positive sign of FC, a metrics considering the incidence of the outdoor light pollution on population, captures the effects of the outdoor light pollution on human health, thus predisposing people to COVID-19 pandemic. The negative relation of FD on PIR, instead, relates to the income effect incorporated in FD, according to which higher income is

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\(^7\) This cross-section is run on a sample of 107 observations which is sufficient for the reliability of the results (see Harrell 2015, Sect 4.4).
associated to an increase of COVID-19 infections. Furthermore, we find that the explanatory power of the model in log-linear form is better than the linear one, thus showing a non linear effect in the relations between the measures of outdoor light pollution and COVID-19 contagions. Our analysis is intended to be seminal to further ones, considering in general the alteration produced by outdoor light pollution on the ecosystem and suggesting policies aimed at mitigating this source of pollution. In addition, outdoor light pollution may also be related to nighttime social activity (non directly related to population density or income). Therefore, our study provides some suggestions on the existence of a link between night activity and COVID-19.

Moreover, it is important to give credit to two limitations of the study: the nature of the employed data – which are not obtained by individual measurement instruments, being of ecological type – and the lack of the analysis of indoor light pollution. Further research can be carried out by removing such constraints.

Finally, we underline that our proposal has not the ambition to find the key variables explaining the spread of the COVID-19. As we show in the paper, the relation between some light pollution measures (namely FC and FD) and PIR is supported by the data concerning the Italian provinces. This can be a suggestion for the inclusion in future analysis and scientific research of the light pollution for disentangling the patterns of pandemic diseases – including COVID-19, of course. In this respect, we have also carried out some preliminary elaborations on the direct relation between air pollution – whose proxy is the number of private vehicles per 1000 inhabitants – and PIR, exploring various models, including the interaction between outdoor light pollution and air pollution. Our results do not support any significant relation between air pollution and PIR, also taking into account the interaction effect between air pollution and outdoor light pollution. Such elaborations are not shown in this note; indeed this research theme deserves a more focused future research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Becchetti, L., Conzo, G., Conzo, P., Salustri, F., 2020. Understanding the heterogeneity of adverse COVID-19 outcomes: the role of poor quality of air and lockdown decisions (Available at SSRN 3572548).

Chepesiuk, R., 2009. Missing the dark: health effects of light pollution. Environ. Health Perspect. 117 (1), A20–A27.

Cinzano, P., Falchi, F., Elvidge, C.D., 2001. The first world atlas of the artificial night sky brightness. Mon. Notices Royal Astron. Soc. 328 (3), 689–707.

Falchi, F., Cinzano, P., Duriscoe, D., Kyba, C.C.M., Elvidge, C.D., Baugh, K., Portnov, B. A., Rybnikova, N.A., Furgoni, R., 2016a. The new world atlas of artificial night sky brightness. Sci. Adv. 2, e1600375.

Falchi, F., Cinzano, P., Duriscoe, D., Kyba, C.C.M., Elvidge, C.D., Baugh, K., Portnov, B., Rybnikova, N.A., Furgoni, R., 2016b. Supplement to the New World Atlas of Artificial Night Sky Brightness. GFZ Data Services.

Falchi, F., Furgoni, R., Gallaway, T.A., Rybnikova, N.A., Portnov, B.A., Baugh, K., Elvidge, C.D., 2019. Light pollution in USA and Europe: the good, the bad and the ugly. J. Environ. Manag. 248, 109277.

Gallaway, T., Olsen, R.N., Mitchell, D.M., 2010. The economics of global light pollution. Ecol. Econ. 69 (3), 658–665.

Harrell, F.E., 2015. Regression modeling strategies, 2nd ed. Springer, Cham.

IARC, 2021. International Agency for Research on Cancer, List of Classifications. https://monographs.iarc.fr/agents-classified-by-the-iarc/ (accessed on January 28, 2021).

ISTAT, 2020. Italian Istitute of Statistics. http://dati.istat.it (accessed on July 18, 2020).

Italian Ministry of Health, http://www.salute.gov.it/imgs/C_17_notizie_4922_1_file.pdf, accessed on July 18, 2020.

Kloog, I., Haim, A., Stevens, R.G., Barchana, M., Portnov, B.A., 2008. Light at night co-occurs with breast but not lung cancer in the female population of Israel. Chronobiol. Int. 25(1), 65–81.

WHO, World Health Organization, https://covid19.who.int/table, accessed on July 18, 2020.

Amedeo Argentiero (Ph.D) is Tenured Associate Professor of Economic Policy in the Faculty of Economics and Law of the Kore University of Enna. His research deals with environmental economics, fiscal policy and unobserved economy. He has published his works on international journals and books, such as Fiscal Studies, Macroeconomic Dynamics and The Energy Journal. He has participated as a speaker to more than 30 international conferences. He is member of the Advisory Board of the Journal of Applied Quantitative Methods. He is Referee of Economic Notes (ISSN 1468–0300), Economic of Governance (ISSN 1435–6104), Review of Economics and Institutions (ISSN 2038–1379), Eurasian Economic Review (ISSN 2147–4294), International Energy Journal (ISSN 0195–6574), B.E. Journal of Macroeconomics (ISSN 1395–1690), Renewable Energy (ISSN 0960–1411), European Journal of Comparative Economics (ISSN 1824–2979), Annals of Operations Research (ISSN: 0254 5330), Economic Policy (ISSN 0301–4215), Journal of Analytical and Institutional Economics (ISSN 1120–2890), Energy Economics (ISSN 0140–9881) and Economics Letters (ISSN: 0165–1765). He has been member of the Scientific Commission of the Italian Statistical Office (ISTAT) for the study and analysis of criminal economy.

Roy Cerqueti (Ph.D) is Tenured Associate Professor of Mathematics for Economics and Finance at Sapienza University of Rome, Italy and Professor of Mathematical Methods for Economics, Finance and Operations Research at the London South Bank University, UK. His research activity includes quantitative methods for business and financial modelling, complex systems, economic theory and data science. He is author of more than one hundred scientific publications, most of them in prestigious international journals.

Mario Maggi (Ph.D) is Tenured Associate Professor of Mathematical Finance at the University of Pavia, Italy, where he teaches Mathematics for Finance and Mathematical Methods for Business. He also taught at other universities, including the University of Piemonte Orientale (Alessandria), Bologna (Rimini) and Bocconi (Milano). Since his PhD in Mathematical Finance (University of Brescia, Italy), his interests span from mathematical finance, behavioral decision making, to empirical analysis and numerical methods. He is the author of textbooks and many research papers published on international reviews, among others, Journal of Economic Psychology, Econometrics and Statistics, Annals of Operations Research, Annals of Finance.