



Assessing the effectiveness of public health interventions for Covid-19 in Greece and Cyprus

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Abstract

In this article, we statistically examine the effectiveness of non-pharmaceutical interventions (NPIs) implemented by the national governments of Greece and Cyprus during 2020 to (a) limit the spread of the SARS-CoV-2 virus, and (b) mitigate the economic fallout brought about by the Covid-19 pandemic. Applying a modified health belief model, we hypothesize that behavioral outcomes at the policy level are a function of NPIs, perceived severity, and social context. We employ a Prais-Winsten estimation in 2-week averages and report panel-corrected standard errors to find that NPIs have clear, yet differential, effects on public health and the economy in terms of statistical significance and time lags. The study provides a critical framework to inform future interventions during emerging pandemics.

KEYWORDS

Covid-19, Cyprus, Greece, non-pharmaceutical interventions, policy effectiveness

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1 | INTRODUCTION

Since the emergence of Covid-19 as a global pandemic, governments across the globe have implemented public measures in the form of non-pharmaceutical interventions (NPIs) to combat the spread of the SARS-CoV-2 virus. At the same time, NPIs have had adverse economic impacts (Deb et al., 2020), highlighting the imperative of saving public health even at the expense of restricting economic growth. The impact of the measures has varied across countries (Zahariadis et al., 2022) mainly due to the different economic structures and containment policies (Battistini & Stoevsky, 2021). This calls for more detailed studies in different contexts.

How effective have NPIs been in containing the pandemic and exacerbating (or not) economic performance? We use a modified health belief model (MHBM) and hypothesize that behavioral outcomes at the policy level, that is, changes in new cases and economic impact, are a function of interventions, perceived severity, and social context. We chose Greece and Cyprus to keep health capacity and cultural and institutional environments somewhat similar and focus more explicitly on NPI effects. The same model is used to answer both public health and economic questions, cognizant that NPIs are primarily geared toward mitigating pandemic health effects. Yet, we know they also have economic side effects and that measures that are effective must be well timed, targeted, temporary and transparent, whereas the existence of tradeoffs between loss of life and economic damages has been debated elsewhere (see Casey, 2020). In other words, there is very little that may be taken for granted when it comes to NPIs. By statistically assessing the effectiveness of NPIs and using the same model, we can estimate policy tradeoffs and capture nuances that the epidemiological literature cannot. We are not writing an epidemiological study; good ones already exist (e.g., Bo et al., 2021; Brauner et al., 2021; Flaxman et al., 2020). Instead, we conduct a policy study aiming to highlight tradeoffs between policy outcomes and NPI effectiveness.

We find that NPIs have a differential effect on public health and the economy and different impact at different lags, a finding that can inform future interventions during emerging pandemics.

2 | HOW EFFECTIVE ARE NPIS?

The voluminous literature on NPI effectiveness is primarily data-driven, public health-focused, and does not address policy trade-offs. The ecological study on NPI impact on transmission for the first 4 months (January–April 2020) of the pandemic in over 400 sites across 190 countries by Bo et al. (2021) found that NPI combinations are important, with social distancing being highly effective in curbing transmission. Utilizing “data-driven, cross-country modeling” in 41 countries, Brauner et al. (2021) studied the same issue for the first 5 months of the pandemic (January–May 2020) and found that school/university closures and targeted non-essential business closures were among the most effective NPIs. Similarly, Flaxman et al. (2020) analyze NPI impact on the transmissibility of Covid-19 for the same period across 11 European countries, finding a major effect of lockdowns.

Zooming into our cases, Agapiou et al. (2021) use various estimation procedures to chart different aspects of the pandemic in Cyprus. Projections therein are then used to build scenarios that would improve the understanding of the likely consequences of public interventions. Looking at Greece, Mavragani and Gkillas (2021) assess NPI impact between March–April 2020 building an autoregressive model to forecast Covid-19 cases and deaths. They find “a 7-day lag...[i]s the optimal time-intervention framework for the NPIs to come into effect” (11). Rachaniotis et al. (2021), using a pre/post-vaccination stochastic network model to stimulate reproduction rates, found that mask-wearing and telecommuting in Greece better managed the pandemic than rolling lockdowns.

Although the literature is methodologically sophisticated, it remains policy atheoretical with little attention to economic impact or policy tradeoffs. In addition, conclusions are drawn from a limited time frame (mainly the first wave), utilizing non-authoritative sources for NPIs (e.g., news articles) often without attention to scalar differentiation (e.g., Bo et al., 2021). We address these shortcomings by applying MHBM to assess NPI effectiveness on public health and the economy over the entire first year of the pandemic in Greece and Cyprus.

2.1 | The Health Belief Model (HBM)

The HBM is one of the most widely used social cognition models of health behavior. Developed originally in the 1950s to assess the effectiveness of U.S. health education programs (Rosenstock, 2005), HBM has since been applied to many national and cultural environments (Glanz & Bishop, 2010; Jones et al., 2015; Tarkang & Zotor, 2015). HBM links perception to action based on valence and expectations, arguing that behavioral change is the end result of rational evaluation of subjective threats and differing courses of corrective action.

HBM is underpinned by six components. Individuals will change behavior, for example, get vaccinated or stop smoking if they believe it has serious consequences (perceived severity); if they consider themselves susceptible to illness stemming from not modifying behavior (perceived susceptibility); if they believe that a given course of action will lead to positive outcomes (perceived benefits); and finally, if they perceive few negative barriers to their actions (perceived barriers) (Jones et al., 2015). HBM hypothesizes that social cues will facilitate the action of individuals. These can be interpersonal or environmental, such as advice from others or media campaigns (Champion & Skinner, 2003). Finally, depending on demographic variables, such as age or education, it asserts that self-efficacy, one's belief in the capacity to optimize performance, is a motivating factor that promotes initiating and maintaining behavioral change (Tarkang & Zotor, 2015).

Despite its wide application, the HBM has its critics. Jones et al. (2015) argue the model provides insufficient guidance as to the relative importance of the variables as well as any possible interactions among them. Moreover, its inability to distinguish between temporally distant cognitions as change moderators—for example, does severity pre-date cues for action?—tempers predictive capacity in health intervention settings. Nevertheless, scholars agree that despite mostly methodological limitations HBM provides a catalog of effective techniques that could enrich a theory-based technology of public health interventions (Abraham & Sheeran, 2005).

2.2 | Building a model of NPI effectiveness

While HBM is highly relevant to our research, it needs to be modified to better suit our purposes. We propose the following modifications:

- We are interested in explaining outcomes, not at the individual but at the policy level. Our model explores how government interventions induce the likelihood of behavioral change. We assume behavioral change is not directly observable, but it can be inferred by examining policy outcomes. We thus “black-box” the relationship between change and outcomes and

suppose that outcomes, for example, fewer new cases, result from behavioral changes that may (or not) be due to NPIs and other factors.

- Because the model is pitched at the policy level, individual beliefs are not directly discernible, but they are shaped by social context.
- We do not distinguish cues to action or benefits as separate variables but enrich other variables with these elements.
- Demographic characteristics and self-efficacy are set aside. The former is time-invariant in the short run and therefore irrelevant to our research design. The latter is impossible to capture at the policy level.

Hence, public interventions (NPIs) contain a mix of barriers, costs, and cues shaping behavior and, consequently, outcomes. NPIs structure barriers through cues discouraging or proscribing indicative behavior. They constitute costly disruptions in the rhythm of social life. Cost through deviations from accepted norms, such as fines, specifies the type and stringency of a barrier. The more stringent the NPIs are, the greater the expected behavioral change, and the bigger the economic or political risks are likely to be. Because NPIs have highly specific aims, the implication is that highly stringent NPIs will likely have more benefits, that is, reduce transmission of the disease, and more costs, that is, lower economic activity. In this way, NPIs are conceptualized as the stick, not the carrot, in public policy.

Public policy interventions are often triggered by a perceived threat, a combination of severity and susceptibility, as defined by the government. (see, e.g., Becker & Maiman, 1975). Such interventions may be part of a broader crisis management response to an event. As Boin, McConnell, and 't Hart note, “[f]aced with a crisis, politicians and public officials have to deal with the immediate threat or damage inflicted, but they also have to come to terms with the vulnerabilities and the public disaffection this may evoke” (2008, p. 4). Policy change (both when it comes to long-term change and short-term interventions such as the ones examined in this article) is not automatic in the aftermath of focusing events (Birkland, 2004; see also DeLeo et al., 2021; Petridou & Sparf, 2017). The mechanisms and appropriateness of policy change depend on political sensitivities and the broader political context of the crisis (Zahariadis et al., 2021).

Tradition or seasonal patterns of behavior shape what people do and affect policy outcomes. Benefits and cues to action are thus combined into a single construct, *social context*. For example, people are more likely to co-mingle during the summer, increasing the likelihood of transmission. This is even more probable in touristic places where locals benefit from creating an inviting and hospitable environment. Such behavioral patterns have public health and economic consequences. All in all, our MHBM predicts that the likelihood of behavioral change, and consequently policy outcomes, is a function of NPIs, perceived threat, and social context. To summarize the argument, we expect *the more stringent the NPIs and the more severe the perceived threat, the greater the likelihood will be to hinder disease transmission and exacerbate economic performance depending on social context.*

3 | RESEARCH DESIGN AND VARIABLES

Our time frame begins the week commencing March 2, 2020, marking the beginning of the pandemic in both countries, and ends with the week commencing December 28, 2020, when vaccines became available. The unit of analysis is the country fortnight. Cyprus started

vaccinating its population in early January of 2021 while Greece did in mid-January. The presence of vaccines in the toolkit of governments altered the dynamics of public policy and changed the calculus of estimates of NPI effectiveness. Some governments (and many people) considered the vaccines to be a cure, following the polio example, rather than mitigating the effects of the disease (Khular, 2020). We, therefore, anticipate a qualitatively different estimate of NPI effectiveness before and after the introduction of vaccines.

The use of fortnightly figures allows us to capture the non-instantaneous nature of the effects and the time lag before they are reflected in behavioral changes and ultimately outcomes. Daily effects are unlikely to have a discernible economic impact and weekly averages are still small and possibly statistically imperceptible. Two-week averages are the best short-term measurement to render effects big enough to have an impact on social life. Second, to our knowledge, economic outcome data are not collected on a weekly basis in either country. Economic activity (GDP) is reported on a quarterly basis, rendering the analysis too general and invariant given our short time frame. But industrial production figures, which account for roughly 13% of GDP in each country, are reported monthly. This is a good compromise to keep the public health and economy equations comparable in terms of time. All in all, we collect data for 22 fortnights in two countries ($N = 44$ observations).

Our study contains two dependent variables: confirmed new cases and industrial production index. Disease transmission is captured by the average confirmed new cases every fortnight per 100,000 inhabitants to mitigate differences in population size. We also include a control variable, the biweekly mean of new tests per 100,000 inhabitants, to account for the possibility of increases being due to more tests being done at that time. All values are converted to their natural logarithm to prevent heteroskedasticity due to a substantially diverse range of rates. Data are taken from the European Centre for Disease Prevention and Control (ECDC, 2021). Because change will not happen instantaneously, we empirically estimate NPI effectiveness by including various lags in our model: $t + 1$ (2), $t + 2$ (4), and $t + 3$ (6 weeks) after their introduction. While Covid-19 deaths or excess mortality are important aspects of the debate (e.g., Kapitsinis, 2021; Mendez-Brito et al., 2021), we opted not to use those figures. The main concern is that there is no theoretical reason why deaths should be more directly affected by NPIs than cases. As the World Health Organization (2019, p. 8) informs, NPIs “include all measures or actions ... that can be implemented to slow the spread of [pandemics such as] influenza in a given population.” In other words, they explicitly aim to reduce transmission but do not directly affect deaths as the latter depends on additional systemic factors, such as quality of care and access to ICUs, as well as individual-level factors, such as underlying medical conditions, age, etc. Our study explicitly excludes the latter, making it impossible to fully model such effects.

Used as a proxy, the industrial production index measures monthly fluctuations in economic performance. The baseline is 100 in both countries (2015) and measures monthly changes as deviations from that benchmark. Higher numbers show increased economic activity. Data are taken from the respective statistical agencies of each country (Cystat—Statistical Service of Cyprus, 2021; Elstat—Hellenic Statistical Authority, 2021).

Our independent variable of interest is NPIs. We use nine indicators for which we have complete data in both countries—three measuring different educational institutions. Data are drawn from the research program “Observatory of government restrictive measures for the COVID-19 pandemic” of the Center for Research on Democracy and Law at the University of Macedonia. It collects daily information on varying stringency of NPIs almost exclusively from national legislation from the beginning of the pandemic (Kyriakidis & Papadopoulos, 2020).

The nine indicators include restrictions in retail stores, mobility controls (excluding domestic or international air travel), the use of masks, limits in public gatherings, constraints in in-store food services (e.g., restaurants, bars, etc.), restrictions at the workplace (e.g., telecommuting), and restrictions in education (e.g., shutting down schools). We capture each NPI's stringency by adapting a scale of severity. For example, recommendations to avoid leaving one's home take the value "1." Partial restrictions, for example, only allowed out for specific reasons or only with members of the same household, are "2." Leaving with notification via text or written authorization is "3." And total restriction of movement is "4." We assign "0" to time periods when the measure is withdrawn or does not exist. The more stringent NPIs are and the longer they last, the greater the benefits for public health but with a likely worse economic impact. To capture nuance, most NPIs have a scale of 1–3. Mobility restrictions and the use of masks go up to 4 gradations, and limits of public gatherings are captured by 6 gradations.

For our purposes, the remainder are control variables. Perceived threat is a variable that combines susceptibility and severity. Because all humans are potentially susceptible to infection, severity matters. Severity is based on countries looking domestically to assess the seriousness of the pandemic,¹ using the natural logarithm of the fortnightly mean of new admissions to Intensive Care Units (ICUs) for each country per 100,000 (ECDC, 2021). Both Greek and Cypriot governments had an absolute priority to reduce transmission considering the pressure on feeble and understaffed health facilities. We record the value of the previous fortnightly period, $t-1$, to model the policy process. Policy-makers take time to absorb new information and deliberate as to the best possible course of action. This is concurrent with findings by other researchers (e.g., An et al., 2021, pp. 1167–1168), who suggest that optimal (in terms of efficiency) timing for adoption of NPIs differs depending on the NPIs and the stage the crisis (in this case the pandemic) is at, and that policy-makers should take this into consideration.

Social context is measured by way of two indicators. Tourism expects behavior during the summer months to substantially differ from the rest of the year because both countries rely heavily on income from tourism. They are likely to favor a more relaxed social environment to attract tourists, and the influx of individuals from abroad or domestic travel will likely result in more cases but have a more beneficial economic impact. Outcomes during the months of June, July, and August receive 1, 0 otherwise. Seasonality hypothesizes that Covid-19 follows a similar pattern to the flu to which the virus is strongly related. Therefore, the fall and winter months are more likely to see higher numbers of cases because people stay indoors, and the likelihood of infection increases in close proximity and enclosed areas. Outcomes during September through December receive 1, 0 otherwise.² Supporting Information: Appendix provides a summary of variables, their measurement, sources, and descriptive statistics.

4 | ANALYSIS

The design takes the form of time-series-cross-section (TSCS) data, 22 time periods for each of the two countries. The benefit of TSCS is raising the number of observations, thereby increasing the reliability of findings. The drawback is that such designs suffer from at least three problems (Beck & Katz, 1995): panel heteroskedasticity, contemporaneous correlation of errors, and serial correlation. In the presence of any one of those problems, ordinary least squares (OLS) estimations will be biased. When $T > N$, Beck, and Katz (1995) propose potential solutions. They recommend using OLS, assuming no serial correlation, with panel-corrected standard

TABLE 1 Non-Pharmaceutical Intervention coefficients using Prais–Winsten estimation and panel-corrected standard errors $N = 44$

	Confirmed new cases			Production index		
	2 weeks	4 weeks	6 weeks	2 weeks	4 weeks	6 weeks
Retail	-0.011	-0.40*	-0.35	-7.57**	1.99	6.01***
Freedom	-0.07	-0.25	-0.24	-3.28	2.1	1.01
Mask	0.5**	0.48**	0.42**	-0.39	0.56	0.18
Work	-0.35	-0.47	-0.22	-9.29**	3.22	10.35***
Public	0.12	-0.06	0.1	-1.53	1.7	2.32**
Food service	-0.22	-0.45*	-0.41*	-6.7***	0.63	5.25**
Edu-uni	-0.64	-0.89**	-0.92**	-8.77*	0.66	5.77
Edu-hs	-0.23	-0.53	-0.69*	-7.77*	1.08	2.49
Edu-ele	-0.85**	-1.06***	-0.86**	-11.39**	-0.94	4.87

* $p \leq 0.10$; ** $p \leq 0.05$; *** $p \leq 0.01$.

errors (PCSEs). The benefit of PCSEs is that they account for both heteroskedasticity and contemporaneous correlation. Because of the long T relative to N , we suspect that our data suffers from significant contemporaneous and possibly serial correlation. We know that countries generally experienced the Covid-19 crisis at roughly the same time and have introduced NPIs, such as the use of masks in closed areas to combat the disease at approximately similar time periods. The inclusion of only two units prevents us from using clusters, so we instead opt to report PCSEs. Beck and Katz claim they constitute a robust alternative to OLS standard errors. Monte Carlo evidence also suggests PCSEs are appropriate and generally the best estimators of hypothesis-testing when handling TSCS data of small to moderate size (Moundigbaye et al., 2018).

We then tested for serial correlation. The Wooldridge test came to a shade above the 0.05 level of rejecting the null hypothesis of no autocorrelation in 8 of our 54 equations (9 NPIs \times 2 dependent variables \times 3 lags), but below in the rest. Considering contradictory evidence, we opted to be cautious and correct for potential serial correlation mainly because it makes sense for theoretical reasons. The effects in the error terms over time are likely to be correlated because the emergence of new cases at time $t + 1$ is likely to an extent be a function of current cases and their capacity to spread the infection.

We used STATA 15.1 to implement all statistical commands and report PCSEs while correcting for a first-order autoregressive process (AR1). Results are reported in Table 1.

5 | DISCUSSION OF FINDINGS

Because the NPIs often coexisted, there is high collinearity among them; so, we assess their effects separately. The remaining variables are only weakly collinear, $VIF \leq 2.84$. The slopes are in the hypothesized direction in most cases. The NPIs measuring restrictions in education show the most consistent negative effects, confirming findings of other studies

(e.g., Brauner et al., 2021) that partial or total closure of schools had a significant effect in reducing the number of new cases. Unlike early work on the pandemic (e.g., Flaxman et al., 2020), our analysis shows restrictions in education for health reasons were very effective. Similarly, mobility restrictions were not as effective, confirming what some epidemiologists have found (Banholzer et al., 2021; Brauner et al., 2021). While Flaxman et al. (2020) find severe restrictions on mobility (lockdowns) had the largest negative effect on reproduction rates, we are unable to replicate their finding, concurrent with research such as An et al. (2021), although, again, timing may play a role in the effectiveness of NPIs. The difference may be due to measurement issues—they conceptualize lockdown as the most stringent NPI while we disentangle the construct into diverse instruments with various gradations—or because they look at January–May 2020. Unlike Banholzer et al. (2021) and Haug et al. (2020), we do not find statistical significance in banning large gatherings (public in our case). Other NPIs had only occasionally significant effects except for the use of masks. This may be explained by the difficulty of disaggregating the effects of using facial protection from other contagion mitigation behaviors at the individual level. Interestingly, our findings diverge from others like An et al. (2021), who find masks have strong negative effects on the transmission of cases. The reasons may be that we use a more robust, nuanced measure than the dummy variable they do, and we assess consistent effects over time rather than one-off early adoption instruments. Overall, it is clear that the impact of different NPIs on transmission rates, and even mortality rates (e.g., Kapitsinis, 2021), depends on a multitude of factors, including crisis-management preparedness, pre-existing policy, and healthcare conditions, and adoption intervals (An et al., 2021).

Shifting attention to economic impact, NPIs have a consistently strong negative effect within the first 2 weeks. For example, moving from recommending to imposing numeric or spatial limitations on businesses, e.g., only ten customers at a time or leaving tables empty in restaurants to separate customers, adversely affect output. In essence, telecommuting, the most stringent work restriction, has on average a strong negative impact in the short run (2 weeks) but a positive effect on industrial output in the long run (6 weeks) after some public subsidies. It appears that once workers get used to restrictions, they “return” to or exceed previous output levels. But statistically significant sign reversal happens with just a few NPIs, not including ones dealing with education.

We conclude that although NPIs have a differential impact on public health and the economy, some NPIs, especially in education, are successful in public health but in some instances detrimental to the economy. In examining the effect of lags on public health and the economy, we see that NPIs have a strong negative economic effect in the short run but reach statistical significance in public health mainly in the medium and long run. The data clearly illustrates the political dilemma, which has been documented in other studies in terms of its polarization effect (for Greece see Chatzopoulou & Exadaktylos, 2021). The Cypriot President knew there would be adverse economic consequences when stringency was increased to protect public health (Petridou et al., 2020). The same goes for Greece. As Alex Patelis, economic advisor to the Prime Minister, said, “the consensus was that the worse the health problem becomes, the worse the economic fallout will be” (quoted in Psaropoulos, 2020). However, our analysis shows bad economic news precedes any behavioral change, likely because of the uncertainty of what might follow. Industrial production falls in anticipation of difficult times ahead. This implies that people’s perceptions change more quickly than their behavior.

6 | ROBUSTNESS CHECKS

Although we have theoretical and methodological reasons for choosing which estimation to use, robustness checks and, more importantly, the presentation of alternative specifications strengthen confidence in the results (Wilson & Butler, 2007). Given the low degrees of freedom in our study, this is good advice.

There are two alternative estimations in TSCS data: fixed effects (FE) and random effects (RE). We ran the Hausman test to determine which model may be appropriate. The inability to reject the null hypothesis of no correlation between regressors and effects prompted us to use RE. Besides, the very low number of units and the likely interesting differences between Greece and Cyprus caution against using FE. We ran an RE model using the `xtgls` command correcting for autocorrelation and compared it to the PCSE model. Reed and Webb (2010) find PCSE's to be less efficient relative to Generalized Least Squares (GLS) estimation in long TSCS data with a high T/N. To further assess the effects of heteroskedasticity (if any), we fit the GLS model assuming homoskedasticity. If the results are not robust, there should be substantial differences between the two estimations.

Table 2 exhibits the results, using restrictions in university education (4-week lag) as an illustrative example. The significant Wald's χ^2 in both estimations suggests a good model fit. The high R^2 in the PCSE estimation shows the model explains 62% of the variance in new cases. The coefficients in both estimations are in the hypothesized direction and identical with a slight difference in standard errors. Moving from partial restrictions in universities, for example, social distancing, and mandatory masks indoors, to complete shutdowns and online teaching reduces the number of new cases per 100,000 by 58% [$\exp(-0.8875) - 1 \times 100$]. Given that the average number of cases per 100,000 in both countries is 55.8 (4-week lag), the actual decrease is a substantial average of 32.4 new cases per 100,000, ceteris paribus. Because students do not congregate in closed spaces, the chances of infection decrease and, therefore, the number of

TABLE 2 Robustness checks ($N = 44$)

	<u>Confirmed new cases (4 weeks)</u>		True infections	Sales retail index
			(4 weeks) ^a	(2 weeks)
	AR(1)		AR(1)	AR(1)
	(PCSE)	(GLS, RE)	(PCSE)	(PCSE)
Education-Uni	-0.89 (0.41)**	-0.89 (0.37)**	-0.7 (0.3)**	
Retail restrictions				-7.52 (2.17)***
Tourism	-1.21 (0.44)**	-1.21 (0.37)***	-1.1 (0.32)***	0.82 (4.6)
Seasonality	1.53 (0.48)***	1.53 (0.42)***	1.64 (0.35)***	2.4 (5.39)
New ICU cases	0.011 (0.10)	0.01 (0.11)	-0.04 (0.08)	1.52 (1.14)
New tests	0.23 (0.11)**	0.23 (0.11)**	0.13 (0.08)*	
Constant	2.77 (1.27)**	2.77 (1.17)**	2.01 (0.92)**	123.02 (6.3)***
Wald χ^2	53.06***	72.09***	77.66***	17.27**
R^2	0.62		0.71	0.68

^aInstitute for Health Metrics and Evaluation model mean estimates of infections.

* $p \leq 0.10$; ** $p \leq 0.05$; *** $p \leq 0.01$.

new cases will likely go down albeit with a delay of 4 weeks. While perceived threat does not seem to have a statistical influence on new cases, the social context makes a difference. The coefficients for tourism are not in the hypothesized direction, that is, during the summer months, new cases went down significantly whereas new cases increased, as expected, during the fall and winter—although this may be explained partly by the higher number of tests conducted.

To check robustness, we also explore different ways to measure the dependent variables. Table 2 presents the results from two models. Instead of measuring confirmed new cases, which some consider under-reported (Noh & Danuser, 2021), we took the biweekly logged mean estimate of “the true number of infections” per 100,000 derived from the Institute for Health Metrics and Evaluation (IHME) (Our World in Data, 2021). IHME’s hybrid model uses statistical and disease transmission elements, such as fluctuation in human mobility, social distancing, population density, age, obesity rates, and pneumonia seasonality, to produce forecasts of what infections and fatalities may be in a given location at a particular time. The results are identical in hypothesized direction and, to an extent, strength with our previous models. Restrictions in higher education still lower “true infections,” but by 50% (as opposed to 58) on average per 100,000 population.

We realize that neither Greece nor Cyprus are major industrial producers, limiting the economic generalizability of our findings. We, therefore, assessed the effectiveness of NPIs on the volume of retail sales index (contributing 11%–12% to annual GDP) excluding motor vehicles (Eurostat, 2021). The index (base year is 2015) better represents the consumption side of the economy and might, therefore, be more susceptible to NPIs. Although the constant term accounts for a significant amount of the variation, restrictions on retail trade have unsurprisingly a strong, negative immediate effect (2 weeks), as the results show on Table 2. As restrictions go up, retail sales decrease, confirming the finding regarding production—the difference between the coefficients in Tables 1 and 2 is 0.05. The effect dissipates in 4 weeks (not significant) and, with help from public subsidies, reverses sign and is statistically significant in 6 weeks (not shown). The help of public subsidies is important. Despite public health costs, by March 2021 Prime Minister Mitsotakis had pumped €11.6 billion in aid to businesses and jobs to mitigate the economic impact of the Covid-19 pandemic (Reuters, 2021). Our results are robust across estimations and alternative measurements.

7 | CONCLUSION

How effective are NPIs in lowering new Covid-19 cases and mitigating economic fallout? We applied an MHBM to Greece and Cyprus during 2020 and arrived at robust results that NPIs have a differential impact on public health and the economy in terms of statistical significance and time lags. Our findings have implications for theory and policy.

In the field of evaluation, which is generally data-driven and focuses more on methods than theory, we applied the MHBM to illuminate the effectiveness of public action. We confirm the literature’s findings (Abraham & Sheeran, 2005) that barriers and cues (NPIs in our case) are a strong and consistent predictor of behavioral change—significant in 22 of 54 equations. We also confirm that cues for action and benefits make a difference in all but five of our equations, as part of the social context construct. But we are puzzled by the lack of confirming perceived threats as a statistically significant predictor in 51 of 54 equations. It does not mean that threats do not matter; politicians often invoked them to legitimize politically controversial

interventions or avoid blame for possible failures (Zahariadis et al., 2020). But the indicator did not have the consistent, strong effect we expected. Pandemics develop their own dynamic policy environment over time and act as drivers of behavioral change no matter how long or intense they are. This matter needs further investigation.

Our study is limited to only two countries, so the findings merit replication in other national settings. We also assumed that policy outcomes are the result of behavioral change. While “black-boxing” this relationship served our purpose, others may want to unpack it. Does behavioral change actually lead to desired outcomes and under what conditions? Finally, the low number of degrees of freedom precluded us from exploring interactions among NPIs. The effects of one NPI may be partially attributed to another implemented at the same time (Banholzer et al., 2021). Is there an optimal mix that maximizes health benefits and limits economic costs?

Our model shows that NPIs work. They have the desired effect, lowering the number of new cases, but their effects only show up in the medium to long term (4–6 weeks). That is good news from a public health point of view but not from a political perspective. Politicians know well that NPIs that “save” lives also economically “harm” them. NPIs are unpopular, especially long-lasting ones, because of the severe impact on a country’s economy and social life, and the potential political costs involved. We show that the tradeoff is very harmful because the country bears the economic cost first before it sees the public health benefits. As the pandemic lingers, the tradeoff becomes less beneficial because of “NPI fatigue” and citizens may comply less. Our study shows economies are resilient, and they do, on average, bounce back, but that assumes public aid, for now, and similar levels of compliance to NPIs. If NPIs are significantly relaxed, the public health benefits may dissipate with unpredictable economic consequences.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

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ENDNOTES

¹ We also theorized that policy-makers look to other countries to assess severity. There are instances when the Greek Prime Minister, for example, mentioned the example of Italy as *the* reason for adopting harsh measures to limit the spread of the infections (Zahariadis et al., 2020). We counted the mean bi-weekly number of new cases (logged per 100,000) in each country’s peer or aspiration group, that is, countries that the government tracks regarding the pandemic or thinks they are models to emulate or avoid. For Greece, the group includes Italy, France, and Germany. For Cyprus, the group includes Greece and the United Kingdom. Unfortunately, this indicator was highly collinear with seasonality ($vif = 7.56$), so we dropped it.

² We also hypothesized a more nuanced approach and predicted different behavior depending on festivals and national holidays. For example, during religious holidays, Easter or Christmas, people will likely want to congregate in churches or travel to traditional destinations, like the island of Tinos in Greece on August 15, regardless of government NPIs. We, therefore, anticipated cases to increase and the economy to briefly pause. However, the indicator was hardly significant in most cases and we decided to drop it.

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