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Nexus between drivers of COVID-19 and country risks

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A B S T R A C T

COVID-19 has disrupted all spheres of life, including country risk regarding the exposure of economies to multi-dimensional risk drivers. However, it remains unexplored how COVID-19 has impacted different drivers of country risk in a probabilistic network setting. This paper uses two datasets on country-level COVID-19 and country risks to explore dependencies among associated drivers using a Bayesian Belief Network model. The drivers of COVID-19 risk, considered in this paper, are hazard and exposure, vulnerability and lack of coping capacity, whereas country risk drivers are economic, financing, political, business environment and commercial risks. The results show that business environment risk is significantly influenced by COVID-19 risk, whereas commercial risk (demand disruptions) is the least important factor driving COVID-19 and country risks. Further, country risk is mainly influenced by financing, political and economic risks. The contribution of this study is to explore the impact of various drivers associated with the country-level COVID-19 and country risks in a unified probabilistic network setting, which can help policy-makers prioritize drivers for managing the two risks.

1. Introduction

There is a growing concern about the disruptions caused by a novel coronavirus disease, named COVID-19, since it sparked in Wuhan, China, in December 2019. As of February 12, 2022, COVID-19 infected nearly 408 million people and killed nearly six million patients worldwide [1]. COVID-19 has significantly disrupted operations across various industries, including healthcare, supply chains, and logistics worldwide [2,3,4]. The impact of this pandemic is more devastating due to increased globalization and dependencies among businesses, economies and communities across the world [5], which necessitates a systemic approach to assess the risk associated with such pandemics [6,7].

The INFORM (Index for Risk Management) is a composite risk indicator developed by a European research consortium to help assess the risk associated with humanitarian crises and disasters [8]. COVID-19 risk aims to identify “countries at risk from health and humanitarian impacts of COVID-19 that could overwhelm current national response capacity, and therefore lead to a need for additional international assistance” [9]. Since multi-dimensional factors associated with health, safety, socio-economic conditions, infrastructure, demographics, technology and governance impact COVID-19 risk [3,10,11], all key factors have been captured in the assessment of COVID-19 risk and its drivers, namely hazard and exposure, vulnerability and lack of coping capacity [9].

COVID-19 risk assessment is gaining increasing interest in the research community due to the significant impact of this pandemic on all spheres of life [9,12,13]. However, the utility of existing studies on this topic is limited due to the treatment of factors influencing COVID-19 risk as individual variables. This assumption can undermine the importance of systemic risk factors cascading across multiple factors, thereby aggravating the overall risk [14]. Subsequently, the resulting risk prioritization scheme can yield sub-optimal decisions regarding the allocation of resources to critical factors.

Country risk represents the overall exposure of individual countries to multi-dimensional risk factors, such as political, economic, financial and other risks [15]. Several rating agencies, including the International Country Risk Guide, Moody’s, and Standard and Poor’s, regularly perform country risk assessments to help governments and businesses prioritize their strategies [16]. “[Country risk assessment] methodology consists of analyzing hundreds of economic indicators, both quantitative and qualitative, to provide the best understanding of the economic, political, business environment, commercial and financing risks” [17].

Several studies have focused on the impact assessment of COVID-19 on logistics and supply chains [18,19], and safety and healthcare [3,11,20,21]. COVID-19 risk assessment [22,23] and the preparedness of communities to this pandemic [4,10,12,24]. However, to the best of the

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authors’ knowledge, the impact of COVID-19 risk has not been explored on country risk to establish dependencies among associated risk drivers in a probabilistic network setting. Exploring dependencies among risk factors in a network setting is critical for effective decision-making under risk and uncertainty [14,25]. However, it is quite challenging to capture cause-effect relations among various drivers in the context of country risk assessment [26,27]. On the other hand, studies that ignore the interdependence of risk factors can yield sub-optimal decisions regarding prioritizing risk factors and allocating resources for managing critical risks [25,28].

The main objective of this study is to explore dependencies among drivers of COVID-19 and country risks in a unified probabilistic network model to help decision-makers understand the relative importance of individual drivers influencing these risks. At a country level, this study can help policy-makers identify the relative importance of drivers influencing both country risk and COVID-19 risk simultaneously. Subsequently, limited resources can be assigned to critical risk drivers in proportion to their relative importance. Similarly, international businesses can plan their offshoring/reshoring strategies concerning the impact of COVID-19 on different drivers of country risk, such as business environment and political risks. Further, international agencies can utilize the results of this study to plan the allocation of resources to critical regions for mitigating the impact of COVID-19 globally. The remainder of the paper is organized as follows: A brief overview of the relevant literature is presented in Section 2. The research methodology is described in Section 3, followed by the presentation of results in Section 4. We discuss the implications of our study in Section 5 and present conclusions and directions for future research in Section 6.

2. COVID-19 and country risks assessment

In the context of disaster risk assessment, risk comprises the following three dimensions: (i) hazard (an adverse event that could occur) and exposure (potentiality of losses due to the hazard), (ii) vulnerability (the susceptibility of communities to hazards) and (iii) lack of coping capacity (lack of resources that can aggravate the impact of hazards) [29]. The COVID-19 risk index developed by INFORM [9] captures multi-dimensional factors associated with all three dimensions of risk and establishes country-level risk related to this pandemic [29]. However, this index treats all factors as independent and ignores their non-linear interactions influencing risk [8]. These assumptions are generally made in most studies on disaster risk assessment [29,30]. Since such assumptions can yield sub-optimal risk prioritization schemes and risk mitigation strategies, it is important to prioritize drivers of COVID-19 risk in a probabilistic network setting while capturing the uncertainty associated with risk assessments and retaining statistical dependencies among multi-dimensional factors [31,32].

Country risk assessment is an active area of research due to the significant impact of country risk on regional development and prosperity [33]. Several studies have explored the assessment of country risk using financial, economic and political factors [27,34,35], and investigated the impact of country risk on regional stability, national development and businesses [26,36,37]. Several studies have assessed the impact of COVID-19 on the financial and economic outlook of economies. Based on the data collected from 64 countries, Ashraf [38] concluded that stock markets responded negatively to the increase in COVID-19 cases. Using a pandemic vulnerability index, Shrestha et al. [39] assessed the potential impact of COVID-19 on globalization in terms of mobility, trade, travel and economies. Using data from 77 countries, Ashraf [40] concluded that the announcements of government social distancing measures have a direct negative effect on economic activity and a positive effect in reducing the number of COVID-19 cases. Using data on the global coronavirus infections and indexes for all stock markets worldwide, Zhang, Hu, and Ji [41] mapped the general patterns of country-specific risks and systemic risks in global financial markets. Rizwan, Ahmad, and Ashraf [42] validated similar patterns related to systemic risks for developed economies. Based on the literature review, Goodell [43] summarized key findings about the impact of COVID-19 on economic costs, banking and insurance, government and public spending behaviors, financial markets and cost of capital.

Several studies have explored the impact of COVID-19 on supply chain and logistics management in a healthcare setting. For instance, Goodarzian et al. [21] introduced a new multi-objective, multi-product and multi-echelon mathematical formulation called Sustainable Medical Supply Chain Network (SMSCN) to help improve supply chain performance. Similarly, Ghasemi et al. [44] proposed a bi-level mathematical model for the location, routing and allocation of medical centers to distribution depots during the COVID-19 pandemic. By integrating sustainability aspects and resiliency concepts, Goodarzian et al. [20] proposed a new sustainable-resilient healthcare network design while capturing production, allocation, location, inventory holding, distribution and flow problems related to the COVID-19 pandemic.

Although there is an exponential growth in COVID-19 research worldwide [24,45], earlier studies highlighted the high number of fragmented studies across diverse disciplines and recommended the need for country-level solid leadership and coordination in transparent and collaborative manner [24]. Further, there is a need to adopt a holistic and interdisciplinary approach to assess and manage multi-dimensional risks associated with such pandemics [46]. In this paper, we aim to address the gaps mentioned above and explore the assessment of COVID-19 and country risks in a unified model such that multi-dimensional drivers of both risks can be prioritized based on their holistic impact in a network setting. The next section delineates the research methodology adopted to address the research objective of this study.

3. Research methodology

We adopted a data-driven Bayesian Belief Network (BBN)-based approach that has been effectively applied in the context of decision-making under risk and uncertainty [47,48,49]. BBNs can be used to effectively model and analyze dependencies among uncertain variables while making it possible to visualize the propagation impact of various risk scenarios [50]. Utilizing two real datasets by INFORM [9] and Euler Hermes [17], we developed a probabilistic network model that helped capture dependencies among multi-dimensional drivers of COVID-19 and country risks.

A comprehensive methodology, including four sequential steps, was adopted to address the research objective. The first stage (data collection and processing) involved collecting and discretizing country-level data related to COVID-19 and country risks assessment. The second stage (BBN modeling) involved developing a data-driven BBN model. Subsequently, the third stage (BBN model validation) was focused on validating the model developed in the previous stage. Finally, the fourth stage (results and interpretation) involved the assessment of dependencies among the selected drivers of COVID-19 and country risks and identifying critical factors influencing these two risks.

3.1. Data collection and processing

The dataset by INFORM [9] was used to assess the country-level exposure to COVID-19 risk because this dataset is publicly available and INFORM is considered a credible international agency for assessing the risk related to natural disasters and pandemics [29]. The data comprised statistics related to 191 countries for the three drivers of COVID-19 risk, namely hazard and exposure, vulnerability and lack of coping capacity (see Table 1 (a)). Similarly, the dataset by Euler Hermes [17] was used for assessing the country-level exposure to various socioeconomic risk factors because these country risk ratings have been widely used in the literature [51,52]. This dataset was publicly available for 188 countries, including the ratings for five drivers of country risk.
discretizing a given dataset relative to various states of uncertain variables, are developed using a structured process that involves the following steps: distributions) of the model. Several software packages, such as Hugin and GeNIe, can be used to develop a data-driven BBN model [59]. Further, several algorithms, such as Naïve Bayes, Greedy Thick Thinning (GTT), PC and Bayesian Search, can be used to develop a network structure [60]. These algorithms either use a scoring function or explore independent relationships among variables. For a comprehensive overview of BBN modeling, interested readers may consult Kelangath, Das, Quigley, and Hirdaris [61] and Kjaerulff and Madsen [62].

Using the discretized data for the variables (see Table 3), we developed a data-driven BBN model in GeNIe 2.0 (see Fig. 2). The model contains ten variables and ten arcs. We used the GTT algorithm to develop the model because this algorithm has been effectively explored in other application areas [60]. The model (see Fig. 2) does not exhibit cause-effect relations among interconnected variables. Rather, it represents statistical dependencies among variables in relation to the specific datasets selected for this study. A similar approach has been adopted in other studies to explore statistical dependencies among variables within the context of decision-making under risk and uncertainty [60,61,63].

It is worth exploring causality among multi-dimensional factors related to COVID-19 and country risks. However, it is a challenging task to establish such cause-effect relations in this particular context because of the complex and dynamic nature of associations among socioeconomic factors and risk factors [22,23,35]. Therefore, we aim to investigate statistical dependencies among variables influencing COVID-19 and country risks in a network setting to establish the relative importance of individual variables.

### 3.2. BBN modeling

BBN is an effective statistical technique to model and assess relations among interconnected variables [53,54]. Its ability to visualize dependencies among variables can help decision-makers prioritize critical factors [49,55,56]. Both expert judgment and empirical data can be used to develop BBN models. Experts involved in the development of a BBN model are required to map a causal (qualitative) structure and establish the strength of associations. The presence of an arc between a pair of variables, in the case of an expert-elicited BBN model, represents a direct cause-effect relationship, whereas the strength of dependency is captured using (conditional) probability distributions [57,58].

Consider a simple network of three interconnected risks represented by binary variables, namely \( R_1, R_2 \) and \( R_3 \) (see Fig. 1). The arcs represent cause-effect relations such that both \( R_1 \) and \( R_2 \) can impact \( R_3 \). The probability of the ‘High’ state of \( R_1 \) and \( R_2 \) is 0.2 and 0.4, respectively. The conditional probability distribution of \( R_3 \) is presented in Table 4.

The conditional probability distributions, which represent the strength of dependency among interconnected variables, establish the posterior probability of individual variables for a given network. For instance, the probability of the ‘High’ state of \( R_3 \) is calculated as 0.28 using Equation (1).

\[
P(R_3=\text{High}) \times P(R_3=\text{High}|R_1=\text{High}, R_2=\text{High}) \\
\times P(R_1=\text{High}) \\
\times P(R_2=\text{High}|R_3=\text{High}) \\
\times P(R_1=\text{High}|R_2=\text{Low}) \\
\times P(R_3=\text{High}|R_1=\text{Low}, R_2=\text{High}) \\
\times P(R_1=\text{Low}|R_2=\text{High}) \\
\times P(R_3=\text{High}|R_1=\text{Low}, R_2=\text{Low}) \\
\times P(R_1=\text{Low}|R_2=\text{Low})
\]

Data-driven BBN models can be developed using a dataset in which arcs connecting variables may represent statistical dependencies. These models are developed using a structured process that involves the following steps: discretizing a given dataset relative to various states of uncertain variables, developing a network structure, and learning the parameters (probability distributions) of the model. Several software packages, such as Hugin and GeNIe, can be used to develop a data-driven BBN model [59]. Further, several algorithms, such as Naïve Bayes, Greedy Thick Thinning (GTT), PC and Bayesian Search, can be used to develop a network structure [60].

### 3.3. BBN model validation

We used the k-fold cross-validation scheme to validate the BBN model developed [65]. The prediction accuracy of the model was assessed as 80.34%. The confusion matrix (see Table 5) indicates the relationship between actual and predicted states. The numbers highlighted across the diagonal represent all those instances where the predicted state accurately matched the actual state. For instance, out of 178 records used in the testing phase, 53 were correctly diagnosed by the model corresponding to 62 for the high state. The relative importance of multi-dimensional factors influencing COVID-19 and country risks is assessed in the next section.

### 4. Results and interpretations

#### 4.1. Probability distributions and identification of critical variables

The probability distribution associated with individual variables is indicated in Fig. 2. It shows that the distribution of COVID-19 risk is symmetric, with 27.3% percent of the countries related to the ‘high’ state. In contrast, the distribution of country risk is skewed, with 34.7% of countries related to the ‘high’ state. Other variables associated with country risk reflect a similar skewed pattern. After normalizing the distributions depicted in Fig. 2, COVID-19 risk is assessed as the least critical variable, whereas economic risk is the most critical variable. Economic risk is the most critical variable for countries with a low level of country risk, whereas vulnerability is the least critical variable.
contrast, financing risk is the most critical variable for countries with a high level of country risk.

4.2. Network-wide impact assessment of individual variables

One of the merits of using a BBN model is its ability to project the network-wide propagation impact of changes introduced to the model. To maintain consistency across different rating scales used for variables in the model (see Table 3), the ratings were normalized and mapped to a scale of 0–1. Subsequently, each variable was set to its extreme state and the variation (spread) in the probability-weighted scores was calculated for every other variable. The assessment of this spread can help identify critical variables associated with the variable of interest.

The relative importance of variables specific to COVID-19 risk is presented in Fig. 3. The lack of coping capacity is assessed as the most critical variable influencing COVID-19 risk. Therefore, countries with a limited coping capacity experienced a higher level of COVID-19 risk than countries with better coping mechanisms. In contrast, vulnerability is the least critical variable, implying that vulnerability alone cannot help assess COVID-19 risk. Among the drivers of country risk, business environment risk and political risk are strongly associated with COVID-19 risk, whereas commercial risk is the least critical driver associated with COVID-19 risk. Country risk also exhibits a significant change relative to the extreme states of COVID-19 risk. If the overall spread is partitioned into three equal ranges (low, medium, and high), the average impact of the extreme states of COVID-19 risk on individual variables corresponds to the medium range.

The relative importance of variables specific to country risk is presented in Fig. 4. Financing risk is the most critical variable influencing country risk. In contrast, vulnerability is the least critical variable. Among the drivers of country risk, political and economic risks are strongly associated with country risk, whereas commercial risk is the least critical variable. Countries associated with the extreme states of country risk have a wide variation in the distribution of COVID-19 risk, implying that countries with a high level of country risk may be associated with a low level of COVID-19 risk and vice versa. Overall, financing, political and economic risks have a high impact (spread between 0.66 and 1), whereas business environment risk and lack of coping capacity have a medium impact (spread between 0.33 and 0.66).

The relative importance of variables specific to business environment risk is presented in Fig. 5. Political risk is assessed as the most critical variable influencing business environment risk. In contrast,
vulnerability is the least critical variable. Country risk is significantly changed with the change in business environment risk, whereas lack of coping capacity is also assessed as one of the critical variables impacting business environment risk. Among the drivers of country risk, the commercial risk is the least critical variable. Political risk, country risk, lack of coping capacity and financing risk have a high impact on the business environment, whereas economic risk and COVID-19 risk have a medium impact.

The relative importance of variables specific to economic risk is presented in Fig. 6. Country risk is assessed as the most critical variable influencing economic risk. On the other hand, COVID-19 risk does not have a strong association with economic risk relative to its extreme states, implying that socioeconomic factors alone may not help determine the exposure to COVID-19 risk. Among the drivers of country risk, financing risk is the most critical variable and commercial risk is the least critical variable. Country risk, financing risk and political risk have a high impact on economic risk, whereas business environment risk and lack of coping capacity have a medium impact.

The relative importance of variables specific to financing risk is presented in Fig. 7. Similar to the pattern observed in Fig. 6, country risk is assessed as the most critical variable influencing financing risk.

### Table 5

Confusion matrix for Country risk (overall accuracy = 80.34% [143/178]).

| Predicted | Low | Medium | Sensitive | High |
|-----------|-----|--------|-----------|------|
| Actual    |     |        |           |      |
| Low       | 21  | 4      | 0         | 0    |
| Medium    | 5   | 31     | 5         | 1    |
| Sensitive | 0   | 4      | 38        | 7    |
| High      | 0   | 0      | 9         | 53   |

Note: The number of correct predictions for individual states appear in bold.
Fig. 4. Network-wide impact assessment for extreme states of Country risk.

Fig. 5. Network-wide impact assessment for extreme states of Business Environment risk.

Fig. 6. Network-wide impact assessment for extreme states of Economic risk.
Fig. 7. Network-wide impact assessment for extreme states of Financing risk.

Fig. 8. Network-wide impact assessment for extreme states of Political risk.

Fig. 9. Network-wide impact assessment for extreme states of Commercial risk.
Moreover, COVID-19 risk does not have a strong association with financing risk relative to its extreme states, which implies that the financial conditions of a region may not help predict the exposure to COVID-19 risk. Among the drivers of country risk, economic risk is the most critical variable and commercial risk is the least critical variable. Country risk, economic risk and political risk have a high impact on financing risk, whereas business environment risk and lack of coping capacity have a medium impact.

The relative importance of variables specific to political risk is presented in Fig. 8. Country risk is assessed as the most critical variable influencing political risk, whereas COVID-19 risk and its drivers, including hazard and exposure, and vulnerability, do not have a strong association with political risk relative to its extreme states. However, lack of coping capacity is strongly associated with political risk and business environment risk is also assessed as one of the most critical variables. On the other hand, political risk has a low impact on commercial risk.

The relative importance of variables specific to commercial risk and vulnerability is presented in Fig. 9 and Fig. 10, respectively. None of the variables have a strong association with commercial risk and vulnerability, thereby validating the results presented in the previous figures. It implies that countries associated with a high or low level of commercial risk or vulnerability depict a wide variation in the distributions for all other variables. Therefore, the variables presented in Figs. 9 and 10 may not be useful in predicting the state of commercial risk or vulnerability for a given country or region.

The relative importance of variables specific to hazard and exposure is presented in Fig. 11. COVID-19 risk is assessed as the most critical variable, whereas country risk is moderately influenced by hazard and exposure relative to its extreme states. Among the drivers of country risk, business environment risk is the most critical variable and commercial risk is the least critical variable. COVID-19 risk, lack of coping capacity and business environment risk are associated with a medium impact, whereas all other variables have a low impact in terms of the overall spread.

The relative importance of variables specific to the lack of coping capacity is presented in Fig. 12. Business environment risk is the most critical variable, whereas vulnerability is the least critical variable influenced by the lack of coping capacity relative to its extreme states. Political risk is also assessed as one of the critical variables. Country risk, financing risk and economic risk have a medium impact on coping capacity. On the other hand, political risk has a high impact.

The relative importance of variables was also assessed in relation to the extreme states of COVID-19 and country risks simultaneously (see Fig. 13), which helped capture the synergistic effects of the two risks. Political and financing risks are assessed as the most critical variables. Among the drivers of COVID-19 risk, the lack of coping capacity is the most critical variable. The least critical variables are commercial risk and political risk.
Fig. 12. Network-wide impact assessment for extreme states of Lack of Coping Capacity.

Fig. 13. Network-wide impact assessment for extreme states of COVID-19 and Country Risks.

Fig. 14. Sensitivity of Country risk to extreme states of individual factors.
and vulnerability. All variables, except hazard and exposure, commercial risk and vulnerability, have a high impact on COVID-19 and country risks simultaneously.

4.3. Sensitivity analysis

The sensitivity of country risk and COVID-19 risk was assessed relative to the extreme states of individual variables (see Figs. 14 and 15). The sensitivity analysis helped validate the results presented in the previous sub-section. Financing, political and economic risks are the most critical variables associated with country risk (see Fig. 14), whereas hazard and exposure, lack of coping capacity and business environment are critical variables associated with COVID-19 risk (see Fig. 15). Commercial risk and vulnerability are the least critical variables concerning COVID-19 and country risks. The overall impact of individual variables relative to the extreme states of country risk corresponds to the medium range, whereas the impact is reduced to the low range for COVID-19 risk.

5. Discussion and implications

5.1. Salient findings

5.1.1. Correlations among variables

Country risk is strongly correlated with economic, business environment, political and financing risks, whereas its correlation with COVID-19 risk and lack of coping capacity is moderate and strong, respectively. Business environment risk is strongly correlated with political risk, COVID-19 risk and lack of coping capacity. COVID-19 risk is strongly correlated with hazard and exposure and lack of coping capacity, whereas it is moderately correlated with economic and political risks. The correlation analysis implies a moderate to a strong association between some drivers of COVID-19 and country risks. However, this correlation analysis cannot help establish non-linear dependencies among these drivers and prioritize drivers based on the specific state of individual risk factors.

5.1.2. Critical variables influencing country risk

While prioritizing variables relative to the extreme states of country risk, financing risk is assessed as the most critical variable. In contrast to the correlation analysis-based results, COVID-19 risk is a relatively non-critical variable, implying that countries associated with one of the extreme states of country risk represent a wide variation in the distribution of COVID-19 risk. However, the lack of coping capacity is still associated with country risk relative to its extreme states, implying that the lack of coping capacity can help determine the exposure of economies to country risk besides COVID-19 risk.

5.1.3. Critical variables influencing COVID-19 risk

The lack of coping capacity is identified as the most critical variable associated with COVID-19 risk relative to its extreme states. Contrary to the results of correlation analysis, hazard and exposure is not a critical variable. Among the drivers of country risk, business environment and political risks are strongly associated with COVID-19 risk. However, the strength of association is not comparable to the correlation analysis-based results. Further, the associations are relatively weaker compared to country risk.

5.1.4. Critical variables influencing business environment risk

Political risk is evaluated as the most critical variable associated with business environment risk relative to its extreme states. Contrary to the correlation analysis-based results, COVID-19 risk is not considered a critical variable, implying that COVID-19 risk does not significantly help establish the outcome of business environment risk. Rather, other variables, such as political risk and lack of coping capacity, determine the magnitude of business environment risk. Commercial risk, representing demand disruptions, does not significantly influence business environment risk because its contribution to country risk is not comparable to other drivers (see Fig. 4).

5.1.5. Impact of COVID-19 on country risk

One of the merits of modeling drivers of COVID-19 and country risks in the same BBN model is the ability to assess the synergistic effects of these risk drivers. For simultaneous changes in the extreme states of COVID-19 and country risks, the relative importance of political risk, financing risk, business environment risk, economic risk and lack of coping capacity is significantly enhanced (see Figs. 3, 4 and 13). However, vulnerability and commercial risk are still considered non-critical variables.

5.2. Implications

This paper makes a theoretical contribution to the literature on disaster risk science while focusing on the impact of pandemics on country risk. Utilizing datasets related to the assessment of COVID-19 and country risks, a data-driven probabilistic model is developed, which is capable of establishing the network-wide relative importance of drivers associated with both risks. To the best of the authors’ knowledge, none of the studies have assessed the relative importance of drivers impacting both COVID-19 and country risks in a holistic network setting. The proposed methodology can be adapted to dynamically predict the outcome of country risk relative to any changes in the drivers of COVID-19 risk.
International agencies, such as the World Health Organization, can utilize the results of this study to prioritize critical drivers of COVID-19 risk across different economies and develop effective strategies to cope with the challenges associated with this pandemic [10]. Similarly, policy-makers at a national level can establish the relative importance of drivers impacting country risk for a specific level of COVID-19 risk. International businesses can make risk-informed decisions regarding off-shoring/reshoring while accounting for the uncertainty surrounding COVID-19 and country risks assessment. This study can also help credit rating agencies establish the impact of COVID-19 risk on country risk, thereby making it possible for insurance companies to capture the impact of COVID-19 risk in their pricing models.

Using the proposed methodology and country-level data specific to individual states and cities, policy-makers can prioritize critical states associated with high exposure to COVID-19 and country risks. Such granular-level analyses can help national agencies effectively utilize limited resources and centrally coordinate a risk mitigation plan while capturing a holistic account of risk-specific information. One of the merits of mapping drivers of both COVID-19 and country risks in a single model is the ability to project the propagation pattern of different risk scenarios and help policy-makers understand the implications of their potential strategies. Without developing such models, policy-makers may not appreciate non-linear interactions among risk drivers, which may lead to making sub-optimal decisions [25].

Country risk assessment can help policy-makers make risk-informed decisions regarding national development and economic growth [30]. However, given the uncertainty surrounding COVID-19, there is a need to capture this uncertainty while developing country risk assessment models. The resulting models can effectively prioritize factors in a network setting [5]. The proposed model can help stakeholders, including international agencies, governments and the business community, appreciate dependencies among different drivers of interest and prioritize drivers holistically for effective strategy development. The proposed methodology can be adopted to help decision-makers assess risks concerning pandemics, disasters, floods, epidemics and other natural calamities.

This study yields a unique set of relative importance weights for different risk drivers concerning COVID-19 and country risks simultaneously, thereby providing valuable information to decision-makers regarding resource allocation. Few studies [22,23,27] have explored the relative importance of different drivers of the two risks separately, but none of the studies have investigated this problem while accounting for interactions among various drivers of the two risks in a unified probabilistic network setting. Without adopting this approach, it may not be possible to establish an optimal resource allocation scheme for managing different risk drivers related to the two risks.

6. Conclusions

This study established the relative importance of drivers associated with COVID-19 and country risks in terms of their network-wide impact in a probabilistic network setting. The main contribution of this study is to explore dependencies among drivers of COVID-19 and country risks in the same model and assess the impact of COVID-19 risk on multiple drivers of country risk, including business environment, financing, economic, commercial and political risks. This study provides unique insights to policy-makers in prioritizing critical drivers of COVID-19 and country risks while capturing statistical dependencies among the drivers.

The lack of coping capacity is the most critical variable influencing COVID-19 risk, whereas vulnerability is the least critical variable. Among the drivers of country risk, business environment risk and political risk are strongly associated with COVID-19 risk, whereas commercial risk is the least critical variable relative to the extreme states of COVID-19 risk. Financing, political and economic risks are the most critical variables influencing country risk, whereas vulnerability is the least critical variable. Political risk is assessed as the most critical variable influencing business environment risk and country risk is also significantly influenced by business environment risk. Commercial risk and vulnerability are the least critical variables specific to COVID-19 and country risks.

This study has certain limitations. Individual variables are discretized in the model. The dynamic behavior of risk is not modeled. Future work can benefit from modeling the drivers of COVID-19 and country risks as continuous variables. The dynamic behavior of risk can be modeled using dynamic BBNs. The sensitivity analysis of the results can be performed relative to the choice of potential discretization schemes and BBN learning algorithms. Additional socio-economic drivers of COVID-19 and country risks may be added to the model to provide better insights to decision-makers. Expert judgment may be utilized in developing the qualitative structure of the model to capture cause-effect relations among risk factors and associated drivers. A comprehensive model combining both risk drivers and potential risk mitigation strategies can be developed to help policy-makers optimize strategies while capturing non-linear interactions among risks and strategies. Country-level models may be developed to help policy-makers capture the variation in the country and COVID-19 risks across various cities and states. A cost and benefit analysis may be performed to establish the costs associated with potential risk mitigation strategies and benefits related to reducing country-level risk.

Author statement

Abroon Qazi: Conceptualization; Methodology; Data curation; Software; Writing – Original draft preparation.

Mecit Can Emre Simsekler: Validation; Writing – Reviewing and Editing.

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