A spatial analysis of the environmental correlates of COVID-19 incidence in Spain

Antonio Paez[*,a], Fernando A. Lopez[b], Tatiane Menezes[c], Renata Cavalcanti[d], Maira Galdino da Rocha Pitta[d]

[a] *School of Geography and Earth Sciences, McMaster University, 1281 Main St W, Hamilton, ON, L8S 4K1, Canada*

[b] *Departamento de Metodos Cuantitativos, Ciencias Juridicas, y Lenguas Modernas, Universidad Politecnica de Cartagena, Calle Real Numero 3, 30201, Cartagena, Murcia, Spain*

[c] *Departamento de Economia, Universidade Federal de Pernambuco, Av dos Economistas, s/n - Cidade Universitária, Recife - PE, 50670-901, Brasil*

[d] *Núcleo de Pesquisa em Inovação Terapêutica NUPIT / UFPE, Av. Prof. Moraes Rego, 1235 - Cidade Universitária, Recife, PE, CEP 50670-901, Brazil*

Abstract

Spreading with astonishing speed, the novel SARS-CoV2 has swept the globe, causing enormous stress to health systems and prompting social distance guidelines and mandates to arrest its progress. While there is encouraging evidence that early public health interventions have slowed the spread of the virus, this has come at a high cost as the global economy is brought to its knees. How and when to ease restrictions to movement hinges in part on the question whether SARS-CoV2 will display seasonality associated with variations in temperature, humidity, and hours of sunshine. In this research, we address this question by means of a spatial analysis of the incidence of COVID-19 in the provinces in Spain. Use of a spatial Seemingly Unrelated Regressions (SUR) approach allows us to model the incidence of reported cases of the disease per 100,000 population, as a function of temperature and humidity, while controlling for GDP per capita, population density, percentage of older adults in the population, and presence of mass transit systems. An interesting aspect of the spatial SUR approach is that it models incidence as a contagion process. Our results indicate that incidence of the disease is lower at higher temperatures and higher levels of humidity, although coefficients for this variable are significant only in some equations. Sunshine, in contrast, displays a positive association with incidence of the disease. Our control variables also yield interesting insights. Higher incidence is associated with higher GDP per capita and presence of mass transit systems in the province; in contrast, population density and percentage of older adults display negative associations with incidence of COVID-19.

[*] Corresponding Author

Email addresses: `paezha@mcmaster.ca` (Antonio Paez), `fernando.lopez@upct.es` (Fernando A. Lopez), `tatiane.menezes@ufpe.br` (Tatiane Menezes), `renata.vcsantos@gmail.com` (Renata Cavalcanti), `mgrpitta@ufpe.br` (Maira Galdino da Rocha Pitta)

Introduction

From a small outbreak linked to a live animal market at the end of 2019 to a global pandemic in a matter of weeks, the SARS-CoV2 virus has threatened to overrun health systems the world over. In efforts to contain the spread, numerous governments in many nations and regions have either recommended or mandated social distancing measures, and as of this writing, millions of people in five continents shelter in place. There are encouraging signs that these measures have arrested the spread of the virus where they have been implemented, and have thus helped to keep a bad situation from becoming even worse (e.g., 2020). However, this has come at a high cost, and the consequences for all spheres of the economy, social, and cultural life have been dire (e.g., Fernandes, 2020; Luo and Tsang, 2020). As a result, there is a sense of urgency to anticipate the progression of the pandemic, in order to plan for progressive lifting of restrictions to movement and social contact (e.g., Kissler et al., 2020). Needless to say, this has become a delicate, and politically charged, balancing act between public health and the economy (Gong et al., 2020).

A salient question in the debate on how and when to ease social distancing measures is whether the virus will display seasonal variations. Earlier, diverse studies have shown the effect of temperature and humidity on the incidence of influenza (e.g., Mäkainen et al., 2009; Jaakkola et al., 2014; Kudo et al., 2019). Jaakkola et al. (2014), for example, found that a decrease of temperature and absolute humidity precedes the onset of symptoms of influenza A and B viruses by 3 days in places where the temperature is low. After the 2002-2004 outbreak of SARS, researchers also began to investigate the relationship between these factors and SARS-CoV. In this way, Casanova et al. (2010) used two surrogates, namely the gastroenteritis (TGEV) and mouse hepatitis viruses (MHV), to find that virus inactivation was more rapid at temperatures of 20C than 4C, and at 40C than 20C; in terms of humidity, these researchers reported that survival of the virus was lower at moderate relative humidity levels. In a similar vein, but working directly with SARS-CoV, Chan et al. (2011) found that viability of the virus was lost at temperatures higher than 38C and relative humidity superior to 95%.

While existing research on similar pathogens suggests that SARS-CoV is more stable and potentially easier to transmit in conditions of low temperature and low humidity, it is far from certain that this will also be the case with the novel SARS-CoV2. If such is the case, there is the possibility of easing restrictions to social contact as the weather warms; however, weeks or possibly months of costly measures could become undone if not, and the restrictions are lifted prematurely. Not surprisingly, given the stakes involved, this issue has already triggered a lively debate.

Some of what is thought about the possible seasonality of COVID-19 is based on analogies to the patterns of other known respiratory viruses. However, de Ángel Solá et al. (2020) note that "not all seasonal respiratory viruses experience the same spatiotemporal patterns" (section 4). This urges caution when extrapolating from known viruses, and indeed, the evidence in this respect is inconclusive. At a global scale, de Ángel Solá et al. (2020) see less risk in the Caribean Basin; however, Coelho et al. (Coelho et al., 2020) warn that at least during the exponential phase, expansion of the virus is not driven by climate. Similarly, whereas Araujo and Naimi (2020) argue that spread of SARS-CoV2 will likely be constrained by climate, Harbert et al. (2020) remain unconvinced that spatial modelling can currently discriminate the distribution of the disease on the basis of climate, at least in the United States. Yao et al. (2020), examined data from China and came to the conclusion that neither temperature nor ultraviolet indices had an association with transmission of COVID-19. This is despite previous research that has linked less exposure to UVB radiation to higher prevalence and severity of acute respiratory tract infections (Zittermann et al. 2016; Dąbrowska-Leonik et al. 2018; Dinlen et al. 2016; Mathyssen et al. 2017; Esposito and Lelii 2015; Jat 2017; Moriyama, Hugentobler, and Iwasaki 2020). To further complicate matters, much of the relevant work has yet to be peer-reviewed and therefore is open to change (see for example the challenge of Harbert et al. (2020) to Araujo and Naimi (2020)). In the United States, the National Academy of Sciences, Engineering, and Medicine was engaged by the Office of the Executive for guidance on this matter (see National Academies of Sciences, Engineering and Medicine, 2020). Their conclusion summarizes the situation well (see p. 6): "Some limited data support a potential waning of cases in warmer and more humid seasons, yet none are without major limitations… Additional studies as the SARS-CoV-2 pandemic unfolds could shed more light on the effects of climate on transmission."

With the above considerations in mind, our objective with this paper is to contribute to the knowledge basis regarding the spread of COVID-19 and the influence of environmental factors, particularly temperature, humidity, and sunshine. We adopt a population health approach, and report results from a spatial model of the incidence of COVID-19 in fifty provinces in Spain, one of the countries hardest hit by the pandemic. We combine data on reported cases of the disease with metereological information, to create a spatio-temporal dataset covering a period of 30 days. We then join this dataset with provincial-level economic and demographic information to act as controls to our key environmental variables. These data are analyzed using a spatial Seemingly Unrelated Regressions (SUR) approach, which allows us to model incidence of COVID-19 as a spatial contagion process.

The results provide evidence of the effect of temperature, humidity, and sunshine on the incidence of COVID-19. The clearest result with respect to these variables is a lower incidence of COVID-19 at higher temperatures and levels of humidity, while the opposite happens with respect to hours of sunshine. Our control variables also provide some intriguing insights. Higher incidence is associated with higher GDP per capita and presence of mass transit systems in the province; in contrast, population density and percentage of older adults display negative associations with incidence of COVID-19. The results of this analysis provide support to the hypothesis of seasonality of the novel SARS-CoV2, and should be of interest to public health officials and policy makers grappling with the question of the trajectory of the pandemic.

Please note that this paper is prepared as a reproducible research document. The source R Markdown document, as well as all data and code needed to reproduce/review/extend the analysis can be obtained from the following repository:

https://github.com/paezha/covid19-environmental-correlates/tree/master/Environmental-Correlates-of-COVID19-Spain

Context, Data, and Methods

Covid-19 in Spain

The first reported case of COVID-19 in Spain was on January 31th, when a German tourist in the Canary Islands tested positive for the virus. However, it was still a few weeks before the first domestic case was reported, on February 27th in Sevilla province (Andalusia). In a short period of time, after this relatively slow start, the outbreak flared. By March 11th the World Health Organization (WHO) declared COVID-19 officially a pandemic. This declaration marked a turning point for the public in Spain too. As of March 13th, the number of cases of COVID-19 reported in Spain was 4,473, with a majority of cases (1,990) concentrated in Madrid: these numbers were at the time the worst outbreak in Europe, after Italy. In response to the situation, on March 13th the Spanish National Government declared a state of emergency, to go into effect on Saturday March 14th. As part of the state of emergency restrictions to most activities were imposed, with the exception of essential services (e.g. food, health) and some economic subsectors of industry and construction. A few days later, on March 17th, Spain closed its lands borders to allow entry only to returnee nationals and permanent residents. The lockdown was further hardened between March 30th and April 12th (including the Easter weekend of April 10th-12th) and during this period only essential activities were allowed. During this period, there was a dramatic reduction in overall mobility, both within provinces as between [1].

Selection of Variables

The global emergence of infectious diseases is mostly driven by environmental, ecological, and socio-economic factors (Jones et al., 2008). In the case of SARS-CoV2, the ecological factors include the interaction between humans and wildlife. Once transmission of a disease begins to happen between humans, socio-economic and environmental factors become increasingly important. As noted in the introduction, the focus of the paper is on environmental variables, namely temperature, humidity, and sunshine. These variables have been implicated in the viability and ease of transmission of similar viruses. In addition to these variables, we also aim to use a set of controls, in the form of specific socio-economic and demographic characteristics of each province.

[1] https://www.mitma.gob.es/ministerio/covid-19/evolucion-movilidad-big-data/movilidad-provincial

The first variable that we consider is GDP per capita. Much has been said about globalization and the spread of infectious disease[2]. The growth in global connections has presented a challenge to spatial approaches in the initial stages of disease management, when its cause may still be unclear (Zhou and Coleman, 2016). In reference to the earlier outbreak of SARS, van Wagner (Van Wagner, 2008) remarks how Toronto's status as a global city was a vulnerability. In our case, we think of GDP per capita as a marker of a region's relative position in a network of global cities, and their potential to be further ahead in the trajectory of the pandemic. Furthermore, wealthier regions also tend to concentrate more activities that produce non-traded goods, including building and construction (Hallet, 2002). Therefore, it is possible that wealthier regions remained relatively more active even during the lockdown. On the other hand, it is also possible the less wealthy regions have a higher proportion of workers in manual occupations that cannot telework.

The percentaje of older adults (over 65) is the second variable that we consider as a control. Early evidence suggest that the case rate mortality is higher at older ages (e.g. The Novel Coronavirus Pneumonia Emergency Response Epidemiology Team, 2020). It is not clear that presence of older adults necessarily translates into higher transmission in the population. The public health tool of choice in containing the spread of the disease has been social distancing. In this respect, the evidence from the field of transportation is that older adults tend to travel less frequently, for shorter distances, and have higher rates of immobility (e.g., Roorda et al., 2010; Morency et al., 2011; Sikder and Pinjari, 2012). In other words, older adults are, by preference or necessity, already in a form of social isolation. Social distancing during the pandemic may actually reinforce that condition for older adults, as the analysis of age-structured social contact in India, China, and Italy of Sing and Adhikari (2020) suggests. Accordingly, our expectation is that in the provinces with higher proportions of older adults will tend to have similarl levels of lower social contact, particularly since age-structured social contact matrix in Spain is similar to Italy (Prem et al., 2017).

The third population variable the we consider is population density, since it directly affects the contact patterns and contact rates between individuals in a population (Hu et al., 2013). The evidence available suggests a positive relationship between the transmission of COVID-19 and population density (e.g. cumulative incidence in urban areas like NYC). For this reason, we anticipate a positive relationship between population density and the incidence of the disease.

The last control variable is the presence of mass transit systems in a province. Every province in Spain offers some form of public transportation, however only five provinces have higher order systems of mass mobility, namely Barcelona, Madrid, Sevilla, Valencia, and Bizkaia. Public transportation has been hypoth-

[2]As the Globe and Mail, Canada's paper of record, put it in relation to the SARS outbreak in 2003: "Globalization means that if someone in China sneezes, someone in Toronto may one day catch a cold" (Editorial, March 28, 2003, p. A18)

esized to relate to the spread of contagious disease by some researchers using agent-based approaches (Perez and Dragicevic, 2009; Wang et al., 2010), and while we find scant evidence of a link in the literature, the idea is intuitively appealing. After all, unlike the isolation that a car offers to travellers, most mass transit system are cauldrons of social contact.

Data

Our dataset includes information about the daily number of cases of COVID-19 reported in Spain at the provincial level (NUTIII in Eurostat terminology) for the period between March 13th and April 11th, inclusive. For our purposes, we consider positive cases reported, but excluding symptomatic cases diagnosed by a doctor without a Polymerase Chain Reaction (PCR) test. The Spanish National Government publishes periodic updates at the regional level (NUTII) and the information is also released at the provincial level as part of a collaborative project [**by whom?**]. This information is compiled from several sources, mainly the official web pages of the Spanish regional goverments. In addition, we consider two sets of explanatory variables. The first one, and the focus of this research, is set of two environmental variables, namely temperature and humidity, which are collected from official sources (i.e., AEMET, the state meteorology agency, and MAPA, the ministry of agriculture, fisheries, and food). The second set provides some relevant controls for multivariate analysis, and refers to economic and demographic attributes of the province (also collected from official sources, i.e., INE, the national statistics institute). Table 1 shows the descriptive statistics and the provenance of the data.

The spatial and temporal coverage of the data is as follows. Our dataset begins on March 13, which is the first date when every province had reported at least one case of COVID-19, and continues until April 11, for a period of 30 days. The unit of analysis is the province. Provinces are the equivalent of states, and are embedded in Autonomous Communities. As an example, Cataluña is an Autonomous Community and consists of four provinces, namely Barcelona, Gerona, Lerida, and Tarragona. The size of the provinces is relatively large, as seen in Table 1. The smallest province is $1,978.12km^2$ (this is smaller than Rhode Island in the US) and the largest province is $21,767.93km^2$ (slightly smaller than New Jersey in the US). While this is a relatively large degree of spatial aggregation, reporting on COVID-19 is inconsistent at smaller geographies, or cases are not reported at that level at all. The analysis must therefore be considered ecological.

An important aspect of working with environmental data such as temperature and humidity is the incubation period of the disease. Lauer et al. (2020) report for the case of COVID-19 a median incubation period of 5.7 days (with a confidence interval between 4.9 to 7.8 days). The vast majority of cases (95%) develop symptoms between 2.6 days (CI, 2.1 to 3.7 days) and 12.5 days (CI, 8.2 to 17.7 days). For this reason, we judge it best to use lagged values of the environmental variables. We test different time lags as follows. We consider a lagged 8-day average, from date-minus-12 to date-minus-5 days (hereafter *lag8*). Secondly, we consider a lagged 11-day average, from date-minus-12 to date-minus-2 days

Table 1: Descriptive statistics

Variable	Note	Min	Mean	Max	SD	Source
COVID-19 Incidence	Incidence in reported cases of SARS-19 per 100,000 people	0.38	153.61	1149.36	186.23	Montera34
Area	Area of province in sq.km	1978.12	10118.79	21767.93	4.77	INE
GDPpc	GDP per capita in €1,000s	16.67	22.51	36.00	4805.98	INE
Older	Percentage of people aged 65 and older in the province	15.16	21.03	31.36	3.95	INE
Population Density	Population density in the province in people per sq.km	8.60	140.04	829.76	181.25	INE
Mean Temperature	Mean temperature in province by date, in C	1.00	12.18	23.20	3.67	AEMET
Humidity	Relative humidity in province by date	2.00	77.82	100.00	10.37	MAPA

Note:
Montera34: https://code.montera34.com:4443/numeroteca/covid19/-/blob/master/README_providencialdata19.md
INE (Instituto Nacional de Estadistica): https://www.ine.es/
AEMET (Agencia Estatal de Meteorologia): http://eportal.mapa.gob.es
MAPA (Ministerio de Agricultura, Pesca y Alimentacion): http://eportal.mapa.gob.es

(hereafter *lag11*). Finally, to account for the likely duration of incubation, we consider a lagged 11-day *weighted* average, from date-minus-12 to date-minus-2 days (hereafter *lag11w*). The weights for this variable are calculated using the parameters of the log-normal distribution reported by Lauer et al. (2020), i.e., a log-mean of 1.621 and a log-standard deviation of 0.418. With these weights, the environmental variables at date-minus-2 and date-minus-12 days are weighted as 0.041 and 0.009 respectively, whereas the environmental variables at date-minus-5 days are weighted as 0.194.

Methods: Spatial SUR

The Seemingly Unrelated Regression equations model (SUR hereafter) is a multivariate econometric model used in different fields when the structure of the data consisits of cross-sections for different time periods. The basis of this approach is well-known since the initial works of Zellner (1962), and has become a popular methodology included in several econometrics textbook (e.g., Greene, 2003). To our knowledge, Anselin (1988) was the first author to discuss SUR from a spatial perspective. In his landmark text, Anselin discussed a model made of "an equation for each time period, which is estimated for a cross section of spatial units" (p. 141). From this milestone, a large body of research has developed to extend the classical SUR into a spatial framework (e.g., Rey and Montouri, 1999; Lauridsen et al., 2010; Le Gallo and Dall'Erba, 2006; López et al., 2017).

The classical SUR model without spatial effects (from here, SUR-SIM) is a stack of equations as follows:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_T \end{bmatrix} = \begin{bmatrix} X_1 & 0 & \cdots & 0 \\ 0 & X_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & X_T \end{bmatrix} \begin{bmatrix} \beta_1 \\ \beta_1 \\ \vdots \\ \beta_T \end{bmatrix} + \begin{bmatrix} \epsilon_1 \\ \epsilon_2 \\ \vdots \\ \epsilon_T \end{bmatrix} \tag{1}$$

where $y_t = (y_{1t}, ..., y_{Nt})$ is a $N \times 1$ vector, and in our case y_{st} is the incidence ratio in the province s $(s = 1, ..., N)$ the day t $(t = 1, ..., T)$; X_t is a $N \times k_t$ matrix of the k_t independent variables, with associated vector of coefficients β_t,; $\beta_t = (\beta_{1t}, ..., \beta_{Nt})$ is a vector of coefficients and $\epsilon_t = (\epsilon_{1t}, ..., \epsilon_{Nt})$ is the vector of residuals.

A key feature of the SUR model is the dependence structure among the vectors of residuals, namely:

$$E[\epsilon_t \epsilon'_{t'}] = \sigma_{tt'} \tag{2}$$

Note that this specification is very flexible, in that it allows changes in the coefficients β_{it} in order to modulate the effect of $X^i_{\cdot t}$ on y_t. This flexibility can be reduced and it is posible to impose restrinctions considering some β coefficients as being constant over time. In this case, we can reformulate the coefficients expression $\beta_t = (\beta_1, \cdots, \beta_{r-1}, \beta_r, \beta_{r+1}, \cdots, \beta_{Nt})$ to restrict the first r coefficients to be constant across equations. This is equivalent to specifying some effects to be invariant over time.

Equation (1) can be rewriten in compact form:

$$\mathbf{Y} = \mathbf{X}\beta + \epsilon \tag{3}$$

where $\mathbf{Y}$ is now a vector of dimension $NT \times 1$, $\mathbf{X}$ is a block-diagonal matrix $NT \times K$ (with $K = \sum_t k_t$) and ϵ is a $NT \times 1$ vector. Using the Kronecker product notation ($\otimes$), the error matrix structure is expressed concisely as:

$$E[\epsilon\epsilon'] = \Sigma \otimes I_N;\ \Sigma = (\sigma_{tt'}) \tag{4}$$

As is the case with cross-sectional data, it is possible to test the residuals of Model (3) for spatial autocorrelation, and several tests have been developed to test the null hypothesis of spatial independence (see López et al., 2014). When the null hypothesis is rejected, several alternative specifications have been proposed to include spatial effects (Anselin, 1988, see also 2016). In this paper we consider a spatial SUR model that incorporates a spatial lag of the dependent variable as an explanatory factor. Spatial analytical approaches were used to understand contagion-difussion processes in the case of infectious disease in general (e.g., Cliff et al., 1998) and the 2003-2004 SARS outbreak in particular (e.g., Meng et al., 2005; Cao et al., 2010). While we are mindful of the same caveat that the novel SARS-CoV2 may not follow the patterns of previous diseases, there is still evidence from the United States that COVID-19 displays spatial patterns that are consistent with a diffusion process (Desjardins et al., 2020). For this reason, the spatial lag model is appropriate to model incidence of COVID-19 geographically, since it accounts for potential spatial patterns that result from a process of contagion, as explained next.

The stack expresion for the spatial lag SUR model (SUR-SLM) is as follows:

$$\begin{aligned} \mathbf{AY} &= \mathbf{X}\beta + \epsilon \\ \epsilon &= N(0, \mathbf{\Sigma}) \end{aligned} \tag{5}$$

where $\mathbf{A} = \mathbf{I_{TN}} - \mathbf{\Gamma} \otimes \mathbf{W}$ with $\mathbf{\Gamma} = \mathbf{diag}(\rho_{\mathbf{1}}, \cdots, \rho_{\mathbf{T}})$.

This specification assumes that incidence in a province (y_{st}) at time t is partially determined by the weighted average ($W y_{st}$) of incidence in neighbouring provinces. Coefficients for the spatially lagged variable are estimated for each time period ρ_t and identifies the intensity and the sign of the impacts of neighbourhood. It is possible test the null hypothesis of identtical levels of spatial dependence ($\rho_i = \rho_j, \forall i, j$). The correspond Wald test is available in the `R` package `spsur`.

The SUR-SLM model can be estimated using maximum likelihood (López et al. (2014)) or instrumental variables (Mínguez et al. (2019)). Another alternative methodologies could be use. By example, a dynamic spatial panel methodology with fixed spatial an temporal effects (e.g. Elhorst 2014, Cap. 4), but those models don't take account correlation between errors. Therefore, a spatial SUR approach is more reasonable for our purpose.

Analysis and Results

Exploratory Data Analysis

We begin with the exploratory analysis of the data.

Figure 1 shows the geographical variation in the incidence of the disease, as well as its temporal progression in weekly averages. Our analysis begins on March 13, which is the first date when every province had reported at least one case of COVID-19. It can be seen that the highest incidence at this early date was in the provice of Álava, in the North of Spain. While not the most populous province, with a population of only 331,549, Álava has the highest GDP per capita of all provinces. Vitoria, its main city, is the capital of the Basque country and has been the focus of efforts to develop a "Global Basque City" (Meijers et al., 2008), along with San Sebastian and Bilbao. The other early focus of the pandemic in Spain was Madrid, which is the most populous province in the country and has the second highest GDP per capita after Álava. The early outbreaks in these two provinces can be traced throughout the progression of the pandemic over time, although by the end of the period under consideration, other provinces had matched and even surpased their incidence rates, including Segovia and Soria to the north of Madrid, and Ciudad Real and Albacete to the south.

To visualize the distribution of temperature and humidity we aggregate the provinces by Autonomous Community. In Figure 2 the communities have been sorted by latitude, so that Principado de Asturias is the northernmost community, and Canarias the southernmost. There is a relatively wide range of values both within and between provinces over the 30 day period examined. The top panel of the figure shows the distribution of mean temperature. The lowest mean temperature for a community on any given day is 2.8C, and the highest is 22.4C for a range of approximately 20 degrees. Likewise, there is a great deal of variability in humidity, as seen in the bottom panel of the figure, where the lowest mean humidity for any community is 48.3 and the highest is 99.6. The actual values for the provinces display somewhat more variability even.

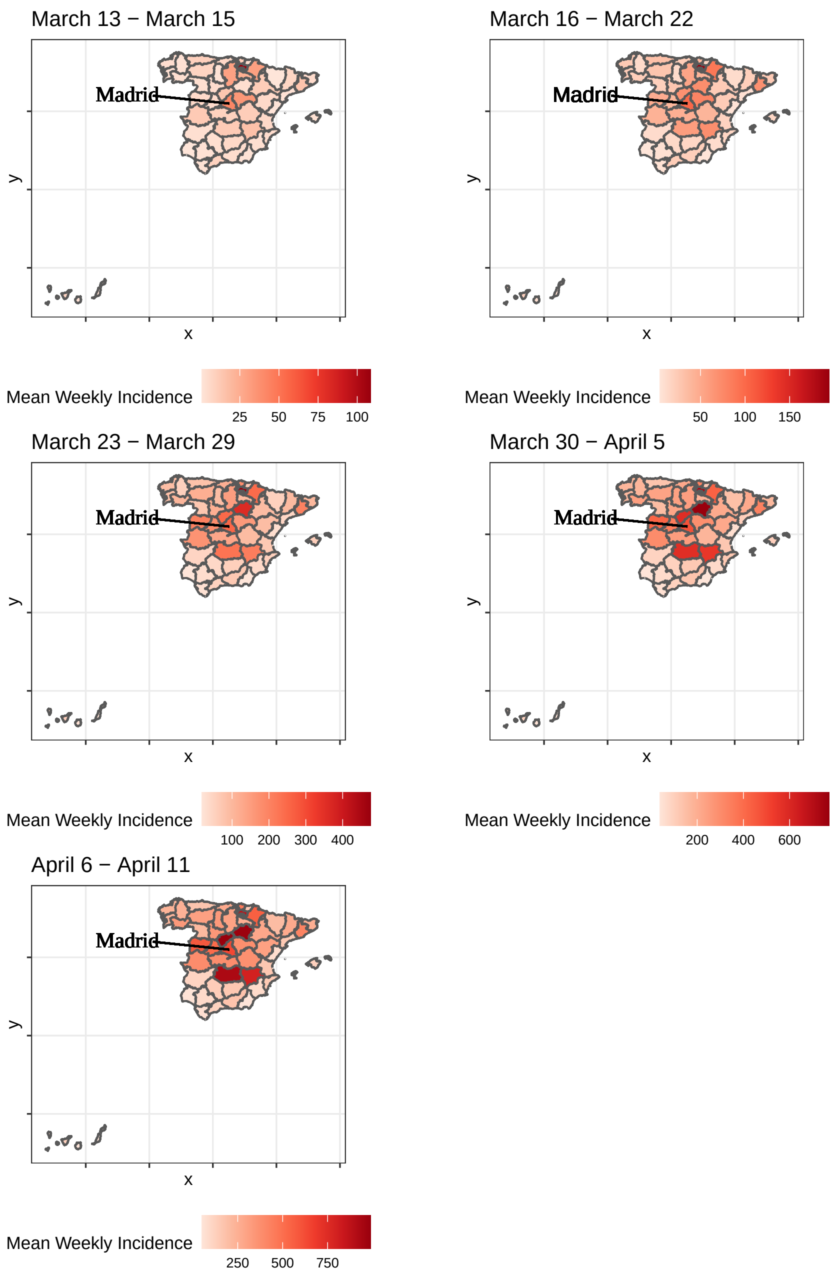


Figure 1: Mean weekly incidence of COVID-19 by province, in reported cases by 100,000 people

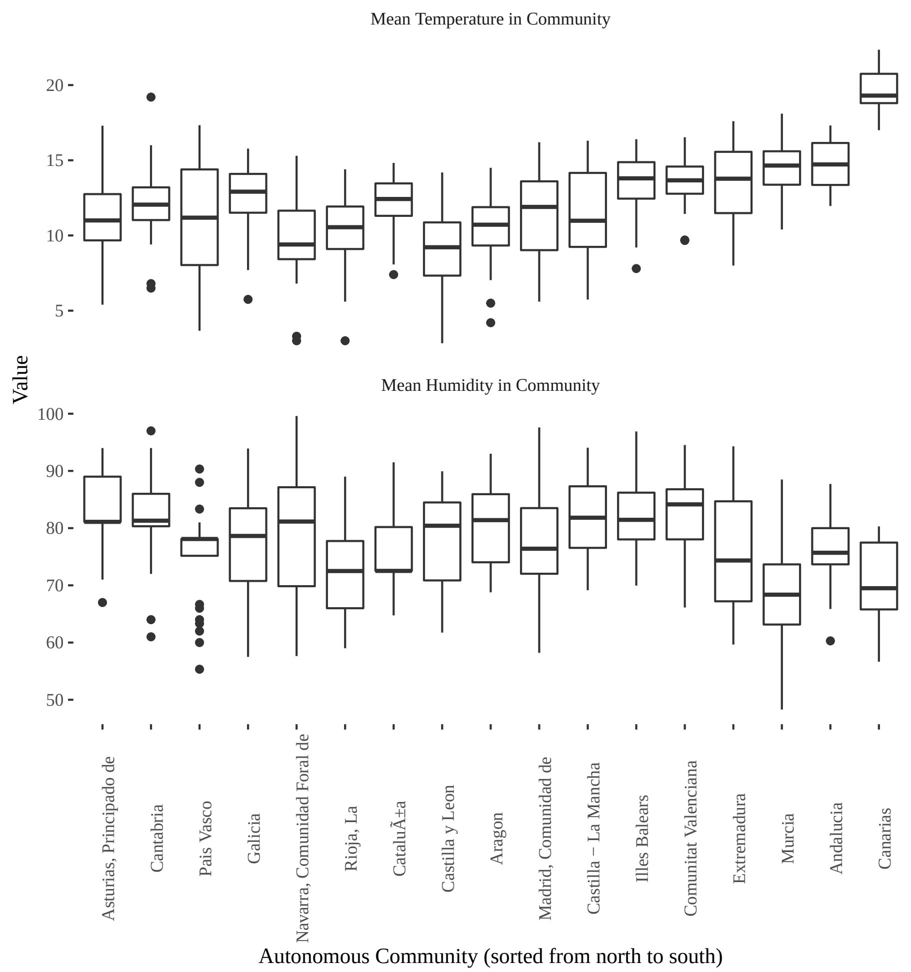


Figure 2: Distribution of mean temperatures and humidities in the Autonomous Communities in Spain between March 12, 2020 and April 11, 2020. The Autonomous Communities have been sorted by latitude, with communities to the left being the northermost, and to the right the southernmost

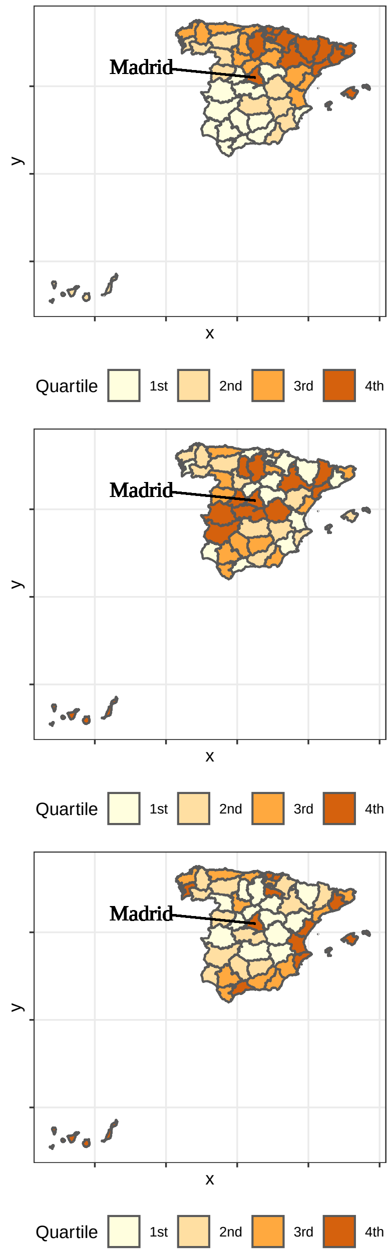


Figure 3: Spatial distribution of control variables by province

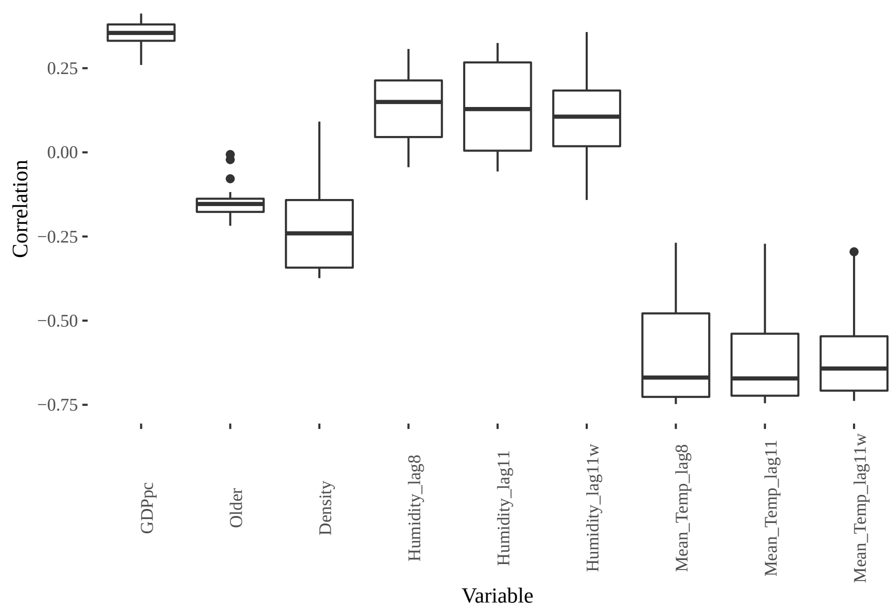


Figure 4: Distribution of daily correlations of the independent variables with daily incidence of COVID-19 (all variables have been log-transformed)

Figure 4 shows the distribution of daily correlations of the independent variables with incidence of COVID-19, after log-transforming all variables. It can be seen there that the correlation of GDPpc and temperature (in its three definitions) have the strongest positive and negative correlations with incidence, respectively. Percentage of older adults displays somewhat weaker negative correlations with incidence, as does density. It can be seen that the humidity variable, in its three forms, tends to be possitively correlated with incidence of COVID-19.

SUR Models

The goodness of fit of the three systems of equations is shown in Figure 5.

Summary of best model.

Discussion

Figure 6 shows the temporal evolution of the spatial autocorrelation coefficient (λ).

Figure 7 shows the temporal evolution of the intercept.

Figure 8 shows the temporal evolution of the coefficient for $\log(Density)$.

Figure 9 shows the temporal evolution of the coefficient for $Transit$.

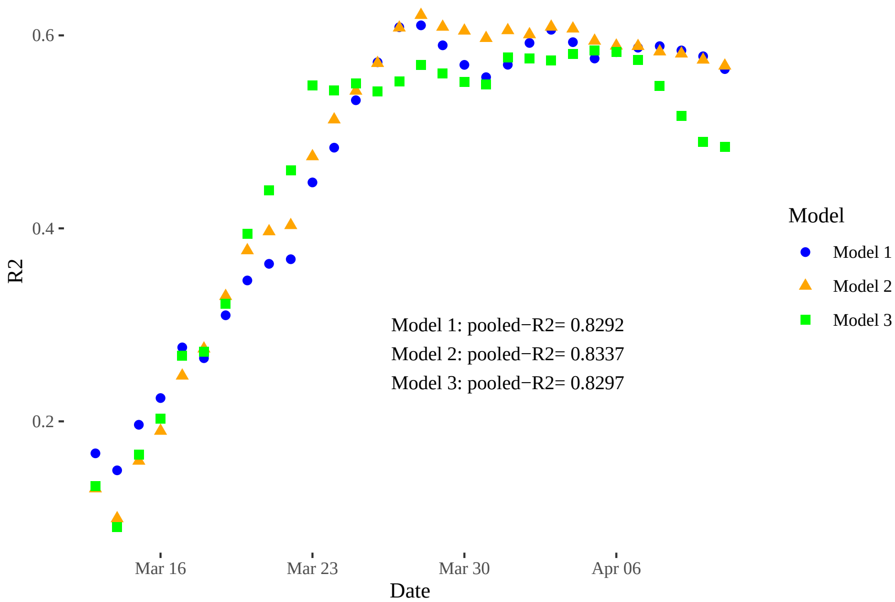


Figure 5: Goodness of fit of the SUR systems: by date and pooled

Table 2: Summary of estimation results best model (lagged 11-day moving average)

	Estimates			Significance			
Variable	Min	Mean	Max	p > 0.10	0.10 <= p < 0.05	p <= 0.05	Note
Intercept	7.370	10.037	12.968	0	0	30	Non-constrained
log(GDPpc)	0.620	0.620	0.620	0	0	1	Constrained
log(Older)	-0.737	-0.737	-0.737	0	0	1	Constrained
log(Density)	-0.220	-0.097	0.153	19	1	10	Non-constrained
Transit	0.314	0.512	0.583	10	9	11	Non-constrained
log(Humidity)	-1.434	-0.534	-0.031	10	1	19	Non-constrained
log(Temperature)	-2.014	-1.406	-0.929	0	0	30	Non-constrained
log(Sunshine)	-0.258	0.097	0.206	7	2	21	Non-constrained

Note:
Significance: This is the number of coefficients with p-values as indicated
Non-constrained: coefficient was allowed to vary across equations
Constrained: coefficient as constant across equations

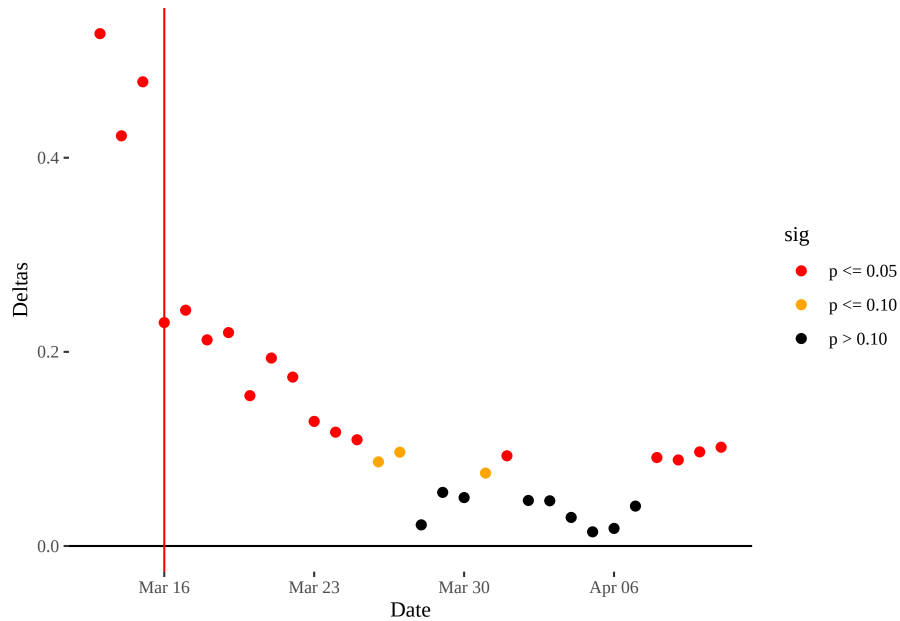


Figure 6: Temporal evolution of spatial autocorrelation coefficient

Figure 10 shows the temporal evolution of the coefficient for $\log(Humidity)$.
Figure 11 shows the temporal evolution of the coefficient for $\log(Temperature)$.
Figure 12 shows the temporal evolution of the coefficient for $\log(Sunshine + 0.1)$.

```
Wsur <- as(spdep::listw2mat(listw), "CsparseMatrix")
trsur <- spatialreg::trW(Wsur, type = "MC")
impacts.sur.slm_lag11 <- impactspsur(sur.slm_lag11, tr = trsur,R = 1000)

impacts.sur.slm_lag11[[1]]
```

```
## Impact measures (lag, trace):
##                                      Direct   Indirect      Total
## log(GDPpc)_1                      0.6736035  0.6395634  1.3131669
## log(Older)_1                     -0.8002302 -0.7597912 -1.5600214
## log(Density)_1                    0.1662437  0.1578427  0.3240864
## Transit_1                         0.3413888  0.3241370  0.6655259
## log(Humidity_lag11)_1            -1.5578465 -1.4791220 -3.0369685
## log(Mean_Temp_lag11)_1           -1.7365494 -1.6487943 -3.3853437
## log(Sunshine_Hours_lag11 + 0.1)_1 -0.2804735 -0.2663000 -0.5467734
```

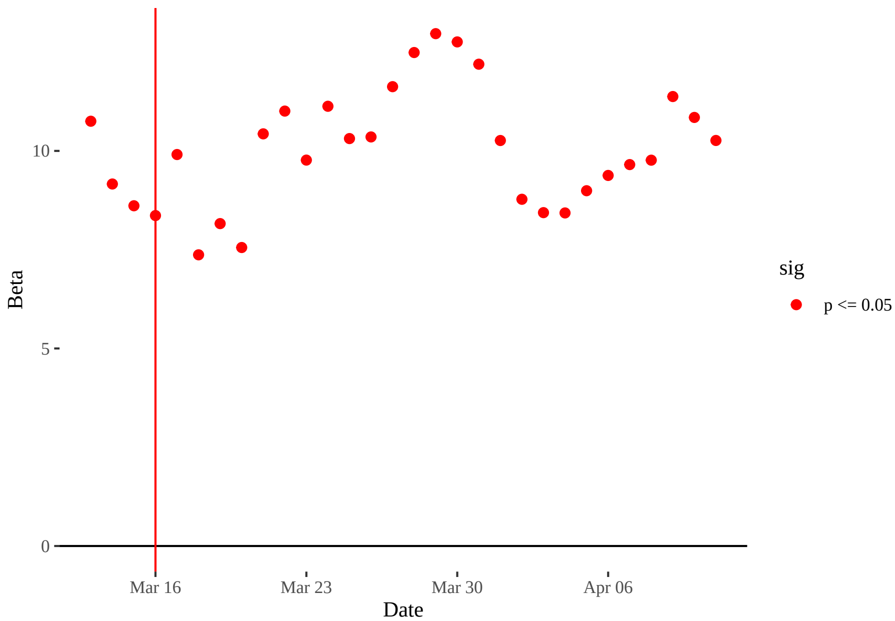


Figure 7: Temporal evolution of intercept

```
impacts.sur.slm_lag11[[2]]
```

```
## Impact measures (lag, trace):
##                                       Direct    Indirect      Total
## log(Density)_2                    0.06248795  0.04048188  0.1029698
## Transit_2                         0.44006548  0.28508982  0.7251553
## log(Humidity_lag11)_2            -1.06244958 -0.68829202 -1.7507416
## log(Mean_Temp_lag11)_2           -1.47760442 -0.95724386 -2.4348483
## log(Sunshine_Hours_lag11 + 0.1)_2 -0.19072953 -0.12356126 -0.3142908
```

```
impacts.sur.slm_lag11[[3]]
```

```
## Impact measures (lag, trace):
##                                       Direct    Indirect       Total
## log(Density)_3                    0.02426235  0.01927572  0.04353807
## Transit_3                         0.43033000  0.34188455  0.77221455
## log(Humidity_lag11)_3            -0.97379005 -0.77364759 -1.74743764
## log(Mean_Temp_lag11)_3           -1.39450981 -1.10789707 -2.50240689
## log(Sunshine_Hours_lag11 + 0.1)_3 -0.09683377 -0.07693158 -0.17376535
```

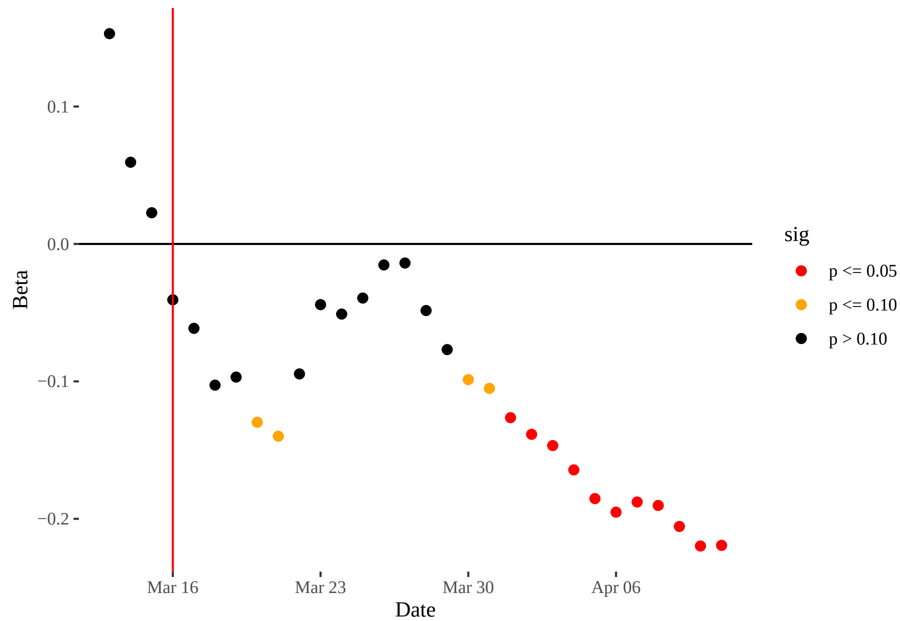


Figure 8: Temporal evolution of coefficient for log(Density)

```
myimpact <- matrix(0,ncol = 5, nrow = 29)
for (i in 2:30){
  myimpact[i-1,] <- impacts.sur.slm_lag11[[i]]$res$direct
}
matplot(myimpact, type='l')
```

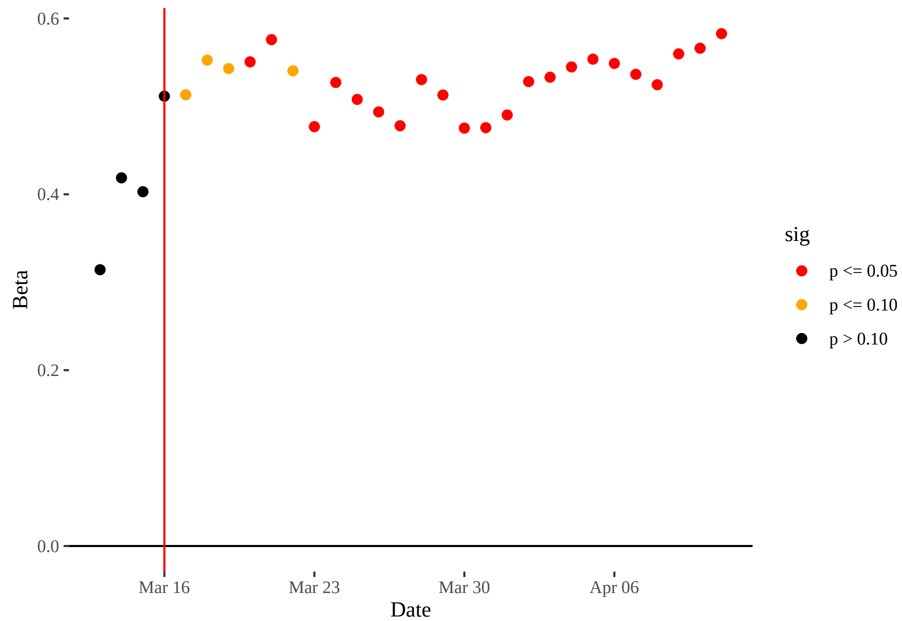
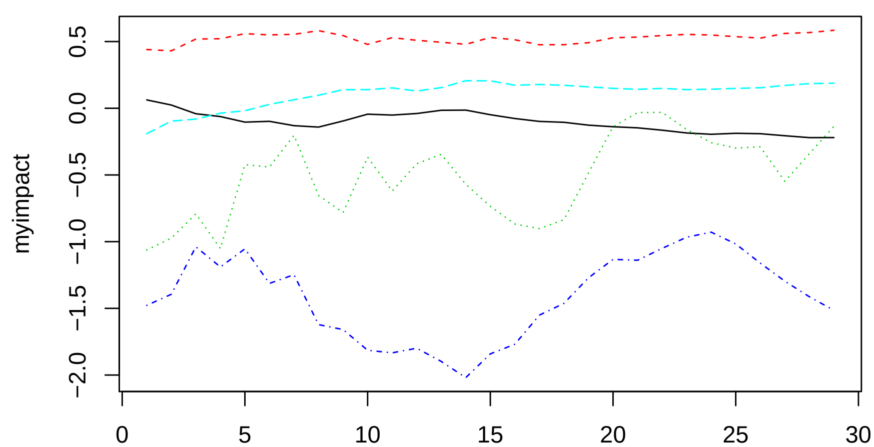


Figure 9: Temporal evolution of coefficient for Transit



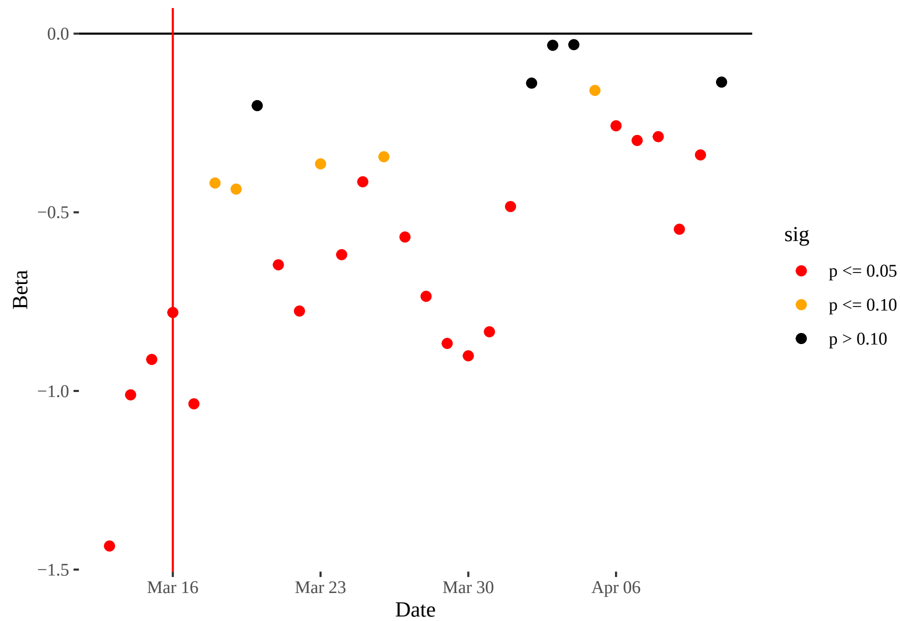


Figure 10: Temporal evolution of coefficient for log(Humidity)

Concluding Remarks

More words go here.
Limitaciones

- La temperatura puedes ser un factor pero cabría esperar que no tuviera un impacto lineal. Por el contrario deberiamos esperar un 'punto de corte': Una temperatua mantenida superior a X grados durante siete días sea la mejor forma de incorporarla al modelo. En nuestro modelo (log-log) en incremento en un 1% de la temperatura se asocia con un incremento beta% en la incidencia. Esto es lo mismo si la temperatura es baja que si es alta.
- Idem para la humedad y horas de sol
- Los datos son 'provisionales'. Hay gran confusión sobre la incidencia real. La ausencia de test de diagnóstico PCRs al inicio de la pandemia (también ahora) puede desvirtuar el número de casos dianosticados.
- Los datos oficiales (que tampoco son fiables) son reportados a nivel de Comunidades Autónomas. La recopilación de datos a nivel de provincial son el resultado de un esfuerzo colaborativo de recopilacion entre distintas fuentes (principalmente gobiernos locales). Nuevamente puede haber sesgos importanes.

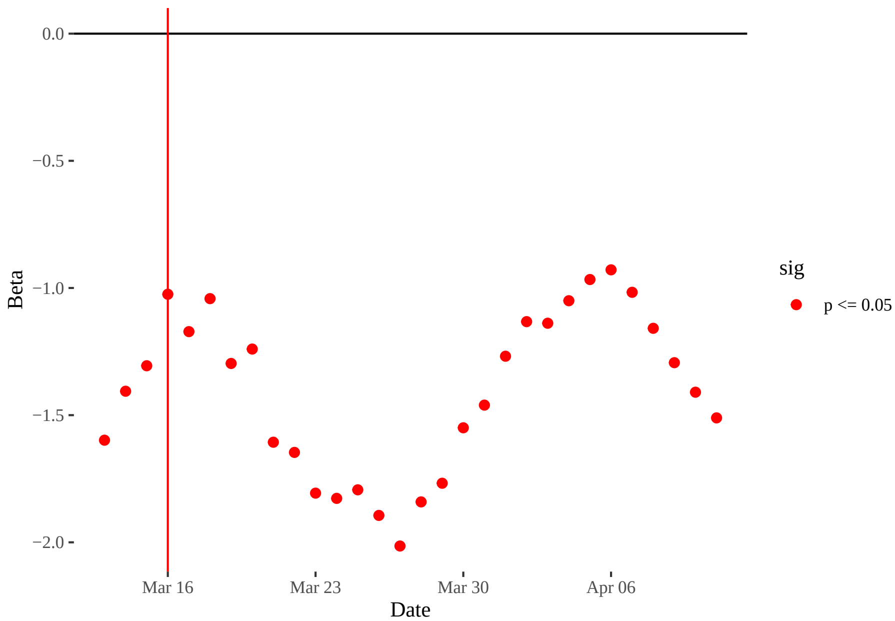


Figure 11: Temporal evolution of coefficient for log(Temperature)

- En carácter insular de las Islas Canarias y de las Islas baleares no se ha tenido en cuenta.
- Baleares se ha linkado artificialmente con 3/4 provincias y debería de haberse dejado aislada para respetar su carácter insular al definir la matriz W.
- La incidencia depende de un estado inicial. Al inicio del estudio había provincias en las que la epidemia estaba muy desarrollada (Madrid/Alava) mientras que en otras apenas habías casos. Este hecho no ha sido considerado en el modelo. Decretar el confinamiento debe tener distintos impactos entre provincias. QUIZAR METER UNA VARAIBLE DUMMY CON COEF BETA CONSTANTE PARA CONTROLAR AQUELLAS PROVINCIAS CON MAYOR NUEMRO DE CASOS AL INICIO DEL CONFINAMIENTO.
- No se ha controlado por el sistema sanitario de cada provincia. Uno de los principales focos de contagio han sido los hospitales y los centros de salud. En aquellas provincias donde se ha promovido el mensaje “NO IR AL MEDICO” han presentado menor incidencia.
- HAY QUE INCLUIR INTERVALOS DE CONFIANZA EN LOS GRÁFICOS QUE HACEMOS DE LOS COEFICIENTES DEL MODELO

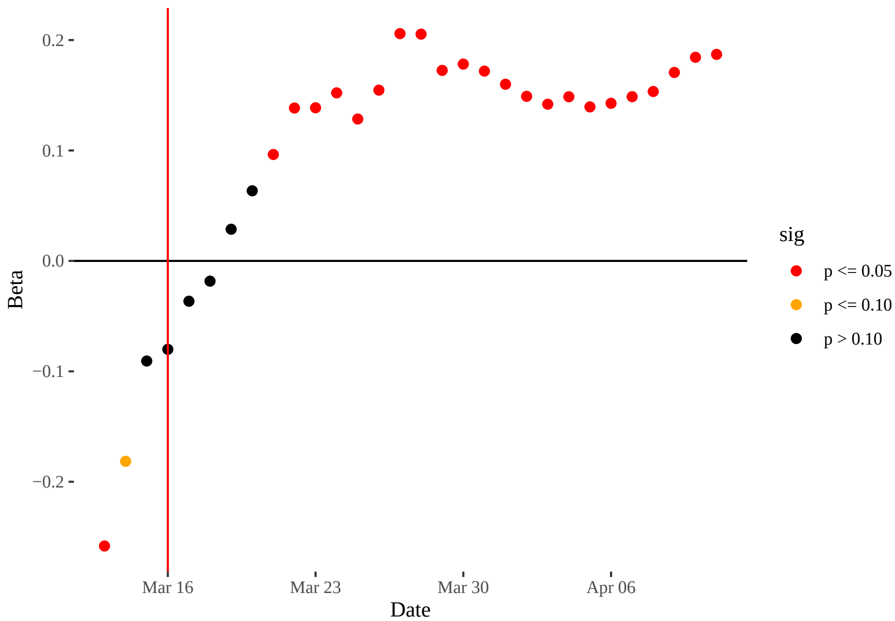


Figure 12: Temporal evolution of coefficient for log(Sunshine + 0.1)

- ¿hasta que punto las variables de control no recojen también factores climáticos? por ejemplo, la gente jóven vive en el sur de España que ha tenido menos incidencia.
- TITULO: A spatial analysis of the environmental correlates ofCOVID-19 incidence in Spain ¿during the lookdown?
- Las estaciones meteorológicas para la obtencion de datos climáticos has sido elegidas aleatoriamente (una para cada provincia). otra seleccion puede dar otros resultados. AQUI SE PODRÍA HACER EL ESFUERZO DE CONSIDERARLAS TODAS (1000) Y CALCULAR LA MEDIA DE LAS VARAIBLES POR PROVINCIA

*IDEM para la humedad. idem para sunshine

- HACE FALTA INCLUIR UN PLOT CON LAS CORRELACIONES DE LOS RESIDUOS PARA DARLE RELEVANCIA A LA ESTIMACION SUR

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