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Guglielmo Maria Caporale, Luis A. Gil-Alana and Nieves Carmona-González

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PARTICULATE MATTER 10 (PM10): PERSISTENCE AND TRENDS IN EIGHT EUROPEAN CAPITALS

Guglielmo Maria Caporale
Brunel University London, UK

Luis A. Gil-Alana
University of Navarra, Pamplona, Spain
and Universidad Francisco de Vitoria, Madrid, Spain

Nieves Carmona-González
Universidad Francisco de Vitoria, Madrid, Spain

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Abstract

This paper examines the statistical properties of daily PM_{10} in eight European capitals (Amsterdam, Berlin, Brussels, Helsinki, London, Luxembourg, Madrid and Paris) over the period 2014-2020 by applying a fractional integration framework; this is more general than the standard approach based on the classical dichotomy between I(0) stationary and I(1) non-stationary series used in most other studies on air pollutants. All series are found to be characterised by long memory and fractional integration, with orders of integration in the range (0, 1), which implies that mean reversion occurs and shocks do not have permanent effects. Persistence is highest in the case of Brussels, Amsterdam and London. The presence of negative trends in Brussels, Paris and Berlin indicates some degree of success in reducing pollution in these capitals.

Keywords: fractional integration, long memory, persistence, trends, air pollutants, PM_{10}

JEL Classification: C22, Q53

Corresponding author: Professor Guglielmo Maria Caporale, Department of Economics and Finance, Brunel University, London, UB8 3PH, UK. Tel.: +44 (0)1895 266713. Fax: +44 (0)1895 269770. Email: Guglielmo-Maria.Caporale@brunel.ac.uk

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1. Introduction

Particulate matter (PM) are microscopic particles of solid or liquid matter suspended in the air. Its sources can be natural or anthropogenic. It has a significant impact on both climate and precipitation, and therefore has both health and social costs. In particular, it affects the amount of incoming solar radiation and outgoing terrestrial radiation. The coarse particles can have a diameter between 2.5 and 10 micrometers (μm) (PM_{10}) and are known to be a very harmful form of air pollution given their ability to penetrate into the lungs and blood streams and cause respiratory and heart diseases as well as premature death. Various countries have therefore set limits for particulars in the air, which are emitted during the combustion of vehicle engine fuels, braking and tyre wearing. In particular, the European Union has defined in a series of directives the acceptable limits for exhaust emissions of new vehicles sold in the European Union and EEA member states.

Numerous studies have analysed the connection between pollution and harmful health effects (e.g., Schwartz and Marcus, 1990; Anderson et al., 1996; Atkinson et al., 1999; Gardner and Dorling, 1999). The present study contributes to another branch of the literature which focuses instead on modelling various pollutants such as sulphur dioxide (SO_2), nitrogen dioxide (NO_2), carbon monoxide (CO), ozone (O_3), $PM_{2.5}$ and PM_{10}. For instance, Zamri et al. (2009) applied the Box-Jenkins ARIMA approach to model CO and NO_2 in Malaysia and found an upward trend. Li et al. (2017) analysed air quality in Beijing from 2014 to 2016 using the Spatio-temporal Deep Learning (StDL) model, the Time Delay Neural Network (TDNN) model, the ARMA model, the Support Vector Regression (SVR) model, and the Long Short-Term Memory Neural Network Extended (LSTME) model, and concluded that the LSTME model is the most suitable one for time series characterised by long-term dependence with optimal time delays.

Naveen and Anu (2017) studied air quality in India using ARIMA, seasonal ARIMA (SARIMA) and other models. Pan and Chen (2008) is one of the few studies using long-memory AutoRegressive Fractional Integrated Moving Average (ARFIMA) models for air pollution data (in Taiwan) and concluding that these are more accurate than AutoRegressive Integrated Moving Average (ARIMA) models.

It is clearly important to investigate the dynamics of air pollution to develop suitable models for prediction purposes and design policies to manage air quality. This paper examines the statistical properties of daily PM_{10} in eight European capitals (Amsterdam, Berlin, Brussels, Helsinki, London, Luxembourg, Madrid and Paris) over the period 2014-2020 by applying a fractional integration framework that is more general than the standard approach based on the classical dichotomy between I(0) stationary and I(1) non-stationary series used in the vast majority of previous studies on air pollutants, since it allows for fractional as well as integer degrees of differentiation and thus for a much wider set of stochastic behaviours. In particular, it enables the researcher to analyse the long-memory properties of the series of interest and the possible presence of trends, to test for mean reversion, and to measure the degree of persistence and the speed of adjustment to the long-run equilibrium level. Therefore, it provides information about whether the effects of shocks are transitory or permanent, which is a crucial piece of information for adopting appropriate policy measures.

The remainder of the paper is structured as follows: Section 2 outlines the methodology used for the analysis; Section 3 describes the data; Section 4 presents the empirical results; Section 5 offers some concluding remarks.

2. Methodology

As mentioned above, we adopt a long-memory approach based on fractional integration. Long memory is a feature of time series that are characterised by a high degree of dependence between observations which are far apart in time. It has been found to be displayed by many time series in different fields such as climatology (Gil-Alana, 2005; 2008; 2017; Vyushin and Kushner, 2009; Franzke, 2012; Ludescher et al., 2016; Bunde, 2017; Yuan et al., 2019); environmental sciences (Barros et al., 2016; Gil-Alana et al., 2016; Tiwari et al., 2016; Gil-Alana and Solarin, 2018); economics and finance (Gil-Alana and Moreno, 2012; Abritti et al., 2017); etc.

There exist a variety of statistical models that can describe this type of behaviour; a very popular one among time series analysts is based on the concept of fractional integration, which occurs when the number of differences required to make a series stationary I(0) is a fractional value. More precisely, a time series is said to be integrated of order d or I(d) if it can be expressed as:

$$(1 - B) x_t = u_t , \qquad t = 1, 2, ..., \tag{1}$$

where B is the backshift operator ($Bx_t = x_{t-1}$), the differencing parameter d can be any real value, and u_t is I(0) defined as a covariance stationary process with a spectral density function that is positive and bounded at all frequencies in the spectrum. This framework encompasses different cases such as short memory (d = 0), stationary long memory (0 < d < 0.5), non-stationary though mean-reverting processes (0.5 ≤ d < 1), unit roots (d = 1) and explosive patterns (d ≥ 1).

3. Data

The series analysed is the daily average air quality taken from the World Air Quality Index (WAQI) at https://aqicn.org/map/world/es/. All data have been converted using the US EPA standard (United States Environmental Protection Agency). Specifically, we use daily data for the past 7 years (2014-2020) concerning eight European capitals: Amsterdam, Berlin, Brussels, Helsinki, London, Luxembourg, Madrid and Paris. The series represents the daily level of air quality (PM10) measured in micrograms per cubic meter of air (ug/m3). The WAQI data come from the following original sources: Madrid: http://www.mambiente.madrid.es/opencms/opencms/calaire/ (Ayuntamiento de Madrid); Paris: http://www.airparif.asso.fr/ (AirParif - Association de surveillance de la qualité de l'air en Île-de-France); Amsterdan: https://www.luchtmeetnet.nl/ (RIVM); Luxembourg: https://environnement.public.lu/fr.html (Portail de l`Environnement du Grand-duché de Luxembourg); London: https://uk-air.defra.gov.uk/ (UK-AIR, air quality information resource - Defra, UK); Helsinki: https://www.ilmatieteenlaitos.fi/ilmanlaatu (Ilmanlaatu Suomessa); Brussels: https://www.irceline.be/en/ (Belgian Interregional Environment Agency); Berlin: https://www.berlin.de/senuvk/umwelt/luftqualitaet/ (Luftqualität).

[TABLE 1 ABOUT HERE]

Table 1 reports the sample periods for each capital and provides some descriptive statistics for each series. It can be seen that Paris exhibits the highest mean value, while Helsinki has the lowest. Paris also has the most volatile series, whilst Luxembourg has the least volatile.

4. Empirical Results

We estimate the following model:

$$y_t = \alpha + \beta t + x_t, \quad (1-B)^{d_o} x_t = u_t, \quad t = 1, 2, ..., \qquad (2)$$

where y_t stands for PM_{10} in each European capital in turn; B is the backshift operator, and x_t is an I(d) process such that the error term u_t is I(0); the disturbances are assumed to follow a white noise (see Tables 2 and 3) and an autocorrelated process (see Tables 4 and 5) in turn, where the latter is modelled using the exponential spectral framework of Bloomfield (1973). In all cases we display the estimated values of d (and their associated 95% confidence bands) for three different specifications: (i) no deterministic terms in (1), i.e., we impose the restriction $\alpha = \beta = 0$ (the results for this case are reported in the second column in Tables 2 and 4); (ii) an intercept only (see the third column in both tables); (iii) an intercept and a linear time trend (see the fourth column in both tables). The estimated values reported in bold in these tables are those corresponding to our preferred specification, which has been selected on the basis of the statistical significance of the regressors.

[TABLES 2 AND 3 ABOUT HERE]

When assuming that u_t is a white noise, the intercept is found to be the only significant deterministic term in all cases; the estimated values of d are in the interval (0, 1), which implies long memory and fractional integration. They range between 0.39 (Amsterdam) and 0.62 (Madrid). For Amsterdam, the values are all within the stationary range ($d < 0.5$); for Brussels, London, Paris and London, they are around the stationary boundary ($d = 0.5$), while non-stationarity ($d \geq 0.5$) is found in the case of Helsinki, Berlin and Madrid.

[TABLES 4 AND 5 ABOUT HERE]

When allowing for autocorrelation (Tables 4 and 5) the time trend appears to be negative and statistically significant in the case of Brussels, Berlin and Paris, which might reflect the anti-pollution policies adopted in these three capitals. In particular, a low emission zone (LEZ) was established in the Brussels region with the aim of meeting the European air quality standards and emission ceilings; in Berlin the German Climate Action Plan 2050 is being implemented to control air pollution by laying down environmental quality standards and emission reduction requirements; a LEZ based on Euro norm vehicle classification has also been introduced in Paris.

The estimated values of d are once more in the interval (0, 1), though they are now significantly smaller than in the previous case. In fact, they are all within the stationary range, specifically between 0.22 (Luxembourg) and 0.33 (Helsinki and Paris). These lower estimates are likely to reflect the competition between the fractional integration and Bloomfield parameters in describing time dependence between the observations. Both sets of estimates, under the assumption of white noise and autocorrelated errors respectively, indicate that the degree of persistence is highest in the case of Brussels, Amsterdam and London, and lowest in the case of Helsinki, Berlin, and Madrid; thus, the effects of shocks are more long-lived in the former capitals.

5. Conclusions

This paper has used fractional integration methods to obtain evidence on persistence and time trends in PM_{10} in eight European capitals (Amsterdam, Berlin, Brussels, Helsinki, London, Luxembourg, Madrid and Paris). This approach is more general than the standard ones used in most of the literature on air pollutants and thus is more informative about the time series properties of the series of interest. The results indicate that all of them display fractional integration with orders of integration in the range

(0,1); this implies that mean reversion occurs and shocks do not have permanent effects. However, the degree of persistence is different in the eight capitals examined; in particular, the effects of shocks take longer to die away in the case of Brussels, Amsterdam and London. Such evidence should be taken into account by policy makers aiming to design effective measures to reduce pollution.

The estimated values of d are lower under the assumption of autocorrelated errors; in this case three of the capitals examined (Brussels, Paris and Berlin) exhibit statistically significant negative time trends, which suggests that the policies they have adopted to reduce pollution (such as the establishment of LEZs) have been successful, at least to some extent.

Other statistical properties of PM_{10} that could be investigated are seasonality, non-linearities and structural breaks; the forecasting properties of rival models could also be examined; all these issues are left for future work.

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Table 1: Descriptive statistics

AMSTERDAM		BERLIN	
Start date	End date	Start date	End date
01/01/2014	13/06/2020	20/08/2014	13/06/2020
No. of observations:	2145	*No. of observations:*	2114
Mean:	25.7	*Mean:*	28.0
Standard deviation:	11.1	*Standard deviation:*	11.9
Variance:	124.1	*Variance:*	140.6
Min./Max.:	8 / 263	*Min./Max.:*	8 / 95
Range:	255	*Range:*	87
BRUSSELS		**HELSINKI**	
Start date	End date	Start date	End date
31/12/2013	13/06/2020	02/05/2014	13/06/2020
No. of observations:	2334	*No. of observations:*	2214
Mean:	24.0	*Mean:*	18.1
Standard deviation:	11.8	*Standard deviation:*	10.0
Variance:	140.4	*Variance:*	99.9
Min./Max.:	1 / 100	*Min./Max.:*	3 / 90
Range:	99	*Range:*	87
LONDON		**LUXEMBOURG**	
Start date	End date	Start date	End date
31/12/2013	13/06/2020	19/06/2015	13/06/2020
No. of observations:	2353	*No. of observations:*	1583
Mean:	26.5	*Mean:*	19.5
Standard deviation:	9.9	*Standard deviation:*	6.8
Variance:	97.1	*Variance:*	46.2
Min./Max.:	5 / 89	*Min./Max.:*	2 / 52
Range:	84	*Range:*	50
MADRID		**PARIS**	
Start date	End date	Start date	End date
31/12/2013	13/06/2020	31/12/2013	13/06/2020
No. of observations:	2323	*No. of observations:*	2227
Mean:	24.3	*Mean:*	39.3
Standard deviation:	11.7	*Standard deviation:*	14.5
Variance:	138.0	*Variance:*	210.5
Min./Max.:	5 / 160	*Min./Max.:*	6 / 122
Range:	155	*Range:*	116

Table 2: Estimates of d: White noise errors

Series	No deterministic terms	An intercept	An intercept and a time trend
AMSTERDAM	0.42 (0.39, 0.46)	**0.39 (0.35, 0.44)**	0.39 (0.35, 0.44)
BERLIN	0.63 (0.58, 0.68)	**0.61 (0.56, 0.67)**	0.61 (0.56, 0.67)
BRUSSELS	0.52 (0.48, 0.56)	**0.50 (0.46, 0.55)**	0.50 (0.46, 0.55)
HELSINKI	0.57 (0.52, 0.61)	**0.54 (0.50, 0.59)**	0.54 (0.50, 0.59)
LONDON	0.54 (0.50, 0.59)	**0.52 (0.47, 0.57)**	0.52 (0.47, 0.57)
LUXEMBOURG	0.56 (0.51, 0.62)	**0.54 (0.48, 0.61)**	0.54 (0.48, 0.61)
MADRID	0.63 (0.58, 0.68)	**0.62 (0.57, 0.67)**	0.62 (0.57, 0.67)
PARIS	0.55 (0.51, 0.59)	**0.53 (0.49, 0.58)**	0.53 (0.49, 0.58)

We report the estimates of d and its 95% confidence band (in parenthesis). In bold, the selected specification for each series.

Table 3: Estimated coefficients in the selected model: White noise errors

Series	d (95% band)	Intercept (t-value)	Time trend
AMSTERDAM	0.39 (0.35, 0.44)	26.0450 (8.77)	---
BERLIN	0.61 (0.56, 0.67)	25.3864 (3.93)	---
BRUSSELS	0.50 (0.46, 0.55)	20.9146 (4.17)	---
HELSINKI	0.54 (0.50, 0.59)	20.4913 (4.57)	---
LONDON	0.52 (0.47, 0.57)	23.0696 (5.23)	---
LUXEMBOURG	0.54 (0.48, 0.61)	15.6394 (4.61)	---
MADRID	0.62 (0.57, 0.67)	16.5249 (2.59)	---
PARIS	0.53 (0.49, 0.58)	32.9226 (5.16)	---

The values in parenthesis in column 3 are the corresponding t-values.

Table 4: Estimates of d: Autocorrelated errors

Series	No deterministic terms	An intercept	An intercept and a time trend
AMSTERDAM	0.34 (0.29, 0.39)	**0.26 (0.21, 0.30)**	0.25 (0.20, 0.30)
BERLIN	0.38 (0.33, 0.43)	0.30 (0.25, 0.36)	**0.29 (0.23, 0.36)**
BRUSSELS	0.33 (0.28, 0.38)	0.26 (0.21, 0.32)	**0.25 (0.21, 0.31)**
HELSINKI	0.40 (0.35, 0.45)	**0.33 (0.29, 0.39)**	0.33 (0.29, 0.38)
LONDON	0.34 (0.30, 0.39)	**0.26 (0.21, 0.31)**	0.27 (0.22, 0.30)
LUXEMBOURG	0.32 (0.28, 0.38)	**0.22 (0.16, 0.29)**	0.21 (0.15, 0.28)
MADRID	0.34 (0.30, 0.39)	**0.30 (0.25, 0.35)**	0.30 (0.25, 0.35)
PARIS	0.41 (0.37, 0.46)	0.33 (0.28, 0.38)	**0.33 (0.28, 0.38)**

We report the estimates of d and its 95% confidence band (in parenthesis). In bold, the selected specification for each series.

Table 5: Estimated coefficients in the selected model: Autocorrelated errors

Series	d (95% band)	Intercept (t-value)	Time trend (t-value)
AMSTERDAM	0.26 (0.21, 0.30)	25.6832 (21.18)	---
BERLIN	0.29 (0.23, 0.36)	32.6088 (16.38)	-0.0046 (-2.92)
BRUSSELS	0.25 (0.21, 0.31)	26.3621 (15.22)	-0.0022 (1.97)
HELSINKI	0.33 (0.29, 0.39)	19.6888 (12.88)	---
LONDON	0.26 (0.21, 0.31)	25.9193 (24.21)	---
LUXEMBOURG	0.22 (0.16, 0.29)	19.2309 (34.57)	---
MADRID	0.30 (0.25, 0.35)	23.5407 (16.78)	---
PARIS	0.33 (0.28, 0.38)	42.2180 (13.79)	-0.0044 (-1.98)

The values in parenthesis in columns 3 and 4 are the corresponding t-values for the intercept and the time trend respectively.