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Operational and Financial risks in supply chain management

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ABSTRACT

Competitiveness and complexity are unavoidable and frequent source of uncertainty affecting the normal execution of supply chain processes. At the same time, unplanned events or risks represent an additional matter of concern for managers, having the responsibility to satisfy customer's demand, while keeping a safe financial status of the company. In this regard, companies are forced to adopt risk mitigation strategies, not only at the individual firm level, but also in a broader supply chain perspective aiming at enhancing resilience of the whole supply chain. The objective of this thesis is to develop a model demonstrating how operational events might negatively affect the ability of companies to comply with their financial obligations towards debtors. This aspect, belonging to credit risk management field, has been scarcely investigated by recent literature from a supply chain perspective. In addition, few studies have linked credit causes with operational risks that have been widely treated by many researchers in supply chain management. The study first presents a review of the literature on supply chain disruption propagation and operational risk management. Next, the thesis proposes a methodology to show operational risk propagation along the supply chain and their cascade effect on companies' default risk. The heart of the methodology has its roots in the probabilistic Bayesian network approach, a powerful methodology that allows to represent the conditional dependence between risks and their probability of occurrence. This study provides managers with an accessible but mathematically rigorous methodology through which measuring and analyzing the propagation dynamics of supply chain operational risks, in order to implement appropriate mitigation strategies. In this sense, the methodology can support not only a smooth supply chain management, but also any stakeholder wishing to assess the riskiness of supply chain processes, even under a financial perspective.

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INTRODUCTION

Nowadays, the complexity of supply chains is considerably increasing, and multiple factors play an important role: managerial strategic decisions, increasing products complexity available on the markets, industry competitiveness and, of course, macroeconomics variables. Also, given the high level of globalization, legal regulation and political decisions have a non-negligible effect. Therefore, an excellent management of supply chain processes becomes crucial to pave the way for a sustainable corporate strategy over long period, while keeping a high level of competitiveness on the market. Supply chain complexity increases considering the turbulent environment in which firms operate, and a high degree of uncertainty makes sometimes unpredictable any future scenario. In this regard, COVID-19 pandemic has been a dramatic example of how uncertainty affects the normal operativity of supply chains and how such long-lasting event caused disruption and threats to the business continuity. Russian's decision to invade Ukraine territories has caused shortage in raw materials procurement and energy supply in many industrial sectors over the world (Espinoza, 2022). This catastrophic circumstance for human lives highlights both the supply chain level of globalisation and the severity of unplanned events on system resilience. However, other types of risks, raising from operations management, can produce equally dramatic effects on business continuity of internal processes and generating supply chain disruptions. In fact, operational risks arise from three factors: the performance of upstream suppliers, the demand of buyers or customers, and from the internal management of individual (focal firms) production processes (Chen et al., 2013; Germainet al., 2008). Over the long-time horizon, a poor management of operational risks can have consequences on the financial term: loss of profitability, credit default and even bankruptcy. According to Thun et al., (2011) and Chen et al., (2013), in 2005 a supplier of a major German company delivered defective products to its buyers, leading to extensive economical losses. The financial performance of companies is not only a matter of concern for an internal supply chain management but also for external creditors who need to evaluate both financial status and risks as a direct link to managers' operational management. External stakeholders may include private creditors, credit institutions (e.g., banks) or even other companies, such as suppliers, that provide short-term liquidity to their direct buyers, as in the case of trade-credit, one of the many instruments provided by the Supply Chain Finance solutions. Operational risks occurrence primary represents an important source of threat for the financial stability of firms and in particular for short-term debt: inventory management and sales, which are in turn dependent on other operational aspects, have a strong impact on firm's net working capital (Shi and Mena, 2021). It represents the ability of firms to comply with their short-term debts. Therefore, the propagation of risks along the supply chain in multi echelons (i.e., the ripple effect) has not only disruptive consequences from an operational point of view (Hosseini et al., 2020) but, in the long run, it produces strong economic consequences by generating losses (Badurdeen et al., 2014).

The ambition of this thesis is twofold. In the first instance, it has been shown how risky events do not have independent probabilities of occurrence from each other, but their frequency is strongly related to other events. From a financial point of view, it is demonstrated how the propagation of operational risk along the supply chain can have significant impacts on the ability of companies to meet their obligations towards creditors and, consequently, cause future losses to stakeholders. The modelling approach adopted in this study is based on Bayesian networks, a powerful mathematical tool that allows to draw the interrelationships between risk events and their probability of occurrence. From a practical point of view, a deep comprehension of these mechanisms can be of interest both to the management internal to the supply chain, who should decide whether to mitigate risks through proper mitigation strategies, and for external creditors, who can introduce additional parameters, related to the operational management, in the assessment of credit risk.

The remainder of the thesis is organised as follow: Chapter 2 presents the literature review following the main keywords and topics touched by the thesis. A theoretical background of Bayesian networks methodology and Mathematical credit risk modelling is proposed in Chapter 3 to formally introduce quantitative instruments that have been adopted in the methodology. The core part of the thesis is Chapter 4 where each step adopted to develop the methodology has been detailed in seven main paragraphs. Finally, the purpose of Chapter 5 is to highlight the managerial and academic implications of the work both under a modeling approach and practical applications. In addition, the methodological limitations of this study and suggestions for future research lines are presented.

1. DISRUPTION PROPAGATION IN SUPPLY CHAINS

The purpose of this chapter is to introduce the problem from a dual perspective: at first, to illustrate the issues related to the default risk of firms. On the other hand, to understand how the propagation of operational disruptions along supply chain negatively affects the default risk of companies operating in complex and interconnected networks.

1.1. Default in supply chains

In order to define default and credit risk it is important to assess preliminary financial considerations. Financing decisions (e.g., investment for a new business expansion, new product development, or on the short-term to run the day-to-day operations) represents a major issue of corporate finance. Financing through debt, primarily guarantees creditors the repayment of the borrowing, without the latter claiming ownership over the company, thus avoiding dilution effects as in the case of equity owners. Sources of debt financing include public debt or bonds, as they are publicly traded and can be held by anyone interested in entering in the contract, and private debt. The latter category includes term loans, which lasts for a specific period, and private placement, which is a bond issue that does not trade on a public market, but it is sold to a group of investors. Debt puts an obligation on the firm since any companies failing in repaying debt is in default (Berk and DeMarzo, 2014). Despite the commercial bank credit remains the most common form of debt-financing in supply chain (Wang et al., 2022), it is worth mentioning other financing modes belonging to the Supply Chain Finance (SCF) mechanisms that have been gaining ground during last decades to improve financing efficiency and to solve the typical liquidity problems of small-medium sized enterprises or SMEs (Jing and Seidmann, 2013) over the short period. SMEs typically face problems in financing their activities, due to low credit rating that does not allow to obtain loans from banking institutions (Wang et al., 2022). The growing popularity of SCF instruments has been observed in 2019 where the Supply Chain Finance global market amounted to 16,500 billion of Euros, with the 42% of the overall amount represented by the Asian market (in particular Japan and China), followed by the American market with 30%. In Europe, Country leaders are France and Great Britain. As Supply chain finance includes several financing modes, based on the nature of the contractual agreement, some of the most relevant SCF solutions are briefly presented in below:

- *Dynamic discounting*: the supplier applies a discount to goods sold to the buyer according to the time elapsed between the issuance of the invoice and payment. The shorter the credit collection time, the greater the discount (Atanasova et al., 2020).
- *Factoring solutions*: under the factoring financing mode, supplier's credits are sold to a financial institution, which pays receivables to the supplier, thus solving short-term liquidity problems (Querci, 2021). Similarly, in the *Reverse factoring*, the supplier sells its accounting receivables to bank under buyer warranty (Zhao and Huchzermeier, 2018).
- *Forfaiting*: this method allows exporters to get liquidity by selling accounting receivables at a discount to a forfaiter (bank or other institutions) [1].
- *Inventory and Warehouse finance*: loans granted by banks on the basis of stock or inventory level respectively received as collateral. These instruments can be used to finance the expansion of production capacity or for the supply of materials (Zhao and Huchzermeier, 2018).
- *Letter of credit*: it is a letter from a bank to a supplier which guarantees that payment from the buyer will follow, under certain conditions, such as the documentation proving the shipment of goods. There are many variations of the letter of credit solution (Zhao and Huchzermeier, 2018).
- *Purchase order finance*: this form of financing involves a loan provided by a lender to a supplier on the basis of the buyer's commitment to purchase the goods ordered by the supplier (Bonzani et al., 2018).

- *Trade credit*: it is a business loan provided for the buyer's purchase of goods from the supplier (Lee and Rhee, 2011). In other words, this instrument allows the buyer to delay the payment for goods delivery until the day specified in the policy (i.e., typically 30, 60 or 90 days as in the supplier early payment discount). The advantage of this instrument under the warranty perspective lies in the availability of buyer information held by suppliers (Figure 1.1).

Figure 1.1 Trade credit principle adapted from [2].

- *Vendor management inventory*: solutions belonging to this category have been inspired by traditional supply chain management techniques in order to foster risk and information sharing between supply chain companies: inventory stocks of the buyer are managed directly by suppliers (Bonzani et al., 2018). Buyer's inventory management policies coordinated by suppliers, information sharing on demand forecasting process or production plans in this case.

Therefore, both the traditional and those showed through SCF instruments introduce the possibility of financing operations, investments or other supply chain activities with debt. For this reason, the risk exposed by borrower's default turns out to be an important aspect to be accounted not only for current creditors, but also for either future external financing entities or other supply chain members. In general, following the definition presented in McNeil et al., (2005), the default risk is defined as

"... the risk that some counterparties cannot repay their loans".

In that statement, the term counterparties refer to the borrower parties. On the other hand, the lender assumes the credit risk, which can be formally defined as

> ***"****… the risk of not receiving promised repayments on outstanding investments such as loans and bonds, because of the "default" of the borrower****"****.*

When the company is definitely unable to repay debt, it may attempt to renegotiate it with creditors or file for bankruptcy. Bankruptcy is legally regulated by countries laws. This ensures creditors the seizing of firm's asset to collect unpaid credit (Berk and DeMarzo, 2014). In this sense, trade credit and other SCF financing instruments represent an additional channel for the propagation of default phenomenon (Wang et al., 2022) along the chain: the creditor (supplier) may suffer from the insolvency of the debtor (buyer), thus encountering default problems in turn suffered by other creditors or external lenders such as banks. Credit institutions financing various supply chain members need to be aware of the mechanisms of default propagation along the chain. Therefore, the financial status of supply chain enterprises depends not only on internal management, but also on the decisions and management of other supply chain members. Those companies in the supply chain that are heavily dependent on the other's revenues are subject to the cascade failure effect of companies within the same network (Carruthers and Makova, 2018). The problem becomes even more complex when considering that some companies serve supply chain for different products: such "contagious" effect can propagate through several supply chains, each of them operating in different markets, thus leading to industry disruption. Consequently, information related to supplier riskiness is crucial not only for external financing channels but also for internal supply chain companies, so as to mitigate disruption propagation. Figure 1.2 adopted from Carruthers and Makova (2018) shows the credit risk distribution of suppliers of some global companies. Seven credit risk categories have been included in the study, from the worst credit profile (class c) to the better one (class aaa). The size of the bars in blue shows the percentage of suppliers that are positioned within each credit band.

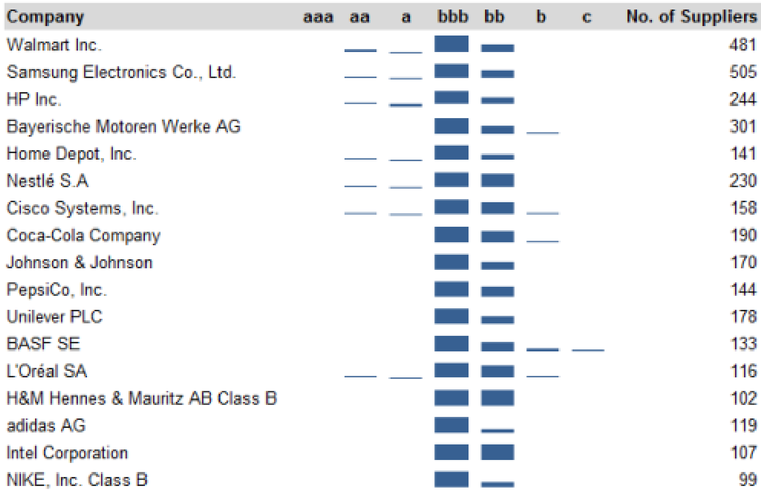

Figure 1.2 Credit rating of some Focal firms' suppliers from Carruthers and Makova (2018).

As it can be seen from the figure above, many supply chains delivering well-known products on the global market cannot be considered as default-free. This is especially true for those supply chains where the number of small enterprises is considerably high. Nowadays, worldwide rating agencies provide opinions about the capacity of companies to meet their obligations toward creditors especially for debt instruments traded in the second market. On the other hand, following the Basel II agreement, financial institutions can decide whether to use internal rating estimation (Rating Based Approach – RBA) to evaluate capital requirements credit risk. In IRB methods, risk weights are a function of an internal rating process that banks perform on borrowers as stated in [3]. However, most of the credit risk assessment models developed by agencies or banks are based on financial information such as debt level or profitability and do not account for other important factors such as management quality and competencies whose integration into classical rating models has improved their predictive capacity. In addition, the traditional credit rating models do not adopt a Supply Chain Finance perspective (Moretto et al., 2019).

Most of the scholars attribute the causes of corporate default to external macroeconomic, industrial or internal financial factors. The number of corporate defaults is positive related to the volume of debts increase [4]. Thus, companies with high leverage seems to be more prone to default. As an example, Mergers and Acquisitions (M&A) are often debt finance. M&A which do not go through, are considered risky for the financial stability of the company. Another important factor is the industry competition, especially in those sectors where it increases the probability of financing unsuccessful project with debt. Price fluctuation is another economical factor closely related to corporate default (Lando and Nielsen, 2008). Industry competition as a source of credit risk propagation has been confirmed also by Agca et al., (2022). In the empirical research of Sgrò et al., (2022), authors have pointed out that industry-specific crisis, global economic crisis and market-specific crisis are relevant macro-drivers of insolvency. On the other hand, debt increase, under-capitalization and wrong strategic choices affects insolvency from the internal management. All of the previous factors can have a contagious effect on other supply chain companies: the financial status of the company will depend also on the ability of its customers to meet payment obligations. Otherwise, the supplier begins to suffer financially, as receivables become uncollectible. This situation can lead to cascading network failure if credit firms propagate their financial difficulties to their neighbours. In Agca et al., (2022), authors underline how information sharing is an important mechanism of shock propagation along supply chains members. In particular, stronger supply chain relationships, measured by the duration of the supply chain links, amplifies shock propagation, as to confirm that default propagation can have devastating effects over other business continuity. In order to preserve business continuity, when facing supplier's risk of default, firms can decide whether to change upper tiers suppliers in order to open relationships to new markets (Nin and Tomás, 2019). This is particularly important when dealing with customer-supplier relationships and in the special case of SCF. An important metrics adopted to evaluate company's credit risk, is the average collection period (average number of days to collect invoiced amounts from customers). When such ratio becomes smaller than one, a company will likely start delaying the payments to its suppliers. If the customer financial distress gets worse, all its suppliers will break ties with it, leading to the so-called "isolation of companies in default". Based on such analysis authors identify financial institutions and energy industry as the most sensitive sectors to default probability independently on the policy the agents followed. Berloco et al., (2021) underline how trade credit can increase losses along the supply chains. In a network company borrowing from each other, a liquidity shock of some firms may cause a reaction where companies are affected by the same distress: firms delay payment to its suppliers as a consequence of customer's late payment and so on. Authors state that this is particularly likely during recessionary phases, because of the lengthening of payments affecting the global market. Despite the fact that default causes are often extremely difficult to investigate, due to the influencing role of multiple factors in firm’s financial status, a lot of measures of credit or default risk do not introduce extra-financial indicators into their assessments.

The recent literature, as will be discussed in Chapter 2, has offered very few examples of how intra-firms operational management of the supply chain affects the probability of default on credit of firms.

1.2. Operational risks effects on Supply chain default propagation

As stated in the Introduction, the purpose of this thesis is to analyse the effects of operational risks on default occurrence of companies along the supply chain. However, several risk definitions are available in literature, and the management of risks represent a growing issue in the supply chain management framework. Most of the authors elaborating a definition agrees with the fact that risk is strictly linked with the concept of “uncertainty”, “unpredictable” or “possible occurrence”: uncertainty and severity of the consequences on activities are the main risk features as stated by Aven and Renn (2009). A definition frequently cited by authors comes from the work of Juttner et al., (2003), where they define supply chain risk as “*the variation in the distribution of possible supply chain outcomes, their likelihoods, and their subjective values*”. Again, uncertainty (likelihood) and consequences (outcomes) are included. In the supply chain framework, risks have been defined as everything that might negatively affect the inward flow of necessary resources to enable operations (Meulbrook, 2000), while Zsidisin (2003) defined supply risk as “*the probability of an incident associated with inbound supply from individual supplier failures or the supply market occurring, in which its outcomes result in the inability of the purchasing firm to meet customer demand or cause threats to customer life and safety*”. Risks that affect the regular execution of supply chain processes can have different origins. In particular, operational risks have been defined as risks related to the supply-demand activity coordination, resulting from an inadequate or failed process (Chen et al., 2013). Similarly, Pham and Verbano (1996) state that operational risks are relatively recurrent events arising from internal and partnership activities which are the set of activities dealing with supply, demand and manufacturing side. Even in Singh et al., (2012) operational risks internal to the supply chain have been identified as risks affecting the production and distribution process and demand-supply matching process. To summarise, operational risks have to do with possible downward variations in supply, demand and process activities from an expected outcome. Network economies, as companies in supply chains are directly connected through operations. Operational risk events might lead to unplanned production stoppages, inability to deliver products on time or inventory shortages or many other undesirable issues (Figure 1.3).

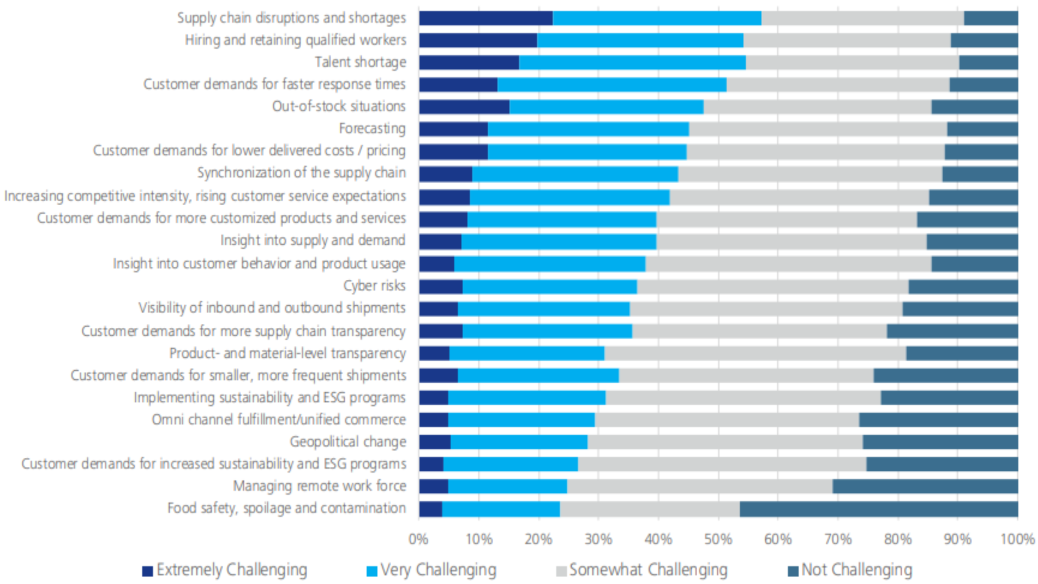

Figure 1.3 Survey on supply chain challenges in 2022, adopted from [5]

As a consequence, they do not affect internal operativity only, but their consequences propagate to the rest of the supply chain. To this end, Carruthers and Makova (2018), through bank-sourced data, state that supply chain problems may initially appear as mere internal operational problems. However, they usually have effects over the credit side for any firm belonging to the network. This has been confirmed by Ko et al., (2019). They statistically tested the positive correlation between operational risk occurrence and a higher likelihood of credit default. Therefore, companies with a poor management of internal operations are more subject to potential credit default events. This can be particularly observed in the short run as operational risks directly affect the ability of firms to comply with short-term obligations. Such circumstance can be measured trough the net working capital, which represent the excess of current assets over current liabilities. In particular it is given by the difference between current assets (i.e., cash and cash equivalents, inventory, account receivables) and current liabilities (i.e., account payables, debt short-term loans, current payments due on long-term debt) as stated by Brealey et al., (2011). In case of low values of net working capital, the company could run out of cash and face financial distress, while for high values the company is not efficient in turning assets into revenue. Therefore, company's financial risks on the short-period, depends on the efficiency of supply chain operations, which in turns depend on the network structure and the product to be delivered on the market. For instance, in the automotive industry, products of the refined raw material suppliers and components suppliers, produce more standardised products than what done by companies in the lower tiers of the supply chain, thus allowing mass production and bigger inventories. This also explains the longer cycle times of inventories. On the other hand, raw material suppliers and components suppliers serve other industries as well, and the manufacturing process differs from the other stages of the supply network (Lind et al., 2012). Delivery and production failures represent an important source of risk for working capital as well, thus for borrower ability to repay short term debts (Mizgier et al., 2012). Even though a business is making a high profit, the company could face the risk of bankruptcy, if it is unable to generate enough cash to cover its obligations. Defining the exact threshold for low working capital is not straightforward. In the case of Mizgier et al., (2012) it has been defined as the average for the entire industry. From here it can be seen how operational risk management is also detrimental on the credit side. This issue becomes even more clear in the case of the trade credit framework where repayment times are much tighter with respect to long-term loan: the internal ability to produce or ship goods to the lower tiers of the supply chain negatively impacts current assets, as a result, encountering difficulties in meeting accounting payables to suppliers. Working capital as key link between inventory risks and financial distress has been investigated also by Shi and Mena (2021). In particular they state that working capital issues could, in turn, lead to operational disruptions for the whole network. Demand also plays an important role: a shutdown in local demand would imply a stop in the normal operational activities, thus affecting companies' revenue and leading to inventory overstocks. In general demand variability limits the ability of companies to forecast volumes, leading to costs increasing in terms of overstock/out-of-stock. This phenomenon is frequently called bullwhip effect, which drives upward demand variability, thus firms in the upper layer of the supply chain face a higher demand uncertainty. Over the long period, the BE is an example of how variability can affect firm's ability to produce and deliver goods to lower tier companies, thus affecting overall revenues and rising operational costs. In extreme case, the Bullwhip effect is a dramatic source of bankruptcy (Lee et al., 2004; Mizgier et al., 2012). The pandemic revealed that a geographical diversified market has enhanced supply chain companies credit profile [6].

2. LITERATURE REVIEW

This section investigates the main progress of literature in the field. In particular, relevant publications have been consulted following the main keywords touched in the thesis. At first, the phenomenon of credit default risk in the context of supply chains has been investigated in order to show the state of the literature and its contributions in risk propagation effects and potential relationships with operational risks. Secondly, the reverse process has been performed: analysis of operational risk propagation along supply chains to assess how the literature related them to default events. Finally, section 2.3 of this chapter has been dedicated to Bayesian network applications in the context of supply chain risk management, as it has been an emerging topic in the last years and further application in risk management fields are expected in future.

2.1. Supply chain default propagation

This section presents the results on supply chain default propagation. In particular, the goal of this section is to understand literature contribution in supply chain default propagation by highlighting its objectives, results, tools adopted, and eventual links to supply chain operations management.

Agca et al., (2022) investigate supply chain credit risks by statistically test the credit default swap market (CDS). In particular, CDS spread changes have been used to evaluate how the credit event propagates to firms following supplier's credit shocks both in terms of favourable and undesirable events. Authors investigate propagation effects through multiple-tiers supply chain founding that, for adverse shocks, the propagation is equally strong for all the tiers regardless network topology. Among the main default triggers, the paper identifies firms' growth, leverage, size, working capital, inventory, product differentiation, working capital and natural disasters as idiosyncratic shocks. Therefore, they weakly investigate operations management as underlying mechanism of default. At the same time, the paper of Nin and Tomás (2019) propose an explanation of the failure cascade along the chain through an agent-based simulation. In their approach, when a company is unable to meet payments to its supplier, the contractual relationship immediately ceases. If the supplier succeeds in identifying an alternative customer, a new business relationship is generated, thus restoring the normal operativity and avoiding disruption. Such process goes on until financial distress do not affect all the network nodes. The default probability faced by network actors depends on a specific infectivity rate that is an industry specific exogenous parameter. However, there is no mention to operational management inefficiency in the simulation since contagious effects are evaluated through exogenous and industry specific variables. A simple supply chain case is presented by Ghadge et al., (2021). Authors examine the manufacturer-supplier relationship when subject to various exogenous financial risks such as foreign-exchange risk (currency conversion changes operating costs), default risk (insolvency to financial obligations), market risk (interest rates) and price fluctuation risks (hike in the price of products/materials). More in detail, authors develop a multi-objective optimisation model for a manufacturer-supplier network where the manufacturer total profit is maximised, and both the equity stake and financial risks of manufacturer and supplier are minimised, subject to capacity and demand satisfaction constraints. This multi-objective optimisation problem has been solved by adding to objective functions and equation constraints measures accounting for the aforementioned risks. As it can be seen, this analysis refers to default risks as a causal factor driving organisational choices in inter-companies' relationship but there is no mention to operational issues in the selection method neither how they might affect the manufacturer-supplier relationship. The case presented by Berloco et al., (2021), introduce a double perspective. In the first case, firm probability of default has been modelled as function of internal financial stability, default history of the firm and rating model. From these variables, authors trained different models, such as logistic regression and random forest in order to learn algorithms. The second perspective estimates the firm probability of default as function of network features: a fragility indicator catching measuring the reliability of trade credit to suppliers or customers, and a neighbourhood indicator measuring the distance of the firm with respect to the other firms experienced a default event. The agent-based simulation has been proposed also by Gatti et al., (2005) where they demonstrated that interdependence of firms and the mutual interaction between companies operating in different sectors are non-deniable causes of default propagation. The analysis gives just an insight in financial causes, such as trade credit or changes in the interest rate without any further investigation on operational issues. Similarly, the simulation methodology proposed by Battiston et al., (2007) and applied to a simple supply chain case, only investigates the consequences of some financial variables such as cash flow shocks or interest rate change on firm's ability to meet its obligations. In the publication of Gatti et al., (2008), the bankruptcy of a firm can lead to an avalanche of bankruptcies along the network, either because of a direct interaction between the defaulted firm and its supplier (trade credit) or due to an indirect interaction through the banking system (high interest rates). Xu et al., (2010), through a multi-agent simulation, have shown that a better cooperation between supply chain actors reduces bankruptcy occurrence: sharing information about demand among members or vendor-management inventory effectively reduce default risk. In the model presented by the paper, bankruptcy occurs when company's total assets are less than total debts. In this framework, operational variables (e.g., inventory positions, goods received, and quantity of orders) are used to model the interaction between companies in the supply chain. Although this paper introduces operational aspects, there is no stochastic representation of reality (i.e., risks representation), subject to variability in inventory levels or in other parameters affecting operational decisions. One of the few papers deeply analysing operational causes of corporate financial distress is presented by Hua et al., (2011). Indeed, the proposed agent-based simulation links different operational parameters on bankruptcy propagation effects along a two-tier supply chain. The main operational decisions that have been included are the order allocation strategies of downstream nodes, selling price of upstream products, production uncertainty of manufacturers, market demand characteristics and the number of retailers. The financial status of firms depends on the operational decisions of the upstream or downstream firms and is classified into three strands: Sound (cash flows are sufficient to repay debt), Financial distress (low cash flows state), and Bankruptcy (if assets are less than debt). More precisely, the net assets of a node along the supply chain are represented as the sum of cash at hand, company overstocks, company capacity level and long-term investments. Based on the simulation carried out by authors, variability and price elasticity coefficient of demand have an impact on operating cost, which increases the probability of bankruptcy at the retailers' level. Supply chain structure has also an impact on default occurrence: as the number of downstream companies increase, the bankruptcy occurrence at the upper tier is reduced. At the same time, reorder policies have an impact on the financial status of companies (overstock and stockout) as they raise operating costs. Finally, both the price of manufacturer's products and the variability of product quality have negative impacts on retailers as they increase stockout phenomenon which increase cash flow risk. In Mizgier et al., (2012), an agent-based approach is proposed to model bankruptcy propagation through a five-stage supply chain. There, firms bankrupt when cash flows are insufficient to continue their operations. Authors introduce several sources of variability into the system, which lead to different default situations: the first element is the variability of connections between nodes reflecting the continuous search for the most favourable supplier in terms of price. This leads to a change in the conformation of the network since firms with few suppliers higher the risk of supply and production shortages. Other included parameters are related to production dynamics such as the linear production of homogeneous goods depending on customers' orders. Because no inventory logic is included, a firm's default occurs when working capital falls below a certain threshold. Importantly, this paper does not model the stochasticity given by some important operational events: machine breakdown, delivery problems such as product wrong quantity delivered and so on. As confirmed by the two later authors, literature has weakly investigated the interrelations between operational risks and default event occurrence in the supply chain. This aspect has even been ignored when considering the perspective of operational risk management.

2.2. Supply chain operational risk propagation

This section shows literature progress in supply chain operational risk management and their effect on the overall network of firms. As before, the goal of this section is to understand literature contribution in supply chain default propagation by highlighting its objectives, tools adopted, and eventual links to what previously discussed.

The propagation of risks along the supply chain originating from companies' internal processes has been analysed by the authors from different perspectives and adopting different modelisation approaches. Such uncontrollable cascade effect along the supply chain, caused by different typology of risks, has been called Ripple effect (Ivanov et al., 2014; Ivanov et al., 2019). As confirmed by authors, this phenomenon has been weakly investigated by literature with respect to the Bullwhip effect, for which several studies are available in literature (Chen et al., 2000; Pastore et al., 2019; Metters, 1997). For example, one of the few papers integrating both perspectives, is the one presented by Cao et al., (2022), where the bullwhip effect (BE) and ripple effect (RE) as source of disruption cascading propagation has been investigated. In particular authors identify, at the macro-level, that when customer demand changes, product design changes as well, thus resulting in supplier replacement. The BE phenomenon has a downstream-to-upstream propagation. At the same time, the ripple effect, in the light of the COVID-19 pandemic, has an inverse propagation direction (i.e., top-down movement) as shown in Figure 2.4. The paper identifies BE on supply chain though inventory levels at different nodes. The system has been studied through closed-loop control theory.

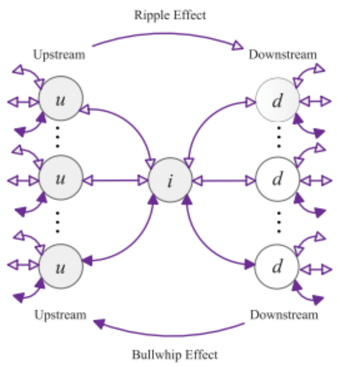

Figure 2.4 Bullwhip and Ripple propagation effect in supply chain from Cao et al. (2022)

Lücker (2019) proposes a double mitigation strategy to locally mitigate ripple effect either based on overstock inventory or by holding additional capacity at reliable source. In particular a single echelon supply chain with inventory level regulated though the (*Q, R*) logic which is extended by including disruption probability and costs depending on the scenario. Author evaluates system resilience through the Conditional Value at Risk measure (CVaR). The paper confirms inventory management policies as an important source to mitigate ripple effects generated by demand. However, only few risks have been modelled: demand and inventory-related risks. In addition, due to the single-tier structure, risks transmission along the chain has not been modelled. Similarly, Xu (2020) focuses on operational risk in make to order (MTO) supply chains. The authors propose a benchmark methodology to minimize the ripple effect. The system allows the status of customer orders to be determined. The primary objective of the article is to give managers a tool to cope with possible late delivery and additional costs arising from these circumstances. Again, there is no link to the implications on companies' credit-debt as a result of the occurrence of these risks. KPIs as important litmus test of risks occurrence along the chain provides managers fast and intuitive measure about supply chain performances. They have been frequently adopted in supply chain risk management (Cagliano et al., 2012; Li et al., 2015; Karl et al., 2018; Ríos et al., 2019). Looking at risk propagation, the approach of by Kinra et al., (2020) models disruption propagation through supplier risk exposure demonstrating the effects of high-impact-low-frequency events and business interruption time on businesses risk exposure, avoiding probability estimation but rather introducing the maximum loss as risk measure. The output of the methodology proposed in the paper, is represented by KPIs, accounting for both operational and financial measures: demand per day, units procured from supplier per day, average inventory days, daily profits have been included. Authors do not provide additional financial risk measures to evaluate default cascade effect along the chain neither as cause of operational risks nor as consequence. Indeed, even if risks are evaluated in terms of performance impacts, there is no cause-effect relationship between them. Instead, the Bullwhip effect has been empirically analysed by Lochan et al., (2021), where it has been used as indicator to evaluate vulnerability of food and non-food consumer supply chain and its exposition to operational risks. In particular, fluctuations in demand and late order formation as source of risk have been investigate by authors. The stochastic simulation model has been carried out considering several internal accounting and analytical documents, reporting operational activities and statistics. From simulation output, it is possible to analyse demand effect on purchasing activity, inventory levels and ordering preparation time. It is interesting to observe that, in risky event certainty scenario, such factors caused a considerably lower revenue with respect to normal conditions as confirmed by publications cited above. At the same time, the impact on productivity and service quality is low. Risk propagation in terms of ripple effect has been modelled through several techniques. In Deng et al., (2019) the Tropos Goal-Risk framework (i.e., a goal-oriented approach) was introduced to model risk propagation in the perishable products supply chain. The paper adopts a multi-actor perspective of the network (i.e., including suppliers, manufacturers etc.). Risks are transmitted along the supply chain and among member enterprises, thus assuming a network structure. There are five modes of risk propagation: risk transfer, contagion, overlap, restraint and mutation. The authors have developed a comprehensive mechanism for investigating risk transmission along the supply chain. However, there is no mention about the financial effects of these risk events. On the other hand, an artificial neural network (ANN) approach has been proposed by Yi et al., (2018) who develop a model to analyse risk propagation effects on supply chain nodes. In particular, authors adopt a network topology approach trough network indicators in order to evaluate node susceptibility to risks and resilience, either based on structural attributes (e.g., number of adjacent neighbourhoods with respect to a focal node) and global attributes (node importance measure based on structural similarity). After that, a principal component analysis has been carried out in order to establish an objective assessment of the supply chain risk transmission capabilities, mapping a series of indicators representing the importance of each node. Even in this case, neither in the theoretical part nor in the example of a 4G smartphone supply chain, authors highlight the interconnection between risk occurrence and the transmission modes. Another example is presented by Yu and Wang (2022), who propose a two-layer evolution model where the upper part is the social network described by hyper-network while the lower part supply chain risk propagation described through an activity-driven network. The purpose of the work is to present parameters influencing the dynamic evolution of supply chain networks. Instead, the intra-firm risk transmission process has been investigated in Levner and Ptuskin (2018) where economic losses caused by environmental risks as consequence of the ripple effect have been analysed through an entropy-based optimisation model. For each company in the network, a set of critical events have been collected during a certain time span: this allows to evaluate the event likelihood through frequency. The subsequent optimisation model is based on the concept of entropy: the entropic approach has to do with the average amount of information contained in a stream of critical events. Thus, the entropy characterises risk knowledge: the less the entropy is, and the more knowledge about risks is present. Under this framework, the linear optimisation model to maximise nodes entropy has been proposed and a case study from the automotive industry is also presented by authors. There authors do not add information about the main operational risk affecting nodes default probability. In addition, cause-effect interconnection of risks is not modelled.

As stated in the introduction of this chapter, another modeling approach that is taking ground during the last decades is represented by Bayesian networks. Therefore, a detailed analysis of the applications of Bayesian networks in supply chain risk management is presented in the following section 2.3.

2.3. Bayesian networks in supply chain risk management

Bayesian networks (BNs), or sometimes Bayesian Belief Networks (BBNs) show the causal probabilistic relationship between random variables, based on their probabilistic conditional dependence. BNs are particularly effective tools not only in case of contexts affected by uncertainty, but also to model complex systems having little historical data at hand. Their popularity has growth during the last decades, thanks also to the increasing computational capability that made Bayesian networks an accessible model for many applications in real-world problems. Their origin is rooted on two fundamental areas of mathematics: probability theory with special reference to Bayes' Theorem and graph theory. To better understand the theoretical background, refer to Chapter 3.

The Bayesian network methodology has been applied not only in supply chain risk modelling as it will be shown in the following paragraphs, but also in other contexts, quite different from the purpose of the present study: for example, in the medical and healthcare sector or medical diagnosis (McLachlan et al., 2020) and epidemiology (Harding, 2011) BNs have been adopted. Other applications include economics and finance, not only for risk management purposes (Shenoy and Shenoy 2000) but also for asset pricing purposing (Hachicha et al., 2020). Environmental studies and applications have introduced BNs to model, among others, the climate change on watersheds or to obtain a fish population viability estimation of certain areas (Uusitalo, 2007). Thanks to the increasing interest of researchers in this area, Bayesian networks have been introduced in artificial intelligence and machine learning area as well (Scanagatta et al., 2019). Just by looking at the subject area categorisation of SCOPUS, the majority of articles published with Bayesian network applications belong to Computer Science, followed by Engineering, Mathematics and then Medicine.

The Bayesian networks application in supply chain risk has increased in the last years (Figure 2.5). The probability of occurrence of unpredictable events and their interrelationships well fit in the modelisation adopted by Bayesian networks. The variety and diversity of publication purposes on the subject is considerable: as it will be shown throughout the chapter, many authors have emphasized different aspects in supply chain risk management with Bayesian networks methodology.

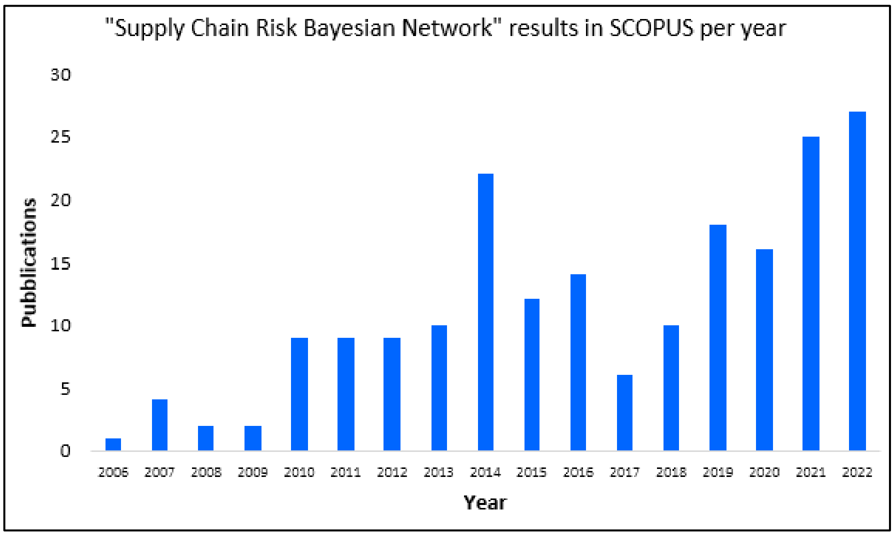

Figure 2.5 Number of publications for "*Supply Chain Risk Bayesian Networks*" per year in SCOPUS database.

After collecting relevant excerpts and publications for this study, the author clustered relevant publications in macro categories, according to the main purpose of the paper: Bayesian networks for real application studies, Measures for resilience and vulnerability, Bayesian networks decision making oriented, Dynamic effect and simulation, Operational and green risk profile assessment and financial risks in supply chain. However, some of the following publications might have some elements in common between different categories. It is important to underline that the clusterization proposed in the following paragraphs has been carried out considering at first the final purpose of the article and then the methodology used by authors.

2.3.1. Bayesian networks for real application studies

The ultimate goal of the publications presented in this section is to give the reader a possible application of Bayesian netoworks in real cases. Indeed, the purposes of papers published in this section is to show a real application study: disruptive events and risks have been modelled from real data sampling and observations of experts directly involved in the day-to-day operations.

The work proposed by Hosseini and Ivanov (2022) introduce BNs to model the consequences of the recent COVID-19 pandemic on supply chain performances. The paper develops a three-level network by clustering risks into triggers, risk events and SC disruption consequences. In addition, the authors used backward and forward propagation analysis to understand which risks had the greatest disruptive impact on the overall industry. The article stresses the effects of the pandemic on the supply chain ecosystem, as well as the need to increase the resilience of the network. Instead, a risk assessment approach in the oil and gas industry through Byesian networks is presented by Philip et al., (2021). There, BNs are modelled with typical hazard events (i.e., threatening circumstance for humans and the environment) that affect such industry. Risks populating the Bayesian networks belong to different categories, each with a specific taxonomy: accident (states that could cause damage), environmental impacts (environmental consequences of the accidents) and impact effects, that represent both the final nodes and the ultimate consequence on the environment. In the work presented by Leerojanaprapa et al., (2013), authors propose a methodology to represent supply chains and risks in Bayesian networks based on expert opinions. To illustrate the methodology, a brief application in the medicine supply system is presented. This publication has been one of the first proposing BNs as a tool in supply chain risk management.

2.3.2 Measures for resilience and vulnerability

Resilience, flexibility, adaptability and other features measuring the network ability to respond and recover from disruptions, cover an important role in research improvements. These have been object of study in supply chain management with Bayesian network modelisation.

Hosseini and Ivanov (2019) have developed a methodology to measure the resilience of a supply chain when exposed to the ripple effect. As the authors point out, supply chain resilience can have several definitions: the ability of the system to return to its original state or the recovery capability of the supply chain system. The study uses BNs to define the resilience of a supply chain when subject to disruption events and to understand how these risks propagate along the network: the resilience measure is a percentage value given by the ratio of recovery level with respect to the loss level. The authors identify a further index given by the ratio between the increase in disruption risk given the supplier is disrupted and when the supplier is fully operational. Among research findings and possible applications, it is important to mention the use of such model as a decision support tool to select suppliers and the right selection of mitigation strategies. Similarly, in the work proposed by Hosseini et al., (2020), authors develop a metrics rooted on the concept of absorptive, adaptive and resilience capacity and a set of strategies whose aim is to recover SC from disruptive events. In particular, SCR is proposed to be measured as a union of successful mitigation and recovery strategies using Bayesian networks. The authors frame the supply chain in an open system context which differs from the traditional closed-system perspective where risks are assessed from the equilibrium in operation performances. In the work of Badhotiya et al., (2022), Bayesian networks are introduced to assess some supply chain features: anticipation (a stage prior to disruption), response and recovery (reactive capability to restore after disruption) and resilience (the resilience of the system at the time of disruption). Each of these characteristics is dependent on certain indicators described by scholars. To illustrate the study implications, three case companies have been selected.

2.3.3 Bayesian network decision making oriented

When dealing with decision-making theory and the problem of selecting the best bundle of mitigation alternatives, the traditional techniques include optimization, multi-criteria decision making (MCDM) methods, decision trees or many others. However, not all of them are able to catch the stochastic dependency of the variable under examination. In some publications, such tools have been integrated with Bayesian networks, while in other papers, BNs aim at prioritizing and selecting the optimal solution among a mix of variables.

Hosseini and Barker (2016) propose a decision-making approach based on Bayesian networks supporting supplier selection and following three main perspectives: primary criteria (traditional criteria such as cost, product quality or service level), green criteria (criteria that comply with recently emissions regulations) and resilience criteria (criteria that measure firm's ability to maintain or recover its steady state even when subject to disruptive events). These criteria, modelled by means of continuous and discrete random variables, represent network nodes. The ultimate goal of this methodology is to give a single indicator by means of the previous criteria. Another interesting work in this area is the one proposed by Ruskey and Rosenberg (2022). Authors have proposed a methodology whose purpose is to find an optimal set of mitigation strategies in order to minimize expected risk caused by unmet demand. Each node in the chain has an upgrading option (mitigation strategy) at a certain cost, to reduce the probability of being non-operational subject to some budget constraints. While the probability of failure among supply chain nodes is implemented with Bayesian Network, the objective of selecting the optimal bundle of mitigation strategies is formulated as a Binary Integer Problem (BIP).

The Bayesian network proposed by Bounou et al., (2017) is placed in the context of spare parts inventory management. Unlike other works, in this case the random variables are exclusively those that typically characterise the inventory reordering policies: supply time and demand quantity. At the same time, utility nodes reproduce the cost associated with the action of the previous random variables. Thanks to the possibility of including decision nodes, the model can be used to find optimal solutions in terms of costs, by minimising the risks of obsolescence and shortages and satisfying customer demand at the same time.

The study developed by Qazi et al., (2015) aims at identifying the optimal mix of strategies to mitigate risks modelled with BNs, that typically affect a supply chain. For each of them, authors associate the relative cost of realisation and benefits in terms of risk reduction, which constitute real constraints in the optimal decision. The ultimate purpose of the study is to minimise the expected loss of the network through two risk measures appropriately introduced by the authors. The Bayesian network proposed by Seong and Lee (2012) is integrated with the Multi-Agent Simulation (MAS) in order to compare benefits derived by a decentralized supply chain system with a just-in-time or just-in-sequence configuration in the automotive industry. The methodology proposes six agents (drivers) such as Market, Factory, Manufacturing Risk or Economic indicators that govern an automotive supply chain. Raw data from 40 years are then considered and standardize to populate the Bayesian network structure. Finally, the multi-agent simulation is implemented to illustrate the interdependence among many agents within an environment: this method allows to reach optimal solutions in term of risk hedging and cost-effective solutions in highly complex environment. In Lockamy III (2018), a Bayesian network is proposed to represent the risk profile of a bundle of suppliers for a given focal company. Factors included in the analysis are random variables: country risk, business climate risk, commercial risk, logistic performance index, and corruption perceptions index. The set of these factors is conditionally related on the supplier external risk event, an index that measures the probability of supplier default, thus allowing their ranking process.

2.3.4. Dynamic effect and simulation

As previously said, supply chains are dynamic systems in which the probability of occurrence of events frequently changes or operational conditions either external or internal to the network mutate after a certain period. In such circumstances it might be useful to integrate or update the Bayesian network methodology with a tool that is able to represent the role played by the time. In other words, it might be useful to represent the temporal evolution of the Bayesian network.

Some authors developed risk effects and propagation through a dynamic version of the BN named Dynamic Bayesian networks. Hosseini et al., (2020), develop a model that integrates Discrete-Time-Markov Chain and Dynamic Bayesian networks to quantify the ripple effect in supply chains, defined by authors as the propagation of disruption along the network. A metric that catches the effect of such phenomenon on the expected utility and service level is also proposed by authors. The advantage of Dynamical Bayesian network is that the temporal dimension is included, unrolling the network on a number of steps equal to the number of time spans needed. Indeed, for each random variable, the evolution over time is described by a number of consecutive nodes, representing the state of the variable at that moment in time. This is a way to model stochastic process in dynamic environment. The total expected utility is calculated as the sum of the expected utility when the variable is in every state. The ripple effect is investigated also in Liu et al., (2021) where a robust Dynamic Bayesian network optimization model is developed to quantify the effect along the supply chain in the worst-case oriented estimation. Authors also presented an exact search algorithm to solve large-scale problems. Despite the growing complexity of Dynamic Bayesian networks with respect to the static version, the paper highlights its equal benefits in case of data scarcity. A different perspective is given by Punyamurthula and Badurdeen (2018) where authors focus on defining internal risk assessment at the production line level, using Bayesian networks and simulating the impact on operations with System Dynamics (SD) approach. In other words, the Bayesian network allows to identify and measuring risks while their impact on the production line is captured by the System Dynamics simulation. Zheng and Zhang (2020) propose a supply chain risk network model in which risks are called risk factors or risk events. Within the network, external risk factors, operation parameters risk factors and supply chain risks can be identified. Each risk factor can take three stages: active, inactive and critical. Based on this scenario, the authors developed a dynamic version of the BN (Dynamic Bayesian Network) to model changes in system states.

2.3.5. Operational and green risk profile assessment

Risk profile of suppliers can be evaluated including multiple perspectives. This section could seem a repetition to what discussed in the previous ones, where BNs for decision making oriented problems have been presented. However, the purpose of the publications in this section is to give the reader an overview about probabilistic indicators by means of Bayesian networks with the objective of complying with specific operational aspects and/or other features such as their green profile.

Among the first applications of Bayesian networks in this context, there is the work of Badurdeen et al., (2014). Authors propose a methodology divided in two steps: first a risk identification process and a risk classification, then a risk analysis process to understand the nature and the risk consequences using Bayesian networks. As last step, they propose a risk evaluation and treatment process in which strategies to mitigate such risks are proposed. The whole methodology is demonstrated with a case study from the aerospace industry. Following the network development, the authors present a graphical representation to prioritise risks based on the BN posterior probabilities. The study of Chhimwal et al., (2021), instead, focuses on creating risk profiles of the various Circular Supply Chain partners with Bayesian networks and to develop an index quantifying the disruption exposure of each partner. The risks are categorised into seven areas: Economic, Environmental, Social, Technological, Waste management, Agile vulnerability and Risk of cannibalisation. In addition to this, the authors measure the potential impacts of risks on network performance with particular regard to sales and costs.

Following the emerging green supply chain management topic, we find the work of Rabbi et al., (2020). In this paper, authors identify and analyse a number of green supply chain performance indicators and they integrate them into a probabilistic model using BNs. Thanks to the convergent configuration of the network, the output of this model is a single indicator representing the level of environmental performances satisfaction for the supply chain.

2.3.6. Financial risks in supply chain

Financial risks can be integrated with operational aspects not only to study a cause-effect relationship for its own sake but also to create a wider picture of the supply chain performances and its ability to sustain the strategy in highly competitive environments. Since financial aspects affect firm's ability to run operations and, vice-versa, sustainable operation management opens the door to financial stability, these perspectives should be integrated in the analysis. This paragraph is the most important to underline the innovation feature of this thesis and to evaluate the state of the art in this field.

The purpose of the work presented by Qazi and Simsekler (2022), is to prioritize supply chain risks, measured in terms of Value at Risk (VaR) at a given confidence level. In particular, the authors suggest developing three distinct Bayesian Networks on the basis of best, expected and worst scenarios each with a different probability of occurrence. Based on the outcome of the probabilistic model and losses of each scenario, risks are prioritized using metrics that measure the vulnerability of the entire chain. Similarly, Qazi et al., (2022) propose a methodology in which risks affecting key performance measures of a supply chain (cost, time, volume of activity etc.) are modelled as random variables and linked as BNs (causal-network). Following this framework, some risk measures are proposed as VaR-related metrics (Risk network value at risk). The objective of this methodology is to prioritize risks using these metrics and assess the Risk Network Value at Risk across individual performance measures.

Lockamy III and McCormack (2012) introduce a methodology to model and evaluate risks on supply chain by creating risk profiles for each supplier and providing managers with a tool to formulate mitigation strategies. Such risks are divided in external, operational and network risks. Each risk is modelled through a discrete random variable. The structure of the Bayesian network allows to obtain a unique revenue impact measure for each supplier. This measure is integrated in the VaR in order to estimate the economic loss due to potential supplier's disruption. The paper of Shi and Mena (2021) analyses risk considering performance metrics with a double perspective: operational and financial, in the light of the concepts of reliability and recoverability. The peculiarity of the paper is the introduction of time as a key variable in the evolution of risk effects in the supply chain. For each node, they model time by introducing a number of possible states equal to the number of discrete time-intervals to be represented. These nodes are continuous random variables. The objective of the excerpt is to link longitudinally operational and financial aspects, highlighting how financial performance influences the overall supply resilience. Garvey et al., (2015) show risk propagation effects on a supply chain measured with BNs. At the same time, they introduce specific risk measures that can be used in this setting. These measures aim at identifying propagation effects considering the cost of scenario occurring and the expected propagated cost given the scenario occurrence. In this framework, scenario refers to the ability to measure the combination of risks that occur in each location of the supply chain. For example, the Expected location risk contribution factor (ELRCF) measures the overall risk of a location calculated by adding the ERCF with the total losses of the scenario or the Risk propagation ratio that measures which nodes have more propagated effects on the subsequent nodes.

2.4. Research gap addressed by the thesis

In light of what has been investigated in the existing literature, the propagation effect of operational risks has been scarcely modelized. Thus, only few authors introduce a financial perspective to stress operationality effects over company's default probability. On the other hand, papers analysing financial distress in supply chains almost ignored the ripple effect caused by operational inefficiencies as source of financial distress along the supply chain. Most of the studies in the field propose analyses with macroeconomic, industry-specific or financial data. Under the methodological perspective, Bayesian networks are becoming a popular tool in supply chain risk management, thanks to their modelling capabilities. So far, a fair number of papers adopt this methodology to describe risk propagation phenomena along supply chains. However, even then few references integrate cause-and-effect perspective between operational and financial risks.

This thesis intends to fill this gap, by proposing a simple Bayesian network approach to model operational risk propagation along supply chain companies and consider their effect on the default risk. A central point of this thesis is represented by the modelisation of the risk transmission process along different tiers of the supply chain which is frequently ignored by literature that usually adopt a focal firm perspective, without giving greater prominence to upper-tier suppliers or lower-tier buyers risks. Despite its limitation, this methodology intends to open the door to further deepening of literature on disruptive events effect on companies' default probabilities. As already mentioned, this study focuses more on operational risks as other disruptive events such as economic shocks or natural disasters have been more investigates in literature.

3. THEORETICAL BACKGROUND

This Chapter formalises the theoretical underpinnings of both Bayesian networks theory and Credit risk management theory. The objective of this section is to provide the reader with the theoretical background on both topics in order to consciously approach the development of the model in the following Chapter 4. To this end, an introduction on Graph theory and Conditional probability theory is presented at first. Then, an example of Bayesian networks is shown. Section 3.2 presents a general introduction on credit risk modelling approaches, while the risk management process adopted in this thesis is described in paragraph 3.2.1.

3.1. Bayesian networks

When studying the relationship between variables, one could be interested to investigate the potential influence of one variable while observing the behaviour of another variable. For instance, in medicine one might evaluate the probability of a specific disease when observing a certain symptom (Pourret et al., 2008). On the other hand, consider the case where more than one cause can have effects on one or more variables. For instance, it could be interesting to know if certain personal habits directly influence two different diseases in a patient (Neapolitan, 2004). More in general, every situation in which the presence or absence of a certain phenomenon has an influence on the occurrence or non-occurrence of another event can be represented through the well-known Bayes' theorem. However, in most real cases, the occurrence of a given event depends on more than one factor, thus making the structure of the problem much more complicated. Bayesian networks (BNs) or sometimes Bayesian belief networks (BBNs) are probabilistic graphical models which allow to represent knowledge in uncertain domain. They offer an intuitive network representation of the joint probability distribution of a set of random variables with causal-effect relationship. BNs are able to describe complex systems even with little data at hand and the possibility to perform quick inference analysis thanks to the availability of commercial software. Bayesian networks are rooted in two fundamental branches of mathematics: conditional probability theory, with particular emphasis on Bayes' theorem, and graph theory. However, they combine principles also from computer science and statistics (Ben-Gal, 2007). Both elements of graph theory and conditional probability theory will be introduced in the paragraphs 3.1.1 and 3.1.2 respectively.

3.1.1 Basics of Graph theory

A Graph $G = (V, E)$ is mathematically represented by two main elements: a set V of nodes $v_1, \dots v_n$ and a set E of edges (or arcs) $e_{ij} = (v_i, v_j)$ linking a pair of nodes. The overall set of edges connecting nodes is called chain. Paths are special cases of chains where the set of edges is oriented in the same direction of the chain. In particular, Bayesian Networks are a special case of graphs called direct and acyclic graphs or DAGs (Stephenson, 2000). Direct acyclic graphs are structures where no cycles or close loops are present:

- A direct graph has ordered vertices within each edge $(v_i, v_j) \neq (v_j, v_i)$, thus arcs have a certain direction usually represented through arrows.
- If there are no loops or cycles the graph is also acyclic.

Once the general structure of a DAG has been discussed, it is possible to introduce some further taxonomy about the constituent elements of the graphs. Given an edge $e_{12} = (v_1, v_2)$ from v_1 to v_2, the former node is called parent node or predecessor while the latter is the successor or child node (Horný, 2014; Stephenson, 2000) with respect to v_1. Considering a general structure of a graph, there are root nodes (i.e., nodes without any predecessor), while nodes with no successor are called leaf nodes. However, general Bayesian networks also have nodes with both successor and predecessors. This is the case of intermediary nodes.

To better illustrate such differences, it is possible to refer Figure 3.1. which highlights both a direct and an indirect graph. While they are both acyclic, Graph A does not have direct edges whereas Graph B is a direct acyclic graph. As a consequence, nodes A and B in Graph B are parent nodes of C, that in turn is the parent of both D and E. Hence, A and B are root nodes, C is an intermediary node, while D and E are leaf nodes.

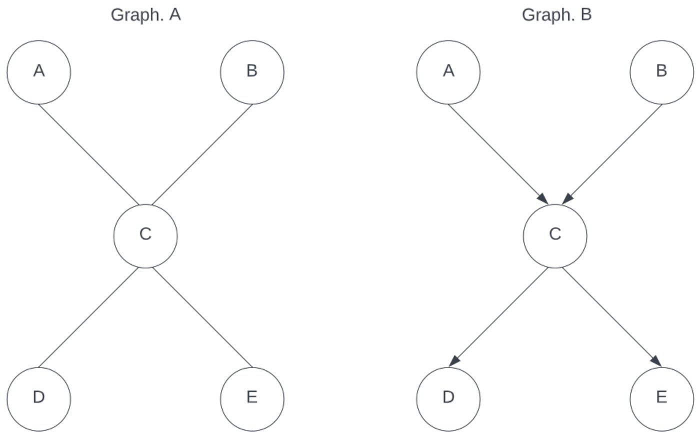

Figure 3.1. The difference between a direct and indirect acyclic graph.

3.1.2 Basics of Conditional probability theory

The DAG just described represents the qualitative part of the Bayesian network, while the quantitative part is described by variables. As previously said, network nodes represent random variables $V = (X_1, \dots X_n)$, each with a given probability distribution, assumed as a discrete distribution in this framework. On the other hand, edges (or arcs) represent the existing dependency between variables (Ben-Gal, 2007). This means that if X_i is the parent node of variable X_j, then the probability value of X_j is dependent on X_i. To mathematically represent the conditional dependence of two events, it is possible to refer to definition 3.1.

Definition 3.1. Given two events A and B with probability distribution P(A) and P(B) such that P(B) ≠ 0, the conditional probability of event A given the event B is:

$$P[A \mid B] = \frac{P\,[A \cap B]}{P[B]} \qquad (3.1)$$

From the previous definition it follows that two events are considered independent if the intersection space is equal to $P\,[A \cap B] = P[A] \cdot P[B]$ that is $P[A \mid B] = P[A]$. Traditionally, the Bayes' theorem has been used to evaluate the conditional probabilities of events from known probabilities (Neapolitan, 2004). The Bayes theorem can be seen from theorem 3.1.

Theorem 3.1. (Theorem of Bayes) Given two events A and B with probability distribution P(A) and P(B) such that both P(A) $\neq$ 0 and P(B) $\neq$ 0, the conditional probability of A given the event B is:

$$P[A \mid B] = \frac{P[B \mid A] \cdot P[A]}{P[B]} \tag{3.2}$$

Where $P[A]$ is called prior probability (i.e., the probability prior to its update using new information) and $P[B]$ is the marginal probability. At the same time $P[A \mid B]$ is the posterior probability (probability occurring after that its prior probability has been updated with new information) while $P[B \mid A]$ is called likelihood [7]. Hower, most of the time both $P[A \mid B]$ and $P[B \mid A]$ are generally called conditional probabilities. Events A and B in the Bayes' theorem can be interpreted as the Cause and the observed Evidence. To illustrate probabilities calculation in Bayesian networks it has been developed an example (Example 3.1).

Example 3.1.

Consider the Graph B of the Bayesian network presented in Figure 3.1. above, where random variable C is conditionally dependent on A and B. At the same time, both D and E are conditionally dependent on C. The probability distribution adopted in this framework is the Bernoulli distribution. Thus, each variable can assume two states only: $True$ with probability p and $False$ with probability $1 - p$. In other words, events A and B can occur with probability $P[A = True] = p_A$ and $P[B = True] = p_B$ respectively. The state of variable *C* depends on the variables A and B. It follows that,

$$P[C = True] = \sum_{A,B} P[C = True \mid A, B] \cdot P[A] \cdot P[B]$$

The conditional probabilities given in the expressions above are usually given in tables called Conditional Probability Table (CPT) as shown in Table 3.1.

Table 3.1. Conditional Probability Table (CPT) of C in Example 1.

	A = T		**A = F**	
	B = T	**B = F**	**B = T**	**B = F**
C=T	$P[C = T \mid A = T, B = T]$	$P[C = T \mid A = T, B = F]$	$P[C = T \mid A = F, B = T]$	$P[C = T \mid A = F, B = F]$
C=F	$P[C = F \mid A = T, B = T]$	$P[C = F \mid A = T, B = F]$	$P[C = F \mid A = F, B = T]$	$P[C = F \mid A = F, B = F]$

Therefore, there are four possible combinations of states assumed by A and B influencing C:

$$\begin{aligned} P[C = True] = {} & P[C = T \mid A = T, B = T] \cdot P[A = T] \cdot P[B = T] + \\ & + P[C = T \mid A = F, B = T] \cdot P[A = F] \cdot P[B = T] + \\ & + P[C = T \mid A = T, B = F] \cdot P[A = T] \cdot P[B = F] + \\ & + P[C = T \mid A = F, B = F] \cdot P[A = F] \cdot P[B = F] \end{aligned}$$

Rewriting with the taxonomy adopted at the beginning of the example:

$$\begin{aligned} P[C = True] = {} & P[C = T \mid A = T, B = T] \cdot p_A \cdot p_B + \\ & + P[C = T \mid A = F, B = T] \cdot (1 - p_A) \cdot p_B + \\ & + P[C = T \mid A = T, B = F] \cdot p_A \cdot (1 - p_B) + \\ & + P[C = T \mid A = F, B = F] \cdot (1 - p_A) \cdot (1 - p_B). \end{aligned}$$

Similarly, for nodes D and E, the posterior probability can be evaluated as

Table 3.2. Conditional Probability Table (CPT) of D in Example 1.

	C = T	**C = F**
D=T	$P[D = T \mid C = T]$	$P[D = T \mid C = F]$
D=F	$P[D = F \mid C = T]$	$P[D = F \mid C = F]$

$$P[D = T] = P[D = T \mid C = T] \cdot p_C + P[D = T \mid C = F] \cdot (1 - p_C).$$

Table 3.3. Conditional Probability Table (CPT) of E in Example 1.

	C = T	**C = F**
E=T	$P[E = T \mid C = T]$	$P[E = T \mid C = F]$
E=F	$P[E = F \mid C = T]$	$P[E = F \mid C = F]$

$$P[E = T] = P[E = T \mid C = T] \cdot p_C + P[E = T \mid C = F] \cdot (1 - p_C).$$

3.2. Credit risk

The credit risk is the risk faced by creditors when debtors do not meet their contractual obligations, generated by default or caused by changes in credit quality. Credit risk management has been studied in different sectors, including financial mathematics. The mathematical models developed over time in this field are traditionally divided into two macro-areas: credit risk management and analysis of credit-risky securities. The former is used to estimate loss distribution and related risk measures. As one can easily guess, the latter focus on the study of financial products with the main purpose of securities pricing (McNeil et al., 2005). As the authors point out, the former can be generally defined as static models since the study is based on a defined time window. Analysis of credit-risky securities models use continuous-time models or stochastic processes. This section will present at first a general overview on the mathematical risk modeling approaches following the classification presented in McNeil et al., (2005), then the specific credit risk model used in this thesis will be presented in the following paragraph.

Among the default structural models (i.e., models that attempt to frame the dynamics of corporate default and the underlying causes), it is worth mentioning Merton's model (Merton, 1974) which considers company's value consisting of both debt and equity. Default occurs when the value of the company is less than the value of the debt. Thus, the firm's equity and debt can be interpreted as European options. Under this framework, Merton's model is a starting point to model credit risk and to price securities through Black-Scholes model. Another relevant example is the model developed by KMV in the 1990s. Its contribution consists of an extension of Merton's model and its implementation on a large database of companies. Other models are based on the concept of credit migration. The credit measures developed by rating agencies such as Moody's or Standard & Poor's allow companies to be assigned appropriate credit risk level. For example, in the Standard & Poor's rating system, categories range from AAA (lowest probability of default) to CCC (highest probability of default). From this classification, credit migration models construct appropriate transition matrices that highlight the probability of moving from one level of credit to another within a certain period. Other credit risk models, called Threshold models, assume that the default happens when a certain random variable exceeds a give deterministic threshold. For example, in the Merton model, the company's debt value B, can be seen as a threshold. In a mixed model, the default depends on a set of factors, such as common economic factors. Once the realisation of such factor occurs, the insolvencies of individual firms represent a direct consequence. The default dependence between firms is based on the set of common factors.

3.2.1 Credit portfolio risk management

The credit risk model of this thesis will refer to the work presented by Fontana et al., (2021), who describe the joint distribution of defaults portfolios where the individual default indicator is represented as Bernoulli random variable. In addition, the authors present bounds for the risk measures Value-at-Risk and Expected Shortfall.

A credit portfolio P of n loans granted to n different entities represented as a n-dimensional vector $P = (w_1, w_2, \dots, w_n)$, where each component $w_i \in [0; 1]$ is the amount granted to obligor i. To normalise the overall budget to 1, the additional constraint $\sum_{i=1}^{n} w_i = 1$ is imposed. Consider also that every company i included in the analysis has a default indicator X_i modelled through a Bernoulli random variable. As Bernoulli random variable, the two states indicating default occurrence or non-occurrence are highlighted in equation (3.4)

$$X_i \sim Bernoulli(p_i) = \begin{cases} 1 & \text{prob.} = p \\ 0 & \text{prob.} = 1 - p \end{cases} \tag{3.4}$$

Coming back at the credit portfolio P, its loss is given by the weighted sum of the individual i losses. In other words, it is a linear combination of n Bernoulli variables.

$$L_P(x) = \sum_{i=1}^{n} w_i X_i \tag{3.5}$$

Because of the previous formulation, it follows that the expected loss of the portfolio is given by the weighted sum of the individual expected losses.

$$EL_P = \sum_{i=1}^{n} w_i E[X_i] \tag{3.6}$$

Another important risk measure widely adopted in financial risk management is the Value-at-Risk or VaR. VaR is probably the most used risk measure, and it has been adopted worldwide during the Basel II Agreement. To formally introduce the Value-at-Risk, consider time horizon T and the portfolio's loss cumulative density function $F_L(\delta) = P\,[\,L\ \leq \delta]$. Therefore, the Value-at-Risk of P at α confidence level is the smallest δ so that the probability that the portfolio's loss L exceeds δ is no larger than $(1 - \alpha)$. In other words, VaR is a quantile at a given confidence level α of the loss distribution shown in equation (3.7). This sentence can be expressed as

$$VaR_\alpha = inf\{\delta\ \in\ \mathbb{R} : P[L >\ \delta] \leq 1 -\ \alpha\} \tag{3.7}$$

Rearranging the cumulative density function in equation (3.8), we get

$$VaR_\alpha = inf\{\delta\ \in\ \mathbb{R} :\ F_L(\delta) \geq \alpha\} \tag{3.8}$$

The usual values for the confidence level α include $\alpha = 90\%$, $\alpha = 95\%$ and $\alpha = 99\%$. The reason for defining the VaR as "*inf*" value is that for discrete random variables, it could not be possible to find a value δ such that $P[L \leq\ \delta] \leq \alpha$. In that case, the Value-at-Risk is the smallest value that gives at least the α probability that the loss is smaller as shown in Example 2.

Example 2.

Consider the cumulative density function in Table 3.4, where the cumulative probabilities are associated to each loss state of the portfolio.

Table 3.4. Cumulative density function of example 2.

Loss	$P[L \leq x]$
0	85%
1500	95%
3000	99.5%
4000	100%

In this case, there is no exact value that give an $\alpha = 99\%$. Therefore, the smallest integer giving at least a probability value equal to α is 3000.

4. MODEL DEVELOPMENT: A CASE STUDY FROM THE AUTOMOTIVE INDUSTRY

This chapter represents the core part of the thesis. At first a general introduction to the methodology is presented to highlights main steps and features, then a brief case from the automotive sector is shown.

4.1. Model introduction

The ultimate goal of the present work is to raise managers awareness about the consequences of operational disruptive events on companies' default risk towards their creditors, as consequence of supply chain risks. At the same time, this methodology can help external creditors in assessing an adequate company's risk profile considering not only the risks resulting from a vulnerable internal management, but also the risk propagation effects in extremely interconnected networks as supply chains. In this chapter, the necessary steps to develop the methodology are discussed and an automotive industry application, taken from scientific literature, is presented as well. The methodology developed in this thesis follows six main strands:

- Supply chain structure and flows.
- Risks identification.
- Marginal and conditional probabilities.
- Bayesian network construction.
- Default-risk profile assessment and credit portfolio.
- Risk mitigation strategies.

The first two steps of the methodology are fundamental to understand the structure of the problem and analysing its characteristics. In this case, data relating to the structure of the automotive industry, as well as the probability values, have been collected from the relevant literature. The Bayesian network construction process, which is the core part of the methodology, is based on the information gathered in the previous steps and it has been realised with GeNIe 4.0 Academic version software. In general, the collection of data relating to risk categories affecting different SC firms and probability values are the preliminar part of most of the Bayesian networks construction in supply chain risk management (Qazi et al., 2015; Garvey et al., 2015; Qazi and Simsekler, 2021; Shi and Mena, 2021). The objective of step 5 is to assess credit risk under a double perspective: estimating credit risk at each tier of the supply chain as a direct consequence of operational disruption and as part of a credit portfolio including debts from other SC companies. The latter result may be of interest to creditors that finance supply chain activities within the same network. To this end, several portfolio scenarios are presented and some risk measures to understand the riskiness of the debt, including Value at Risk (VaR), are proposed. The last step of the methodology includes the proposal of operational risk mitigation strategies that can be adopted to reduce the probability of risk event occurrence and, consequently, reduce the company's default risk. This last step is closely linked to the supply chain industry, and it is strictly dependent on the strategy adopted. To this end, this thesis will just highlight the main benefits and implications of this phase, without proposing numerical results that could be modelled in future works. Also, this methodology can be seen as an operational-credit benchmark process where a change in probability conditions due to the introduction of risk mitigation strategies or different internal operational conditions, changes both the credit risk profile of the company and that of potential credit portfolios. Therefore, this iterative process could help managers in selecting the best mitigation strategy to reduce the probability of the company's insolvency. These steps have been summarised in Figure 4.1.

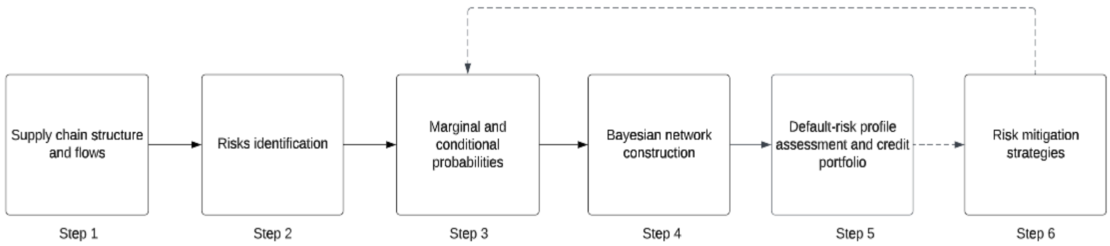

Figure 4.1. Steps adopted in the case study methodology.

In this thesis, the automotive industry will be considered as exemplification of the methodology, because of its global importance in terms of turnover and its presence in the world market. Despite a non-negligible contraction during the economic crisis in 2008-2009, the automotive market has faced an uninterrupted growth in the last decades, reaching 97 million of cars sold in 2017 [8]. On the other hand, the recent pandemic and their unavoidable consequences on the global economy leaded to considerable reductions in the global sales (Pfeifer, 2021). Despite disruptive events listed above could be considered as mere external factors driving severe internal risks, a great number of operational risks continuously affects internal operativity leading to heavy losses. These considerations must be placed in the global automotive supply chain environment, where thousands of companies take part in the production, assembly and shipping process of single modules, components and, finally, of finished products. Thus, the automotive industry can be considered as one of the most complex supply networks among different sector's supply chains. Indeed, although a stable financing mode, the large number of participants makes credit risks still occurring in the automotive supply chain industry (Zhang et al., 2021). Some of the most well-known bankruptcies in this industry include the two large American auto manufacturers: Chrysler LLC and General Motors Corp both occurred in 2009. In addition, in 2011 Saab Automobile filed after fighting for three years against default (Tanguy et al., 2013). Authors have shown that the automotive industry can be placed at a level 4 (moderately high risk) on Standard&Poors' Business Risk Analysis rating scale. This assessment is the result of a high industry's cyclicality and an intermediate competitiveness risk. Firms that operate in such uncertain environment require instruments and rigorous techniques not only to identify disruptive events that might affect internal organizations but also to deeply understand their consequences under the financial perspective dictated by both local and global risks. Hence, the importance to analyse risks in such critical context and to propose mitigation strategies in order to higher the resilience of the global supply chain is of primary importance. The application of the methodology to the automotive industry was produced through a literature analysis of both Bayesian networks in supply chain risk management papers and the empirical results obtained by various authors in automotive industry risk assessment field. Therefore, the steps adopted in this study and detailed below can be adapted to different industrial contexts.

4.2. Supply chain structure and flows

Identifying supply chain boundaries and firms involved in the network represents the first stage of the proposed methodology. Mapping the structure of the supply chain is a primary step (Garvey et al., 2015) towards understanding the different nature of activities carried out in each industry thus, the risks typically encountered by supply chain companies. However, this step becomes even more important in order to understand the number of firms involved in the product creation, the type of contractual relationship that exists between them, their geographical location and in general their impact on the global and local economy. It is crucial to understand which actors have a primary role in delivering the final product to end-users and which of them have only a marginal influence: in large industries defining boundaries and firms' connections might be laborious due to great variety of components flowing through the supply chain and the number of firms contractually involved in the daily activities even though, as in any mathematical model, the more complete the structure and the more powerful the methodology.

Supply chains can be described as networks or graphs (Hearnshaw and Wilson, 2013) composed by a set of nodes linked by arcs representing companies and companies interchanged flows respectively. Typical network flows include financial, information and material flows. Financial flows refer to the exchange of financial resources between different actors operating in the supply chain, while the information flow represents the transfer of information, such as the monthly demand by the consumer or a retailing company located in the lower tiers of the chain. Material flows represent the exchange of raw materials, components and products between companies. Some authors identify further subsets of flows that are usually exchanged in supply chains such as money manpower and capital equipment (Rahman et al., 2007). For the sake of clarity, it is necessary to emphasise that in any product-manufacturing industry each of these flow categories is always present. However, each flow may connect different nodes within the same network: for example, an information flow between two companies located in two different tiers of the chain may be upward (i.e., from the bottom to the top) while the flow of material typically occurs from the higher chain layers (e.g., raw material suppliers) to lower levels in the direction of the final consumers. Therefore, depending on the type of flow to be represented, the network assumes different topologies (Hearnshaw and Wilson, 2013). In addition, Hearnshaw and Wilson (2013) pointed out that the flow representation changes depending on the type of flow to be shown. In fact, the representation of supply chain based on material flow is a directional graph, while the one based on the contractual relationship is non-directional, as contracts are agreed by both parties.

Other authors focus their analysis with respect to a certain company of interest within the network. In particular, they rely on the concept of supply chain tiers residing upstream or downstream of a given focal firm. For example, first-tier companies are defined as the set of firms that directly supply information, material or financial flows to the focal firm. Obviously, the analysis can be extended to the suppliers of the suppliers (second-tier) and so on (Li et al., 2022; Mori et al., 2014). It is important to emphasise that such analysis gives greater prominence to the central firm, even if this perspective can eventually be adopted for every firm in the network, since each of them can be seen as a focal firm (Figure 4.2). The focal firm might be an Original Equipment Manufacturing (OEM) firm, which is the company supplying the product in accordance with third party's specifications. In other words, it is a business that manufactures products in line with detailed requirements from its buyers. In general, the representation of the supply chain as a network of companies allows not only to better represent the overall structure in a hierarchical manner, but also to facilitate the subsequent representation of risks via Bayesian networks.

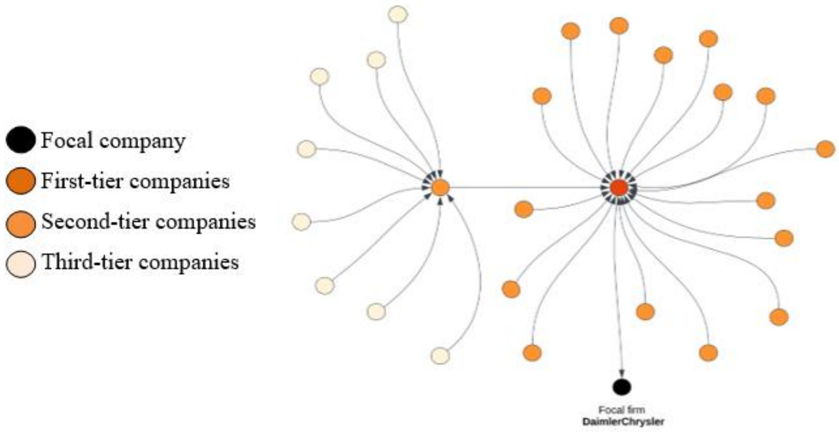

Figure 4.2. Supply chain material flow for DaimlerChrysler (DCX) Grand Cherokee adapted from of Kim et al., (2011).

Looking inside the typical supply chain organisation, it is possible to furtherly identify different structures. Linear structures (i.e., structures in which every tier has one company performing a single activity) are generally unusual, reflecting in most cases, to simple products with local demand. On the other hand, convergent supply chains, are typical for products that require consecutive assembly processes after the production of single components. Finally, diverging or arborescent structures are typical for distribution processes, where finished products are shipped from central warehouses to regional repositories, much closer to the end consumer (Brandimarte and Zotteri, 2007). As the authors illustrate, these theoretical networks are, in reality, embedded in hybrid structures. In fact, the supply chain responsible for producing, assembling and distributing products generally combine both divergent and convergent networks: a divergent configuration to process final product from raw materials and a convergent architecture for the following final-product delivery process. As highlighted by Berloco et al., (2021), the structure of supply chains is not a static feature as relationships among firms evolve and even the firms carrying out activities change.

The generic automotive supply chain structure includes suppliers, manufacturers and retailers as stated by Tuncel and Alpan (2019). Each of the thousand's supplier is responsible for transferring material to manufacturers which produce individual components of the final product. These components are then assembled together in one or more stages of the chain, until reaching the ultimate car assembly phase, where the product is completed and ready to be distributed. Such supply chain complexity depends on the great modular structure of cars (Kuys et al., 2016) which allows to produce components by different industrial producers and to ship them to the assembly plant (Baldwyn and Clark, 2006). Car's modularity architecture has also other managerial implications: it allows to enhance local performances by substituting a given components with a better one and avoid redesigning the whole product. On the strategic point of view, modular architectures allow fast changes between product generations but also to offer product variants simultaneously in order to address different market segments (Cantamessa and Montagna, 2016). Obviously, these added-value activities may unfold along one or more tiers depending on the network design, which may vary from product to product. A more detailed generic structure is reported by Dehdar et al., (2018) where the design, raw material suppliers, part production, assembly, marketing and distribution and sales stages are included. Similarly, the 4-tiers supply chain presented in Mohammaddust et al., (2017) consists of suppliers, manufacturers, distribution centres and retailers serving different markets. Choi and Hong (2002) analyzed three supply chains from the automotive industry: Honda Accord, Acura CL/TL, and DaimlerChrysler (DCX) Grand Cherokee reported in Figure 4.2. For each the case study presented in the paper, the activities involved in the product value creation have been classified as raw material supplier, trader, manufacturer, and assembler. Finally, the structure presented by Fredriksson and Gadde (2005) of Volvo company for build-to-order production is composed by four main steps: components manufacturing and shipment (suppliers), module pre-assembly process, car assembly process and distribution. As can be seen from this analysis, the essential activities constituting the supply chain structure include suppliers and manufacturers of raw materials and components as an initial step. Subsequently, components are assembled in one or more stages until the complete car assembly. Once the production/assembly process is completed, the distribution process starts. The outbound logistics can be organised through one or more nodes. Finished products are usually shipped to distribution centres to serve regional/national demand. As last step, vehicles are shipped to dealers across the region (Boujelben et al., 2012).

As the general structure of the automotive supply chain is extremely complex, only some of the most relevant stages will be considered as examples here. To this end, the example of Punyamurthula and Badurdeen (2018) will be taken as reference. Authors present a case study of a multinational manufacturing company operating in the automotive sector in both North America (i.e., USA, Mexico and Canada) and China. In particular, the article describes the metal component manufacturing process in an US division. For the purpose of this thesis and based on the description provided by authors, it can be reasonably assumed that raw materials are shipped by a raw material supplier located in an upstream tier, with respect to the manufacturing company. In order to complete the example, this thesis assumed that the supply chain is provided with a parallel process (raw material supplier and manufacturing company) as a Mexican division. Both products from this stage are assembled in order to produce subsequent components in the following assembly stage. The description of the supply chain scenario just described is shown in Figure 4.3.

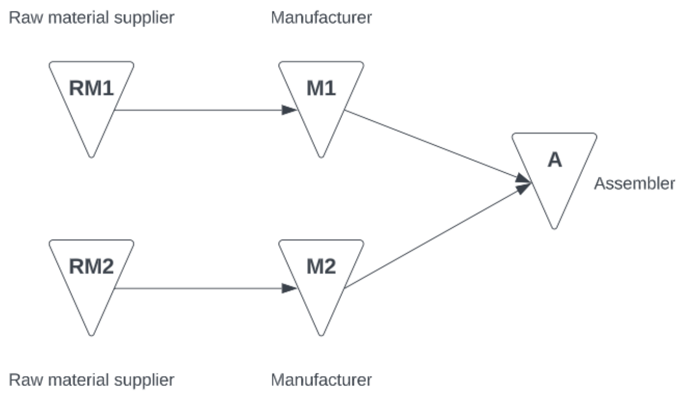

Figure 4.3. The automotive supply chain with material flow adopted as example.

Each supply chain node (i.e., firms) can be furtherly broken down into internal sub-processes. To this end, it could be useful to follow the Supply Chain Operations Reference Model (SCOR-Model) [9]. Its architecture is regularly updated, and the structure adopted by the SCOR aligns the representation of activities with business functions and objectives. The processes presented in the SCOR model include the activities most companies perform to effectively execute their supply chain such as order process (i.e., the set of activities associated with ordering or purchasing materials or services) or transform process (i.e., the set of activities associated with creating value to the product such as manufacturing or assembly) and others (Figure 4.4). The aspiration of mapping every business sub-activity involved in the product value creation might be extremely ambitious depending on the complexity of the supply chain and, for this reason, it is usually adopted for mapping the business internal structure only.

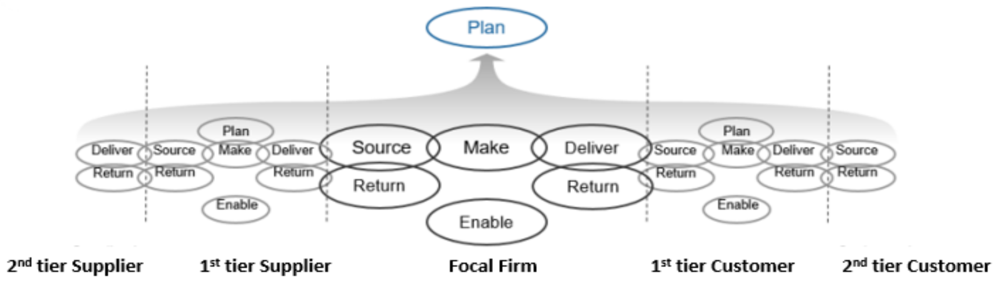

Figure 4.4. General description of Supply chain processes adopted in the SCOR model version 12.0 [10].

For *ex-novo* applications, it could be useful to interview industry stakeholders, managers and personnel (Leerojanaprapa et al., 2013) to explore network performances and refine the structure.

4.3. Risks identification

The main goal of this section is to detail, to the best of author's knowledge in literature, the nature and type of risks present at the different nodes of the chain. The risk identification process represents an important step in the risk assessment procedure (Punyamurthula and Badurdeen, 2018; Qazi and Simsekler, 2021) and it has been carried out through an extensive literature review in the automotive supply chain risk assessment field with particular emphasis on operational risks. Most of the publications only give the focal firm perspective in order to assess internal potential risk sources (i.e., controllable risks through a better management of internal operations or the introduction of mitigation strategies) and external's one which are not directly manageable but depends on upstream or downstream operations. As previously said, this perspective gives greater prominence to risks that might threat focal firm operativity, without giving a detailed description of risks affecting other network nodes. Indeed, risky events at the supplier level are usually categorised as external's without giving further details with respect to the tier or the specific activity position in the network. However, such approach fails in capturing risks effects on those activities that are external with respect to the focal company but, that are internal to the supply network. In addition, risks dependency is ignored. Other publications, roughly capture this alternative point of view, by listing risks with respect to upstream/downstream source from an inside/outside network perspective (Christopher and Peck, 2004). Only few authors give a detailed description of risks affecting individual nodes as stated in Tuncel and Alpan (2010). With the help of literature, this section summarises the main risk events and factors affecting each node of the automotive supply chain illustrated above.

Operational risks are potential losses arising from the day-to-day operations disruption as already described in Chapter 1. Risk events affecting supply chain activities may differ in nature depending on the activities that are performed at any node. However, as illustrated in the previous paragraph, some internal processes are present in every company regardless of the industry under investigation. The decision to breakdown business internal activities as well as the risks depends on the level of detail of the analysis: given the complex nature of the automotive supply chain, a lot of disruptive events have to be included for an in-depth analysis. Risk event occurrence can be reduced if companies adopt proper risk mitigation strategies in order to minimize consequences on internal and external activities and economical losses as well (Blos et al., 2009). These issues will be discussed in the paragraph 4.7 of this chapter, while the following risk classification has been made through the analysis of the different literature sources on automotive supply chain operational risks.

Accident risk

Accident risks are caused by lack of business safety. Internal safety must be always ensured to protect human health, physical assets integrity as well as operations continuity. Production line accidents, exposure to toxic substances, fires, or explosions (Jiantong et al., 2016) are just examples of potential disruptive events that can negatively have consequences on firm’s internal operativity. Despite many further sub-risk categories are available, there is no process in the supply chain that can be considered as accident-free. Protiviti (2006) and Guedes et al., (2015) identify “*Crash of critical systems for the business continuity*” as a source for business operation continuity risk.

Delivery process risk

Companies are not only contractually bounded to supply the product according to the technical specifications but also to deliver products on time (Wang et al., 2013) and in the agreed quantity. Supply chain upper-tiers activities, such as components producers (Lockamy and McCormack, 2012; Punyamurthula and Badurdeen, 2018) are the one which most of the time encounter inadequate delivery process risk (Sharma and Bhat 2012). A different perspective is proposed by Puspitasari and Yuwono (2022), that points out the threats of such risk category faced by lower tiers activities in the network, such as the finished-product distribution. They identify additional delivery process sub-risks: "*Incorrect product packaging*", "*damage to the product occurring during delivery" and "delays in delivery of products to customers*". In the light of these observations, it can be seen that delivery process risks are not node-specific within the chain. Thus, under such classification, it is possible to identify late inbound supply delivery or wrong number of components delivered by suppliers.

Demand forecasting risk

Changes in demand due to high volatility or seasonality rise the risk of an inaccurate demand forecasting. Errors in demand forecasting led to company losses as stated in Junaid et al., (2020), which classify this risk as downstream. In fact, an inaccurate demand forecasting (Jiantong et al., 2016) is a common risk faced by supply chain lower tiers activities as highlighted by Thun et al., (2011). Although demand-related risks are considered by some literature source as non-operational, due to the exogenous factors driving demand variability, they are functional to the internal activity planning process. Indeed, following the definition given by Pham and Verbano (1996), that has been previously illustrated, operational risks deal also with supply and demand side. For that reason, such risk category could be placed in the in the broader classification of operational risks as they are an input for the internal management of processes.

Inventory risks

The risk of low stock level is faced by every supply chain company, in both inbound and outbound logistic operations (Shi and Mena, 2021). As an example, Badurdeen et al., (2014) point out that the low level of incoming stock due to the earthquake in Japan in 2011 caused a strain on the subsequent production of automotive components in that region. Honda and Toyota sales decreased by 28% and 23% respectively compared to July of the previous year. Under this framework, it is also important to stress that a high inventory can lead to excessive holding costs: the holding cost increases as the stock to be stored in the inventory undergoes processing. Thus, raw material holding cost is less relevant than the one faced by finished goods inventories (Chhimwal et al., 2021). Therefore, authors included the risk of "inventory management problem" among the operational risks. Looking at the SCOR-model for an internal activity classification, inventory-related risks primary affect both the "Source" and the "Deliver" phase.

IT system risks

Nowadays, IT systems represent a fundamental infrastructure deeply integrated to the manufacturing and distribution process of supply chain companies. Thus, IT system interruption or breakdown can be seen as an internal threat for any supply chain node (Thun et al., 2011). A breakdown (Blackhurst et al., 2008) could cause the interruption of the internal operativity, thus leading to losses, damages and breakdown of communication within or outside the organisation (Junaid et al., 2020). IT systems risks are not only influenced by an internal software or hardware fail, but also from cyberattacks (Schmittner et al., 2020).

Machine breakdown risk

Manufacturing disruptions is a relevant risk for manufacturing firms in the automotive industry (Punyamurthula and Badurdeen, 2018). Machines operating in the production or assembly lines are the core part of the primary stages in the automotive supply chain. Any machines or plants breakdown (Sharma and Bhat, 2012) would result in disruption of internal operations (Thun et al., 2011), leading to delays and unplanned costs (Junaid et al., 2020). This risk primary affects the "Make" process of the SCOR-model classification.

Manufacturing delay risk

The delay of material flow can occur at the manufacturing process level as a consequence of other unplanned events, such as delay in procurement, system breakdown or production failures (Mohammaddust et al., 2017; Babu et al., 2021). This risk affects the "Make" process of the internal SCOR-model classification.

Punyamurthula and Badurdeen (2018) state that the manufacturing delay risk is directly related with the procurement delay risk. In addition, poor-quality goods from suppliers lead to re-work processes which in turn causes production delays (Blos et al., 2009).

Operations capacity flexibility risk

According to Guedes et al., (2015) and Protiviti (2006), capacity risk is the circumstance occurring when either the production capacity is not able to meet market demand, or when internal resources are underutilised. On the other hand, risk arises even when not exploiting the whole utilisation capacity that is internally available (Junaid et al., 2020). For that reason, lack of flexibility of resources in the production process is an important source of risk (Sharma and Bhat, 2012; Jiantong et al., 2016; Blackhurst et al., 2008). A metrics widely adopted to evaluate operations capacity is the Overall Equipment Effectiveness (OEE), which is a performance measurement for equipment effectiveness in terms of productivity, based on three factors: Availability, Performance, and Quality (Tobe et al., 2018; Stamatis, 2010). As it can be seen, OEE includes also other metrics that have been described as different risk measure.

Procurement delay risk

Similarly to what has been discussed for the manufacturing delay risk, procurement delay has to do with any delays experienced by manufacturers in the procurement process of raw materials and components from suppliers, which in turns affects the regular execution of the production process (Zhang et al., 2018; Punyamurthula and Badurdeen, 2018). For this reason, it is related with the "Source" process of the SCOR-model classification, as it describes the activities of procuring and scheduling orders.

Product quality risk

Supplying low quality products or components can have negative effects on product value as presented in Blackhurst et al., (2008). The risk of producing low product quality is mainly faced by upstream tiers in the supply chain (Sharma and Bhat, 2012; Thun et al., 2011) which are in charge of components production and their subsequent assembly into the final product. The impact of the component poor quality risk is extremely important, so that it has been a key element in the supplier selection process, as presented in Lockamy III and McCormack, (2012).

Raw material shortage risk

Generally speaking, any production process aimed at transforming inputs in outputs needs raw materials. However, companies residing in the upper part of the supply chain might face higher raw materials shortage risks, since primary components and parts take place (Tuncel and Alpan, 2019; Punyamurthula and Badurdeen, 2018). However, different production processes are performed at any tier of the supply chain every production process can seek shortage in raw material supply (Badurdeen et al., 2014).

Shipment delay risk

Canbolat et al., (2008) state that shipment delay risk is a primary matter of concern for managers since it frequently led to extra costs and loss of revenues. It is also worth mentioning that delay in shipment is an important source of intra-firm risk transmission (Qazi and Simsekler, 2021) as it directly delays the subsequent start of manufacturing processes in the following stage. For this reason, the shipment delay can be considered as risk "Deliver" process of the Supply-Chain Operations Reference (SCOR) model.

Transportation risk

Logistics is not only a primary issue for activities involved in distributions, but also to deliver semi-finished products between supply chain companies: transportation represents a crucial means to connect every node of the network. Thus, having poor infrastructure or lack of professionalism in the logistic sector is a matter of concern for managers of the whole supply chain (Sharma and Bhat, 2012).

To further illustrate the application of the methodology, based on the example showed in Figure 4.3. above, a subset of the aforementioned risks will be considered. Punyamurthula and Badurdeen (2018) state that the automotive manufacturer company suffer from raw material shortage and delivery issues which delays the following component production (i.e., manufacturing process stage delays). As previously said, manufacturing process delays strictly depends on equipment availability, production quality issues and its performances. However, since the raw material risks might not be directly controllable by the manufacturing company, it has been assumed as risk affecting the raw material supplier (RM1) which is part of this model in the initial tier. A similar consideration can be done for the delivery process risk which impacts at first the raw material supplier and then the procurement of the manufacturer (M1). In addition, inventory issues have been included by the thesis as an internal risk for the raw material supplier and for the manufacturing company in order to model the subsequent losses derived by the internal operativity. As previously said, it has been assumed that the supply network has another path so as to model the Mexican division of production components. As already mentioned, such division includes a raw material supplier (RM2) and a manufacturing company (M2) which are affected by same kinds of risks with respect to RM1 and M1. The difference relays in the probability values, which will be described in paragraph 4.4 since they have been collected from the survey of Cano-Olivos et al., (2022) about Mexican automotive industry. The final stage of the supply network is represented by the assembly process. Again, probability values and network links have been collected from Ju and Pan (2016) who investigated risks in a Chinese assembly line. In particular, Ju and Pan (2016), state that assembly productivity (i.e., named efficiency) depends on both a correct materials timely delivery and equipment down rate as operational status of the equipment. To model losses, it has been added shipment delay as an internal risk for the assembly process (Figure 4.5).

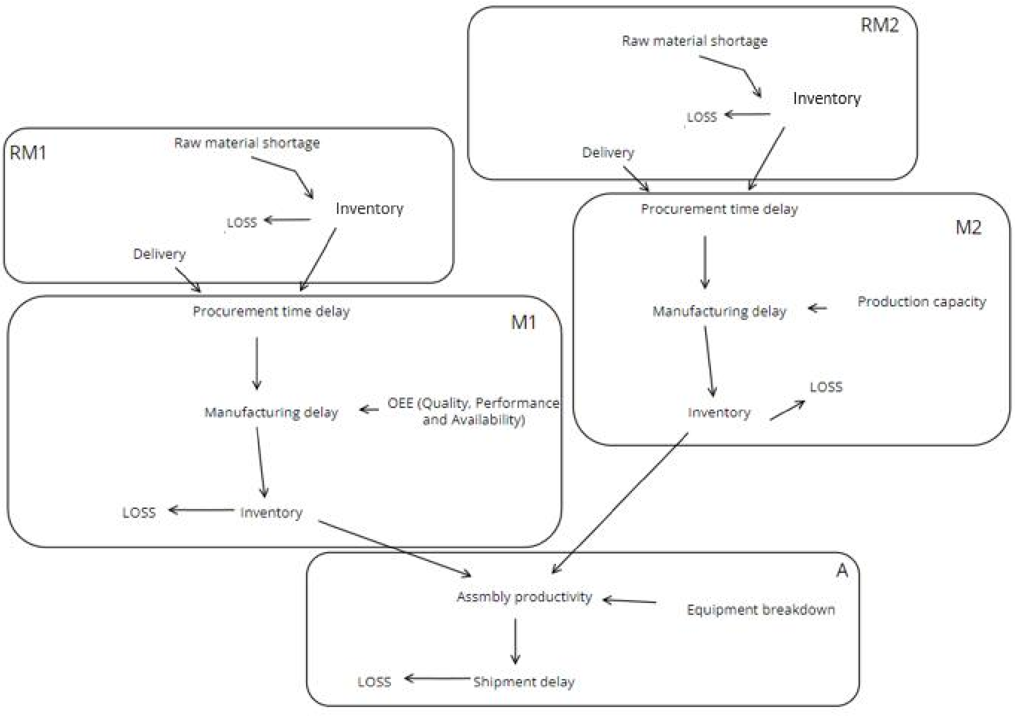

Figure 4.5. Risk dependency structure adopted for the example.

Since the main purpose of this thesis is to highlight the connection between operational risks and default effects, the intra-company risk-transmission process proposed by Hosseini and Ivanov (2019) will be assumed. Authors proposed a risk-transmission model where the dependence among companies' risks along the supply chain is given by material, components or products flows. Indeed, Hosseini and Ivanov (2019) model the supply chain disruption path from an upstream supplier *q* to the following tier *r* as the consequence of materials flow from supplier *q* to supplier *r*. Following the internal interrelationship of risks described above, it produces a conglomerate of cause-effect events, leading to default events as ultimate consequence. From this point of view, in this methodology the losses generated by supply chain companies can be interpreted as the "impact" of the operational risks.

4.4. Marginal and conditional probabilities

In this section, data related to the risk event occurrence for both root events (i.e., marginal probabilities) and the intermediate or leaf nodes (i.e., conditional probabilities) are presented. In particular marginal and conditional probabilities for raw material supplier 1 (i.e., RM1) and manufacturer 1 (i.e., M1) have been collected from the work of Punyamurthula and Badurdeen (2018). It is important to state that the paper models both delivery risks and OEE with truncated normal distribution. However, they also present mean as reference, which allowed to consider such value as input for the present model. The same consideration has been done for OEE risks. As the other branch (i.e., RM2 and M2) has been assumed to follow the same internal processes of RM1 and M1, conditional probabilities for internal and leaf nodes have been maintained the same in the example of Punyamurthula and Badurdeen (2018). However, since RM2 and M2 operates in a different division, risks affecting that part of supply chain assume, reasonably, different probability values. To this end it has been considered the paper of Cano-Olivos et al., (2022) which estimates probability values for the Mexican automotive industry, and it will be accounted as marginal probabilities. In particular, delivery risks, raw material shortage and production capacity have been collected by the survey of Cano-Olivos et al., (2022). Operational risks for assembly process company have been derived from the work of Ju and Pan (2016). To consult values of marginal probabilities and conditional probability tables just mentioned for the example, the reader can refer to Appendix A.

The conversion of some data described above reflects the need to fit probability values to the Bernoulli distribution in order to populate the Bayesian network, which will be described in section 4.5. In fact, this modelling approach assumes the risk event can have two states: presence of risk event (with probability p) or absence of risk event (with probability 1-p). Instead, the loss occurring as consequence of firm default is function of the risk event occurrence to whom it is connected. Such risk event will be named critical risk or critical node in this framework. This means that after risk occurrence, the loss is sure. On the other hand, the absence of risk has no consequence in terms of loss. For instance, the loss function for a given node x dependent on the risk event E can be mathematically expressed as in equation (4.1):

$$L_x(E) = \begin{cases} 1000 & \text{if E} = \text{occurrs} \\ 0 & \text{if E} = \text{does not occur} \end{cases} \tag{4.1}$$

However, the risky event on which the loss function depends is a random variable. Thus, the loss function can also be interpreted as a random variable as well.

Of course, in real case studies, expert opinion on the interdependence of risks as well as the sampling of probability values remains an essential guide for a correct modelling approach. Other studies acquire graph structure of BN trough machine learning techniques or heuristic approaches such as local greedy search (Hosseini and Ivanov, 2021). The traditional probability estimation method adopted in literature is the frequency as the ratio between the event occurrence number over the total number of cases during a fixed timespan (Neapolitan, 2003). Given the great background specificity in which each supply chain is embedded, it implies that experts and stakeholders' opinion directly involved in activities remains an unavoidable source of knowledge (Pitchforth et al., 2013). Therefore, questionnaires and interviews could facilitate the process of data collection. Prior probability values can be collected from specific performance indicators previously used to establish a correct cause-effect relationship between events (Rabbi et al., 2020). In some parameter modelling approach, probabilities are instead entered by developing recovery timelines over the subsequent period following an event occurrence (Lawrence et al., 2020). Shi and Mena (2021) suggest using operational and financial performance measures while, again, relationships between risky events can be estimated through expert opinion. Qazi and Simsekler (2021), suggest developing three versions of the same Bayesian network introducing different probability values according to the worst, expected or most likely and best scenario.

4.5. Bayesian network construction

To implement the Bayesian model and to evaluate posterior probability values along the network, it might be useful to adopt a commercial software. Software tools allows not only to evaluate posterior probability values but also to perform additional analysis such as sensitivity and strength of influence analysis, or to run simulations. BUGS, Java Bayes, Hugin or BayesiaLab are some examples of online downloadable software. In the present study, GeNIe 4.0 Academic version software has been used. Its intuitive interface grants a quick usage, even in case of complex networks.

After modelling the risk structure described paragraphs 4.3 and 4.4 and entering the probability values from Appendix 1, it is possible to run the model and observe its behaviour. The result obtained in this case can be seen in Figure 4.6.

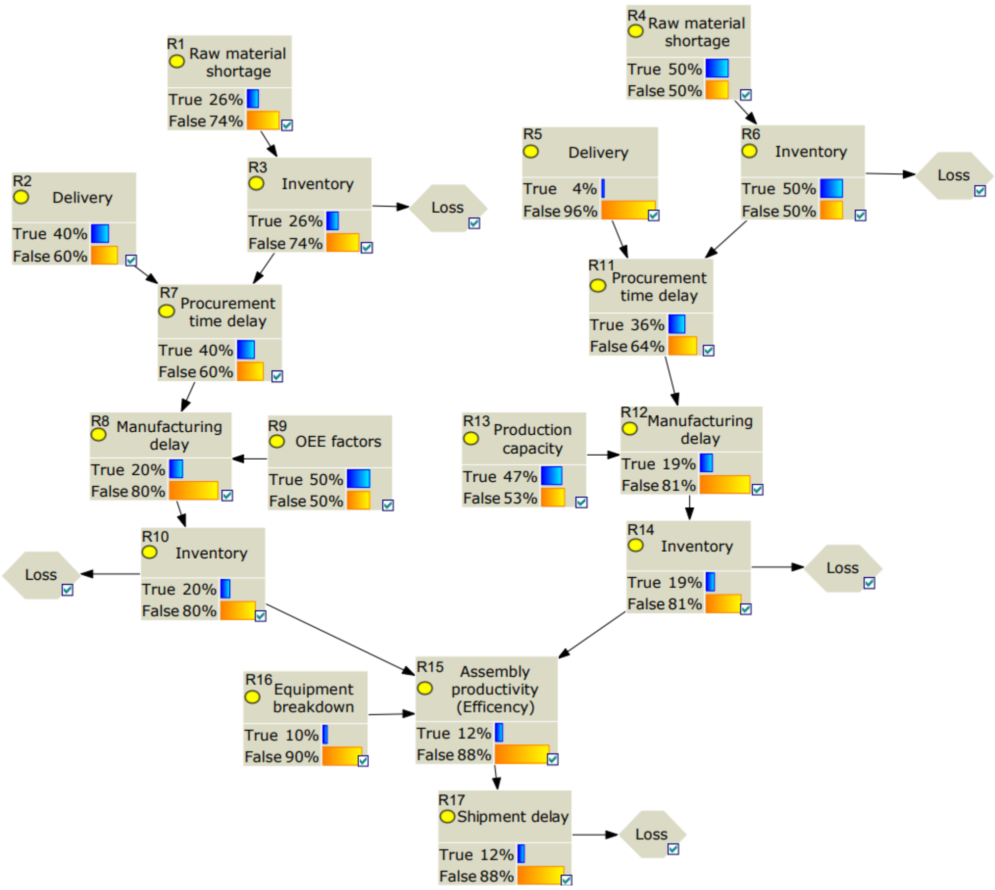

Figure 4.6. Bayesian network model developed with GeNIe 4.0 Academic version.

As can be seen from figure above, the square elements represent the risk event described as binary random variables. There, it is possible to highlight posterior probabilities for intermediary and leaf nodes. Arcs reflect the cause-effect relationship between these risks. The diamond-shaped elements show the losses associated with the realisation of the individual risk. They allow to assign the loss value (i.e., 1000) in case of critical risk event realisation and to keep a null value otherwise. In addition, risks have been translated with an alphanumerical code.

Looking at the numerical results, it can be seen the delivery risk (R2) is a primary matter of concern for RM1 rather than the raw material shortage (R1). The latter will then influence the inventory risk (R3) that will affect the probability of timely procurement by M1 (R7). Conversely, RM2 faces a higher probability of Raw material shortage (R4) rather than a wrong delivery process (R5), which turns out to be significantly lower than in the previous case. In fact, the probability of procurement time delay (R11) by M2 is lower than what experienced by M1 (R7). The manufacturing delay risk of M1 (R8) shows a 20% probability of occurrence, similarly

M2 face a probability of occurrence of 19% for the same risk (R12). These values directly affect inventories (R10 and R14) which consequently causes a lower yield of the assembly process by A (R15). However, this risk is conditionally dependent from the equipment breakdown rate (R16) which lower the likelihood of occurrence of the previous risk and allows the process to recover efficiency.

4.6. Default-risk profile assessment and credit portfolios

On the basis of the Bayesian network discussed above, and the results presented in Figures 4.6, this paragraph introduce a default risk profile assessment for supply chain companies as well as some credit risk measures such as Value at Risk and expected loss that allow the creditor to choose suboptimal credit allocation solutions among different supply chain debtors. Indeed, this paragraph adopts the creditor perspective, that is not directly involved in supply chain management, but that is interested in introducing a measure that can account for his/her credit riskiness based on the management of internal activities. In order to understand how the interaction of risks has consequences not only within the company but it can negatively affect other supply chain nodes, some credit portfolio cases will be analysed. Formally speaking, the credit portfolio models introduced in this paragraph are those already introduced in section 3.2.1. As such, the lender is interested in understanding how to allocate the overall budget by deciding whether to grant credit to a small set of companies, thus selecting only few of them in his/her portfolio or deciding the amount of credit to assign to each supply chain company (i.e., a certain percentage of the total budget). The cases of portfolio presented in this section allows to identify some heuristics in order to minimise the overall portfolio loss in terms of expected loss and Value at Risk measure.

In the first case, the Portfolio is composed by receivables from two companies not mutually influenced by their operational risks (i.e., M1 and M2). Here, weights of assets allocated to each security are uniformly allocated, $P_1 = (w_{M1}, w_{M2}) = (50\%, 50\%)$. The corresponding loss distribution of such a portfolio can be seen in Figure 4.7.

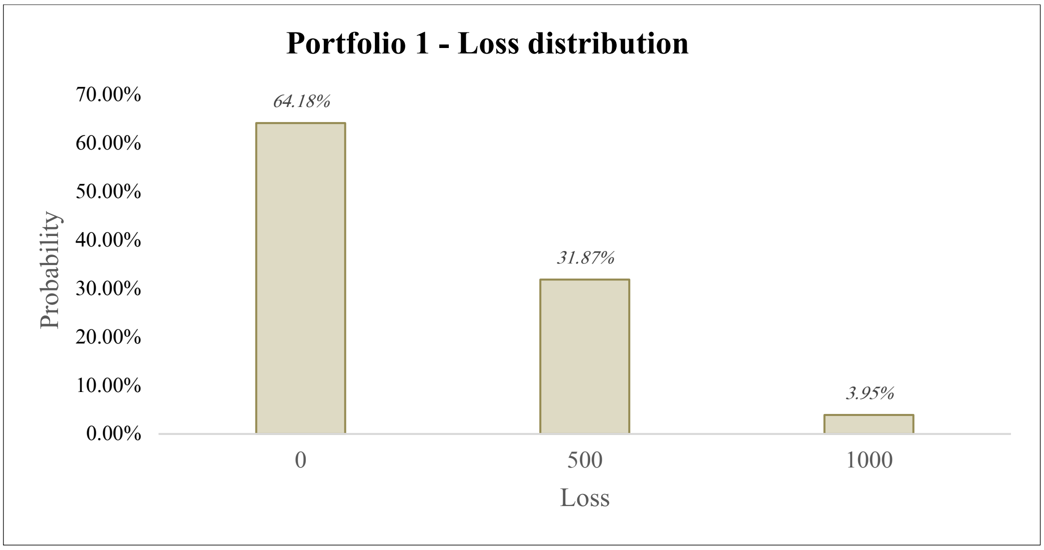

Figure 4.7 Loss distribution for the first portfolio P_1 scenario

Analysing the distribution, it shows that the portfolio has an expected loss of 198.8. At the same time, the Value at Risk (VaR) for this case, at a confidence value of both 90% and 95%, is 500. These measures show a high-risk profile for this portfolio. The holder of the portfolio should allocate the budget more wisely in order to minimise potential losses derived by debtor insolvency. Now, suppose a second case of a portfolio consisting of three securities, instead of two. This new portfolio will be composed by debts from RM1, M1 and M2. As before, also in this case the weights allocation strategy remains the same (i.e., weights are distributed uniformly for each security), $P_2 = (w_{RM1}, w_{M1}, w_{M2}) = (33\%, 33\%, 33\%)$. The corresponding loss distribution for P_2 is shown in Figure 4.8.

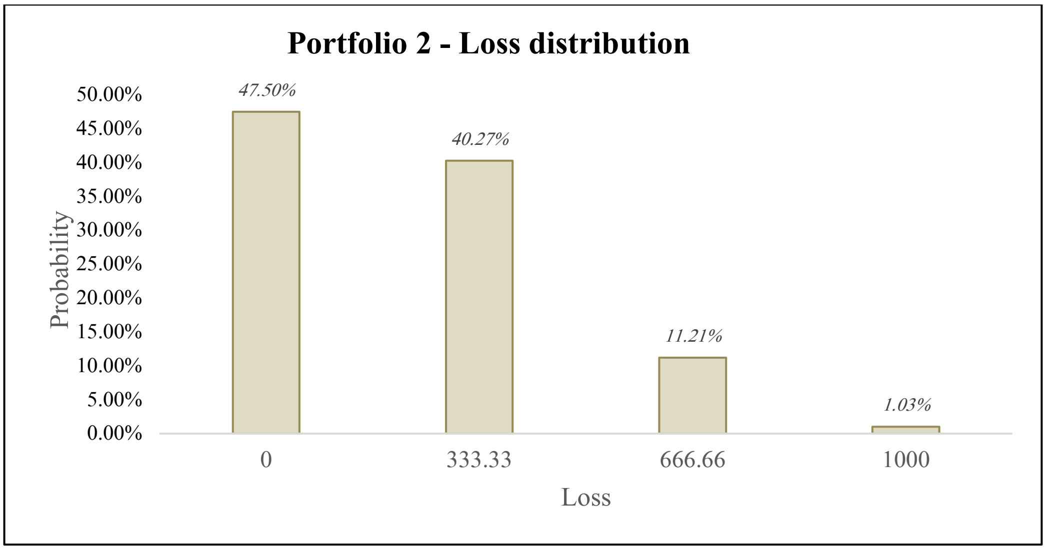

Figure 4.8 Loss distribution for portfolio scenario P_2

As can be seen from the distribution analysis, this portfolio shows worse credit risk than in the previous case. This assumption is confirmed by the relative risk measures: the expected loss accounts a value of 219.2 compared to 198.8 of P_1, while the Value at Risk, which is again equal for both confidence intervals, reported a value of 666.7. It is now clear that the risk profile of RM1, which has not been previously included, raise the loss values of the portfolio. The latter asset shows an expected loss value of 260. In the light of these considerations, let us assume a third scenario in which debit from RM1 has been replaced with another less risky security. The portfolio holder could adopt a credit risk mitigation strategy by substituting a risky asset with a less risky one, while keeping equal relative weights for each security (i.e., 33% allocated to each of them). At this point it is obtained a portfolio $P_3 = (w_{M1}, w_{M2}, w_A) = (33\%, 33\%, 33\%)$. The loss distribution is shown below (Figure 4.9).

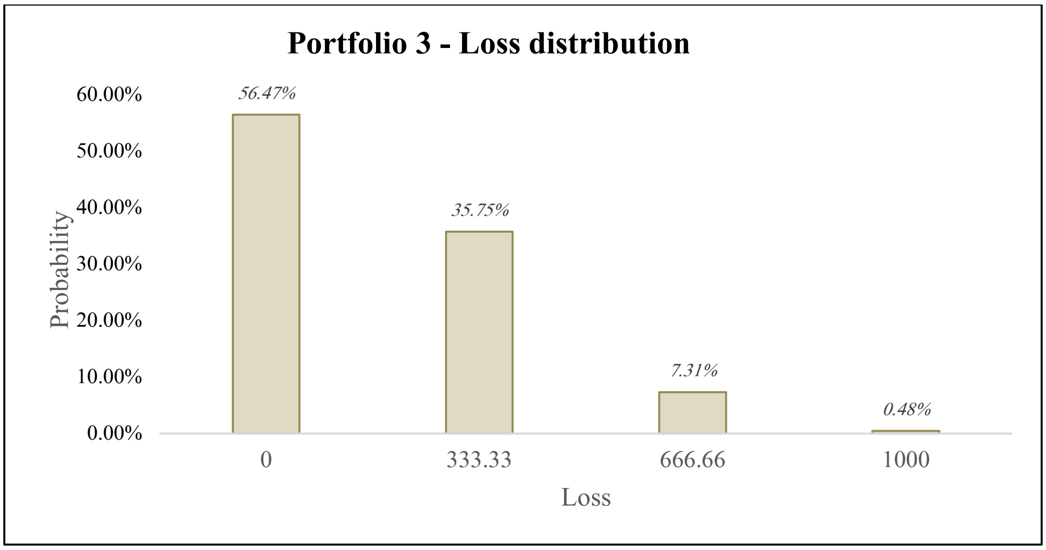

Figure 4.9 Loss distribution for portfolio scenario P_3

The risk measures already adopted for other portfolios confirm what stated above: it shows less risk in terms of credit. The expected loss is now equal to 172.6, the Value at Risk at 90% is 333.3, while the same measure at a level of 95% is equal to 666.7. Therefore, it has been enhanced the situation of the portfolio. Similarly, another strategy could update the relative weights of assets based on company's relative riskiness, and not by their mere replacement. To this end, it is possible to introduce a heuristic for the expected loss of individual companies. A possible solution could be to calculate the relative weight based on the probability of default of one firm with respect to the other in the portfolio as shown in equation 4.1.

$$w_i = \frac{P_i[E_i = True]}{\sum_{k=0}^{N} P_k[E_k = True]} \tag{4.1}$$

Where w_i is the relative weight for asset i, N is the set of assets to include in the portfolio and $P_k[E_k = True]$ the probability that every risky event of firm $i, k \in N$ occur. However, equation 4.1. would bring to misleading results since the security from the riskiest firm would have the highest budget allocation. Instead, the objective of the creditor is the opposite: the riskiest firm must have the overall lowest budget allocation. Such problem can be solved by substituting the expected loss with its inverse.

$$w_i = \frac{\frac{1}{L_i}}{\sum_{k=0}^{N} \frac{1}{L_k}} = \frac{1}{L_i}\left[\sum_{k=0}^{N} \frac{1}{L_i}\right]^{-1} \quad (4.2)$$

Where w_i is the relative weight for asset i, N is the set of assets to be included in the portfolio with L_k as expected loss for every $i, k \in N$. This study deals with Bernoulli distribution where the loss value occurs only in the case of a risky event and does not occur in the opposite case. However, equation 4.2 can be applied for every probability distribution either discrete or continuous including different levels of losses.

In the light of these considerations, it is possible to review all the previous portfolio scenarios, by adopting the weights calculation procedure shown in equation 4.2, in order to check the effectiveness of this heuristic. Let introduce again the case of portfolio 1, where the loans granted to M1 and M2 were allocated. By introducing equation 4.2, the weights will be then 48.5% of the overall budget to M1 and 51.47% to M2. In other words, the new portfolio $P_4 = (w_{M1}, w_{M2}) = (48.5\%, 51.5\%)$. The loss distribution for this scenario is shown below (Figure 4.10).

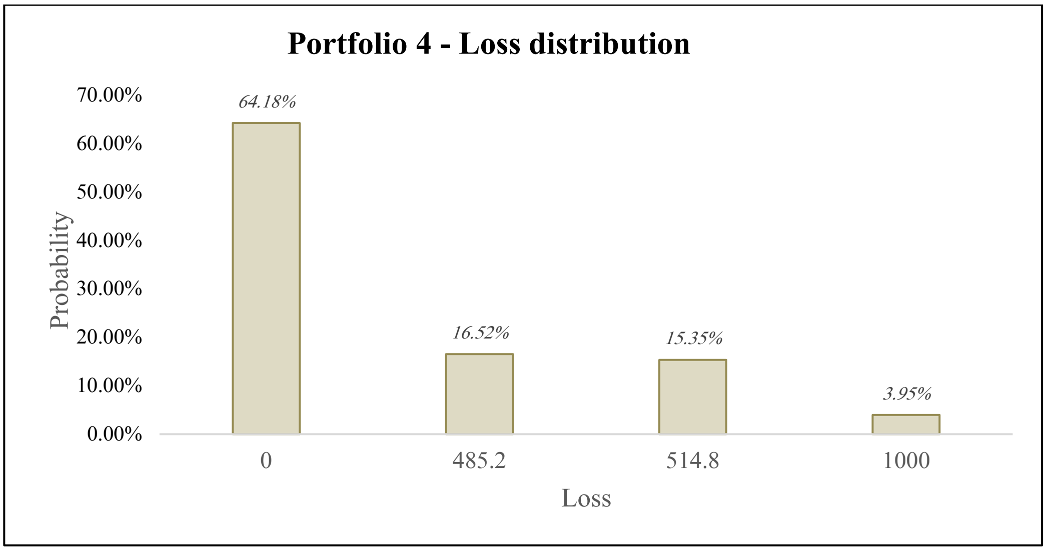

Figure 4.10 Loss distribution for portfolio scenario P_4

The expected value of the loss distribution is equal to 198.65 compared to 198.82 in the previous case. However, the VaR shows higher values with respect to portfolio 1: in this case, either considering a confidence interval of 90% or 95%, the VaR is equal to 514.7, while it was 500 in the previous case. The explanation lies in the fact that Bayesian network are dealing with discrete distributions, whose relative VaR values require approximations to the nearest upper integer, as already illustrated in Chapter 3. A similar process can be adopted to evaluate portfolio 2 again, which included debt from RM1, M1 and M2. Using equation 4.2 it is possible to find again the relative weights. In this case $P_5 = (w_{RM1}, w_{M1}, w_{M2}) =$ (27.64%, 35.11%, 37.25%). In Figure 4.11, the loss distribution of this portfolio is shown.

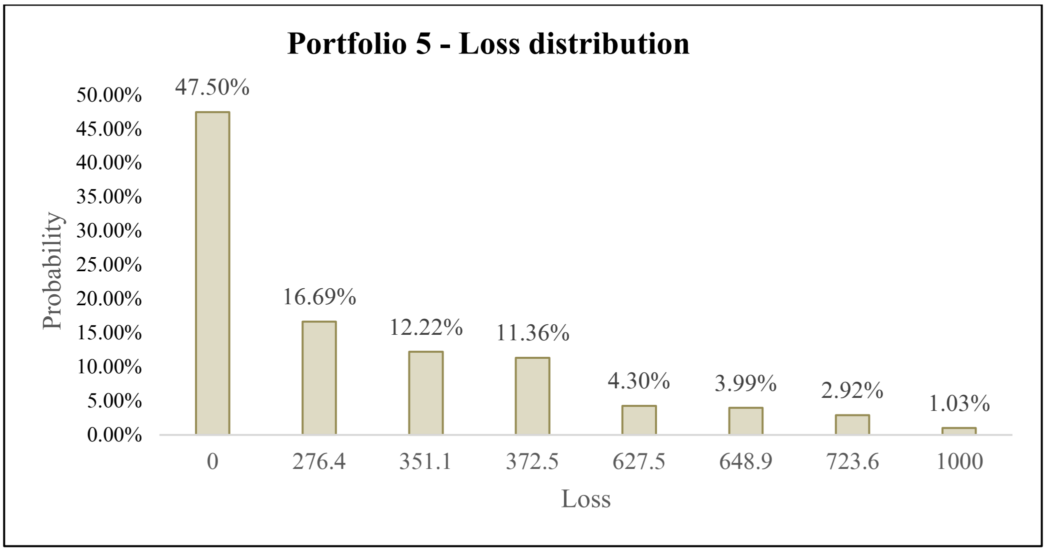

Figure 4.11 Loss distribution for portfolio scenario P_5

With weights adjustments, the expected loss is now equal to 215.61 compared to 219.2 calculated with uniform weights for each security. At the same time the Value at risk at 90% is equal to 627.5, while considering a confidence interval of 95% it has been obtained a value of 648.9. In this scenario, a clear improvement in the credit risk profile of the portfolio can be appreciated. This suggests that, given a portfolio, not only the choice of the assets themselves represents a crucial point, but also the criterion for allocating the quantities rise different scenarios of riskiness. Finally, the calculation of portfolio weights by means of equation 4.2 for the third scenario (i.e., portfolio 3). It should be remembered that the portfolio was previously composed by equal weights on M1, M2 and A. Following the calculation, it is obtained an allocation of weights as $P_6 = (w_{M1}, w_{M2}, w_A) =$ (26.58%, 28.19%, 45.23%). Figure 4.12 shows the loss distribution.

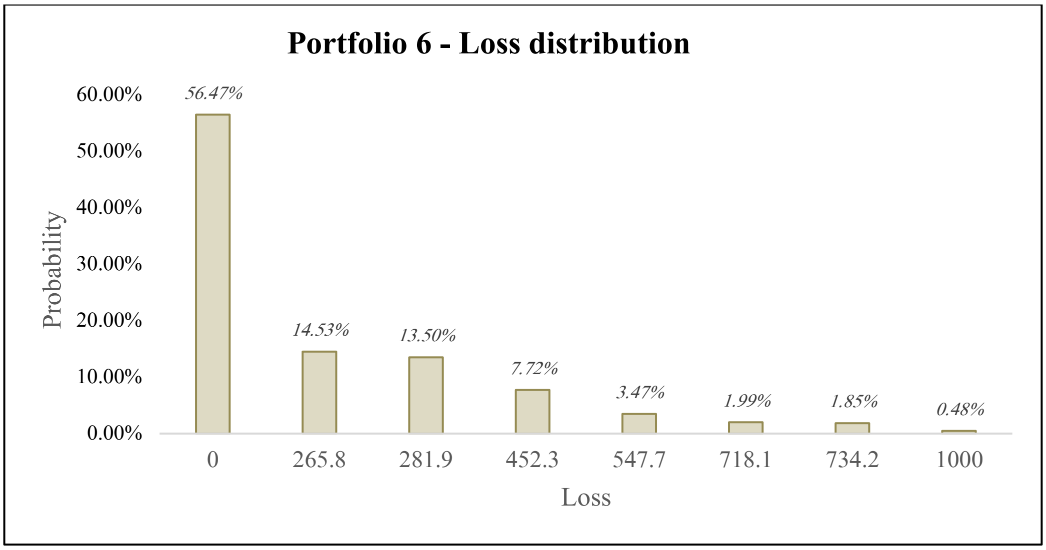

Figure 4.12 Loss distribution for portfolio scenario P_6

It should be remembered that in the previous case (i.e., portfolio case 3), where all the weights have been equally allocated to each security, it has showed the lowest risk profiles in terms of Expected loss and Value at Risk among all the previous portfolios. In this case, the expected loss of P_6 is equal to 163.2 compared to 172.6 of the previous case (P_3). Therefore, also for this portfolio it is possible to appreciate considerable improvements in terms of expected loss minimisation. The Value at Risk at 90% is equal to 372.5 while at 95% it is equal to 627.5. In the third scenario these values were equal to 333.33 and 666.7 for a confidence interval of 90% and 95% respectively. In general, all the portfolios for which heuristic introduced in equation 4.2 has been applied, a better risk allocation both in terms of expected loss and of Value at Risk have been observed. Based on the available data about probability of loss associated with the occurrence of operational risks, it is possible to appreciate how creditors can consciously build portfolio based on the risk profile of supply chain companies. Both the reasoning adopted in the building process of credit portfolios and the heuristics for the choice of weights introduced in this paragraph, do not allow to find optimal solutions. In future, it might be interesting to introduce optimisation methods that can minimise risks on the basis of available data. For example, it could be useful to adopt optimization techniques to minimize Value at Risk (Larsen et al., 2002) or the risk measures such as Conditional Value at Risk (CVar) as suggested by Andersson et al., (2001).

4.7. Risk mitigation strategies

In supply chain management, risk mitigation strategies represent managerial actions aimed at minimizing the impact of risks or their probability of occurrence. Risk mitigation strategies can be divided in two basic categories: proactive and reactive strategies. The purpose of proactive strategies is to reduce the probability of occurrence of risks in advance with respect to a certain unplanned event. On the other hand, reactive strategies allow to manage the supply chain capacity following the occurrence of a given risk (Sharma and Bhat, 2012). This thesis will deal with the case of preventive strategies as they can be used by managers to evaluate the reduction in the probability of occurrence of risks over a certain period of time. Indeed, reactive strategies are not aimed at diminishing the probability of occurrence of risks but rather to recover the overall supply chain operativity following the occurrence of a certain disruptive event. In other words, these measures can either reduce the probability of occurrence of risks (Tuncel and Alpan, 2010; Dehdar et al., 2018) or limit their impact on the supply chain (Sharma and Bhat, 2012; Cano Olivos et al., 2022). In this study, risk mitigation strategies are intended to be the set of measures necessary to reduce the occurrence of operational risks in supply chains, whose impact is concretised over the financial status of the company. In the light of what has been discussed in previous chapters, the introduction of risk mitigation strategies allows not only to reduce the probability of occurrence of risks directly affected by the action of such strategies, but they can also benefit the subsequent probability of occurrence of intermediate and child nodes, as consequence of Bayesian network structure and conditional probabilities. In a real methodology development, the decision whether to mitigate a certain risk is strictly dependent on the type and nature of such event, as they can produce different effects (Çıkmak and Ungan, 2022). Despite the introduction of risk mitigation strategies to the example showed in this thesis is not possible, some of the strategies mostly developed by literature in the automotive sector can be illustrated.

On the procurement process side, Thun and Hoenig (2009) state that multiple procurement sourcing allows to ensure the delivery of parts in case one of them fails in the supply process. Therefore, a broad portfolio of suppliers, where some of them guarantee a material supply in case of failure of another supplier, is an important risk mitigation strategy (Dehdar, et al., 2018) for manufacturing and assembly companies as it allows to run internal operations and to avoid interruptions. This has been confirmed by Sharma and Bhat (2012) which state that dependency of firms with their suppliers might cause disruptions, while a closer relationship can increase efficiency. In particular, a flexible procurement process has the ability to adapt procurement needs in order to follow changes in customers behaviour. The term flexibility represents a core part of risk mitigation strategy, as it allows to cope with uncertainty due frequently changing conditions either external or internal to the supply chain (Çıkmak and Ungan, 2022). Another important enhancement can be provided by flexibility in production capacity which is the ability to adjust the overall manufacturing production capacity in terms of resource utilisation. In this sense, information related to change in national and internal market as well as their continuous updating process represents a fundamental mitigation approach (Cano-Olivos et al., 2022) to guarantee manufacturing and assembly companies a match between supply and demand. Indeed, operational flexibility allows firms to react in case of such circumstances: this could be achieved through the introduction of a multifunctional workforce or the use of machinery and equipment interchangeably, allowing an adaptation of production processes to demand variability (Çıkmak and Ungan, 2022). Inventory holding is another key risk mitigation strategy, even if this practice is often considered undesirable and avoided by automotive companies (Çıkmak and Ungan, 2022). An inventory-related risk management strategy is the creation of buffer inventories for critical parts in order to prevent supplier delays, while reducing the impact of disruption. Inventory safety stocks allows to create redundancies (Thun and Hoenig, 2009), that are the processes of keeping additional stocks in order to guarantee operations continuity in case of lack of raw materials, defective parts or changing demand (Dehdar, et al., 2018). On the demand side, a standardise delivery times with companies' customers (e.g., cars dealers, distributors or for suppliers, manufacturing companies) might enhance the process of order fulfilment and mitigate demand variability. Cano-Olivos et al., (2022) state that knowing the demand forecasting process as well as the planning horizon of forecast can provide benefits on the demand side. Flexibility can also improve the strategic process of goods transportation: it allows to reduce overall costs of shipping goods and raising transportation capabilities. Multimodal transportations represent an effective method to provide flexibility. This practice can be integrated by adopting different transportation providers and alternative routes (Çıkmak and Ungan, 2022).

As previously said, the case study does not allow to introduce risk mitigation strategies and to measure their effectiveness on the supply chain risk management process. However, to illustrate Bayesian network effectiveness in managing and monitoring mitigation strategies, an example from a methodological point of view can be now presented. In particular it is supposed that, following a certain risk mitigation strategy, from managers of RM1, the risk occurrence of delivery issues becomes 24% with respect to the 40% introduced in the standard scenario (Figure 4.13).

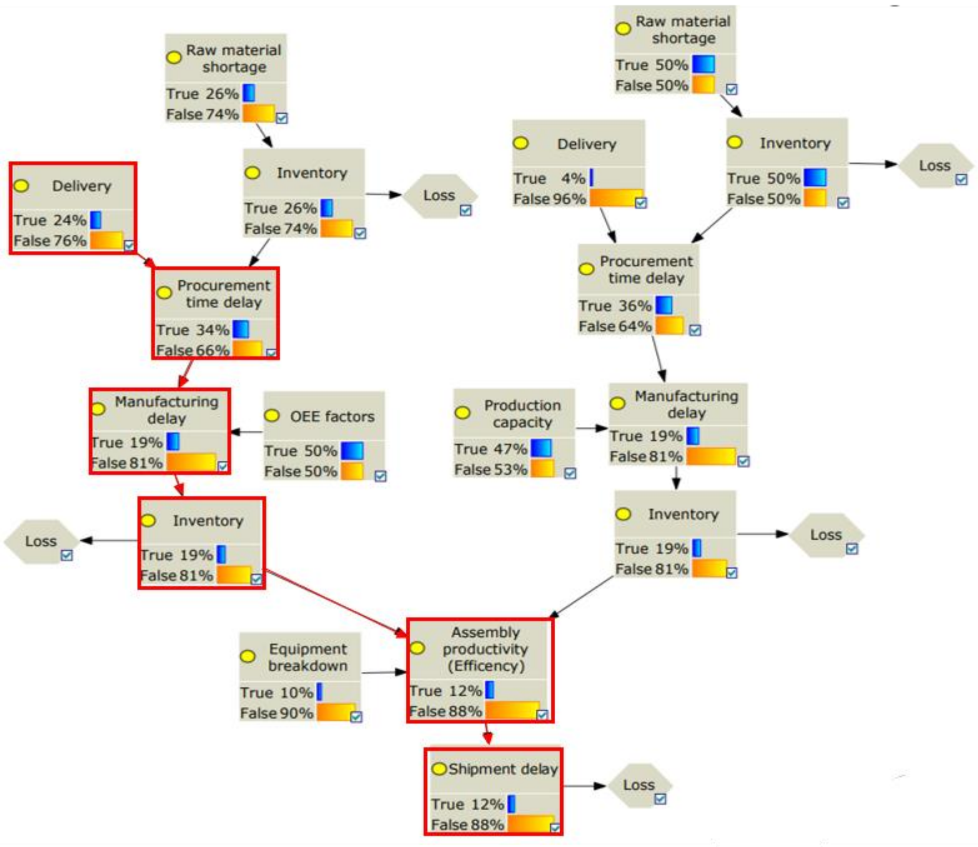

Figure 4.13 The Bayesian network after the introduction of the mitigation strategy.

The beneficial effects of this improvement are appreciable on the subsequent risk probability of occurrence of M1 which reports a lower probability of default: procurement time delay risk becomes 34% with respect to the 40% of before, while inventory risks occurrence was 20% but now they show a probability of 19%. In addition, both the assembly productivity (efficiency) risk and shipment delay probability at the assembly tier are now 11.72% with respect to the 12.13% before introduction of the mitigation strategy. These improvements can be observed in terms of credit risk as well. In this regard, consider the example of portfolio 5 illustrated in paragraph 4.5. This portfolio was made up of credits to RM1, M1 and M2 and the weights related to this scenario have been calculated using equation 4.2. Since the operating conditions have changed, the weights mentioned above need to be evaluated again, by adopting the same logic as before. It follows that the new credit portfolio will be $P_7 = (w_{RM1}, w_{M1}, w_{M2}) =$ (21.93%, 29.42%, 48.63%). Figure 4.14 shows the loss distribution for this scenario.

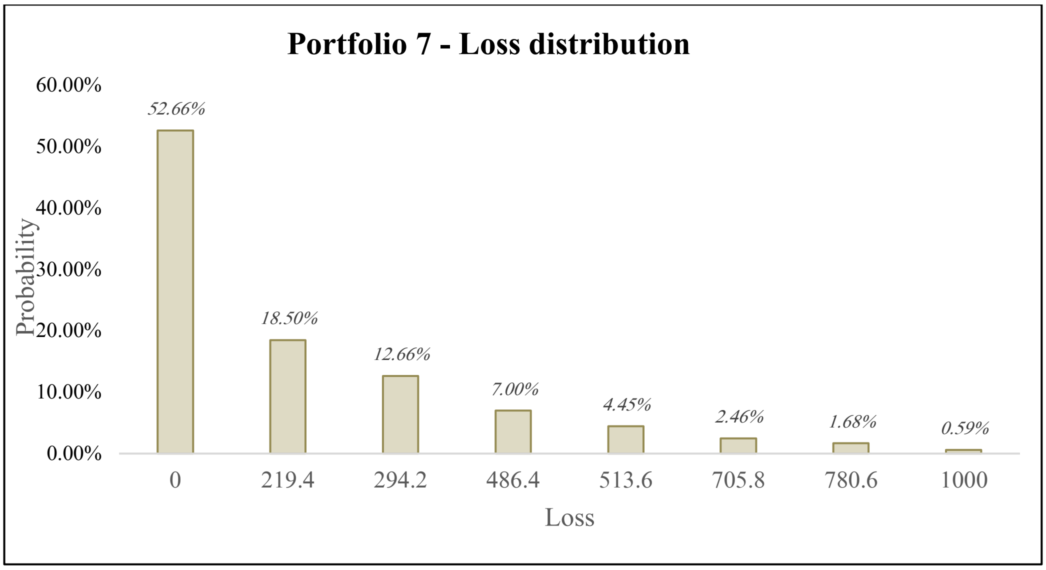

Figure 4.14 Loss distribution for portfolio scenario P_7

From this portfolio analysis it follows that the expected loss is now equal to 171.10 with respect to the 215.6 shown in P_5. In other words, the risk mitigation strategy led to a reduction in the portfolio expected loss of the 21%. At the same time the Value at risk at 90% is equal to 372.5 while it was 627.5 in P_5. With a confidence interval of 95%, the VaR is now 627.5 whereas in P_5 it has been obtained a value of 648.9. Under every risk measure, the mitigation strategies showed an enhancement in the portfolio losses. It has been proved that even external creditors can benefits from the adoption of supply chain risk mitigation strategies.

In conclusion, it can be said that this methodology could also be used to understand how best to deploy risk mitigation strategies in order to minimise the disruption effects along the supply chain. In fact, the Bayesian network structure can be exploited to regularly update the probability conditions, both marginal and conditional, of risks occurrence and to appreciate their effects in the long run. On the other hand, the effect of risk mitigation strategies can also be observed on the probability of default of companies placed along the distribution chain, as these can guarantee, in a preventive manner, a smooth execution of operations, minimising the occurrence of risks.

5. CONCLUSIONS

The purpose of this last section is to summaries the main findings of this work and their implication on the academic and managerial perspective. Since this is a theoretical study, it is affected by some limitations either from a modeling perspective and, consequently, also from the point of view of its predictive capacity. For this reason, the work is open to future deepening and improvement, briefly outlined in section 5.3.

5.1. Academic and practical implications of the work

This work has shown how the inter-dependency between risks can have effects on the occurrence of other disruptive events along a multi-tier supply chain: an internal operation performance measure monitoring the actual impact of risks is not sufficient to provide an overall prediction of the company's financial distress as risks can be conditionally dependent. Despite its limitation from a modeling point of view, this work can contribute to literature in the supply chain management field in two ways: first, it confirms the importance of information sharing to better understand potential risks and opportunities related to typical supply chain business agreements. In this sense, it confirms what stated in Badurdeen et al., (2014), where authors underline the need of a better collaboration between network companies and their suppliers in order to identify risks in advance and improving the reliability of supplies. This consideration is even more important when one considers that supply chain companies are often contractually bounded by supply chain financing modes as well: a greater information sharing can enhance the willingness of members to introduce SCF contracts, on the basis of the risks. Thanks to the mathematical rigorousness provided by Byesian networks, the methodology may indicate to managers how to focus risk mitigation efforts so as to guarantee operational continuity and avoiding debt-repayment insolvency events. Out of the supply chain, this model can be used by creditors, mostly interested in knowing the actual probability of default of supply chain companies given the riskiness of internal operations. Indeed, default measures introduced to evaluate risk profile of debtors, rarely consider operational aspects that can enhance the predictive ability of default models. In addition, the risks measure that have been introduced to evaluate the risk of credit faced by external creditors (i.e., loss distributions, expected loss or Value at risk) are widely used in finance, thus allowing an easy adoption in case of real applications. Value at risk estimated within a probabilistic setting is also able to capture the overall risk of a supply network, which would not be caught in case of point estimations as they do not capture the loss distributions (Qazi and Simsekler 2022). In this sense, the thesis has introduced a double perspective on the supply chain risk management field: operational and financial risks have been integrated in a cause-effect relationship.

Considering the modeling approach, Bayesian networks represent a powerful tool, that is able to catch the interdependence between risks along several nodes of the network, even in case of little data availability (Pitchforth and Mengersen, 2013). By means of conditional probabilities, BNs carries out additional information with respect to classical risk assessment approaches, which usually relies on the concept of probabilities and impacts. In fact, one of the many advantages of BNs in this thesis is represented by its modeling capacity in case of heterogeneous data and few information at hand. For this reason, they can be nimbly introduced into business practices, without resorting to overly laborious analysis, since most of the software currently available on the market allows an accessible representation of Bayesian networks. In addition, the risk structure developed in this thesis can be populated with different probabilities values depending on the nature and context of application, and regularly updated in order to observe real effects of supply chain risk mitigation strategies.

5.2. Limitations

As a natural consequence of many other studies, this methodology is affected by limitations. First of all, it is necessary to mention the scarcity of data available from the literature, business, or industry reports, which did not allow to elaborate a more comprehensive example, including additional risk sources. On the other hand, this consideration confirms the fact that the risk modelling approach, by means of Bayesian networks, and their consequences over the financial point of view is still an underdeveloped research topic. If the academic side revealed undeniable difficulties in the development of the case study, this limitation can be overcome when dealing with a real case implementation. In fact, the probability of occurrence of risks can be easily calculated from expert judgement or historical data. However, the methodology assumes that both risks and probability values of each company in the chain are perfectly known and regularly updated. On the other hand, a risk mapping process accounting for internal company risks only represents a partial solution to the problem, as it limits the decision-making ability of managers in adopting the appropriate risk mitigation strategies. From a financial point of view, it is clear that the amount of information available to potential external creditors does not allow for a complete representation of loss distributions. The first reason, already experienced in the development of the thesis, lies in the fact that much of the information is confidential and therefore not released to stakeholder outside the company (Qazi et al., 2015). It must be also emphasized that the methodology is not capable to fully represent the probability of default of a company, even in the rare case of perfectly known probabilities. This is due to the fact that many other factors play a crucial role in assessing the financial risk of a corporate. In this regard, the model, accounts for business riskiness in terms of its operational management and do not consider other source of financing mode which might be included in case of future applications.

From a methodological point of view, only a few operational risks have been included in the work due to the difficulty in defining both conditional probability values and risk dependence for a specific industry. Although this methodology can be adopted in any industry, regardless of the structure of the supply chain, the nature and type of risks illustrated in the thesis is purely specific to the automotive industry context. Indeed, the structure of the Bayesian network, as a measure of risk interdependence, is related to the type of supply chain of interested and there can be no general scheme to draw on (Shi and Mena, 2021). As mentioned in other chapters, this thesis only considers the downstream ripple effect as a mode of risk transmission process, ignoring the upstream transmission modes, which typically affects information flows (Cao et al., 2022). This aspect represents an important limitation of the study since risks related to information flows might affects supply chains with equally dramatic consequences. Furthermore, this study does not model upside potential risks that could improve the predictive ability of the model. Operational risks have been modelled using binary variables, thus losing much of the information that would have been gathered using different distributions depending on the nature of the risks (Hosseini and Barker, 2016).

In addition, the interaction between financial risks has been ignored. It is also necessary to emphasize that an optimal portfolio in terms of minimum risk has not been introduced. As a consequence, the introduction of heuristics in the choice of weights leads to sub-optimal solutions that could be improved with appropriate optimization approaches.

5.3. Future research

This section defines possible future research developments by highlighting their benefits under both the modeling and application point of view. Therefore, future research could focus on the development of other case studies, where data are collected by means of questionnaires and interviews to managers and databases about past risk occurrence. Risk mitigation strategies could be included in the methodology in order to test its effectiveness in predicting and monitoring risk occurrence. At the same time, it could be worth to introduce other risky events, out of the operational scope, in order to increase the representative capacity of the model. For example, Environmental risks (e.g., natural disasters, pandemic etc.), economic (such as price volatility, change in exchange rate, inflation etc.) political (related to the country legislation) can be included in the model. Although identifying the right dependency between these categories could not be an easy task, some authors have attempted to include these risks in studies of supply chain management (Lockamy and McCormack, 2012; Badurdeen et al., 2014; Lockamy III 2018; Philip et al., 2021; Badhotiya et al., 2022). At the same time, another future improvement of the work can include other risk transmission processes related to information or financial flows from downstream supply chain firms to upstream companies. This would allow to study other contagious modes as in the case of the bullwhip effect. To comply with the choice of an optimal portfolio in terms of minimum credit risk, future research could introduce optimization techniques in order to find optimal solutions rather than portfolio construction by means of heuristic techniques in the choice of the weights. For example, optimization techniques which include the minimization of the Value at Risk (Larsen et al., 2002) or through other risk measures such as Conditional Value at Risk (CVar) as suggested by Andersson et al., (2001).

Under the methodological perspective, a possible future line of research could model risk events by means of other probability distributions, different from the

Bernoulli variables to model probabilities of occurrence, depending on the type of risks described at the beginning of paragraph 5.1. Variables with different distributions, either discrete or continuous, could describe more accurately the probability of occurrence of risk events. For example, the probability that a product delivered by the supplier is defective can be modelled with a Beta distribution (Hosseini and Barker, 2016). Of course, the risk events modelling approach trough continuous random variables raise the difficulties of the problem: the management of conditional probabilities within the Bayesian network requires a discretization of the states. Another further improvement could include the modelling approach of a dynamic version of Bayesian networks (i.e., Dynamic Bayesian Networks – DBN) to model system behavior as both internal and external conditions change over time. Mitigation strategies can be included in the Bayesian network model as network decision nodes in order to allows managers in the subsequent selection of the proper risk mitigation strategy. To facilitate the integration of this methodology with typical risk management identification processes, it could be useful to adopt risk matrix to collect data used in the subsequent creation of the quantitative model (Qazi et al., 2022). Thanks to the availability of commercial software that can be easily introduced in real applications, it might be possible to adopt further statistical analyses such as sensitivity analysis or strength of influence. For example, the sensitivity analysis allows to analyze which variables have a predominant impact on another variable of interest (Hosseini and Ivanov 2019; Shi and Mena 2021).

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APPENDIX A – Conditional probabilities table

For each risk described in the example shown in Figure 4.6, conditional probabilities tables are presented.

PARENT NODES																	CHILD NODES																																	
R1	R2	R3	R4	R5	R6	R7	R8	R9	R10	R11	R12	R13	R14	R15	R16	R17	R1		R2		R3		R4		R5		R6		R7		R8		R9		R10		R11		R12		R13		R14		R15		R16		R17	
																	T	F	T	F	T	F	T	F	T	F	T	F	T	F	T	F	T	F	T	F	T	F	T	F	T	F	T	F	T	F	T	F	T	F
																	0.3	0.7	0.4	0.6																														
T																					1	0																												
F																					0	1																												
																							0.5	0.5	0	1																								
			T																								1	0																						
			F																								0	1																						
	T	T																											0.7	0.3																				
	T	F																											0.6	0.4																				
	F	T																											0.7	0.4																				
	F	F																											0.1	0.9																				
						T		T																							0.4	0.6																		
						T		F																							0.2	0.8																		
						F		T																							0.2	0.8																		
						F		F																							0.1	1																		
																																	0.5	0.5																
							T																												1	0														
							F																												0	1														
				T	T																																0.7	0.3												
				T	F																																0.7	0.4												
				F	T																																0.6	0.4												
				F	F																																0.1	0.9												
										F		T																											0.2	0.8										
										T		F																											0.2	0.8										
										F		F																											0.1	1										
										T		T																											0.4	0.6										
																																									0.5	0.5								
											T																																1	0						
											F																																0	1						
									T				T		T																														1	0				
									T				T		F																														1	0				
									T				F		T																														1	0				
									T				F		F																														0.2	0.8				
									F				T		T																														1	0				
									F				T		F																														0.1	0.9				
									F				F		T																														0.1	0.9				
									F				F		F																														0	1				
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														F																																			0	1
														T																																			1	0