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IZA DP No. 13927

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ABSTRACT

Interventions with Positive Side-Effects: COVID-19 Non-Pharmaceutical Interventions and Infectious Diseases in Europe

To assess the efficacy of Covid-19 non-pharmaceutical interventions (NPIs) on infectious disease containment in Europe, we first use weekly 2015-20 data on the spread of influenza and respiratory syncytial virus (RSV) to compare the 2019-20 season of these diseases with the previous five. Although the magnitude of results differs between countries, we document much stronger end-of-season declines in infections in the most recent outbreak than in the earlier ones, implying that they may be driven by NPIs implemented in 2020 to combat Covid-19. To test this conjecture, we use detailed country-specific weekly information on Covid-19 NPIs to estimate several panel models that relate NPI implementation to disease incidence across countries. Not only do certain measures significantly reduce the spread of Covid-19, they also curtail the spread of influenza and RSV. Nonetheless, although we identify workplace closures as a particularly effective measure, we find no evidence for the efficacy of other NPIs such as travel restrictions.

JEL Classification: H30, H23, H12, I18

Keywords: non-pharmaceutical interventions, infectious diseases, Europe, COVID-19

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Interventions with Positive Side-Effects: COVID-19 Non-Pharmaceutical Interventions and Infectious Diseases in Europe[1]

1. Introduction

According to recent research, mitigation measures against Covid-19 have had at least one unforeseen positive outcome: no apparent 2020 flu season in the southern hemisphere (*Economist,* 2020), and a particularly mild one in Europe, with much lower influenza activity and at least a 2 week shorter duration than in the previous 3 seasons (Goerlitz et al., 2020). Germany's Robert Koch Institute (RKI) attributes this shortening to the nationwide measures to contain and slow Covid-19, whose transmission methods resemble those of influenza. In particular, given children's essential role in spreading the annual flu, the RKI hypothesizes that school closings from the 12th week of 2020 may have contributed to the influenza decline in Germany.

Nonetheless, despite ample anecdotal evidence of nonpharmaceutical Covid-19 interventions (NPIs) influencing the spread of non-Covid-19 infectious respiratory diseases, few studies directly address this issue. One analysis of 2020 US laboratory surveillance data does document at least a 20% decline in respiratory syncytial virus (RSV) transmission in the US at the start of the NPI period (Baker et al., 2020). Likewise, an intervention analysis using a spatiotemporal regression model to compare multiple possible drivers of decreased influenza in the US associates a smaller 2019-2020 influenza season and earlier decline with the increase in Covid-19 risk perceptions or increased isolation (Zipfel and Bansal, 2020). A study for China also shows a 64%

1 We would like to thank Maddalena Ferranna for valuable comments on an earlier version of this paper.

reduction in the 2019-20 mean influenza post-Covid-19 preventive NPIs implementation, which is significantly higher than the reported efficiency of single anti-flu interventions like school closures and community use of facemasks (Lei et al., 2020). An analysis of influenza surveillance data for outpatients of all ages and hospitalized children in Hong Kong records a similarly positive 44% reduction in community transmissibility following implementation of social distancing measures and changes in population behaviors in late January 2020 (Cowling et al., 2020).

Nonetheless, although assessing the effect of Covid-19 NPIs on other respiratory infections is interesting in its own right, such analysis may also provide valuable information about their efficacy for Covid-19 infections. One major difficulty in this endeavor, however, is the short time that the Covid-19 virus has been in circulation (mostly since early 2020 in Europe), which prevents determination of NPI effectiveness using long time-series. Given no data from previous seasons and limited information from (often insufficient) testing, documentation, and reporting practices that vary over time and between countries (Sridhar and Majumder, 2020), most analyses of Covid-19 related NPI efficacy employ mathematical models. This modeling approach, however, is the subject of much debate regarding model validity and limitations for policymaking (Hunter, 2020; Sridhar and Majumder, 2020). Modeling results may thus be less useful than empirical evidence on the (non-)efficacy of currently applied NPIs (Hunter, 2020). In this study, therefore, we employ long time-series data for Europe on two infectious diseases with similar properties to Covid-19 – influenza and RSV − to assess whether and to what extent specific NPIs can control Covid-19 infections.

Our findings make two contributions to the literature: First, our direct measurement of NPIs is particularly important to determining any causal relation between NPIs and infectious respiratory diseases. Although comparing periods with and without NPIs is informative, actually measuring the type of NPI and its strength provides a more differentiated picture and a more convincing causal analysis. Second, not only is our study possibly the first of its kind for Europe, but this region is particularly useful for analysis because of the large degree of NPI variation among its member states.

2. Data and Methodology

Our dataset, compiled from the *Surveillance Atlas of Infectious Diseases*,[2] comprises weekly country-level data on influenza and RSV[3] for all EU countries (except Malta) between January 2015 and September 2020 (see Table 1), with total number of positive samples differentiated from positivity rate (proportion of positive specimens to total). It should be noted that our dataset, rather than reflecting the actual incidence (or prevalence) of a disease in each country, represents reports from selected sentinel primary health care providers (mostly general practitioners), with only a subset of sentinel patients tested for influenza.[4] These same European Center for Disease Control (ECDC) data are used successfully elsewhere to assess NPI effects on Covid-19 containment (Hunter et al., 2020).

To measure the impact of NPIs on infections in EU countries, we rely on the Blavatnik School of Government's Oxford Covid-19 Government Response Tracker (OxCGRT), which produces daily ratings of the nature and degree of different government responses to the ongoing pandemic on a 100-point scale (0 "no response" to 100 "strong

[2] European Center for Disease Control [ECDC], Surveillance Atlas of Infectious Diseases: https://www.ecdc.europa.eu/en/surveillance-atlas-infectious-diseases for more details.

[3] These data are provided by the European Influenza Surveillance Network (EISN) and collected through the European Surveillance System (TESSy). Although we also compiled data on rubeola and rubella, low overall prevalence and resulting low data validity prevented analysis of these two diseases.

4 This choice, rather than being medical or epidemiological, was necessitated by their being the only infectious diseases for which the ECDC database currently provides monthly or weekly data.

response"). Our analysis employs three OxCGRT ratings (as reported daily up until September 2020): the *government response index*, which serves as a proxy for overall response, and the *containment and health index* and *stringency index,* which cover specific sets of pandemic-related measures (see Table 1). To capture social distancing measures in more detail, we also analyze the impact of eight nonpharmaceutical interventions (also reported daily by the OxCGRT): closing of schools, workplaces, and public transport; restrictions on gatherings, internal movement, and international travel; public event cancelation, and stay at home requirements (see Table 2). Whereas coding of the overall indexes ranges between 0 and 100 (from no to strong response), each NPI rating follows an ordinal scale from 0 (no intervention) to 4 (maximum level of intervention). Combining the two data sources yields an initial sample size of about 7,000 observations, which missing values and different model specifications reduce to between 1,161 and 4,520 observations, depending on the specified parameters.

Table 1: Infectious respiratory diseases and nonpharmaceutical interventions studied

Outcomes / NPI	Reporting	Period (week no./year)	Description	Coding
Infectious diseases				
Influenza virus sentinel specimens	Weekly	01/2015-34/2020	Number of sentinel specimens positive for influenza virus at the country level	Cases
RSV sentinel specimens	Weekly	01/2015-34/2020	Number of sentinel specimens of RSV at the country level	
Influenza virus sentinel positivity rate	Weekly	01/2015-34/2020	Share of positive sentinel specimens at the country level	% share
RSV sentinel positivity rate	Weekly	01/2015-34/2020	Share of positive sentinel specimens at the country level	
Nonpharmaceutical intervention indexes				
Government response index	Daily	01/01/2020-26/09/2020	Records how the government response has varied across all indicators in the OxCGRT database	Units between 0 (no response) and 100 (full response)
Containment and health index	Daily	01/01/2020-26/09/2020	Records lockdown restrictions and closures with measures such as testing policy and contact tracing, short-term investment in healthcare and investment in vaccines	
Original stringency index	Daily	01/01/2020-26/09/2020	Records the rigor of the lockdown restrictions that primarily affect individual behavior	

Source: Oxford Covid-19 Government Response Tracker (2020) and ECDC (2020).

For a more detailed description, see https://www.ecdc.europa.eu/en/surveillance-atlas-infectious-diseases and

https://github.com/OxCGRT/covid-policy-tracker/blob/master/documentation/index_methodology.md

Table 2: Social distancing measures

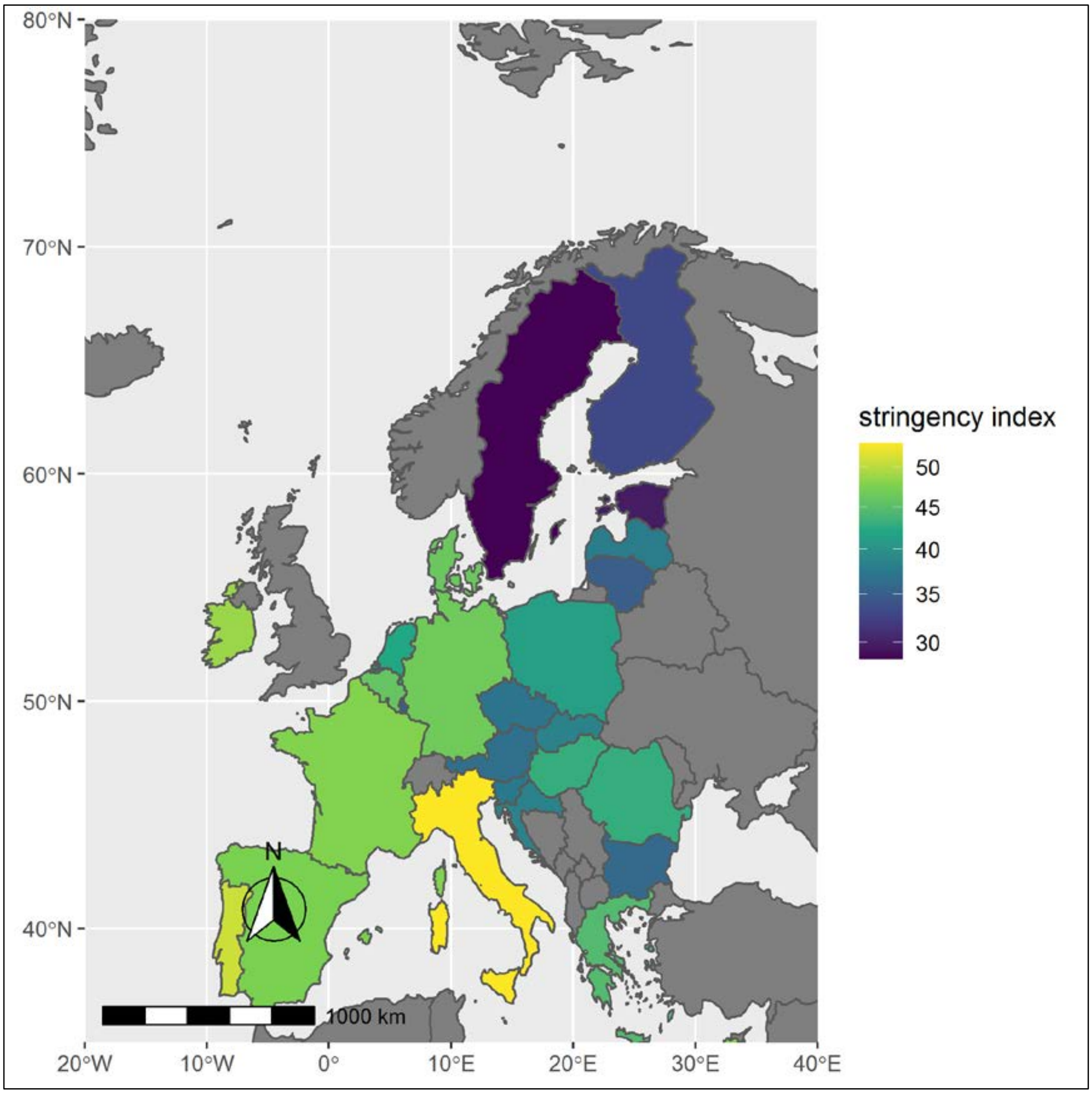
	Workplace closings (WPC)	School closings (SC)	Cancelation of public events (CPE)	Restrictions on gatherings (RG)	Public transport closings (CPT)	Stay at home orders (SH)	Restrictions on movement (MR)	Travel controls (TC)
Reporting type	Daily	Daily	Daily	Daily	Daily	Daily	Daily	Daily
Period	01/01/2020-26/09/2020	01/01/2020-26/09/2020	01/01/2020-26/09/2020	01/01/2020-26/09/2020	01/01/2020-26/09/2020	01/01/2020-26/09/2020	01/01/2020-26/09/2020	01/01/2020-26/09/2020
Description	Recorded workplace closing	Recorded school and university closings	Recorded canceling of public events	Recorded limits on private gatherings	Recorded closings of public transport	Recorded orders to shelter in place and otherwise confine to the home	Recorded restrictions on internal movement between cities/regions	Recorded restrictions on international travel (for foreign travelers)
Coding method	0 no measures 1 recommended closing (or recommended work from home) 2 required closings (or work from home) for some sectors or categories of workers 3 required closings (or work from home) for all-but-essential workplaces (e.g. grocery stores, doctors)	0 no measures 1 recommended closing 2 required closing (only some levels or categories, e.g. just high school, or just public schools) 3 required closing all levels	0 no measures 1 recommended cancelation 2 required cancelation	0 no restrictions 1 restrictions on very large gatherings over 1,000 2 restrictions on 101-1,000 3 restrictions on 11-100 4 restrictions on 10 or fewer	0 no measures 1 recommended closings (or significantly reduced volume/route/means of transport) 2 required closings (or prohibited use for most citizens)	0 no measures 1 recommended not to leave house 2 required not to leave house with exceptions for daily exercise, grocery shopping, and essential trips 3 required not to leave house with minimal exceptions (e.g. allowed to leave once a week, or only one person at a time)	0 no measures 1 recommended not to travel between regions/cities 2 restricted internal movement	0 no restrictions 1 screening arrivals 2 quarantine arrivals from some or all regions 3 ban arrivals from some regions 4 ban arrivals from all regions or total border closure

Source: Oxford Covid-19 Government Response Tracker (2020).

For more information see: https://github.com/OxCGRT/covid-policy-tracker/blob/master/documentation/index_methodology.md

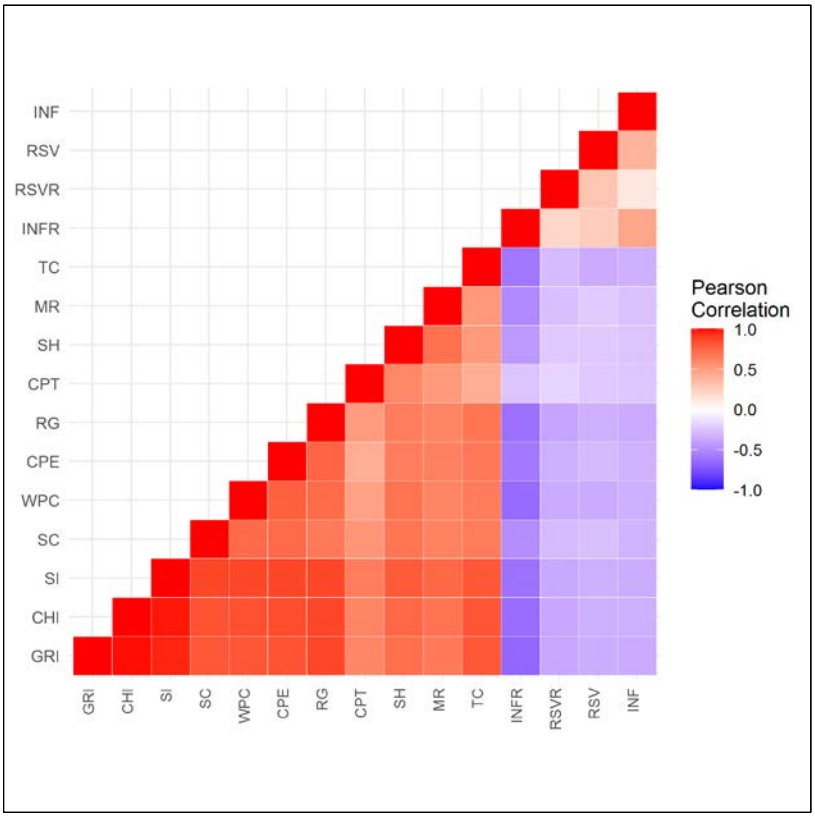
In addition to measuring the effects of the three indexes listed in the lower half of Table 1, we also estimate the impacts of the eight social distancing measures outlined in Table 2. Figure 1, which graphs the stringency index for the 26 EU countries in our dataset, underscores the notable differences in the degree of lockdown restrictions and closures adopted since the pandemic began, the largest being in Italy (56), Portugal (53), and Germany (51) with the relatively weakest in Estonia (29), Sweden (32), and Finland (34). To better illustrate these differences, in Figure 2, we compile a heat map of the correlations between all the aggregated indexes and the disaggregated measures that comprise them, as well as between the influenza and respiratory disease infections and the positive rate of the laboratory tests examined. On the one hand, the aggregate indexes (government response index, containment and health index, original stringency index) correlate strongly and positively with each other but somewhat less strongly with the individual measures. For example, the government response index shows a correlation of 0.96 with the stringency index but only 0.8 with school closures. Unsurprisingly, we also observe a strong positive correlation among the four infectious disease measures, with the highest correlation for influenza cases and the influenza positivity rate (correlation of 0.46) and the lowest correlation between influenza cases and the RSV positivity rate (0.12). On the other hand, the indexes and individual measures show negative correlations of between -0.2 and -0.36 with influenza and RSV cases, with the strongest (darker blue) being between workplace restrictions (-0.64), gathering restrictions (-0.62), and travel controls (-0.59) and the positive rate of influenza laboratory tests.

Figure 1: Average stringency index in 2020 for all countries for which it is available.



Source: Based on data from Oxford Covid-19 Government Response Tracker (2020) and ECDC (2020).

Figure 2 Correlation heatmap showing the Pearson correlation among all variables in the sample for 2020.



Source: based on data from Oxford Covid-19 Government Response Tracker (2020) and ECDC (2020).

To estimate the effect of NPIs on the number of infectious respiratory diseases, we rely on the following two specifications:

$$x_{cwy} = \beta NPI_{cwy} + \gamma_c + \delta_w + \alpha_y + \varepsilon^i_{cwy} \quad (1)$$

$$x_{cwy} = \beta NPI_{cwy} + \gamma_c + \delta_w \times \alpha_y + \eta^i_{cwy} \quad (2)$$

$$x \in \{Rates, Cases\}$$

$$\varepsilon^1_{cwy} \text{ and } \eta^1_{cwy} \sim N(\mu, \sigma) \qquad \varepsilon^2_{cwy} \text{ and } \eta^2_{cwy} \sim NB(r,p)$$

We then determine any causal relation between each disease positivity rate (cases) and the degree of a specific NPI_{cwy} (weekly averages of the daily reported values in our sample) in country *c* in week *w* and year *y* by estimating two different fixed effects models, one standard and one negative binomial. The first assumes a normally distributed i.i.d. error term ($\varepsilon^1_{cwy}\ and\ \eta^1_{cwy}$) and the second, a negative binomially distributed one ($\varepsilon^2_{cwy}\ and\ \eta^2_{cwy}$), a necessary choice given our count data and signs of data overdispersion (Lloyd-Smith et al. 2005). We use these models to estimate the impact of NPIs on positivity rates (*Rates)* and number of positive specimens (*Cases*), respectively. Last, to properly account for the panel structure of our data, we include country γ_c together with year α_y and week δ_w fixed effects, using the latter two first as additive dummies (Equation 1) and then as an interaction term (Equation 2). Whereas the former allows identification of the average causal deviations from seasonal influenza and RSV trends across all countries and all years, the latter more precisely and explicitly addresses potential confounding factors for the year 2020. Hence, whereas the identification strategy for Equation (1) assumes the same weekly seasonal pattern of influenza and RSV over all years, that for Equation (2) more rigorously allows for (and assumes) different seasonal patterns over all years that could be caused by confounding factors. In performing these calculations, because the incidence of influenza and RSV shows a highly seasonal pattern, we follow the ECDC definition of the influenza season and restrict our analysis to observations from the 40th to the 20th calendar week (of the following year).

3. Results

In Figure 3, we map the trend of influenza and RSV cases for calendar weeks 10 to 20 aggregated on the level of the 26 EU countries, with black (red) lines representing the trend for 2015‒2019 (2020) and the blue line depicting the stringency index for 2020. We focus on the stringency index because it best captures the containment and closure policies most likely to directly affect the spread of influenza and RSV. The other two indexes, in contrast, include additional nonhealth-related information, such as the (non-)provision of income support or emergency investment in health care (see https://github.com/OxCGRT/covid-policy-tracker for more details). As Figure 3 clearly illustrates, simultaneous with the sharper decline in influenza and RSV in 2020 that holds at an almost constantly lower level than in previous years, the stringency index increases sharply and maintains this high level from around week 13 onward. The index's relation to the proportion of positive laboratory tests (Figure 4) is very similar, a strong indication that lockdown measures have led to a more rapid and stronger decline in the infectious respiratory diseases analyzed. The trend of the red line also indicates an earlier end to the 2019-20 influenza season than in previous years.

Figure 3: Influenza and RSV cases for all countries relative to the NPI stringency index, with black (red) lines indicating 2015-2019 (2020). The blue line depicts the stringency index.

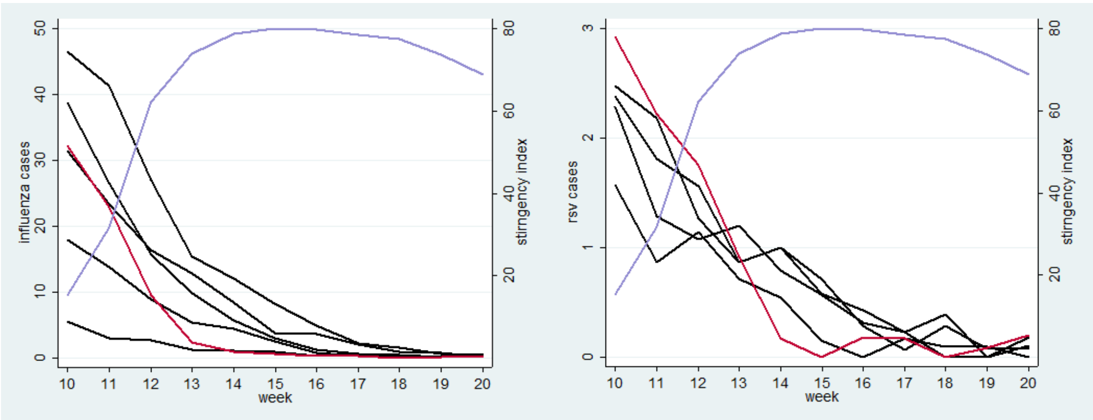
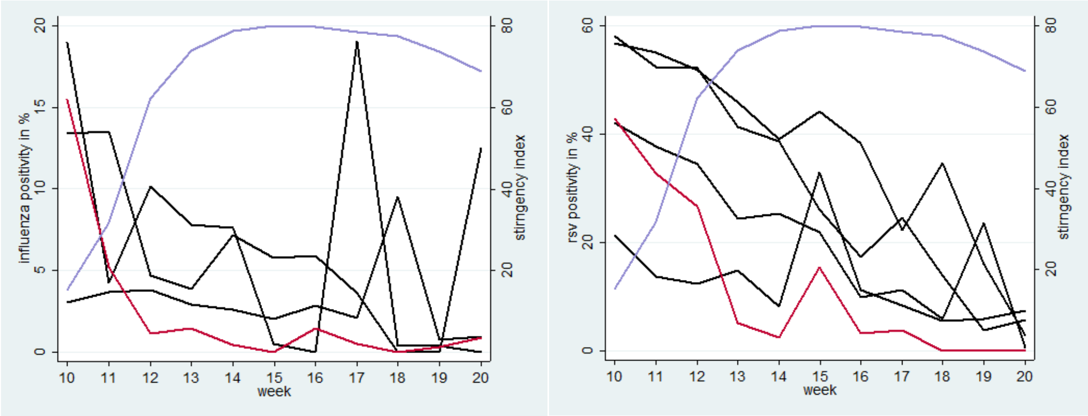


Figure 4: Influenza and RSV positivity rate for all countries relative to the NPI stringency index, with black (red) lines indicating 2015-2019 (2020). The blue line depicts the stringency index.



In Figures 5 and 6, we illustrate the influenza and RSV trends in two countries whose NPI responses to the pandemic were notably different: Sweden and Italy. Whereas Sweden had a relatively low NPI stringency, reaching its maximum of 48 in week 15, Italy's stringency index reached a value of 95 in week 13 and remained high until week 18, before falling to 65 by week 20. With the implementation of NPIs, however, both the cases and the rates of influenza declined in both countries, although the decline in Italy was substantially stronger (relative to past years) than that in Sweden (see the Appendix for corresponding figures for Germany, Spain, and France).

Figure 5: Influenza cases and positivity rate for Sweden relative to the NPI stringency index, with black (red) lines indicating 2015-2019 (2020). The blue line depicts the stringency index.

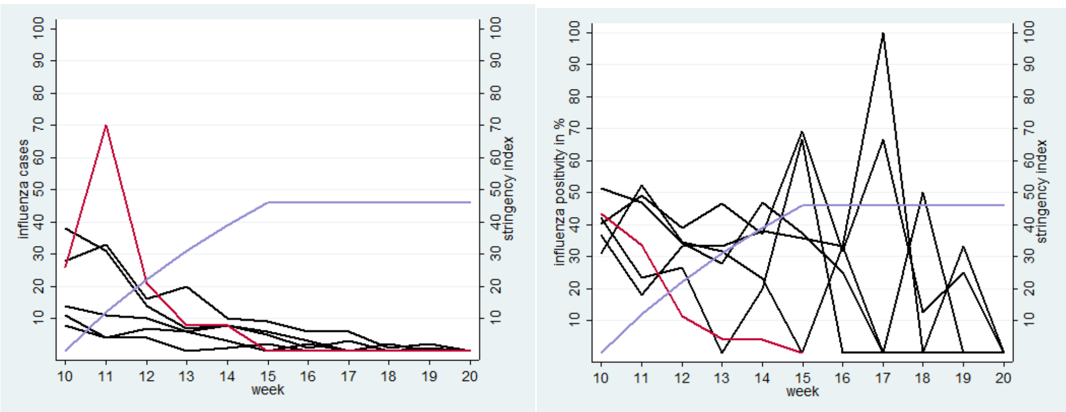
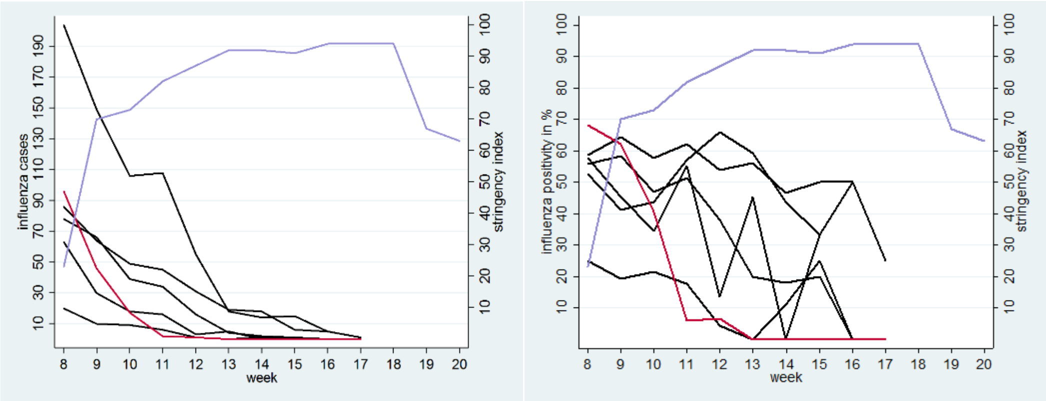


Figure 6: Influenza cases and positivity rate for Italy relative to the NPI stringency index, with black (red) lines indicating 2015-2019 (2020). The blue line depicts the stringency index.



To control for the seasonal effects of infection patterns, the specifications in the first multivariate analysis (Table 2) include years and weeks as separate dummy variables, meaning that for any given week (e.g., calendar week 1), the dummy variable indicates the average weekly effect over the study period (i.e., the average effect of calendar week 1 over 2016-2020). In addition to fixed effects models (columns (a) and (b)), we also estimate negative binomial fixed effects models (columns (c) and (d)). As models (1) to (3) clearly show, the results for all three aggregated indexes have negative coefficients, which are highly significant both in the fixed effects model with influenza as the dependent variable (column (a)) and the two negative binomial fixed effects models (columns (c) and (d)). In model (4), which uses the eight individual lockdown measures that comprise the stringency index as separate independent variables, workplace closures have a strongly significant negative effect on number of influenza cases (column (a)), but no other measures are significant. Workplace closures also have a significant negative effect in the negative binomial fixed effects model with influenza as the dependent variable (column (c)), but again, no other measures are significant. In the models examining the NPIs' effects on RSV (columns (b) and (d)), none of the eight lockdown measures has a significant effect. We also note that the point estimates for the school closings variable are negative, but insignificant at conventional levels. However, without the Bonferroni correction (which is known to be conservative), significance can be observed.

The magnitude of the effects is best illustrated using the standard fixed effects model (Table 2, specification 1), in which a one standard deviation increase in the stringency index (in 2020) leads to an approximately 6.23 percentage point decrease in the influenza positivity rate. Given that the average positive rate for influenza in our sample during the first 20 weeks of 2020 is about 36%, this decline represents an approximately 20% decrease in the influenza positivity rate. Focusing again on Sweden and Italy, the estimated difference between this positivity rate and the observed differences in these countries' stringency index is -5.5 percentage points. That is, hypothetically, if Sweden had implemented the NPI with the same stringency as Italy, it could have reduced the positivity rate by about 10% based on the around 41% average influenza positivity rate observed for the first 20 weeks of 2020 in Sweden. The effect size of workplace closing on influenza can also be best illustrated by the FE model (column (a)): a change from no measures (level 0) to a full lockdown (level 3) reduces the positivity rate by about 40 percentage points – which is substantial considering the average positivity rate in the first 20 weeks of 2020 in all EU countries was about 40%.

Table 2: Fixed effects regression estimates: Specification I

	Model specification			
	(a) FE	(b) FE	(c) Negative binomial	(d) Negative binomial
	Disease			
	Influenza sentinel (positivity)	RSV sentinel (positivity)	Influenza sentinel (positive specimens)	RSV sentinel (positive specimens)
	Reporting: weekly			
Index	Period: calendar week 40 to 20			
	Model (1)			
Government response	-0.2417***	-0.0616	-0.0150***	-0.0121***
	(0.063)	(0.037)	(0.002)	(0.004)
	Model (2)			
Containment and health	-0.2283***	-0.0622	-0.0139***	-0.0114***
	(0.060)	(0.037)	(0.002)	(0.004)
	Model (3)			
Stringency	-0.2214***	-0.0547	-0.0142***	-0.0110***
	(0.059)	(0.033)	(0.002)	(0.004)
Subindex	*Model (4)*			
Workplace closings	-13.3764***	-0.4212	-0.8793***	-0.5836
	(3.679)	(0.825)	(0.210)	(0.377)
School closings	-3.3651	-0.7318	-0.3917	-0.3467
	(2.975)	(1.338)	(0.183)	(0.352)
Cancelation of public events	4.3064	-0.9398	0.2937	0.6082
	(4.447)	(2.014)	(0.215)	(0.444)
Restrictions on gatherings	3.2718	-0.8373	0.1234	-0.3201
	(1.843)	(0.873)	(0.100)	(0.170)
Closing of public transport	6.3025	-1.1175	0.1507	-1.1887
	(4.143)	(0.923)	(0.265)	(0.789)
Stay at home orders	1.5946	-0.0783	0.1830	0.4149
	(4.152)	(1.299)	(0.233)	(0.386)
Movement restrictions	-4.0362	0.2129	0.2631	0.8030
	(3.550)	(1.478)	(0.213)	(0.465)
Travel controls	1.6681	1.4127	0.0906	-0.0408
	(1.881)	(1.191)	(0.046)	(0.106)
Year effects	✓	✓	✓	✓
Week effects	✓	✓	✓	✓
Year and week effects	×	×	×	×
Observations	3660	1161	4520	2350

Note: The table reports fixed effect regression estimates for the relation between several NPIs (according to OxCGRT classification) and two infectious respiratory diseases in EU countries (excluding Malta), with country and time fixed effects included. Robust (OLS specification) and Bonferroni corrected standard errors (model 4) are in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.

The regression results presented in Table 3 are based on a slightly modified specification with a separate dummy variable for each week, for a total of 184 week dummies (see Equation 2). On the one hand, this modeling takes into account that seasonal weekly effects vary within each year, giving infections different seasonal patterns across years. On the other hand, the year and week effects act as catch-all variables that on a weekly basis absorb all other influences not represented by the indexes or their subindex measures. Using models (1) to (3) (Table 3), only the negative binomial fixed effects models (columns (c) and (d)) show significant effects for the three aggregated indexes; in the fixed effects models, the coefficients for both dependent variables − influenza (a) and RSV (b) – are insignificant. As regards the subindexes (lower half, Table 3), the only significant negative effects estimated by both the fixed effects and fixed effects negative binomial models are workplace closings and the regressions with influenza as a dependent variable.

These numerous insignificant coefficients should come as no surprise given the difficulty in separating NPI effects from the week dummies added to the model in Table 3, which may well absorb any effect of the European population's behavioral changes associated with (and driven by) the NPIs. In fact, given the high degree of multicollinearity in model 4 – for example, a variance inflation factor (VIF) over 10 for 5 of the 8 explanatory variables in specification (a) of model (4) – all point estimates reported in Table 3 should be treated with caution.[5]

5 For the same reason, it is impossible to test whether there are any interaction effects among the NPIs.

Table 3: Fixed effects regression estimates: Specification II

	Model specification			
	(a)	(b)	(c)	(d)
	FE	FE	Negative binomial	Negative binomial
	Disease			
	Influenza sentinel (positivity)	RSV sentinel (positivity)	Influenza sentinel (positive specimens)	RSV (positive specimens)
	Reporting: weekly			
Index	Period: calendar week 40 to 20			
	Model (1)			
Government response	-0.0052	-0.3912*	-0.0124**	-0.0730***
	(0.132)	(0.186)	(0.005)	(0.014)
	Model (2)			
Containment and Health	0.0388	-0.3949*	-0.0114**	-0.0597***
	(0.110)	(0.188)	(0.005)	(0.011)
	Model (3)			
Stringency	-0.0042	-0.2568	-0.0130***	-0.0432***
	(0.103)	(0.159)	(0.005)	(0.011)
Subindex	*Model (4)*			
Workplace closing	-13.0822**	-1.1163	-0.7883***	-0.2826
	(3.989)	(1.382)	(0.200)	(0.401)
School closing	-2.3372	-0.7269	-0.4738*	-0.1892
	(2.584)	(2.684)	(0.175)	(0.309)
Cancelation of public events	10.1007	-2.9724	0.2285	0.1621
	(5.241)	(3.705)	(0.236)	(0.575)
Restrictions on gatherings	4.4268	-1.3103	0.1738	-0.4249
	(2.130)	(1.087)	(0.098)	(0.183)
Closing of public transport	7.1063	-1.4486	0.2358	-1.5257
	(3.604)	(1.114)	(0.263)	(0.767)
Stay at home orders	1.4860	-0.1378	0.2030	0.5982
	(3.868)	(1.544)	(0.223)	(0.368)
Movement restrictions	-4.2875	0.9477	0.5091	1.5343*
	(3.099)	(1.550)	(0.207)	(0.612)
Travel controls	2.8844	0.5733	0.0537	-0.1897
	(1.874)	(1.231)	(0.045)	(0.108)
Year effects	×	×	×	×
Week effects	×	×	×	×
Year and week effects	✓	✓	✓	✓
Observations	3660	1161	4520	2350

Note: The table reports fixed effect regression estimates for the relation between several NPIs (based on OxCGRT classification) and two infectious respiratory diseases in EU countries (excluding Malta), with country and time fixed effects on weekly levels included. Robust (OLS specification) and Bonferroni corrected standard errors (model 4) are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

4. Discussion

Two shortcomings of previous studies assessing NPIs' impact on infectious diseases are their focus on one country and their simultaneous use of different NPI measures, which makes it difficult to disentangle the effects of specific measures (Cowling et al., 2020). Given our cross-national dataset covering many European countries, as well as the substantial cross-country variation in NPI implementation, we are able to shed useful light on how different measures (and their stringency) influence the spread of infectious respiratory diseases.

Overall, our results indicate that NPIs have a significant effect on the containment of influenza and RSV, although certain measures may be more effective in controlling disease spread than others. For example, despite earlier mixed evidence for their efficacy in controlling influenza (Fong et al., 2020), in our study, workplace closures show the highest level of efficacy. This finding lends credence to earlier evidence that both paid leave benefits and business practices that actively encourage employees to stay home while sick can reduce workplace transmission of influenza (see, e.g., Zhai et al., 2020; Ahmed et al., 2020). We also provide some support for the benefits of school closures, previously documented as effective in containing influenza spread (Fong et al., 2020), although in our case, the significance levels are low. Our results similarly confirm earlier indications that travel restrictions have only a marginal effect on the spread of Covid-19 (Anzai 2020; Chinazzi et al., 2020). We thus concur with scholars who argue that community-based public health measures such as physical distancing, contact tracing, and isolation can be equally successful but less restrictive than constraining freedom of movement (Meier et al. 2020).

Numerous cost-benefit analyzes have emerged that examine the benefits of Covid-19 NPIs (Miles et al., 2020; Rowthorn and Maciejowski, 2020; Scherbina, 2020; Thunström et al., 2020). These studies use different methodologies and often come to very different conclusions. None however, capture the positive externality of Covid-19 NPIs on other infectious diseases. Although our study only analyzes influenza and RSV, it is safe to assume that Covid-19 NPIs would also affect the spread of other infectious diseases such as pneumococcal disease or Haemophilus influenzae type b (Hib). Considering the large economic costs associated with some of these diseases (Pike et al., 2020), the benefits of Covid-19 NPIs could be substantially higher than currently documented. On the other hand, the positive externalities associated with NPIs may be substantially reduced as mass vaccination against Covid-19 begins and compensating behavior naturally ensues (Brewer et al., 2007). The full societal benefits of Covid-19 vaccination should naturally account for such behavioral changes. Variations in compensating behavior by occupational sector or demographic group may also have implications for the optimal allocation of initially limited supplies of Covid-19 vaccines.

Our study is also subject to certain limitations, in particular, the strong correlation between individual NPIs, which makes it difficult to identify the effect of any specific NPI, or the interaction effects among different NPIs. In addition, because our source data do not represent actual infection prevalence (only a subset of sentinel specimens from select primary health care providers), the reported incidence in some countries can be low. A further drawback, encountered by all studies that analyze Covid-19 NPIs, is that we can only assess NPI effects during the final months of the 2019-20 influenza and RSV seasons. More robust results could be achieved from investigating NPIs across the entire influenza or RSV seasons, which may well be possible in 2021 as additional Covid-19 waves begin and new NPIs are implemented. Due to lack of data, we cannot rule out that people got vaccinated at the same time as the NPIs were introduced, although we believe that this is very unlikely (very few people get vaccinated in late winter or early spring in Europe). The ECDC makes recommends for vaccinations in all EU countries and their recommendation is early autumn.[6] Although there is some evidence that lockdowns have caused a change in healthcare-seeking behavior, with individuals avoiding healthcare facilities (Moustakis et al., 2020), we do not believe that this applies to influenza and RSV in Europe, especially as, in Europe, individuals with flu-like symptoms are encouraged to get tested and also have a strong incentive to do so. Nevertheless, certain strains in the healthcare system might have prevented some people infected with influenza from being tested and treated, particularly in Italy and Spain (Verelst et al., 2020).

In conclusion, our study echoes Cowling et al. (2020) in highlighting that the measures taken to control Covid-19 transmission have been effective in Europe in containing the spread of other infectious respiratory diseases. Our results also support earlier evidence that these NPIs have indeed limited the spread of Covid-19 (Hunter et al., 2020). These consistencies strongly suggest that, given the lack of any ideal counterfactual when studying this topic (i.e., no opportunity to compare with other time periods), the mathematical modeling of infectious diseases with similar properties to Covid-19 is an appropriate method for measuring NPI effectiveness during the Covid-19 pandemic.

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6 See https://www.ecdc.europa.eu/en/seasonal-influenza/prevention-and-control/vaccines/timing.

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Appendix

Figure A1: Influenza cases/positivity rate for Germany relative to the NPI stringency index, with black (red) lines indicating 2015-2019 (2020). The blue line depicts the stringency index.

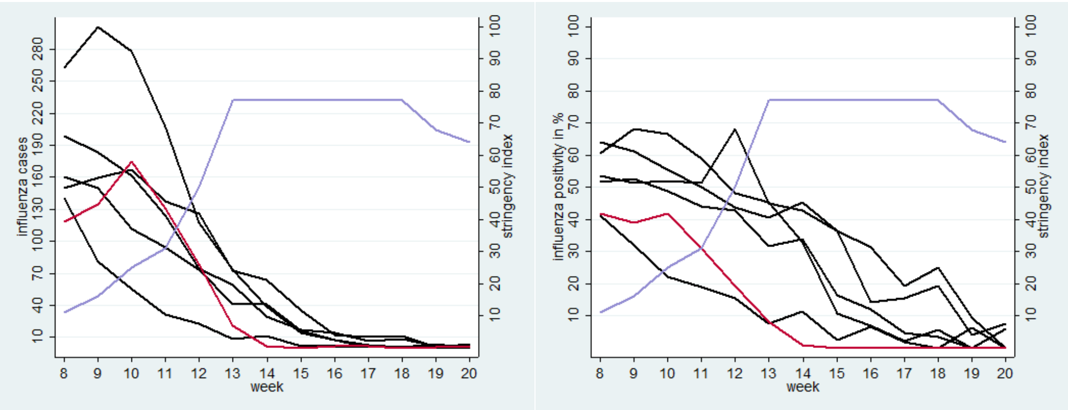

Figure A2: Influenza cases/positivity rate for Spain relative to the NPI stringency index, with black (red) lines indicating 2015-2019 (2020). The blue line depicts the stringency index.

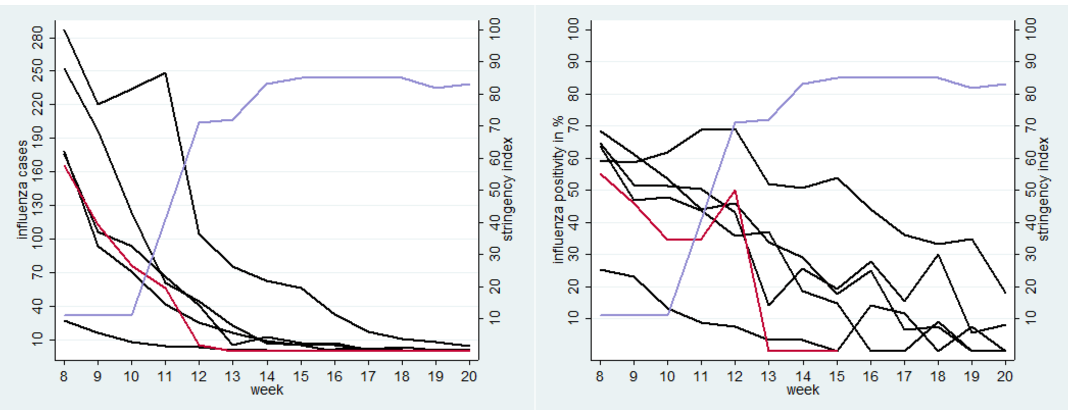

Figure A3: Influenza cases/positivity rate for France relative to the NPI stringency index, with black (red) lines indicating 2015-2019 (2020). The blue line depicts the stringency index.