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ORIGINAL PAPER

THE EFFECTS OF DEMAND PLANNING ON THE NEGATIVE CONSEQUENCES OF OPERATIONAL RISK IN SUPPLY CHAINS

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ABSTRACT. **Background:** Although extant studies have highlighted the importance of specific demand planning practices in risk mitigation, there is a scarcity of research that shows the simultaneous effects of demand planning practices on the disruptions induced by operational risks in supply chains. In order to reduce this gap, this paper aims to explore the impact of the demand planning process on operational risk, and thereby reveal if operational risk factors and their negative consequences may be mitigated through the application of specific demand planning practices in supply chains.

Methods: The study involves two stages of multivariate statistical analysis. In stage one, independent and dependent variables are reduced through factor analysis in order to highlight the main, underlying, multi-item factors. In the second stage of the study, a multiple regression analysis is conducted to compare the general contribution to variance in operational risk accounted for by demand planning practices and their combinations. The conducted analysis provided regression models for particular operational risks.

Results: The study reveals that all activities in the demand planning process contribute more or less to lower operational risk in the examined supply chains. In particular, there are strong relationships between demand planning practices and both control and demand risks. On the other hand, the lesser effects of demand planning may be observed in process and supply risks.

Conclusions: The study shows that different managerial instruments, which are not inherently dedicated to risk management, when appropriately applied, may have an indirect impact on the mitigation of supply chain risk. In particular, the concept of demand planning might be very helpful for managers when dealing with demand and control risks.

Key words: planning process, demand, risk, supply chain.

INTRODUCTION

The demand planning process, as a component of the concept of Sales and Operations Planning (S&OP), encompasses the set of processes and technologies which enable a supply chain to effectively address the issue of supply and demand [Muzumdar, Fontanella 2006]. Extant studies have highlighted the importance of specific demand planning practices in risk mitigation [Blome, Schoenherr 2011, Jonsson, Mattsson 2013, Petropoulos et al. 2014, Blackhurst et al. 2011]. Despite a large body of research on the relationships between individual demand planning practices and risk consequences, there is a scarcity of studies that show the simultaneous effects of demand planning practices on the disruptions induced by risks in supply chains. In order to reduce this gap, the current research attempts to demonstrate whether demand planning contributes to mitigating the consequences of operational risks in supply chains. So as to bridge this gap, we solicited a sample of companies operating in European supply chains. The obtained survey data were then used to perform a multivariate statistical analysis to yield findings and test hypotheses. This paper is

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organized into several sections. Following the introduction, we distinguish major practices in the demand planning process and theoretically justify their hypothesized impact on the consequences of operational risk factors. After developing the methodology, we finally depict empirical findings derived from the statistical analysis, draw conclusions and demonstrate the implications for further empirical research.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Definition of the demand planning process

There are a number of previous studies demonstrating individual practices of the demand planning process. Among them, the strand of research dealing with forecasting practices prevails [Lockamy, McCormack 2004]. Kahn and Mentzer [1996] emphasize that a company ought to be capable of forecasting its market opportunities in order to make demand planning accurate. However, forecasting, though important, is not the sole activity in the demand planning process. There are several other activities of strategic and operational characteristics, including goal formulation, data gathering, demand forecasting, communication of demand predictions and determination of synchronization procedures [Croxton et al. 2001, Crum, Palmatier 2003, Croxton et al. 2008].

The overriding goal of demand planning is to ensure the balance between supply and demand in a supply chain [Croxton et al. 2008]. However, from the standpoint of demand planning, the goal is not principally to generate the sale, but rather to provide a portfolio of the most beneficial clients. The pertinent activities are embedded in the process of physical distribution, especially in its three dimensions of availability, timeliness and delivery quality [Lockamy, McCormack 2004]. Each customer's expectations in these three dimensions may differ. Therefore, the goal of the demand planning process is neither to meet customers' expectations more effectively, nor to serve customers more cheaply, but to offer superior value as a result of a meticulous understanding of market requirements, possible benefits and requisite supply abilities [Juttner et al. 2007]. In other words, the goal of the demand planning process consisting in balancing supply and demand means that the organization advantageously caters to different market requirements with diverse supply chain capabilities.

Data sources used in forecasting usually cover historical data on demand volume or sales, data from production (e.g. production capacity, line loads, current schedules), warehouses (e.g. storing capacity, inventory level), marketing department (e.g. historical and future marketing activities for products and services) and financial records [Tuomikangas, Kaipia 2014]. Data from several sources are then used in qualitative and quantitative demand forecasting [Moon 2013], involving causal models [Cohen et al. 2013], and time series models [Moon 2013]. The use of quantitative methods of forecasting should be extensively supported by computerized applications [Waller, Fawcett 2013]. The following four categories of forecasting are commonly used: software spreadsheets (e.g. Excel), broad-based statistics (e.g. SAS, SPSS, Minitab) – designed to offer a wide range of tools confined into modules – forecasting modules, and business forecasting packages dedicated to forecasting, such as Box-Jenkins, Forecast Pro, Autobox, SmartForecats, and forecasting engines [Snapp 2012]. The completed forecasts should then be transmitted to the other companies in a supply chain and/or other departments of the organization, as they offer essential input for matching customer demand with the firms' supply ability [Croxton et al. 2001]. Finally, the last activity of demand planning is to determine synchronization procedures. Generally, decision synchronization seeks to facilitate a harmonization of planning and decision making between supply chain partners [Simatupang et al., 2002]. As independent decisions may not generate an optimal result, the joint decision-making process produces synergistic benefits for the companies in a supply chain [Lee et al. 1997]. Synchronization requires balancing the demand forecast with the manufacturing, supply and logistics capabilities of the supply chain [Cloxton et al., 2008]. In other words, the synchronization procedures in demand planning cover the identification of a supply chain's operational capacity and flexibility at all points in its structure [Croxton et al. 2001].

The relationships between demand planning and operational risks

Contemporary supply chains are challenged to identify an infinite number of different risks emanating from many sources. The negative effects of risks may be triggered by external or internal risk factors. External risk factors are located outside the supply chain, while internal ones remain within the supply chain [Rao, Goldsby 2009]. In the opinion of Mentzer et al. [2004], internal risk factors in supply chains should be referred to as operational risks. Based on the literature review, we follow a two-dimensional approach while identifying the operational risk factors in supply chains [Cavinato 2004, Christopher, Peck 2003]. The first approach posits that operational risk factors encompass the potential and actual negative consequences in supply and customer demand [Tang, 2006], whilst the second one argues that the group of operational risk factors includes process and control risks [Rapana 2009]. Christopher and Peck [2003] notice that process and control risks are internal to the firm, while demand and supply risks are external to the firm, but internal to the supply chain. Based on this classification, in our study we identify the following operational risk factors: supply risks, demand risks, process risks and control risks.

Supply risk describes disruptions affecting the activities performed in the flow of products, information and money. Accordingly, it deals with the negative consequences of risk occurring in the links located upstream in supply chains. In order to mitigate supply-side risks, upstream supply chain links should establish integrative relationships [Swink et al. 2007]. Consequently, Lin and Zhou [2011] argue that many focal supply chain companies establish long-term partnerships with their suppliers in order to decrease a certain level of supply risk. In the same vein, Donovan [2015] argues that demand planning helps to mitigate supply chain disruptions and costs by reducing demand variability and improving its planning and flexibility upstream in the supply chain. In other words, demand planning efforts put upstream supply chain partners in a better position in order to grasp the requirements of subsequent links, and thus alleviate the negative consequences of risks [Swink et al. 2007]. Therefore, we define the following hypothesis:

H1. The demand planning practices decrease the disruptions driven by supply risks.

Similarly, demand risk is the downstream equivalent of the above, and concerns disruptions to the activities performed in the flow of products, information and money within the supply chain, downstream of the focal firm [Christopher, Peck 2003]. In order to reduce the disruptions caused by demand-side risks, supply chain companies ought to develop integrative relationships with their customers [Manuj, Mentzer 2008]. Consequently, the integration of downstream players into a supply chain is strongly linked to demand planning as it contributes to a greater visibility in sharing information on future demand [Boon-Itt, Wong 2011]. Following the opinion of Giunipero and Eltantawy [2004], we allege that demand planning seeks to reduce risks and their negative effects by strongly integrating inner functions within a focal company and successfully linking them to the outside operations of downstream players in a supply chain. Accordingly, we offer the following hypothesis:

H2. The demand planning practices in supply chains mitigate the disruptions driven by demand risks.

Process risk refers to disruptions in the sequence of value-adding activities undertaken by individual companies in a supply chain. The execution of value-adding activities is usually dependent upon owned or managed assets, as well as on infrastructure. Therefore, both assets and dependability of infrastructure should be carefully considered while analyzing process risk [Christopher, Peck 2003]. Among the concepts that contribute to mitigating the disruptions induced by certain process risk factors is demand planning [Fuchs, Otto 2015]. The link between the negative consequences of risks emanating from the physical operations and selected practices of demand planning is also mentioned by Ma Gloria [2015]. In light of the presented evidence, we offer the following hypothesis:

H3. The demand planning practices alleviate the negative consequences of process risks in supply chains.

Control risk concerns disruptions in the methods, techniques and procedures that govern the processes. From the perspective of a supply chain, they are manifested by errors in order quantities, misconceptions in batch sizes, mistakes in determining safety stock, deviations in future customer demand, etc. [Christopher, Peck 2003]. The intervening role of demand planning in mitigating the negative consequences of control risks is described by Stitt [2004]. He provides several examples of disruptions driven by control risks that may be reduced by demand planning. The relationship between the consequences of control risks and selected practices of demand planning is also mentioned by Zhao et al. [2013]. In a similar vein, Lambert et al. [2006] argue that the success of planning is determined by the consequences of control risk generated by managers. In light of this, we advance the following hypothesis:

H4. The demand planning practices in supply chains mitigate the disruptions driven by control risks.

RESEARCH METHODOLOGY

Questionnaire design and variables

Data for the study were gathered from a questionnaire that consisted of three sections covering the demography of the sample, demand planning practices and the negative consequences of operational risks (disruptions). The first section included variables examining the general demographic characteristics. Two demographic variables, industry type and firm size, were used as control variables to offer a test of the hypothesized conceptual relationships.

As the study involved a sample of firms operating in many industries, it is possible that effects from the sector may have a significant impact on such an investigation of a multilateral issue of supply chain risk [Juttner, 2005]. Therefore, the first control variable was measured using a nominal scale, whose role was to identify and classify objects belonging to the specific industry types. On the other hand, firm size is usually measured by the number of employees [Cui and Jiao, 2011]. The second and third sections of the questionnaire included 44 items for measuring operational risk and 36 items for measuring demand planning practices. The variables grouped into these two sections were an input in the survey via literature review.

Sample characteristics and study setting

The sample was compiled from surveys of European supply chains and originally consisted of 371 organizations. The questionnaires were usually filled in by a director of logistics, manufacturing, marketing or distribution.

The process of data gathering consisted of two stages. In the first stage, the subsample was obtained using purposive sampling. The questionnaire was sent out to 231 Polish companies. In the second round, we adopted a convenient sampling method. First, using Europe's 500 List and national company lists, we identified a group of 584 companies from Germany, Czech Republic, Italy and the Netherlands. Then, the survey instrument was forwarded to these companies via electronic mail or fax. The obtained response rate was roughly 24 percent and formed the second subsample. The data retrieved from two survey rounds were combined and underwent an initial analysis which produced a group of 293 valid responses. It included companies from Poland (53 percent), Czech Republic (17 percent), Germany (12 percent), the Netherlands (9 percent), and Italy (9 percent). The majority of surveyed companies were engaged in supply chains operating in the manufacturing industry (51%), followed by the commercial sector (38%) and the service industry (11%). In terms of the number of employees, the sample is mostly composed of medium and large companies. The prevailing share of 47 percent of the sample employed from 50 to 249 persons, followed by 44 percent of the companies employing above 250 people, and 9 percent of the companies with 10 to 49 employees.

First, we addressed the problem of common-method bias at an early stage of the study. Following the view of Podsakoff et al. [2003], we separated the measurement items at the stage of questionnaire design. With the aim of recognizing the potential effects of common-method bias, we carried out a single factor analysis [Podsakoff et al. 2003]. Accordingly, the set of variables was loaded into the Exploratory Factor Analysis (EFA), however, not a single factor was derived from the analysis. This suggested that there was no general factor that may give rise to the majority of covariance. This may evidence that a considerable amount of common-method bias is absent in the study. Additionally, since two different samples were combined in the study, the findings need to be controlled for by including a dummy variable manifesting if the companies belong to the first or second subsample. Through introducing this control variable, we wanted to test whether our results were consistent across two subsamples. In order to investigate the effects of the demand planning process on the consequences of operational risk in supply chains, we carried out a statistical analysis consisting of two stages [Hair et al., 2017]. In the first stage, we reduced independent variables through factor analysis in order to highlight the major factors. In the second stage of the study, we carried out a multiple regression analysis to compare the contribution to variance in operational risk accounted for by the demand planning practices and their combinations (Hair et al. 2017). The analysis provided regression models of particular operational risks.

Measurement of dependent variables

We grouped the dependent variables into four constructs reflecting the disruptions driven by certain operational risks – control, process, supply and demand. The respondents were asked to determine the level of risk impact by assessing seven-point Likert-type scale items. The scales were anchored by "1 – strongly disagree […] 7 – strongly agree" for all constructs. In order to verify the internal consistency, we calculated Cronbach's alpha for each construct. Their values in all instances were above .7 and may thus be considered to be reliable [Hair et al., 2017]. The coefficients of CR estimated for the underlying constructs were above the value of .7, which is considered to be a satisfactory result [Hair et al. 2017]. The values of an average variance extracted (AVE) exceeded .5 across all constructs, which is an acceptable outcome. It suggests that, on average, all factors are capable of explaining more than half of the variance of its indicators. We also assessed the unidimensionality of the key constructs using Principal Component Analysis. It enabled a verification of whether or not the variables load sufficiently onto their hypothesized factors. All factor loadings for particular variables in their constructs exceeded .5. The Kaiser-Meyer-Olkin measure scores, ranging from .76 to .87, suggest a middling or meritorious result which supports the use of factor analysis in the sample of companies (Schmidt and Hollensen, 2006). Twelve variables that measure the negative consequences of control risk formed a single factor and explained 54 percent of variance. Similarly, nine variables for disruptions driven by process risk, twelve items for the consequences emanating from supply risk and eleven variables for disruptions originating from demand risk, each grouped into single factors, accounted for 41, 49 and 63 percent of variance, respectively. The obtained classification of variables indicate a good level of adequacy in terms of the operational risk factors in the conceptual model. The factors capture most of the variation of their constituent variables and indicate the overall operational risk.

STATISTICAL ANALYSIS

Exploratory Factor Analysis (EFA) for independent variables

A Factor Analysis was performed to summarize the information manifested by many variables and compress them into a smaller set of constructs. In order to perform the Exploratory Factor Analysis for the group of independent variables, a Principal Component Analysis (PCA) with a Varimax Rotation was employed. The factor analysis produced a clear pattern of constructs with minimal cross-loadings and high loading on one construct. The individual sampling adequacy scores exceeded .5 across all variables. Based on the Kaiser criterion, the analysis conducted on 36 items, revealed four factors. The obtained factors explain 63.12 percent of variance. With the results of the factor analysis, KMO coefficient was calculated. It accounts for .685, which is a middling result, indicating acceptable suitability of the sample for factor analysis. Regarding the content-related aspect of the classified variables, the analysis produced the following factors: Formulating the goal of demand planning (GDP), Data gathering (DG), Demand forecasting (DF), Communicating the forecasts and synchronizing demand with supply (C&S).

The first factor refers to formulating the goal of demand planning. The analysis suggests that this construct generates the greatest value of 27.36 percent. The second factor pertains to data gathering. The outcome of the analysis shows that this factor accounts for 13.83 percent of the information. The third construct links to demand forecasting and covers 12.71 percent of the information. The fourth factor includes the two following activities of demand planning - communicating the forecasts and synchronizing demand with supply and explains the value of 9.22 percent of total variance.

For an assessment of reliability, we calculated internal consistency and composite reliability (CR). For each of the four constructs, internal consistency, as measured by the Cronbach's alpha, exceeded .7 and coefficients of CR estimated for the four constructs were above .7. Accordingly, the results of reliability may be considered satisfactory at this initial stage of the study [Nunnally, Bernstein 1994]. In order to determine validity, we calculated both convergent and discriminant validity. The average variance extracted (AVE) measuring the convergent validity, was above .5 for all constructs. This indicates that all constructs are capable of explaining, on average, more than 50 percent of the variance of its indicators (Chin, 1998). Thus, a set of variables reflect the same major factor that may be depicted through unidimensionality. The constructs have an appropriate discriminant validity when the value of AVE for each construct is larger than the squared correlations between the construct and any other considered construct. All constructs analyzed in the study met this criterion.

Multiple regression analysis

In the following stage of the analysis, we developed multiple regression models, used to test the hypotheses. The models enabled a comparison of the contribution of disruptions driven by the operational risk factors to variance. Only the variables with p-values of less than .05 were maintained in the model. We developed models for each of the four response variables indicating specific types of disruptions induced by operational risks in supply chains.

In general, the regression analysis revealed that each analyzed type of the consequences of operational risk has a model with significant independent variables and adjusted coefficients of determination (R2adjusted) ranging from .042 to .340. The strongest model, as measured by R2adjusted, was developed for the consequences of control risk. The second model in terms of R2adjusted is demonstrated by the disruptions originating from demand risk, followed by two remaining models that show the negative consequences of supply and process risk, though with clearly lower coefficients of determination. It is also interesting to highlight that two first regression models for the consequences of control and demand risks contain all four significant factors indicating the demand planning activities. The explanatory variables are negatively associated with the response variable in both models. This suggests that, generally, the more intense demand planning practices, the lower the level of the strength of disruptions driven by either control or demand risks in supply chains. Three control variables (industry type, firm size and subsample number), though positive, are insignificant in two models. Two other models developed for the consequences of process and supply risks do not indicate significant relationships with any demand planning practices. They are accompanied by a low value of adjusted coefficients of determination for these two models. In addition, some control variables may influence the relationships in the proposed models.

DESCRIPTION OF THE FINDINGS

The effects of demand planning practices on the consequences of control risk

The regression model developed for the consequences of control risk demonstrates the negative and significant relationships with all demand planning practices – Table 1. Therefore, the obtained findings lend a support to H4 and demonstrate that the sequence of demand planning practices contribute to mitigating the negative consequences of control risk, regardless of industry type, company size and subsample number.

Table 1. Regression analysis for H4

Dependent variable	Independent variables	Std. Coef.	t-value	Sig.	*adj. R sq.*[*]
Control risk	F1: Formulating the goal of demand planning (GDP)	-.314	-2.13	.034[*]	.340
	F2: Data gathering (DG)	-.675	-4.08	.000[**]	
	F3: Demand forecasting (DF)	-.013	-1.98	.048[*]	
	F4: Communicating the forecasts and synchronizing demand with supply (C&S)	-.334	-3.25	.001[**]	
	Industry type	.031	.433	.665	
	Company size	.006	.091	.928	
	Subsample number	.051	.893	.373	

* p-value <.05
** p-value < .01

The most influential factor for the disruptions induced by control risk is data gathering (-.675, .000). This may suggest that intense data gathering contributes to a mitigation of the negative consequences driven by the control risk factors. First of all, this activity might decrease the systematic forecast error while developing predicting models in demand planning. Data gathering may also mitigate the negative consequences of an inadequate employment policy and mistakes made by top managers in the decision-making process, by providing a wide range of detailed data. Similarly, the demand planning activity of communicating forecasts and synchronizing demand with supply seems to play a vital role in mitigating disruptions (-.334., .001). This construct is especially important while reducing the negative consequences of inefficient information and communication systems, mistakes in order transmission and data processing, inefficient communication links and data transfer. The intense activity of communicating forecasts and synchronizing demand with supply might also be significant while reducing the detrimental consequences of mistakes made by regular employees and mismatch between their qualifications and imposed tasks. The next activity of formulating the goal of demand planning also significantly mitigates the disruptions induced by control risk (-.314, .034). In particular, this factor might play a vital role while reducing the consequences of inadequate employment policy and mistakes made by top managers in the decision-making process. Additionally, this activity also contributes to lowering the perturbation caused by systematic forecast errors. Interestingly, demand forecasting contributes to a decrease in the negative effects of control risk, though this activity seems to be less significant in the whole model (-.013, .048). The factor of demand forecasting is particularly important while mitigating the negative consequences of inventory control inaccuracy and inadequate or unsound scheduling methods.

The effects of demand planning practices on the consequences of demand risk

Similarly to the control risk model, there are four significant constructs demonstrating predictive capability for demand risk – Table 2.

Table 2. Regression analysis for H2

Dependent variable	Independent variables	Std. Coef.	t-value	Sig.	adj. R sq.*
Demand risk	F1: Formulating the goal of demand planning (GDP)	-.617	-4.35	.000**	.214
	F2: Data gathering (DG)	-.150	-1.99	.047*	
	F3: Demand forecasting (DF)	-.178	-2.07	.039*	
	F4: Communicating the forecasts and synchronizing demand with supply (C&S)	-.587	-3.85	.000**	
	Industry type	.018	.285	.776	
	Company size	.024	.304	.761	
	Subsample number	.015	.221	.825	

* p-value <.05
** p-value < .01

The obtained findings give support to H2 and evidence that the sequence of demand planning practices contributes to mitigating the negative consequences of demand risk, regardless of industry type, company size and subsample number. In particular, formulating the goal of demand planning has the strongest impact on the negative consequences induced by demand risk (-.617, .000). This demand planning activity might be significant while reducing the difficulties to meet certain logistics service levels. It stems from the fact that one should consider the standards of logistics service while formulating the goal of demand planning. Moreover, formulating the goal of demand planning contributes to a mitigation of the negative consequences of greater seasonality and volatility of product demand, as well as larger product variety/volume, and uncertainty of customer demand. The other demand planning activity that mitigates the disruptions stemming from demand risk is communicating forecasts and synchronizing demand with supply (-.587, .000). This construct is particularly important while reducing difficulties in meeting certain logistics service levels and other disruptions in a delivery process. Communicating forecasts and synchronizing demand with supply may also reduce the negative consequences of greater seasonality and volatility of product demand, as well as helping to overcome the obstacles of new product adoptions. Two remaining demand planning activities, data gathering and demand forecasting, have a substantially lower impact on the consequences of demand risk ((-.150, .047) and (-.178, .039), respectively). These two constructs seem to play an important role while reducing the negative consequences of greater seasonality and volatility of product demand, as well as mitigating the disruptions caused by product variety, volume and a short product life cycle. Data gathering may also contribute to lowering the perturbations caused by competitors' promotions, market rivalry and the emergence of substitute products.

The effects of demand planning practices on the consequences of supply risk

The findings suggest that there is a lesser number of significant demand planning practices that have an impact on the disruptions driven by supply risks – Table 3. Generally, the research results show that not all of the demand planning practices are addressed to mitigate and limit the consequences of this type of risk. The smaller number of predicting variables stems from the fact that the disruptions driven by supply risk are not inherently associated with demand planning practices, as they are rather related to the upstream part of supply chains. Therefore, the obtained findings do not offer support to H1 and demonstrate that only a portion of demand planning practices contribute to mitigating the negative consequences of supply risk. Moreover, the influence is dependent upon the company size. In the case of the supply risk model, there are three significant constructs demonstrating demand planning activities, namely data gathering (-.512, .000), demand forecasting (-.410, .000) and communicating forecasts/synchronizing demand with supply (-.417, .000). Data gathering may offer up-to-date, specific and precise information that may have a mitigating influence on the negative consequences of supply risk. Moreover, intense demand forecasting may result in lesser disruptions in the seasonality and volatility of material demand and decrease the uncertainty of supply chain requirements.

Table 3. Regression analysis for H1

Dependent variable	Independent variables	Std. Coef.	*t*-value	Sig.	*adj. R sq.*[*]
Supply risk	F1: Formulating the goal of demand planning (GDP)	-.007	-0.165	.869	.156
	F2: Data gathering (DG)	-.512	-5.35	.000[**]	
	F3: Demand forecasting (DF)	-.410	-4.31	.000[**]	
	F4: Communicating the forecasts and synchronizing demand with supply (C&S)	-.417	-4.55	.000[**]	
	Industry type	.241	1.92	.056	
	Company size	.371	2.18	.030[*]	
	Subsample number	.008	.480	.632	

* p-value <.05
** p-value < .01

Finally, demand forecasting may also contribute to mitigating the consequences stemming from the variety and volume of purchased materials, and deal in a much better way with the disruptions caused by a short product life cycle. Although, as the findings report, demand forecasting may offer support in mitigating the consequences of supply risk, it might be difficult to translate some qualitative demand forecasts that do not take a numeric form and make them usable. Furthermore, forecasting concerns customer demand and does not refer directly to supply. This may limit the potential effects of demand forecasting in mitigating the consequences of supply risk, as demonstrated by the low value of the standardized regression coefficient (beta) in the model. It is also worth noting that communicating forecasts and synchronizing demand with supply may contribute to decreasing the negative consequences originating from the seasonality and volatility of material demand, as well as the variety and volume of the purchased materials.

The effects of demand planning practices on the consequences of process risk

As demonstrated by the results of the study, there are only two significant factors negatively associated with the consequences of process risk, namely formulating the goal of demand planning and communicating forecasts and synchronizing demand with supply ((-.218, .000) and (-.324, .000), respectively – Table 4). Since process risk rather concerns the physical flow of products in supply chains, disruptions cannot be fully mitigated by performing regulatory practices of demand planning. Consequently, the obtained findings do not support H3 and show that a limited number of demand planning practices contribute to mitigating the negative consequences of process risk. This impact is dependent upon company size and industry type. It means that the intensity and scope of demand planning practices used to mitigate the negative consequences of process risk might differ regarding their contextual variables. In particular, formulating the goal of demand planning in a more explicit and precise way, as well as more intense processes of communicating forecasts and synchronizing demand with supply, may contribute to a mitigation of the disruptions caused by lower quality, and rework issues associated with the internal manufacturing and technical processes, mistakes of employees performing specific technical operations, and mismatch between employees' qualifications and tasks.

Table 4. Regression analysis for H3

Dependent variable	Independent variables	Std. Coef.	t-value	Sig.	*adj. R sq.*[*]
Process risk	F1: Formulating the goal of demand	-.218	-3.82	.000**	.042
	planning (GDP)	-.041	-0.85	.396	
	F2: Data gathering (DG)	-.019	-0.31	.756	
	F3: Demand forecasting (DF)	-.324	-4.42	.000**	
	F4: Communicating the forecasts and synchronizing demand with supply (C&S)				
	Industry type	.185	2.31	.021*	
	Company size	.198	3.48	.000**	
	Subsample number	.015	.027	.787	

* p-value <.05
** p-value < .01

Moreover, an intense communication of forecasts and synchronization of demand with supply may decrease the negative consequences of variation in manufacturing yields. The two remaining factors, data gathering and demand forecasting, indicate no significant association with the negative consequences of the process risk model. This probably stems from the fact that these two constructs are more connected with customer demand than with the physical flow of products in supply chains. As such, there is a lack of coherence between demand forecasting data, which are more externally oriented, and the information needs of process risk management, which are required to be focused more internally. Consequently, in order to reduce the disruptions caused by process risk factors, other managerial methods that refer to manufacturing and logistics ought to be applied. Data gathering and demand forecasting probably enrich the management of the flow of products and make decision processes more effective and efficient. However, on the other hand, the output of forecasting is not usable while mitigating the consequences of process risk.

DELIVERABLES AND MANAGERIAL IMPLICATIONS

The findings of the study show that there is a sequence of specific demand planning practices which contributes to the mitigation of disruptions induced by some operational risks in supply chains. Table 5 summarizes the deliverables obtained from the study with the corresponding hypotheses. The most noticeable effects of demand planning might be observed in mitigating the negative consequences of control and demand risks. This is confirmed by a number of significant and negatively associated constructs forming a sequence of demand planning practices and strong regression models for these two types of disruption.

Table 5. Summary of the results

Hypothesis		Results
H1.	The demand planning practices decrease the disruptions driven by supply risks	Not supported
H2.	The sequence demand planning practices in supply chains mitigate the disruptions driven by demand risks	Supported
H3.	The demand planning practices in supply chains alleviate the negative consequences of process risks	Not supported
H4.	The demand planning practices in supply chains mitigate the disruptions driven by control risks	Supported

This is a very important contribution of our study as, even though previous research investigated the effects of demand planning on the negative consequences of risks, they usually employed a very general perspective and did not examine a holistic structure of practices forming the process of demand planning. Moreover, when mentioning the relationships between disruptions and demand planning, the extant studies, based on theoretical considerations, offer conceptual propositions that are not supported by the findings of quantitative research. Accordingly, the coherence and robustness of the obtained deliverables are confirmed by the findings of statistical tests, conducted to determine the significance of the estimated coefficients. In addition, the results of our study do not differ in terms of sample, company size or industry type. On the other hand, the lesser impact of demand planning is noticed in the case of disruptions driven by process and supply risks. There is a limited number of significant and negatively related demand planning practices that contribute to mitigating the negative consequences of risks. This finding confirms the results derived from previous studies. However, our findings, in contrast to the results derived from other research, employ the demand planning perspective. In other words, the study does not investigate loosely coupled practices, but a specific sequence of demand planning practices forming the whole process. Also, the strength of the models for process and supply risks is much less when compared to other regression models, as measured by adjusted coefficients of determination. In addition, the effects of selected demand planning practices on the disruptions in both models are dependent upon the contextual variables of industry type and company size. This finding highlights that there is not any uniformity or standardization in terms of the role of demand planning in alleviating the negative consequences of supply and process risks.

In light of the aforementioned, the research results provide valuable suggestions for managers that tend to apply demand planning in order to mitigate the disruptions caused by operational risks in supply chains.

Managers should be aware that applying an effective demand planning process may contribute to a reduction in the level of disruptions caused by operational risks. In particular, the concept of demand planning might be very helpful for managers when dealing with the consequences of demand and control risks. In addition, the model relationships among demand planning practices and consequences of control and demand risks were found to be robust, regardless of the settings of the contextual variables, such as industry type, company size and subsample number.

Understandably, the conducted research showed that demand planning is not the only concept that is dedicated to alleviating disruptions. The coefficients of determination obtained in the study suggest that there are other variables and constructs that have potential predictive capability with reference to the disruptions caused by operational risks. In other words, the strength of the negative impact of certain risk factors is not explained only through the lens of demand planning practices. In fact, there are activities performed in supply chain management that might have a more direct impact on the disruptions caused by operational risks. Arguably, the practices of risk management seem to play the most significant role. In light of this, managers should pay attention to the fact that the demand planning process, as a managerial concept, embraces a number of specific activities in order to deal with demand. However, performing these activities might also complement the risk management concept and lead to a mitigation of the negative consequences of operational risks. In other words, different managerial instruments, which are not directly linked to the risk management concept, when appropriately applied, may also have an indirect impact on the mitigation of the consequences of risk. It is worth saying that the demand planning process should not act as the sole tool for the mitigation of risk consequences, but rather as a complementary concept reinforcing the effectiveness of appropriate risk management. All these implications would require further in-depth investigation regarding the different sources of risk and their mutual relationships that have a potential and actual impact on supply chains.

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WPŁYW PLANOWANIA POPYTU NA NEGATYWNE SKUTKI RYZYKA OPERACYJNEGO W ŁAŃCUCHACH DOSTAW

STRESZCZENIE. **Wstęp:** Mimo faktu, że w literaturze przedmiotu podejmowano problem dotyczący roli określonych czynności planowania w łagodzeniu ryzyka i jego skutków, niemniej wciąż brakuje badań podejmujących problematykę jednoczesnego wpływu czynności w planowaniu popytu na zakłócenia wywołane przez czynniki ryzyka operacyjnego w łańcuchach dostaw. W związku z tym celem artykułu jest identyfikacja wpływu procesu planowania popytu na zakłócenia wywołane przez ryzyko operacyjne. Innymi słowy, celem niniejszej pracy jest rozpoznanie czy operacyjne czynniki ryzyka i ich negatywne konsekwencje mogą zostać ograniczone za pomocą aplikacji czynności w procesie planowania popytu w łańcuchach dostaw.

Metody: W artykule przeprowadzono dwa etapy wielowymiarowej analizy statystycznej. W pierwszym etapie zmienne zostały zredukowane za pomocą analizy czynnikowej w celu identyfikacji podstawowych konstruktów. W drugim etapie badania, przeprowadzono analizę regresji wielorakiej po to, aby porównać wpływ poszczególnych czynności w planowaniu popytu na konsekwencje ryzyka operacyjnego.

Wyniki: W rezultacie przeprowadzonego badania stwierdzono, że czynności planowania popytu w mniejszym lub większym stopniu przyczyniają się do ograniczenia ryzyka operacyjnego w łańcuchach dostaw. W szczególności, istnieją silne relacje między planowaniem popytu i konsekwencjami ryzyka decyzyjnego oraz ryzyka popytowego. Z drugiej strony, mniejszy wpływ planowania popytu można obserwować w przypadku ryzyka związanego z fizycznym przepływem produktów oraz ryzyka w sferze dostaw.

Wnioski: Badanie pokazuje, że metody zarządzania, niekoniecznie dedykowane dla potrzeb ograniczania ryzyka, mogą istotnie przyczyniać się do zmniejszenia jego konsekwencji w łańcuchach dostaw. W szczególności koncepcja planowania popytu może zostać wykorzystana przez menedżerów w przypadku ograniczania konsekwencji ryzyka decyzyjnego i ryzyka popytowego.

Słowa kluczowe: proces planowania, popyt, ryzyko, łańcuch dostaw

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