Searching for the peak
Google Trends and the COVID-19 outbreak in Italy

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Abstract

One of the difficulties faced by policy makers during the COVID-19 outbreak in Italy was the monitoring of the virus diffusion. Due to changes in the criteria and insufficient resources to test all suspected cases, the number of 'confirmed infected' rapidly proved to be unreliably reported by official statistics. We explore the possibility of using information obtained from Google Trends to predict the evolution of the epidemic. Following the most recent developments on the panel data literature, we estimate a dynamic heterogeneous panel model that takes into account the presence of common shocks and unobserved components in the error term. We find that Google queries contain useful information to predict number patients admitted to the intensive care units, number of deaths and excess mortality in 14 Italian regions.

Keywords: COVID-19, Google Trends, Dynamic panel data.
JEL: I18, D83, C10.

I BACKGROUND

Italy was the first European country to discover a serious outbreak of COVID-19, the infectious disease caused by severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2). For this reason, policy makers around the globe have been looking carefully at the responses implemented in Italy and their effectiveness in slowing the spread of the disease. Italy struggled for weeks trying to respond to the Coronavirus pandemic and was the first Western country to implement a strict limitation of the freedom of movement of its citizens, on March 9 [19].

Since January 30 2020, when two Chinese tourists in Rome tested positive, authorities have constantly monitored COVID-19 diffusion. Nevertheless, days after days it became clear that the official 'number of confirmed infected' cases were hardly useful to monitor the COVID-19 widespread. The measured number of infected critically depends on the number people tested, and the latter number is to a large extent determined by the health care system testing capacity and the criteria adopted to recommend the test.

The stringency of Italian criteria led many experts to warn against the possibility that the official number of infections could be severely downward biased. Moreover, later in March, the worsening of the health crisis put into question the viability of performing tests in many areas of the country. This is likely to have sharpened the underestimation of the diffusion, making official statistics less and less reliable over time: i.e. Mr. Borrelli, head of the Italian Civil Protection Department, in a conference press on March 24th, declared that the number of daily infected could have been 10 times higher than what officially reported. Even if during the summer the monitoring system was greatly reinforced, in the autumn of 2020 the testing system still appears inadequate to face the second wave [18]. This explains why the attention of media and experts, in Italy and in other severely affected countries, has increasingly focused on the number of hospital admissions, the number of occupied beds in intensive care units (ICU), and, eventually, the number of deaths/excess mortality [20].

In cases for which reliable official statistics are not readily available, the use of big data can improve our understanding and our ability to predict the evolution of complex phenomena. Data coming from search engines, in particular, can provide early signal of disease diffusion in almost real time. The use of Google queries to predict the outbreak of infections was first proposed in 2008 [9]. The idea is surprisingly simple: users suspecting an illness tend to search information about the symptoms and complications. Based on this premise, Google launched the tool Google Flu Trends in 2008, which operated until 2015 in predicting, almost in real-time, how influenza and dengue fever were spreading based on peoples queries. Although the algorithm was updated to minimize its prediction error, Google Flu Trends was criticized for having overestimated flu prevalence for more than one season [14] and for having underestimated N1H1 influenza activity in 2009 [7]. Nevertheless, a strong correlation between queries and integrated flu surveillance data, such as the U.S. Outpatient Influenza-like Illness Surveillance Network, is found in all contributions [24].

In this respect COVID-19 pandemic represents an interesting case study both because the need to predict the virus diffusion was of fundamental importance to protect the health care system from collapsing and because certain COVID-19 symptoms were initially only partially known by the scientific community and to a large extent unknown by the population. A few contributions have investigated the possible use of Google Trends to predict COVID-19 diffusion. A recent contribution [15] finds a positive correlation between state-level Google queries for the term "coronavirus" and COVID-19 cases/deaths in the US. Other authors [2] focusing on Google queries concerning loss of smell and taste in the US and Italy draw opposite conclusions and suggest that Google Trends may not be reliably used to predict COVID-19 cases. Nevertheless [1] show that search interest in common gastrointestinal symptoms tend to correlate with coronavirus data recorded in the U.S. hotpots. Finally, a statistically significant correlation between Google search related to smell loss with COVID-19 cases and death has been proven for eight countries [21].

Given the interest on searches about COVID-19 symptoms at the beginning of September

2020 Google has published a COVID-19 trends database. Collected from users' search the dataset includes aggregated anonymized search trends for more than 400 symptoms and health-related queries [10]. The dataset contains trends at the U.S. county-level for the entire country and is likely to attract further attract scholars' attention in the near future.

II METHOD AND DATA

To verify whether internet searches could have been used to predict early COVID-19 diffusion in the Italian regions we focus on the number of patients admitted to ICU and number of deaths. We believe that considering such numbers is far more reliable than the number of tested positive in the current situation. Further, as a robustness check, we also employ data on excess mortality for the first six months of 2020.

The symptoms considered are the most frequently observed in positive patients: "fever", "dry cough", "cough", "sore throat", "loss of sense of smell", and "loss of sense of taste" (European Centre for Disease Prevention and Control: www.ecdc.europa.eu/en/covid-19/latest-evidence/clinical). Figure 1 reports the trend in Google searches for COVID-19 symptoms and daily number of deaths in Italy between the end of February and the end of June 2020. The peak in Google Trends is recorded in the same days for all symptoms and precedes by a couple of weeks the peak of the number of deaths.

Notice that the key weakness of using Google queries to predict virus diffusion, in the case of Coronavirus, is the massive media coverage received by the outbreak. Media emphasis has certainly influenced Google users queries. Many are likely to have searched information about the virus, including symptoms, without really suspecting to be infected. Nevertheless, Figure 2, which plots the number of deaths together with the media coverage for the same terms in 100 Italian on-line journals, suggests that this may not be too worrying. We notice an early peak of the media coverage for the terms "dry cough" and "cough" followed by a peak in the coverage of the term "fever" the first days of the lockdown. The term "sore throat", "loss of smell" and "loss of taste" peak late, in April, after the number of deaths started to decline.

The sharp correlation depicted in Figure 1 does not allow to conclude that Google queries are useful predictor of Coronavirus diffusion. To properly model such a dynamic phenomenon we exploit both its heterogeneity over time, monitoring the covariance of searches and COVID-19 diffusion trends, and across space, performing a statistical analysis at a regional-level.

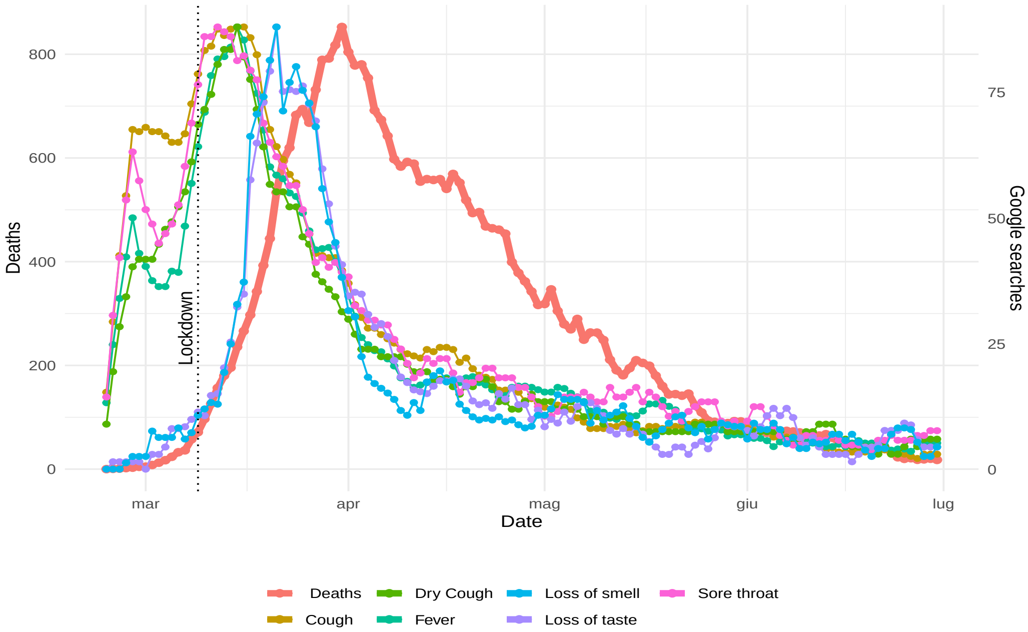
Hence, we consider a sample of 14 out of the 20 Italian regions observed daily from 2020-02-24 to 2020-09-16 and construct the variable Google Trend as the sum of Google queries for words related to the most common symptoms of COVID-19 considered in Figure 1. We exclude the five smallest regions (Friuli Venezia Giulia, Trentino-Alto Adige, Umbria, Basilicata, Molise, and Valle d'Aosta) because of lack of robust Google Trends available for the items selected in the considered period (daily search in smallest regions are mainly zeros and 100 - i.e., the maximum normalised). This is particularly problematic because, in our study, we implicitly assume that all regions have the same weight. However, since the sum of population in the excluded regions is 4.163 millions out of the 60.359 Italian inhabitants, the following analysis is representative of about 93% of Italian population.

Building on the recent developments in the literature of dynamic heterogeneous panel data - which allows for dynamic heterogeneity and cross-sectional dependence - we estimate an augmented Autoregressive-Distributed Lag model (ARDL), such as:

$$y_{it} = \alpha_i + \sum_{l=1}^{p} \delta_{il} y_{it-l} + \sum_{l=0}^{q} \beta'_{il} x_{it-l} + \sum_{l=0}^{k} \psi'_{il} \Delta \bar{z}_{t-l} + \varepsilon_{it} \tag{1}$$

where y_{it} is the number of deaths per million inhabitants for COVID-19 or the number of patients admitted to ICUs per million inhabitants in region i the day t; $x_{it} = \sum_{j=0}^{n} Trends_{it}^{j}$ is the volume of the sum of Google queries from region i the day t; α_i is the regional fixed effect and

Figure 1: Number of deaths per day and Google searches for commonly reported symptoms of Covid19 (from 2020-02-24 to 2020-06-30)



Data: Google Trends and Istituto Superiore di Sanità (Downloaded from https://github.com/pcm-dpc/COVID-19, last update September 16 2020).
Note: Simple Moving Averages n=5. Google Trends normalizes search volumes by setting the maximum recorded in the period considered to 100.

ε_{it} represents the idiosyncratic errors. Further, $\bar{z}_t$ are the cross section averages of the dependent and independent variables, such as $\bar{z}_t = \frac{1}{N}\sum_{i=1}^{N} z_{it}$ with z=y,x which proxy for common factors.

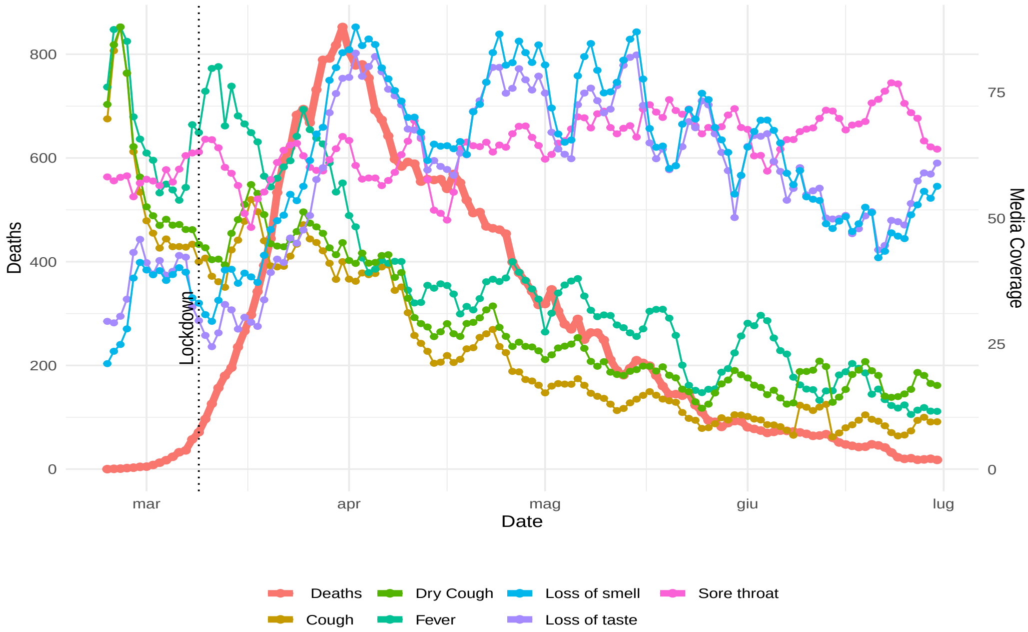
The proposed ARDL specification considers heterogeneous coefficients and, therefore, allows the correlation between y and x to vary across regions. This heterogeneity captures regional-specific factors such as institutions, geographical location, or cultural factors which might potentially affect individual attitudes towards the use of search engines for health self-assessment searches as well as regional differentiation in timing and intensity of the COVID-19 spread. Indeed, territorial differences in Italy are widely spread across a number of dimensions including health, income levels, and social and human capital [11]. Furthermore, as each region has a relevant share of responsibility for the organization and financing of the health system [8], a regional heterogeneity is also expected in the prevention and in the treatment of COVID-19 cases [4].

Importantly, we also take into account of the effect of cross section dependence such as dependence across space or social networks by introducing a factor structure. Factor models proxy for common shocks which not only affect number of patients admitted to the intensive care or the number of deaths - thorough the heterogeneous loadings - but also affect Google searches. The dissemination of news on the COVID, the general attention on the Italian case that has aroused national concern (in addition to the typical regional ones) together with social distancing measures, such as the national lockdown implemented starting from 2020-03-09, might be interpreted as potential shocks common to all regions. In the empirical literature, it is increasingly recognized that conditioning on variables specific to the cross-section units alone need not deliver cross-section error independence, and neglecting such dependencies can lead to biased estimates and spurious inference, see [6] among others.

Following [16] and [5], we estimate (1) by the Dynamic Common Correlated Effects (DCCE) proposed by[5].

The choice of estimating specification (1) by DCCE has been driven by two main motivations:

Figure 2: Number of deaths per day and Media coverage for commonly reported symptoms of Covid19 (from 2020-02-24 to 2020-06-30)



Data: Media Cloud (https://mediacloud.org) and Istituto Superiore di Sanità (Downloaded from https://github.com/pcm-dpc/COVID-19, last update September 16 2020).
Note: Simple Moving Averages n=5. Media coverage is normalised by setting the maximum recorded in the period considered to 100.

(i) by means of the [17] and the [3] tests we find evidence in favour of existence of strong cross-section dependence in our dataset, (ii) by applying the the Westerlund and Edgerton [22] test we register the absence of cointegration between y_{it} and x_{it} , see Table 1.[1]

Further, before estimating (1), we implemented the conventional time series analysis for each region and also detected the lag order the ARDL model by means of the AIC selection criteria. The results are briefly summarized as follows: y_{it}'s are mostly AR(1) whereas x_{it} turns out to be more heterogeneous across regions, Google Trend is more persistent showing the significance of 5/10 autoregressive lags; the results of the unit root tests show that the series are $I(0)$ or $I(1)$; lastly, the AIC criteria shows that the selected lag order for the ARDL regional models goes from an ARDL(1,13) to - in 5 out of 14 regions - an ARDL(1,30).

On the basis of this evidence, we estimate (1) as an ARDL(1,30) panel model with variables defined in first difference and focus on the significance of the lagged coefficients to predict the patterns of the number of deaths for COVID-19 or the number of patients admitted to the intensive care.

The parameters of interest are $\beta_{il}, l = 1, ..., 30$, which capture the effect of the volume of Google queries, at day $t-l$, on the number of deaths for COVID-19 or on the number of patients admitted to the intensive care, at day t.

III RESULTS

Table 1 shows results of the Mean Group DCCE estimator when including three lags of the cross section averages, $\bar{z}_t$, i.e. k=3 in (1). The first column shows the model in which the dependent variable is the number of deaths officially recorded for COVID-19 and the independent variable is the sum of Google queries for words related to symptoms. Coefficients associated to Google Trends are positive with all the lags tested ($l = 1, ..., 30$), lags from 1 to 29 are significant in explaining deaths (p<0.1). Similar results are obtained using ICU patients as dependent variable (third column). Also in this case coefficients associated to Google Trends - in all the tested lags - are positive. Significant queries in explaining regional intensive care cases for COVID-19 at time t are Google searches for symptoms made on $t - l, l = 1, ..., 22$. Overall, the regional analysis suggests that the time between searches and deaths/intensive care cases is between 1 and 29 days. Remarkably, results in Table 1 show that there is about a week of difference between the significant Google Trends predicting ICU patients, and the significant Google Trends predicting deaths: i.e., Google Trends have more memory in terms of lags in the case of deaths. This is a reasonable result considering that COVID-19 deaths usually come after a critical health condition.

As robustness check we also tested the model specification to the daily excess mortality estimated on the difference between daily deaths in 2020 and daily average deaths in 2017, 2018 and 2019 . Excess mortality is based on data published by Istituto Nazionale di Statistica for the first six months of 2020 [13]. Results in Table A1 show that the association between Google Trends and the excess morality is positive for $t - l, l = 1, ..., 29$ and significant (p<0.1) for $l = 2, l = 4, ..., 8, l = 13, ..., 16$.

Table 1: Dynamic Common Correlated Effects Results

	Deaths		Intensive care cases	
Deaths l=1	0.1561	***		
	(0.030)			
Intensive care cases l=1			0.9112	***
			(0.014)	
Google Trends l=1	0.0034	***	0.0014	***
	(0.001)		0.0000	
Google Trends l=2	0.0064	**	0.0015	***
	(0.003)		*0.0000*	
Google Trends l=3	0.0080	**	0.0016	***
	(0.003)		*(0.001)*	
Google Trends l=4	0.0060	**	0.0023	***
	(0.002)		*(0.001)*	
Google Trends l=5	0.0074	***	0.0026	***
	(0.002)		*(0.001)*	
Google Trends l=6	0.0090	***	0.0026	***
	(0.003)		*(0.001)*	
Google Trends l=7	0.0110	***	0.0036	***
	(0.003)		*(0.001)*	
Google Trends l=8	0.0106	***	0.0046	***
	(0.003)		*(0.001)*	
Google Trends l=9	0.0116	***	0.0042	***
	(0.003)		*(0.001)*	
Google Trends l=10	0.0108	***	0.0040	***
	(0.003)		*(0.001)*	
Google Trends l=11	0.0132	***	0.0048	***
	(0.004)		*(0.001)*	
Google Trends l=12	0.0145	***	0.0041	***
	(0.004)		*(0.001)*	
Google Trends l=13	0.0145	***	0.0035	***
	(0.004)		*(0.001)*	
Google Trends l=14	0.0143	***	0.0035	***
	(0.004)		*(0.001)*	
Google Trends l=15	0.0141	***	0.0034	***
	(0.004)		*(0.001)*	
Google Trends l=16	0.0124	***	0.0026	***
	(0.003)		*(0.001)*	
Google Trends l=17	0.0100	***	0.0027	***
	(0.002)		*(0.001)*	
Google Trends l=18	0.0093	***	0.0027	***
	(0.002)		*(0.001)*	
Google Trends l=19	0.0079	***	0.0023	***
	(0.002)		*(0.001)*	
Google Trends l=20	0.0069	***	0.0020	***
	(0.002)		*(0.001)*	
Google Trends l=21	0.0056	***	0.0018	***
	(0.002)		*(0.001)*	
Google Trends l=22	0.0044	***	0.0016	**
	(0.002)		*(0.001)*	
Google Trends l=23	0.0056	***	0.0007	
	(0.002)		*(0.001)*	
Google Trends l=24	0.0089	***	0.0008	
	(0.002)		*(0.001)*	
Google Trends l=25	0.0084	***	0.0015	
	(0.003)		*(0.001)*	
Google Trends l=26	0.0070	***	0.0004	
	(0.002)		*(0.001)*	
Google Trends l=27	0.0075	***	0.0004	
	(0.003)		*(0.001)*	
Google Trends l=28	0.0054	***	0.0003	
	(0.002)		*(0.001)*	
Google Trends l=29	0.0035	**	0.0001	
	(0.002)		*(0.001)*	
Google Trends l=30	0.0016		0.0000	
	(0.002)		*(0.000)*	
CD	9.451	***	9.541	***
alpha	0.974	(CI: 0.811 - 1.139)	0.941	(CI: 0.799 - 1.128)
WE	0.222	(0.412)	-0.836	(0.202)

Notes: *** $p<0.01$; ** $p<0.05$; * $p<0.1$. CD is the [17] CD test; *alpha* is the and the [3] exponent test, WE is the cointegration test as proposed by [22].

IV DISCUSSION

Our dynamic heterogeneous panel model based on Google queries takes into account of cross section dependence and show a systematic positive relationship between number of searches for symptoms and number of deaths. The same model showed a similar predictive ability to explain critical cases recorded in the Italian hospitals and excess mortality rates in Italian regions. Moreover, our analysis suggests that the time between searches and deaths/intensive care cases is between 1 and 30 days. This time lag lies within the range between first symptoms and deaths/critical cases depicted by literature [12, 21, 23].

Our estimates conflict with what recently suggested by other authors that have focused on a similar research question and reach opposite conclusions [2]. Such differences can be explained by a number of methodological aspects. [2] look at static and country-level weekly correlations between Google searches and reported cases, while we consider deaths/ICU admission and we go beyond studying correlations considering a dynamic panel model.

The possibility to predict outbreaks based on web searches of Google users to supplement epidemiological models has been severely criticized in the last decade [14]. Nevertheless, during a crisis, when institutions struggle to operate normally and the reliability of official statistics is questioned, supplementing official data sources with data obtained from Google Trends appears as a promising option.

V POLICY RECOMMENDATIONS

Among the problematic aspects of the early COVID-19 outbreak in Italy, the difficulties of institutions to provide real-time and reliable information about the spread of the virus stands out. Lack of precise information represented a major issue in a moment of crisis in which effective decisions to respond to the pandemic had to be made immediately. In such extreme situation, a high tech/statistical system to support institutional decision-makers in the management of emergency and in preventive perspective can be of crucial importance.

Our empirical analysis has shown that some signals are already present in unstructured data freely available on-line. Such low-cost, real-time information can be used as a complement to official statistics for data analysis, decision-making, and policy-making. However, it is fundamental to avoid to incur in the "big data hubris", policy makers should never be tempted to consider big data analysis as a (cheaper) substitute for traditional data collection and analysis. The parable of Google Flu Trend should warn policy makers about both the risks and the limitations of using Google Trends data to predict a virus diffusion. Nevertheless, the torrents of data produced every day by our mobile phones, online shopping, social networks, and electronic communications represent a great opportunity for national health care systems, especially in periods of emergency.

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A APPENDIX

Table A1: Dynamic Common Correlated Effects Results for Excess Mortality

		Excess Mortality	
Excess Mortality l=1		0.0449	
		(0.029)	
Google Trends l=1		0.0034	
		(0.002)	
Google Trends l=2		0.0046	**
		(0.002)	
Google Trends l=3		0.0045	
		(0.003)	
Google Trends l=4		0.0067	**
		(0.003)	
Google Trends l=5		0.0073	**
		(0.003)	
Google Trends l=6		0.0083	**
		(0.003)	
Google Trends l=7		0.0076	**
		(0.004)	
Google Trends l=8		0.006	*
		(0.003)	
Google Trends l=9		0.0047	
		(0.003)	
Google Trends l=10		0.005	
		(0.004)	
Google Trends l=11		0.0045	
		(0.003)	
Google Trends l=12		0.0045	
		(0.003)	
Google Trends l=13		0.0072	***
		(0.003)	
Google Trends l=14		0.0077	***
		(0.002)	
Google Trends l=15		0.0039	**
		(0.002)	
Google Trends l=16		0.0022	*
		(0.001)	
Google Trends l=17		0.0029	
		(0.003)	
Google Trends l=18		0.0017	
		(0.003)	
Google Trends l=19		0.0045	
		(0.004)	
Google Trends l=20		0.0069	
		(0.004)	
Google Trends l=21		0.0073	
		(0.005)	
Google Trends l=22		0.0065	
		(0.004)	
Google Trends l=23		0.0055	
		(0.004)	
Google Trends l=24		0.0033	
		(0.003)	
Google Trends l=25		0.0033	
		(0.004)	
Google Trends l=26		0.0021	
		(0.004)	
Google Trends l=27		0.0022	
		(0.004)	
Google Trends l=28		0.0026	
		(0.002)	
Google Trends l=29		0.0014	
		(0.002)	
Google Trends l=30		-0.0004	
		(0.002)	
CD	2.251	**	
alpha	0.818	(CI: 0.695 - 0.942)	
WE	-0.14	(0.443)	

Notes: *** p<0.01; ** p<0.05; * p<0.1. CD is the [17] CD test; *alpha* is the and the [3] exponent test, WE is the cointegration test as proposed by [22].