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Fighting the COVID pandemic: National policy choices in non-pharmaceutical interventions

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Abstract

The COVID-19 pandemic pushed countries to adopt various non-pharmaceutical interventions (NPIs). Due to the features of the pandemic, which spread over time and space, governments could decide whether or not to follow policy choices made by leaders of countries affected by the virus before them. In this study, we aim to empirically model the adoption of NPIs during the first wave of COVID-19 in the 14 European countries with more than 10 million inhabitants, in order to detect whether a policy diffusion mechanism occurred. By means of a multivariate approach based on Principal Component Analysis and Cluster Analysis, we manage to derive three clusters representing different behaviour models to which the different European countries belong in the different periods of the first wave: pre-pandemic, summer relaxation and deep-lockdown scenarios. These results bring a two-fold contribution: on the one hand, they may help us to understand differences and similarities among European countries during the first wave of the COVID-19 outbreak and guide future quantitative or qualitative studies; on the other, our findings suggest that with minor exceptions (such as Sweden and Poland), different countries adopted very similar policy strategies, which are likely to be due more to the unfolding of the pandemic than to specific governmental strategies.

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1. Introduction

2020 is a year that will probably long be remembered for the pandemic that afflicted the world. In its first stages, most countries appeared substantially unprepared to address the issue and were forced to adopt exceptional measures to contain the spread of the new coronavirus. National policies based on so-called non-pharmaceutical interventions (NPIs) were accompanied by an intense political debate at the international level regarding the best strategy to adopt. In the event, throughout 2020 countries followed various strategies to reduce the outbreak of coronavirus infectious disease (COVID-19) and bring the epidemic under control. Political rhetoric from some national governments as well as anecdotal evidence\(^1\) praised the so-called Italian model to fight coronavirus, as opposed to the approach of other countries (Nicola, 2021). One and a half years after the pandemic began, although some important conditions have changed, above all the availability of a number of different vaccines, several countries have continued to be forced to adopt severe NPIs.

While some articles in the literature have focused on the effectiveness of certain policies (for instance Kumar et al., 2021 and Alfano & Ercolano, 2020 on lockdowns; Khairulbahri, 2021, on the policy mix in southeast Asia; Alfano, 2021 and Alfano et al., 2020 on policies aimed at closing schools), the fact that different approaches were put in place to counter the diffusion of the virus means that it is difficult to compare in a cross-country perspective the unfolding of the pandemic and the effectiveness of the measures adopted to face it.

Understanding the effectiveness of the different responses posed by various countries to COVID-19 seems essential if we are to establish the best route to emerge definitively from the pandemic. It may also be useful for future reference, or to help guide the choices of countries that are facing stages of the epidemic that other countries around the world have already passed. The issue is highly complex. Indeed, to the best of our knowledge, even though governments around the world share the same policy objective, i.e. balancing the protection of citizens’ health with an easing of restrictions to favour spending and avoid excessive damage to economies and social spheres, no government has taken the same approach toward the epidemic through the various stages of the COVID-19 outbreak. Although the pandemic has afflicted the entire world over the last year and a half, it has ebbed and waned in various places. In addition to institutional and political factors, national governments have modulated their policy interventions depending on the availability of more data on the unfolding of the outbreak, and the outcomes of policies adopted in other countries.

For all these reasons, it seems a daunting task to compare the effectiveness of the different remedies that have been adopted, since it is a problem involving several dimensions at once, for which scholars lack a reliable map. A spatial dimension is certainly involved, since the location of different countries plays a role, due to specificities in terms of climate, geographical borders and vicinity to severe COVID-19 outbreaks. But there is also a temporal dimension, given the fact that in different points of 2020 the virus had different levels of diffusion, leading to policies of varying degrees of stringency being put in place. Finally, there is a governmental dimension, involving the individual choices that each government decided to implement to pursue an optimal strategy for emergence from the epidemic. In this complex scenario, a synthetic map of all these peculiarities would be a useful tool for understanding how much governmental responses varied from country

\(^1\) https://hbr.org/2020/03/lessons-from-italy-s-response-to-coronavirus.
to country along spatial and temporal dimensions, and whether the mixture of policies adopted by each government depended on the evolution of the pandemic.

The aim of the present study is to describe and categorize the different approaches of the largest European countries in the fight against COVID-19. This operation could shed some light on the process that triggered different governments to choose and adopt a certain mix of measures. To do so, we adopt a multivariate approach based on Principal Component Analysis (PCA) and Cluster Analysis (CA), allowing us to model and group by similarity of reaction (in terms of containment measures imposed on citizens and social distancing policies implemented within national borders, as well as the severity of the growth of COVID-19 cases) the policies enforced by governments of the fourteen most populous European countries (those with more than 10 million inhabitants) during the first wave of COVID-19, i.e. between January and October 2020.

We use data from the Oxford University Coronavirus Government Response Tracker (OxCGRT) dataset (Hale et al., 2020) about the unfolding of the infection rate and the policies put in place by different countries to combat the pandemic.

We think that mapping the response of the largest European states is an important issue, since future studies on the spread of COVID-19, as well as policy evaluations and case studies of remedies and intervention effectiveness, will necessarily require a simplification of the various moments of the first wave all over Europe, in order to distinguish and discriminate between the different situations in European countries during the months of the first COVID-19 wave.

Moreover, given that the pandemic is characterized by a non-linear evolution, so-called ‘waves’, the identification of models in countries’ behaviour during the first wave could be helpful also in providing some explanation regarding the consecutive waves that we have observed in the course of the pandemic. This point may also be useful from a theoretical perspective. Indeed, the methodology proposed in the paper allows us to understand whether certain policy mechanisms are at work when some countries, affected by the pandemic later than others, manage to exploit the advantage of observing the behaviour of countries affected earlier by the virus, in terms of NPI policy choices. On this particular point it is worth noting that, according to the literature, it is possible to detect two principal phenomena: policy diffusion when we are interested in the countries’ choices in term of NPI adoption, and policy convergence if we are interested in the evolution of the output of such policies over time.

From a policy perspective the present paper does not try simply to suggest a model for prediction, but instead offers a methodology that can be used to support the organization of complex information empirically. More specifically, the identification of policy models in the fight against COVID-19 may be a theoretical and empirical aid for conceiving and organizing appropriate policy responses to economic change – i.e. structural shifts, external shocks – and, generally, a support in the search for better socio-economic conditions.

To the best of our knowledge, the most similar approach is that of Tallon et al. (2020), who study the impact of NPIs on certain epidemiological variables. Nonetheless, while they also employ a PCA, they only consider 9 countries, and only distinguish between NPIs imposed before and after March 17 (only going up to 4 May), thus without considering the monthly mix of policies, and its change over time. The present contribution offers a longer timespan, and includes in its analysis the entire first wave of the pandemic (thereby including a whole period, from beginning to end, and offering the full spectrum of responses to the different stages of the pandemic). We thus consider ours to be an important step forward in mapping the responses of governments facing COVID-19 with NPIs and other policies, and a valuable contribution to the literature that traces and categorizes the different approaches adopted by the largest European governments, a matter
of the utmost importance in the more general framework of policy modelling and evaluation (as highlighted by Bonatti & Fracasso, 2019; Castaneda & Guerrero, 2019).

The remainder of the paper is organized as follows: after the present introduction, Section 2 introduces the principal literature dealing with policy diffusion and policy convergence. Section 3 illustrates the data and methodology adopted in the present study, Section 4 comments on the main results of the analysis, and Section 5 concludes the paper.

2. Policy diffusion and policy convergence

Is it possible to detect mechanisms capable of explaining whether a process of policy diffusion exists among different governments in different policy fields? In the social sciences two principal strands of literature have emerged regarding this phenomenon, the one focused on the concept of policy diffusion, the other focused on the concept of policy transfer. Following the suggestion of Marsh and Sharman (2009), the literature identifies policy diffusion as a process able to affect the policy choice of one country on the basis of the choices adopted in another country (Simmons & Elkins, 2004; Braun & Gilardi, 2006; Simmons et al., 2006). Policy transfer can be defined as “knowledge about policies, administrative arrangements, institutions and ideas in one political setting (past or present) is used in development of policies, administrative arrangements, institutions and ideas in another political setting” (Dolowitz & Marsh, 2000, p. 5). Nevertheless, despite some differences among these concepts (Newmark 2002; Busch & Jörgens, 2005), according to Marsh and Sharman (2009) these strands of literature “share an overlapping conceptual core and a complementary interest in a related class of empirical phenomena”.

The literature identifies four mechanisms of policy diffusion/transfer: learning, economic competition, imitation, and coercion. Learning derives from the observation and reproduction of policies adopted in other countries/institutions the easiest way to find a solution to an internal problem (Berry & Baybeck, 2005). Clearly, observation is followed by an assessment of policy success or, when it is hard to measure, by certain shortcuts (Ercolano & Romano, 2018). Economic competition refers to a process triggered by globalization that pushes countries to adopt similar policies aimed at incentivizing capital inflows. This mechanism derives from a rational analysis of the spillover effect that a certain policy may have on neighbouring countries. For example, considering two countries, when these spillovers are negative, the strategic behaviour of one country will lead it to avoid adopting a policy so as not to encourage the other country to adopt the same policy. When the spillovers are positive, each government has more incentive to adopt the policy in question (Shipan & Volden 2008). The third mechanism, imitation, is based on the idea of copying a policy in order to resemble the other country. This process is quite different from learning because it is not based on an analysis of the policy and its related effects. Imitation is more focused on other governments’ choices and is aimed at appealing to voters. For this reason, it is often adopted as an explanatory mechanism for local policy (Shipan & Volden 2008). The last mechanism for policy diffusion/transfer is coercion, which, in a cross-country perspective, is based on the political pressure of international bodies like the United Nations (and related agencies).

It is worth noting that these mechanisms are interesting theoretical explanations for policy diffusion but can often interact in a synergic way. In the case of COVID, and more specifically the adoption of NPI measures, it is possible to hypothesize that learning is the principal mechanism through which these policies tend to be adopted among countries. Rationally, the fact that the pandemic phenomenon tends to affect all countries, albeit at different times (though not very far
apart), should push governments to evaluate the set of policies adopted by countries that were affected earlier.

It is also important to note that another strand of literature in the social sciences seems to suggest that over the last years it has been possible to observe a process of cross-national policy convergence among countries (Heichel et al., 2005). Following Knill (2005), we can define policy convergence as “any increase in the similarity between one or more characteristics of a certain policy (e.g. policy objectives, policy instruments, policy settings) across a given set of political jurisdictions over a given period of time”. Despite the fact that policy diffusion/transfer and policy convergence investigate the same phenomenon, the first can be described as process-oriented, whereas the second is more output-oriented. More specifically, policy convergence is more focused on the time dimension and the policy output of governments’ choices, while policy diffusion is more focused on the mechanism through which this process happens. Policy convergence has been triggered by globalization (Drezner, 2001), although several scholars have shown that, in the framework of the EU, heterogeneity of policies rather than convergence has happened, as an effect of various political pressures (Windhoff-Héritier et al., 2001; Jörgens et al., 2014).

This heterogeneity seems to have been reflected in the political debate across EU countries at the beginning of the COVID pandemic. Nevertheless, at progressive steps of the virus diffusion, that heterogeneity seemed to blur gradually. This supports the idea that policy convergence is an appropriate framework to consider when analysing policy behaviour in the pandemic. Unlike policy transfer and diffusion, policy convergence indicates the results of a process of policy change over time, regardless of the causal processes (Knill, 2005).

Finally it is worth noting that NPIs are a set of policies that governments can mix in different ways. In this perspective, we are more likely to observe models of different behaviour in policy adoption, rather than a single and monolithic process. As illustrated in the following sections, the methodology adopted in this study allows us to strengthen our understanding not only in terms of policy diffusion and convergence, but also in terms of the definition of different models of country behaviour.

3. Data and methodology

Government interventions aimed at reducing the diffusion of the virus include a set of measures aimed at influencing several dimensions of social life. Following the approach proposed by Hale et al. (2020), it is possible to group government responses into three main areas: containment and closure policies, economic policies, and health system policies. The authors propose a unique dataset, the so-called Oxford COVID-19 Government Response Tracker (OxCGRT), which is based on a set of indicators that collect information about different governments’ responses to the pandemic. Our contribution focuses on the first group of interventions, namely containment and closure policies, given their relevance in the first wave (Alfano & Ercolano, 2020), and their direct impact on the growth of coronavirus cases.

This group of policies, as collected by Hale et al. (2020), is summarized by the following proxies:

- School closure (labelled C1)
- Workplace closure (labelled C2)
- Cancellation of public events (labelled C3)
- Restrictions on gathering size (labelled C4)
• Closure of public transport (labelled C5)
• “Stay at home” requirements (labelled C6)
• Restrictions on internal movement (labelled C7)
• Restrictions on international travel (labelled C8)

The OxCGRT offers ordinal indicators for each country and day, which try to measure the intensity of such interventions (if a policy is in place), thereby making them comparable across countries. This mainly takes into account whether they are applied at a local, regional or national level. The modalities in the proxies change slightly for each indicator, even though higher values always correspond to a more stringent implementation of the policy: for details refer to OxCGRT Index methodology, version 3.3.

It is worth noting that the indicators proposed by Hale et al. (2020) are built in a way that reports the implementation and stringency of the various government policies listed above. At the same time it is important to highlight that the values in OxCGRT should be interpreted only as a way of grading the stringency of a country’s response, rather than its appropriateness or effectiveness. Since a government’s choices could also be driven by the diffusion of the pandemic, in order to take into account this aspect of reverse causality to model countries’ behaviours, we also include the growth rate for new cases (labelled growthcases). The choice of this variable is justified by the fact that this is more comparable in a cross-country perspective, unlike deaths, which are affected by a number of country-specific factors, such as median age, condition of the health system, and family composition.

The final sample used in our study is made up of the 14 European countries with more than 10 million inhabitants (see Table 1). The final dataset is thus composed of 140 observations, given by the values registered by each of the 14 countries for each of the 10 months considered (which are those of the first COVID-19 wave, i.e. the months between January and October 2020).

We consider it appropriate to focus our analysis on Europe because it was the second continent, in terms of time, to be afflicted by COVID-19, and furthermore a continent that experienced a particularly severe outbreak of the pandemic. It is also a continent in which the existence of a number of countries makes it possible to see whether different strategies have been adopted by different governments to combat the pandemic.

When looking at each government’s behaviour in terms of containment and closure policies, this consists of a mixture of different measures, i.e. a combination of the previous indicators, implemented in a more or less stringent way. It should also be borne in mind that, as previously mentioned, these mixtures are very likely to change over time, as governments recalibrate their
approaches in the fight against COVID-19. For these reasons, a multivariate approach seems to be the most appropriate strategy for modelling how different countries have adopted different policy instruments.

More specifically, our empirical approach is based on a two-step procedure described in more detail in the following sub-sections.

3.1. First step: synthetizing the phenomenon by means of PCA

In the first step, the whole phenomenon is synthetized by means of PCA (Pearson, 1901; Cooley & Lohnes, 1971; Shlens, 2005; Stathis & Myronidis, 2009). This non-parametric technique allows us to reduce the complexity of the phenomenon by finding certain latent variables that are linear combinations of the original variables. In more formal terms, as illustrated in Ercolano and Romano (2018), starting from an original matrix with $p$ variables and $n$ cases, by means of principal axis transformation we may obtain the new uncorrelated variable $zi$ ($i = 1 \ldots p$), which represents the principal components (or latent variables) of the original variables. The $i$-th $z$ latent variable can be formalized as follows:

$$zi = \mu_i' [x - \bar{x}]$$

where $x$ and $\bar{x}$ represent the $p \times 1$ vectors of observations on the original variables ($x$) and their means ($\bar{x}$).

PCA is useful when we are interested in which original variables can be synthetized in statistically coherent subsets (Ercolano & Romano 2018). Following this rationale, the technique extracts latent variables (e.g. the principal components) able to reflect the correlation process in the original variables that describe the phenomenon under investigation (Tabachnick & Fidell, 2007), as in our case for the set of containment and closure policies measured through OxCGRT. Previous contributions have shown how these kinds of techniques can be useful for synthesizing and modelling countries’ behaviour when looking at public expenditures (Ferreiro et al., 2010), environmental spending (Ercolano & Romano 2018), and social protection spending (De Simone et al., 2012), or when aggregating a set of variables in a synthetic index (OECD, 2008; Ercolano & Romano, 2013). It is worth noting that a recent contribution adopted PCA to categorize the spread rate of COVID-19 in France, Germany, Iran, Italy, Spain, the United Kingdom, and the Unites States (Mahmoudi et al., 2021).

In the present paper, we carried out PCA on the eight indicators compiled by Hale et al. (2020), considering the monthly mean value for each country and for each variable. Although Hale et al.’s (2020) database offers daily data, we believe that our approach improves the analysis in two ways. On the one hand it is a useful way to reduce the number of observations, which is a very important goal in a non-parametric estimation like ours, since it simplifies the readability of the results, making the output more understandable for the reader, and consequently more useful. A very detailed map, incapable of providing information to its reader because of the excess of small details, is not a useful tool. On the other hand, a second advantage of employing monthly mean values is that this transformation is useful when it comes to controlling and mitigating biases due to daily fluctuations, errors of measurement, and other factors that may affect point estimates. Indeed, all these errors are diluted (and possibly become asymptotically correct on average) when using monthly averages as values rather than daily values.
3.2. The second step: grouping countries’ behaviour by means of CA

Identification of the space generated by the correlation between the original variables allows us to detect a synthetic structure between two latent variables (e.g. the principal components) through PCA. Following this, in the second step of the analysis we directly group countries on the basis of the results of the Cluster Analysis (CA). This technique allows us to classify the different observations into clusters that are characterized by statistically similar values of the variables considered. Among the several methods that exist for grouping statistical units, we rely on a hybrid procedure (PARTI-DECLA) that is developed in the statistical package DECISIA SPAD 5.6, and which has been used in the previous literature (Ercolano & Romano 2013, 2018). In other words, this procedure performs a CA in the subspace determined by the latent variables extracted in the PCA.

There are important statistical advantages to using this method. The main one is that it clusters observations without the definition of an ex-ante determined number of clusters. The procedure is thus data driven, and very useful in a context, like ours, that so far lacks a theory to guide the empirical analysis. Furthermore, as reported in Ercolano and Romano (2018), this hybrid procedure requires PCA to be carried out before proceeding with a clustering procedure (Awasthi et al., 2006). As a further step, after implementing a K-means cluster analysis (Everitt, 1974; Meila & Heckerman, 1998), the procedure classifies the data on the basis of the value obtained on the factorial plane of the PCA. Finally, the units are grouped through a hierarchical agglomerative clustering (Ward, 1963), iteratively grouping the clusters closer to one another (Abraham et al., 2009).

To the best of our knowledge, this two-step approach (i.e. an analysis formed of a PCA and a subsequent CA) is used for the first time in this context, and analyses different responses across countries and time to a common threat. As observed by Ercolano and Romano (2018), the methodology has previously been employed with success by contributions that study the composition of public expenditure in the EU (De Simone et al., 2012; Ferreiro et al., 2013; Pinto, 2019). Nonetheless, we believe that it is appropriate to extend the methodology to this context, and that it offers an interesting tool for comparison of the behaviour of governments in enforcing different mixtures of policies to halt the COVID-19 outbreak throughout the first wave of the pandemic.

4. Results

The results of the PCA carried out on the sample we have described are of high quality. If we consider only the first two factors (e.g. the latent variables), the model explains 70% of the phenomenon explored.2 Looking at Fig. 1, we can observe that the two factors extracted differ significantly: there is a first one, which is characterized by most of the measures adopted by national governments to address the COVID-19 pandemic; and a second one, which is instead mostly characterized by growthcases, the variable that captures the growth of individuals who tested positive for COVID-19.

At first glance, this picture suggests a clear-cut division between the growth rate of COVID-19 cases and the proxy of the measures adopted, which appear to be quite uncorrelated. Indeed,

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2 In order to save space, tables with eigenvalue results are not reported here, but are available from the authors upon request.
the orientation between *growthcases* and the group of variables describing the measures adopted clearly follows an angle that is close to the perfect orthogonality. This graphically suggests the relative independence of one from the other. The correlation matrix (Table 2) confirms this finding, and also helps us to better analyse the correlation among all the original variables processed through the PCA. The overall correlation level among the different measures variables is quite high; it may be seen that the lowest grade of correlation is observed between C5 (restriction on public transport) and C8 (restriction on international travel), which is 0.24, and between C5 and C2 (closure of workplaces), which is 0.39. On the other hand, the most highly correlated variables are C2 and C1 (closure of schools and universities), and C2 and C3 (cancellation of public events), which are both 0.78.

Nevertheless, a more detailed analysis of the PCA results can be deduced from Table 3, which reports the characterization of the factors extracted. It allows us to observe that, among other things, some specific measures mainly contribute to the first factor: these are C2 and C3 (i.e. the variables that include interventions devoted to workplace closures and cancellations of public events).
Moreover, it is worth noting that C1 and C4 (i.e. school closures and restrictions on gatherings) also have high coordinates on this axis. For the second factor, together with growthcases, a certain contribution is made by some variables proxying the presence in the country and month of given NPI measures, such as C5, C6 and C7. These variables refer to interventions aimed respectively at closing public transport, at restricting movements inside cities/regions, and “stay at home” requirements.

Looking at the factorial plane generated by the PCA (Fig. 2), when we move along the vertical axis, we can observe countries in periods characterized by higher or lower growth rates of cases of COVID-19; in the same vein, by moving along the horizontal axis, we can observe how countries have managed the pandemic over time, through the adoption of more restrictive measures. Overall, cases that report positive values on the horizontal axis (namely, the countries that in a given month have adopted a given mix of measures) are plotted on the right side of the graph, and vice versa on the left side. On the upper side, we find cases that report higher values of growthcases. It is worth noting that the growth in cases is mainly associated with the adoption of measures aimed at reducing or stopping the circulation of people, at different grades. On the other side, the set of measures that are mainly oriented toward closures (of different kinds: from workplaces to schools and universities) appears to be quite independent from the growth of cases.
The picture that emerges from the PCA therefore seems to suggest that, on the one hand, the package of measures adopted by national governments aimed principally at closing places and banning public events explains a latent variable of the countries’ behaviour: it seems to be relatively independent from (and thus uncorrelated to) the average growth of cases. On the other hand, the package of more radical interventions regarding the limitation of individual freedom of movement seems to explain another latent variable of countries’ behaviour, and is more closely linked to the monthly growth rate of COVID-19 cases.

It is worth noting that the effectiveness of the policies and their impact on the increase in cases is difficult to derive directly from this picture. Indeed, these results may be driven by a lagged effect on the increase in cases, as well as the delayed results of policies, at least because 97.5% of those who develop symptoms (and are thus among those who are more likely to be counted as positive) do so within 11.5 days of infection (with a 95% confidence interval of between 8.2 and 15.6 days, Lauer et al., 2020).

It may be that the closing measures follow the growth in cases that happened in the previous month. This explanatory hypothesis could be supported by a more detailed analysis of the distribution of cases on the factorial plane. In order to facilitate the reading of results, in Figs. 3 and 4 we have separately reported the right and left sides of the factorial plane.

Since each observation corresponds to one of the countries photographed in each of the months from January to October, by looking at Figs. 3 and 4 we can observe how countries moved over time on the different axes. During the first months of 2020, all the countries appear to be on the left side of the graph, very close to the horizontal axis. In particular, in February, when the number of cases began to increase, but countries had not yet adopted restricting measures, most of them are plotted on the upper left side (Fig. 3). The only exception is Italy (ITA), which in February appears as an outlier on the edge of the upper-right side of the chart (Fig. 4). Indeed, ITA was ahead of other EU countries by about one month with regard to the sudden increase of cases, and also to the adoption of restrictive measures (since it was the first European country to be severely affected by COVID-19). This shift in the growth of cases and adoption of measures was very intense in February.

Looking at Fig. 4, we can note that most countries move to the right side of the chart (mainly on the upper side, but still very close to the horizontal axis) in March and April (note that this shift includes ITA). It is worth noting that ITA is at the edge of the chart (in both March and April),
and appears as the country that adopted the largest number of restrictive measures. It was soon followed by Romania (ROU) in April, and by France (FRA) and the United Kingdom (UKR) over the same months.

From May onwards, most countries started to shift slowly towards the left-hand side of the chart. On the left (Fig. 3), close to the centre of the chart, we find some countries that reduced restrictive measures more radically over the summer, and registered a low or negative growth in cases. These are ROU and the Czech Republic (CZE) from June; the Netherlands (NLD) and FRA and Poland (POL) from July; and finally ITA from September. In this area we also find Sweden (SWE), which, as is well known, has a very specific profile, since it adopted a light approach in the fight against COVID-19 and implemented much less restrictive policies than other European countries. Indeed, it can be seen in our chart that after March SWE does not move to the right-hand or upper sides. Spain (ESP), Ukraine (UKR) and Greece (GRC) move toward the left-hand side over one or two of the summer months, but then quickly shift back toward the right-hand side. In Fig. 4 we find several countries that moved even further to the left, as late as October: ITA, Germany (DEU), SWE, GBR, BEL, FRA and POL. On the other hand, in the same period, other countries plotted on the right-hand side: GRC, UKR, ESP, Portugal (PRT) and NLD.

Overall, we can conclude that most countries moved rapidly from the left towards the edge of the right side at the beginning of the pandemic (i.e. March–April) and then more or less gradually shifted back towards the left; some are plotted on the left and on the bottom of the chart, while others remain on the right and upper sides.

As explained in Section 3, the next step of our analysis is to synthesize the different countries’ behaviours by grouping them through a CA. This allows us to investigate the PCA results more thoroughly, by allowing us to observe how cases group among them and which original variables characterize their clustering.

Following the PARTI-DECLA procedure, CA detects three clusters.

The first is characterized by negative values for all the measure variables, and is plotted at the edge of the left side. As already observed, this includes all countries in January and February (with the exception of ITA), plus POL in September and October. The variables that show the highest negative values, namely those that appear to be more important in the characterization of this cluster, are those concerning restrictions on gatherings and public events (C4 and C3), followed by
C2 (workplace closures), and C8 (restriction on international travels). It is a cluster of countries that presents a typical “pre-pandemic” scenario, where neither restrictions on individual and collective freedom, nor limitations on workplace activities exist, yet. This was the situation of all the countries in January and February. Surprisingly, POL also belongs to this cluster in September and October, suggesting that this north-eastern European country had a radical reduction in restrictions and NPIs after the summer.

A second cluster is plotted on the bottom of the chart, at the centre of the factorial plane, with the barycentre on the left. It is mainly characterized by having only one variable with positive values (C8), with negative values for C5, C6, C7 and growthcases. Therefore, compared to the other observations, those grouped in this cluster are countries characterized by openings of international travel, by a reduction in cases of COVID-19, and by an absence of limitations to internal movements (between regions and within cities) and the use of public transport. It includes most of the countries from June to October, with the exception of CZE (from April), SWE (from March) and POL (in March). It essentially describes the scenario over the summer in which countries relaxed, as the pandemic eased and the level of COVID-19 diffusion decreased. In consequence, most of the countries reduced the limitations to individual freedom that had previously been imposed. It is worth noting that some of the countries are plotted here in the period before the summer months, suggesting that their governments adopted a management of the COVID-19 outbreak that was different from other countries (such as SWE and CZE) or, at least, not synchronous with them (such as POL).

Finally, the third cluster identified by the CA is characterized by positive values for all the variables proxying the measures, and is plotted on the right side of the graph, on the upper side. The variables that show the highest values are those concerning restrictions on internal movements (C7 and C6), followed by closures of schools and workplaces (C1 and C2). Taken together, these measures define a “deep lockdown” scenario, where significant work activities, universities, and schools are closed, and the “stay at home” requirements are very firm. The composition of the cluster confirms this interpretation: it includes most countries from March to May, with some
important exceptions. ESP, GBR, UKR and PRT stay in this cluster during and after the summer months (until October in the case of ESP and UKR, until September for GBR). GRC and CZE in October and DEU in June also belong to this cluster. Of course, the distance of each case from the centre allows us to determine its position in the cluster more accurately, and therefore to gauge the rigidity of the restriction measures that were adopted.

Tables 4a, 4b and 4c summarize the three clusters and the characteristic variables.

Finally, in order to merge the results obtained in the PCA and CA and facilitate an overlapped interpretation, this procedure also allows us to report the position of the centre of each cluster on the factorial plane, as reported in Fig. 5.

5. Conclusions

The COVID-19 outbreak has been an enormous challenge for governments across the world, and institutions have reacted by enforcing various policies and implementing a mixture of NPIs. Political rhetoric and some national narratives suggest that the European countries adopted different strategies to face the threat in the first wave of the outbreak.

Our analysis, which employed an original method exploiting a two-step approach based on PCA and CA and taking the time factor into account, mapped the response of the fourteen largest European countries (e.g. those with a population of more than 10 million) over the months that constituted the first wave of COVID-19 (i.e. between January and October 2020). Our results show that the countries’ behaviour was dictated principally by the unfolding of the pandemic, and thus by the timing of COVID-19 outbreak, rather than by different policy choices. With the exception of minor outliers, such as Sweden and the Czech Republic, and small differences that are largely imputable to slight differences in timing, with some countries ahead of the rest (such
Table 4c
Cluster 3: cases and characteristic variables.

| Case         | d     | Case     | d     | Case  | d     | Characteristic variables |
|--------------|-------|----------|-------|-------|-------|--------------------------|
| GRCmar       | 0,58  | GRCmay   | 2,71  | PRTaug| 5,16  |                          |
| PRTjun       | 0,77  | ESPapr   | 3,05  | ITAmar| 5,17  | c7 (9,49)                |
| GRCapr       | 1,16  | ESPaug   | 3,15  | UKRmay| 5,24  |                          |
| PRTjul       | 1,20  | ESPsept  | 3,18  | UKRapr| 5,25  | c6 (9,08)                |
| FRAmay       | 1,27  | ESPjul   | 3,31  | ROUapr| 5,41  |                          |
| POLapr       | 1,63  | GBRsept  | 3,32  | ITAapr| 5,45  | c1 (8,57)                |
| POLmay       | 1,64  | BELmay   | 3,35  | ESPoct| 5,64  |                          |
| GBRjun       | 1,70  | PRTmar   | 3,63  | DEUjun| 6,62  | c2 (7,74)                |
| GBRaug       | 1,76  | ROUmay   | 3,82  | GBRmay| 6,67  |                          |
| FRAapr       | 1,77  | DEUapr   | 3,89  | GBRapr| 6,86  | c5 (7,34)                |
| PRTmay       | 1,77  | NLDmar   | 4,09  | UKRoc  | 7,05  |                          |
| ESPmay       | 1,86  | ESPmar   | 4,18  | GBRmar| 7,20  | c3 (7,04)                |
| NLDmay       | 1,86  | CZEmar   | 4,23  | UKRsept| 7,52  |                          |
| FRAmar       | 1,90  | DEUmar   | 4,23  | UKRaug| 8,58  | c4 (6,79)                |
| GBRJul       | 2,30  | GRCoct   | 4,25  | ITAmay| 8,65  |                          |
| PRTapr       | 2,31  | BELapr   | 4,52  | UKRmar| 9,53  | c8 (4,35)                |
| NLDapr       | 2,37  | CZEmar   | 4,65  | UKRjun| 10,49 |                          |
| ROUmar       | 2,70  | BELmar   | 4,67  | ITAfeb| 70,64 |                          |

Note: cases ordered on the basis of d (distance from cluster’s centre).

* t-value in parentheses.

as Italy at the beginning of the crisis), or behind them (such as Poland after the summer), the major European countries had very similar reactions throughout the first coronavirus wave.

By synthetizing these countries’ behaviour in terms of the adoption of NPIs over the time considered, the CA allowed us to group the European countries into three clusters. While showing different levels of severity or lack of national restrictions, such clusters clearly identify three different stages of the so-called first wave. The first describes a pre-pandemic scenario, between January and February 2020, where no country, with the notable exception of Italy, adopted NPIs. The second cluster is characterized by the relaxation of restrictions and decrease in the severity of the outbreak that took place over the summer, when countries opened to international and internal...
movements. The third describes a deep lockdown scenario, with a number of restrictions put in place all over Europe, and a significant growth in observed cases.

In a nutshell, our study shows that these countries’ response to the first wave of the COVID-19 pandemic was less heterogeneous than is usually believed to be the case in terms of the policy mix of NPIs. Anecdotal evidence often creates the impression of country-specific strategies to counter the virus diffusion, a narrative that, with the important exception of Sweden, is not the story our analysis tells. The only further notable distinction is that Spain, Great Britain, Ukraine and Portugal did not enjoy the summer relief in restrictions and growth in cases experienced by other European countries.

The main issue that arises from the evidence provided in this paper is that, despite the political rhetoric and initial intentions, as well as cultural and institutional factors that significantly distinguish one European country from another, time is a crucial dimension of the COVID-19 outbreak. Indeed, the notable heterogeneity that initially emerged in the international debate regarding the best strategy to be adopted to fight COVID-19 seems to have been dramatically blurred when each country was faced with a certain threshold of the infection rate. This appears to be a useful policy lesson not only for the future, but also in the current search for the best way to emerge from the pandemic. In fact, at the time of writing this paper at the end of 2021, European countries are facing what has been identified as the fourth wave of the pandemic. In this context, about two years after the initial appearance of the virus, political debate on the best strategy to adopt seems to replicate some features of the political debate that took place in the spring of 2020, with the notable difference that politicians now have the possibility to consider a large set of measures and choices that other countries have adopted since.

It is worth noting that the issue of the choice of the mixture of NPIs and the centrality of time as a factor able to explain countries’ behaviour constitute a very current topic also in the context of the recommendations provided by the World Health Organization (WHO). Maria Van Kerkhove, COVID-19 Technical Lead for WHO, declared on 14 December 2021: “If we’re talking to governments right now, our message to governments is: don’t wait to act. […] So, we want governments to act now to take measures to increase vaccination coverage among those who are most at risk in all countries, as well as take measures to drive down transmission. This is about having policies in place to reduce the spread, wearing of a mask, physical distancing, improving ventilation, supporting people to work from home who can, and making sure you take measures to keep yourself safe when it comes to gatherings. There’s a lot of things that people can do to reduce the risk of spread when they come into contact with others.”

From a theoretical perspective the analysis of countries’ behaviour over the first wave reveals a very large ‘convergence’ in policy choices. This appears to be an exceptional event in the European Union, which, according to the mainstream narrative, as well as that of some scholars (Jörgens et al., 2014), has been characterized since its establishment by a notable heterogeneity of policy preferences. This is probably a partial and simplistic narrative: the peculiar features of the pandemic, which pose very similar issues for all countries, at some point force them to adopt very similar, if not identical, policy tools. If we look behind the output of this dynamic, it also suggests that a process of ‘policy diffusion’ took place. In this theoretical framework, the ‘economic competition’ hypothesis could offer a plausible explanation of the observed change in different countries’ behaviour. In fact, one could speculate that in an initial stage, countries that

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3 https://elpais.com/ciencia/2021-12-14/nos-enfrentamos-a-un-tsunami-de-infecciones-por-covid-en-el-mundo-tanto-de-delta-como-de-omicron.html.
had not yet experienced a high infection rate were worried principally about the economic costs of unprecedented limitations on social and economic life. Gradually increasing the internal growth rate and the number of countries adopting NPIs, governments may have differently perceived the negative externalities of such measures by partner countries and updated the evaluation of the cost-benefit ratio of their own adoption of similar measures.

Our result contributes to knowledge about policy spreading in Europe in the case of the first wave of the pandemic, and can be useful both from a national perspective, in terms of individual governments adopting the most efficient strategy, and from a supra-national perspective, as a means to understand and predict the spread of policies within a region. Further studies may try to extend the analysis to a larger number of countries or a longer timespan, or focus on the role of vaccination campaigns and the adoption of linked measures such as a ‘green pass’ or compulsory vaccination. Our framework might also be applied to successive waves of COVID-19, enabling a comparative study of countries’ behaviour. Our findings may also be used to provide a more effective framework for qualitative single country studies or small comparative studies of European countries.

Data availability statement

The datasets generated and/or analysed during the current study are derived from a public dataset, namely the Oxford COVID-19 Government Response Tracker (available at www.bsg.ox.ac.uk/covidtracker). These are public available.

Compliance with ethical standards

No funding was received in order to pursue this research. The authors declare no conflict of interest.

Authors’ contributions

The authors conceived the presented idea together, and jointly developed the theoretical framework and performed the computations.

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