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Changes in Community Mobility and Covid-19 Cases: A Multiscale Analysis for Portuguese Districts¹

Alterações na mobilidade comunitária e casos de Covid-19: uma análise multi-escala para os distritos portugueses

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Abstract

Confinement has been part of the fight against Covid-19 all over the world, with Portugal being no exception. In order to understand whether conditions in different regions allow different measures to be taken, the Detrended Cross-Correlation Analysis correlation coefficient was applied. It was demonstrated that levels of mobility are correlated with new cases of the disease, although some types of mobility, such as that related to the workplace, do not present a statistically significant relationship with new cases. In addition, correlation levels vary between the different districts of Portugal, leaving open the possibility of measures to contain the disease being designed taking these differences into account.

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Keywords: correlation coefficient; Covid-19; Detrended Cross-Correlation Analysis; mobility indices; Portuguese districts

JEL Code: C60, I12, I18

Resumo

Os confinamentos têm feito parte da luta contra a Covid-19, um pouco por todo o mundo, sendo que Portugal não tem sido exceção. Para perceber se as condições em diferentes regiões poderão permitir a tomada de medidas diferenciadas, aplicou-se o coeficiente de correlação da Detrended Cross-Correlation Analysis. Foi possível verificar que os níveis de mobilidade estão correlacionados com os novos casos da doença, ainda que alguns tipos de mobilidade, como a relativa aos locais de trabalho, não apresentam relação estatisticamente significativa com os novos casos da doença. Além disso, os níveis de correlação são distintos nos diferentes distritos de Portugal, deixando em aberto a possibilidade de as medidas de contenção da doença serem desenhadas tendo em conta essas diferenças.

Palavras-chave: coeficiente de correlação; Detrended Cross-Correlation Analysis; distritos de Portugal; índices de mobilidade

Códigos JEL: C60, I12, I18

1. INTRODUCTION

After being identified in China in the last days of 2019, Covid-19 spread to Europe during the first weeks of 2020 and was first identified in Portugal at the beginning of March of that year. Although the mortality rate of SARS-CoV-2 appears to be lower than SARS-CoV and MERS-CoV, it is transmitted much more quickly and widely, resulting in a global healthcare and financial crisis (Ochani et al. 2021).

As of 14th July 2021, more than 188 million cases were reported all over the world, with more than 4 million deaths, while Portugal reported more than 912 000 cases and about 17 170 deaths. The country, like many others, during periods of more severe infection rates, introduced measures to reduce citizens' mobility, aiming to break the spread of the disease, and in more critical moments, severe lockdowns were in force, with different economic effects (see, for example, Fernandes, 2020 or Baker et al., 2020) and other kinds of social problems (see for example, the work of Blustein et al. 2020; Kawohl and Nordt, 2020; Lucas, 2020; Sumner et al., 2020, among others).

In this context, governments' role is important in minimizing these effects, as reported by König and Winkler (2020), so knowing about the dynamics of the disease is crucial for those governments to act. Among the different factors contributing to the spread of this kind of respiratory viral infection, the number of social contacts is one of the most relevant (see, for example, Moryiama et al., 2020). Other factors like population density or demographic and socioeconomic aspects could also be relevant (Zaldo-Aubanell et al. 2021), some of which will be identified during the analysis.

As the spread of the disease is directly related to contacts between people, their mobility is a crucial element of this problem. Until the implementation of a more complete vaccination program, social distancing measures have been the key strategy for controlling coronavirus transmission (Zhang et al., 2021), with mobility data as a possible proxy of social distance (Nouvellet et al., 2021). A very rich database that has been used in recent empirical research is Google's Community Mobility Reports (CMR), which is described in detail in Aktay et al. (2020). Based on the Android operating system, and considering its scope, CMR is able to capture individuals' movements more than any other provider, including Apple, which although providing mobility information, does not discriminate the type of mobility (Drake et al., 2020).

Considering the CMR data, and the possibility that social contacts, proxied by that mobility, could affect the number of infections in the different regions, we propose to evaluate the cross-correlation between mobility and new infections, on a daily basis. Our hypothesis is that, in general, a positive relationship could be found between mobility and new infection rates. Considering the different CMR

indices, that pattern could be expected for the different indices, except for the one measuring mobility in residences, as people spending more time at home, as happens in lockdown, could lead to a reduction in the number of new infections. Besides mobility, the application of non-pharmacological measures could also be related to the spread of Covid-19, such as using masks and restricting users in some closed spaces. However, as during most of the period under analysis those non-pharmacological measures did not change significantly, this ensures the usefulness of our analysis.

Our analysis is of the particular case of Portugal and its districts, as analyzing different regions could give important insights for potential decisions about territorially differentiated measures. Considering the interest of analyzing the relationship between new cases of Covid-19 and the mobility indices supplied by Google, we used the Detrended Cross-Correlation Analysis correlation coefficient. This coefficient has the particularity of being a multiscale measure, which will enable us to distinguish between the correlations' behavior for different time scales, allowing, for example, differences over time to be identified.

Our main results show that mobility could be related to the spread of the disease, although mobility in certain places, such as retail and recreation has higher effects, while mobility in workplaces seems to be insignificant. Obviously, mobility in residential places, i.e., spending more time at home because of lockdown, is negatively correlated to the spread of the disease. Another relevant result is the difference between coastal and inland districts, associated with population density.

The remainder of the paper is organized as follows: Section 2 presents the data and the methodology used, Section 3 presents the results while Section 4 discusses those results and concludes.

2. LITERATURE REVIEW ABOUT THE USE OF CMR INDICES TO STUDY COVID-19 TRANSMISSION

The literature contains some work using CMR information related to Covid-19. Table 1 summarizes the information from the following papers.

Considering data for different countries, Sulyok and Walker (2020) analyzed Covid-19 cases and mobility in 135 countries and Yilmazkuday (2021) for a set of 130 countries, both finding evidence about the direct relationship between those variables. McGrail et al. (2020) compared mobility in 134 countries and found that social distancing policies significantly reduced Covid-19 cases by around 65% over a 2-week period. Nouvellet et al. (2021) used a smaller sample (52 countries) but also found a reduction in contamination due to the sharp drop in mobility in the early stages of the pandemic. However, these authors found a detachment in the relationship between mobility and contamination for most countries, interpreting this as a possible loosening of control of the pandemic.

Several studies find a significant relationship between reduced mobility and Covid-19, regardless of the countries studied. For example, Zhu et al. (2020) found an association between social isolation and the reduction in infections in Latin America, a region also hit hard by the pandemic. Murphy et al. (2020) analyzed sparsely populated countries in the Caribbean region, but where tourism is very relevant in the economy, and found similar evidence.

Some studies center their analysis on individual countries. In the case of Australia, identified as a relative success in the fight against Covid-19, Wang et al. (2020) found evidence that mobility restriction measures reduced the spread of the disease, with a relevant impact after 7 days, albeit with some differences between different territories (but consistent with the incubation period identified, for example, by Qin et al., 2020, Rokni et al., 2020, or Wassie et al., 2020). Munawar et al. (2020), also referring to Australia, analyzed the particular case of transport (air, public and freight), finding a negative association between the demand for transport and worsening of the pandemic.

Considering just data for the US, one of the countries hardest hit by the pandemic. Li et al. (2020) analyzed the association between Covid-19 and mobility in that country, finding evidence of the impact of mobility restrictions on controlling the disease, but with differences between urban and rural locations. Still in the US, in an analysis of 771 counties in different metropolitan areas, Hamidi and Zandiatashbar (2021) found that residents in more densely populated areas made significantly fewer trips to essential destinations, such as supermarkets, pharmacies or public transport stations and visited parks less.

Regarding Europe, Wielechowski et al. (2020) studied the relationship between mobility in public transport and Covid-19 in Poland, from March to July 2020, and found that government restrictions

contributed to reduced mobility, although the association between Covid-19 and mobility varied between the provinces of the country, depending on the strictness of state regulations.

Table 1: Summary of the findings of the literature review

Author(s)	Type of region	Main conclusion
Sulyok and Walker (2020)	135 countries	Positive relationship between mobility and disease incidence
Yilmazkuday (2021)	130 countries	Positive relationship between mobility and disease incidence
McGrail et al. (2020)	134 countries	Social distance contributes to reduced incidence
Nouvellet et al. (2021)	52 countries	Reduction of incidence with the reduction of mobility
Zhu et al. (2020)	Latin America	Social distance contributes to reduced incidence
Murphy et al. (2020)	Low population density regions in the Caribbean region	Limiting mobility had a direct impact on the reduction of incidence
Wang et al. (2020)	Australia	Mobility restrictions reduced the spread of the disease
Munawar et al. (2020)	Australia	High demand in the transport sector is related with worsening of the pandemic
Li et al. (2020)	US	Restrictions in mobility helped to control the disease
Hamidi and Zandiatashbar (2021)	771 counties in the US	Population density is related with mobility levels, with different implications for the result of measures
Wielechowski et al. (2020)	Poland	The reduction of mobility has different impacts on Covid-19 depending on strictness of state regulations

3. DATA AND METHODOLOGY

Our data was provided by Sistema Nacional de Vigilância Epidemiológica (SINAVE), of the Portuguese Health Ministry, and consists of information about the number of registered infected cases in Portugal until 31st December 2020, considering data availability at the moment of data retrieval. During the period under analysis, a total of 419910 cases were registered in Portugal. For our analysis, we consider the data from mainland Portugal, and because the interest lies in crossing with the mobility in the different districts, we just considered cases which were registered in a given municipality, for later consideration in the respective district, resulting in a total of 404967 cases.

Then, we calculated the daily incidence of Covid-19 in each district, to match with the mobility information. For this purpose, we used the mobility information provided by Google’s Community Mobility Reports, which identifies trends in mobility in different regions and consists of six indices: 1) Retail and recreation (showing mobility trends in restaurants, cafes, shopping centers, theme parks, museums, libraries or movie theaters) – identified as I1; 2) Grocery and pharmacy (grocery stores, food

warehouses, farmers' markets, specialty food shops, drug stores or pharmacies) – identified as I2; 3) Parks (local and national parks, public beaches, marinas, dog parks or public gardens) – identified as I3; 4) Transit stations (public transport hubs) – identified as I4; 5) Workplaces – identified as I5; and 6) Residential – identified as I6.² The information is given on a daily basis and was retrieved on a daily basis, for Portugal and the different districts. The data starts on 15th February 2020 and ends on 31st December 2020, a total of 321 observations. For some districts, there is a break in the information about mobility during some days in August and September, so in those districts those observations were not considered (the number of observations there is 296). Table 2 shows the distribution, by district, of the total number of cases as well as the number of observations used in the correlation analysis, while Table 3 provides some socio-economic information about the different districts.

For some districts, the information for some mobility indices is not available. For this reason, for some districts we just performed the correlation with the available indices. In other cases, we have several missing daily values. When those missing values are frequent, we do not consider those indices in the analysis. If those missing values are a small percentage of the total, we considered that the index took the value of the previous day.

Table 2: Distribution of Covid-19 cases by district

District	Total cases	Obs.	District	Total cases	Obs.
Aveiro	30552	321	Leiria	9649	321
Beja	2638	296	Lisbon	90125	321
Braga	54597	321	Portalegre	2972	296
Bragança	5215	296	Porto	114083	321
Castelo Branco	4927	296	Santarém	10440	321
Coimbra	11125	321	Setúbal	26475	321
Évora	4176	296	Viana do Castelo	6776	296
Faro	7515	321	Vila Real	8042	296
Guarda	5411	296	Viseu	10249	296

Table 3: Socio-economic information for the different districts

District	Pop. Density (inh/km ² , 2019)	Pop ≥ 65 (% , 2019)	District	Pop. Density (inh/km ² , 2019)	Pop ≥ 65 (% , 2019)
Aveiro	249.0	21.5	Leiria	129.9	23.0
Beja	13.7	25.4	Lisbon	812.9	22.2
Braga	306.1	18.4	Portalegre	17.2	27.5
Bragança	18.8	30.9	Porto	730.5	20.0
Castelo Branco	26.8	29.2	Santarém	64.0	25.0
Coimbra	102.0	25.7	Setúbal	163.8	21.7
Évora	20.6	26.2	Viana do Castelo	103.8	25.3
Faro	87.7	21.9	Vila Real	44.4	27.0
Guarda	25.9	29.6	Viseu	70.3	25.1

source <https://gee.gov.pt/pt/lista-publicacoes/estatisticas-regionais/distritos-concelhos/>

To make the correlation between daily Covid-19 cases in Portuguese districts and the respective mobility indices, we used the Detrended Cross-Correlation Analysis (DCCA) and its respective correlation

²For more information, see, <https://www.google.com/covid19/mobility/index.html?hl=en>.

coefficient (ρ_{DCCA}). DCCA was proposed originally by Podobnik and Stanley (2008) to measure long-range correlation between two different time series Y_i and X_i of the same length N . The first step of DCCA consists of integrating the time series, i.e., calculating

$$Y_k = \sum_{i=1}^k (y_i - \langle y \rangle) \tag{1}$$

and

$$X_k = \sum_{i=1}^k (x_i - \langle x \rangle) \tag{2}$$

$\langle x \rangle$ and $\langle y \rangle$ being the mean values of both time series and $k = 1, 2, \dots, N$. After obtaining the integrated series, the second step is the division of the profiles of Equations (1) and (2) into $(N-n)$ overlapping boxes, starting in $n = 4$ and ending in $n = \frac{N}{4}$ (in this paper, we used sequential time scales from 4 to 80 in the districts with larger samples and 4 to 74 in the districts with smaller samples). Thirdly, in those boxes, local trends $\tilde{Y}_{k,i}$ and $\tilde{X}_{k,i}$ are calculated with ordinary least squares (OLS) and are used to detrend Y_k and X_k , the fourth step, in order to obtain the covariance of the residuals for each box given by

$$f_{xy}^2(n, i) = \frac{1}{(n+1)} \sum_{k=1}^{i+n} (X_k - \tilde{X}_{k,i})(Y_k - \tilde{Y}_{k,i}) \tag{3}$$

Finally, the fifth step consists of obtaining the covariance of the residuals, considering the information for all $N - n$ boxes and is given by

$$F_{xy}^2(n) = \frac{1}{(N-n)} \sum_{i=1}^{N-n} f_{xy}^2(n, i) \tag{4}$$

Based on this covariance, Zebende (2011) proposed the DCCA correlation coefficient, which is given by

$$\rho_{DCCA} = \frac{F_{xy}^2(n)}{F_{xx}(n)F_{yy}(n)} \tag{5}$$

The numerator of Equation (5) is the covariance from the DCCA from Equation (4) and the numerator values correspond to the root mean square fluctuation functions of the Detrended Fluctuation Analysis proposed by Peng et al. (1994), used to analyze the long-range behavior of individual time series.

This correlation coefficient, which presents the desirable property of being $-1 \leq \rho_{DCCA}(n) \leq 1$, is robust to the existence of non-linearities and non-stationarity in time series (Kristoufek 2014a, 2014b), making it desirable, for example, compared to other correlation coefficients like Pearson. Another advantage of the coefficient is the fact that it has a multiscale behavior, i.e., it can analyze phenomena distinguishing between the short and long run. For more details about its properties, see, for example, Wang et al., (2013), Kristoufek, (2014a), (2014b) or Zhao et al.(2017). We followed the procedure proposed by Podobnik et al. (2011) to obtain the lower and upper limits of the critical values to test the statistical significance of the correlation coefficients. Table 4 presents lower and upper limits, with a 95% level of confidence, for the set of time scales identified. For the remaining time scales, we considered interpolation values.

The DCCA correlation coefficient shows its robustness by being used in several research areas, such as physics, criminology, meteorology, finance, geology or even in medical sciences (see, respectively, Brito et. al, 2018; Machado Filho et. al, 2014; Paiva et. al, 2018; Zebende et. al, 2018; Marinho et. al, 2013; Chen et. al, 2018).

Table 4: Lower and Upper limits considering a 95% level of confidence

Time Scale	LL 95%	UL 95%
4	-0.123	0.126
5	-0.128	0.131
7	-0.138	0.138
9	-0.147	0.145
11	-0.157	0.153
13	-0.168	0.161
16	-0.184	0.175
20	-0.205	0.191
23	-0.221	0.203
28	-0.245	0.222
33	-0.266	0.238
38	-0.282	0.252
45	-0.302	0.267
52	-0.321	0.283
60	-0.343	0.303
69	-0.369	0.328
80	-0.399	0.357

4. RESULTS

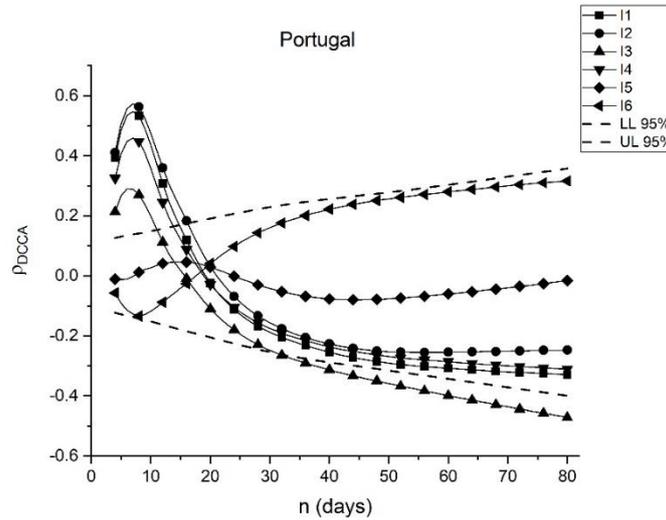
We started our analysis by performing the correlation coefficient between new Covid-19 cases and the mobility indices for Portugal as a whole, with the results presented in Figure 1. This shows that some indices present a significant positive correlation with the daily number of Covid-19 cases, for lower time scales. This happens with mobility in Grocery and pharmacy facilities, as well as in Retail and recreation. These results could also be related to transmission by contact with other surfaces and subsequently touching mucosal membranes (see, for example, Hussain et al. 2020). Transit stations and Parks also present a positive significant correlation, for the first scales in analysis. There is an inversion of the value of the correlation on the 7th/8th day, basically meaning that restricted mobility (i.e., confinement) could take between 7 and 8 days before finding a decline in the correlation with new Covid-19 cases. This result is consistent with the information about the disease's incubation period, as in the work of Qin et al. (2020), which identifies a median incubation period of 7.76 days. The results are also consistent with previous evidence of the impact of reduced mobility on the disease, as identified by Wang et al. (2020) in a study in Australia.

About the 14th day, the significance of the correlation vanishes, meaning that confinement measures do not have an automatic impact on the reduction of new cases, which is also supported by Vinceti et al. (2020) and Saez et al. (2020) and found empirically in McGrail et al. (2020). Another important result is that mobility measured by Workplace and Residential indices is not significantly correlated with the number of Covid-19 cases in Portugal.

Next, we estimated the same relationship for the 18 districts of mainland Portugal (Figures A1 and A2 can be consulted in Appendix 1). Several districts have patterns similar to the national one in terms of the impact of the indices represented by I1, I2, I3 and I4, namely Aveiro, Braga, Castelo Branco, Leiria, Lisbon, Porto, Santarém, Vila Real and Viseu. However, other districts present different behavior. For example, Beja, Bragança, Coimbra, Évora, Faro, Guarda, Portalegre, Setúbal and Viana

do Castelo present less evidence of a significant positive correlation between indices and new Covid-19 cases, with at least two distinct features: normally they just show evidence of significance for I1 and I2 indices and most of them have lower absolute values of correlations, meaning that the correlation coefficients are reduced when compared with other districts. Moreover, another common trend is that after the 8th day the correlation decreases, but in this case for all districts.

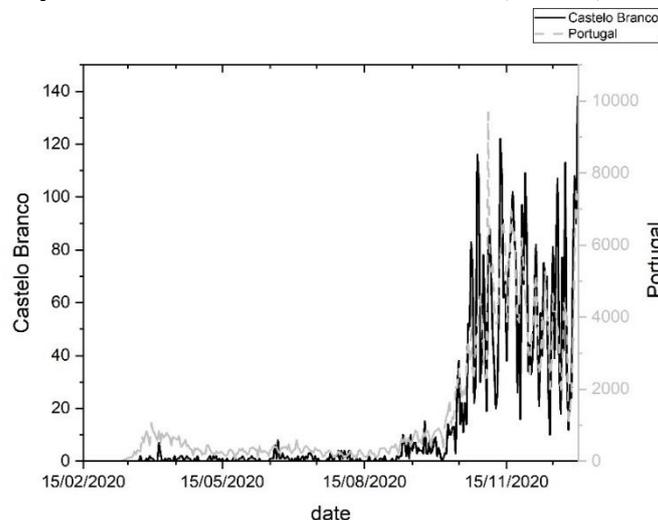
Figure 1. DCCA correlation coefficient for the analysis between daily new Covid-19 cases and Google mobility indices, depending on the time scale (in days), for Portugal. Dashed lines correspond to lower and upper limits of the confidence interval, to analyze the statistical significance of the correlation coefficients calculated.



We find some other interesting results. In some cases, and for lower scales, increased mobility in residences shows a significant negative correlation with new Covid-19 cases. This is visible in Aveiro, Braga, Portalegre, Viana do Castelo, Vila Real and Viseu and to a lesser extent in Lisbon. This means that in these districts the impact of the confinement measures was more efficient.

One interesting result, which is different from the other districts, concerns Castelo Branco, which is the only one where the Residential mobility index is positively correlated, in the short run, with new Covid-19 cases. This could happen because at the start of the national confinement imposed in 2020 there were few cases in Castelo Branco, as seen in Figure 2, which shows the evolution of new cases in the district and in the whole territory, confirming the different dynamics in the Covid-19 outbreak

Figure 2: Evolution of daily new Covid-19 cases in Castelo Branco (left axis) and Portugal (right axis)



Analysis of Figures A1 and A2 reveals some differences in the behavior of correlations between Portuguese districts. However, for more clarity, we designed geographical heat maps, and to analyze the evolution of the correlations over time, we show the different maps for time scales of 4, 7, 8 and 14 days. We chose these days for different reasons: 4 days because it is the minimum time scale considering the approach used; 7 and 8 days because they reflect the maximum correlation levels of the different indices with the new Covid-19 cases; 14 days because it is the number of days consistent with the end of the disease's incubation period. All this information is presented in Figures 3, 4, 5, 6, 7 and 8.

Those figures show some interesting patterns. Firstly, it confirms that retail and recreation and grocery and pharmacy mobility indices have a closer relationship with new Covid-19 cases, followed by mobility in transit stations. Moreover, in these indices, the degree of correlation increases from the scale of 4 days until that of 7/8 days, when it declines. In fact, in two of the indices, in Faro, the correlation becomes negative.

The workplace mobility index reflects lower correlation coefficients (lighter color) and shows more stability across the different daily scales of the analysis. It seems that workplace mobility does not have a high correlation with new Covid-19 cases, probably meaning that in those places some correct measures are taken. Nevertheless, it seems that on the 14th day the correlation is slightly higher than in the lower time scales (but analysis of Figures 1, A1 and A2 shows that the correlation is not statistically significant).

Slightly different behavior is shown in the parks mobility index, where mobility is not only less significant in the increase of Covid-19 cases but also has a negative correlation as time goes on. This could be related to parks being open spaces, where the contagion effect is not so relevant.

Finally, the map of residential mobility, for most of the country, shows the expected result of a negative correlation, which is more evident on the 7th and 8th day, confirming its relevance in confinement measures.

Besides these features, another interesting pattern appears from the map analysis: the strength of the correlations is different on the coast and inland. In fact, the incidence of the correlations seems to be lower in inland areas, where population density is lower, which in some cases could help to reduce contacts, and consequently, the risk of contagion. The exception is Castelo Branco, with the possible explanation already given.

Figure 3: DCCA correlation coefficient between daily new Covid-19 cases and retail and recreation mobility index (I1), for time scales of 4, 7, 8 and 14 days (colored online).

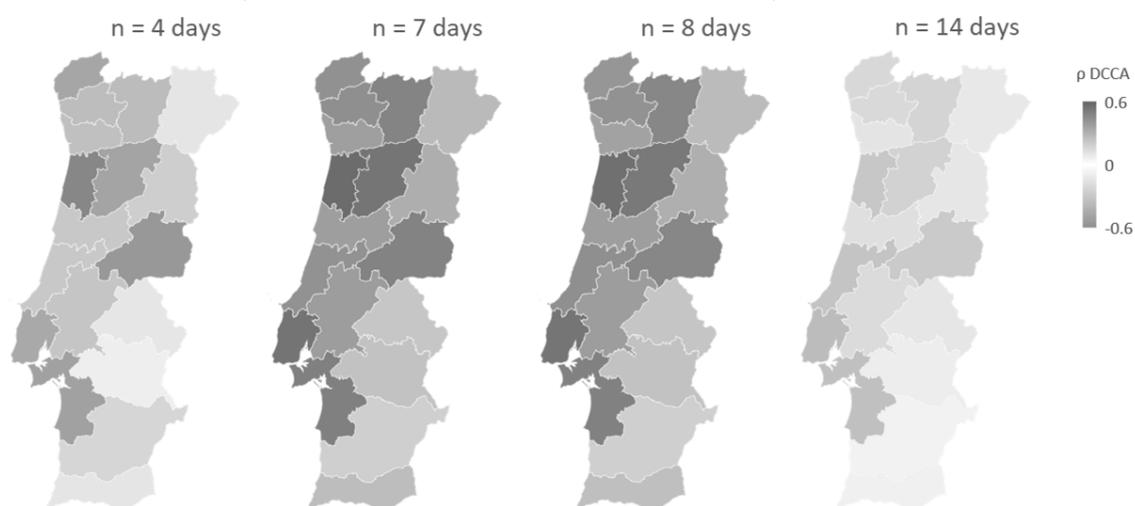


Figure 4: DCCA correlation coefficient between daily new Covid-19 cases and grocery and pharmacy mobility index (I2), for time scales of 4, 7, 8 and 14 days (colored online).

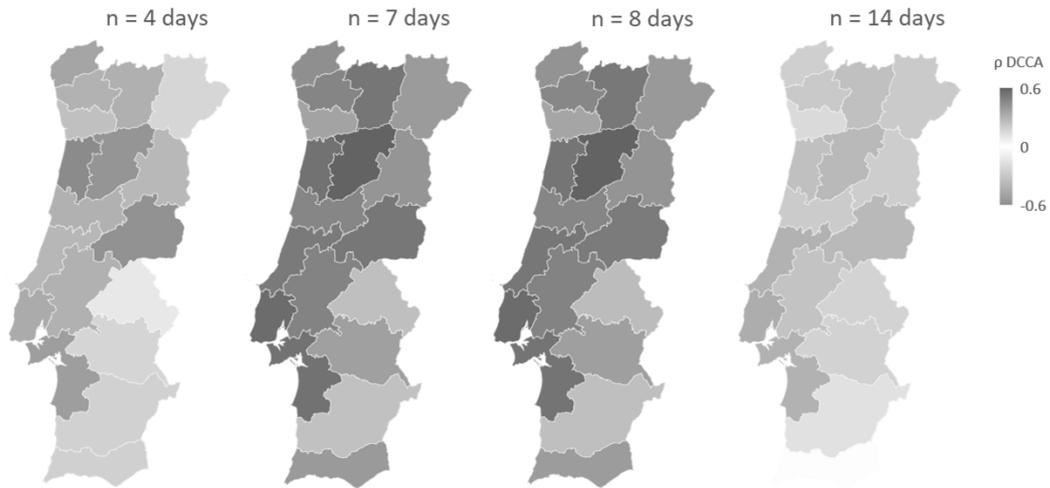


Figure 5: DCCA correlation coefficient between daily new Covid-19 cases and parks mobility index (I3), for time scales of 4, 7, 8 and 14 days. Bragança and Guarda districts do not have information for I3 index (colored online).

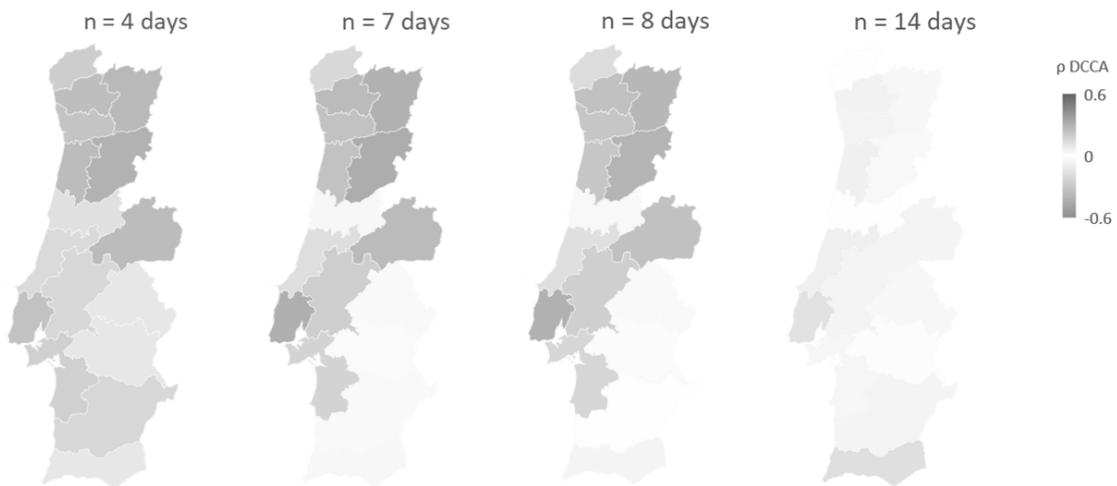


Figure 6: DCCA correlation coefficient between daily new Covid-19 cases and transit stations mobility index (I4), for time scales of 4, 7, 8 and 14 days. Beja, Bragança, Évora, Guarda, Portalegre and Viana do Castelo do not have information for I4 index. (colored online).

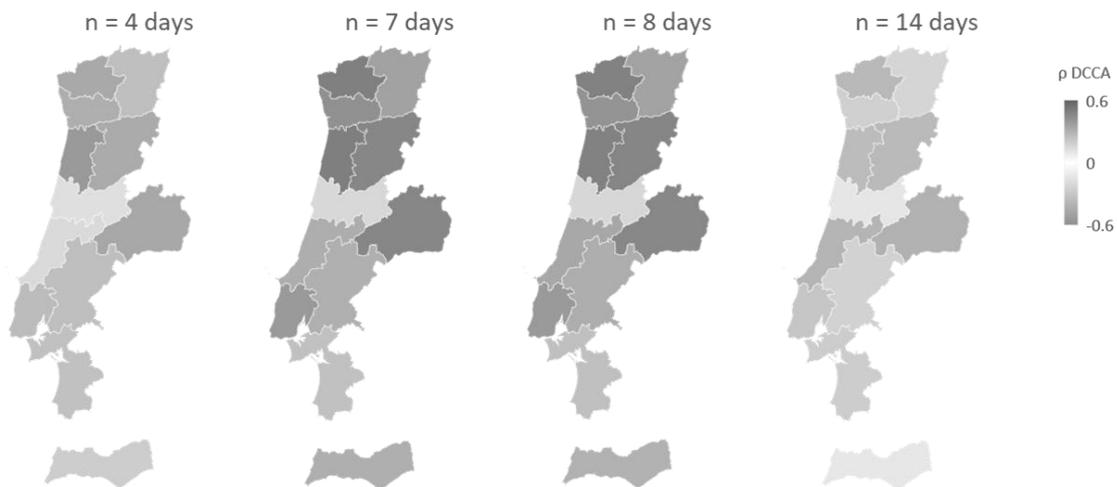


Figure 7: DCCA correlation coefficient between daily new Covid-19 cases and workplace mobility index (I5), for time scales of 4, 7, 8 and 14 days (colored online).

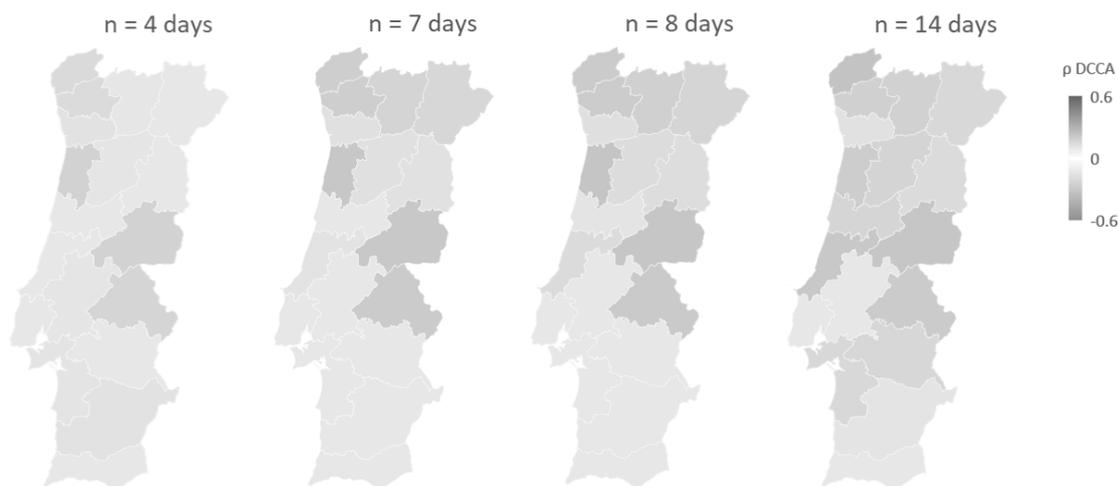
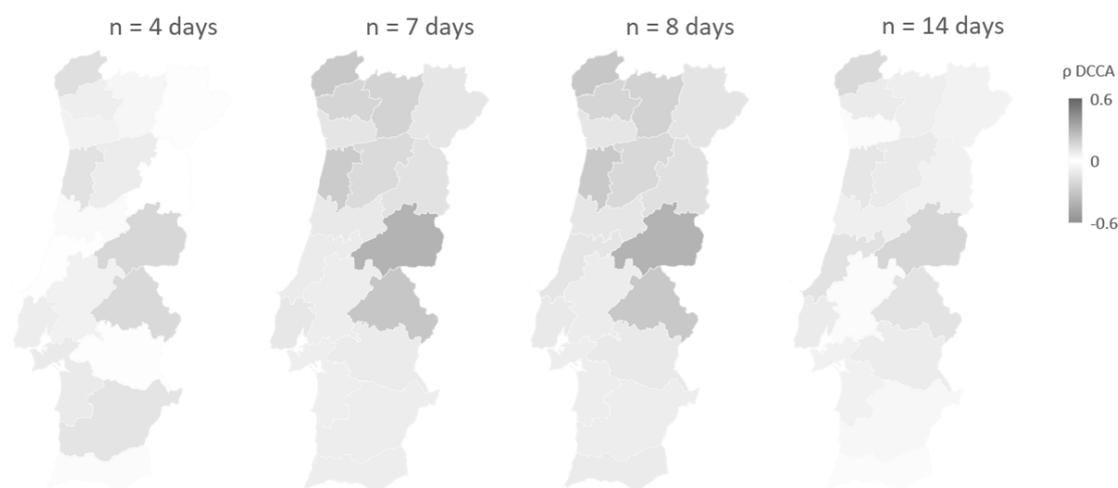


Figure 8: DCCA correlation coefficient between daily new Covid-19 cases and residential mobility index (I6), for time scales of 4, 7, 8 and 14 days (colored online).



4. DISCUSSION AND CONCLUSIONS

The results presented identified interesting patterns. Briefly, we can conclude that some mobility indices have a higher relationship with new Covid-19 cases in Portuguese districts, in particular those referring to retail and recreation, grocery and pharmacy and transit stations (although to a lesser extent). Workplaces show a non-significant relationship with new cases of the disease while the residential mobility index shows a negative relationship with those cases. Moreover, the effects are different in the different districts, with coastal districts showing greater evidence of correlations, while in inland ones, mobility indices seem to have less effect on new cases (with the exception of Castelo Branco). Finally, the effects seem to be higher on the 7th and 8th days, and on the 14th day the effects are reduced.

The different magnitude of the correlations could mean that districts had different incidences of the disease, so differentiated measures could be adopted. Our findings suggest that some district-level policies could be crucial, and implementation and the scaling up of possible partnerships at the regional level could be important in preventing the effects of the pandemic. The fact that the correlations vanished on the 14th day may lead to the conclusion that lockdown measures had the desired effect. However, it is possible that in some regions the measures could have been adopted too early (see, for example, the case of Castelo Branco). In conclusion, the correlations between human mobility and the spread of

COVID-19 vary between districts and it is important to consider the mobility-spread relationship with the degree of lockdown in different areas.

These results are important for many sectors of society. Firstly, for citizens, because the results clearly show the importance of measures such as lockdown and reduced mobility. Despite the toughness of these measures and their economic and social effects, they seem to be relevant and necessary to break the spread of the disease. The relationships found between workplace mobility and Covid-19 cases could indicate that workplaces are safe places, probably related to the actions taken for that purpose.

The results could also be important for the government, when monitoring the different measures and deciding on new ones. One of the important lessons could be that measures could vary according to the different incidences of the disease, for example, with the possibility of having different measures for different territories. Appropriate measures considering the differences could minimize impacts in some territories, especially as some districts where mobility seems not to have a great effect on Covid-19 are known to be weaker economically. Moreover, these districts of inland Portugal generally have lower population density and lower general mobility levels, which could also be relevant for decision-makers. There, the application of lighter restrictions, if safety conditions are fulfilled, could be important in diminishing the economic impacts.

However, citizens must always understand those differences clearly, because failing to comply with the measures could defeat their purpose. We could take the example of public spaces, where the correlation between the parks mobility index and new Covid-19 cases is reduced. The government could adopt less restrictive measures for mobility in some of these spaces, although, as previously mentioned, they would only have the expected impact if citizens obeyed them.

Finally, this information could also be important for the health authorities involved in all the decision-making process, not only in the field but also in the help given to the government in taking those decisions. It could be important, for example, to adopt measures and programs to raise awareness as well as communication initiatives to help citizens understand the need for the measures.

Obviously, our conclusions can be considered valid only during the time sample under analysis. The continuous monitoring of these issues is important, because Covid-19 has been a dynamic disease. For example, analysis of a longer time sample could give important information about this kind of relationship, providing information about other waves of the disease. In the particular case of Portugal, where mobility at Christmas could have had some effect on cases at the beginning of 2021 and the third wave, such an analysis could provide new insights into the matter. Moreover, the use of other techniques such as the spatial autocorrelation analysis, which takes into account possible geographical proximity as relevant, could also help in understanding this phenomenon, as a possible methodology to be applied in future research.

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APPENDIX

Figure A1: DCCA correlation coefficient for the analysis between daily new Covid-19 cases and Google mobility indices, depending on the time scale (in days) for Aveiro, Beja, Braga, Bragança, Castelo Branco, Coimbra, Évora, Faro and Guarda districts. Dashed lines correspond to lower and upper limits of the confidence interval, to analyze the statistical significance of the correlation coefficients calculated.

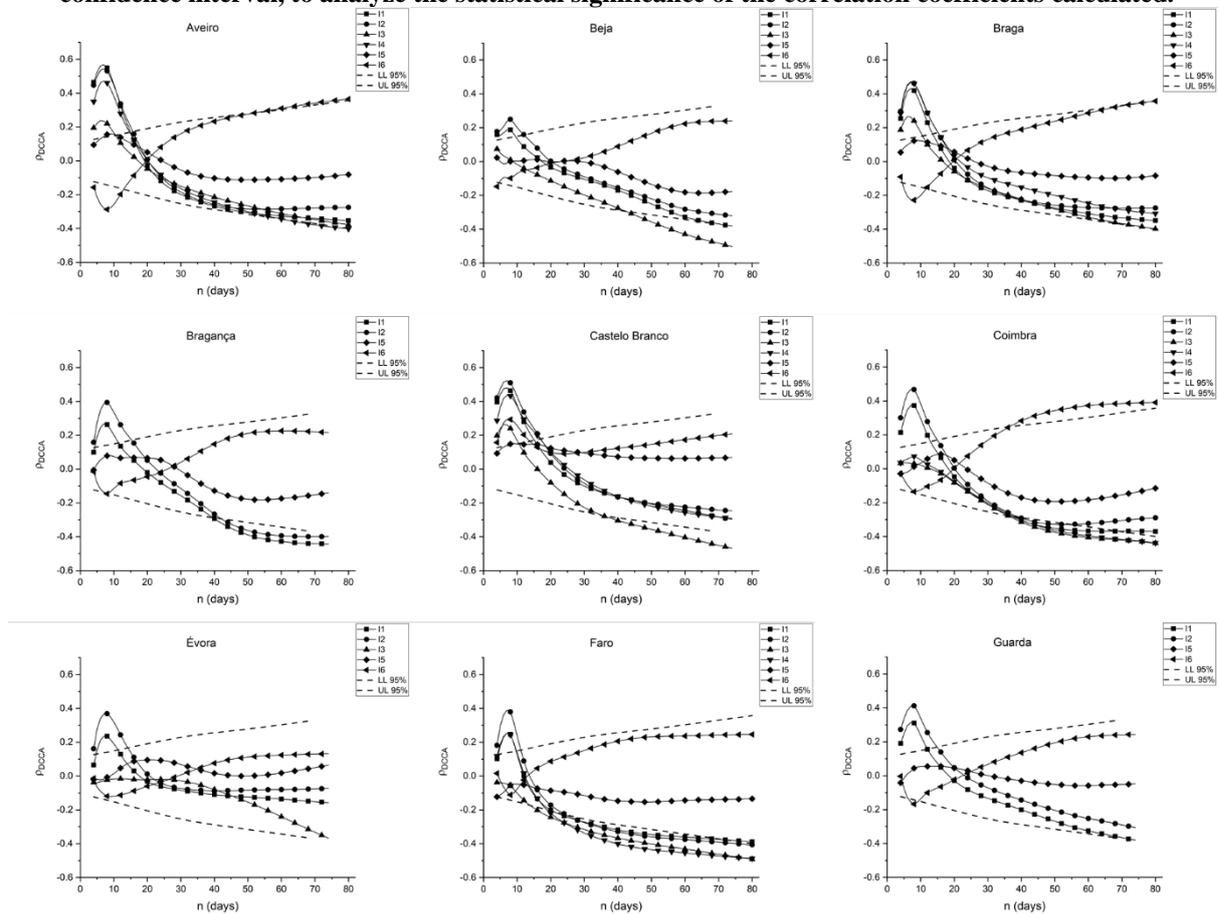


Figure A2. DCCA correlation coefficient for the analysis between daily new Covid-19 cases and Google mobility indices, depending on the time scale (in days) for Leiria, Lisbon, Portalegre, Porto, Santarém, Setúbal, Viana do Castelo, Vila Real and Viseu districts. Dashed lines correspond to lower and upper limits of the confidence interval, to analyze the statistical significance of the correlation coefficients calculated.

