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8 A latent factor risk model for COVID-19

8.1 Introduction

The term "Pandemic" originates from the old Greeks, where "pan" means "all" and "demos" means "the people" [Qiu et al., 2017]. A pandemic affects thus all the people and, as it was witnessed for COVID-19, also the whole world [Wikipedia, 2022]. Pandemics extend over several months or years and usually come in multiple waves. The spread, duration, and extent of pandemics are characterized by high uncertainty. The decline in severity of detrimental effects might signal the end of the pandemic or merely the end of a wave; i.e., the silence before the next storm. Due to the rapidly fluctuating condition of a pandemic, pandemic risk management pertains to the field of operational risk management Beroggi and Wallace [1994].

Various risk concepts for modeling pandemics have been proposed. They all include elements of preparedness, followed by mitigation measures, response measures, and finally recovery measures. Mounier-Jack and Coker [2006] analyzed 21 national preparedness plans for pandemics. They concluded that preparation for logistic aspects were to some extend good, while response and intervention were probably inadequate. Marin-Ferrer et al. [2017] introduced an index for risk management (INFORM), meant to identify countries at risk of humanitarian crisis and disaster that would overwhelm national response capacity. Morse et al. [2012] proposed several research and surveillance opportunities and goals to move the global pandemic strategy from response to preemption. Lesmanawati [2020] developed a multifactorial risk analysis tool, called "Epi-Risk". The tool allows to gain rapid insight into the potential severity of emerging epidemics. It does so by combining disease-related parameters and country-related risk parameters. By predicting the risk of emerging outbreaks in real-time, EpiRisk should provide the means for timely intervention and thus prevent catastrophic epidemic outcomes. PAHO [2020] developed a checklist for COVID-19 pandemic risk and impact management. The checklist serves as a tool for national authorities to develop or revise national pandemic preparedness and response plans to COVID-19. Roberts [2019] investigated the role of big data and the application of algorithmic processing techniques for the real-time surveillance of infectious disease outbreaks. Kyea and Hwang [2020] analyzed the causal effect of a pandemic crisis and institutional responses on social trust using empirical data during COVID-19. They concluded that trust in South Korean society, people, and the central and local governments improved substantially, whereas trust in judicature, the press, and religious organizations sharply decreased. The World Health Organization (WHO) has established in 2005 the International Health Regulations (IHR), to which 196 countries are committed to [WHO, 2021]. The IHR constitutes an international treaty to combat the global spread of diseases. Each year, the 196 countries bound by the IHR must file a self-assessment report

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to the WHO, stating their status of preparedness for health emergencies. However, the veracity of these self-reports can be questionable, making them possibly an inadequate tool for pandemic risk assessment and management [Guardian, 2021]. For reasons like these, world-leaders are calling for an international pandemic treaty that enables countries to be better able to predict, mitigate, and respond to pandemics in an internationally coordinated way [BBC, 2021].

8.2 Latent factor risk model

The traditional risk models for pandemic risk management are based on operational factors that affect the potentially adverse effects of a pandemic. These factors refer to preparedness, mitigation, and response aspects. They typically include the number of available vaccines, the amount of available protective equipment (e.g., face masks), and the number of available intensive care beds.

Contrary to the traditional risk models, the risk model presented here is based on latent factors (see Figure 8.1). These latent factors are used to characterize various characteristics of nations, such as the people's general health, the economic state and potential, the overall prosperity, etc. Starik and Rands [1995] identify four key factors that contribute to an organization's sustainability: economic, political, social–cultural, and ecological environments. Accordingly, three meta latent factors are identified to be included into the proposed risk model: (1) business, (2) political, and (3) population.

Business factors: Roy and Goll [2014] identify corruption (*Crr*) and social responsibility (*Rsp*) as critical economic factors to predict sustainability of nations. As an alternative measure of economic freedom, business friendliness (*Bus*) is considered in this model. Gravito Hernández and Rueda Galvis [2021] discuss innovation and patents as business success factors, suggesting that the number of patents (*Ptn*) should also be considered as a latent factor. COVID-19 has had a major impact on workers and workplaces all over the world [Kniffin et a., 2021]. Consequently, the employment rate (*Emp*) is an important latent factor to be considered for this risk model.

Political factors: Various political factors have been used in studying nations' characteristics. Bayerlein et. al (2021) analyzed how populistic governments (mis) handle the COVID-19 pandemic. They provide empirical evidence that countries governed by populistic government did get hit worse by the pandemic. Bollen [1993] proposes two method factors to subsume a large number of political indicators. These are *political liberty* (e.g., civil liberties, political participation, and personal autonomy) and *democratic rule* (e.g., electoral process and pluralism, functioning of government, and clean elections). Elff and Ziaja (2018) extend Bollen's two-dimensional concept to three and four dimensions. For the purposes of

the risk model presented here, Bollen's two-dimensional model will be operationalized with the latent factors political liberty (*Frd*) and democratic rule (*Dmc*).
Population factors: The implications of COVID-19 have been linked to preexisting health conditions, such as obesity, which in turn has an effect on life expectancy [Rychter et.al, 2020]. For this reason, the two latent factors *life expectancy* (*Exp*) and *population health* (*Hlt*) are considered.

The nine latent factors introduced above can all be influenced by the stakeholders of a nation. Freeman [2010, p. 25] defines stakeholders to be "all of those groups or individuals that can affect, or are affected by, the accomplishment of organizational purpose." Business factors can be influenced by enterprises and unions, political factors can be influenced by all political stakeholders, and population factors can, to some extent, be influence by the population.

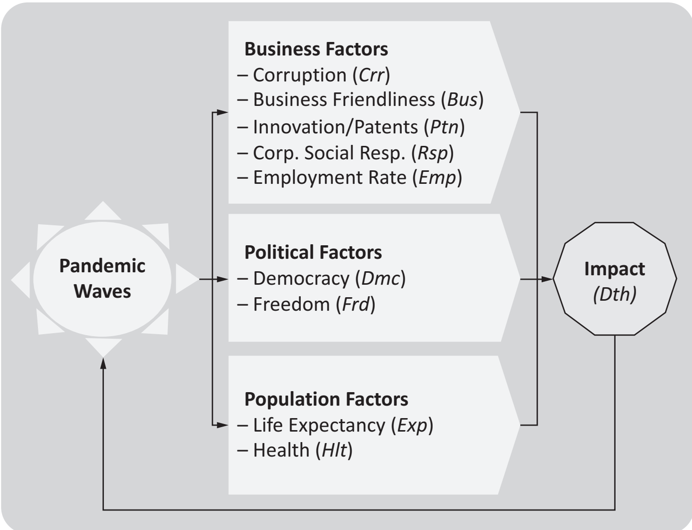

Figure 8.1: Latent factor risk model with three meta latent factors and nine latent factors.

8.3 Dimensions of latent factors risk model

8.3.1 Data collection

The data for the proposed latent factors were obtained from various online sources, which were accessed on September 24, 2020, after the first COVID-19 wave. Characteristics about the factors, their three letter abbreviations (*italic*) used as factor names, and details about the online sources are subsequently presented.

Business factors:

1. *Crr*: Corruption Perception Index (CPI), as defined by Transparency International (transparency.org/cpi). Transparency International states that the CPI scores and ranks countries/territories based on how corrupt their sector is perceived to be by experts and business executives. It is supposed to be a composite index, consisting of a combination of more than a dozen surveys and assessments. The data used in this context are the corruption scores of the nations, meaning that less corrupt nations have higher scores, while more corrupt nations have lower scores.
2. *Bus*: This variable stands for business friendliness and is recorded as the ease of doing business index (EBI). EBI is an index created jointly by Simeon Djankov and Gerhard Pohl, two leading economists at the Central and Eastern Europe sector of the World Bank Group. The data (2020) was taken from The World Bank.
3. *Ptn*: The number of patents per one million inhabitant reflects the latent factor patents. The number of patents data (2019) was taken from (https://statnano.com/report/s135). (https://www.doingbusiness.org/en/data/doing-business-score?topic=starting-a-business).
4. *Rsp*: The Corporate Social Responsibility (CSR) data (2019) were taken from the CSRHub (csrhub.com/). The CSRHub generates consensus ratings using a big data algorithm. The algorithm first aggregates 279 million data points, which then are converted into almost ten thousand metrics. These metrics are mapped into 12 areas. After normalization and weighting of the data, the country score is derived. These country scores are used as the responsibility measure.
5. *Emp*: The employment data were taken from the World Bank for the year of 2019 (https://data.worldbank.org/indicator/SL.EMP.TOTL.SP.ZS).

Political factors:

1. *Dmc*: The Democracy Index (2019) was taken from Wikipedia (wikipedia.org/wiki/Democracy_Index). The index is compiled by the Economist Intelligence Unit (EIU), a UK-based company. The purpose of this index is to measure the state of democracy in more than 100 countries.
2. *Frd*: The freedom score is assessed by Freedom House and refers to people's access to political rights and civil liberties. The score is composed of political rights and civil liberties. The data for the global freedom score were taken from the Freedom House website (https://freedomhouse.org/countries/freedom-world/scores) for the year 2020.

Population factors:

1. *Exp*: The life expectancy data were taken from Wikipedia as the UNDP data from 2018(https://en.wikipedia.org/wiki/List_of_countries_by_life_expectancy).
2. *Hlt*: As a health measure of a nation, the Global Obesity Level was taken. The data (2016) were taken from ProCon.org (obesity.procon.org/global-obesity-levels).

Dependent factor:

1. *Dth*: As the dependent or impact factor for COVID-19, the number of deaths per one million inhabitants was taken. The data were taken from Worldometer (worldometers.info/coronavirus/).

Because the data come from different sources and are generally reported by the different countries, the measurement approach and the quality of the data will also vary along these dimensions. Especially for the reported COVID-19 deaths, there could be quite some uncertainty about the data consistency and quality. Data quality and considerations for modeling and analysis have been addressed by various institutions, such as the U.S. Government Accountability Office [GAO, 2020]. Moreover, the pandemic's different dynamics around the globe is another source of limited comparability of the data. Due to these different limitations and for the sake of straightforward reevaluation of the performed analyses, no additional formatting of the reported data has been done.

8.3.2 Data cleaning

The data analysis was conducted with the R-Software [R Core Team, 2021]. Data for the latent factors identified in the risk model were collected from the referenced sources. A total of 85 countries (observations) were considered for the ten variables of the risk model. Only countries with a minimum population of one million inhabitants were considered for this purpose. For the remaining 72 countries, 5% were missing values. Discarding all countries with missing values would have left only 44 countries, which would be too few to conduct meaningful analyses. The variables *Dth*, *Crr*, *Dmc*, and *Frd* have no missing values. The variables *Bus*, and *Emp* have one missing value, *Exp* has two, *Hlt* five, *Ptn* 12, and *RSP* 19 missing values. The correlation matrix for the ten variables with the missing values and the correlation matrix for the ten variables with imputation do not differ significantly. This implies that the imputation has only marginal impact on the correlations among the ten variables. By proceeding this way, the number of complete observations could be increased from 44 to 72.

The imputation was done iteratively, starting with the factor having the least missing values. The missing values of this factor were then imputed with linear regression, where all factors without missing values served as independent factors. Thereby, *Dth* was not included in the imputation. This procedure was repeated until the missing values of all factors were imputed.

An outlier analysis revealed that there were quite some outliers for several variables. Considering the rather small number of observations (72), some of these outliers were eliminated. The criteria to include countries for the analysis were the following: *Dmc* > 5, *Hlt* > 0.05, *Exp* > 40, and *Emp* > 45. As a result, 50 nations could be used for the following data analyses.

8.4 Validation of the latent factor risk model

8.4.1 Latent factor analysis

The correlations among the impact factor *Dth* and the nine latent factors are illustrated with a correllograph (Figure 8.2), computed with the R-Package *PerformanceAnalytics* [Peterson and Peter, 2020]. On the diagonal, from top left to bottom right, in Figure 8.2, the histograms of the ten variables are shown. Below the diagonal, the scatterplots of any two of the ten variables are shown with a fitted trend curve. Above the diagonal, the correlation values (between −1.0 and +1.0) with the level of significance are plotted. Cells with at least one star (*) imply that the correlation is significant at the 5% level, while a dot (.) indicates a level of significance of 10%.

The first row shows the correlations between *Dth* and the nine latent factors. Only two latent factors (*Bus* and *Rsp*) do not have a statistically significant correlation with the impact factor *Dth* (level of significance 10%). *Dth* correlates strongest with *Exp* (34%), followed by *Hlt* (33%), *Frd* (30%), *Dmc* (29%), *Ptn* (28%), *Crr* (27%), and *Emp* (−25%). The only significant negative correlation with *Dth* stems from *Emp*. This implies that higher employment values result in lower *Dth* values, and vice versa.

The correllograph in Figure 8.2 shows, that the latent factors relating to the meta latent factor *Business* have a quite high pairwise correlations, except with *Emp*. The two latent factors referring to *Politics* (*Dmc* and *Frd*), have the highest correlation (81%). The two latent factors referring to *Population* (*Exp*, *Hlt*) have a correlation of 43%.

8.4.2 Meta latent factor analysis

The assignment of the nine latent factors to the three meta latent factors can be tested with a confirmatory factor analysis (CFA). This is done with the R-Package "sem" [Fox et al., 2020). The results show a model Chi-square of 63,94, with 24 degrees of freedom and $p < 0.01$ (AIC = 105.94, BIC = −29.95). This implies that the model is statistically significant; i.e., the assignment of the nine latent factors to the three meta latent factors is statistically significant. The parameter estimates are summarized in Table 8.1.

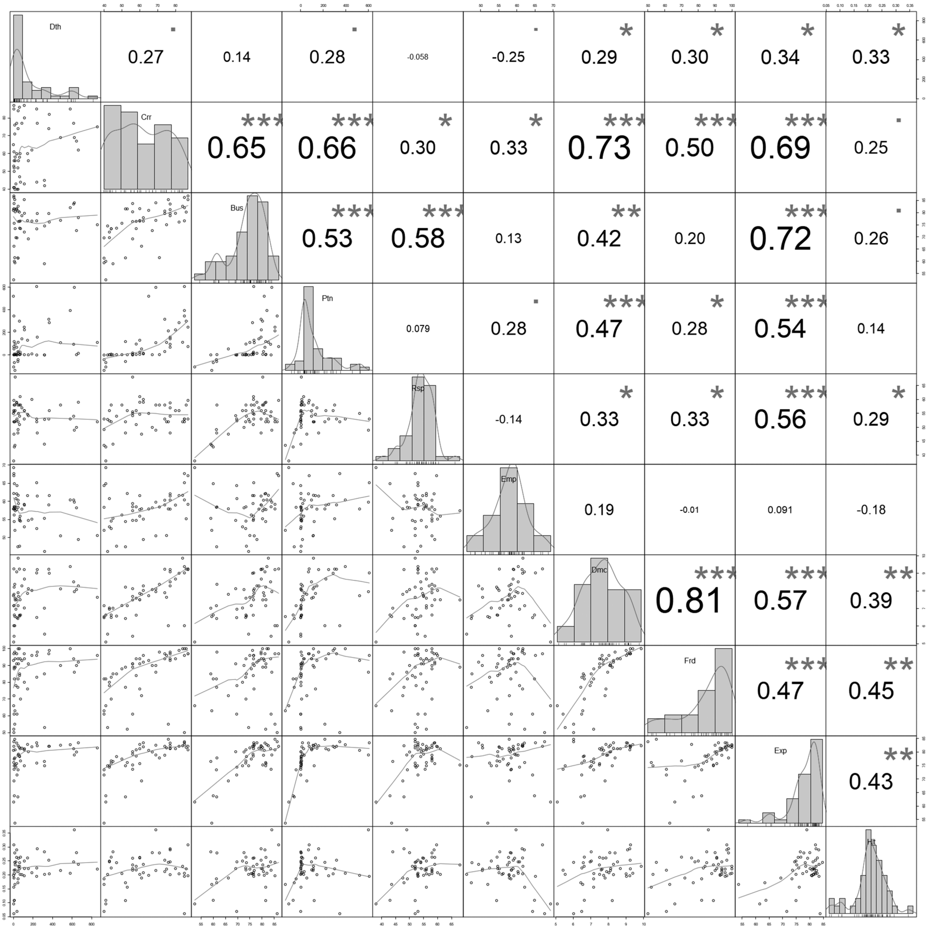

Figure 8.2: Correllograph for the impact factor *Dth* and the nine latent factors.
Note: Signif. codes: 0 "***" 0.001 "**" 0.01 "*" 0.05 "." 0.1 " " 1)

Table 8.1: Parameter estimates with confirmatory factor analysis for the grouping of the nine latent factors (LF) to the tree meta latent factors (MLF).

Estimate	Std Error	z value	Pr(>|z|)	LF		MLF
13.54	1.78	7.60	<0.01	*Crr*	<—	*Business*
6.22	1.00	6.24	<0.01	*Bus*	<—	*Business*
113.53	21.73	5.23	<0.01	*Ptn*	<—	*Business*
2.43	0.73	3.35	<0.01	*Rsp*	<—	*Business*
1.32	0.74	1.77	0.08	*Emp*	<—	*Business*
1.29	0.14	9.45	<0.01	*Dmc*	<—	*Politics*

Table 8.1 (continued)

Estimate	Std Error	z value	Pr(>|z|)	LF		MLF
10.17	1.89	5.37	<0.01	*Frd*	<—	*Politics*
7.05	1.25	5.63	<0.01	*Exp*	<—	*Population*
0.02	0.01	2.54	0.01	*Hlt*	<—	*Population*

8.5 Predictive risk models for COVID-19

Two sets of regression models will be analyzed, one for the three meta latent factors and one for the nine latent factors.

8.5.1 Regression modeling with meta latent factors

With the R-Package "FactoMineR" [Le et al., 2008], the rotated coordinates for the three principal components are calculated. The correllograph in Figure 8.3, is calculated for the three meta latent factors and the independent variable *Dth*, using the R-Package *PerformanceAnalytics* [Peterson and Peter, 2020].

From Figure 8.3 it can be seen that *Dth* only correlates significantly with the meta latent factor *Business*. Therefore, only *Business* can be used for a predictive regression model. The result of the linear regression model is illustrated in Table 8.2.

The residual standard error is 211 on 48 degrees of freedom. The multiple R-squared is 0.0973, the adjusted R-squared is 0.0785, the F-statistic is 5.17 on 1 and 48 degrees of freedom, and the p-value is 0.02.

It can therefore be conclude that the meta latent factor *Business* is the only significant meta latent factor affecting the reported number of deaths, while the meta latent factors *Politics* and *Population* are not statistically significant. The interpretation of this result could be that business factors are directly affecting the interaction of people, while political factors (democracy and freedom) are of a more strategic nature. Population factors (life expectancy and health) can very well affect the behavior of people, but probably not to such an operational level as the business factors do.

8.5.2 Regression modeling with latent factors

At the level of the nine latent factors, four separate models are built, one for each of the three meta latent factors and one considering all nine latent factors simultaneously.

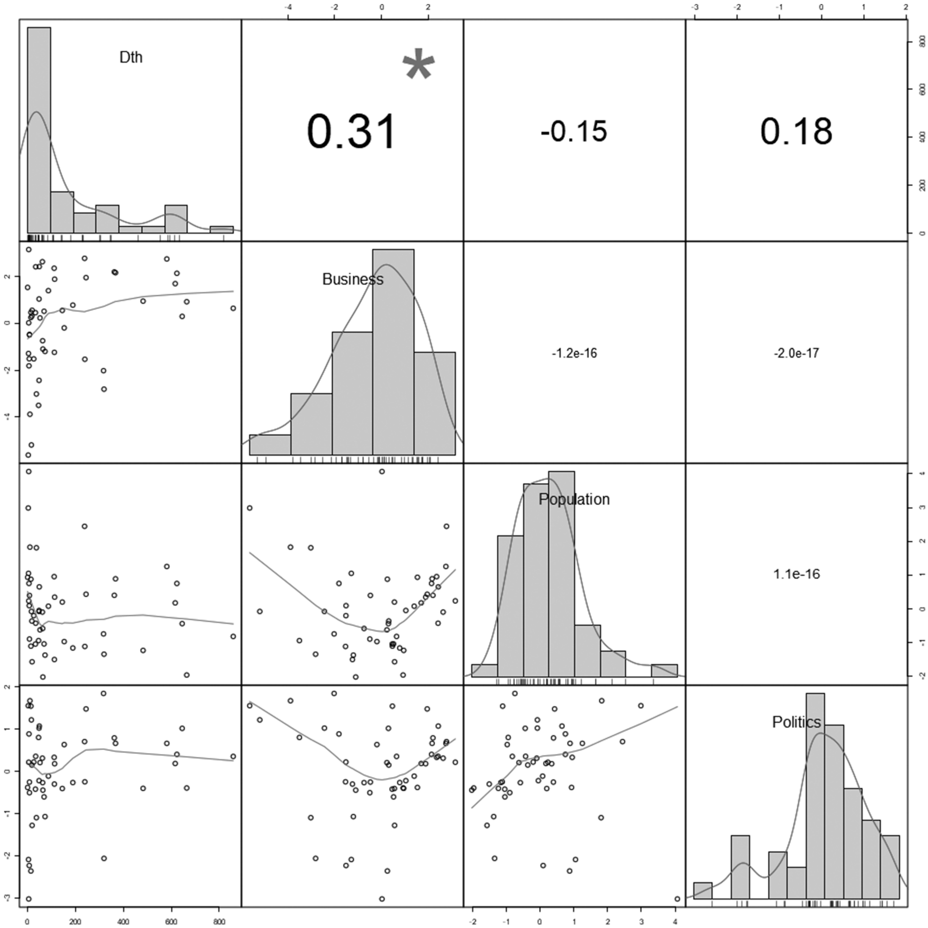

Figure 8.3: Correllograph for the three meta latent factors and the independent variable *Dth*.
Note: Signif. codes: 0 “***” 0.001 “**” 0.01 “*” 0.05 “.” 0.1 “ “ 1

Table 8.2: Result of linear regression analysis.

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	166.1	29.8	5.58	< 0.01
Business	32.7	14.4	2.27	< 0.31

(a) Business latent factors

The initial model for the latent factors referring to *Business* is the following: *Dth ~ Crr + Bus + Ptn + Rsp + Emp*. In words: *Dth* is the independent variable, while the variables to the right of the "~" sign are the independent variables, separated by "+". This model is not statistically significant. A step-wise regression reveals the statistically significant model: *Dth ~ Crr + Emp*. Obviously, only corruption and employment are significant predictors for *Dth*. Table 8.3 shows the results of the analysis.

Table 8.3: Result of stepwise regression to predict *Dth* with only the business latent factors.

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	758.91	326.54	2.32	0.02
Crr	5.58	1.97	2.84	0.01
Emp	−16.29	5.95	−2.74	0.01

The residual standard error is 200 on 47 degrees of freedom, the multiple R-squared is 0.2, the adjusted R-squared is 0.166, the F-statistic is 5.87 on 2 and 47 degrees of freedom, and the p-value is < 0.01. This is thus a statistically significant model to predict *Dth* with two latent factors, *Crr* and *Emp*, pertaining to *Business*.

The model in Table 8.3 shows that the corruption score (*Crr*) is positively correlated with *Dth*, while the employment rate (*Emp*) is negatively correlated with *Dth*. This implies that higher *Crr* values (which means less corrupt nations), coupled with lower *Emp* values (which means a lower employment rate), lead to higher *Dth* values. In words: less corrupt nations (higher *Crr* values) with lower employment rate tend to have higher number of deaths due to COVID-19. On the other hand, more corrupt nations (lower *Crr* values) with higher employment rates tend to have lower number of deaths due to COVID-19. However, *Crr* and *Emp* have a positive correlation (33%), which implies that less corrupt nations (higher *Crr* values) have a higher employment rate (higher *Emp* values).

The relative importance of the two latent business factors entering the final model to predict *Dth* are calculated with the R-Package "relaimpo" [Grömping, 2006].

Figure 8.4 shows that the two latent business factors account for 20% of the total variability. Thereby, *Crr* is slightly more influential than *Emp*.

(b) Politics latent factors

The initial model for the latent factors referring to *Politics* is the following: *Dth ~ Dmc + Frd*. However, this model is not statistically significant. A step-wise regression leads to the statistically significant model: *Dth ~ Frd*. However, also the model with the other latent factor, *Frd* (i.e., *Dth ~ Dmc*) is statistically significant. The model with *Frd* as the independent variable has the higher adjusted R-squared (0.07), compared to the model with *Dmc* as the independent variable (0.06). Because *Dmc* and *Frd* are

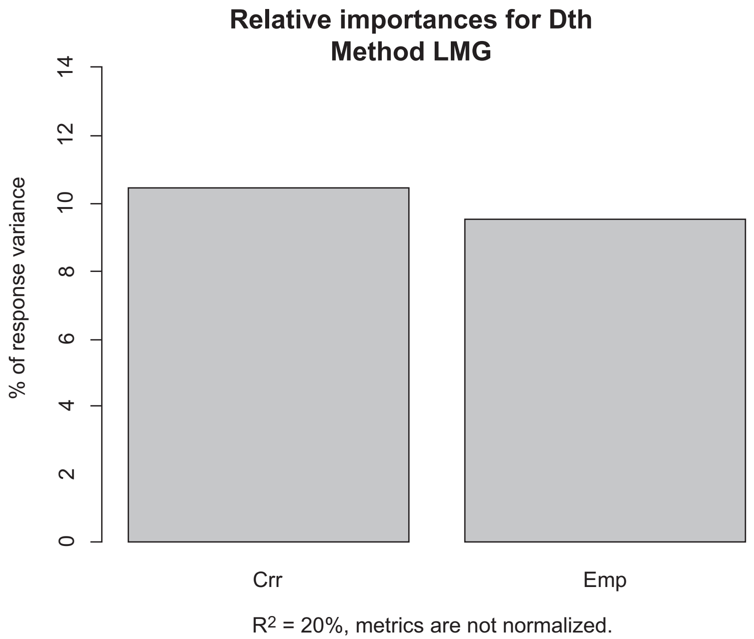

Figure 8.4: Relative importance of the two latent business factors entering the predictive model for *Dth*.

highly correlated (81%) it is not surprisingly that only one of the two latent factors entered the predictive model. Table 8.4 shows the results of the analysis.

Table 8.4: Result of regression analysis to predict *Dth* with only *Frd* as independent variable (left) and only *Dmc* (right).

	Estimate	Std. Error	t value	Pr (>|t|)
Intercept	−225.09	183.65	−1.23	0.23
Frd	4.61	2.14	2.16	0.04

	Estimate	Std. Error	t value	Pr (>|t|)
Intercept	−254	205.6	−1.24	0.22
Dmc	54.8	26.5	2.07	0.04

For the slightly stronger model with the latent factor *Frd*, the results are the following: The residual standard error is 212 on 48 degrees of freedom, the multiple R-squared is 0.0885, the adjusted R-squared is 0.0695, the F-statistic is 4.66 on 1 and 48 degrees of freedom, and the p-value is 0.04. Although it is a statistically significant model to predict *Dth*, the model is quite weak and thus not suited to make any inference. It basically implies that nations with higher values of political freedom reported higher numbers of death. The same holds for *Dmc*. This implies that more democratic freedom tends to result in higher expected fatalities due to COVID-19.

(c) Population latent factors

The initial model for the latent factors referring to *Population* is the following: *Dth ~ Exp + Hlt*. However, this model is not statistically significant. A step-wise regression leads to the statistically significant model: *Dth ~ Exp*. Here too, the model with the other latent factor, *Hlt* (i.e., *Dth ~ Hlt*) is also statistically significant. The model with *Exp* as the independent variable has the higher adjusted R-squared (0.095), compared to the model with *Hlt* as independent variable (0.088). Table 8.5 shows the results of the analysis.

Table 8.5: Result of stepwise regression to predict *Dth* with only *Exp* as independent variable (left) and only *Hlt* (right).

	Estimate	Std. Error	t value	Pr (>|t|)
Intercept	−102.4	116	−0.88	0.38
Hlt	1234.7	515.8	2.394	0.02

	Estimate	Std. Error	t value	Pr (>|t|)
Intercept	−745.87	369.88	−2.017	0.05
Exp	11.74	4.746	2.474	0.02

For the slightly stronger model with the latent factor *Exp*, the results are the following: The residual standard error is 208.7 on 48 degrees of freedom, the multiple R-squared is 0.113, the adjusted R-squared is 0.095, the F-statistic is 6.12 on 1 and 48 degrees of freedom, and the p-value is 0.02.

Because health and life expectancy are rather highly correlated (43%) it is not surprisingly that only one variable entered the final model, in this case life expectancy. Health is operationalized as the obesity level of the countries, implying that higher obesity levels lead to higher expected fatalities due to COVID-19. This confirms results reported, e.g., by Rychter et.al [2020].

(d) All nine latent factors

After looking at the nine latent factors separately, grouped into their meta level factors, an overall predictive model is derived that considers all nine factors simultaneously. The initial model for all nine latent factors is the following: *Dth ~ Crr + Bus + Ptn + Rsp + Emp + Dmc + Frd + Exp + Hlt*. This model is not statistically significant. A step-wise regression reveals the statistically significant model: *Dth ~ Rsp + Emp + Exp*. Table 8.6 shows the results of the analysis.

The residual standard error is 184.8 on 46 degrees of freedom, the multiple R-squared is 0.334, the adjusted R-squared is 0.290, the F-statistic is 7.69 on 3 and 46 degrees of freedom, and the p-value is < 0.01.

Table 8.6: Result of stepwise regression to predict *Dth* considering all nine latent factors simultaneously.

	Estimate	Std. Error	t value	Pr(>|t|)
Intercept	444.21	460.75	0.96	0.34
Rsp	−19.77	6.34	−3.12	<0.01
Emp	−16.14	5.36	−3.01	<0.01
Exp	22.10	5.20	4.25	<0.01

Corporate social responsibility (*Rsp*) has a negative coefficient (−19.77). This implies, that higher values of *Rsp* lead to lower values of *Dth*. Similarly, higher employment values (*Emp*) lead to lower *Dth* values, because the coefficient of *Emp* is also negative (−16.14). Corporate social responsibility and life expectancy have a strong social component. This suggests, that higher social scores result in lower impacts. Considering that COVID-19 has had a major impact on workers and workplaces [Kniffin et a., 2021] it seems still to be safer to have a higher employment rate, instead of avoiding workplaces.

The relative importance of the three latent factors entering the final model to predict *Dth* are calculated with the R-Package “relaimpo” [Grömping, 2006]. Figure 8.5 shows that live expectancy (*Exp*) has the strongest influence on the prediction model. The coefficient of life expectancy is positive (22.1) which implies that higher values of *Exp* lead to higher *Dth* values, while nations with lower values of *Exp* can expect lower values of *Dth*. This suggests, that COVID-19 affects primarily older people and that, consequently, nations with more older people suffer more negative impacts – a finding that has been reported since the beginning of the pandemic (CDC, 2022).

A comparison of the model considering all nine latent factors (all-factors model) with the three models derived for the three meta latent factors reveals some interesting results. The three models for the three meta latent factors are the following. *Business*: *Dth ~ Crr + Emp*, *Politics*: *Dth ~ Frd* and *Population*: *Dth ~ Hlt*. The all-factors model is the following: *Dth ~ Rsp + Emp + Exp*. Of the four latent factors that made it into the three meta factor models, only *Emp* made it into the all-factors model. Regarding the business latent factors, *Rsp* replaced *Crr* in the all-factors model. None of the political factors made it into the all-factors model. While *Hlt* was the only latent factor in the population model, it got replaced by *Exp* in the all-factors model. Quite interesting is the fact that *Rsp* has no significant correlation with *Dth* but made it anyway into the all-factors model. This is the case, because *Exp* is the most important latent factor in the all-factors model, while *Rsp* has been used to further improve the performance of the model.

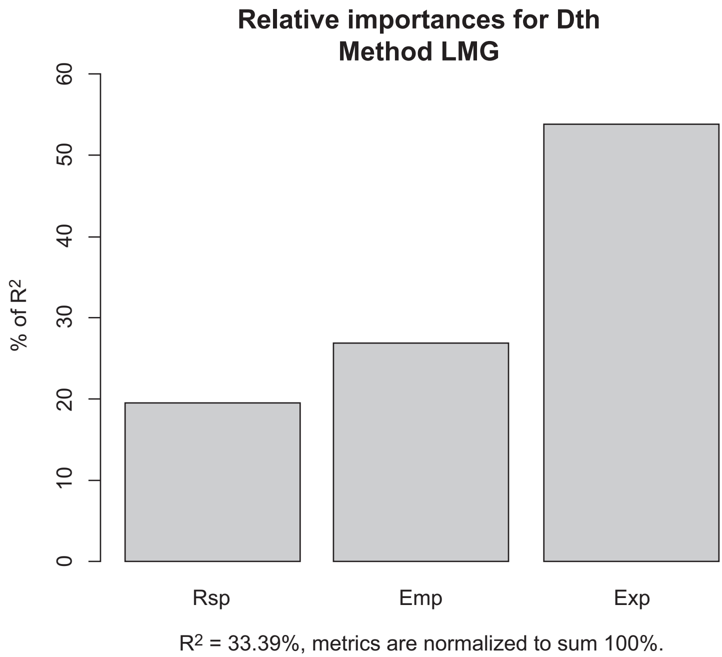

Figure 8.5: Relative importance of the latent factors entering the predictive model for *Dth*.

8.6 Post-event risk model

Finally, the learning effect of nations, as the pandemic progresses in multiple waves, is investigated. The progression of the pandemic in terms of *Dth* is shown in Figure 8.6.

The correlograph (computed with the R-Package *PerformanceAnalytics* [Peterson and Peter, 2020]) in Figure 8.7 shows that *Dth* strongly correlates among the five time periods. Pairwise correlation is highest between two neighboring periods (i.e., above the diagonal in Figure 8.7), while it slowly declines over time (i.e., towards the top right corner), starting at 0.84 in September 2020 and declining to 0.33 in January 2022. All correlations are statistically significant at the 5% level of significance. It can be concluded that the characteristics or the behavior of nations did not change substantially along the development of the pandemic.

8.7 Conclusions

A latent factor risk model was proposed to explain and predict the consequences of COVID-19 at a national level. Nine latent factors and three meta latent factors were

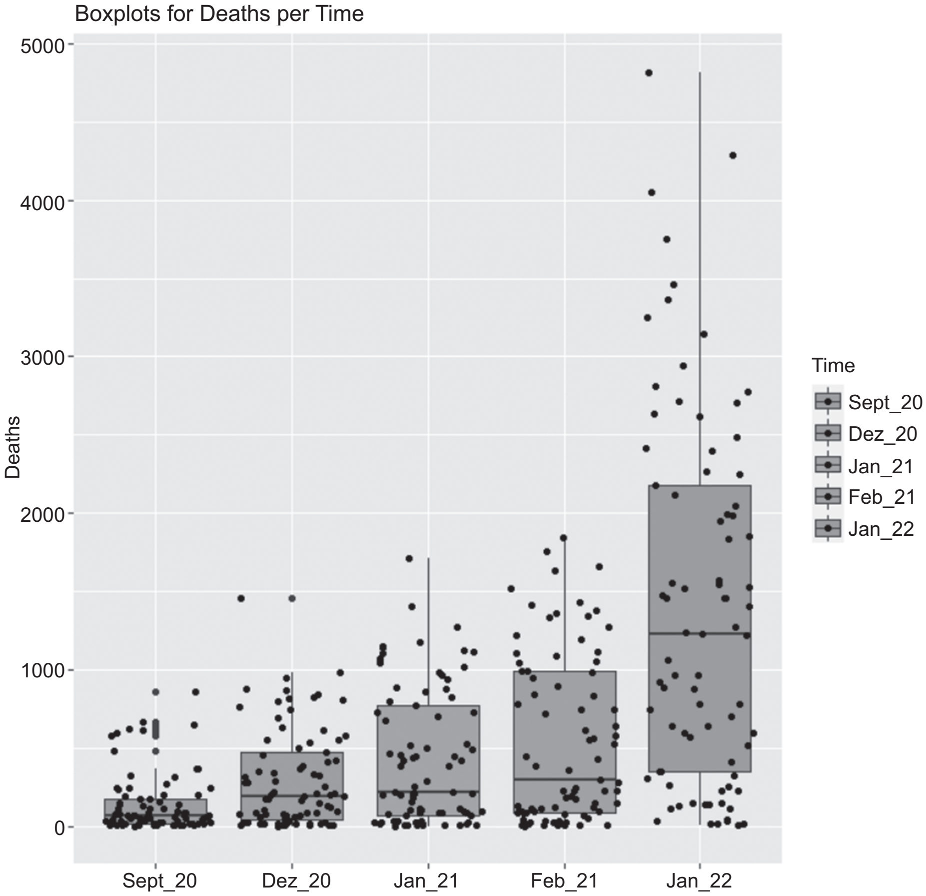

Figure 8.6: Boxplots for *Dth* at different Times.

defined. As the impact measure of COVID-19, the number of deaths per million population (*Dth*) was chosen.

The following results were obtained:

- The latent factor risk model, with nine latent factors and three meta latent factors, could be validated with empirical data.
- *Dth* can be predicted with a regression model using the three latent factors *Rsp* (corporate social responsibility), *Emp* (employment), and *Exp* (life expectancy). While higher standards of corporate social responsibility and higher rates of employment reduce the reported number of deaths, higher life expectancy has the opposite effect.
- *Dth* can also be predicted with a regression model, using only the meta latent factor *Business*, but not the meta latent factors *Democracy* and *Population*.

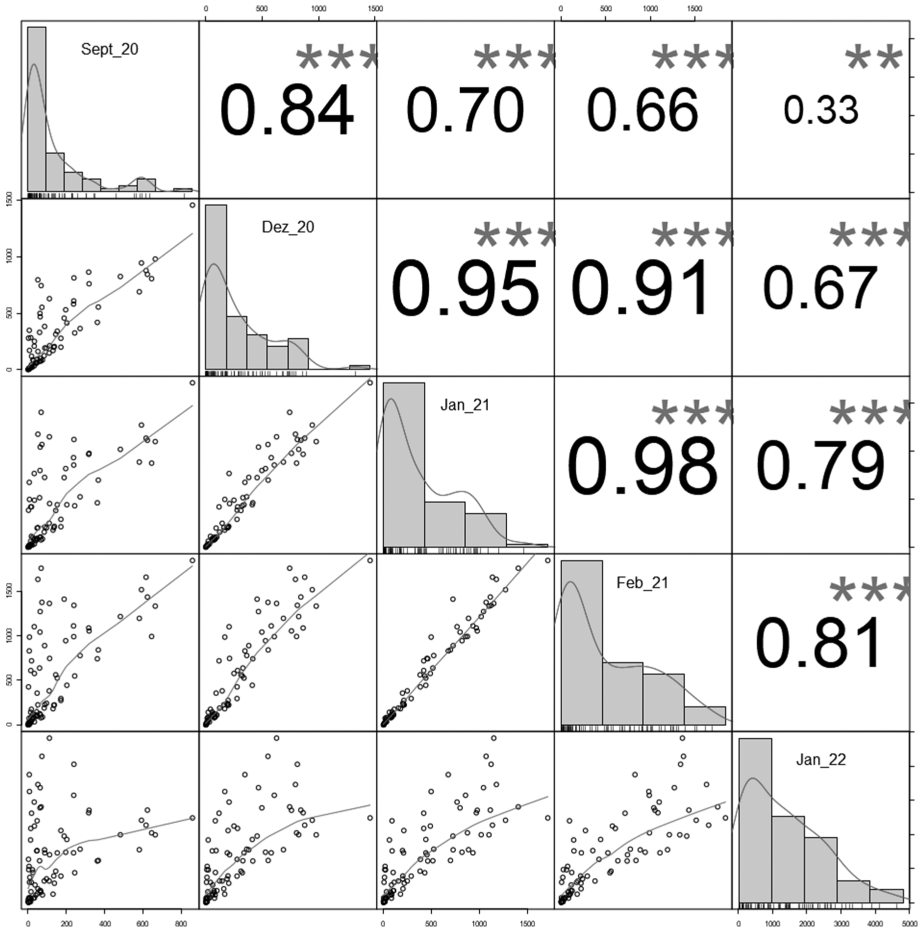

Figure 8.7: Correlograph for five time periods.

- The linear regression model considering all nine latent factors was compared to other regression techniques, based on machine learning. Basically, no improvement of the linear model could be obtained ridge regression, lasso regression, or elastic net regression.
- The results did not change significantly along the timely progression of the pandemic. This implies that nations did not alter their original influence on the latent factors as the pandemic progressed.

The analyses have also several limitations:

- The small number of nations (50) used for the analyses makes any result rather sensitive. This means that small changes regarding, e.g., the elimination of

outliers and imputation can have some impact on the results of the analyses, especially on the statistical significance of multivariate statistical models.
- The data quality and veracity of the nine latent factors as well as of *Dth* varies over the different organizations and nations. Instead of the reported number of deaths, alternative measures, such as the number of excess deaths could have been considered. However, the purpose was to analyze the publicized data, which was a primary source for public debate.
- The selection of *Dth* as the measure of consequence for COVID-19 is arbitrary. The number of infections per million population was, especially in the initial stages of the pandemic, the more important criterion to derive mitigation measures, such as curfews and shutdowns. However, the number of infections was, especially in the initial stages of the pandemic, very much dependent on the national testing strategies.
- COVID-19 hit different nations worldwide during different periods of time. This resulted in different peaks in time of the multiple waves. However, the waves were defined according to the global distribution of *Dth* from a world-wide perspective.

The proposed latent factor risk model was validated with empirical data. Regression analysis with the nine latent factors, as well as with the three meta latent factors, were performed to assess the predictive validity of the latent factor risk model. The results of these analyses provide ample evidence for face validity as well as of construct validity of the proposed latent factor risk model. Autocorrelation effects make the model also useful along the progression of the pandemic.

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