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The Effects of Social Distancing Measures on COVID-19 Spreads in European Countries

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Abstract: This study investigates the effects of social distancing measures on various types of social mobility, using country- and day-fixed effects on a panel of daily data comprising 29 European countries. Although social distancing measures proved to be significant for all types of mobility in the examined period, they are best captured by retail and recreation mobility. Linear effects of restrictive measures on COVID-19 cases and deaths are examined by OLS regression with country- and day-fixed effects on a panel of 29 European countries, while non-linear effects were investigated by quantile regressions. Stricter mobility restrictions significantly reduced COVID-19 cases and deaths, but the variant of the virus was also an important determinant. Although the Delta variant was much more infectious, its mortality reduced. However, the impact of social distancing measures on COVID-19 cases and deaths was not constant but strengthened with increasing quantiles of the distribution of cases and deaths, suggesting that an early response from policy-makers was very important. Vaccination brought benefits for both cases and deaths, but a particularly beneficial effect can be seen on COVID-19 deaths. The vaccination benefits grew with the share of the vaccinated population. Distrust in public institutions proved to have a negative impact on both COVID-19 cases and deaths. The inclusion of a set of control variables (health, economic, social and demographic) revealed that country characteristics such as cardiovascular mortality, the share of male smokers, economic development, the proportion of the population living in extreme poverty, population density, the quality of education or the share of rural population were important determinants of COVID- 19 spreads. The analysis of the linear and nonlinear effects of the stringency of measures on various categories of sales according to the digital cash collection system (eKasa) in Slovakia revealed that sales in essential sectors for consumers, such as retail and grocery stores, were relatively resistant to tightening measures, while sectors that are less essential for consumers were more sensitive to social distancing measures.

Keywords: Coronavirus, Mobility, Quantile Regression, Stringency

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1. Introduction

The COVID-19 outbreak in early 2020 has raised concerns among global governments that have responded with various social distancing measures to slow the spreading of the virus. Similarly, policy-makers in European countries have taken various measures to reduce the virus spreading and support the impacted economy. Most of the measures aimed at restricting population mobility, which was supposed to reduce the spread of the virus. Especially at the very beginning, the restrictions, including mobility restrictions, were not very targeted as policy-makers lacked experience with a global pandemic. Targeted lockdowns may be useful as policy-makers face trade-offs between health concerns and the economic slowdown, particularly when some groups of people may be more vulnerable to the COVID-19 virus.

In this study, we first investigate the effects of social distancing measures on various types of social mobility in European countries. We base our investigation on the assumption that the initial strategy of the policymakers was to introduce measures limiting social mobility, which should lead to a reduction in the spread of the virus, and subsequently eliminate the number of deaths from COVID-19. Second, we examine the impact of changes in population mobility on COVID-19 cases and deaths, respectively. To this end, we use country[2]- and/or day-fixed effects on daily panel data of European countries to examine the linear relationship between mobility and the spread of the COVID-19 virus, taking into account the significantly different characteristics of the Delta variant, the effect of vaccination and the population's trust in public institutions. Next, we control for a set of country-specific (time-invariant) control variables, which we divide into 4 categories – health, economic, social, and demographic characteristics. Third, to examine non-linear effects, we use quantile regressions, which allow us to examine the mobility effects in individual quantiles of the dependent variable's distribution (i.e., COVID-19 cases or deaths). It can be assumed that the response to social distancing measures differs at the beginning when the virus is spreading slightly and gaining strength (corresponding to lower distribution quantiles) and when the virus is at its peak and is spreading uncontrollably in the population (higher distribution quantiles). For decision-makers, understanding the effects of the measures on new COVID-19 cases and deaths, alongside noting the phase of the virus spread, is of crucial importance.

We further supplement our investigation with a country-specific analysis, in which we examine the impact of restrictive measures on daily sales in Slovakia. We make use of the daily frequency of data on different types of sales (i.e., retail, grocery stores, restaurants, accommodation) reported by a digital tax collection system (the so-called eKasa) in Slovakia. Although the data do not cover sales in the entire economy (for example, sales from the internet purchases or sales in the industry where payments are made

[2] We use data at the national level, although a lower regional level could provide much greater variability. Moreover, within countries, a high degree of heterogeneity is likely due to regional differences within countries. Nevertheless, we use data at the national level, as obtaining regional data of sufficient quality for all countries would be a challenge. Even in variables such as the number of COVID-19 cases or deaths, there could be slight differences between individual countries. For example, people could be vaccinated also outside the district where they had permanent residence. Likewise, the stringency was expressed (especially from the beginning) for the entire country. Therefore, by using regional data, we could introduce misleading signals into the estimation.

through invoices are missing), they provide a quite accurate, and especially immediate overview of the effects of social distancing measures on various economic sectors (mainly services and retail). The daily frequency will help us reveal the immediate and longer-lasting impact of social distancing measures on selected sectors of the economy, such as retail, groceries, restaurants and accommodation.

The rest of this study is organised as follows: Section 2 presents a review of the relevant literature and findings of studies dealing with a similar topic. In Section 3, we describe the methodology used to measure the linear and non-linear effects of social distancing measures on COVID-19 cases and deaths. We also describe our empirical strategy with respect to measuring the impact of restrictive measures on daily sales in Slovakia. The dataset applied is introduced in Section 4. The empirical results are presented in Section 5, where we also confront our results with the findings from similar studies. Section 6 concludes.

2. Literature Review

The COVID-19 pandemic's effects have already been addressed in literature from various perspectives. For example, the impacts of face masks on the spread of a pandemic were investigated by Esposito et al. (2020), or Garcia (2020). While many studies have examined the effects of the COVID-19 virus on human health (e.g., del Rio et al., 2020; or Carfì et al., 2020), a large number of studies have looked specifically at the impact on mental health (e.g., Druss, 2020; or Fiorillo and Gorwood, 2020). The effects on education were studied by Vlachopoulos (2020), or Abumalloh (2021). However, we are particularly interested in the findings of other authors related to the impact of restrictive measures on social mobility; and the effects of mobility restrictions on the spread of the COVID-19 virus, especially in European countries. We are also interested in the economic consequences of the COVID-19 pandemic, especially the development of sales in various sectors.

The effects of restrictive measures on social mobility are relatively intuitive and addressed in several studies. Already in 2020, shortly after the outbreak of the COVID-19 virus, Lapatinas (2020) found in his study involving all EU countries that the reductions in out-of-home social interactions and visits to public and private places are driven by a combination of restrictive measures introduced by the Member States. His analysis suggests that partial and full lockdowns have the strongest causal impact on increasing presence at home and reducing visits to workplaces, public transport hubs, grocery stores, pharmacies, restaurants, and other places. Barbieri et al. (2021) studied the impact of COVID-19 on mobility in ten countries around the globe. Their empirical results quantify significant disruptions for both commuting and non-commuting travels, highlighting substantial reductions in the frequency of all types of trips and the use of all modes of transport. A more recent study that investigated the relationship between COVID-19 restrictive measures and mobility patterns across Europe in the period from February 2020 to February 2021 was conducted by Kallidoni et al. (2022). Using SARIMAX time-series models, the authors found that school closing was the most important exogenous factor for describing driving or walking, while stay-at-home orders did not have a significant effect on the evolution of people's movements.

Sufficient attention is also paid in the literature to the impact of mobility restrictions on the spread of the COVID-19 virus, with many studies focusing on the situation in China and the US. Oka et al. (2021) found that the spread of the disease in China was predominantly driven by community transmission within regions, which dropped substantially after local governments imposed various lockdown policies. Acemoglu et al. (2020), on the basis of the SIR model applied to the parameters for the USA, state that a strict and long lockdown for the most vulnerable group both reduces infections and enables less strict lockdowns for the lower-risk groups. A more recent study carried on the data from US counties, which also deals with the effect of mobility restrictions on COVID-19 cases and deaths, taking into account counties' characteristics, is that of Yilmazkuday (2022). The author concludes that the positive effects of mobility on COVID-19 cases or deaths increase with population, per capita income, or commuting time as well as with having certain occupations, working in certain industries, attending certain schools, or having certain educational attainments.

The COVID-19 pandemic has also affected the whole of Europe, first involving only some European countries, Italy in particular, and gradually spreading to all member states.[3] A study that examines the degree of impact of the epidemic in the first six months (February to July 2020) of the pandemic in nine EU countries based on their characteristics was carried out by Cheshmehzangi et al. (2021). They found that the timeliness of relevant policies and the effectiveness of government implementation indirectly limit the spread of the epidemic by reducing population mobility. The authors further argue that better medical standards would contribute to detecting, isolating, and treating patients, and help control the epidemic. Docquier et al. (2022) investigated the impact of non-pharmaceutical interventions and infection threats on the daily evolution of cross-border movements of people during the COVID-19 pandemic using Facebook mobility data for Europe. They conclude that containment measures in the destination country and school closures in the origin country have the strongest impact on cross-border movements. Simulation by Linka et al. (2020) shows that unconstrained mobility would have significantly accelerated the spreading of COVID-19, especially in Central Europe, Spain, and France. Fazio et al. (2022) propose an agent-based model to simulate the impact of mobility restrictions on the spreading of COVID-19 at a large-scale level, by considering different factors that can be attributed to the diffusion and lethality of the virus and population mobility patterns. Similarly to our model design, they also consider several control characteristics, including the mean winter temperature, housing concentration, healthcare density, population mobility, air pollution and the percentage of the population over 60 years old. Their analysis, carried out on data for Italy, points out that the identification of risk factors allows local policies to be adopted, improving the trade-off between socio-economic benefits and health impacts.

Oh et al. (2021) addressed non-linearities by examining the association between the changes in mobility and the ratio of the number of newly confirmed cases on a given day to the total number of cases over the past 14 days from the index day per million population, using LOESS regression and logit regression. On a sample of 34 OECD countries plus Singapore and Taiwan, they found that in two-thirds of the examined countries,

[3] For a more detailed description of the effects of the COVID-19 pandemic for Italy, refer to the study by Gabutti et al. (2021).

reductions of up to 40% in commuting mobility (to workplaces, transit stations, retailers, and recreation) were associated with decreased cases, especially early in the pandemic. Once both mobility and incidence had been brought down, further restrictions provided little additional benefit. The authors argue that their findings highlight the importance of early and decisive action during a pandemic. Similar conclusions were already reached by Deb et al. (2020), who also took a deeper look at the characteristics of countries affecting the spread of the virus. They found that the effectiveness of containment measures increases in countries with cooler temperatures and population density, as well as countries with a higher proportion of older people in the total population and stronger health systems.

There are also many studies in the literature dealing with the economic consequences of the Covid-19 pandemic. For example, Chen et al. (2020) analysed the economic impact of COVID-19 in Europe and the US during the early phase of the pandemic. They document that European countries and US states that experienced larger outbreaks also suffered larger economic losses. They found that the heterogeneous impact of COVID-19 is mostly captured by observed changes in people's mobility. A more recent empirical study by Tan et al. (2022) shows that assuming a GDP growth rate of 4–8% in the absence of COVID-19 in China, the GDP growth in 2020 would be -8.77 to -12.77% after COVID-19. The companies and activities associated with transportation and service sectors are among the most impacted, and the companies and supply chains related to the manufacturing subsector lead in the economic losses. Škare et al. (2021) measured the potential effects of the COVID-19 pandemic on the tourism industry. Using panel data from 185 countries, they estimated that the recovery of the tourism industry after the COVID-19 pandemic would take more time than the average expected recovery period of 10 months observed after a pandemic in history. The COVID-19 pandemic has caused a serious shock also in the labour markets. Soares and Berg (2021) found that governments that favoured wage subsidies over other forms of income support were able to lessen labour market volatility. However, in all seven middle- and high-income countries they studied, the COVID-19 pandemic has exacerbated labour market inequalities.[4]

The findings in the field of sales activities in individual sectors are particularly interesting. For example, Ferreira et al. (2021) employ the World Input-Output Database to depict the interdependencies among both industries and countries, which provides a full representation of global value chains. They demonstrated asymmetric effects on production by industry and international trade, leading to asymmetric relative impacts on national economies. Their results indicate that if the demand for nonessential goods and services decreases by 50%, the global gross domestic product will decline by 23%, leading to relative impacts that are larger in China, Indonesia, and some European countries. Vărzaru et al. (2021) argue that travel restrictions and stopping the activities in hotels and restaurants to obey social distancing rules have generated the worst global crisis in tourism since World War II. The authors found that the countries that had a significant contribution of tourism to GDP suffered the most from the measures to combat the effects of the pandemic. Gyódi (2021) investigated the impact of the COVID-19 pandemic on the traditional hotel industry and Airbnb in nine major European cities. His findings suggest that a significant share

[4] Many studies also dealt with gender inequalities in the labour market caused or exacerbated by the COVID-19 pandemic – see for example Farré et al. (2021) or Couch et al. (2022).

of hosts shifted from short-term accommodation provision and used their property differently, e.g. rented it on a long-term basis.

In this study, we contribute to the existing literature by investigating the effects of social distancing measures on COVID-19 spreads in European countries, considering the effect of the Delta variant and controlling for their sociodemographic, health and economic characteristics. We use panel regressions with country and/or day-fixed effects on daily panel data of European countries to investigate the linear relationship between mobility and COVID-19 spreads. To examine nonlinear effects, we employ quantile regressions, which enable us to examine the stringency effects in individual quantiles of the dependent variable's distribution. For decision-making, understanding the effects of the measures on new COVID-19 cases and deaths, alongside noting the phase of the virus spread, is considered to be imperative.

The analyses thus outlined will impede us from directly investigating the economic effects of restrictive measures. As the effects are heterogeneous across different population groups, it is highly important for policy-makers to know the effects of selected sectors by individual quantiles of distribution. However, data on daily economic activity are limited. We, therefore, extended our analysis to a case from Slovakia, where we examined the linear and nonlinear effects of the stringency of measures on various categories of sales from a digital cash collection system, eKasa (e.g., retail, grocery, restaurants and accommodation). The use of high-frequency data on sales, and even by category, is unique and can provide important additional information when settings policies.

3. Methodology

3.1. Impact of Restrictive Measures on Mobility

To examine the effects of restrictive measures taken by governments to reduce the spread of COVID-19 on population mobility, we consider the following panel regression model with fixed effects for individual countries:

Eq.(1) $$Mobility_{i,t}^{j} = \beta_0 + \beta_1 Stringency_{i,t} + \beta_2 Holiday_{i,t} + \theta_i + \varepsilon_{i,t}$$

where $Mobility_{i,t}^{j}$ represents a particular type of mobility j in country i on day t. Note that the superscript j represents 4 cases estimated separately, as we examine the impact on 4 types of mobility, namely Grocery & Pharmacy Mobility, Retail & Recreation Mobility, Transit Stations Mobility and Workplaces Mobility. $Stringency_{i,t}$ captures the strictness of government measures in country i on day t as a response to the COVID-19 virus. The index is rescaled to a value from 0 to 100 (100 = the strictest response; see Table A.3 in Appendix A). $Holiday_{i,t}$ is a dummy variable that takes the value of 1 on a day when there is a public holiday (or on a general non-working day) in country i. For all other days, the dummy variable takes the value of 0.

Term θ_i in Eq. (1) represents country-fixed effects, ensuring that the time-invariant country-specific factors are controlled during the investigation. The parameter β_0 is a constant and β_1 is the regression coefficient for the impact of the restrictive measures, which we are interested in. The parameter β_2 is a regression coefficient for holidays and $\varepsilon_{i,t}$ represents residuals. Note that Eq. (1) abstracts from dynamic effects as we do not consider any lags. The reason is that the impact of the explanatory variables on population mobility is immediate, within the same day.

Eq. (1) does not capture some important characteristics of population mobility related to the season or the current day of the week (e.g., mobility on Monday is different from mobility on Saturday) or other characteristics related to seasons. To overcome this deficiency, we add day-fixed effects in Eq. (2):

Eq.(2) $$Mobility_{i,t}^{j} = \beta_0 + \beta_1 Stringency_{i,t} + \beta_2 Holiday_{i,t} + \theta_i + \gamma_t + \varepsilon_{i,t}$$

where γ_t represents day-fixed effects.

Eq. (2) is therefore a potentially more appropriate specification of country mobility than Eq. (1). Nevertheless, even the specification given by Eq. (2) is far from good enough. For example, it is likely that some important characteristics are still missing, causing the omission variable bias – e.g., daily temperature, precipitation, important sporting/cultural/political events that occurred and other factors that may affect population mobility in a given country. However, the inclusion of the above-mentioned variables is tricky at least for two reasons. First, obtaining the mentioned variables is complicated, especially at the national level. All the mentioned factors are characterized by high regionality, which cannot be correctly captured on the national level. Second, the restrictive measures likely caused the above-mentioned effects to have a smaller impact on mobility in the observed period. In other words, the social distancing measures likely contributed to a change in the standard behaviour of people who were more indifferent to the changes in weather and other factors. Most of the events were even cancelled.

Finally, it is necessary to pay attention to the endogeneity issue – the measures probably reflect not only the historical development of the epidemic but also the predictions about its future development. The policy response function did not directly monitor the mobility of the population, but rather the number of new cases, the reproduction rate of the virus, or other virus-related parameters. Nevertheless, we admit that we cannot unequivocally rule out the presence of endogeneity in the specifications.

3.2. Linear Effects of Mobility Restrictions on the Spread of COVID-19

The linear effects of mobility restrictions on the number of COVID-19 cases are examined by using panel data regression. The model with country-fixed effects can be formally expressed as follows:

Eq.(3)
$$\begin{aligned}\Delta Cases_{i,t} = \beta_0 + \beta_1 Mobility_{i,t-21} + \beta_2 Delta_{i,t-21} \\ + \beta_3 \left(Mobility_{i,t-21} \times Delta_{i,t-21}\right) + \beta_4 Vaccination_{i,t} \\ + \beta_5 Institutions_{i,t} + \theta_i + \varepsilon_{i,t}\end{aligned}$$

where $\Delta Cases_{i,t}$ represents the weekly percentage change in total (cumulative) daily cases in country i on day t, and $Mobility_{i,t-21}$ stands for the change (with respect to the pre-pandemic benchmark period) in retail & recreation mobility in country i on day $t -$

21.[5] The lagged change in mobility captures the time delay needed for the effects of mobility to be reflected in COVID-19 cases. However, there is a considerable variation in the literature regarding the time it takes for mobility effects to be reflected in COVID-19 cases. Zhou et al. (2020) reported that the inferred duration of the infectious period of COVID-19 was from 6.5 to 21 days for various subpopulations in Shenzen. Zhang et al. (2021) showed that the number of new daily cases of COVID-19 is most correlated with the 14-day lagged retail and recreation mobility. However, they used the variable for retail and recreation mobility transformed into a 7-day moving average. We follow Yilmazkuday (2022) who used a 21-day lag in mobility. However, the length of the period during which the effects of mobility are reflected in new cases depends crucially on the variant of the virus. To capture the effects of the Delta variant, we use the dummy variable $Delta_{i,t}$, which takes the value of 1 from the day Delta became the dominant variant in the given country and the value of 0 on all other days. The vaccination effect is captured by the variable $Vaccination_{i,t}$, which represents the total number of people who received at least one vaccine dose per 100 people in country i on day t. Finally, the variable $Institutions_{i,t}$ reflects the level of distrust of the population in public institutions according to public opinion polls. The variable captures the share of people in country i who declared that they do not tend to trust public institutions in a given year.

Term θ_i in Eq. (3) represents country-fixed effects, ensuring that country-specific factors are controlled for. We explain COVID-19 cases (and later also deaths) using a relatively small number of explanatory variables. Concerning that, at least at the beginning of the examined period, there was likely not too much variability in many variables, country-fixed effects should thus contribute to the elimination of the omitted-variable bias. The parameter β_0 is a constant and β_1 is the regression coefficient for the effect of mobility on the spread of the virus we are interested in. The parameter β_2 is a regression coefficient capturing the effect of the Delta variant on the number of cases, *ceteris paribus*. The parameter β_3 is the estimated coefficient for the interaction term, which captures the effect of mobility on the number of new cases if Delta was the dominant variant. Such a diff-in-diff design allows us to better evaluate the effect of mobility on the spread of the virus depending on the Delta variant. Coefficient β_4 captures the estimated impact of vaccination on the number of new cases, while coefficient β_5 measures the impact of citizens' distrust in public institutions. Finally, $\varepsilon_{i,t}$ represents residuals.

Eq. (3) does not capture some important time-specific characteristics that could influence the spreading of the virus across all countries. For example, Yilmazkuday (2022) showed that a National Emergency concerning COVID-19 on March 13th, 2020 declared by the

[5] Note that the retail & recreation category was selected based on the analysis performed in Section 1.1., which concludes that the type of mobility best explained by the stringency of measures is retail & recreation mobility. Zhang et al. (2021) documented that retail and recreation mobility (together with workplace mobility) were most strongly correlated with the number of daily new cases in Hong Kong. Consequently, the authors suggest that these two categories should be targeted in an effective epidemic control. Freeman and Schug (2021) used principal component analysis to determine the factor loadings of individual types of mobility to create an overall geographic mobility measure for each day in a particular country. They found that the category of retail and recreation achieved the highest eigenvalue, indicating that retail and recreation is the most important category of population mobility.

White House likely had an impact on the spreading of the virus. To control for these time-specific factors, we add day-fixed effects in Eq. (4):

Eq.(4)

$$\Delta Cases_{i,t} = \beta_0 + \beta_1 Mobility_{i,t-21} + \beta_2 Delta_{i,t-21} + \beta_3 \left(Mobility_{i,t-21} \times Delta_{i,t-21}\right) + \beta_4 Vaccination_{i,t} + \beta_5 Institutions_{i,t} + \theta_i + \gamma_t + \varepsilon_{i,t}$$

where γ_t represents day-fixed effects.

To eliminate the omission variable bias, we sequentially include individual control variables in Eq. (5).

Eq.(5)

$$\Delta Cases_{i,t} = \beta_0 + \beta_1 Mobility_{i,t-21} + \beta_2 Delta_{i,t-21} + \beta_3 \left(Mobility_{i,t-21} \times Delta_{i,t-21}\right) + \beta_4 Vaccination_{i,t} + \beta_5 Institutions_{i,t} + Control_i + \varepsilon_{i,t}$$

The variable $Control_i$ represents all the control variables that may have a potential effect on the spread of the virus. We classified the control variables into 4 categories – health, economic, social, and demographic characteristics. We examine the influence of a total of 17 control variables. Note that the control variables are time-invariant as they are country-specific but do not change over time. For this reason, it is not feasible to use fixed effects and Eq. (5) therefore estimates random effects.

Similar to Eq. (3), the linear effects of mobility on COVID-19 deaths are examined using the following equation with country-fixed effects:

Eq.(6)

$$\Delta Deaths_{i,t} = \beta_0 + \beta_1 Mobility_{i,t-35} + \beta_2 Delta_{i,t-35} + \beta_3 \left(Mobility_{i,t-21} \times Delta_{i,t-21}\right) + \beta_4 Vaccination_{i,t} + \beta_5 Institutions_{i,t} + \theta_i + \varepsilon_{i,t}$$

where $\Delta Deaths_{i,t}$ represents the weekly percentage change in total (cumulative) daily deaths in country i on day t, and $Mobility_{i,t-35}$ is the change (with respect to the pre-pandemic benchmark period) in retail & recreation mobility in country i on day $t-35$. The lagged change in mobility captures the time delay required for the effects of mobility to be seen on COVID-19 deaths. Note that the change in mobility will be reflected in deaths two weeks later than in cases. We decided to choose a 35-day lag according to Yilmazkuday (2022).

In Eq. (7), we add day-fixed effects, similarly as in Eq. (4):

Eq.(7)

$$\Delta Deaths_{i,t} = \beta_0 + \beta_1 Mobility_{i,t-35} + \beta_2 Delta_{i,t-35} + \beta_3 \left(Mobility_{i,t-21} \times Delta_{i,t-21}\right) + \beta_4 Vaccination_{i,t} + \beta_5 Institutions_{i,t} + \theta_i + \gamma_t + \varepsilon_{i,t}$$

Finally, we include a set of time-invariant control variables in Eq. (8) using random effects, similar to Eq. (5):

Eq.(8)

$$\Delta Deaths_{i,t} = \beta_0 + \beta_1 Mobility_{i,t-35} + \beta_2 Delta_{i,t-35} + \beta_3\left(Mobility_{i,t-21} \times Delta_{i,t-21}\right) + \beta_4 Vaccination_{i,t} + \beta_5 Institutions_{i,t} + Control_i + \varepsilon_{i,t}$$

Endogeneity is again likely to be present in the specifications given by Equations (3) to (8). An example of endogeneity can be a situation when people anticipate the spreading of the virus (based on epidemiologic forecasts) and modify their mobility in advance accordingly. They may prefer, for example, working from home or online shopping, depending on the expected epidemic situation. The endogeneity problem is partly solved by including lags. Nevertheless, we acknowledge that the endogeneity was likely not completely eliminated.

3.3. Non-Linear Effects of Mobility Restrictions on the Spread of COVID-19

The analysis outlined in the previous section allows us to investigate the linear effects of mobility on COVID-19 cases and deaths, respectively. However, there are likely nonlinear effects that are not visible from the previous analysis. For example, we do not see the effects of a change in mobility for different numbers of infections. Understanding how the spread of the virus responds to measures, depending on the current spread of the virus (i.e., the number of infected people), is therefore essential for taking an adequate decision. A deeper analysis can be performed by quantile regression, which allows investigation of the effects, depending on the various quantiles of the dependent variable (i.e., the number of cases and deaths).

Our benchmark panel regression model includes both country- and day-fixed effects explaining cases (Eq.4) and deaths (Eq.7), respectively. Taking the same structure, the quantile regression model equation for the number of COVID-19 cases for the τ quantile is as follows:

Eq.(9)

$$Q_\tau\left(\Delta Cases_{i,t}\right) = \beta_0(\tau) + \beta_1(\tau) Mobility_{i,t-21} + \beta_2(\tau) Delta_{i,t-21} + \beta_3(\tau)\left(Mobility_{i,t-21} \times Delta_{i,t-21}\right) + \beta_4(\tau) Vaccination_{i,t} + \beta_5(\tau) Institutions_{i,t} + \theta_i + \gamma_t + \varepsilon_{i,t}(\tau)$$

where the structure is similar to Equation (4), and the beta coefficients are now functions depending on the quantile of the dependent variable $\Delta Cases_{i,t}$.

The quantile regression model equation for the effects on deaths for the τ quantile is as follows:

Eq.(10)

$$Q_\tau\left(\Delta Deaths_{i,t}\right) = \beta_0(\tau) + \beta_1(\tau) Mobility_{i,t-35} + \beta_2(\tau) Delta_{i,t-35} + \beta_3(\tau)\left(Mobility_{i,t-21} \times Delta_{i,t-21}\right) + \beta_4(\tau) Vaccination_{i,t} + \beta_5(\tau) Institutions_{i,t} + \theta_i + \gamma_t + \varepsilon_{i,t}(\tau)$$

where the structure is similar to Equation (7), and the beta coefficients are now functions depending on the quantile of the dependent variable $\Delta Deaths_{i,t}$. Estimators are assumed to be asymptotically normal. The optimisation in both Equation (9) and Equation (10) is performed using the Markov Chain Monte Carlo (MCMC) simulation, drawing from

1,000 draws. The distributions of both dependent variables suggest that the data is suitable for quantile regression, which we have verified by the Breusch-Pagan test for heteroscedasticity (i.e., the data are heteroscedastic).

For a more detailed discussion on quantile regression, we refer to Koenker and Bassett (1978) or Powell (2014 and 2016).

3.4. Impact of Restrictive Measures on Daily Sales in Slovakia according to eKasa

So far, we have focused mainly on the effects of restrictive measures on COVID-19 cases and deaths, respectively. We have barely considered the economic impact of the restrictions. Subsequently, we investigate the linear and nonlinear effects of epidemic measures on daily sales. As we have daily data on economic activity (or sales according to the eKasa system) only for Slovakia, this analysis focuses only on the effects of the stringency of measures on sales in Slovakia. This means that we depart from the panel framework and use time series. We used daily data on sales from the digital cash collection system operated by the Financial Administration of the Slovak Republic (so-called eKasa) to measure sales activity. The Dickey-Fuller test for a unit root confirms that the dependent variables are already stationary, so we can apply time series methods. The linear model has the following form:

Eq.(11)

$$eKasa_t^j = \beta_0 + \beta_1 Stringency_t + \beta_2 Delta_t + \beta_3 (Stringency_t \times Delta_t) + \beta_4 Holiday_t + \varepsilon_t$$

where $eKasa_t^j$ represents the index of sales from eKasa in Slovakia on day t. Note that the superscript j represents various types of eKasa sales. We consider 4 types of eKasa sales, namely retail sales, sales in grocery stores, sales in restaurants and sales in accommodation. $Stringency_t$ represents the stringency index measuring the restrictiveness of epidemic measures in Slovakia, while $Delta_t$ is a dummy variable which takes the value of 1 from the day the Delta variant became the dominant variant in Slovakia and the value of 0 on all other days. The variable $Holiday_t$ is a dummy variable that takes the value of 1 on a non-working day in Slovakia. For all other days, the dummy variable takes the value of 0.

The parameter β_0 is a constant and β_1 is the regression coefficient measuring the effect of restrictive measures on eKasa sales we are interested in. The parameter β_2 is a regression coefficient capturing the effect of the Delta variant on sales, *ceteris paribus*. The parameter β_3 is the estimated coefficient for the interaction term, which captures the effect of restrictiveness on eKasa if Delta was the dominant variant. The parameter β_4 is a regression coefficient for holidays and ε_t represents residuals.

The distributions of individual categories of sales from eKasa indicate that the data is suitable for quantile regression, which we have also formally verified by the Breusch-Pagan test for heteroscedasticity (i.e., the data are heteroscedastic). Therefore, we again used quantile regression to determine nonlinear effects:

Eq.(12)

$$Q_\tau(eKasa_t^j) = \beta_0(\tau) + \beta_1(\tau)Stringency_t + \beta_2(\tau)Delta_t + \beta_3(\tau)(Stringency_t \times Delta_t) + \beta_4(\tau)Holiday_t + \varepsilon_t(\tau)$$

where the structure is the same as in Equation (11), but the beta coefficients are now functions depending on the quantile of the dependent variable $eKasa_t^j$.

4. Data

Daily country-level data on COVID-19 **cases** and **deaths** in 29 European countries are obtained from the Our World in Data (OWiD) database, and they enter the equations as the weekly percentage change in total (cumulative) confirmed daily COVID-19 cases and deaths per million people.[6] To get a better data overview, descriptive statistics for the data on cases of COVID-19 is available in Table A1 and for the data on deaths due to COVID-19 in Table A2, Appendix A.

The response of governments to the spread of the virus is measured by the **stringency index**, daily country-level data on which are obtained from the Our World in Data (OWiD) database. The index is constructed by the University of Oxford based on recording the strictness of the 'lockdown style' policies that primarily restrict people's behaviour. It is calculated using all ordinal containment and closure policy indicators, plus an indicator recording public information campaigns. The index ranges from 0 to 100, with 100 representing the strictest policy response. For a more detailed overview, see Table A3 in Appendix A.

Daily country-level data on **vaccination** are obtained from the Our World in Data (OWiD) database, and they enter the equations as the total number of people who received at least one vaccine dose per 100 people in the total population. We consider everyone who has received at least one dose to be a vaccinated person, because we assume that even the first vaccination will contribute to strengthening immunity against the COVID-19 virus, similar to how it is in the case of getting over the virus. In the analysis, we do not differentiate between the type of vaccine administered. Descriptive statistics is available in Table A4, Appendix A.

Daily country-level data on population **mobility** are obtained from Google Mobility Reports. Public mobility reports show the trends in movement by region, based on different categories of locations. Utilizing GPS data from individual smartphones, daily mobility data measure how visitors went to (or spent time in) a particular location relative to the pre-pandemic period between January 3 and February 6, 2020. The data can thus be interpreted as a change compared to the pre-pandemic period. Descriptive statistics for the data on individual types of mobility are available in Tables A5 to A8, in Appendix A.

[6] The methodology of reporting the number of cases or deaths from COVID-19 may vary across countries. In general, case counts include a positive result for both the PCR test and the antigen test. New case counts can include probable cases. Due to varying protocols and challenges in the attribution of the cause of death, the number of confirmed deaths may not accurately represent the true number of deaths caused by COVID-19.

The COVID-19 virus has mutated several times since its first variant. While the earlier variants[7] were very similar in terms of their infectiveness and the incubation period, the **Delta variant** was much more infectious and spread faster in the population (see for example Hart et al., 2022). To capture the effects of the Delta variant, we constructed a dummy variable Delta based on the overview of the mutation of the COVID-19 virus according to the Our World in Data (OWiD) database. The dummy variable takes the value of 1 from the day the Delta variant became the dominant variant[8] in that country and the value of 0 on all other days. The Delta variant became dominant on May 25, 2021 in the first two European countries under consideration – the United Kingdom and Portugal. The last country where the Delta variant gained dominance is Luxembourg (July 18, 2021). At the time of writing this paper, the latest variant is the Omicron variant, which differs from all previous variants significantly – for a comprehensive comparison of the Delta and Omicron variants, refer to Menni et al. (2022). For this reason, days when the Omicron variant became dominant in the first country out of all the examined countries are excluded from the analysis. The first European country where the Omicron virus became dominant was the United Kingdom, where it gained dominance on December 19, 2021 – the time span of our analysis therefore ends on this date.

Another variable we constructed is a dummy variable **holidays**, which captures the effect of non-working days. The variable takes the value of 1 if a particular day was a holiday (i.e., a non-working day) in a given country and 0 in all other cases.

The data from the public opinion polls on the **distrust in public institutions** are obtained from Eurobarometer and express the share of respondents who declared that they do not tend to trust public institutions in a given year. Country-level data are expressed as an index. The higher the value of the index, the higher the distrust in public institutions in a given year in a particular country.

Daily data on **sales** in Slovakia, used in Eq. (11) and (12), were obtained from the digital cash collection system operated by the Financial Administration of the Slovak Republic (so-called eKasa). Data on daily sales from eKasa system do not cover the entire economy, as they record only those business transactions that are carried out by card or mobile payment via POS terminals. They do not capture, for example, transactions carried out via invoice or the internet. For this reason, the data do not cover the industrial sector at all. On the other hand, they capture a significant part of household consumption, with the exception of the already-mentioned internet sales. The results must therefore be taken with caution, since internet shopping increased during the pandemic. The data has the potential to show the impacts on some sectors such as accommodation or retail trade. We differentiate between 4 types of eKasa sales, namely retail sales, sales in grocery stores, sales in restaurants and sales in accommodation. Daily sales from eKasa enter equations as an index, with a start value of 100 equal to the average sales in the pre-pandemic period

[7] By earlier variants we mean variants Alpha, Beta, Gamma, Eta, Iota, Kappa, Mu, and others that occurred before the Delta variant based on the World Health Organization (data obtained from the OWiD database).

[8] By dominance of the variant of the COVID-19 virus, we mean the situation when the number of cases infected with the given variant exceeded the number of cases infected with all other variants in the given country. For example, if on a given day 40 people were infected with virus A, 35 people were infected with virus B, and 25 people were infected with virus C, virus A was dominant.

between February 5 and 11, 2020. The index is further transformed into a 7-day moving average to exclude weekly seasonality. Descriptive statistics for the data on individual types of eKasa sales in Slovakia is available in Table A9, Appendix A.

All the other variables are control variables entering Equations (5) and (8) and are time-invariant, i.e. fixed for a specific country. We classified the control variables into 4 categories – health, economic, social and demographic characteristics. They are mostly obtained from the Our World in Data (OWiD) database, with the exception of the data on populism (obtained from Timbro), education (obtained from UNDP), quality of education (obtained from OECD) and quality of healthcare (obtained from SPI). Descriptive statistics for all time-invariant control variables is available in Table A10, Appendix A.

The total database of daily data covers the period from May 1, 2020 to December 18, 2021, which gives us 17,313 daily observations.[9] Data with negative values for COVID-19 cases and deaths were excluded from the sample as those were errors in the dataset. The time series analysis of daily sales in Slovakia covers the same time period, which gives us 597 daily observations. Before the quantile regressions, all dependent variables used were tested for heteroscedasticity using the Breusch-Pagan test. Similarly, before using time series techniques, the stationarity of the dependent variables was verified using the Dickey-Fuller test for a unit root.

5. Results

This section presents the estimation results of the restrictive measures' impact on social mobility. Next, the estimates for both linear and non-linear effects of mobility restrictions on the spread of the virus are presented. The section also presents the effects of social distancing measures on various types of sales based on eKasa system in Slovakia.

5.1. Impact of Restrictive Measures on Mobility

Panel regression results with country- and day-fixed effects based on Eq. (1) and (2) are presented in Table 1. The results show that government social distancing measures represented by the stringency index have a significant impact on all types of mobility in the examined period. Such a finding is consistent with the results presented in other studies – e.g., Lapatinas (2020), or Barbieri et al. (2021). The only exception is grocery and pharmacy mobility in a firmer specification including also day-fixed effects, which is in line with the conclusion of Ferreira et al. (2021). Food and pharmaceuticals are essential goods that were in many cases subject to a less stringent regime or were even exempted entirely.

The first finding based on the R^2 is that including day-fixed effects improves the model accuracy in all cases. The results further indicate that social distancing measures are best reflected in retail and recreation mobility, which is why we use this type of mobility in the analyses in the following sections. On the contrary, Kallidoni et al. (2022) state that the most effective measure is to limit commuting to schools. Yilmazkuday (2022), on the other hand, defines mobility more generally as "time spent away from home". However,

[9] The data set starts from May 1, 2020. Earlier observations were excluded from the dataset because there were multiple errors at the beginning of the recording (e.g., negative COVID-19 cases or deaths).

using Google data based on GPS location, we consider retail and recreation mobility to be a sufficient proxy for the strictness of measures. This type of mobility reflects the mobility for essential goods, which is consistent with the study of Ferreira et al. (2021). An important finding is that social distancing measures reduced all types of social mobility (controlling for the non-working days). For example, in the case of retail and recreation mobility, an increase in strictness corresponding to 1 point in the stringency index led to a decrease in mobility by 0.35% on average (compared to the pre-pandemic period). It can therefore be concluded that the governments' measures have resulted in a decrease in social mobility, which is in line with Lapatinas (2020), or Barbieri et al. (2021). Put differently, retail and recreation mobility captures the strictness of government measures the best among all the monitored mobility categories.

5.2. Linear Effects of Mobility Restrictions on the Spread of COVID-19

The linear effects of mobility restrictions on ***COVID-19 cases*** were examined using panel regressions in Eq. (3) to (5). The results, considering various control characteristics, are presented in Tables 2 to 5.

Let us first focus on the results for the country-fixed effects specification in Eq. (3), which is later extended to day-fixed effects in Eq. (4). The results for the country-fixed effects specification show that the **retail and recreation type of mobility** has a positive and significant impact on the increase in the number of COVID-19 cases. The estimate suggests that a one percent increase in retail and recreation mobility results in a 9.8 percent week-on-week increase in the number of COVID-19 cases 21 days later, all else being equal. Yilmazkuday (2022) found a similar effect of mobility on COVID-19 cases, although his estimate is lower, which may be due to a different model specification.

According to our estimates, the **Delta variant** caused a significant increase in the number of new cases. However, the coefficient for the interaction term indicates that the effect of mobility during the period when Delta was the dominant variant was much lower. In fact, the change in the sign of the coefficient for mobility was negative ($0.098 - 0.161 = -0.063$) and statistically significant. Such a result seems counterintuitive at first glance, but there are at least 2 reasons that could explain our result. First, Delta was a much more infectious variant that spread exuberantly regardless of social mobility. The virus spread mainly in households and closed communities, and the impact of mobility itself may have been muted. Second, the time it takes for the Delta variant to show up in new cases has been significantly shortened compared to the previous variants, which would mean that the 21-day lag may not apply. Such reasons are consistent with the characteristics of the Delta variant reported by Menni et al. (2022) or von Wintersdorff et al. (2022).

Turning to the estimated effects of **vaccination**, we observe that vaccination had a favourable effect on the number of new cases. Our estimate suggests that each additional vaccine dose per 100 people in the total population caused a 17 percent week-on-week decrease in the number of COVID-19 cases on average if all else remains constant. However, it should be noted that the estimated effect represents an average value. It is clear that the beneficial effect of vaccination increases with the proportion of the vaccinated population. The common assumption is that the effect is negligible at a low share of the vaccinated population, but it increases significantly with an increasing share of the vaccinated population. Nonetheless, the beneficial effect of vaccination is apparent, which is consistent with the results of Moghadas et al. (2021) or Nixon et al. (2022).

With respect to our results regarding **distrust in public institutions**, we conclude that the distrust in public institutions worsens the pandemic situation. Each additional point in the index of distrust in public institutions leads to a 2.6 percent week-on-week increase in the number of COVID-19 cases on average, holding everything else constant. Our findings thus support the conclusions of Nickel et al. (2022), who claim that a lack of confidence and trust are fundamental drivers of vaccine hesitancy, which could have an effect on COVID-19 cases and deaths.

The inclusion of both **day- and country-fixed** effects based on Eq. (4) confirms our core results from Eq. (3). Note that including day-fixed effects improved the overall fit of our estimate, which is in line with Yilmazkuday (2022). However, the addition of daily fixed effects changed the estimated coefficient for vaccination – to such an extent that the sign changed to negative. Such a result seems counterintuitive at first glance, but it is actually rational under the given specification. Recall that the data on vaccination enters the equation at the current time, so without any lag. It is clear that the effect of vaccination will not be manifested immediately on the day of vaccination, but with a certain time lag. However, vaccination can induce the symptoms of COVID-19 disease, which can cause a false positive result even though the individual does not actually have the disease, only the post-vaccination syndrome. Although the inclusion of day-fixed effects may seem to contribute to the increase in cases of COVID-19, this false effect should not be reflected in COVID-19 deaths – which is indeed confirmed in Table 6.

Before proceeding to the examination of the health, economic, social and demographic characteristics given by Eq. (5), note that the inclusion of individual control variables confirms the results of the baseline specification in Eq. (3) and (4). The results for ***health characteristics*** are available in Table 2. As we can see, none of the examined health characteristics is a significant determinant of the number of COVID-19 cases – as we will see later, this is not the case for COVID-19 deaths (Table 6). Social mobility, vaccination and trust in institutions appear to be key determinants of the spread of COVID-19. Estimates containing ***economic characteristics*** are available in Table 3. Of the economic variables we examined, only the share of the population living in extreme poverty appears to be significant for COVID-19 cases. Our result suggests that the greater the share of the population living in extreme poverty in a given country, the lower the number of COVID-19 cases. Such a result is somewhat counterintuitive, but it can be explained by the lower ability to travel in regions with high extreme poverty. Limited social interactions can therefore contribute to a slower spread of the virus. Looking at the results in Table 4, ***social characteristics*** are not significant determinants of COVID-19 cases in European countries. Finally, Table 5 shows that the only ***demographic characteristic*** that has an impact on the number of COVID-19 cases is population density, which confirms the conclusions of Yilmazkuday (2022). Our estimate suggests that the higher the population density, the higher the number of COVID-19 cases, which is in line with expectations. The results are broadly in line with the findings of Fazio et al. (2022).

We can now proceed to examine the linear effects of mobility restrictions on ***COVID-19 deaths*** using the panel regressions in Eq. (6) to (8). The results, taking into account the control characteristics, are shown in Tables 6 to 9.

The results for the country-fixed effects in Eq. (6) are extended to day-fixed effects in Eq. (7). The country-fixed effects estimate shows that the **retail and recreation type of mobility** has a positive and significant impact on the increase in the number of COVID-19 deaths, which confirms our result for the COVID-19 cases presented in Table 2. A one percent increase in retail and recreation mobility results in a 2.3 percent week-on-week increase in the number of COVID-19 deaths 35 days later, all else being equal. The effect of mobility on both COVID-19 cases and deaths is similar to the findings of Yilmazkuday (2022). However, the size of the effect is higher in our case due to a different specification (e.g., he uses US data and a different mobility specification).

The estimate for COVID-19 deaths during the **Delta variant** confirms our estimate for COVID-19 cases, as the Delta variant caused a significant increase in the number of deaths. As the estimate for the interaction term shows, the effect of mobility on COVID-19 deaths growth was reduced when the Delta variant was dominant, similarly to the estimate for the number of COVID-19 cases. The sign has changed ($0.023 - 0.095 = -0.072$), which confirms two hypotheses. First, the mortality rate of the Delta variant, despite its greater infectivity, decreased. Second, the Delta variant spread much faster, which made the role of mobility marginal. At the same time, the incubation period, and thus the time from infection to death, has likely been significantly shortened. Again, the results are in line with the findings of Moghadas et al. (2021) or Nixon et al. (2022).

The **vaccination** decreased COVID-19 deaths significantly. Our result suggests that each additional vaccine dose per 100 people leads to a 10.7 percent week-on-week decrease in the number of COVID-19 cases on average if all else is being fixed. The beneficial effect of vaccination is obvious, which is in line with the results of other studies, for example Moghadas et al. (2021) or Nixon et al. (2022).

The **distrust in public institutions** increases not only the number of the infected but also the number of COVID-19 deaths. Each additional point in the index of distrust in public institutions leads to a 2.2 percent week-on-week increase in the number of COVID-19 deaths. Although the result for the country-fixed effects is not statistically significant, the estimate with country- and day-fixed effects as well as in all other estimates, distrust in public institutions has a statistically significant effect on the number of COVID-19 deaths.

The inclusion of both **day- and country-fixed** effects based on Eq. (7) confirms our results of country-fixed effects from Eq. (6). The inclusion of day-fixed effects improved the overall fit of our estimates considerably. Note that even after including day-fixed effects, the benefits of vaccination can be observed to about the same extent as in the baseline model given by Eq. (6). The estimate for COVID-19 deaths is statistically significant, unlike the estimate for COVID-19 cases. Moreover, after including day-fixed effects, the coefficient for distrust in public institutions appears to become statistically significant.

Adding individual control variables based on Eq. (8) confirms the results of the baseline specification in Eq. (6) and (7). While no ***health characteristic*** was a significant determinant of the number of COVID-19 cases, Table 6 shows that cardiovascular disease and the share of male smokers increase the risk of death from COVID-19. Our estimate suggests that an increase in the number of deaths from cardiovascular disease by 1 unit per 100,000 people corresponds to a 1.2 percent week-on-week increase in the number of COVID-19 deaths on average, keeping all else fixed. Such a result is broadly in line with the findings of Vasbinder et al. (2022) who documented that cardiovascular risk factors were the major contributors to outcomes in critically ill patients with COVID-19. The consequences for smokers are also significant – an increase in the share of male smokers by 1 unit results in a 12.9 percent week-on-week increase in the number of COVID-19 deaths on average, ceteris paribus. The estimates with ***economic characteristics*** are available in Table 7. Our results suggest that the more developed the country, the lower the number of COVID-19 deaths. The result for GDP per capita is confirmed with the coefficient for the Human Development Index. Such a result is in line with expectations, since richer countries probably have better health systems, better access to clean water, and better overall hygiene. Looking at the results for ***social characteristics*** in Table 8, only the quality of education is a significant determinant of COVID-19 deaths. The higher the quality of education, the lower the number of deaths. Finally, the results for ***demographic characteristics*** captured in Table 9 show that the greater the proportion of rural population, the greater the number of deaths. This conclusion is confirmed by the results for the share of urban population. The most likely reason is the better access to healthcare in larger cities, which is in line with Deb et al. (2020).

5.3. Non-Linear Effects of Mobility Restrictions on the Spread of COVID-19

In this section, we investigate the nonlinear effects on COVID-19 cases (Eq. 9) and deaths (Eq. 10) using quantile regressions on a data panel for European countries. First, we show the linear effects using OLS panel regression with day-fixed and country-fixed effects (Eq. 4 for cases and Eq. 7 for deaths). Subsequently, we investigate the nonlinear effects of retail and recreation mobility and other explanatory variables in individual quantiles of the distribution of COVID-19 cases and deaths, using day- and country-fixed effects. The results for OLS panel regression and 0.25th, 0.50th and 0.75th quantiles are available in Table 10. The effects on the entire distribution of COVID-19 cases are shown in Figure 1 and on the entire distribution of COVID-19 deaths in Figure 2.

Table 10 shows that in the 25th quantile of the COVID-19 cases, the **mobility** coefficient is much lower than the OLS panel regression estimate and significantly different from zero and the OLS panel regression coefficient. Regarding the 50th quantile, the coefficient is slightly higher, and still significantly different from zero and the OLS panel regression coefficient. The coefficient for the 75th quantile is even larger, and although it is still significantly different from zero, it is already statistically insignificant from the panel OLS estimate. Figure 1 clarifies the effects of mobility on COVID-19 cases across the distribution. The upper left graph shows that the panel OLS estimate overlaps with the quantile estimate only in a narrow part around the 75th quantile. While the coefficients are below the panel OLS coefficient in the lower quantiles, the coefficients are considerably above the OLS coefficient in the higher quantiles. A very similar picture is in the upper left graph in Figure 2, showing the effect of mobility on COVID-19 deaths. The shape of the curve is very similar, but the size of the coefficients for the COVID-19 deaths estimation is lower than the size of the coefficients for the COVID-19 cases estimation. These results suggest that an early response of policy-makers is very important, which is a similar conclusion to Oh et al. (2021) or Deb et al. (2020). It is crucial to take the necessary measures before the breaking point is reached, when it is much more difficult to influence the spread of the virus.

The effect of mobility on both COVID-19 cases and deaths weakens as the number of the Delta variant cases increases, as can be seen in the estimate for the interaction term shown in the middle left graph in Figures 1 and 2. This confirms our previous assumption that the Delta variant was much more infectious than the previous variants and the restriction of mobility brought much smaller benefits.

The non-linear effects of **vaccination** on COVID-19 cases and deaths can be examined on the right graph in the middle in Figures 1 and 2. The vaccination benefits (i.e., the decrease in cases and deaths) grow with COVID-19 cases or deaths. In other words, the larger share of the population is vaccinated, the lower the increase in the number of COVID-19 cases or deaths. Interestingly, the absolute value of the estimated coefficients for COVID-19 deaths (Figure 2) is very close to the absolute value of the estimated coefficients for COVID-19 cases (Figure 1). In Table 10, we see that the linear panel OLS estimate for deaths is even higher in absolute terms than for cases. Such a result suggests that vaccination brings benefits for both cases and deaths, but a particularly beneficial effect can be seen on COVID-19 deaths.

Finally, we can examine the non-linear effects of **distrust in public institutions** on COVID-19 cases and deaths. The bottom left graph in Figures 1 and 2 shows that the negative impact of distrust in government institutions on cases and deaths is particularly pronounced in the upper quantiles, when the virus is spreading very quickly and uncontrollably. The key is therefore to prevent such spread by introducing an appropriate combination of targeted measures (especially vaccination).

5.4. Impact of Restrictive Measures on Daily Sales in Slovakia according to eKasa

In this section, we present our results for the linear and non-linear effects of epidemic measures on daily sales according to a digital tax collection system – eKasa. The analysis was performed on daily data for Slovakia. Linear effects were obtained using linear OLS regressions, while non-linear effects were obtained from quantile regressions for different types of sales according to eKasa. The estimated coefficients are available in Table 11, while Figure 3 captures the effects of the stringency of the measures on individual types of sales according to eKasa across their entire distributions.

The OLS regression estimates captured in Table 11 and Figure 3 show that higher stringency results in lower **retail sales**, and this linear effect is statistically significant. Furthermore, the effect of stringency on retail sales is not constant and varies across quantiles. The coefficient value gradually increases until it flips to a positive value at the highest quantiles, when this effect is no longer statistically significant. At the same time, in most quantiles, the estimates for the stringency measure from the quantile regression are not statistically significant from the linear OLS estimate.

We obtain similar results for sales in **grocery stores**. It is evident from the linear OLS regression that the estimated coefficient representing the stringency of the measures is negative and statistically insignificant. The results of quantile regressions reveal that although the coefficients significantly differ from zero in some parts of the distribution, it does not differ much from the OLS estimate. The values of the coefficient increase with quantiles, similar to the estimation of retail sales.

The results for retail and grocery sales are not surprising, as the purchase of food is essential for consumers, which is consistent with the findings of Ferreira et al. (2021). It is, therefore, unlikely that people will stop buying essential goods for a long time. However, there may be a frontloading effect, which may increase sales slightly. Restricting mobility to these essential items is not very effective, and therefore, we do not observe such a significant drop in sales. Even online shopping cannot fully compensate for the purchase of fresh food and medicine in stores and pharmacies.

The situation in restaurants and accommodation facilities is completely different. First of all, the coefficient from linear OLS regression is negative and significant for both types of sales. **For restaurant sales**, the estimated coefficients for the stringency measures are very close to the coefficient estimate from the OLS regression across the entire distribution. However, for sales in **accommodation facilities**, it is evident that the estimated coefficients for stringency measures decrease sharply with higher quantiles. The estimates from the quantile regression are significantly different from zero and the OLS estimate at most quantiles.

These results suggest that sales in essential sectors to consumers, such as retail and grocery stores, are relatively resilient to the tightening measures. In contrast, sales in less essential sectors, such as restaurants or accommodation, are particularly sensitive to social distancing measures, which is in line with Vărzaru et al. (2021). An asymmetric impact on essential versus non-essential goods was also documented in the study of Ferreira et al. (2021). It follows that while restrictions effectively reduce mobility to restaurants and hotels, policymakers should be prepared to compensate entrepreneurs in gastronomy, restaurants, hotels and tourism. Restricting mobility in stores to buy essential goods is less effective in slowing down the spread of the virus.

6. Conclusion

In this paper, we first examined the effects of restrictive measures on social mobility using country- and day-fixed effects on a panel of European countries. We then investigated the linear and non-linear effects of restrictive measures on COVID-19 cases and deaths. Linear effects were examined by OLS regression with country- and/or day-fixed effects on a panel of European countries, while non-linear effects were examined by quantile regressions. We controlled for a set of country-specific (time-invariant) control variables, which we divide into 4 categories – health, economic, social and demographic characteristics. Also, we extended our analysis to a case from Slovakia, where we looked at the linear and non-linear effects of the stringency of measures on various categories of daily sales according to a digital tax collection system – eKasa. The results are consistent across estimates and parallel general expectations and the results of similar studies.

The results show that government **social distancing measures** represented by the stringency index have a significant impact on all types of mobility (controlling for the non-working days) in the examined period. The only exception is grocery and pharmacy mobility in a firmer specification including also day-fixed effects. Food and pharmaceuticals are essential goods that were in many cases subject to a less stringent regime or were even exempted entirely. The social distancing measures are best reflected in retail and recreation mobility, which is why we further use this type of mobility as a proxy for the strictness of measures.

Linear panel OLS regressions using country-fixed effects confirmed that stricter mobility restrictions significantly reduce COVID-19 cases and deaths. The estimates suggest that a one percent increase in retail and recreation mobility causes a 9.8 percent week-on-week increase in the number of COVID-19 cases 21 days later and a 2.3 percent week-on-week increase in the number of COVID-19 deaths 35 days later on average, all else being equal. Although the Delta variant caused a significant increase in both COVID-19 cases and deaths, the impact of social mobility during the period when the Delta variant was dominant was much lower on both cases and deaths. This confirms that the Delta variant was a much more infectious variant that spread rampantly regardless of social mobility. However, the mortality rate of the Delta variant has decreased despite its greater infectivity. At the same time, the incubation period, and thus the time from infection to death, has shortened.

Turning to the effects of vaccination, we estimate that each additional vaccine dose per 100 people in the total population caused a 17 percent week-on-week decrease in the number of COVID-19 and a 10.7 percent week-on-week decrease in the number of COVID-19 cases on average if all else is being fixed. With respect to our results regarding distrust in public institutions, we conclude that each additional point in the index of distrust in public institutions leads to a 2.6 percent week-on-week increase in the number of COVID-19 cases and a 2.2 percent week-on-week increase in the number of COVID-19 deaths on average, holding everything else constant. The inclusion of day-fixed effects improved the overall fit of our estimates. Among the examined control variables, the share of the population living in extreme poverty and the population density are shown to be significant determinants of COVID-19 cases. Another important determinant of COVID-19 deaths is the economic development of the country. Our results indicate that the more developed the country, the lower the number of COVID-19 deaths. The quality of education is also an important factor for COVID-19 deaths. Of the demographic characteristics, the share of rural population appears to be important – the greater the share of rural population, the higher the number of COVID-19 deaths. This conclusion is also confirmed by the results for the share of urban population.

Quantile regressions allowed us to investigate the **non-linear effects of mobility restriction on COVID-19 cases and deaths**. Although the results of quantile regressions confirmed our linear results in general, they revealed that the linear effects were not constant at all stages of the virus spread. The linear OLS estimate for both COVID-19 cases and deaths overlaps with the quantile estimates only in a narrow part of the distribution. Although the profile of quantile estimates for both cases and deaths is very similar, the absolute size of the coefficients for the COVID-19 deaths estimation is lower than the size of the coefficients for the COVID-19 cases estimation. This indicates that an early response from policy-makers is very important. However, the effect of mobility on both COVID-19 cases and deaths weakens as the number of the Delta variant cases increases. This confirms that the Delta variant was much more infectious than the previous variants and the restriction of mobility brought much smaller benefits.

The vaccination benefits grow with COVID-19 cases or deaths – the larger share of the population is vaccinated, the lower the increase in the number of COVID-19 cases or deaths. We conclude that vaccination brings benefits for both cases and deaths, but a particularly beneficial effect can be seen on COVID-19 deaths. The negative impact of distrust in government institutions on COVID-19 cases and deaths is particularly pronounced in the upper quantiles, when the virus is spreading very quickly and uncontrollably.

Finally, our results for the linear and nonlinear effects of epidemic measures on daily sales from the eKasa in Slovakia suggest that sales in essential sectors for consumers, such as retail and grocery stores, are relatively resistant to tightening measures. On the contrary, sales in less essential sectors, such as restaurants or accommodation, are extremely sensitive to social distancing measures. As a consequence, restrictions effectively reduce mobility to restaurants and hotels. Therefore, it is necessary for policy-makers to be prepared to compensate entrepreneurs in sensitive sectors.

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References

Abumalloh, R. A., Asadi, S., Nilashi, M., Minaei-Bidgoli, B., Nayer, F. K., Samad, S., Mohd, S., & Ibrahim, O. (2021). *The impact of coronavirus pandemic (COVID-19) on education: The role of virtual and remote laboratories in education*. In Technology in Society (Vol. 67, p. 101728). Elsevier BV. https://doi.org/10.1016/j.techsoc.2021.101728

Acemoglu, D., Chernozhukov, V., Werning, I., & Whinston, M. (2020). *Optimal Targeted Lockdowns in a Multi-Group SIR Model*. National Bureau of Economic Research. https://doi.org/10.3386/w27102

Barbieri, D. M., Lou, B., Passavanti, M., Hui, C., Hoff, I., Lessa, D. A., Sikka, G., Chang, K., Gupta, A., Fang, K., Banerjee, A., Maharaj, B., Lam, L., Ghasemi, N., Naik, B., Wang, F., Foroutan Mirhosseini, A., Naseri, S., Liu, Z., … Rashidi, T. H. (2021). *Impact of COVID-19 pandemic on mobility in ten countries and associated perceived risk for all transport modes*. In A. H. Pakpour (Ed.), PLOS ONE (Vol. 16, Issue 2, p. e0245886). Public Library of Science (PLoS). https://doi.org/10.1371/journal.pone.0245886

Carfì, A., Bernabei, R., & Landi, F. (2020). *Persistent Symptoms in Patients After Acute COVID-19*. In JAMA (Vol. 324, Issue 6, p. 603). American Medical Association (AMA). https://doi.org/10.1001/jama.2020.12603

Chen, S., Igan, D., Pierri, N., & Presbitero, F. P. (2020). *Tracking the Economic Impact of COVID-19 and Mitigation Policies in Europe and the United States*. In IMF Working Paper (WP/20/125).

Cheshmehzangi, A., Sedrez, M., Ren, J., Kong, D., Shen, Y., Bao, S., Xu, J., Su, Z., & Dawodu, A. (2021). *The Effect of Mobility on the Spread of COVID-19 in Light of Regional Differences in the European Union*. In Sustainability (Vol. 13, Issue 10, p. 5395). MDPI AG. https://doi.org/10.3390/su13105395

Couch, K. A., Fairlie, R. W., & Xu, H. (2022). *The evolving impacts of the COVID-19 pandemic on gender inequality in the US labor market: The COVID motherhood penalty*.

In Economic Inquiry (Vol. 60, Issue 2, pp. 485–507). Wiley. https://doi.org/10.1111/ecin.13054

Deb, P., Furceri, D., Ostry, J. D., & Tawk, N. (2020). *The Effect of Containment Measures on the COVID-19 Pandemic*. In IMF Working Paper (WP/20/159).

Docquier, F., Golenvaux, N., Nijssen, S., Schaus, P., & Stips, F. (2022). *Cross-border mobility responses to COVID-19 in Europe: new evidence from facebook data.* In Globalization and Health (Vol. 18, Issue 1). Springer Science and Business Media LLC. https://doi.org/10.1186/s12992-022-00832-6

Druss, B. G. (2020). *Addressing the COVID-19 Pandemic in Populations With Serious Mental Illness*. In JAMA Psychiatry (Vol. 77, Issue 9, p. 891). American Medical Association (AMA). https://doi.org/10.1001/jamapsychiatry.2020.0894

Esposito, S., Principi, N., Leung, C. C., & Migliori, G. B. (2020). *Universal use of face masks for success against COVID-19: evidence and implications for prevention policies*. In European Respiratory Journal (Vol. 55, Issue 6, p. 2001260). European Respiratory Society (ERS). https://doi.org/10.1183/13993003.01260-2020

Farré, L., Fawaz, Y., González, L., & Graves, J. (2021). *Gender Inequality in Paid and Unpaid Work During Covid-19 Times*. In Review of Income and Wealth (Vol. 68, Issue 2, pp. 323–347). Wiley. https://doi.org/10.1111/roiw.12563

Fazio, M., Pluchino, A., Inturri, G., Le Pira, M., Giuffrida, N., & Ignaccolo, M. (2022). *Exploring the impact of mobility restrictions on the COVID-19 spreading through an agent-based approach*. In Journal of Transport & Health (Vol. 25, p. 101373). Elsevier BV. https://doi.org/10.1016/j.jth.2022.101373

Ferreira, J., Ramos, P., Barata, E., Court, C., & Cruz, L. (2021). *The impact of COVID-19 on global value chains: Disruption in nonessential goods production*. In Regional Science Policy & Practice (Vol. 13, Issue S1, pp. 32–54). Wiley. https://doi.org/10.1111/rsp3.12416

Fiorillo, A., & Gorwood, P. (2020). *The consequences of the COVID-19 pandemic on mental health and implications for clinical practice*. In European Psychiatry (Vol. 63, Issue 1). Royal College of Psychiatrists. https://doi.org/10.1192/j.eurpsy.2020.35

Freeman, J. D., & Schug, J. (2021). *Freedom to Stay-at-Home? Countries Higher in Relational Mobility Showed Decreased Geographic Mobility at the Onset of the COVID-19 Pandemic*. In Frontiers in Psychology (Vol. 12). Frontiers Media SA. https://doi.org/10.3389/fpsyg.2021.648042

Gabutti, G., d'Anchera, E., De Motoli, F., Savio, M., & Stefanati, A. (2021). *The Epidemiological Characteristics of the COVID-19 Pandemic in Europe: Focus on Italy*. In International Journal of Environmental Research and Public Health (Vol. 18, Issue 6, p. 2942). MDPI AG. https://doi.org/10.3390/ijerph18062942

Garcia, L. P. (2020). Uso de máscara facial para limitar a transmissão da COVID-19. In Epidemiologia e Serviços de Saúde (Vol. 29, Issue 2). FapUNIFESP (SciELO). https://doi.org/10.5123/s1679-49742020000200021

Gyódi, K. (2021). *Airbnb and hotels during COVID-19: different strategies to survive*. In International Journal of Culture, Tourism and Hospitality Research (Vol. 16, Issue 1, pp. 168–192). Emerald. https://doi.org/10.1108/ijcthr-09-2020-0221

Hart, W. S., Miller, E., Andrews, N. J., Waight, P., Maini, P. K., Funk, S., & Thompson, R. N. (2022). *Generation time of the alpha and delta SARS-CoV-2 variants: an epidemiological analysis*. In The Lancet Infectious Diseases (Vol. 22, Issue 5, pp. 603–610). Elsevier BV. https://doi.org/10.1016/s1473-3099(22)00001-9

Kallidoni, M., Katrakazas, C., & Yannis, G. (2022). *Modelling the relationship between covid-19 restrictive measures and mobility patterns across Europe using time-series analysis*. European Journal of Transport and Infrastructure Research, Vol. 22 No. 2 (2022). https://doi.org/10.18757/EJTIR.2022.22.2.5728

Koenker, R., & Bassett, G. (1978). *Regression Quantiles*. In Econometrica (Vol. 46, Issue 1, p. 33). JSTOR. https://doi.org/10.2307/1913643

Lapatinas, A. (2020). *The effect of COVID-19 confinement policies on community mobility trends in the EU*. Publications Office of the European Union. https://doi.org/10.2760/875644

Linka, K., Peirlinck, M., Sahli Costabal, F., & Kuhl, E. (2020). *Outbreak dynamics of COVID-19 in Europe and the effect of travel restrictions*. In Computer Methods in Biomechanics and Biomedical Engineering (Vol. 23, Issue 11, pp. 710–717). Informa UK Limited. https://doi.org/10.1080/10255842.2020.1759560

Menni, C., Valdes, A. M., Polidori, L., Antonelli, M., Penamakuri, S., Nogal, A., Louca, P., May, A., Figueiredo, J. C., Hu, C., Molteni, E., Canas, L., Österdahl, M. F., Modat, M., Sudre, C. H., Fox, B., Hammers, A., Wolf, J., Capdevila, J., … Spector, T. D. (2022). *Symptom prevalence, duration, and risk of hospital admission in individuals infected with SARS-CoV-2 during periods of omicron and delta variant dominance: a prospective observational study from the ZOE COVID Study*. In The Lancet (Vol. 399, Issue 10335, pp. 1618–1624). Elsevier BV. https://doi.org/10.1016/s0140-6736(22)00327-0

Moghadas, S. M., Vilches, T. N., Zhang, K., Wells, C. R., Shoukat, A., Singer, B. H., Meyers, L. A., Neuzil, K. M., Langley, J. M., Fitzpatrick, M. C., & Galvani, A. P. (2020). *The impact of vaccination on COVID-19 outbreaks in the United States*. Cold Spring Harbor Laboratory. https://doi.org/10.1101/2020.11.27.20240051

Nickel, B., Pickles, K., Cvejic, E., Copp, T., Dodd, R. H., Bonner, C., Seale, H., Steffens, M., Meyerowitz-Katz, G., & McCaffery, K. (2022). *Predictors of confidence and trust in government and institutions during the COVID-19 response in Australia.* In The Lancet Regional Health - Western Pacific (Vol. 23, p. 100490). Elsevier BV. https://doi.org/10.1016/j.lanwpc.2022.100490

Nixon, D. F., Schwartz, R. E., & Ndhlovu, L. C. (2022). *Booster vaccines for COVID-19 vaccine breakthrough cases?* In The Lancet (Vol. 399, Issue 10331, p. 1224). Elsevier BV. https://doi.org/10.1016/s0140-6736(22)00044-7

Oh, J., Lee, H.-Y., Khuong, Q. L., Markuns, J. F., Bullen, C., Barrios, O. E. A., Hwang, S., Suh, Y. S., McCool, J., Kachur, S. P., Chan, C.-C., Kwon, S., Kondo, N., Hoang, V. M., Moon, J. R., Rostila, M., Norheim, O. F., You, M., Withers, M., … Gostin, L. O.

(2021). *Mobility restrictions were associated with reductions in COVID-19 incidence early in the pandemic: evidence from a real-time evaluation in 34 countries*. In Scientific Reports (Vol. 11, Issue 1). Springer Science and Business Media LLC. https://doi.org/10.1038/s41598-021-92766-z

Oka, T., Wei, W., & Zhu, D. (2021). *The effect of human mobility restrictions on the COVID-19 transmission network in China*. In B. Xue (Ed.), PLOS ONE (Vol. 16, Issue 7, p. e0254403). Public Library of Science (PLoS). https://doi.org/10.1371/journal.pone.0254403

Powell, d. (2014). *Did the Economic Stimulus Payments of 2008 Reduce Labor Supply? Evidence from Quantile Panel Data Estimation*. In Working Papers WR-710-3, RAND Corporation.

Powell, D. (2016). *Quantile Regression with Nonadditive Fixed Effects*. RAND

del Rio, C., Collins, L. F., & Malani, P. (2020). *Long-term Health Consequences of COVID-19*. In JAMA (Vol. 324, Issue 17, p. 1723). American Medical Association (AMA). https://doi.org/10.1001/jama.2020.19719

Škare, M., Soriano, D. R., & Porada-Rochoń, M. (2021). *Impact of COVID-19 on the travel and tourism industry*. In Technological Forecasting and Social Change (Vol. 163, p. 120469). Elsevier BV. https://doi.org/10.1016/j.techfore.2020.120469

Sosares, S., & Berg, J. (2022). *The labour market fallout of COVID-19: Who endures, who doesn't and what are the implications for inequality*. In International Labour Review (Vol. 161, Issue 1, pp. 5–28). Wiley. https://doi.org/10.1111/ilr.12214

Tan, L., Wu, X., Guo, J., & Santibanez-Gonzalez, E. D. R. (2021). *Assessing the Impacts of COVID-19 on the Industrial Sectors and Economy of China*. In Risk Analysis (Vol. 42, Issue 1, pp. 21–39). Wiley. https://doi.org/10.1111/risa.13805

Vărzaru, A. A., Bocean, C. G., & Cazacu, M. (2021). *Rethinking Tourism Industry in Pandemic COVID-19 Period*. In Sustainability (Vol. 13, Issue 12, p. 6956). MDPI AG. https://doi.org/10.3390/su13126956

Vasbinder, A., Meloche, C., Azam, T. U., Anderson, E., Catalan, T., Shadid, H., Berlin, H., Pan, M., O'Hayer, P., Padalia, K., Blakely, P., Khaleel, I., Michaud, E., Huang, Y., Zhao, L., Pop-Busui, R., Gupta, S., Eagle, K., … Leaf, D. E. (2022). *Relationship Between Preexisting Cardiovascular Disease and Death and Cardiovascular Outcomes in Critically Ill Patients With COVID-19*. In Circulation: Cardiovascular Quality and Outcomes (Vol. 15, Issue 10). Ovid Technologies (Wolters Kluwer Health). https://doi.org/10.1161/circoutcomes.122.008942

Vlachopoulos, D. (2020). COVID-19: *Threat or Opportunity for Online Education?* In Higher Learning Research Communications (Vol. 10, Issue 1). Walden University. https://doi.org/10.18870/hlrc.v10i1.1179

von Wintersdorff, C. J. H., Dingemans, J., van Alphen, L. B., Wolffs, P. F. G., van der Veer, B. M. J. W., Hoebe, C. J. P. A., & Savelkoul, P. H. M. (2022). *Infections with the SARS-CoV-2 Delta variant exhibit fourfold increased viral loads in the upper airways compared to Alpha or non-variants of concern.* In Scientific Reports (Vol. 12, Issue 1). Springer Science and Business Media LLC. https://doi.org/10.1038/s41598-022-18279-5

Yilmazkuday, H. (2022). *Nonlinear effects of mobility on COVID-19 in the US: targeted lockdowns based on income and poverty*. In Journal of Economic Studies. Emerald. https://doi.org/10.1108/jes-11-2021-0596

Zhang, R., Liang, Z., Pang, M., Yang, X., Wu, J., Fang, Y., Ji, H., & Qi, X. (2021). *Mobility Trends and Effects on the COVID-19 Epidemic — Hong Kong, China*. In China CDC Weekly (Vol. 3, Issue 8, pp. 159–161). Chinese Center for Disease Control and Prevention. https://doi.org/10.46234/ccdcw2021.020

Zhou, Y., Xu, R., Hu, D., Yue, Y., Li, Q., & Xia, J. (2020). *Effects of human mobility restrictions on the spread of COVID-19 in Shenzhen, China: a modelling study using mobile phone data*. In The Lancet Digital Health (Vol. 2, Issue 8, pp. e417–e424). Elsevier BV. https://doi.org/10.1016/s2589-7500(20)30165-5.

Table 1. The Impact of Restrictive Measures on Different Types of Mobility According to Google

Dependent:	***Retail & Recreation Mobility***		***Grocery & Pharmacy Mobility***		***Transit Stations Mobility***		***Workplaces Mobility***	
	Eq.(1)	***Eq.(2)***	***Eq.(1)***	***Eq.(2)***	***Eq.(1)***	***Eq.(2)***	***Eq.(1)***	***Eq.(2)***
Stringency	-1.0934***	-0.3469***	-0.4617***	-0.0694	-0.7986***	-0.1892***	-0.3174***	-0.1730***
	(0.0613)	*(0.0638)*	*(0.0454)*	*(0.0513)*	*(0.0476)*	*(0.0605)*	*(0.0239)*	*(0.0229)*
Holiday	-24.6176***	-19.1446***	-43.9320***	-36.2780***	-23.5679***	-17.6854***	-53.4666***	-44.3689***
	(2.5575)	*(2.6911)*	*(5.1262)*	*(5.3278)*	*(1.5932)*	*(1.6068)*	*(1.3324)*	*(1.9679)*
Constant	44.2187***	-28.1337***	31.6003***	-18.4583***	21.7185***	-36.2892***	-3.3106**	-25.7719***
	(3.3659)	*(6.0242)*	*(2.4907)*	*(5.3699)*	*(2.6249)*	*(5.2397)*	*(1.3177)*	*(3.0779)*
Day Fixed Effects	no	yes	no	yes	no	yes	no	yes
Country Fixed Effects	yes	yes	yes	yes	yes	yes	yes	yes
Sample Size	17,313	17,313	17,313	17,313	17,313	17,313	17,313	17,313
Number of Country Groups	29	29	29	29	29	29	29	29
R^2	0.5049	0.7839	0.2314	0.5670	0.4388	0.7391	0.2992	0.8089
Adjusted R^2	0.505	0.776	0.231	0.552	0.439	0.730	0.299	0.802

Notes: Estimates are from regressions in Equations (1) and (2). The dependent variable is the particular type of social mobility represented by the percentage change index of particular type of mobility with respect to the pre-pandemic period (Jan 3 – Feb 6, 2020). Robust standard errors are given in parenthesis.
*Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*
Source: own calculations

Table 2. Linear Effects of Mobility on COVID-19 Cases – Health Characteristics

Dependent:	***Cases Eq.(3)***	***Cases Eq.(4)***	*Cases Eq.(5)*	*Cases Eq.(5)*	*Cases Eq.(5)*	*Cases Eq.(5)*
Mobility$_{t-21}$	**0.098*** **	**0.094*** **	0.097***	0.098***	0.098***	0.097***
	(0.013)	***(0.004)***	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*
Delta $_{t-21}$	**2.264*** **	**0.863** **	2.233***	2.246***	2.243***	2.234***
	(0.659)	***(0.355)***	*(0.228)*	*(0.228)*	*(0.228)*	*(0.228)*
Mobility $_{t-21}$ × Delta $_{t-21}$	**-0.161*** **	**-0.097*** **	-0.159***	-0.160***	-0.160***	-0.160***
	(0.029)	***(0.007)***	*(0.008)*	*(0.008)*	*(0.008)*	*(0.008)*
Vaccination	**-0.173*** **	**0.085*** **	-0.172***	-0.172***	-0.172***	-0.172***
	(0.017)	***(0.006)***	*(0.004)*	*(0.004)*	*(0.004)*	*(0.004)*
Institutions	**0.026**	**0.073*** **	0.029***	0.028***	0.026**	0.023**
	(0.173)	***(0.011)***	*(0.009)*	*(0.010)*	*(0.011)*	*(0.011)*
Cardiovasc. Death Rate			0.000			
			(0.002)			
Diabetes Prevalence				-0.010		
				(0.117)		
Female Smokers					0.023	
					(0.045)	
Male Smokers						0.026
						(0.027)
Constant	**9.749**	**7.244*** **	9.531***	9.633***	9.127***	9.040***
	(9.531)	***(1.116)***	*(0.528)*	*(0.868)*	*(1.052)*	*(0.785)*
Day Fixed Effects	**no**	**yes**	no	no	no	no
Country Fixed Effects	**yes**	**yes**	no	no	no	no
Random Effects	**no**	**no**	yes	yes	yes	yes
Sample Size	**16,662**	**16,662**	16,662	16,662	16,662	16,662
Number of Country Groups	**29**	**29**	29	29	29	29
R^2	**0.214**	**0.629**				
Adjusted *R^2*	**0.214**	**0.615**				

*Notes: Estimates are from regressions in Equations (3), (4) and (5). The dependent variable is the weekly percentage change in cumulative daily COVID-19 cases. The presented coefficients for mobility represent the effects of "retail & recreation" mobility. Robust standard errors are given in parenthesis. Significance: *** p < 0.01, ** p < 0.05, * p < 0.1*
Source: own calculations

Table 3. Linear Effects of Mobility on COVID-19 Cases – Economic Characteristics

Dependent:	***Cases Eq.(3)***	***Cases Eq.(4)***	*Cases Eq.(5)*	*Cases Eq.(5)*	*Cases Eq.(5)*
Mobility$_{t-21}$	**0.098*****	**0.094*****	0.097***	0.098***	0.098***
	(0.013)	***(0.004)***	*(0.003)*	*(0.003)*	*(0.003)*
Delta$_{t-21}$	**2.264*****	**0.863****	2.236***	2.267***	2.244***
	(0.659)	***(0.355)***	*(0.228)*	*(0.228)*	*(0.228)*
Mobility $_{t-21}$ × Delta$_{t-21}$	**-0.161*****	**-0.097*****	-0.160***	-0.160***	-0.160***
	(0.029)	***(0.007)***	*(0.008)*	*(0.008)*	*(0.008)*
Vaccination	**-0.173*****	**0.085*****	-0.172***	-0.173***	-0.172***
	(0.017)	***(0.006)***	*(0.004)*	*(0.004)*	*(0.004)*
Institutions	**0.026**	**0.073*****	0.025**	0.035***	0.028***
	(0.173)	***(0.011)***	*(0.011)*	*(0.010)*	*(0.011)*
GDP per capita			-0.325		
			(0.600)		
Extreme Poverty				-0.487***	
				(0.177)	
HDI					-0.371
					(5.641)
Constant	**9.749**	**7.244*****	13.155**	9.547***	9.927*
	(9.531)	***(1.116)***	*(6.657)*	*(0.554)*	*(5.395)*
Day Fixed Effects	**no**	**yes**	no	no	no
Country Fixed Effects	**yes**	**yes**	no	no	no
Random Effects	**no**	**no**	yes	yes	yes
Sample Size	**16,662**	**16,662**	16,662	16,662	16,662
Number of Country Groups	**29**	**29**	29	29	29
R^2	**0.214**	**0.629**			
Adjusted *R^2*	**0.214**	**0.615**			

*Notes: Estimates are from regressions in Equations (3), (4) and (5). The dependent variable is the weekly percentage change in cumulative daily COVID-19 cases. The presented coefficients for mobility represent the effects of "retail & recreation" mobility. Robust standard errors are given in parenthesis. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*
Source: own calculations

Table 4. Linear Effects of Mobility on COVID-19 Cases – Social Characteristics

Dependent:	**Cases** ***Eq.(3)***	**Cases** ***Eq.(4)***	Cases *Eq.(5)*	Cases *Eq.(5)*	Cases *Eq.(5)*	Cases *Eq.(5)*
Mobility$_{t-21}$	**0.098*** **	**0.094*** **	0.098***	0.098***	0.098***	0.098***
	(0.013)	***(0.004)***	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*
Delta$_{t-21}$	**2.264*** **	**0.863** **	2.246***	2.241***	2.251***	2.251***
	(0.659)	***(0.355)***	*(0.228)*	*(0.228)*	*(0.228)*	*(0.228)*
Mobility $_{t-21}$ × Delta$_{t-21}$	**-0.161*** **	**-0.097*** **	-0.160***	-0.160***	-0.160***	-0.160***
	(0.029)	***(0.007)***	*(0.008)*	*(0.008)*	*(0.008)*	*(0.008)*
Vaccination	**-0.173*** **	**0.085*** **	-0.172***	-0.172***	-0.173***	-0.173***
	(0.017)	***(0.006)***	*(0.004)*	*(0.004)*	*(0.004)*	*(0.004)*
Institutions	**0.026**	**0.073*** **	0.028***	0.032***	0.030***	0.030***
	(0.173)	***(0.011)***	*(0.010)*	*(0.009)*	*(0.010)*	*(0.010)*
Populism			0.006			
			(0.013)			
Education				0.201		
				(0.169)		
Education Quality					0.002	
					(0.003)	
Healthcare Quality						0.322
						(0.454)
Constant	**9.749**	**7.244*** **	9.498***	6.947***	6.645	8.400***
	(9.531)	***(1.116)***	*(0.610)*	*(2.263)*	*(4.539)*	*(1.760)*
Day Fixed Effects	**no**	**yes**	no	no	no	no
Country Fixed Effects	**yes**	**yes**	no	no	no	no
Random Effects	**no**	**no**	yes	yes	yes	yes
Sample Size	**16,662**	**16,662**	16,662	16,662	16,662	16,662
Number of Country Groups	**29**	**29**	29	29	29	29
R^2	**0.214**	**0.629**				
Adjusted *R^2*	**0.214**	**0.615**				

*Notes: Estimates are from regressions in Equations (3), (4) and (5). The dependent variable is the weekly percentage change in cumulative daily COVID-19 cases. The presented coefficients for mobility represent the effects of "retail & recreation" mobility. Robust standard errors are given in parenthesis. Significance: *** p < 0.01, ** p < 0.05, * p < 0.1*
Source: own calculations

Table 5. Linear Effects of Mobility on COVID-19 Cases – Demographic Characteristics

Dependent:	***Cases Eq.(3)***	***Cases Eq.(4)***	*Cases Eq.(5)*	*Cases Eq.(5)*	*Cases Eq.(5)*	*Cases Eq.(5)*	*Cases Eq.(5)*	*Cases Eq.(5)*
Mobility$_{t-21}$	**0.098*****	**0.094*****	0.098***	0.098***	0.098***	0.098***	0.098***	0.098***
	(0.013)	***(0.004)***	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*
Delta$_{t-21}$	**2.264*****	**0.863****	2.256***	2.241***	2.241***	2.248***	2.245***	2.246***
	(0.659)	***(0.355)***	*(0.228)*	*(0.228)*	*(0.228)*	*(0.228)*	*(0.228)*	*(0.228)*
Mobility $_{t-21}$ × Delta$_{t-21}$	**-0.161*****	**-0.097*****	-0.161***	-0.160***	-0.160***	-0.160***	-0.160***	-0.160***
	(0.029)	***(0.007)***	*(0.008)*	*(0.008)*	*(0.008)*	*(0.008)*	*(0.008)*	*(0.008)*
Vaccination	**-0.173*****	**0.085*****	-0.173***	-0.172***	-0.172***	-0.173***	-0.173***	-0.173***
	(0.017)	***(0.006)***	*(0.004)*	*(0.004)*	*(0.004)*	*(0.004)*	*(0.004)*	*(0.004)*
Institutions	**0.026**	**0.073*****	0.033***	0.027**	0.027**	0.030***	0.030***	0.030***
	(0.173)	***(0.011)***	*(0.010)*	*(0.011)*	*(0.011)*	*(0.010)*	*(0.010)*	*(0.010)*
Population Density			0.001*					
			(0.001)					
Rural Population				0.006				
				(0.018)				
Urban Population					-0.006			
					(0.018)			
Median Age						-0.064		
						(0.100)		
Age above 65							-0.126	
							(0.098)	
Age above 70								-0.140
								(0.112)
Constant	**9.749**	**7.244*****	9.089***	9.529***	10.09***	12.22***	11.89***	11.261***
	(9.531)	***(1.116)***	*(0.644)*	*(0.595)*	*(1.722)*	*(4.173)*	*(1.905)*	*(1.465)*
Day Fixed Effects	**no**	**yes**	no	no	no	no	no	no
Country Fixed Effects	**yes**	**yes**	no	no	no	no	no	no
Random Effects	**no**	**no**	yes	yes	yes	yes	yes	yes
Sample Size	**16,662**	**16,662**	16,662	16,662	16,662	16,662	16,662	16,662
Number of Country Groups	**29**	**29**	29	29	29	29	29	29
R^2	**0.214**	**0.629**						
Adjusted R^2	**0.214**	**0.615**						

*Notes: Estimates are from regressions in Equations (3), (4) and (5). The dependent variable is the weekly percentage change in cumulative daily COVID-19 cases. The presented coefficients for mobility represent the effects of "retail & recreation" mobility. Robust standard errors are given in parenthesis. Significance: *** p < 0.01, ** p < 0.05, * p < 0.1. Source: own calculations*

Table 6. Linear Effects of Mobility on COVID-19 Deaths – Health Characteristics

Dependent:	***Deaths Eq.(6)***	***Deaths Eq.(7)***	*Deaths Eq.(8)*	*Deaths Eq.(8)*	*Deaths Eq.(8)*	*Deaths Eq.(8)*
Mobility$_{t-35}$	**0.023****	**0.037*****	0.024***	0.024***	0.024***	0.024***
	(0.011)	***(0.004)***	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*
Delta$_{t-35}$	**1.471*****	**0.090**	1.456***	1.485***	1.482***	1.466***
	(0.475)	***(0.358)***	*(0.202)*	*(0.202)*	*(0.202)*	*(0.202)*
	-	-	-	-	-	-
Mobility $_{t-35}$ × Delta$_{t-35}$	**0.095*****	**0.073*****	0.093***	0.095***	0.094***	0.094***
	(0.022)	***(0.008)***	*(0.008)*	*(0.008)*	*(0.008)*	*(0.008)*
	-	-	-	-	-	-
Vaccination	**0.107*****	**0.120*****	0.107***	0.108***	0.108***	0.107***
	(0.017)	***(0.006)***	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*
Institutions	**0.022**	**0.041*****	0.028***	0.037***	0.033***	0.021*
	(0.153)	***(0.011)***	*(0.010)*	*(0.011)*	*(0.012)*	*(0.012)*
Cardiovasc. Death Rate			0.012***			
			(0.002)			
Diabetes Prevalence				0.248		
				(0.172)		
Female Smokers					0.088	
					(0.065)	
Male Smokers						0.129***
						(0.035)
Constant	**5.555**	**3.399*****	2.979***	3.283***	2.819*	1.455
	(8.446)	***(1.130)***	*(0.643)*	*(1.201)*	*(1.536)*	*(1.076)*
Day Fixed Effects	**no**	**yes**	no	no	no	no
Country Fixed Effects	**yes**	**yes**	no	no	no	no
Random Effects	**no**	**no**	yes	yes	yes	yes
Sample Size	**16,211**	**16,211**	16,211	16,211	16,211	16,211
Number of Country Groups	**29**	**29**	29	29	29	29
R^2	**0.128**	**0.510**				
Adjusted *R^2*	**0.128**	**0.491**				

*Notes: Estimates are from regressions in Equations (6), (7) and (8). The dependent variable is the weekly percentage change in cumulative daily COVID-19 deaths. The presented coefficients for mobility represent the effects of "retail & recreation" mobility. Robust standard errors are given in parenthesis. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$*
Source: own calculations

Table 7. Linear Effects of Mobility on COVID-19 Deaths – Economic Characteristics

Dependent:	***Deaths Eq.(6)***	***Deaths Eq.(7)***	*Deaths Eq.(8)*	*Deaths Eq.(8)*	*Deaths Eq.(8)*
Mobility$_{t-35}$	**0.023****	**0.037*****	0.024***	0.024***	0.024***
	(0.011)	***(0.004)***	*(0.003)*	*(0.003)*	*(0.003)*
Delta$_{t-35}$	**1.471*****	**0.090**	1.469***	1.489***	1.465***
	(0.475)	***(0.358)***	*(0.202)*	*(0.202)*	*(0.202)*
Mobility $_{t-35}$ × Delta$_{t-35}$	**-0.095*****	**-0.073*****	-0.094***	-0.094***	-0.094***
	(0.022)	***(0.008)***	*(0.008)*	*(0.008)*	*(0.008)*
Vaccination	**-0.107*****	**-0.120*****	-0.107***	-0.108***	-0.107***
	(0.017)	***(0.006)***	*(0.003)*	*(0.003)*	*(0.003)*
Institutions	**0.022**	**0.041*****	0.022*	0.040***	0.024**
	(0.153)	***(0.011)***	*(0.012)*	*(0.011)*	*(0.012)*
GDP per capita			-2.676***		
			(0.859)		
Extreme Poverty				-0.091	
				(0.265)	
HDI					-26.148***
					(7.729)
Constant	**5.555**	**3.399*****	33.672***	4.662***	29.071***
	(8.446)	***(1.130)***	*(9.341)*	*(0.687)*	*(7.257)*
Day Fixed Effects	**no**	**yes**	no	no	no
Country Fixed Effects	**yes**	**yes**	no	no	no
Random Effects	**no**	**no**	yes	yes	yes
Sample Size	**16,211**	**16,211**	16,211	16,211	16,211
Number of Country Groups	**29**	**29**	29	29	29
R^2	**0.128**	**0.510**			
Adjusted R^2	**0.128**	**0.491**			

*Notes: Estimates are from regressions in Equations (6), (7) and (8). The dependent variable is the weekly percentage change in cumulative daily COVID-19 deaths. The presented coefficients for mobility represent the effects of "retail & recreation" mobility. Robust standard errors are given in parenthesis. Significance: *** p < 0.01, ** p < 0.05, * p < 0.1*
Source: own calculations

Table 8. Linear Effects of Mobility on COVID-19 Deaths – Social Characteristics

Dependent:	***Deaths Eq.(6)***	***Deaths Eq.(7)***	*Deaths Eq.(8)*	*Deaths Eq.(8)*	*Deaths Eq.(8)*	*Deaths Eq.(8)*
Mobility$_{t-35}$	**0.023****	**0.037*****	0.024***	0.024***	0.024***	0.024***
	(0.011)	***(0.004)***	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*
Delta $_{t-35}$	**1.471*****	**0.090**	1.486***	1.489***	1.477***	1.481***
	(0.475)	***(0.358)***	*(0.202)*	*(0.202)*	*(0.202)*	*(0.202)*
Mobility $_{t-35}$ × *Delta*$_{t-35}$	**-0.095*****	**-0.073*****	-0.095***	-0.094***	-0.094***	-0.094***
	(0.022)	***(0.008)***	*(0.008)*	*(0.008)*	*(0.008)*	*(0.008)*
Vaccination	**-0.107*****	**-0.120*****	-0.108***	-0.108***	-0.108***	-0.108***
	(0.017)	***(0.006)***	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*
Institutions	**0.022**	**0.041*****	0.038***	0.042***	0.033***	0.035***
	(0.153)	***(0.011)***	*(0.012)*	*(0.011)*	*(0.012)*	*(0.012)*
Populism			-0.000			
			(0.020)			
Education				0.197		
				(0.257)		
Education Quality					-0.008*	
					(0.004)	
Healthcare Quality						-0.851
						(0.662)
Constant	**5.555**	**3.399*****	4.694***	2.100	16.722**	7.724***
	(8.446)	***(1.130)***	*(0.782)*	*(3.329)*	*(6.568)*	*(2.460)*
Day Fixed Effects	**no**	**yes**	no	no	no	no
Country Fixed Effects	**yes**	**yes**	no	no	no	no
Random Effects	**no**	**no**	yes	yes	yes	yes
Sample Size	**16,211**	**16,211**	16,211	16,211	16,211	16,211
Number of Country Groups	**29**	**29**	29	29	29	29
R^2	**0.128**	**0.510**				
Adjusted R^2	**0.128**	**0.491**	.	.	.	.

*Notes: Estimates are from regressions in Equations (6), (7) and (8). The dependent variable is the weekly percentage change in cumulative daily COVID-19 deaths. The presented coefficients for mobility represent the effects of "retail & recreation" mobility. Robust standard errors are given in parenthesis. Significance: *** p < 0.01, ** p < 0.05, * p < 0.1*
Source: own calculations

Table 9. Linear Effects of Mobility on COVID-19 Deaths – Demographic Characteristics

Dependent:	***Deaths Eq.(6)***	***Deaths Eq.(7)***	*Deaths Eq.(8)*	*Deaths Eq.(8)*	*Deaths Eq.(8)*	*Deaths Eq.(8)*	*Deaths Eq.(8)*	*Deaths Eq.(8)*
Mobility$_{t-35}$	**0.023****	**0.037*****	0.024***	0.024***	0.024***	0.024***	0.024***	0.024***
	(0.011)	***(0.004)***	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*
Delta$_{t-35}$	**1.471*****	**0.090**	1.491***	1.471***	1.471***	1.485***	1.486***	1.487***
	(0.475)	***(0.358)***	*(0.202)*	*(0.202)*	*(0.202)*	*(0.202)*	*(0.202)*	*(0.202)*
Mobility $_{t-35}$ × Delta$_{t-35}$	**-0.095*****	**-0.073*****	-0.095***	-0.094***	-0.094***	-0.094***	-0.095***	-0.095***
	(0.022)	***(0.008)***	*(0.008)*	*(0.008)*	*(0.008)*	*(0.008)*	*(0.008)*	*(0.008)*
Vaccination	**-0.107*****	**-0.120*****	-0.109***	-0.108***	-0.108***	-0.108***	-0.108***	-0.108***
	(0.017)	***(0.006)***	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*	*(0.003)*
Institutions	**0.022**	**0.041*****	0.042***	0.028**	0.028**	0.037***	0.039***	0.040***
	(0.153)	***(0.011)***	*(0.012)*	*(0.012)*	*(0.012)*	*(0.012)*	*(0.011)*	*(0.011)*
Population Density			0.001					
			(0.001)					
Rural Population				0.052**				
				(0.025)				
Urban Population					-0.052**			
					(0.025)			
Median Age						0.039		
						(0.146)		
Age above 65							-0.103	
							(0.145)	
Age above 70								-0.187
								(0.165)
Constant	**5.555**	**3.399*****	4.235***	3.907***	9.151***	3.038	6.602**	6.976***
	(8.446)	***(1.130)***	*(0.765)*	*(0.789)*	*(2.240)*	*(6.150)*	*(2.782)*	*(2.139)*
Day Fixed Effects	**no**	**yes**	no	no	no	no	no	no
Country Fixed Effects	**yes**	**yes**	no	no	no	no	no	no
Random Effects	**no**	**no**	yes	yes	yes	yes	yes	yes
Sample Size	**16,211**	**16,211**	16,211	16,211	16,211	16,211	16,211	16,211
Number of Country Groups	**29**	**29**	29	29	29	29	29	29
R^2	**0.128**	**0.510**						
Adjusted R^2	**0.128**	**0.491**						

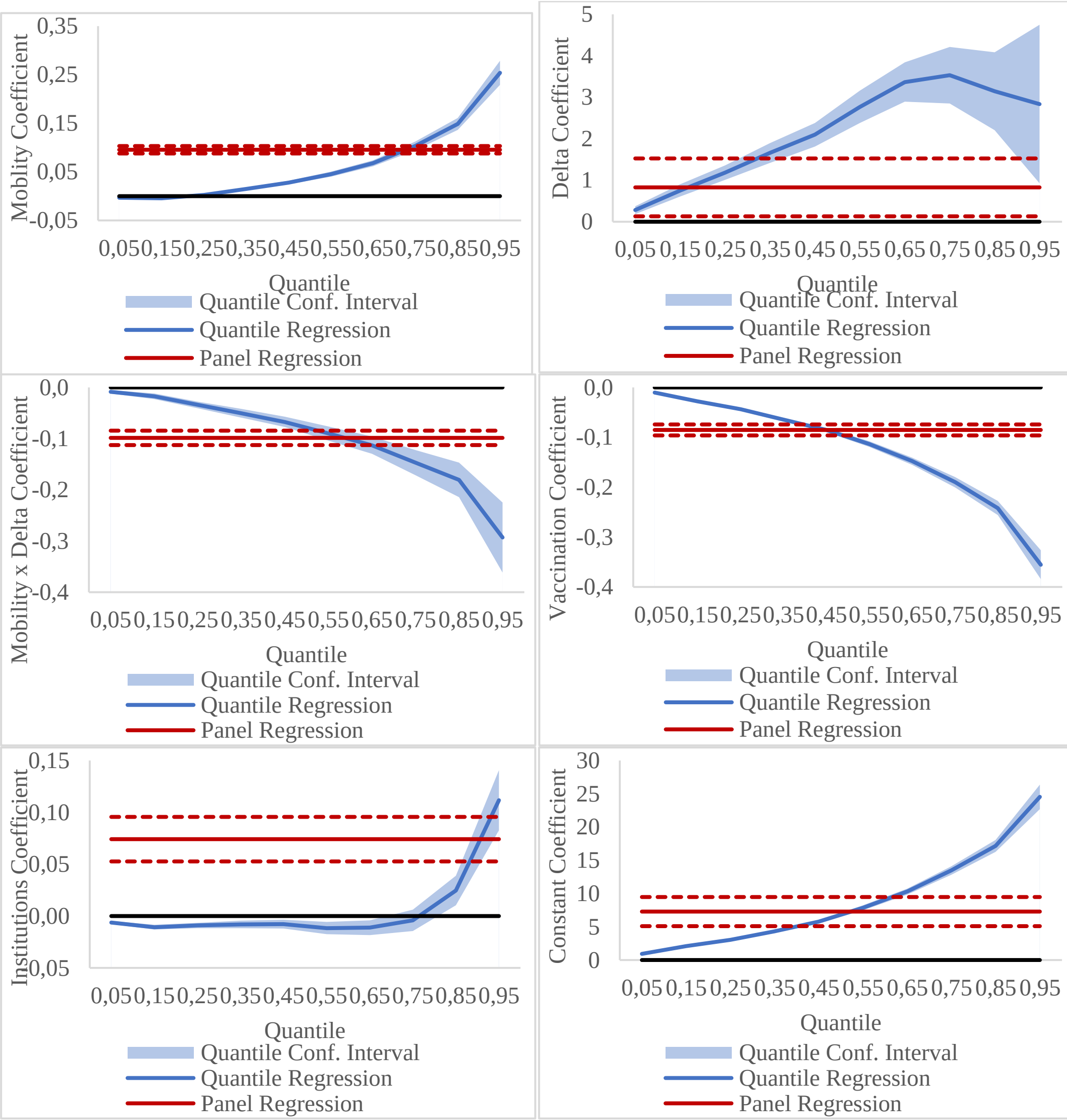
*Notes: Estimates are from regressions in Equations (6), (7) and (8). The dependent variable is the weekly percentage change in cumulative daily COVID-19 deaths. The presented coefficients for mobility represent the effects of "retail & recreation" mobility. Robust standard errors are given in parenthesis. Significance: *** p < 0.01, ** p < 0.05, * p < 0.1*
Source: own calculations

Table 10. Nonlinear Effects of Mobility on COVID-19 Spread Using Quantile Regressions

	Dependent: Weekly % Changes in COVID-19 Cases				**Dependent: Weekly % Changes in COVID-19 Deaths**			
	Panel	Quantile $\tau = 0.25$	Quantile $\tau = 0.5$	Quantile $\tau = 0.75$	**Panel**	Quantile $\tau = 0.25$	Quantile $\tau = 0.5$	Quantile $\tau = 0.75$
	Eq.(4)	Eq.(9)	Eq.(9)	Eq.(9)	**Eq.(7)**	Eq.(10)	Eq.(10)	Eq.(10)
Mobility	**0.096***	0.002**+	0.035***+	0.104***	**0.037***	-0.012***+	-0.004**+	0.030***
	(0.004)	*(0.001)*	*(0.002)*	*(0.005)*	***(0.004)***	*(0.001)*	*(0.001)*	*(0.003)*
Delta	**0.828**	1.183***	2.397***+	3.533***+	**0.090**	0.536***	1.253***+	1.974***+
	(0.356)	*(0.089)*	*(0.176)*	*(0.349)*	***(0.358)***	*(0.055)*	*(0.106)*	*(0.253)*
Mobility × Delta	**-0.099***	-0.034***+	-0.078***	-0.147***+	**-0.073***	0.004**+	-0.014***+	-0.036***+
	(0.007)	*(0.003)*	*(0.006)*	*(0.013)*	***(0.008)***	*(0.002)*	*(0.004)*	*(0.010)*
Vaccination	**-0.085***	-0.044***+	-0.098***	-0.190***+	**-0.120***	-0.013***+	-0.049***+	-0.116***+
	(0.006)	*(0.001)*	*(0.003)*	*(0.005)*	***(0.006)***	*(0.001)*	*(0.002)*	*(0.004)*
Institutions	**0.074***	-0.009***+	-0.011***+	-0.004+	**0.041***	0.004***+	0.014***+	0.020***
	(0.011)	*(0.001)*	*(0.003)*	*(0.005)*	***(0.011)***	*(0.001)*	*(0.002)*	*(0.004)*
Constant	**7.285***	3.028***+	6.791***	13.456***+	**3.399***	0.428***+	2.089***	6.737***+
	(1.118)	*(0.086)*	*(0.170)*	*(0.336)*	***(1.130)***	*(0.056)*	*(0.108)*	*(0.256)*
Day Fixed Effects	**yes**	yes	yes	yes	**yes**	yes	yes	yes
Country Fixed Effects	**yes**	yes	yes	yes	**yes**	yes	yes	yes
Sample Size	**16,704**	16,704	16,704	16,704	**16,211**	16,211	16,211	16,211
R^2	**0.628**				**0.510**			

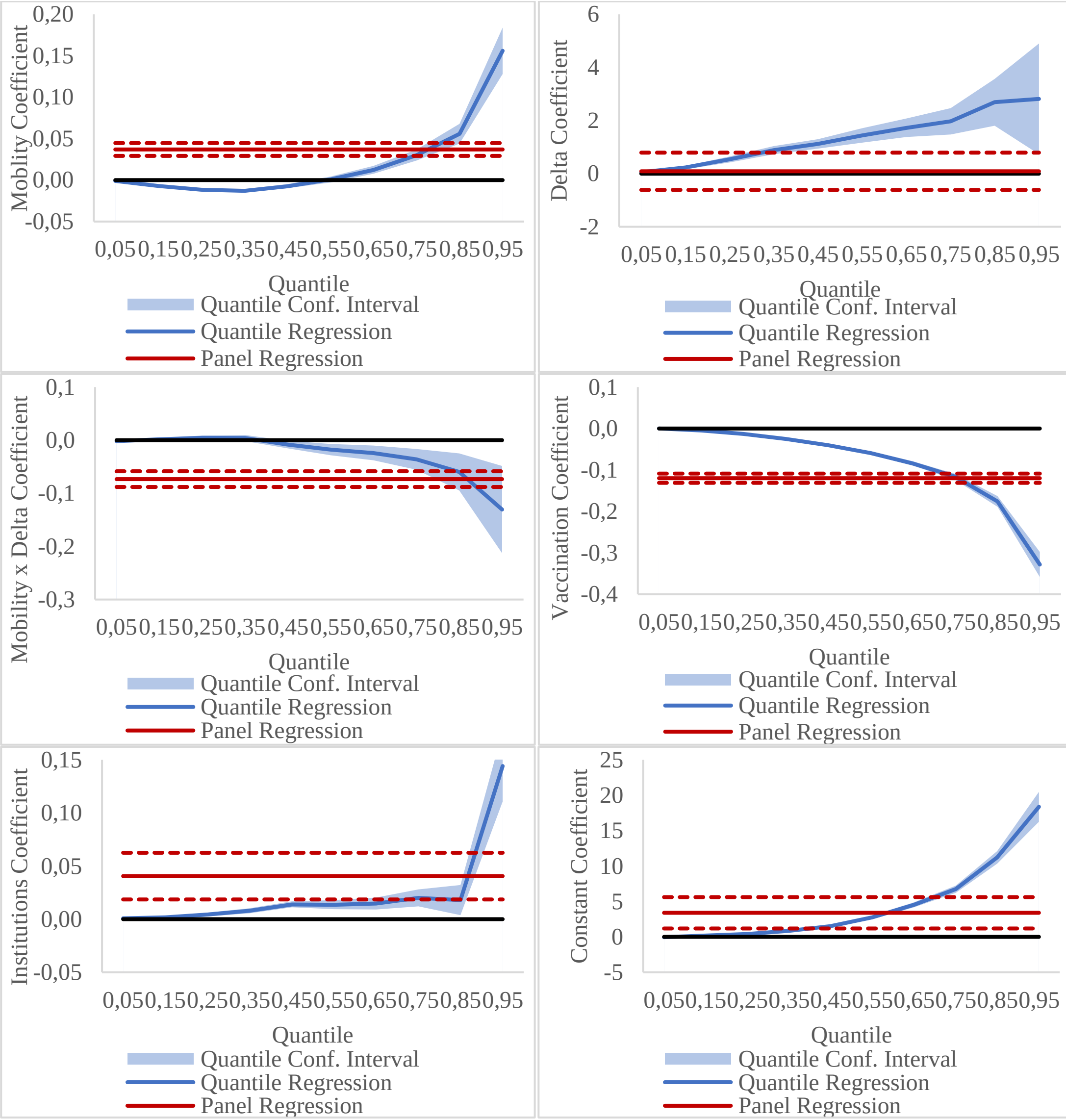
*Notes: Estimates are from regressions in Equations (4), (9), (7) and (10). The dependent variable is the weekly percentage change in cumulative daily COVID-19 cases and deaths, respectively. The presented coefficients for mobility represent the effects of "retail & recreation" mobility. 21 lags (for variables Mobility, Delta and their interaction) are used to determine the effects on COVID-19 cases and 35 lags (for variables Mobility, Delta and their interaction) on COVID-19 deaths. Robust standard errors are given in parenthesis. Significantly different quantile regression estimates (Eq. 9 and 10) from panel regression with country- and day- fixed effect estimates (Eq. 4 and 7) at the 5% significance level are indicated by sign +. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.   Source: own calculations*

Figure 1. Nonlinear Effects of Mobility on COVID-19 Cases Using Quantile Regressions



Notes: Estimates are based on Equations (4) and (9), and the results are presented in Table 10.
Source: own calculations

Figure 2. Nonlinear Effects of Mobility on COVID-19 Deaths Using Quantile Regressions



Notes: Estimates are based on Equations (7) and (10), and the results are presented in Table 10.
Source: own calculations

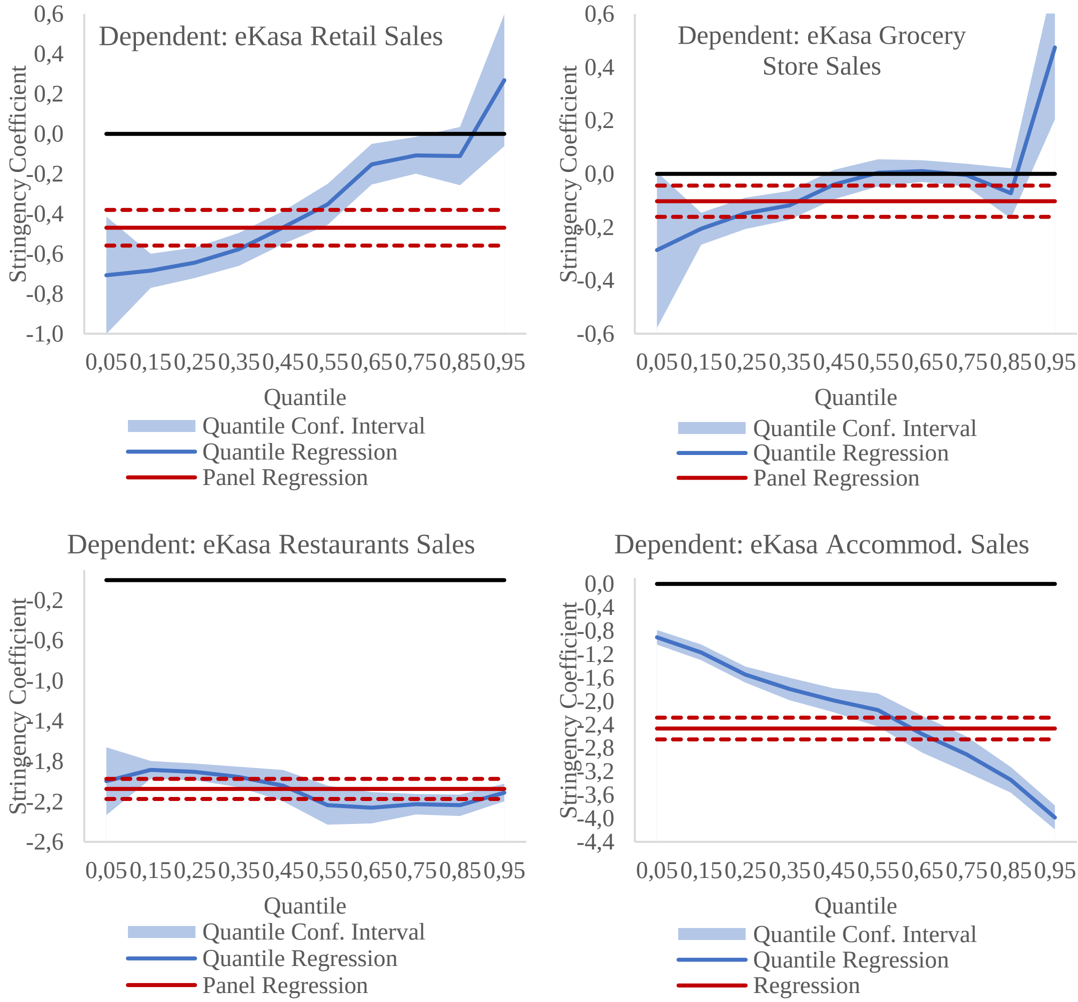
Table 11. Linear And Nonlinear Effects of Restrictive Measures on eKasa Sales in Slovakia

	Dependent: eKasa Retail Sales (% change)				**Dependent: eKasa Grocery Store Sales (% change)**			
	OLS regression Eq.(11)	Quantile $\tau = 0.25$ Eq.(12)	Quantile $\tau = 0.5$ Eq.(12)	Quantile $\tau = 0.75$ Eq.(12)	**OLS regression Eq.(11)**	Quantile $\tau = 0.25$ Eq.(12)	Quantile $\tau = 0.5$ Eq.(12)	Quantile $\tau = 0.75$ Eq.(12)
Stringency	**-0.470*** **	-0.645***	-0.452***	-0.107**	**-0.103*** **	-0.148***	-0.032	-0.005
	(0.045)	*(0.039)*	*(0.052)*	*(0.047)*	***(0.030)***	*(0.030)*	*(0.028)*	*(0.022)*
Delta	**-16.790*** **	-17.448***	-12.214**	-2.912	**-16.296*** **	-18.802***	-10.890***	-9.251***
	(5.315)	*(4.506)*	*(6.126)*	*(5.503)*	***(3.494)***	*(3.526)*	*(3.310)*	*(2.557)*
Stringency × Delta	**0.524*** **	0.612***	0.457***	0.196	**0.514*** **	0.590***	0.389***	0.363***
	(0.119)	*(0.101)*	*(0.137)*	*(0.123)*	***(0.078)***	*(0.079)*	*(0.074)*	*(0.057)*
Holiday	**3.145**	4.106	7.482*	3.743	**2.913**	5.154**	4.839**	4.731***
	(3.758)	*(3.185)*	*(4.331)*	*(3.890)*	***(2.470)***	*(2.493)*	*(2.340)*	*(1.808)*
Constant	**134.231*** **	134.499***	130.959***	122.091***	**115.018*** **	112.765***	111.045***	113.357***
	(2.677)	*(2.269)*	*(3.086)*	*(2.771)*	***(1.760)***	*(1.776)*	*(1.667)*	*(1.288)*
Sample size	**591**	591	591	591	**591**	591	591	591
R^2	**0.248**				**0.142**			

	Dependent: eKasa Restaurants Sales (% change)				**Dependent: eKasa Accommodation Sales (% change)**			
	OLS regression Eq.(11)	Quantile $\tau = 0.25$ Eq.(12)	Quantile $\tau = 0.5$ Eq.(12)	Quantile $\tau = 0.75$ Eq.(12)	**OLS regression Eq.(11)**	Quantile $\tau = 0.25$ Eq.(12)	Quantile $\tau = 0.5$ Eq.(12)	Quantile $\tau = 0.75$ Eq.(12)
Stringency	**-2.074*** **	-1.906***	-2.131***	-2.227***	**-2.467*** **	-1.545***	-2.055***	-2.907***
	(0.051)	*(0.042)*	*(0.103)*	*(0.052)*	***(0.094)***	*(0.070)*	*(0.118)*	*(0.155)*
Delta	**-37.077*** **	-38.316***	-23.306*	-95.380***	**-26.654** **	1.036	30.114**	-15.931
	(5.941)	*(4.905)*	*(12.091)*	*(6.057)*	***(11.038)***	*(8.188)*	*(13.816)*	*(18.127)*
Stringency × Delta	**0.754*** **	0.517***	0.354	2.461***	**0.836*** **	-0.075	-0.473	0.984**
	(0.133)	*(0.110)*	*(0.270)*	*(0.135)*	***(0.247)***	*(0.183)*	*(0.309)*	*(0.405)*
Holiday	**-9.556** **	-6.024*	-11.086	2.180	**-18.154** **	-13.557**	-14.408	-4.293
	(4.200)	*(3.468)*	*(8.548)*	*(4.282)*	***(7.804)***	*(5.789)*	*(9.768)*	*(12.816)*
Constant	**183.570*** **	166.331***	185.740***	200.551***	**185.307*** **	119.068***	158.100***	222.951***
	(2.992)	*(2.470)*	*(6.090)*	*(3.050)*	***(5.559)***	*(4.124)*	*(6.959)*	*(9.130)*
Sample size	**591**	591	591	591	**591**	591	591	591
R^2	**0.786**				**0.643**			

*Notes: Estimates are from regressions in Equations (11) and (12). The dependent variable is an index of individual types of daily sales from eKasa cash collector system in Slovakia (100 = average of pre-pandemic period ranging from 5–11 February 2020, which is transformed into 7-day moving averages). Robust standard errors are given in parenthesis. Significantly different quantile regression estimates (Eq. 12) from time series OLS estimates (Eq. 11) at the 5% significance level are indicated by sign +. Significance: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.*

Figure 3. Effects of Restrictive Measures on eKasa Sales in Slovakia



Notes: Estimates are based on Equations (11) and (12), and the results are presented in Table 11. Figure shows the coefficients only for stringency effect on each type sales from eKasa.
Source: own calculations

Appendix A: Data Description

Table A1. Data on COVID-19 Cases

	Num.	Mean	SD	Var	Skew	Kurt	Min	Max
AUT	590	5.6	7.6	57.0	2.7	10.8	0.1	40.1
BEL	590	4.7	7.6	58.2	3.8	17.5	0.3	45.4
BGR	590	7.8	9.0	81.8	1.8	5.8	0.1	42.7
CHE	590	4.7	8.2	67.2	3.7	17.2	0.1	49.5
CZE	590	7.5	10.6	112.6	2.4	8.4	0.1	50.0
DEU	590	4.6	5.1	26.1	2.1	7.4	0.1	24.7
DNK	590	5.1	5.2	27.0	1.5	4.4	0.4	23.9
ESP	590	4.0	4.2	17.4	1.1	2.9	-1.4	14.2
EST	590	6.2	6.8	45.7	1.5	4.4	0.1	27.6
FIN	590	4.4	3.4	11.5	1.1	3.8	0.4	15.9
FRA	590	4.9	6.0	35.9	2.1	7.0	-5.0	31.6
GBR	590	5.0	5.1	26.4	1.6	4.9	0.2	23.2
GRC	590	7.6	7.5	56.7	2.1	7.5	0.6	40.5
HRV	590	7.4	9.3	86.4	1.8	6.2	0.0	46.8
HUN	590	7.9	11.4	130.6	2.0	6.1	0.0	49.8
IRL	590	4.2	5.7	32.4	4.2	25.6	0.2	45.3
ITA	590	4.1	6.7	44.8	3.1	12.4	0.1	34.9
LTU	590	7.8	11.2	124.4	2.4	8.3	0.1	55.7
LUX	590	4.1	6.3	39.9	2.1	10.6	-15.5	34.2
LVA	590	7.4	9.1	83.3	1.7	4.6	0.2	36.3
MLT	590	5.6	6.6	43.4	1.5	4.8	0.0	31.6
NLD	590	5.4	6.4	40.4	2.4	8.5	0.3	30.9
NOR	590	4.6	3.7	13.8	1.6	5.9	0.5	19.9
POL	590	7.3	10.1	102.6	2.6	9.6	0.0	49.9
PRT	590	4.8	5.6	31.7	1.7	5.3	0.3	25.3
ROU	590	6.1	5.9	34.3	0.9	2.8	0.0	23.1
SVK	590	9.0	12.2	149.0	2.1	6.9	0.0	56.7
SVN	590	7.6	12.3	151.6	3.4	16.1	0.1	76.9
SWE	590	5.0	5.5	30.5	1.3	3.3	0.1	21.1
Total	**17 110**	**5.9**	**7.9**	**62.8**	**2.9**	**14.0**	**-15.5**	**76.9**

Note: AUT – Austria, BEL – Belgium, BGR – Bulgaria, CHE – Switzerland, CZE – Czechia, DEU – Germany, DNK – Denmark, ESP – Spain, EST – Estonia, FIN – Finland, FRA – France, GBR – The United Kingdom, GRC – Greece, HRV – Croatia, HUN – Hungary, IRL – Ireland, ITA – Italy, LTU – Lithuania, LUX – Luxembourg, LVA – Latvia, MLT – Malta, NLD – The Netherlands, NOR – Norway, POL – Poland, PRT – Portugal, ROU – Romania, SVK – Slovakia, SVN – Slovenia, SWE – Sweden, SD – standard deviation, Var – variance, Skew – Skewness, Kurt - Kurtosis
Source: own calculations based on Our World in Data (OWiD) database

Table A2. Data on COVID-19 Deaths

	Num.	Mean	SD	Var	Skew	Kurt	Min	Max
AUT	590	4.1	6.7	45.0	2.7	9.7	0.1	32.2
BEL	590	1.5	2.4	5.5	2.7	10.0	-1.0	11.8
BGR	590	7.6	7.7	59.5	1.6	5.4	0.1	35.2
CHE	590	2.4	4.9	23.8	2.7	9.9	0.0	23.8
CZE	590	6.5	11.3	128.7	2.9	11.4	-0.3	57.3
DEU	590	3.4	5.0	24.7	1.8	4.9	0.1	20.2
DNK	590	2.3	3.5	12.5	2.5	8.5	0.0	17.0
ESP	590	1.5	1.9	3.4	0.9	4.9	-5.7	8.5
EST	590	4.4	5.9	34.6	1.3	4.6	-8.7	28.7
FIN	590	2.1	2.2	4.9	1.8	6.2	0.0	10.9
FRA	590	1.9	2.3	5.1	1.8	6.0	0.1	10.2
GBR	590	2.0	2.7	7.2	1.6	4.6	0.0	12.9
GRC	590	6.3	8.8	77.6	3.1	12.7	0.0	48.6
HRV	590	6.4	8.3	68.6	2.0	6.6	0.0	41.3
HUN	590	6.0	7.8	60.3	1.7	5.1	0.0	34.7
IRL	590	1.8	2.8	7.9	2.8	10.4	-0.1	13.9
ITA	590	1.9	2.5	6.1	1.9	5.9	0.1	10.5
LTU	590	7.0	10.5	110.0	2.2	7.0	0.0	49.2
LUX	590	2.8	4.6	21.4	2.5	8.8	0.0	25.3
LVA	590	7.2	9.4	87.9	1.7	4.7	0.0	38.0
MLT	590	6.2	10.6	113.2	2.8	12.2	0.0	70.6
NLD	590	1.7	1.9	3.8	1.4	4.1	-0.2	9.5
NOR	590	2.1	2.2	5.0	1.7	5.7	0.0	11.7
POL	590	6.2	7.8	61.4	2.2	7.3	0.0	37.3
PRT	590	3.6	5.0	24.6	1.5	4.2	0.0	19.8
ROU	590	5.3	3.9	15.5	1.0	4.7	0.0	24.1
SVK	590	8.8	14.7	214.5	2.8	12.3	0.0	93.9
SVN	590	5.4	10.8	117.4	3.1	12.3	0.0	61.3
SWE	590	2.1	3.3	10.6	2.6	11.0	0.0	20.6
Total	**17 110**	**4.2**	**7.2**	**51.8**	**3.8**	**23.4**	**-8.7**	**93.9**

Note: AUT – Austria, BEL – Belgium, BGR – Bulgaria, CHE – Switzerland, CZE – Czechia, DEU – Germany, DNK – Denmark, ESP – Spain, EST – Estonia, FIN – Finland, FRA – France, GBR – The United Kingdom, GRC – Greece, HRV – Croatia, HUN – Hungary, IRL – Ireland, ITA – Italy, LTU – Lithuania, LUX – Luxembourg, LVA – Latvia, MLT – Malta, NLD – The Netherlands, NOR – Norway, POL – Poland, PRT – Portugal, ROU – Romania, SVK – Slovakia, SVN – Slovenia, SWE – Sweden, SD – standard deviation, Var – variance, Skew – Skewness, Kurt - Kurtosis
Source: own calculations based on Our World in Data (OWiD) database

Table A3. Data on Oxford Stringency Index

	Num.	Mean	SD	Var	Skew	Kurt	Min	Max
AUT	597	61.9	14.1	198.2	-0.3	2.1	36.1	82.4
BEL	597	55.7	9.2	85.1	0.8	2.9	43.1	81.5
BGR	597	46.2	10.2	104.0	-0.6	3.6	20.4	73.2
CHE	597	50.2	8.4	70.5	-0.1	2.5	29.2	69.4
CZE	597	53.3	15.7	247.0	0.4	1.8	32.4	81.5
DEU	597	64.4	11.4	129.1	0.0	2.4	37.0	85.2
DNK	597	50.9	12.9	166.2	-0.6	2.8	24.1	70.4
ESP	597	60.0	12.0	144.9	-0.2	1.8	41.2	85.2
EST	597	39.7	11.6	133.6	0.8	3.2	23.2	75.0
FIN	597	42.7	10.2	103.0	0.2	2.4	23.2	68.5
FRA	597	62.9	11.9	141.0	-0.2	1.7	44.0	88.0
GBR	597	63.1	14.1	197.7	0.1	2.0	41.2	88.0
GRC	597	69.6	12.8	162.9	-0.4	2.2	41.7	88.9
HRV	597	43.8	12.1	145.6	1.2	5.0	28.7	89.8
HUN	597	51.8	18.0	324.4	-0.1	1.6	25.0	79.6
IRL	597	63.6	17.8	315.1	0.1	1.4	38.9	90.7
ITA	597	72.1	7.0	48.9	-0.8	5.0	47.2	93.5
LTU	597	48.3	16.1	257.8	0.2	1.8	25.0	77.8
LUX	597	47.0	8.6	74.4	0.0	3.1	22.2	70.4
LVA	597	50.4	9.3	85.9	0.1	2.5	28.7	70.4
MLT	597	51.6	12.7	161.2	1.3	4.2	31.5	87.0
NLD	597	58.5	14.7	216.0	0.0	1.7	32.4	82.4
NOR	597	48.3	15.6	243.9	-0.1	2.1	20.4	73.2
POL	597	54.8	17.0	289.1	0.1	1.6	23.2	83.3
PRT	597	62.5	11.1	122.8	0.0	3.2	40.7	88.0
ROU	597	56.4	14.0	196.3	0.3	2.0	31.5	87.0
SVK	597	52.5	16.0	255.3	0.1	1.4	28.7	75.0
SVN	597	57.8	14.9	222.9	0.5	2.1	35.2	87.0
SWE	597	53.2	16.5	271.7	-1.0	2.7	19.4	69.4
Total	**17 313**	**54.9**	**15.4**	**237.6**	**0.1**	**2.3**	**19.4**	**93.5**

Note: AUT – Austria, BEL – Belgium, BGR – Bulgaria, CHE – Switzerland, CZE – Czechia, DEU – Germany, DNK – Denmark, ESP – Spain, EST – Estonia, FIN – Finland, FRA – France, GBR – The United Kingdom, GRC – Greece, HRV – Croatia, HUN – Hungary, IRL – Ireland, ITA – Italy, LTU – Lithuania, LUX – Luxembourg, LVA – Latvia, MLT – Malta, NLD – The Netherlands, NOR – Norway, POL – Poland, PRT – Portugal, ROU – Romania, SVK – Slovakia, SVN – Slovenia, SWE – Sweden, SD – standard deviation, Var – variance, Skew – Skewness, Kurt - Kurtosis
Source: own calculations based on Our World in Data (OWiD) database

Table A4. Data on Vaccination

	Num.	Mean	SD	Var	Skew	Kurt	Min	Max
AUT	597	24.8	28.7	824.6	0.5	1.5	0.0	74.2
BEL	597	27.0	32.2	1 034.2	0.6	1.5	0.0	76.8
BGR	597	7.6	9.1	82.8	0.8	2.3	0.0	28.1
CHE	597	22.8	26.9	724.0	0.6	1.6	0.0	68.3
CZE	597	21.7	25.5	650.2	0.6	1.5	0.0	64.6
DEU	597	25.4	29.8	888.4	0.6	1.5	0.0	74.5
DNK	597	26.6	32.1	1 032.7	0.7	1.6	0.0	80.5
ESP	597	27.2	33.0	1 088.7	0.7	1.7	0.0	81.9
EST	597	21.3	24.3	592.4	0.6	1.6	0.0	63.0
FIN	597	27.5	31.9	1 017.7	0.6	1.5	0.0	77.3
FRA	597	26.1	31.5	990.7	0.7	1.7	0.0	78.4
GBR	597	32.5	32.0	1 024.7	0.2	1.2	0.0	76.5
GRC	597	22.2	26.4	698.8	0.6	1.7	0.0	70.1
HRV	597	17.2	20.2	406.2	0.6	1.6	0.0	55.2
HUN	597	25.1	27.4	749.8	0.3	1.2	0.0	64.1
IRL	597	26.9	32.1	1 031.2	0.6	1.6	0.0	78.6
ITA	597	26.8	32.3	1 041.4	0.6	1.6	0.0	80.9
LTU	597	22.6	26.4	694.5	0.6	1.7	0.0	68.2
LUX	597	23.9	28.6	815.2	0.6	1.6	0.0	71.7
LVA	597	18.1	23.2	538.2	0.9	2.4	0.0	69.5
MLT	597	31.8	35.0	1 227.5	0.4	1.4	0.0	83.1
NLD	597	25.1	30.2	911.4	0.6	1.6	0.0	72.2
NOR	597	26.1	31.7	1 004.8	0.7	1.8	0.0	79.2
POL	597	19.7	22.6	508.5	0.5	1.4	0.0	55.8
PRT	597	29.4	36.0	1 298.1	0.7	1.8	0.0	90.8
ROU	597	12.2	13.6	183.9	0.6	1.8	0.0	40.6
SVK	597	18.0	19.8	393.1	0.5	1.4	0.0	50.3
SVN	597	19.5	22.6	511.7	0.6	1.6	0.0	58.6
SWE	597	24.2	28.9	835.4	0.6	1.6	0.0	73.1
Total	**17 313**	**23.4**	**28.5**	**812.6**	**0.8**	**2.0**	**0.0**	**90.8**

Note: AUT – Austria, BEL – Belgium, BGR – Bulgaria, CHE – Switzerland, CZE – Czechia, DEU – Germany, DNK – Denmark, ESP – Spain, EST – Estonia, FIN – Finland, FRA – France, GBR – The United Kingdom, GRC – Greece, HRV – Croatia, HUN – Hungary, IRL – Ireland, ITA – Italy, LTU – Lithuania, LUX – Luxembourg, LVA – Latvia, MLT – Malta, NLD – The Netherlands, NOR – Norway, POL – Poland, PRT – Portugal, ROU – Romania, SVK – Slovakia, SVN – Slovenia, SWE – Sweden, SD – standard deviation, Var – variance, Skew – Skewness, Kurt - Kurtosis
Source: own calculations based on Our World in Data (OWiD) database

Table A5. Data on Mobility in Grocery and Pharmacy

	Num.	Mean	SD	Var	Skew	Kurt	Min	Max
AUT	597	-3.7	20.1	405.3	-1.9	9.2	-93.0	47.0
BEL	597	3.3	15.8	248.0	-1.3	7.4	-83.0	39.0
BGR	597	8.6	13.5	182.4	-0.1	4.1	-66.0	41.0
CHE	597	3.7	15.2	231.9	-2.6	14.7	-90.0	47.0
CZE	597	10.8	19.9	394.0	-2.7	13.6	-91.0	48.0
DEU	597	5.2	22.5	506.1	-0.6	10.0	-94.0	94.0
DNK	597	-0.4	10.0	99.9	-1.9	13.7	-74.0	33.0
ESP	597	1.6	16.4	269.6	-1.1	7.7	-88.0	59.0
EST	597	8.7	11.1	123.2	0.1	4.3	-52.0	47.0
FIN	597	3.8	11.3	127.2	-0.7	8.4	-69.0	48.0
FRA	597	5.4	17.1	293.7	-1.0	7.7	-87.0	57.0
GBR	597	-5.7	11.8	139.1	-1.1	7.8	-89.0	23.0
GRC	597	24.6	29.6	875.5	0.4	5.4	-76.0	148.0
HRV	597	16.5	25.4	644.6	-0.4	6.0	-90.0	93.0
HUN	597	6.8	20.2	408.1	-2.1	10.6	-91.0	56.0
IRL	597	5.8	13.5	183.0	-1.1	8.5	-92.0	55.0
ITA	597	-0.3	17.6	310.0	-1.4	7.3	-90.0	46.0
LTU	597	26.2	20.0	397.9	-0.8	5.6	-87.0	75.0
LUX	597	-1.0	19.4	378.1	-1.4	9.1	-95.0	64.0
LVA	597	4.2	13.6	185.9	-0.5	3.5	-63.0	44.0
MLT	597	4.1	14.4	206.1	-0.1	2.7	-60.0	31.0
NLD	597	1.4	10.5	110.6	-1.9	14.4	-77.0	22.0
NOR	597	6.5	19.1	364.2	-0.4	15.6	-92.0	128.0
POL	597	10.1	31.2	974.1	1.6	11.6	-89.0	199.0
PRT	597	8.4	23.2	538.0	-0.2	3.0	-87.0	59.0
ROU	597	5.8	14.6	213.8	-1.1	8.4	-83.0	39.0
SVK	597	4.5	25.1	631.3	-1.8	7.2	-92.0	60.0
SVN	597	-12.0	32.3	1 043.0	-1.3	3.7	-94.0	44.0
SWE	597	0.6	9.5	90.7	-0.4	8.7	-58.0	48.0
Total	**17 313**	**5.3**	**20.6**	**422.4**	**-0.4**	**10.4**	**-95.0**	**199.0**

Note: AUT – Austria, BEL – Belgium, BGR – Bulgaria, CHE – Switzerland, CZE – Czechia, DEU – Germany, DNK – Denmark, ESP – Spain, EST – Estonia, FIN – Finland, FRA – France, GBR – The United Kingdom, GRC – Greece, HRV – Croatia, HUN – Hungary, IRL – Ireland, ITA – Italy, LTU – Lithuania, LUX – Luxembourg, LVA – Latvia, MLT – Malta, NLD – The Netherlands, NOR – Norway, POL – Poland, PRT – Portugal, ROU – Romania, SVK – Slovakia, SVN – Slovenia, SWE – Sweden, SD – standard deviation, Var – variance, Skew – Skewness, Kurt - Kurtosis
Source: own calculations based on Google Mobility Reports

Table A6. Data on Mobility in Retail and Recreation

	Num.	Mean	SD	Var	Skew	Kurt	Min	Max
AUT	597	-27.2	23.3	543.6	-0.6	2.2	-90.0	14.0
BEL	597	-19.4	21.5	462.7	-0.4	2.2	-83.0	25.0
BGR	597	-15.0	18.7	349.9	-0.3	2.3	-75.0	25.0
CHE	597	-20.5	16.7	279.2	-1.2	3.8	-88.0	16.0
CZE	597	-18.6	25.8	666.9	-0.6	2.0	-90.0	19.0
DEU	597	-19.9	21.8	473.8	-0.7	2.7	-87.0	26.0
DNK	597	-1.6	20.5	420.7	-1.0	3.9	-83.0	34.0
ESP	597	-25.0	16.9	285.6	-1.0	4.4	-94.0	12.0
EST	597	-6.2	18.3	336.1	-0.6	3.1	-74.0	29.0
FIN	597	-10.9	15.2	230.3	-0.8	4.3	-81.0	21.0
FRA	597	-22.0	20.3	412.6	-0.6	2.8	-91.0	18.0
GBR	597	-31.3	21.4	455.9	-0.4	2.0	-92.0	3.0
GRC	597	-15.0	30.0	897.6	-0.3	2.0	-76.0	50.0
HRV	597	-3.9	27.7	766.2	-0.1	2.8	-90.0	61.0
HUN	597	-6.8	22.3	494.9	-0.5	3.0	-88.0	44.0
IRL	597	-27.8	21.9	479.5	-0.3	2.1	-94.0	22.0
ITA	597	-19.3	20.0	401.5	-0.9	3.5	-92.0	14.0
LTU	597	-25.8	19.3	374.2	-0.7	2.9	-91.0	17.0
LUX	597	-23.0	18.9	355.9	-1.0	4.1	-94.0	19.0
LVA	597	-13.9	18.2	330.9	-0.4	2.2	-77.0	22.0
MLT	597	-7.4	21.9	479.5	-0.2	2.4	-67.0	45.0
NLD	597	-17.7	20.5	419.1	-0.6	2.6	-83.0	22.0
NOR	597	-5.7	18.5	341.2	-1.3	5.4	-88.0	29.0
POL	597	-10.1	22.3	497.6	-0.5	3.6	-88.0	60.0
PRT	597	-19.1	24.0	576.1	-0.6	2.5	-83.0	27.0
ROU	597	-15.4	16.2	263.5	-0.4	4.1	-84.0	23.0
SVK	597	-18.2	27.5	756.0	-0.5	2.2	-93.0	32.0
SVN	597	-20.1	27.1	732.6	-0.7	2.3	-92.0	25.0
SWE	597	-8.3	14.1	197.9	-0.8	4.7	-74.0	24.0
Total	**17 313**	**-16.4**	**22.7**	**515.6**	**-0.5**	**3.0**	**-94.0**	**61.0**

Note: AUT – Austria, BEL – Belgium, BGR – Bulgaria, CHE – Switzerland, CZE – Czechia, DEU – Germany, DNK – Denmark, ESP – Spain, EST – Estonia, FIN – Finland, FRA – France, GBR – The United Kingdom, GRC – Greece, HRV – Croatia, HUN – Hungary, IRL – Ireland, ITA – Italy, LTU – Lithuania, LUX – Luxembourg, LVA – Latvia, MLT – Malta, NLD – The Netherlands, NOR – Norway, POL – Poland, PRT – Portugal, ROU – Romania, SVK – Slovakia, SVN – Slovenia, SWE – Sweden, SD – standard deviation, Var – variance, Skew – Skewness, Kurt - Kurtosis
Source: own calculations based on Google Mobility Reports

Table A7. Data on Mobility in Transit Stations

	Num.	Mean	SD	Var	Skew	Kurt	Min	Max
AUT	597	-24.9	16.3	265.7	-0.2	2.8	-78.0	19.0
BEL	597	-25.5	14.4	207.2	0.0	3.3	-76.0	24.0
BGR	597	0.7	21.3	451.8	0.0	2.4	-63.0	51.0
CHE	597	-19.3	11.2	125.8	-0.5	3.7	-68.0	13.0
CZE	597	-13.9	18.4	339.0	-0.5	2.3	-71.0	24.0
DEU	597	-23.7	14.3	204.2	-0.4	3.4	-75.0	13.0
DNK	597	-24.0	15.5	240.6	-0.4	2.8	-71.0	15.0
ESP	597	-24.5	14.2	201.3	-0.6	3.6	-86.0	-1.0
EST	597	-15.3	14.4	206.9	-0.2	2.3	-61.0	18.0
FIN	597	-34.1	9.7	93.1	-0.8	3.5	-76.0	-15.0
FRA	597	-20.1	18.7	351.3	-0.4	3.2	-87.0	24.0
GBR	597	-41.4	13.4	179.1	-0.3	2.4	-85.0	-12.0
GRC	597	-16.7	27.6	764.0	0.1	2.4	-75.0	59.0
HRV	597	-11.4	27.9	779.8	1.4	6.5	-83.0	120.0
HUN	597	-15.6	17.2	295.5	-0.1	3.1	-73.0	34.0
IRL	597	-42.8	14.4	207.1	-0.3	2.2	-86.0	-12.0
ITA	597	-26.6	16.7	277.6	-0.5	3.1	-86.0	11.0
LTU	597	-17.9	19.2	368.4	-0.6	2.5	-79.0	21.0
LUX	597	-19.1	16.9	284.0	-0.1	4.2	-84.0	40.0
LVA	597	-21.5	16.9	286.5	0.0	2.2	-72.0	24.0
MLT	597	-10.4	14.8	220.1	0.2	2.1	-46.0	20.0
NLD	597	-38.2	12.9	167.3	0.3	2.9	-75.0	1.0
NOR	597	-28.9	13.7	187.3	-0.2	2.7	-77.0	5.0
POL	597	-19.3	18.3	333.0	0.0	2.7	-76.0	34.0
PRT	597	-32.4	18.7	348.0	-0.2	2.2	-81.0	6.0
ROU	597	-21.4	13.1	171.3	-0.6	4.2	-75.0	13.0
SVK	597	-22.4	19.6	385.5	-0.4	2.4	-82.0	18.0
SVN	597	-16.0	22.5	506.5	0.0	2.8	-79.0	49.0
SWE	597	-30.7	10.6	112.3	-0.1	4.0	-70.0	4.0
Total	**17 313**	**-22.7**	**19.5**	**381.5**	**0.3**	**4.2**	**-87.0**	**120.0**

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Source: own calculations based on Google Mobility Reports

Table A8. Data on Mobility in Workplaces

	Num.	Mean	SD	Var	Skew	Kurt	Min	Max
AUT	597	-24.7	15.2	230.3	-1.3	6.9	-87.0	6.0
BEL	597	-24.5	19.1	364.1	-0.2	3.4	-84.0	19.0
BGR	597	-21.6	13.0	168.9	-1.0	6.9	-85.0	10.0
CHE	597	-19.5	12.7	161.4	-1.7	10.0	-86.0	5.0
CZE	597	-17.2	16.9	284.5	-1.1	6.0	-87.0	16.0
DEU	597	-18.6	15.6	243.9	-1.0	7.1	-88.0	16.0
DNK	597	-21.3	18.2	329.7	-0.9	4.2	-88.0	15.0
ESP	597	-23.2	15.2	231.5	-0.9	4.9	-86.0	12.0
EST	597	-20.3	16.1	260.6	-0.8	5.2	-88.0	14.0
FIN	597	-22.8	19.1	364.4	-0.3	3.9	-86.0	62.0
FRA	597	-24.0	17.2	294.7	-0.6	4.6	-88.0	20.0
GBR	597	-33.6	15.9	252.9	0.1	2.9	-85.0	-1.0
GRC	597	-20.6	14.5	210.9	-0.8	4.6	-80.0	11.0
HRV	597	-17.0	16.3	264.2	-0.8	6.1	-86.0	29.0
HUN	597	-18.8	17.5	304.6	-0.6	7.2	-88.0	75.0
IRL	597	-32.3	17.6	311.3	0.1	3.2	-86.0	8.0
ITA	597	-22.7	14.5	209.2	-0.8	6.5	-86.0	21.0
LTU	597	-17.2	19.9	397.6	-0.3	3.9	-90.0	28.0
LUX	597	-25.2	19.1	362.7	-0.3	3.9	-90.0	19.0
LVA	597	-22.9	19.0	360.3	0.7	9.1	-89.0	88.0
MLT	597	-18.4	15.1	227.4	-1.1	5.3	-78.0	11.0
NLD	597	-23.3	18.3	334.0	0.1	3.2	-83.0	24.0
NOR	597	-23.5	16.8	282.5	-1.2	5.1	-87.0	8.0
POL	597	-14.7	16.8	281.5	-1.0	6.6	-87.0	34.0
PRT	597	-23.1	16.7	280.3	-0.7	3.8	-87.0	12.0
ROU	597	-20.8	14.8	218.5	-0.6	4.2	-82.0	9.0
SVK	597	-19.9	16.6	276.9	-1.0	5.7	-88.0	14.0
SVN	597	-20.2	14.7	216.4	-1.4	6.6	-88.0	4.0
SWE	597	-23.4	19.0	362.1	-0.6	3.6	-85.0	13.0
Total	**17 313**	**-21.9**	**17.2**	**294.2**	**-0.6**	**4.8**	**-90.0**	**88.0**

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Source: own calculations based on Google Mobility Reports

Table A9. Data on Sales from eKasa

	Num.	Mean	SD	Var	Skew	Kurt	Min	Max
eKasa Retail Sales	591	111.0	16.5	271.7	-0.4	5.0	61.3	172.8
eKasa Grocery Store Sales	591	111.0	10.1	102.9	0.2	7.8	76.4	157.2
eKasa Restaurants Sales	591	73.0	34.6	1195.6	0.0	1.5	16.9	127.2
eKasa Accommodation Sales	591	57.8	49.7	2472.0	0.7	2.2	5.3	167.1

Note: SD – standard deviation, Var – variance, Skew – Skewness, Kurt - Kurtosis
Source: own calculations based on Financial Administration of the Slovak Republic

Table A10. Country Characteristics (Time Invariant)

	GDP per capita	Extreme Poverty	HDI	Pop. Density	Rural Pop.	Urban Pop.	Median Age	Age > 65	Age > 70	Cardio. Death Rate	Diabetes Prev.	Female Smokers	Male Smokers	Populism	Educ.	Educ. Quality	Health. Quality
AUT	45 436.7	0.70	0.92	106.7	41.3	58.7	44.4	19.2	13.7	145.2	6.4	28.4	30.9	16.9	12.5	1 473.1	3.82
BEL	42 658.6	0.20	0.93	375.6	1.9	98.1	41.8	18.6	12.8	114.9	4.3	25.1	31.4	20.6	12.1	1 499.7	3.79
BGR	18 563.3	1.50	0.82	65.2	24.3	75.7	44.7	20.8	13.3	424.7	5.8	30.1	44.4	14.4	11.4	1 280.0	2.57
CHE	57 410.2	0.03	0.96	214.2	26.1	73.9	43.1	18.4	12.6	99.7	5.6	22.6	28.9	28.0	13.4	1 494.5	3.85
CZE	32 605.9	0.01	0.90	137.2	25.9	74.1	43.3	19.0	11.6	227.5	6.8	30.5	38.3	20.2	12.7	1 486.5	3.87
DEU	45 229.3	0.00	0.95	237.0	22.5	77.5	46.6	21.5	16.0	156.1	8.3	28.2	33.1	22.3	14.2	1 501.3	3.76
DNK	46 682.5	0.20	0.94	136.5	11.9	88.1	42.3	19.7	12.3	114.8	6.4	19.3	18.8	19.8	12.6	1 503.2	3.68
ESP	34 272.4	1.00	0.90	93.1	19.2	80.8	45.5	19.4	13.8	99.4	7.2	27.4	31.4	28.1	10.3	1 451.8	3.57
EST	29 481.3	0.50	0.89	31.0	30.8	69.2	42.7	19.5	13.5	255.6	4.0	24.5	39.3	17.8	13.1	1 576.5	3.66
FIN	40 585.7	0.06	0.94	18.1	14.5	85.5	42.8	21.2	13.3	153.5	5.8	18.3	22.6	18.7	12.8	1 549.3	2.82
FRA	38 605.7	0.02	0.90	122.6	19.0	81.0	42.0	19.7	13.1	86.1	4.8	30.1	35.6	28.1	11.5	1 481.0	3.62
GBR	39 753.2	0.20	0.93	272.9	16.1	83.9	40.8	18.5	12.5	122.1	4.3	20.0	24.7	2.9	13.2	1 510.4	3.56
GRC	24 574.4	1.50	0.89	83.5	20.3	79.7	45.3	20.4	14.5	175.7	4.6	35.3	52.0	44.7	10.6	1 360.4	3.36
HRV	22 669.8	0.70	0.85	73.7	42.4	57.6	44.0	19.7	13.1	253.8	5.6	34.3	39.9	13.2	11.4	1 415.6	3.02
HUN	26 777.6	0.50	0.85	108.0	28.1	71.9	43.4	18.6	12.0	278.3	7.6	26.8	34.8	68.9	12.0	1 438.0	2.45
IRL	67 335.3	0.20	0.96	69.9	36.4	63.6	38.7	13.9	8.7	126.5	3.3	23.0	25.7	3.2	12.7	1 513.8	2.96
ITA	35 220.1	2.00	0.89	205.9	29.0	71.0	47.9	23.0	16.2	113.2	4.8	19.8	27.8	56.7	10.4	1 430.9	3.73
LTU	29 524.3	0.70	0.88	45.1	31.9	68.1	43.5	19.0	13.8	343.0	3.7	21.3	38.0	15.4	13.1	1 439.1	3.52
LUX	94 278.0	0.20	0.92	231.4	8.6	91.4	39.7	14.3	9.8	128.3	4.4	20.9	26.0	9.6	12.3	1 430.2	3.78
LVA	25 063.9	0.70	0.87	31.2	31.7	68.3	43.9	19.8	14.1	350.1	4.9	25.6	51.0	25.5	13.0	1 462.1	3.20
MLT	36 513.3	0.20	0.90	1 454.0	5.3	94.7	42.4	19.4	11.3	168.7	8.8	20.9	30.2	0.5	11.3	1 376.5	3.80
NLD	48 472.5	0.10	0.94	508.5	7.8	92.2	43.2	18.8	11.9	109.4	5.3	24.4	27.3	26.0	12.4	1 507.4	3.85
NOR	64 800.1	0.20	0.96	14.5	17.0	83.0	39.7	16.8	10.8	114.3	5.3	19.6	20.7	17.7	12.9	1 490.8	3.89
POL	27 216.5	0.00	0.88	124.0	40.0	60.0	41.8	16.8	10.2	227.3	5.9	23.3	33.1	50.4	12.5	1 538.5	3.05
PRT	27 936.9	0.50	0.86	112.4	33.7	66.3	46.2	21.5	14.9	127.8	9.9	16.3	30.0	18.2	9.3	1 476.0	3.19
ROU	23 313.2	5.70	0.83	85.1	45.8	54.2	43.0	17.9	11.7	370.9	9.7	22.9	37.1	9.7	11.1	1 283.4	2.29
SVK	30 155.2	0.70	0.86	113.1	46.2	53.8	41.2	15.1	9.2	288.0	7.3	23.1	37.7	19.4	12.7	1 408.2	3.12
SVN	31 400.8	0.00	0.92	102.6	44.9	55.1	44.5	19.1	12.9	153.5	7.3	20.1	25.0	30.9	12.7	1 511.3	3.04
SWE	46 949.3	0.50	0.95	24.7	12.0	88.0	41.0	20.0	13.4	134.0	4.8	18.8	18.9	25.8	12.5	1 507.6	3.28
Total	**39 085.7**	**0.60**	**0.90**	**179.2**	**25.3**	**74.7**	**43.1**	**18.9**	**12.7**	**188.4**	**6.0**	**24.2**	**32.2**	**23.2**	**12.2**	**1 462.0**	**3.40**

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Source: own calculations based on Our World in Data (OWiD) database; Timbro; United Nations Development Programme (UNDP); OECD, PISA; Social Progress Imperative (SPI)

Appendix B: Data Overview

Table B1. Data Overview

Variable	Source	Unit	Time Variant	Description
Cases	OWiD	weekly percentage change in cumulative cases per million people	yes	total (cumulative) confirmed cases of COVID-19 per 1 000 000 people; counts can include probable cases, where reported
Deaths	OWiD	weekly percentage change in cumulative deaths per million people	yes	total (cumulative) deaths attributed to COVID-19 per 1 000 000 people; counts can include probable deaths, where reported
Stringency	OWiD	index	yes	Government Response Stringency Index: composite measure based on 9 response indicators including school closures, workplace closures, and travel bans, rescaled to a value from 0 to 100 (100 = strictest response)
Holiday	own created based on calendar	dummy	yes	a dummy variable taking the value of one on the days when it was a national holiday (i.e. not going to work or school) in the given country except for weekends and zero on all other days
Delta	own created based on OWiD	dummy	yes	a dummy variable taking the value of one on the days when the Delta variant gained dominance over all other variants in the given country and zero on all other days
Vaccination	OWiD	number of vaccinated people per 100 people (in the days before vaccination, a value of 0 was assigned, missing values were added by interpolation)	yes	total number of people who received at least one vaccine dose per 100 people in the total population
Institutions	Eurobarometer	percentage share	yes	public opinion polls, the share of people who declared that they do not tend to trust to institutions - the higher the value, the higher the distrust in public institutions
Grocery & Pharmacy Mobility	Google Mobility Report	index, percentage change compared to our baseline days	yes	utilizing GPS data from individual smartphones, the data shows how visitors to (or time spent in) grocery and pharmacy (together considered as essential trips) change compared to baseline days, a baseline day represents a normal value for that day of the week, the baseline day is the median value from the 5-week period Jan 3 – Feb 6, 2020

Table B1. Data Overview - Continue

Variable	Source	Unit	Time Vari-ant	Description
Retail & Recrea-tion Mo-bility	Google Mobility Report	index, per-centage change compared to our baseline days	yes	utilizing GPS data from individual smartphones, the data shows how visitors to (or time spent in) retail and recreation change compared to baseline days, a baseline day represents a normal value for that day of the week, it is the median value from the 5-week period Jan 3 – Feb 6, 2020
Transit Stations Mobility	Google Mobility Report	index, per-centage change compared to our baseline days	yes	utilizing GPS data from individual smartphones, the data shows how visitors to (or time spent in) transit stations (subway station, sea port, taxi stand, highway rest stop, car rental agency) change compared to baseline days, a baseline day repre-sents a normal value for that day of the week, the baseline day is the median value from the 5-week period Jan 3 – Feb 6, 2020
Work-places Mobility	Google Mobility Report	index, per-centage change compared to our baseline days	yes	utilizing GPS data from individual smartphones, the data shows how visitors to (or time spent in) workplaces change compared to baseline days, a baseline day represents a normal value for that day of the week, the baseline day is the median value from the 5-week period Jan 3 – Feb 6, 2020
Cardio-vascular Death Rate	OWiD	number of deaths per 100 000 people	no	death rate from cardiovascular disease in 2017 (annual number of deaths per 100 000 people) - the higher the number, the higher the death rate
Diabetes Preva-lence	OWiD	percentage share	no	diabetes prevalence (% of population aged 20 to 79) in 2017, the higher the number, the higher the diabetes prevalence
Female Smokers	OWiD	percentage share	no	share of women who smoke, most recent year available - the higher the number, the higher the share of female smokers
Male Smokers	OWiD	percentage share	no	share of men who smoke, most recent year availa-ble - the higher the number, the higher the share of male smokers
GDP per capita	OWiD	EUR per capita, transformed in log	no	gross domestic product at purchasing power parity (constant 2011 international dollars), most recent year available - the higher the value, the higher GDP per capita
Extreme Poverty	OWiD	percentage share	no	share of the population living in extreme poverty, most recent year available since 2010 - the higher the number, the higher the share of popul. living in extreme poverty
HDI	OWiD	index	no	a composite index measuring average achievement in three basic dimensions of human development (a long and healthy life, knowledge and a decent standard of living) - the higher the index, the more developed society

Table B1. Data Overview - Continue

Variable	Source	Unit	Time Variant	Description
Populism	Timbro	index based on vote share	no	Timbro authoritarian populism index - the higher the value of the index, the higher the share of votes for populist parties
Education	United Nations Development Programme (UNDP)	number of years	no	mean years of schooling - the higher the number of years of schooling, the higher the education
Education Quality	OECD, PISA	score in points	no	the sum of the points obtained in the PISA tests in mathematics, reading and science in 2018 - the higher the score, the higher the quality of education
Healthcare Quality	Social Progress Imperative	index	no	index measures an equal access to quality healthcare in 2020 - the higher the value of the index, the higher the quality of healthcare
Population Density	OWiD	number of people per km²	no	number of people divided by land area, measured in km², most recent year available - the higher the number, the higher the density
Rural Population	OWiD	percentage share	no	share of people living in rural areas in 2020 - the higher the number, the higher the share
Urban Population	OWiD	percentage share	no	share of people living in urban areas in 2020 - the higher the number, the higher the share
Median Age	OWiD	number of years	no	median age of the population - the higher the number, the older the population
Age above 65	OWiD	percentage share	no	share of the population that is 65 years and older, most recent year available - the higher the number, the higher the share
Age above 70	OWiD	percentage share	no	share of the population that is 70 years and older in 2015 - the higher the number, the higher the share
eKasa Retail Sales	Financial Administration of the Slovak Republic	index (100 = Feb 5 to Feb 11, transformed in 7-day moving average)	yes	index representing retail sales reported by digital tax collection system in Slovakia; index starts with value of 100 equal to average sales in the pre-pandemic period between February 5 and 11, 2020; index is further transformed into a 7-day moving average to exclude weekly seasonality
eKasa Grocery Store Sales	Financial Administration of the Slovak Republic	index (100 = Feb 5 to Feb 11, transformed in 7-day moving average)	yes	index representing sales in grocery stores reported by digital tax collection system in Slovakia; index starts with value of 100 equal to average sales in the pre-pandemic period between February 5 and 11, 2020; index is further transformed into a

				7-day moving average to exclude weekly seasonality
eKasa Restaurants Sales	Financial Administration of the Slovak Republic	index (100 = Feb 5 to Feb 11, transformed in 7-day moving average)	yes	index representing sales in restaurants reported by digital tax collection system in Slovakia; index starts with value of 100 equal to average sales in the pre-pandemic period between February 5 and 11, 2020; index is further transformed into a 7-day moving average to exclude weekly seasonality
eKasa Accommodation Sales	Financial Administration of the Slovak Republic	index (100 = Feb 5 to Feb 11, transformed in 7-day moving average)	yes	index representing sales in accommodation reported by digital tax collection system in Slovakia; index starts with value of 100 equal to average sales in the pre-pandemic period between February 5 and 11, 2020; index is further transformed into a 7-day moving average to exclude weekly seasonality

Source: own prepared