Outdoor light pollution and COVID-19: The Italian case

Amedeo Argentiero*

KORE University of Enna — Faculty of Economics and Law

Roy Cerqueti

Sapienza University of Rome — Department of Social and Economic Sciences

London South Bank University — School of Business

Mario Maggi

University of Pavia — Department of Economics and management

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.

Keywords: Light pollution, COVID-19 pandemic

JEL: D62, I18, Q51

*Corresponding author

Email address: amedeo.argentiero@unikore.it (Amedeo Argentiero)

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. 2009, 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. (2009), 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, diabetes, obesity, depression of the immune system. The World Health Organization (WHO) has found that night workers – hence, those exposed to artificial light – have probably a higher onset of cancer in that night work disrupts the circadian rhythm. In this context, the exposure to artificial light is classified as probably carcinogenic (see IARC). For this reason, light pollution may be considered related to probably carcinogenic factors.

Based on data availability, this note aims at evaluating whether the specific case of outdoor light pollution has an impact on the Population-Infected Ratio (PIR) associated to SARS-CoV-2 (COVID-19) pandemic. The ground of the study is the scientific evidence that outdoor light pollution may affect human health (see e.g. Chepesiuk, 2009 and Kloog et al., 2008).

Our analysis is based on Italian provincial data. Italy is the fifth country in the world by number of deaths (35,123) and the fifteenth nation by number of infected people (246,488) with a fatality rate of 14.25% [1]. Furthermore, contagions and deaths in Italy are mainly concentrated in some regions of the northern Italy (Lombardia, Piemonte and Emilia Romagna)with a high degree of territorial heterogeneity.

Becchetti et al. (2020) find for Italy at a provincial level a statistically significant positive correlation of the poor quality of air with COVID-19 outcomes. In particular, provinces with high levels of PM10 or PM2.5 have a high number of contagions and deceases for COVID-19.

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

We analyze another important source of pollution, i.e. outdoor light pollution, and we wonder whether it has a role in explaining COVID-19 contagions. In words, due to the effects of light pollution on human health, in particular way the weakening of immune system, in provinces with high levels of outdoor light pollution is it more likely to have higher contagions?

We estimate a cross-section model for Italian provinces and we find that there is a relation between some measures of outdoor light pollution and the COVID-19 PIR.

To the best of our knowledge, this is the first paper dealing with the possible effects of outdoor light pollution on COVID-19 contagions.

Following Falchi et al. (2019), we use three different measures of outdoor light pollution: radiance (R), flux per capita (FC) and flux per dollar (FD). We find strong evidence concerning the FC and FD measures of outdoor light pollution. The positive relation between FC and PIR may confirm that high levels of outdoor light pollution per capita exposure are connected with high COVID-19 spread. The negative relation between FD and PIR is strongly influenced by the effect of gross domestic product (GDP), according to which territories with higher income are more likely to be exposed to COVID-19 contagions (see Becchetti et al. 2020). The results hold after the introduction of control variables concerning 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.

The note is structured as follows. Section 2 describes the dataset and the methods used for the empirical analysis. In Section 3 we present and discuss the results. Section 4 concludes.

2. Data and methods

2.1. Data

Our sample concerns the 107 Italian provinces (NUTS-3 level). Different 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[2]. Data on FC, FD and R are provided by Falchi et al. (2019) and are referred to 2014[3]. The range of varia-

[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, 2).

[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/LP_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.statista.com/statistics/270471/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 of light pollution as well as of urbanization level from 2014 to 2019/2020. Therefore, the data related to 2014 – which, we repeat, are the most recent ones of high quality at a provincial level – can be suitably used as a good proxy for

tion of R is 0.0819 (Bolzano) - 3.63 (Monza Brianza) mcd/m^2 (Millicandela per square meter), while those of FC and FD are[4] 7.75 (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), the value added per capita of 2017 (ISTAT), the fraction of the population over 65 years old of 2019 (ISTAT), the number of motor vehicles per 1,000 inhabitants in 2012[5]. 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:
`http://www.salute.gov.it/imgs/C_17_notizie_4922_1_file.pdf`. The considered 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. For having a clear view of the data, PIR is multiplied by 1,000.

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 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

provincial light pollution in Italy in 2020.

[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 $10^{-7}Wsr^{-1}$." (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.

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 1,000 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[6].

Starting from the light pollution variables (R, FD, FC), 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.

[6]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 regions capitals) and provincial data are obtained by distributing regional data according to population weights. In our case, Vehicles is already available at a NUTS-3 level.

3. Results and discussion

3.1. Univariate analysis

3.1.1. Descriptive

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

Figures 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 juxtapposed, when the slope of the line is statistically significant. Notice the inverse relation

Variable	Mean	Median	Minimum	Maximum
PIRx1000	3.9875	2.5740	0.27085	18.354
R	0.59964	0.48500	0.081900	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	PIR
.	1.0000	−0.3622*	−0.3819*	0.1599	−0.0482	0.9231*	−0.1638	R
.	.	1.0000	0.6836*	−0.1480	−0.0162	−0.4738*	0.0377	FC
.	.	.	1.0000	−0.2850*	0.0712	−0.3856*	0.1060	FD
.	.	.	.	1.0000	0.8833*	0.1258	0.1602	VAC
.	.	.	.	.	1.0000	−0.0394	0.1969*	Over65
.	.	.	.	.	.	1.0000	−0.1126	Dens
.	.	.	.	.	.	.	1.0000	Veh.

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 are also reported. A star indicates correlations that are significant at 5% level.

between R and the other two indicators, FC and FD, while FC and FD show a clear positive relation.

Figure 2 (left panels) presents the scatter plots of the relations between PIR and the outdoor light pollution measures. A positive relation is found between R and PIR, while a negative one is found between FD and 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 Figure 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 radiance R (as suggested by Figure 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.

[7] This cross-section is run on a sample of 107 observations which is sufficient for the reliability of the results (see Harrel 2015, Sect 4.4).

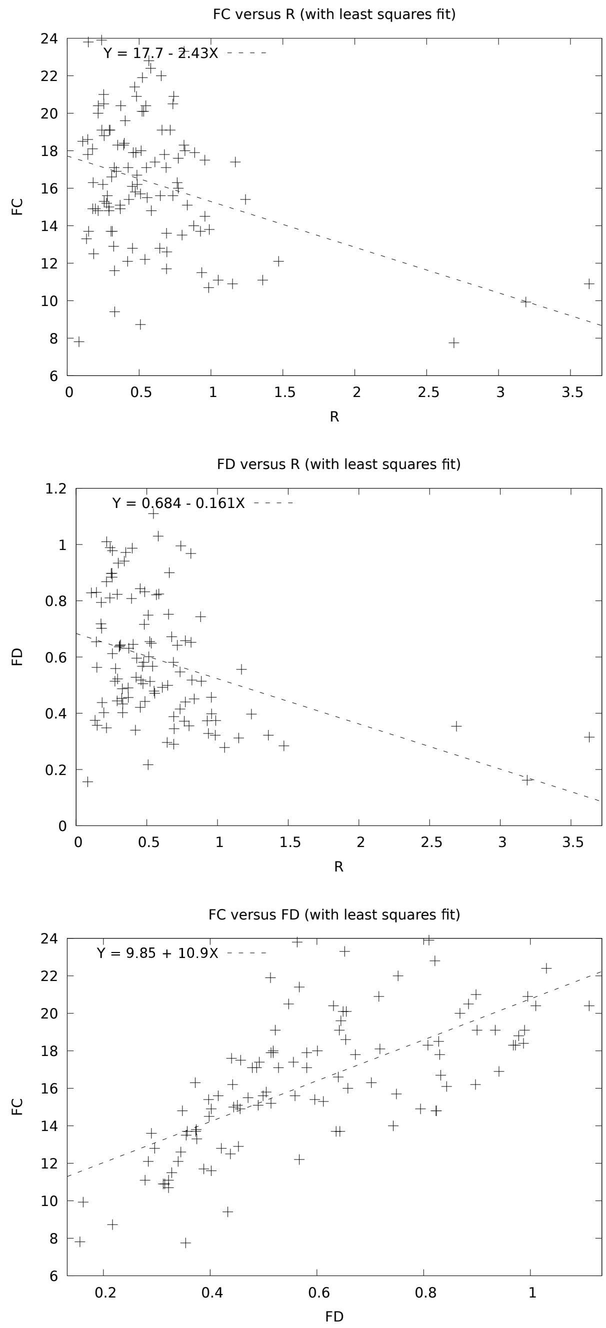

Figure 1: Graphical representation of the relationship between the measures of outdoor light pollution R, FC and FD.

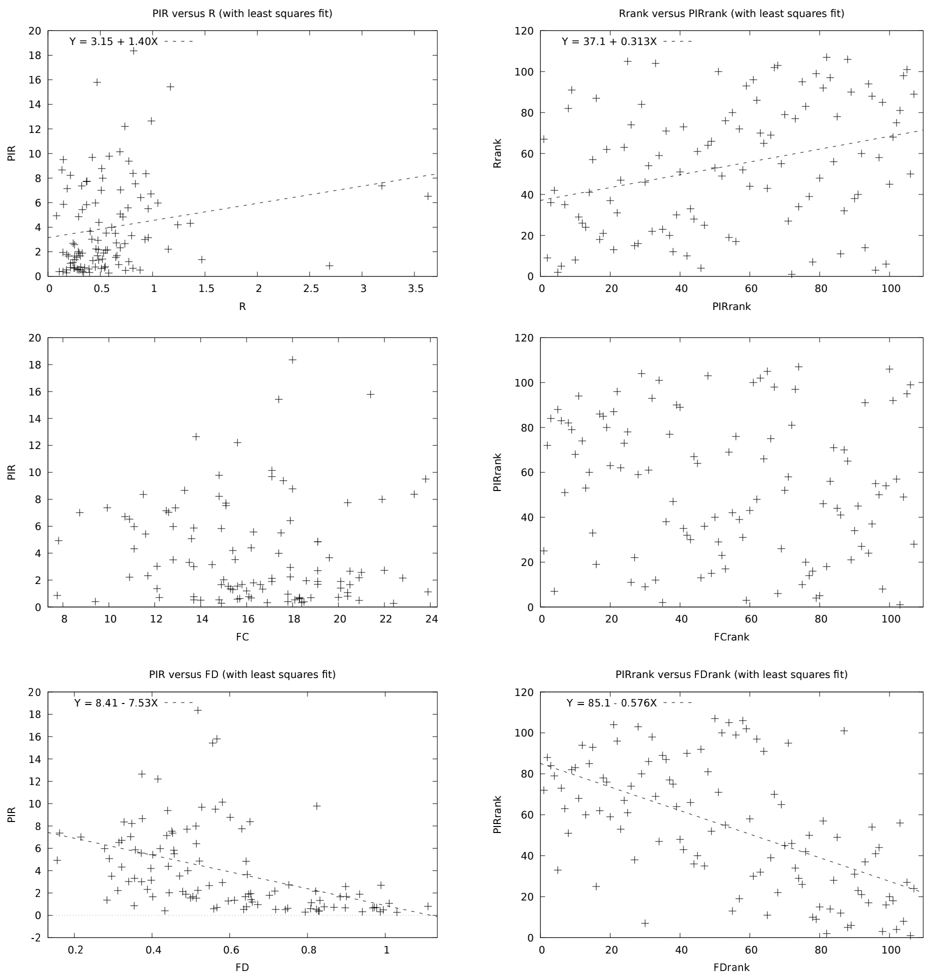

Figure 2: Graphical representation of the relationship between the PIR and the measures of light pollution R, FC and FD: left panels raw data; right panels ranked data.

	M1	M2	M3	M4	M5
const	3.1493^{***}	2.8313^{*}	1.1671	1.1315	0.4875
	(0.0000)	(0.098)	(0.4987)	(0.5349)	(0.2384)
R	1.3977^{**}	0.6134	0.6821	0.6875	0.1139
	(0.042)	(0.3339)	(0.2644)	(0.2676)	(0.4162)
FC	–	0.4955^{***}	0.5287^{***}	0.5291^{***}	0.1756^{***}
	–	(0.0001)	(0.0000)	(0.0000)	(0.0000)
FD	–	-12.3820^{***}	-12.9729^{***}	-12.9802^{***}	-4.8374^{***}
	–	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Over65	–	–	6.1147^{***}	6.0911^{***}	2.0061^{***}
	–	–	(0.0027)	(0.0034)	(0.0000)
Vehicles	–	–	–	4.3839e–5	−1.8415e–4
	–	–	–	(0.9498)	(0.2436)
R^2	0.0389	0.3159	0.3741	0.3741	0.6105
AdjR^2	0.0298	0.2960	0.3496	0.3431	0.5912
AIC	585.5347	553.1609	545.6461	547.6419	229.5880
BIC	590.8804	563.8522	559.0102	563.6788	245.6250

Table 2: Estimation summary for different regression models (p-values between parentheses). The dependent variable is PIRx1000 in models M1 to M4, while it is logPIRx1000 in model M5. Some goodness of fit indicators are reported: R^2, AdjR^2, Akaike information criterion (AIC), and Schwarz or Bayesian information criterion (BIC). Significance codes: * 10%, ** 5%, *** 1%.

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 ($\text{VIF}_{Dens} > 8$ and unstable coefficient of R). Therefore, we discard Dens and proceed including VAC. Also VAC introduces collinearity, even stronger than Dens ($\text{VIF}_{VAC} > 14$) 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:

$$\log(\text{PIRx1000}) = \alpha + \beta_1\text{R} + \beta_2\text{FC} + \beta_3\text{FD} + \beta_4\text{Over65} + \beta_5\text{Vehicles} + \varepsilon. \quad (1)$$

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 (1) 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 positive effect of income on COVID-19 outcomes. Economic activities generate social interactions that increase the virus diffusion and for this reason *lockdown policies* adopted by the Government have dealt with not only the households but also the firms.

4. Conclusions

In this note we show that outdoor light pollution may have a role in explaining 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 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 night 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 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. Our results do not support any significant relation between air pollution and PIR. Such elaborations are not shown in this note; indeed this research theme deserves a more focused future research.

References

[1] 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.

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

[3] Cinzano, P., Falchi, F., & Elvidge, C. D. (001. The first world atlas of the artificial night sky brightness. Mon. Notices Royal Astron. Soc. 328(3), 689-707.

[4] 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, e1600377.

[5] 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.

[6] 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, 109227.

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

[8] Harrell, F. E. (2015). Regression modeling strategies (2^{nd} Ed.). Springer, Cham.

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

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

[11] ISTAT, Italian Istitute of Statistics, `http://dati.istat.it`, accessed on July 18, 2020.

[12] Italian Ministry of Health, `http://www.salute.gov.it/nuovocoronavirus`, accessed on July 18, 2020.

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

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