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The influence of supply chain vulnerability drivers on the impact of disturbances in supply chain performance: a natural experiment around the 2018 Brazilian truck drivers' strike.

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Dissertação apresentada à Escola de Administração de Empresas de São Paulo, da Fundação Getulio Vargas, em cumprimento parcial dos requisitos para obtenção do título de Mestre em Administração de Empresas.

Linha de Pesquisa: Operações

Orientador: Profa. Dra. Susana Carla Farias Pereira

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Dissertação

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UDESC

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Resumo

Uma perturbação pode ter impactos distintos em diferentes Cadeias de Suprimentos (CS). A literature sobre Gestão de Risco na Cadeia de Suprimentos (GRCS) sugere que algumas características da CS funcionam como Direcionadores da Vulnerabilidade da Cadeia de Suprimentos (DVCS), efetivamente alterando o impacto causado pelas perturbações na CS. Essa dissertação tem por finalidade testar a hipótese acima, avaliando em que medida características da CS direcionam a Vulnerabilidade da CS a perturbações, e quais características são mais influentes. A Greve dos Caminhoneiros de 2018 ocorrida no Brasil oferece uma rica oportunidade de pesquisa, sob a forma de um experimento natural. Dados secundários do ERP de um varejista foram analizados sob a lente de um quasei-experimento, Secondary data from a retailer ERP was gathered and analyzed as a quasi-experiment, examinando a relação entre três características da CS (densidade da CS, complexidade da CS, criticalidade de nó da CS) e o impacto da greve na performance da CS (disponibilidade na loja, entrega de ordens de cliente no prazo). Apenas a complexidade da CS mostrou-se influente nas métricas de performance escolhida, e provavelmente como um proxy de CS curtas. A falta de influência da densidade e criticalidade de nó da CS pode indicar que nem todas as características da CS funcionam como DVCS para todas as perturbações.

Palavras-chave

Risco na Cadeia de Suprimentos, Vulnerabilidade da Cadeia de Suprimentos, Direcionadores de Vulnerabilidade da Cadeia de Suprimentos, Quasi-experimento, Experimento Natural, Características da Cadeia de Suprimentos.

Abstract

A disturbance can have different impacts in different supply chains. The Supply Chain Risk Management (SCRM) literature suggests that some Supply Chain (SC) characteristics work as Supply Chain vulnerability drivers (SCVD), effectively changing the impact of disturbances in SCs. The aim of this dissertation is to test the aforementioned hypothesis, assessing in what measure supply chain characteristics drive the supply chain vulnerability to disturbances, and which characteristics are more influential. The 2018 Brazilian Truckers' strike offers a rich research opportunity under the form of a natural experiment to test the research hypotheses. Secondary data from a retailer ERP was gathered and analyzed as a quasi-experiment, probing the relationship between three SC characteristics (SC density, SC complexity, SC node criticality) and the impact of the strike on SC performance (in store availability, client order on time delivery). Only SC complexity was found to influence the performance metrics, and probably as a proxy for short Supply Chains. The missing influence from SC density and SC node criticality may suggest that not all SC characteristics can play the role of SCVD for all disturbances.

Keywords

Supply Chain Risk, Supply Chain Vulnerability, Supply Chain Vulnerability Drivers, Quasi-experiment, Natural Experiment, Supply Chain Characteristics

Summary

1 Introduction

In May 21st 2018, independent truck drivers started a strike to manifest against the diesel high price. Ten days later, the strike came to an end, leaving the Brazilian economy at least 75 billion reais poorer (Moura et al., 2019). Losses, however, were not evenly distributed among economy sectors. The construction sector estimated a loss of R$3,8 billion (Moura et al., 2019). Retailing and services sector losses were close to R$27 billion (Moura et al., 2019). Between May 25th and 28th, retailers lost in average 15% of their sales. Yet, supermarkets sold 7% more goods during the same period (Amorim, 2018). The same pattern of unequal impact distribution can be expected at all levels of analysis (regions, cities, neighborhoods, industries, supply chains, companies, etc.) and virtually in all disruptions. However, knowledge on the factors that drive the impact of disturbances on the SC is still scarce.

The search for this knowledge is at the heart of many studies in Supply Chain risk management (SCRM). Supply Chain risk management (SCRM) is defined as “the identification and management of risks for the supply chain, through a coordinated approach amongst supply chain members, to reduce supply chain vulnerability as a whole” (Jüttner et al., 2003, page 201). To be effective, SCRM must look outside for risk sources, but also inside for the SC vulnerability (SCV) (Heckmann et al., 2015). In accord with the Normal Accident Theory (NAT), modern supply chains are naturally risky systems because of their ever-increasing complexity and tight coupling of nodes (Perrow, 1999). The impact of a disturbance is a function of both risk sources and SCV (Wagner & Bode, 2006). SC vulnerability drivers are the SC characteristics that determine to a certain extent the likelihood and impact of SC risks (Jüttner & Maklan, 2011; Wagner & Neshat, 2010).

SC density is an example of SC characteristic that may work as SC vulnerability driver, as sustained by Craighead et al. (2007). Density is a measure of proximity between SC nodes, where a dense SCs have its nodes within a short distance from one another. A disturbance limited to a geographic area could impact differently two Supply Chains depending on their density. The impact on the denser SC are expected to be greater, as more nodes can be impacted simply for their close proximity. Besides SC density, Craighead et al. (2007) identified SC node criticality and SC complexity as SC vulnerability drivers (SCVD).

The concept of Supply Chain vulnerability driver needs more empirical support, and its main propositions must be tested in different settings and using different methods (Craighead et al., 2007; Wagner & Bode, 2006). To this author knowledge, only a few articles studied the

relationship between SC characteristics and SCV (Craighead et al., 2007; Papadakis, 2006; Todo et al., 2015; Wagner & Bode, 2006; Wagner & Neshat, 2010, 2012). Among these, only Craighead et al. (2007) considered the SC as unit of analysis, instead of a focal firm point of view. Todo et al. (2015) is the only paper to quantitatively study the SC impact and recovery from a disaster using a quantitative approach. Moreover, none used secondary data from firms' ERP systems nor approached the subject using a quasi-experiment design.

As an effort to contribute to the aforementioned body of research, this dissertation aims to assess in what measure supply chain characteristics drive the vulnerability of supply chains to disruptions, and which characteristics are more influential. The focus is on the impact of one disturbance, the 2018 Brazilian Truckers' Drivers Strike, into the performance of the product supply chains from one home improvement retailer. Following a trend in SCM research, this work considers the triad to be the smallest unit of analysis (Mena et al., 2013). Links between suppliers, stores, DCs and clients from the retailer are to be uncovered in a way that triads emerge and can be studied.

As a normal science on the terms defined by Kuhn & Hacking (2012), the SCRM field expands through an incremental process, with each research work contributing to the overall knowledge. That knowledge is substantiated when different researchers and methods are imposed on the same research problem (Reichardt, 2019). Based on a qualitative study, Craighead et al. (2007) developed three hypothesis relating SC characteristics (SC density, SC complexity, SC node criticality) and the vulnerability of the SC to harm. This dissertation put their hypotheses to test under a quantitative research strategy.

A quasi-experiment design was used to model the effect of the interaction between the 2018 Truck drivers' strike (treatment) and three SC characteristics of interest (SC density, SC complexity, SC node criticality) upon the performance (in store availability, client order on time delivery) of each of the 1009 product supply chains from the retailer. If a SC characteristic is in fact a SCVD, there must be an interaction between it and the treatment. In other words, the impact on SC performance during the strike must differ for different levels of the characteristic. The retailer's ERP systems were used as data source.

As a path to fulfill its aim, this dissertation pursues the following objectives:

a) To identify all product supply chains that compose the full assortment from a Brazilian home center, from the supplier to the customer.
b) To characterize each supply chain using the network characteristics of SC complexity, SC density and SC node criticality.

c) To measure in store availability and on time client order delivery levels for each supply chain before and after the strike.
d) To measure the impact of the interaction between each supply chain characteristic and the truckers' strike of 2018 on each SC performance measurement.

The present work contributions can be divided into theoretical, empirical and methodological. The concept of SCVD being conditional on disturbance properties can be considered the main theoretical contribution from this dissertation. The literature on SCVD focus on the level of different SC characteristics and how this would impact SC vulnerability. A hidden assumption is that if a SC characteristic is a SCVD, it would influence the vulnerability of the SC, no matter the disturbance that menaces this SC. That is also the case in Craighead et al. (2007) hypotheses used as a basis to our own. As all three hypotheses have been refused within our research, we propose that the properties of the disturbance are also determinant on the role played by SC characteristics. The ability of a SC characteristic to drive vulnerability not only depends on the SC characteristic level, but also on properties of the disturbance. A second theoretical contribution is the clarification of the distinction between SCR driver (SCRD) and SCVD.

The empirical contribution is related to the quasi-experiment result. Managers can use the case description and findings to better prepare for disruptions. Client flow and last mile capabilities are two main points that should be included in SCRM strategies and recovery plans. At last, the use of the quasi-experiment method and secondary data from the firm ERP can be considered methodological contributions to the research on SCRM. The research strategy of choice answers the call for more empirical research at the field of SCRM, specially studies on high impact-low frequency events (Sodhi et al., 2012).

This document is organized as follow. Chapter 1 introduces the theme of study and describes the document organization. Chapter 2 discuss the relevant body of knowledge. It starts with the definition of SC risks and SC risk sources. Later, under the lights of Normal Accident Theory and SC risk drivers, the concepts of SC vulnerability and SC vulnerability driver are defined. Finally, after reviewing important articles on SCVD, the research hypotheses are developed relating SCVD and SCV. Chapter 3 details the research methodology. The chapter starts with an overview of the research strategy, followed by the definition of the treatment impersonated by the 2018 Truck drivers' strike, and continues to define the unit of analysis as the product supply chain from a home center retailer. Next, the quasi-experiment design is discussed, and the chapter concludes with the variables' description. Chapter 4 brings the

findings and relevant data analysis. Chapter 5 entails a discussion relating the findings to the research hypothesis and aim. Chapter 6 ends the dissertation with its limitations and possible future researches.

2 Literature Review

SCRM can be seen from two difference stances. The first stance is atomistic and external. It searches for risk sources outside the supply chain and focus on disruptive events (Heckmann et al., 2015). Three main topics of research are covered in this stance: risk sources, mitigation strategies, SCRM processes. The second stance is systemic and internal. It seeks to address the inherently system characteristics that expose SC to risks (Heckmann et al., 2015). A major branch of research on this stance investigates SC resilience, while the other studies SC vulnerability. A mind-map representing this split can be seen in figure 1.

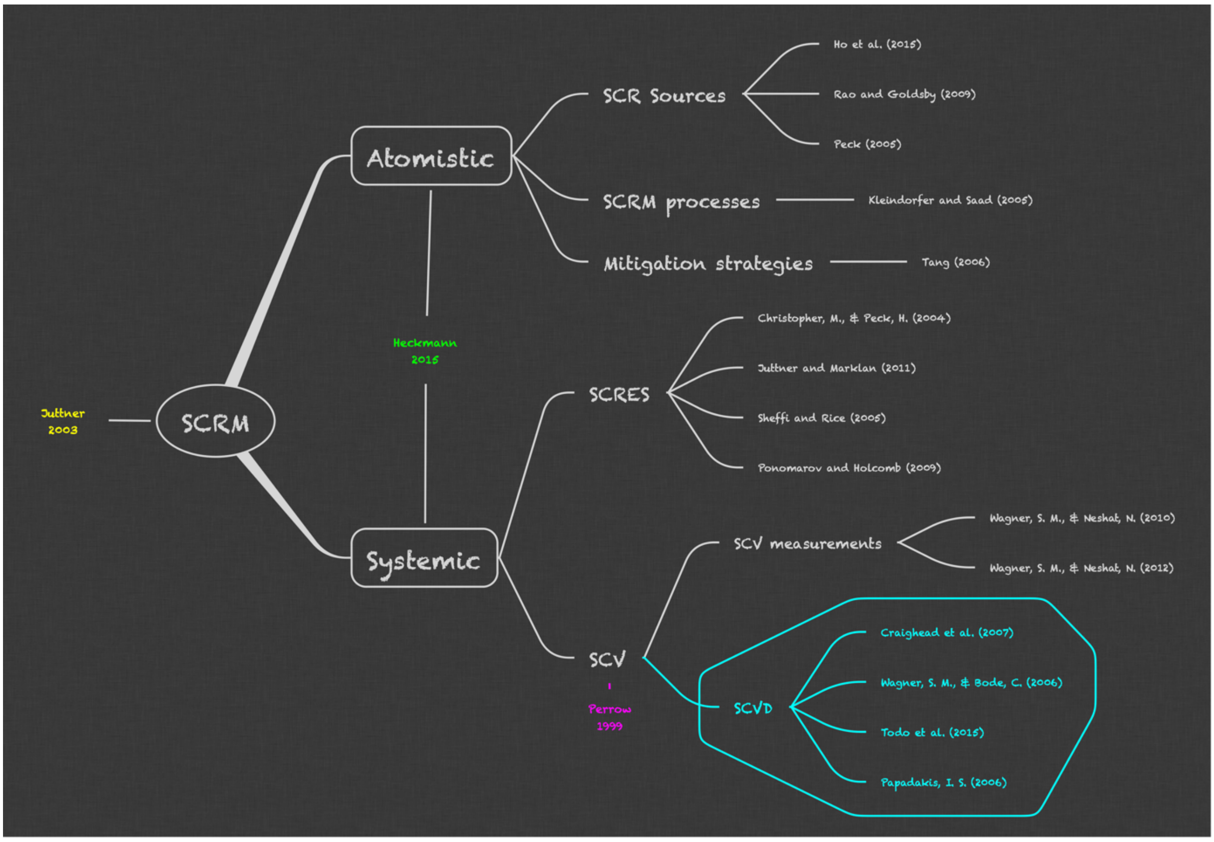

Figure 1 – SCRM Literature structure (the author).

This dissertation partakes of the systemic stance and dives into the theme of SC vulnerability. It probes the theoretical influence of some SC characteristics into the vulnerability level of Supply Chains. This chapter uses the literature on SCRM in general and SCV in especial to conceptualize and structure this relationship under the form of falsifiable hypothesis. First, un understanding of risk impact and how it comes to be is needed. The

definitions of both SC risk and SC risk source should be enough to shed light on both. Then the concept of SC vulnerability is developed in relation to the Normal Accident Theory. The next step is to introduce the concept of SC vulnerability driver and to identify the SC characteristics that may fit the role. Finally, the research hypotheses are built upon Craighead et al. (2007) work.

2.1 Supply Chain risk: a multi-faceted concept

This section defines SC risk and discuss the first piece of the conceptual model used in this research: SC risk impact. Supply chain risks are risks to the flow of products and/or information at any point of the network (Jüttner et al., 2003). They can be defined as:

"the likelihood and impact of unexpected macro and/or micro level events or conditions that adversely influence any part of a supply chain leading to operational, tactical, or strategic level failures or irregularities" (Ho et al., 2015, page 5035).

Influential definitions of risk are based on probabilistic concepts, and many papers considers risk as a probability (Heckmann et al., 2015). The Royal Society, for example, defined risk in 1983 as "the probability that a particular adverse event occurs during a stated period of time, or results from a particular challenge. As a probability in the sense of statistical theory, risk obeys all formal laws of combining probabilities" (Royal Society 1983 apud Peck, 2006).

Risk and uncertainty are closely related, but they are not synonyms. It is the profile of their likelihood that differentiates both concepts. There is risk when the probability distribution is known. If it is unknown, there is uncertainty (Knight, 1921). Many of the disruptions faced by SCs cannot have their odds forecasted in advance. Despite this lack of information, managers must prepare and respond to them. Therefore, Supply Chain risk in practice includes risk and uncertainty (Heckmann et al., 2015).

The second component found on the definition of SCR is Supply Chain risk consequences or impacts. They manifest as the variance on Supply Chain performance metrics (Jüttner et al., 2003) as revenue, cost and availability (Jüttner & Maklan, 2011), and are the losses that will be suffered by the Supply Chain if the risk is realized.

Supply chain risk impacts have several time dependencies. First, they depend on the duration of the disruption. The longer the disruption, the longer the impact (Heckmann et al., 2015). Second, they depend on the moment the disruption occurs (Heckmann et al., 2015). A disruption at the peak of the seasonal period is normally worse than one that happens after

season. And last, they depend on the velocity of the disruption, or the loss per unit of time (Jüttner & Maklan, 2011).

The first piece of the conceptual model is set. SC risk impacts are the losses that will be suffered by the Supply Chain if the risk is realized, and can be related to revenue, cost and availability (Jüttner & Maklan, 2011). The next section will give the second piece, SCR source.

2.2 SC risk sources: an endeavor to understand risk causes

SCR source is a composite concept encompassing the threat, the triggering event and the disturbance (Asbjørnslett, 2009; Wagner & Bode, 2006). Threat is the latent adverse factor that becomes real after the triggering event takes place (Asbjørnslett, 2009). It captures the origin of the disturbance that lead to a SC risk, from where it emanates. Supply chain risk is realized only when a triggering event creates a supply chain disturbance, an unplanned fateful situation, which in turn leads to a negative deviation of the supply chain outcome (Wagner & Bode, 2006).

Much effort has been applied to create risk sources typologies. By knowing the cause, scholars and managers hope to devise successful SC risk management strategies (Heckmann et al., 2015). Many existing risk sources classifications see the Supply Chain as a landscape of firms, with the focal firm at its center (Christopher & Peck, 2004; Ho et al., 2015; Svensson, 2000; Wagner & Bode, 2006). One example is the typology proposed by Ho et al. (2015): supply, demand, manufacturing, infrastructure and macro risk. The hidden assumption behind these typologies is that SC risks are risks that can affect the focal firm by disrupting at least one of the SC flows. A demand risk to the manufacturer (demand forecast error) can be seen as a supply risk by the retailer (insufficient production capacity).

However, if SC risks are risks to the SC, the unit of analysis must be the SC itself, not the focal firm. A few authors take the Supply Chain as unit of analysis when categorizing risk sources (Jüttner et al., 2003; Peck, 2005). Peck (2005), for example, offers a four-level categorization of risk sources: level 1 value stream/product or process, level 2 assets and infrastructure dependencies, level 3 organizations and inter-organizational networks, level 4 environment. See figure 2.

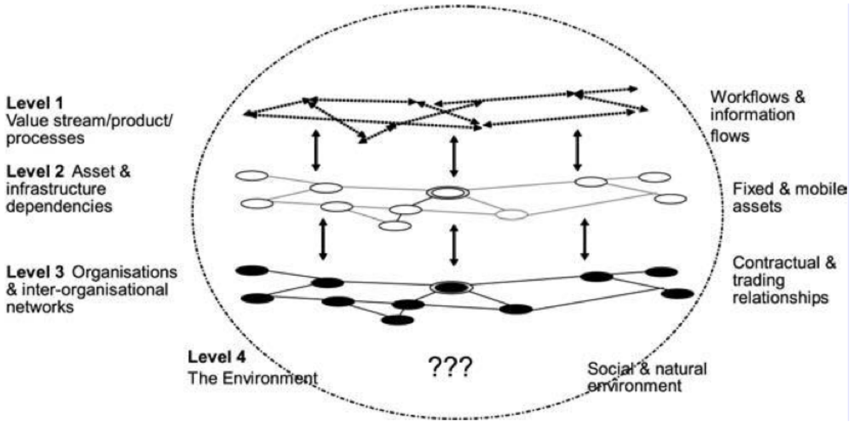

Figure 2 - Supply chain risk sources from Peck (2005)

SCR source is the second piece of the conceptual model. The concepts on this section can be used to map the 2018 strike. The 2018 Truckers drivers' strike would be the SC risk source, the strike declaration in May 21st 2018 the triggering event, and the reduction on cargo transportation services availability the disturbance. Based on the SC risk source classification from Peck (2005), the 2018 strike emanates from level 2 (asset & infrastructure dependencies), impacting mobile assets. The next section discusses the third piece: SC vulnerability.

2.3 Supply Chain vulnerability (SCV): a measure of risk exposition

The global economy is one of fierce competition. The way SCs answer to this highly competitive environment is by focusing on efficiency (Wagner & Neshat, 2010), with practices as globalization of the SC (Craighead et al., 2007; Stecke & Kumar, 2009; Wagner & Bode, 2006), supplier base reduction (Craighead et al., 2007; Stecke & Kumar, 2009; Svensson, 2002; Wagner & Bode, 2006), outsourcing (Stecke & Kumar, 2009; Svensson, 2002; Wagner & Bode, 2006), and lean inventory (Jüttner et al., 2003; Stecke & Kumar, 2009; Svensson, 2002; Wagner & Bode, 2006). Despite the success these practices bring to companies on the short term, they also increase their risk on the long run (Wagner & Bode, 2006). Jüttner et al. (2003) call these practices supply chain risk drivers (SCRD), the forces that push the SC risk level up. For Stecke and Kumar (2009), some SC practices work as SCRDs by changing SC characteristics which in turn increase vulnerability (see table 1 for examples).

Supply chain management practices	Vulnerability causing factors: Increase in the number of exposure points	Increase in distance/time	Decrease in flexibility	Decrease in redundancy
Globalization	X	X		
Decentralization	X	X		
Outsourcing	X	X		
Sole sourcing			X	
JIT			X	X
Product/process complexity	X			
Litigation	X			

Table 1 - Supply chain practices and their effect on vulnerability causing factors. (Stecke & Kumar, 2009)

There is not to say managers can or should opt out of all efficiency practices. Competitive stance is an all-important matter and companies can hardly step down without jeopardizing their survival. At least part of the risk is taken willingly in search of a more competitive position (Jüttner et al., 2003; Svensson, 2002). Anyhow, managers should take some precautions and include risk considerations when deciding on the implementation of new practices (Craighead et al., 2007; Jüttner et al., 2003; Peck, 2006).

As a result of the SCRDs discussed above, supply chains are increasingly complex (more nodes, spread throughout the world, and interacting in nonlinear ways) and lean (less slack, more tightly integrated) (Wagner & Neshat, 2012). That puts modern supply chains in the realm of high-risk systems where accidents are inevitable and even normal per the Normal Accident Theory (NAT) (Perrow, 1999). For NAT, the risk level of any system is defined by two key system characteristics: interactive complexity and tight coupling (Perrow, 1999). In complex and tightly coupled systems, accidents albeit rare are unavoidable (Perrow, 1999).

Interactive complexity (components interacting in nonlinear ways) opens the door to unpredictable interactions among subsystem and parts (Perrow, 1999). It increases the chance of failure in parts, components or subsystems to affect other parts in unforeseen ways (Perrow, 1999). In tightly coupled systems there is no slack between interacting parts and subsystems (Perrow, 1999). Tight coupling increases the chance of local failures becoming system failures for the fast spreading of errors and the lack of alternative paths to achieve results (Perrow, 1999).

The concept of SC vulnerability (SCV), as it shall be seen in the ensuing text, expands NAT and attributes part of the SC risk to SC characteristics beyond complexity and tight coupling. SCR source and SCV can be seen as opposing one another as internal-external factors but also systemic-atomistic views of risk. Supply Chain risks are easily confounded in the literature with disruptive events (Heckmann et al., 2015). Although many SC risk sources are

internal to the SC, the concept carries within itself the idea of externality and fate (Heckmann et al., 2015). With this external-atomistic stance, risk emanates from risk sources that cannot be fully controlled. Risk management is about knowing all that is to be known about potential risk sources, and to match each one of them with mitigation strategies. For the internal-systemic stance, on the other hand, risk emanates from the underlying system characteristics, and risk management is all about manipulating those characteristics in a way that reduces overall vulnerability. Figure 3 illustrates the concepts.

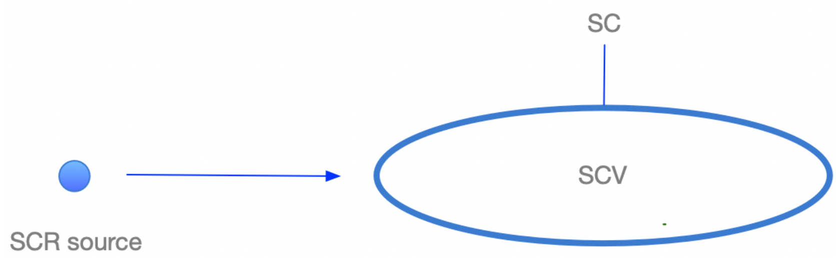

Figure 3 - SCR source and SCV opposing themselves as internal-external and atomistic-systemic (the author).

One of the first authors to discuss Supply Chain vulnerability was . A considerable part of his research on the subject was made about Volvo, the Swedish car manufacturer. He defines vulnerability as:

"… the existence of random disturbances that lead to deviations in the supply chain of components and materials from normal, expected or planned schedules or activities, all of which cause negative effects or consequences for the involved manufacturer and its sub-contractors." (Svensson, 2000). This definition is quite close to some Supply Chain risk definitions.

On a latter work, Svensson (2002) delimitates and complements the vulnerability construct. To the author, vulnerability comes from the dependencies between firms. These dependencies may be related to functional or time sequencing of activities (Svensson, 2002). In this sprit, risk and uncertainty differ from vulnerability for they can exist without dependencies (Svensson, 2002). Despite the depth of the reflection on the vulnerability's nature, the definition does not deviate from his previous work. It stays based on the existence of disturbances and the negative impacts of those (Svensson, 2002).

Jüttner et al. (2003) positioned vulnerability and risk as different concepts. In their paper, vulnerability is presented as "the propensity of risk sources and risk drivers to outweigh risk mitigating strategies, thus causing adverse supply chain consequences" (Jüttner et al., 2003, page 200). It is a property of the SC system. Jüttner & Maklan (2011) also believe SCV to be a property of the SC, a measure of risk exposure to disruptions in terms of their likelihood and impact. These definitions are in line with the laic use of the concept, as stated by the Cambridge Dictionary: "the quality of being vulnerable (= able to be easily hurt, influenced, or attacked)". Different from SC risk and yet a passive construct.

Wagner & Bode (2006) gave a somewhat active or moderator role to vulnerability in regard to SC risk impact. In spite of Supply Chain risk sources being the direct cause of Supply Chain risk, the final result depends also on the SC susceptibility to harm (Wagner & Bode, 2006). The loss suffered by a SC is at some level a consequence of its vulnerability to harm (Wagner & Bode, 2006). Vulnerability, therefore, is a Supply Chain property that determines to a certain extent the likelihood and impact of risk (Jüttner & Maklan, 2011). The latter definition was adopted to guide the current study. Table 2 brings some vulnerability definitions found in the SCRM literature.

Vulnerability definition

Year	Authors	Page	Vulnerability definition
1995	Albino and Garavelli	73	. . .aimed to estimate the system sensitivity to changes, in terms of damages to performance due to the intrinsic system incapacity of reaction to unexpected events'.
2000	Svensson	732	However, as a guide to further reading of the article, vulnerability is defined by the author as the existence of random disturbances that lead to deviations in the supply chain of components and materials from normal, expected or planned schedules or activities, all of which cause negative effects or consequences for the involved manufacturer and its sub-contractors.
2002	Svensson	112 119	Vulnerability is a condition that affects a firms goal accomplishment dependent upon the occurrence of negative consequences of disturbance. The degree of vulnerability for a given disturbance may be interpreted as being proportional to the chance of disturbance and the expected negative consequence of the disturbance, given that it has occurred. Vulnerability is interpreted as a random disturbance, whose consequences are not completely absorbable in the inbound, internal and outbound logistics flows in the assembly plant
2003	Juttner et al.	200	Supply chain vulnerability is "the propensity of risk sources and risk drivers to outweigh risk mitigating strategies, thus causing adverse supply chain consequences''.
2004	Christopher and Peck	6	This provided a working definition of supply chain vulnerability as "an exposure to serious disturbance, arising from risks within the supply chain as well as risks external to the supply chain".
2005	Barnes and Oloruntoba	527	. . .susceptibility or predisposition to change or loss because of existing organizational or functional practices or conditions'.
2006	Wagner and Bode	304	We posit that supply chain vulnerability is a function of certain supply chain characteristics and that the loss a firm incurs is a result of its supply chain vulnerability to a given supply chain disruption.
2006	Peck	132	…Supply chain vulnerability is taken to be related to risk, in the sense that something is "at risk; vulnerable: likely to be lost or damaged".
2009	Asbjørnslett	18 18	…the properties of a supply chain system; its premises, facilities, and equipment, including its human resources, human organization and all its software, hardware, and net-ware, that may weaken or limit its ability to endure threats and survive accidental events that originate both within and outside the system boundaries. Vulnerability is the concept that may be used to characterize a supply chain system's lack of robustness or resilience with respect to various threats that originate both within and outside its system boundaries. The vulnerability of a supply chain system may be manifested both in its infrastructures – both nodal and modal, its processes, as well as the operation and management of the supply chain.
2009	Bakshi and Kleindorfer	588	. . .possibility of occurrence of a disruption. It is determined by a combination of the kind of infrastructure already in place for risk mitigation, as well as environmental factors such as political turmoil, proximity to a fault line/volcano, etc.'. . . 'Mathematically, we capture the concept of vulnerability through the supplier's marginal probability of disruption as a function of investment'.
2011	Juttner and Marklan	248	SCV is the susceptibility of the supply chain to the likelihood and consequences of disruptions.
2015	Heckmann et al.	125	The concept used to describe the extent to which a supply chain is susceptible to a specific or unspecific risk event is called supply chain vulnerability.

Table 2 - Vulnerability definition. Based on (Wagner & Neshat, 2012) and expanded by the author.

SCV presents itself in two states: latent and manifested (Jüttner & Maklan, 2011). The occurrence of a SC disturbance is the turning point from one state to the other. After the realization of a risk, the SC vulnerability can be assessed by the extent of the damage suffered by the Supply Chain (Jüttner & Maklan, 2011).Thus, manifested vulnerability equals the SC risk impact given a risk likelihood of 1. From the previous discussion on SC risk impact, losses can be classified in three risk effect dimensions: revenue, cost, availability (Jüttner & Maklan, 2011). At the latent state vulnerability is a possibility, not a certainty. Even highly vulnerable SCs may never suffer a disruption (Jüttner & Maklan, 2011).

When latent, SC vulnerability is a measure of the SC exposition to risks (Jüttner & Maklan, 2011). Moreover, SC latent vulnerability evaluation is not an easy task. To Sheffi & Rice (2005) a general measurement of the vulnerability level is out of reach, and only rough risk classifications for specific risk sources as the probability x impact matrix are possible. They attribute the difficulty of the task to a combination between a nuanced subject and the bluntness of the research toolkit (Sheffi & Rice, 2005). Although largely in use by practitioners and scholars (Lavanya & Malarvizhi, 2018; Oke & Gopalakrishnan, 2009), the probability x impact matrix is not a tool to measure vulnerability. It focuses on the estimation and mapping of risk sources. One starts with risk sources and defines the likelihood and impact to the SC. It is an outside-in approach. SC vulnerability should start from the inside, the underlying SC system, and them connect it to risk. To Wagner & Neshat (2010), vulnerability cannot even be directly observed. However, there are visible aspects of SC vulnerability - the SC characteristics that drives vulnerability (Wagner & Bode, 2006).

Applying the SCV concept to this dissertation, SC Vulnerability can be considered as a property of the SCs impacted by the strike of 2018. As the Strike already happen, the vulnerability can be observed in the SC risk impact beared by each SC, and it is called manifested vulnerability (Jüttner & Maklan, 2011). The next section will allow us to identify the SCV drivers at work during the 2018 Strike.

2.4 Supply Chain vulnerability drivers (SCVD): the engine behind vulnerability

In line with NAT tradition, vulnerability is considered a function of certain SC characteristics (Wagner & Bode, 2006). These characteristics received different names in the literature: SC vulnerability antecedents (Wagner & Bode, 2006), SC vulnerability drivers (Wagner & Bode, 2006) and SC vulnerability causing factor (Stecke & Kumar, 2009). Through the SC vulnerability, they influence both the likelihood and impact of risk sources (Craighead et al., 2007). In this dissertation the term SC vulnerability driver is used to identify those characteristics that drive the SC vulnerability level.

Some of these characteristics are inherently to the business strategy, as the assortment size customizations (Svensson, 2000) and product complexity (Wagner & Neshat, 2010). But for the most part, they are manifestations of SCRD, the implementation of efficiency driven practices that shape the SC into a more vulnerable form (Wagner & Neshat, 2010). In other words, SCRD push SCs to change their SCs characteristics embracing more efficient but also more vulnerable ones.

The frontier between SCRD and SCVD is not always straightforward to define. Global sourcing and outsourcing, for example, have been pointed out both as SCRD (Stecke & Kumar, 2009) and SCVD (Wagner & Neshat, 2010). SCRDs are strategies, policies or management practices. SCVDs are SC characteristics, in many cases resulting from the implementation of SCRDs. The definitions can be applied to global sourcing as an illustration. Global sourcing can be considered a SC practice. It englobes a set of beliefs about key success factors to pursue (low production cost) and how to achieve them (centralized production of components in specialized suppliers from countries with low labor cost, late differentiation with regional or local assembly). When implemented, it increases SC complexity, a SC characteristic, as new actors integrate the network (government agencies, freight forwarders, brokers, etc.). The increased number of SC nodes drives complexity up and with it SC vulnerability. Thus, global sourcing is a SCRD, and SC complexity the SCVD.

The literature offers an array of possible SCVDs (see table 3). It is worth noting that not all SC characteristics are positioned as SCVD. With a focal firm frame of reference, customers, internal operations and suppliers base respond for the SCVD: supplier and customer dependence, supplier concentration (Wagner & Bode, 2006; Wagner & Neshat, 2010), financial situation of clients and suppliers, product lifecycle, product complexity, low in house production, centralized storage of finish goods(Wagner & Neshat, 2010), assortment size, no lead time slack(Svensson, 2000).

When taking the SC frame of reference, a different set of SCVD emerge: Node criticality, SC density, SC complexity (Craighead et al., 2007), number of exposure points, distance and lead time, SC inventory level (Stecke & Kumar, 2009).

	Svensson (2000)	Wagner and Bode (2006)	Stecke and Kumar (2009)	Craighead et al. (2007)	Wagner and Neshat (2010)	Wagner and Neshat (2012)
Supplier dependence		x			x	x
Customer dependence		x			x	x
Supplier concentration		x	x		x	x
Single sourcing		x	x	x	x	x
High number of exposure points		x	x		x	
Long distance and/or lead time		x	x		x	
Low redundancy			x			
High SC density				x		
SC complexity (nb of nodes and ties)				x	x	x
Node criticality			x	x	x	
Short product's life cycles					x	x
Low in-house production					x	x
Global sourcing		x	x		x	x
Lean inventory			x		x	x
Centralized storage of finished goods				x	x	x
Assortment size	x					
No slack on lead time	x					
Financial situation of customers					x	
Product complexity					x	
Demand variability					x	
Financial situation of suppliers						
Supplier controlled by a competitor						
Outsourcing			x		x	

Table 3 - Examples of Supply Chain vulnerability drivers (the author)

It is clear that SCVDs interact to define the final vulnerability level (Wagner & Neshat, 2010). In some cases, SCRD will push SCVD in different directions, increasing vulnerability from one side, and decreasing it from the other (e.g. Single sourcing reduces complexity and increases node criticality) (Craighead et al., 2007). In others, SCRD will push more than one SCVD toward riskier configurations (ex. Global sourcing with complexity and lead time) (Stecke & Kumar, 2009).

Applying these concepts to this dissertation, the Lean movement can be identified as a major SCRD. One of its tenants, stock reduction, has been pursued by top management for the last 5 years at the retailer. As a result, the XD became the default replenishment flow for many product category SCs driving up SC criticality. The overall system vulnerability followed suit: to bring most product category SCs to a halt is suffices to strike the retailer’s XD site.

Figure 4 illustrates the main concepts discussed in the literature review. These concepts are used to translate Craighead et al. (2009) propositions into SCRM related hypotheses at the last section of this chapter.

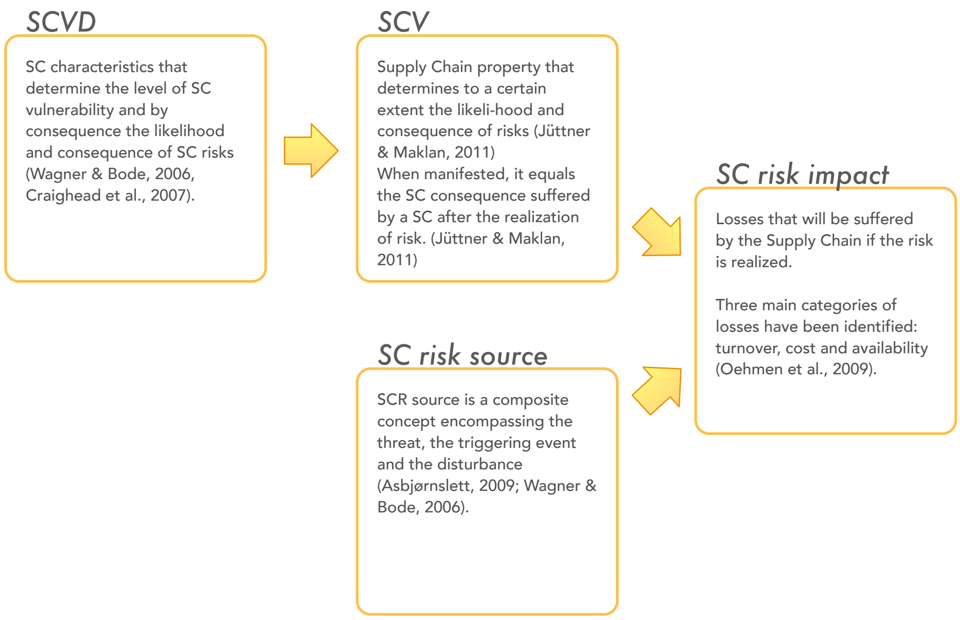

Figure 4 – Main concepts explored in the literature review

2.5 Empirical papers on SCVD

This section reviews some of the existing papers that strived to empirically identify SCVDs. Each paper will be briefly reviewed, shedding light to its contributions and limitations. The first paper, Craighead et al. (2007), is at the base of this dissertation by offering the hypotheses to be probed. It was chosen mainly for their SC frame of reference as in opposition to a focal firm point of view, and the empirical origin of its hypotheses. Five other papers (Papadakis, 2006; Todo et al., 2015; Wagner & Bode, 2006; Wagner & Neshat, 2010, 2012) were included here for they greatly influenced this work through concrete examples of empirical research applied to SCVD.

The first work presents the results of an exploratory qualitative empirical research performed by Craighead et al. (2007). The authors applied a 3-stage method research to understand why one supply chain disruption would be more severe than other. Severity is defined as the number of disrupted nodes within the network. They identified three SC characteristics positively related with severity (node criticality, density, complexity), and two mitigation capabilities negatively related (recovery, warning) (Craighead et al., 2007). The qualitative nature of the work did not allow for the quantification of the identified relationships, nor the probing of the hypotheses. Both limitations are addressed in this dissertation by the use of a quantitative research strategy.

On the second paper, Wagner & Bode (2006) did a massive survey to investigate the relationship between SC characteristics (customer dependence, supplier dependence, supplier

concentration, single sourcing, global sourcing) and firm exposure to SC risk sources (demand-side risk, supply-side risk, catastrophic risk). They got answers from 760 German executives. Ordinary Least Square model (OLS) was used to analyze the data. Results were quite promising with a positive correlation having been found among the set of Supply Chain characteristics and all three SC risk sources (Wagner & Bode, 2006). In more details, customer and supplier dependence are strongly correlated to demand-side risks. Supplier dependence, single sourcing and global sourcing are correlated to supply-side risks. Global sourcing is correlated with catastrophic risks. Nevertheless, the set of chosen SCVD explain only a small part of the data variance (Wagner & Bode, 2006). Surveys can only convey perceptions, which can be considered a limitation of the method. This dissertation addresses this limitation by using real data from the retailer's ERP system.

The third article presents Papadakis (2006) analysis on the stock valuation of major PC producers after the Taiwan earthquake of 1999. Make to order (MTO) producers stocks value have been negatively impacted after the disturbance event, when those from Make to stock (MTS) producers were not. The devaluation could be explained by the investor perception of the greater exposure of MTO producers to component price increases. MTO buy the component after having sold the computer to the client. In normal situations, as the components prices are in constant reduction, this offers an important cost advantage against MTS producers. However, with sudden price increases the situation is inverses. MTO producers have a cost disadvantage.

Papadakis (2006) used a linear regression model to calculate the expected valuation based on past data (1-year history). Then he compared the expected value with the real value at the event window. Even though the impact is real, the financial result of MTO firms was still greater than MTS producers. Also, SC agility was used to drive the demand toward less memory intensive products (Papadakis, 2006).

The fourth paper is from Wagner and Neshat (2010). The authors apply graph theory to develop a Supply Chain Vulnerability Index (SCVI). SCVD are nodes of the graph, and links between SCVDs become weighted direct edges. Edge weight represents the strength of the correlation. The sign represents its direction (Wagner & Neshat, 2010).An adjacency matrix is used to represent the graph, which is more apt to calculations. In the adjacency matrix, a_{ii} cells store the SCVD strength, while a_{ij} cells keep the correlation index between SCVD i and j. From the calculation of the matrix permanent one can derives the SCVI (Wagner & Neshat, 2010).

Wagner and Neshat (2010) used data from the same survey presented in Wagner and Bode (2006) to illustrate their method. They calculated SCVI for 9 different industries after

using principal component analysis to create super SCVD (demand-side, supply-side, SC structure) based on SC characteristics available on the survey (customer dependence, supplier dependence, supplier concentration, single sourcing, global sourcing) (Wagner & Neshat, 2010). The automotive industry appeared as the highest SCVI (28.85) and wholesale/Retail the lowest (20.67) (Wagner & Neshat, 2010). The paper does not offer a way to validate if the SC characteristics used to calculate SCVI do have an impact on SCV vulnerability. Our work tries to address this limitation by measuring the role of each individual SC characteristic on SC vulnerability.

On a subsequent paper, the fifth on our list, Wagner and Neshat (2012) continued their research about SCVI. They were out to investigate how other aspects of the firm (Supply chain performance, Number of employees, Sales revenues, Production type, Logistics importance, Supply chain risk planning, Supply chain risk management) correlate with the SCVI (Wagner & Neshat, 2012). Each aspect was split in 2 levels, high and low, and the authors used data from the previous survey to calculate SCVI for each combination (Wagner & Neshat, 2012).

Wagner and Neshat (Wagner & Neshat, 2012) build their hypothesis and analyzed their results using three theoretical lenses: SCRM, NAT, and High Reliability Theory (HRT). In line with SCRM theory, SCVI was found to be negatively correlated with SC performance (Wagner & Neshat, 2012). From NAT, the bigger the firm, the more complex the system becomes and more susceptible to SCRD influence (Wagner & Neshat, 2012). Firm size and batch size were found to be positively correlated with SCVI. HRT states that managers are not at the mercy of accidents. They have many strategies at their disposals to fight the fate projected by NAT (Wagner & Neshat, 2012). One of HRT origins can be traced back to a field research performed by the Berkley University on 3 organizations that should present high levels of failures given their characteristics but instead hold to a free-failure standard (LaPorte & Consolini, 1991). The importance given by the company to logistics, the extensive use of SC planning and the implementation of SCRM practices are all key leverages for HRT (Wagner & Neshat, 2012). Aligned with HRT, SCVI was found to be positively correlated with Logistics importance, Supply chain risk planning and Supply chain risk management (Wagner & Neshat, 2012).

The last paper on our list is from Todo et al. (2015). The authors studied the relationship between firms SC extension and their recovery from the Great East Japan Earthquake (Todo et al., 2015). After their paper, long SCs improve short term production re-start, while short SCs help to re-establish sales in the medium term. Their research combines two data sets. The first dataset is the result of a survey intended to collect data on suppliers and suppliers of suppliers from Japanese firms. The survey was performed prior to the earthquake and offer data on SC

characteristics. The second data set comes from a survey done just after the earthquake to assess its impact on local firms. A linear regression model was used to assess the relationship between SC extension and recovery (short and medium term).

Inspired by all previous empirical research, we are now ready to define the hypothesis related to specific SCVD.

2.6 SCVD related hypothesis

Craighead et al. (2007) proposed 3 hypotheses relating each of 3 SC characteristics - SC node criticality, SC density and SC complexity - to the severity of a disruption using a qualitative research strategy. This dissertation probes these hypotheses within a quantitative framework. Better and sound knowledge can be obtained if the same object is studied using different methods (Reichardt, 2019).

The three original propositions from Craighead et al. (2007, pages 140, 141 and 143) are:

> "P1: An unplanned event that disrupts a dense supply chain would be more likely to be severe than the same supply chain disruption occurring within a relatively less dense supply chain."
>
> "P2: An unplanned event that disrupts a complex supply chain would be more likely to be severe than the same supply chain disruption occurring within a relatively less complex supply chain."
>
> "P3: An unplanned event disrupting a supply chain with many critical nodes would be more likely to be severe than the same supply chain disruption occurring within a supply chain with few critical nodes."

All three propositions are written under a general form:

P: An unplanned event disrupting a supply chain with a higher level of characteristic X would be more likely to be severe than the same supply chain disruption occurring within a supply chain with a lower level of the same characteristic.

It should be clear to the reader that Craighead et al. (2007) dealt in their paper with some of the main concepts of SCRM, without using the SCRM vocabulary. To establish a conversation between their propositions and the SCRM literature and facilitate their probing and later interpretation, they must be stated using the SCRM vocabulary defined throughout

this chapter. Three immediate translations are in order. First, the unplanned event that disrupts the SC is a disturbance in SCRM terms, part of the SRC source concept:

P*: A disturbance affecting a supply chain with a higher level of characteristic X would be more likely to be severe than the same disturbance affecting a supply chain with a lower level of the same characteristic.

For the second translation, the severity level of the disruption is in fact the SCR impact:

P**: A disturbance affecting a supply chain with a higher level of characteristic X would have a greater impact than the same disturbance affecting a supply chain with a lower level of the same characteristic.

For the third translation, SCR impact conditional on SC characteristics is in fact the SCV concept:

P***: Supply Chains presenting a higher level of the characteristic X are more vulnerable than those who show a lower level of the same characteristic.

A last adjustment is needed to help the operationalization of the SCV construct. Earlier on this chapter, we discussed the distinction between manifested and latent vulnerability. It has been said that manifested vulnerability can be assessed directly from the extent of the impact suffered by the supply chain after the realization of risk (Jüttner & Maklan, 2011). This makes manifested vulnerability the ideal aspect of vulnerability to assess within an empirical frame of research, when the disturbances have already impacted the SC. For this reason, manifested vulnerability and not latent vulnerability will be used:

P****: Supply Chains with a higher level of the characteristic X also presents a greater level of manifest vulnerability.

The reader should note that all the previous paraphrasing and translations were not without impact on meaning. For Craighead et al. (2007) severity is the number of disrupted nodes within the network. The synonym proposed, SCR impact, is much broader in scope and has been defined as the variance on Supply Chain performance metrics (Juttner et al. 2003) of revenue, cost and availability (Jüttner & Maklan, 2011). Measuring vulnerability in relation to this broader view of SCR impact seems a richer research contribution than to use the limited definition of number of affected nodes.

The ensuing text discuss each hypothesis in turn, as a derivation of Craighead et al. (2007) propositions, but under the general form that employs SCRM nomenclature and the expanded view of SCV and SCR impact. Also, two SC performance metrics (In store availability, Client order on time) are defined as manifest SCV proxies and used to create 2 versions of each hypothesis (A and B).

2.6.1 SC Node criticality

> "P3: An unplanned event disrupting a supply chain with many critical nodes would be more likely to be severe than the same supply chain disruption occurring within a supply chain with few critical nodes." (Craighead et al., 2007, page 143)

Node criticality is a measure of the importance of a specific node for a given SC (Craighead et al., 2007). It reflects the level of dependence the SC has on the node. Node criticality can also be calculated as a property of the entire network. In this case, the measure can be called SC node criticality and is simply the number of critical nodes the SC contains (Craighead et al., 2007).

The dependence of the SC on critical nodes reduces flexibility (Stecke & Kumar, 2009), considering there is no alternative way of meeting SC desired or planned outcomes in case of failure. Dependence can usually be translated as the share of the flow or value that is under the node responsibility (Craighead et al., 2007). In general, it also relates with the node connectedness to other nodes in the SC (Craighead et al., 2007). Critical nodes tend to partake on a disproportional share of flows and be connected to many other nodes. For this reason, criticality is also considered a type of centrality. Example of critical nodes abound in SC: concentration of flows through one port or distribution center (DC), few or single supplier (Craighead et al., 2007), customer dependence (Wagner & Bode, 2006; Wagner & Neshat, 2010).

When disrupted, critical nodes are in position to impact an important part of the flow, and to spread the issue to many connected nodes on the network (Craighead et al., 2007), and even bring the entire SC down, should they fall (Craighead et al., 2007). Figure 5 shows a graphical representation of a network with an exaggerated critical node.

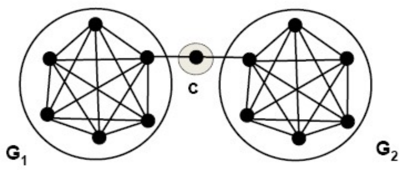

Figure 5 – Graphical representation of a network with an exaggerated critical node (Colak, 2008).

Therefore, it can be hypothesized that:

H1. SCs with higher node criticality presents a greater level of manifest vulnerability.

2.6.2 SC density

"P1: An unplanned event that disrupts a dense supply chain would be more likely to be severe than the same supply chain disruption occurring within a relatively less dense supply chain." (Craighead et al., 2007, page 140)

SC density is a measure of the geographical concentration of nodes. Dense SC chains have nodes closer to one another (Craighead et al., 2007). SC density can also be seen as a measure of region importance and criticality, with flows concentrating in regions more easily than they do in nodes. The concentration of actors from an industry on the same geographical region have been considered a major factor in defining competitiveness and innovation level on a global market (Castellacci, 2008). In this manner, density may become a stronger vulnerability driver than node criticality to some SCs (Craighead et al., 2007). SC density drives vulnerability because many nodes could be disrupted in case of a disruption in the area. An example is what happened during the Great Est Japan Earthquake in 2011, where an entire region was devastated (Todo et al., 2015). Figure 6 represents two SCs with different density levels.

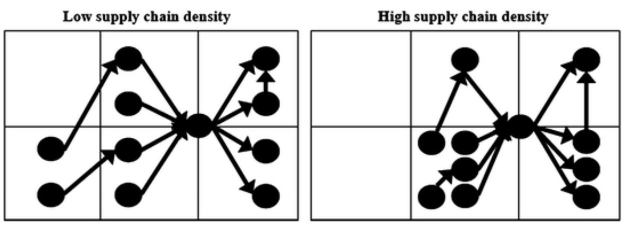

Figure 6 – Graphical representation of 2 networks with different density levels (Rienkhemaniyom & Pazhani, 2015).

For the above reasons, it is hypothesized that:

H2. SCs with higher density presents a greater level of manifest vulnerability.

2.6.3 SC complexity

"P2: An unplanned event that disrupts a complex supply chain would be more likely to be severe than the same supply chain disruption occurring within a relatively less complex supply chain." (Craighead et al., 2007, page 141)

It has been theorized that company size increases complexity creating barriers to communication and coordinated action (Wagner & Neshat, 2012). By analogy, the same could be said about SCs, turning big SCs in error-prone networks, i.e., vulnerable. Each step on the material and information flows is an exposure point where a disturbance can hit (Stecke & Kumar, 2009). The increased number of moving parts in the system, augment the chance of interactive complexity, as defined in NAT. Disturbances can propagate in unforeseen paths, as flight delay that ends up impacting many flights and even airports (Craighead et al., 2007).

Complexity in SCs can be measured by the total number of nodes and ties among those nodes. The higher the number of nodes and ties, the higher the risk. SCRDs of global sourcing and outsourcing usually increase the number of SC nodes and with it SC complexity (Craighead et al., 2007). Global SCs extend themselves through many countries and can suffer from specific risk sources (e.g. Warfare) in each of them (Stecke & Kumar, 2009). Outsourcing creates webs of interconnected companies, while single sourcing, in contrast, greatly reduces complexity although increasing node criticality.

Therefore, it is hypothesized that:

H3. SCs with higher complexity presents a greater level of manifest vulnerability.

2.6.4 SC performance metrics

The SC performance indicators used as dependent variables in the quasi-experiment where chosen to reflect the differences in client needs and expectations. They try to measure two key services offered by the retailer: in store service and home delivery.

From the company marketing research, clients go to the store primarily to have immediate access to products. No waiting. The second most common reason is show-rooming, where the clients go to be acquainted to the store assortment. In both cases, out of stock can result in sales loss and in extreme cases, the loss of the client to a competitor. For this reason, availability is so important.

Clients also have a third reason to visit the retailer’s stores: sizable projects. When doing renovation or construction projects, the client sees herself with a huge purchase list and a low level of knowledge about most items. Projects are tied to schedules and different materials must arrive at the client home in accordance to the schedule. Delivery punctuality is far more important than immediately availability of products.

Most part of brick and mortar sales are done with stock-on-hand, with clients buying the stock available to them at the store. It is clear that in this configuration In store availability

is key to fulfill consumer needs. Stockout is one of the main KPIs to measure in store availability. It is the ratio between the number of items without stock at the point of sales (store or retailer's DC) and the total number of items on the assortment (Beamon, 1999). In store availability can be calculated as 1-stock out level.

For many product families (e.g. tiles), especially heavy or bulky products, home delivery and not in store pick up is the preferred flow by customer. Clients do their purchases in accord to construction or renovation schedules, and often must spend their day at home to receive the products. Under this light, to respect the delivery date is a major strategic goal to many supply chains enrolled in home improvement. On time delivery rate tracks the performance level on client order delivery. It is calculated as a ratio between the number of orders delivered prior or on their promise date and the total number of orders delivered within a period (Beamon, 1999).

Both measurements, In store availability rate and On time client order delivery rate, will be used as performance metrics in this research and thus SCV proxies. Each hypothesis will be tested twice, once against each performance metric.

2.6.5 Hypothesis model

Three falsifiable hypotheses have been derived relating SC characteristics and SC manifest vulnerability. Each hypothesis was then split in A and B to accommodate the two SC performance metrics.

H1. SCs with higher node criticality presents a greater level of manifest vulnerability.

- H1A. SCs with higher node criticality presents a greater impact on in store availability rate when facing a disturbance.
- H1B. SCs with higher node criticality presents a greater impact on client order on time delivery rate when facing a disturbance.

H2. SCs with higher density presents a greater level of manifest vulnerability.

- H2A. SCs with higher density presents a greater impact on in store availability rate when facing a disturbance.
- H2B. SCs with higher density presents a greater impact on client order on time delivery rate when facing a disturbance.

H3. SCs with higher complexity presents a greater level of manifest vulnerability.

- H3A. SCs with higher complexity presents a greater impact on in store availability rate when facing a disturbance.
- H3B. SCs with higher complexity presents a greater impact on client order on time delivery rate when facing a disturbance.

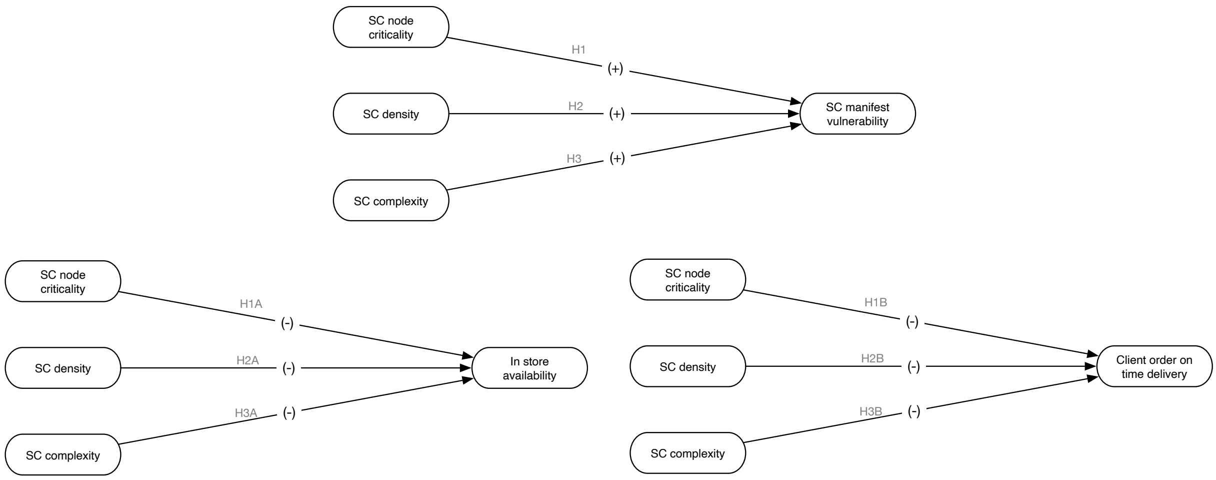

Figure 7 - Research hypotheses

They will be tested under the quasi-experiment framework.

3 Methodology

The aim of this dissertation is to assess in what measure supply chain characteristics influences the supply chain vulnerability to disturbances, and which characteristics are more influential. It is then an evaluative work as it strives to assess performance and compare options(Saunders et al., 2015). It follows a deductive approach deriving hypothesis from the SCVD literature to be latter tested in real world settings (Saunders et al., 2015)

A quantitative approach supports the research aim as it allows for the measurement of the relation between variables of interest (Creswell & Creswell, 2018). However, the data needed to investigate these relationships is of a sensitive nature. The knowledge of SC characteristics and performance metrics can be used by competitors to jeopardize an individual company strategic position. Access is of supreme importance to perform the research and difficult to obtain at the same time.

Negotiating access to this kind of information with many companies is a too great effort for a dissertation. It would require time and connections far beyond the author's capabilities. As a solution, the research scope was limited to a single retailer in Brazil. Major retailers work as a nexus for huge and complex supply networks. They have thousands of suppliers selling tens of thousands of items, that are bought by millions of clients spread throughout the country. There is room and need for many types of logistics flows creating the richness required for this research. This author has access to the board of directors from a major home improvement retailer. For ease of access and fit to the study needs, the home improvement retailer has been chosen to be our focal company.

In order to exploit the occurrence of a natural experiment around the low frequency-high impact disturbance (2018 Strike), a quasi-experiment was chosen as research strategy. A natural experiment occurs when a treatment is imposed on participants, but the researcher has no control over where and when the treatment is implemented, not over which participants are to receive it (Leatherdale, 2019). Quasi-experiments are used to estimate the effects of treatments when participants are assigned to treatment conditions non at randomized (Reichardt, 2019). Effects estimation are part of theory testing (Reichardt, 2019) fitting well with this dissertation aim.

In sum, a quasi-experiment was used to probe the hypothesis defined in the previous chapter. Two designs were used for the quasi-experiment. The first design is a non-equivalent group design and it modeled the 2018 strike as treatment, the SC characteristics of interest as covariates, two other characteristics (total treated quantity, number of items managed) as

confounding variables, and two measurements of SC performance as dependent variables (On time client order delivery rate, In store availability rate). The unit of analysis is the product supply chain, composed of physical storage or handling locations. The second design is a set of 3 2x2 factorial design, one for each of the 3 SC characteristics of interest. Here both the 2018 strike and SC characteristic are considered independent variables, two other characteristics (total treated quantity, number of items managed) confounding variables, and two measurements of SC performance dependent variables (On time client order delivery rate, In store availability rate).

In the next subsections, each component of the research methodology will be detailed. First, the 2018 Truck Drivers Strike is established as treatment. Just after, a deep dive into the retailer operations is followed by the definition of our unit of analysis: the product supply chain. With a better understanding of the research environment, the quasi-experiment designs are presented, followed by the operationalization of variables.

3.1 Treatment: 2018 Truck Drivers Strike

In July 2017, a new price policy from Petrobras would allow fuel price at the refinery to fluctuate almost daily following oil price at the international market (Moura, 2018). The combination of a global risen on oil price and the depreciation suffered by the Real (Brazilian's currency) culminated on a 57,78% increase on the price of diesel between July 2017 and April 2018{2018a}. Inflation during the same period registered only 2,68% increase {2018a}. Fuel represents 42% of the total cost of transport. With an economy in recession, the cost increase could not be passed to shippers.

At the beginning of 2018, drivers had 3 main requests for the government. First, they fought for a reduction on the costs beared by truck drivers. Taxes account for 28% of the total diesel cost (see figure 8). The category wanted the exemption of CIDE and PIS/COFINS taxes (13%) on diesel. In 2017, the government had increase in 86% PIS/COFINS imposed on diesel, as a measure to reduce public deficit (Watanabe et al., 2018). Another cost related request asked for the end of the toll charging on the suspended axle of empty trucks. It was already prescribed in the law (Art. 17 da lei 13.103/2015), but not respected by road operators.

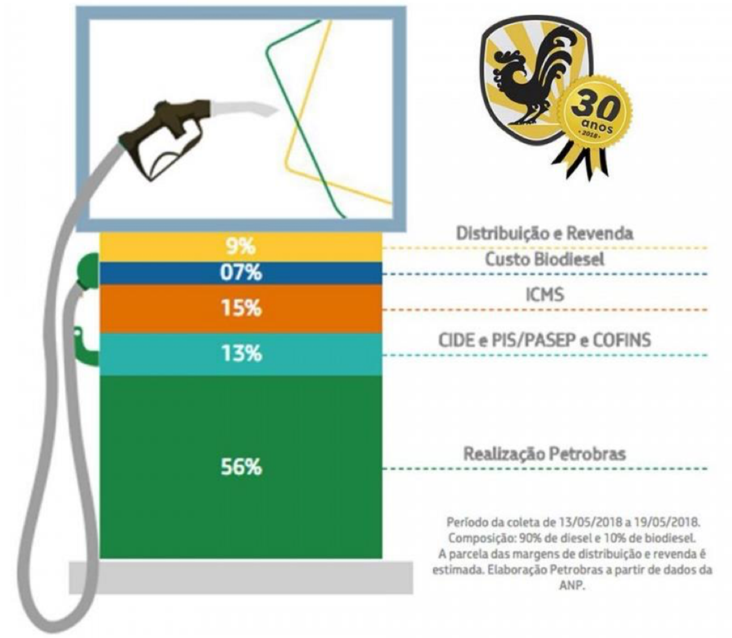

Figure 8 - Diesel price composition (Petrobras)

Second, they asked for the end of the daily adjustment on fuel prices at the refinery. With daily updates, freight negotiations were quite challenging. Drivers working on long distance routes could start the trip with a health profit and end it 15 days later paying it all as fuel cost.

Third, a minimum freight was to be defined by the government for each route following the law project 121/2017 in discussion by the congress (LEI No 13.103, DE 2 DE MARÇO DE 2015, 2015). With the recent recession, transportation costs were hard to negotiate with shippers. Truck drivers had to reduce their income or risk not working at all.

Negotiations with government were not easy nor fast. Fighting the fiscal debt, government was not keen on reducing tax collection(Moura, 2018). At the same time, Petrobras was still recovering from the political and economic crisis and the price policy was part of the recovery plan (Moura, 2018). Finally, shippers strongly resisted the minimum freight price.

In May 21st, independent truck drivers started a strike to manifest against the diesel high price (Moura et al., 2019). Ten days later, the national movement was called to an end, albeit some local manifestations continued. Manifestations spread throughout the country with roadblocks on the main highways. Drivers that did not adhere to the movement were pulled off from the road by strikers. Less and less trucks were available to hire. One major impact was the fuel shortage on fuel stations. Fuel needed to be transported as everything else. Citizens had to leave their cars at home or avoid going out altogether.

Twice, the government announced the end of the strike after negotiations with the movement leadership (Darlington & Andreoni, 2018). A diffuse leadership did not help negotiations either. ABCAM (Associação Brasileira dos Caminhoneiros) and Confederação Nacional dos Transportadores Autônomos (CNTA) have been both cited on the news as the strike organizers.

Despite the government agreement to all demands, roadblocks continued(Darlington & Andreoni, 2018). Fuel tanks had to be escorted by the army and law enforcement to replenish gas stations.

Official forces also had to be used after the strike has been called off by ABCAM in May 30rd. Soldiers and policemen escorted trucks out of roadblocks and into cities (Darlington & Andreoni, 2018). Special support was offered to major ports and airports as an effort to expedite the supply chain recovery. Notwithstanding the effort, Brazilian supply chains took a while to stabilize.

Just after the strike's end, the gross domestic product (GDP) and inflation forecasts for 2018 were negatively affected. GDP growth expectation went down from 2,18% to 1,94%. Inflation increased from 3,65% to 3,82% (Martello, 2018). Expectations were met with even worse results. 2018 GDP grew only by 1,1%, repeating 2017 performance(Alvarenga & Silveira, 2019). The 1st quarter spectacular result was followed by a less than mediocre growth for the rest of the year (see figure 9). The result can be at least partially associated with the strike impact.

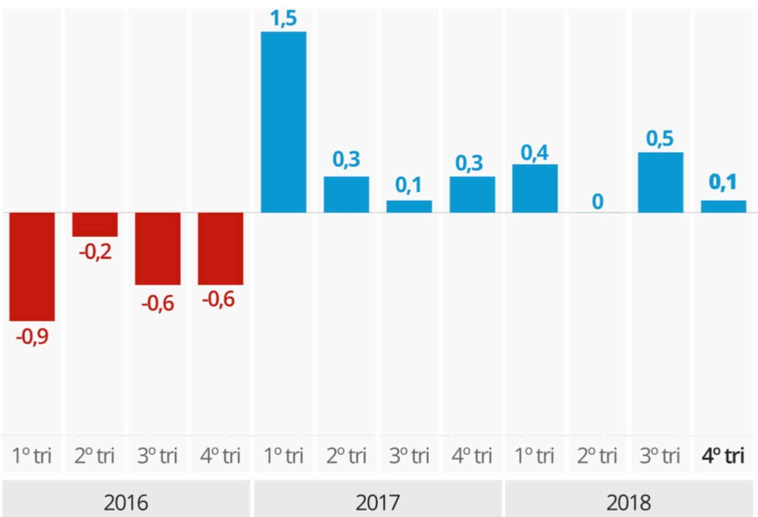

Figure 9 - 2018 Brazilian GDP percentage evolution by quarter (Alvarenga & Silveira, 2019)

The Brazilian economy total loss have been estimated between 75 and 100 billion reais during the 10 days of the strike (Moura et al., 2019). Construction sector estimated a loss of

R$3,8 billion. Retailing and services losses were close to R$27 billion (Moura et al., 2019). Shortages on food and fuel pressed the prices up during the period. Inflation (IPCA) went from 0,22 in April to 0,4% in May. June registered 1,26%, the highest inflation in 23 years (Moura et al., 2019).

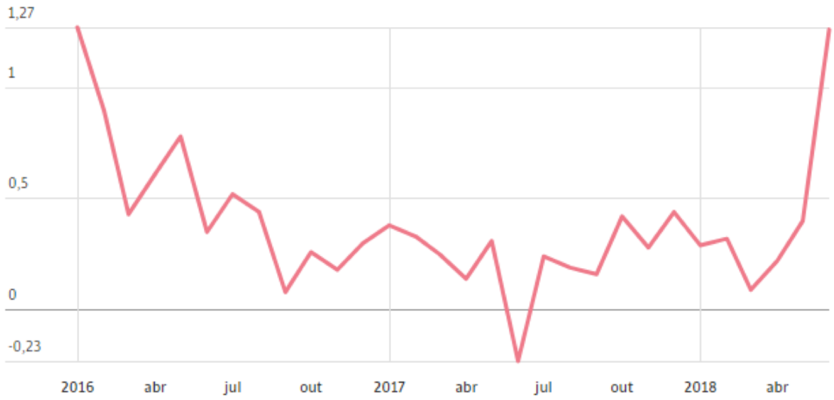

Figure 10 - Monthly inflation in Brazil (IBGE, 2018)

Many similarities can be drawn between this event and two similar manifestations occurred in UK: the truckers' strike of 1979 and the fuel protest of 2000. Both UK disturbances have been discussed and documented by McKinnon (2006). In all 3 events, both in UK and the 2018 in Brazil, heavy truck availability was reduced by a strike. Distribution of goods was impaired, and consumption had to rely on stocks carried by retailers. Fuel distribution was also impacted, limiting the use of non-truck vehicles as well (McKinnon, 2006). Our society vulnerability to road transport interruption is flagrant. The risk is quite real, and history repeats itself.

From May 21st to May 30th, virtually all shippers had to face the same issues to get their cargo transported. Even though the strike did not spread equally in all states and routes, it is safe to assume that all nation-wide supply chains had been impacted. Silva (2018) reported heavy losses in several verticals of the economy, going from agriculture (wheat 225 million reais, sugar 740 million reais) to health care (1,6 billion reais), and passing by services (27 billion reais). Roads are connected and the truck fleet is finite. Roadblocks and fuel scarcity had a far-reaching area of impact. For these reasons, the natural experiment treatment is defined as 2018 Brazilian Truck Drivers' Strike occurred between May 21st and May 30th. All product supply chains from the focal firm that operated during this period received the treatment being part of the treatment group. Therefore, all SCs have been afflicted by the national reduction in cargo transportation service offering during this period.

3.2 Unit of analysis: The Retailer's Supply Chains

The focal firm is a home center operating stores in almost all major Brazilian cities. Home centers are retailers specialized in home improvement products and services. The retailer offer is quite large, including construction materials (sand, cement, doors, water tank, etc.), finishing items (tiles, taps, plumbing, toilets, bathroom sinks, metals, etc.), tooling (screwdrivers, drilling machine, etc.), electrical items (power connectors, wires and cables, etc.), ornaments (cushions, chandeliers, painting, etc.), external areas (swimming pools, plants, garden furniture, lawn-moaner, etc.). Products differ greatly in size, composition and value, but it is possible to identify group of products or categories that are interrelated or interchangeable from consumer's point of view (Nielsen Marketing Research 1992 apud Agrawal, 2009). Categories can be seen as independent business units inside the retailer (Agrawal, 2009). No one would expect curtains and sand to share the same supply chain as they are supplied from quite different paths since their raw materials. In fact, being able to buy both products from the same retailer is a major market development. Each of these supply chains can have their own characteristics, and thus vulnerability level. Our unit of analysis is therefore the product category Supply Chain, and all available product category supply chains will be initially included.

All the characteristics of interest on this research are linked to the physical flow of products between facilities on the supply chain. Thus, we borrow from Helen Peck (2005) second level of analysis and define supply chain as the set of nodes and links that take part on the storage and/or manipulation of goods from the last storage location on the supplier network to the point where the client takes possession of the goods. Four location types can be identified as physical storage points for products: supplier distribution centers, retailer distribution centers, retailer stores, client homes. These are the nodes and main components of each product category supply chain.

The use of ERP data from the retailer imposes a set of constraints on the frontiers of the SC, effectively limiting the research scope. First, the retailer system sees only the last departure point of the supplier network. If a supplier has regional warehouses serving different stores, they are considered different suppliers by the retailer's ERP. Transfers between supplier's facilities are invisible to the retailer including most part of international sourcing activities. Second, the retailer has no visibility whatsoever on the actual route carriers take during goods transportation. To the ERP system, goods leave one facility and arrive at another one sometime after. If the carrier uses facilities of its own, they cannot be mapped into the SC. Third, after the

General Data Protection Regulation no personal data can be used without the explicit consent of its owner (GDPR, 2016). The final SC node will be the client postal code to respect the legislation. Each node type will be briefly described in the following paragraphs.

Figure 11 - The SC boundaries for this study (the author).

Suppliers are usually specialized by product family (e.g. painting), considering raw materials and production machinery. However, some suppliers offer more than one related product family (screwdrivers and drilling machine). In other cases, the same product can be produced using different raw materials and process, as with wooden and metal doors. Here, different industries source the same product family.

The supplier base is large counting more than 1400 registered suppliers at the moment of the research. Most replenishment parameters (e.g. lead time) and commercial definitions (e.g. cost) are location dependent. Suppliers with more than one distribution center can negotiate different prices and lead times depending on the product departure point. Each shipping location is thus considered to be a different supplier, even when they are managed by the same parent company.

Cheap and heavy products cannot afford long distance transportation costs and are sourced close to the consumption area. Other products are heavily dependent of raw materials creating a production cluster and forcing national sourcing. Many products are imported from low cost countries as China, Russia and Poland. For the most part, suppliers are on a make-to-order contract, where the production starts only after order reception. The lead time is quite long, between 5 and 6 months. Imported items has been excluded from this research for data about purchase orders is scarce.

The retailer has two types of operational facilities: stores and distribution centers (DC). During the period of interest for the current study, the retailer counted more than 40 locations. Stores can sell the entirety of the company national catalog (around 100 thousand items). Part of it (between 30 and 50 thousand depending on the store size and positioning) is immediately available to the store clients from the stock kept in the store. The rest of the catalog is available on DCs or must be ordered from suppliers. Stores can be replenished directly from suppliers, or they can pass by the retailer's DC. When passing through the DC, store replenishment can happen in two ways: storage and cross docking (XD). Imported products and some slow-moving items are kept on DC storage, but the vast majority uses cross-docking. In XD flow,

stores send purchase orders to suppliers. Suppliers invoice each store separately but deliver all cargo together at the DC. The DC mix cargo from different suppliers and deliver them to each store. XD reduces total transportation costs and tend to improve service level over direct to store delivery. Figure 12 shows the three possible replenishment flows: direct to store, cross-docking and storage.

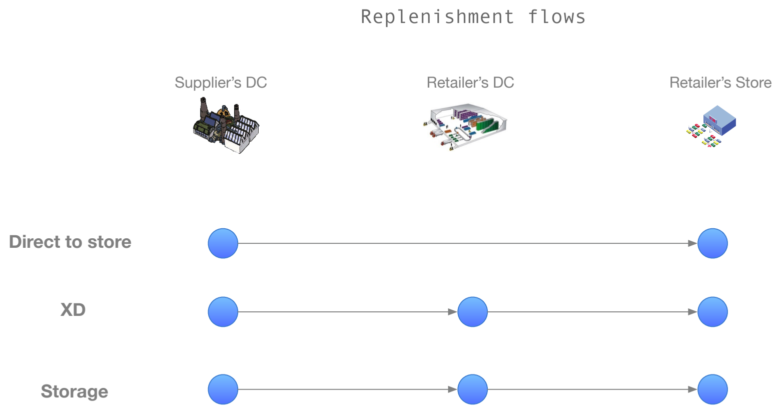

Figure 12 – Replenishment flows (the author)

Clients can opt to be delivered at the address of their choice instead of carrying the purchased items themselves. When the store is in charge of last mile delivery, the operation is called ship from store. Most part of the deliveries done by stores are considered short trips by carriers. DCs can also deliver their products direct to the clients without passing through stores. This operation is called ship from DC. However, it is limited to a regional level as transportation costs are too high. Stores distant from the DC's network usually receive customer orders within their replenishment flow and perform the last mile delivery.

Regional DCs specialize on ship from CD operations although doing store replenishment on a limited scale. Fast moving heavy and bulky products (tiles, doors, windows, earth, sand cement, swimming pools, water tanks, etc.) are stored at regional DCs and home delivered to clients. This greatly reduces in store operations costs and complexity without compromising on service level. Clients hardly retrieve this type of product from the store preferring to be home delivered, and DCs have an edge over stores in difficult handling operations like this.

The retailer has more than ten million registered clients. Most of them retrieve purchased goods straight from the store shelf. Others use the delivery service offered by stores and regional DCs. A small part places an order to retrieve the products at a future date at the store. Figure 13 shows last mile deliveries for products with stock available at the shipping

point. If no stock is available, a replenishment flow is performed prior to the client order fulfillment.

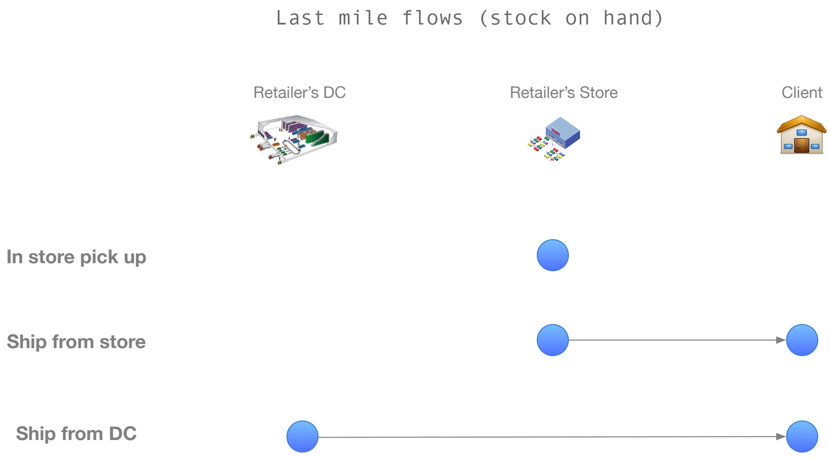

Figure 13 – Last mile flows (stock on hand)

Inside the same product family, products may use different facilities and flows depending on operational and client needs. The difference in flow may come from a supplier's capability. An example would be when a supplier has enough volume and expertise to deliver goods directly to stores, and its competitors must use the retailer's warehouse and distribution network. The difference in flow can also come from the client decision on the pickup point. Clients with urgent needs may go to a store as retrieve goods from there, where others may wish to receive the goods at home a couple of days later. Finally, sourcing and stock policy also interfere on product flow. Fast moving items can use a XD mode, leaving slow moving items to be stored at the DC. Figure 14 shows the possible flows for one retailer, combining replenishment and last mile flows:

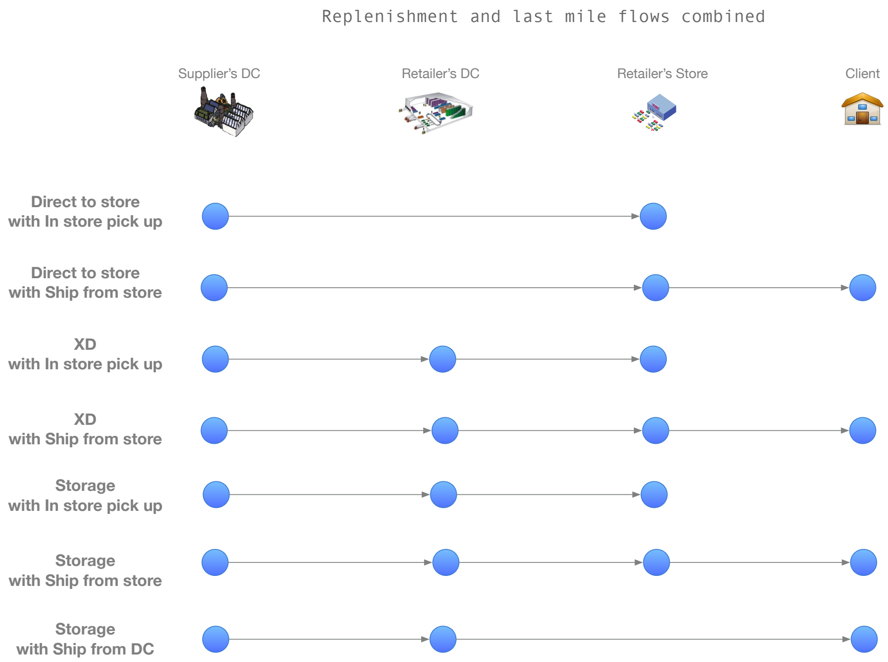

Figure 14 - Replenishment and last mile flows combined (the author)

Now that we know all possible flows, the next step is to uniquely identify each product supply chain. The retailer offers a categorization of products in product families. A product family offers a solution to a client problem, like hand tools or curtains. The product family was used as the entry key to define each supply chain. Adjusting our previous definition, a supply chain is the *set of nodes and links* that take part on the storage and/or manipulation of goods pertaining to a *specific product family* from the last storage location on the supplier network to the point where the client takes possession of the goods.

In accord with the new ERP master data, 1009 product families were active in May 21th 2018, defining the total SC population. In the ninety days prior to the 2018 Strike, 999 product supply chains have had activity. During the same period the year before, 993 handled items. Comparing 2017 and 2018, the product supply chains seemed to remain quite stable. 97,2% of 2017 supply chains remained in activity and only 42 have been created (4,8% increase). The total number of items followed the same trend, with 2,4% of increase. Despite this apparent stability, a great deal of change occurred in each supply chain. For the number of items in each SC, an absolute variation of 39,3% was accounted for. The total quantity moving through all supply chains also changed considerably, with a 18,4% overall increase, and 194,9% of variation within supply chains.

The identified changes can be attributed to changes in the product catalog, client tastes, pricing or economic trends. In any case, there are enough change to create doubts over the stability of a single supply chain over time. For this reason, data was considered as pooled

cross-sectional data and not panel data (Wooldridge, 2013). In other words, supply chains will be identified in each period using the product category code, but even when the same supply chain has activity in both periods, each is considered as an independent unit of observation. The supply chains from 2017 and 2018 are cohorts sharing many characteristics, but they are not exactly the same object. We'll come back to cohorts when discussing treatment and control groups in the next section.

3.3 Quasi-experiment designs

More knowledgeable about the treatment (2018 Trucker's Strike) and the unit of analysis (product supply chain from a home center retailer), we can move forward and complete the experiment design.

In simple terms, this dissertation probes a set of hypotheses about the effect of a disturbance in supply chain performance depending on characteristics of the supply chain. The best possible way to do it is to compare the performance of a given supply chain during and after the 2018 Strike to the performance of the same supply chain if the strike never occurred. Unfortunately, from the counterfactual definition of treatment effect (Reichardt, 2019) we know it is impossible to do so. One can compare different moments of the same supply chain, one affected by the 2018 Strike and the other not. Another possibility is to compare different supply chains during the 2018 Strike, one in Brazil (impacted) and the other in Germany (not impacted). But one can never compare the same supply chain at the same moment but in two different states. As put by Reichardt (Reichardt, 2019) "researchers cannot directly observe cause and effect; they can only infer it from imperfect data".

With this limitation about experimental designs in mid, we now describe both designs used in this research: non-equivalent group design and 2x2 factorial design.

3.3.1 The non-equivalent groups design

From the previous discussion on experimental designs, it should be clear now that we are looking for two populations: a treatment and a comparison group. If the groups are reasonably alike, comparing their performance will offer an estimate of the effect of the 2018 Strike on SC performance. The go-to method to create similar groups is by randomly assigning participants from the same population into treatment and control groups (Campbell & Stanley, 1967). Meantime, in many natural experiments like our own, the treatment group is a given,

not a researcher's choice. The researcher's effort is needed to find a valid comparison group instead.

The treatment group in our research was already mentioned, and it is straightforward: all product supply chains from the focal firm that had any activity between 120 and 30 days before the beginning of the 2018 Strike (May 21st 2018). For the control group, no such easy choice was available. The strike impacted virtually all national supply chains in Brazil. The spread of roadblocks and fuels scarcity was too fast to isolate any state. Other countries do not share enough infrastructure and socio-economic characteristics with Brazil to serve as proxies. The best fit for a control group was the product supply chains from the retailer on a previous moment in time. Which period to choose was guided by the nature of the business. The retailer' business suffers from a very strong seasonality from October to March restricting any comparison to the months between April and September. With this limitation, the control group was defined as all product supply chains from the focal firm that had any activity one year before the treatment group, or between 120 and 30 days before May 21st 2017. In principle, the groups share many traits and can be considered cohorts (Reichardt, 2019).

Drawing on the quasi-experimentation literature (Campbell & Stanley, 1967; Reichardt, 2019), a modified version of the non-equivalent pre-test post-test group design with cohorts was build. Figure 15 shows the quasi-experiment design used on this dissertation.

	21/04/2017	20/06/2017	21/04/2018	21/05/2018	20/06/2018
Treatment group			O3	X	O4
Comparison group	O1	O2			

Figure 15 – Non-equivalent groups design applied to this research.

In this design, four observations take place. In each observation, data is collected about the outcome variables of interest. The comparison group is observed in two points in time (O1,O2) before the treatment takes place in the treatment group. The treatment group on its turn is observed before and after the treatment (O3,O4). The time interval between O1 and O2 is equal to the time interval between O3 and O4 (60 days). The 60 days are in fact the sum of two 30 days periods, one before and the other after the first day of the 2018 Strike.

Based on Sheffi and Rice (2005) disturbance lifecycle model (see figure 16), the impact of a disturbance in SC performance starts right after the triggering event, but deepens sometime after, and takes a while to dissipate completely. The 30 days period following the beginning of

the strike tries to capture at least part of the three phases, but mainly the second one. The 30 days period prior to the Strike serves as performance benchmark, just after the seasonality frontier. And to accommodate for randomness in the performance, outcomes must reflect the average performance during the 30 days preceding the observation date.

Figure 16 - SC disturbance lifecycle (Sheffi & Rice, 2005)

Disregarding threats to validity, any difference between O2 and O4 that cannot be explained solely by the initial state of the groups (O1, O3) is possibly a treatment effect. This can be obtained by fitting an ANCOVA model to the gathered data considering O1-O3, O2-O4 as coming from the same period. The model can be seen below represented by equation 1:

$$Y_i = \alpha + \beta_T T_i + \beta_{lag} Ylag_i + \varepsilon_i$$

Where,

a) Y_i is the score on the outcome variable of interest for the ith participant on the post-test;
b) T_i is a dummy variable representing the assignment of i to the treatment group (T=1), or comparison group (T=0);
c) $Ylag_i$ is the score on the outcome variable of interest for the ith participant on the pre-test;
d) ε_i is the residual for the ith participant;
e) α is the intercept of the regression line from the control group with Y-axis;
f) β_{lag} is the estimate of the effect of Ylag;
g) β_T is an estimate of the treatment effect;

Notwithstanding, to test our hypothesis the SC characteristics of interest must be included on the previous model, together with confounding variables to increase internal validity. They are all continuous variables and can be considered co-variates. The modified model can be seen below represented by equation 2:

$$Y_i = \alpha + \beta_T T_i + \beta_{lag} Ylag_i + \beta_X X_i + \beta_C C_i + \varepsilon_i$$

Where,

a) X_i is the score on the SC characteristic of interest for the ith participant;

b) C_i is the score on the confounding for the ith participant;

c) β_X is an estimate of the SC characteristic effect;

d) β_C is an estimate of the confounding effect;

Covariates and confounding variables are intended as lasting attributes of each Supply Chain and cannot be affected by the treatment. To that end, their measurement must average results collected through a considerably long time-interval preceding the post-test. Conforming to that logic, covariates and confounding variables scores will calculated based on events occurring between 120 and 30 days before each post-test. No covariates and confounding variables scores will be calculated on pre-test.

Coming back to the ANCOVA model, our hypotheses, however, are not about the SC characteristics per se, but on their interaction with a disturbance. To account for this, interaction terms between all covariates and the treatment dummy variable were added to equation 2, forming equation 3:

$$Y_i = \alpha + \beta_T T_i + \beta_{lag} Ylag_i^* + \beta_X X_i^* + \beta_C C_i^* + \beta_{Tlag} T_i Ylag_i^* + \beta_{TX} T_i X_i^* + \beta_{TC} T_i C_i^* + \varepsilon_i$$

Where,

a) $Ylag_i^*$ is the score on the outcome variable of interest for the ith participant on the pre-test centered for the overall mean, i.e. $Ylag_i^* = Ylag_i - \overline{Ylag}$, where $\overline{Ylag}$ is the Ylag sample mean;

b) X_i^* is the score on the SC characteristic of interest for the ith participant centered for the overall mean;

c) C_i^* is the score on the confounding for the ith participant centered for the overall mean;

d) $T_i Ylag_i^*$, $T_i X_i^*$ and $T_i C_i^*$ are interaction terms between the treatment and each covariate centered for their overall means;

e) β_{Tlag}, β_{TX} and β_{TC} are estimates of the interaction effects.

As we expect interactions, centering is used here to generate estimates when all covariates are at their mean values and not at zero (Wooldridge, 2013).

The most important term to our hypothesis testing is β_{TX}, for it measures effect of the interaction between SC characteristics and the 2018 Strike on SC performance. If statistically significant and with a considerable effect size, there is empirical support to the hypothesis.

The experiment used two independent variables (client order on time rate, in store availability) with pre and post-test measurements, three SC characteristics as covariates (SC

density, SC node criticality, SC complexity) and two confounding variables (number of items, total quantity moved). One model was fitted for each independent variable, including main effects and interactions for covariates, confounding variables and lag variable. Equations 4 and 5 show the final models.

Equation 4, On time rate ANCOVA Model:

$$
\begin{aligned}
Y\_ot_i = {} & \alpha + \beta_T T_i + \beta_{lag} Y\_ot\_lag_i^* + \beta_{X\_density} X\_density_i^* + \beta_{X_{complexity}} X_{complexity}{}_i^* \\
& + \beta_{X_{criticality}} X_{criticality}{}_i^* + \beta_{C_{items}} C_{items}{}_i^* + \beta_{C_{quantity}} C\_quantity \\
& + \beta_{Tlag} T_i Y_{ot_{lag}}{}_i^* + \beta_{TX_{density}} T_i X\_density + \beta_{TX_{complexity}} T_i X_{complexity}{}_i^* \\
& + \beta_{Tx_{criticality}} T_i X\_criticality + \beta_{TC\_items} T_i C\_items_i^* \\
& + \beta_{TC\_quantity} T_i C\_quantity_i^* + \varepsilon_i
\end{aligned}
$$

Equation 5, In store availability rate ANCOVA Model:

$$
\begin{aligned}
Y\_avail_i = {} & \alpha + \beta_T T_i + \beta_{lag} Y\_avail_i^* + \beta_{X\_density} X\_density_i^* + \beta_{X_{complexity}} X_{complexity}{}_i^* \\
& + \beta_{X_{criticality}} X_{criticality}{}_i^* + \beta_{C_{items}} C_{items}{}_i^* + \beta_{C_{quantity}} C\_quantity \\
& + \beta_{Tlag} T_i Y_{ot_{lag}}{}_i^* + \beta_{TX_{density}} T_i X\_density + \beta_{TX_{complexity}} T_i X_{complexity}{}_i^* \\
& + \beta_{Tx_{criticality}} T_i X\_criticality + \beta_{TC\_items} T_i C\_items_i^* \\
& + \beta_{TC\_quantity} T_i C\_quantity_i^* + \varepsilon_i
\end{aligned}
$$

Now that the first quasi-experiment design is properly defined, we pass the reader to the definition of the 2x2 factorial design.

3.3.2 2x2 Factorial design

Factorial designs allow for the manipulation and concomitant investigation of more than one independent variable or factor (Anderson et al., 2010). The combination of different levels for each factor creates conditions that can be analyzed in search of primary effects but also interactions between factors. The 2x2 refers to a design with 2 factors with 2 values each.

The first factor is the same used on the non-equivalent groups design: the 2018 Strike. In this case, the possible values are no (observations from 2017, the year without the strike) and yes (observations from 2018, the year with the strike). The second factor is the SC characteristic of interest, also with 2 values: low and high. SCs with an above average value of the characteristic are classified as high and those with below average as low.

SC characteristic		2018 Strike	
		No	Yes
	Low	LN	LY
	High	HN	HY

Figure 17 – 2x2 factorial design applied to this research.

In this design, four conditions emerge: LN, HN, LY, HY (see figure 17). In each condition, data is collected about the outcome variables of interest in two points in time. The conditions positive for the 2018 Strike are measured 30 days before (O3) and 30 days after (O4) the beginning of the strike in May 21st 2018 (21/04/2018, 20/06/2018). The conditions negative for the 2018 Strike are measured at the same dates 1 year before (O1 - 21/04/2017, O2 - 20/06/2017). Figure 18 illustrates the design with its observations.

SC characteristic		2018 Strike				
		No		Yes		
		21/04/2017	20/06/2017	21/04/2018	21/05/2018	20/06/2018
	Low	O1	O2	O3	X	O4
	High	O1	O2	O3	X	O4

Figure 18 – 2x2 factorial observations.

As explained on the previous section, the 30 days period has been chosen based on Sheffi and Rice (2005) disturbance lifecycle model. To accommodate for randomness in the performance, scores are measured as the average performance during the 30 days preceding the observation date. The scores for the outcome variables in each condition is defined as the difference between the second and the first observations. That means O4-O3 for Yes and O2-O1 for No values of the 2018 Strike factor.

The statistical analysis of the 2x2 factorial design can be performed by fitting and ANOVA model to the data. The model can be seen below represented by equation 6:

$$Y_i = \alpha + \beta_T T_i + \beta_X X_i + \beta_{TX} T_i X_i + \varepsilon_i$$

Where,

h) Y_i is the score on the outcome variable of interest for the ith participant. It is calculated as the difference between O4-O3 if $F1_i$ =1 and O2-O1 if $F1_i$ =0;

i) T_i is a dummy variable indicating if the participant i was under the influence of the 2018 Strike (F1=1) or not (F1=0);

j) X_i is a dummy variable indicating if the participant i had a high level of the characteristic of interest (F2=1) or a low level (F2=0);

k) ε_i is the residual for the ith participant;

l) α is the intercept of the regression line from the control group with Y-axis;

m) β_T is an estimate of the effect of the 2018 Strike factor (F1);

n) β_X is an estimate of the effect of the SC characteristic level (F2);

o) β_{TX} an estimate of the effect of the interaction between both factors (SC characteristic level and 2018 Strike);

The most important term to our hypothesis testing is β_{f1f2}, for it measures the effect of the interaction between SC characteristics and the 2018 Strike on SC performance. If statistically significant and with a considerable effect size, there is empirical support to the hypothesis.

The quasi-experiment used two independent variables (client order on time rate, in store availability) and three SC characteristics as factors (SC density, SC node criticality, SC complexity). One model was fitted for each pair of independent variable and SC characteristic. The final models are represented by equations 7 to 12.

Equation 7, client order on time delivery and SC density:

$$Y\_ot_i = \alpha + \beta_T T_i + \beta_{X\_density} X_{density_i} + \beta_{TX_{density}} T_i X_{density} + \varepsilon_i$$

Equation 8, in store availability and SC density:

$$Y\_avail_i = \alpha + \beta_T T_i + \beta_{X\_density} X_{density_i} + \beta_{TX_{density}} T_i X_{density} + \varepsilon_i$$

Equation 9, client order on time delivery and SC complexity:

$$Y\_ot_i = \alpha + \beta_T T_i + \beta_{X\_complexity} X_{complexity_i} + \beta_{TX_{complexity}} T_i X_{complexity_i} + \varepsilon_i$$

Equation 10, in store availability and SC complexity:

$$Y\_avail_i = \alpha + \beta_T T_i + \beta_{X\_complexity} X_{complexity_i} + \beta_{TX_{complexity}} T_i X_{complexity_i} + \varepsilon_i$$

Equation 11, client order on time delivery and SC node criticality:

$$Y\_ot_i = \alpha + \beta_T T_i + \beta_{X\_criticality} X_{criticality_i} + \beta_{TX_{criticality}} T_i X_{criticality_i} + \varepsilon_i$$

Equation 12, in store availability and SC node criticality:

$$Y\_avail_i = \alpha + \beta_T T_i + \beta_{X\_complexity} X_{complexity_i} + \beta_{TX_{complexity}} T_i X_{complexity_i} + \varepsilon_i$$

The following section defines each variable used in equations 4, 5, 7, 8, 9, 10, 11, 12 and details how their values were computed from secondary data.

3.4 Variables operationalization

Prior to the definition of each variable, it is worth to discuss the secondary data with which they had to be operationalized.

The last two decades saw the digitalization of both documentation and control over business operations in Brazil. ERP systems store the legal truth of business operations. Sales and purchases, deliveries and payments are all registered in ERPs after receiving online validation from government agencies. ERPs emerge as an important source of secondary data for research. Secondary data from ERPs is rich and facilitates longitudinal studies(Saunders et al., 2015). The retailer offering secondary data to this research is no exception. Every transaction is stored for legal reasons, but also to allow for internal control and process automation.

When the 2018 Strike hit, the company was in the middle of an IT project to replace their old ERP with a brand new one. Data for the period is in consequence split between two systems. Access to the old system was restricted to the technical team, and knowledge about the system data model was scarce. A technical resource had to be allocated on this project by the company IT team before any data was retrieved. Raw data from the new system was technically available on the Business Intelligence (BI) system. However, after an initial screening, many data quality issues ignored by the company team where found. More than once, data had to be extracted directly from the system database, recreating the same friction found in the old system. System documentation, discussions with users and specialists (see table 4) and many hours of trial and error were needed to define the right queries and proceed with data extraction. Thou the majority of the research data needs were fulfilled, many rows had to be discarded based on flagrant data inconsistencies. An example is the purchase orders with issue data latter then delivery date. Also, some variables had to be amended to comply with the limitations found on the data. After each data extraction and latter during score calculation, aggregated data was discussed with key users from the retailer's SC team, as a measure of

quality insurance. Key employees were also consulted during result's analysis and proved to offer invaluable insight into the reality of the business. Table 4 presents employees consulted and the perimeter of their knowledge.

Role	Knowledge area	Research phase participation
Transportation manager	Transportation network	Project, Results analysis
Operations director	2018 Strike impact on DCs and transportation	Results analysis
Store director	2018 Strike impact on stores	Results analysis
Old ERP expert	Data extraction	Data Gathering
IT Architecture manager	Data extraction	Data Gathering
Store operations KU	Data quality validation	Data Gathering
SC B2C project manager	Data quality validation	Data Gathering
New ERP expert (SC modules)	Data modeling and extraction	Methodology, Data Gathering
Replenishment project manager	Data modeling and extraction	Methodology, Data Gathering
Replenishment KU	Data quality validation	Data Gathering
BI specialist	Data modeling and extraction	Methodology, Data Gathering
Data Engineer	Data extraction	Data Gathering
Master Data Manager	Data modeling	Methodology
Master Data Key User	Data extraction and data quality validation	Data Gathering

Table 4 – Retailer's employees consulted during the research project.

In total, data from five sources was used: retailer's old ERP, retailer's new ERP, retailer's BI, retailer's data lake, qualocep.com. From the BI, purchase orders data was extracted, including data from both the old and new systems. The old ERP supplied data from transfer orders between retailer's facilities, inventory, and client orders. The new ERP was queried for transfer orders, client orders, locations master data and product master data. The data lake was used only to extract inventory data. At last, from the site qualocep.com a database was sourced that contained latitude and longitude coordinates for postal codes in Brazil. Figure 19 illustrates the data sources. Based on the extracted data (purchase orders, transfer orders, client orders, inventory, location master data, product master data, geo-coordinates) it was possible to calculate scores for all variables. All data wrangling and an important part of data gathering was performed using Python 3 within an Anaconda installation. Once gathered, all data was stored at the retailer's data lake in Google Big Query (GBQ). Calculated variables are also stored there. The decision to keep data inside the client's own infrastructure was taken as a measure of risk mitigation.

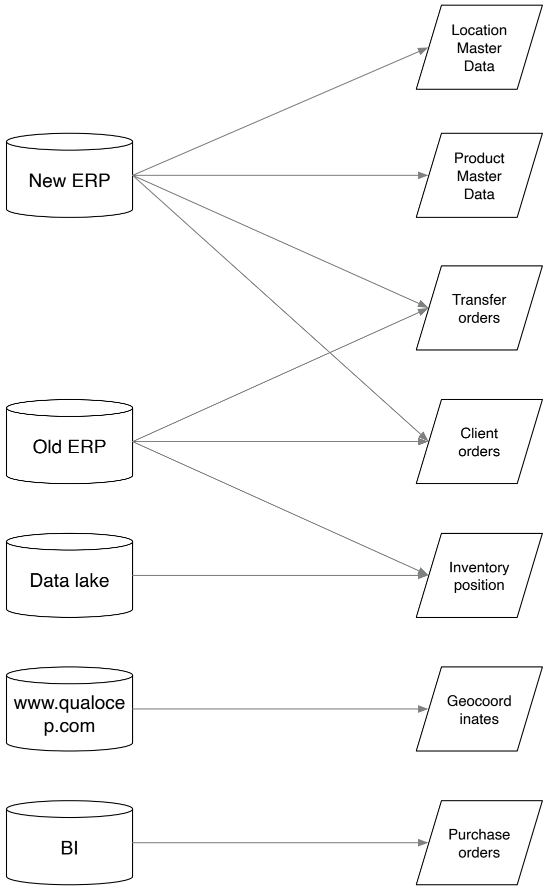

Figure 19 – Data sources by object.

Besides all limitations and difficulties generated by the use of secondary data, this research endeavor could not have been done using primary data. There are too many locations and transactions to keep track of, and one need data from months spreading over more than one year.

Table 5 list all variables used in this dissertation. In what follows, each variable operationalization is defined.

Name	Symbol	Type	Definition	Data source
In store availability	Y_avail	Dependent	Ratio between the number of items with stock at the beginning and the end of the period.	Product master data, inventory.
Client order on time delivery	Y_ot	Dependent	Percentage of client line orders delivered on time within the period.	Client orders, product master data.
SC complexity	X_complexity	Independent	Number of nodes and edges of the SC. Only edges with at least an interaction (stock transfer) within the period are considered.	Product master data, purchase orders, transfer orders, client orders.
SC node Criticality	X_criticality	Independent	Percentage of SC nodes that have an above average edge connection (EC). A node EC is the sum of inward and outward quantity in a given period. Exclude client nodes.	Product master data, purchase orders and transfer orders.
SC density	X_density	Independent	Average distance between all SC nodes. Excludes client nodes.	Product master data, geocoordinates, client orders, purchase orders, transfer orders, location master data.
Number of distinct items	X_items	Confounding	Number of distinct items transfered among all nodes within the period.	Product master data, purchase orders, transfer orders, client orders.
Quantity passing through	X_quantity	Confounding	Total quantity transferred among nodes withing the period.	Product master data, purchase orders, transfer orders, client orders.

Table 5 – List of variables.

3.4.1 In store availability

Even thou the stock out level is followed by the retailer as one of the main business indicators, past data is available only at the aggregated level, and disaggregation is impossible. Each store can choose from the retailer's assortment the items for which it desires to keep in stock. These items are considered the total store assortment and used to calculate the stockout rate. Nevertheless, there is no historization of this decision in any system. It is impossible to know the list of items that was flagged as part of the store catalog in a given day. Stockout is calculated daily at an aggregated level, buy only the resulting score is persisted on BI.

The best possible proxy available is the ratio between the number of items with stock at the beginning and the end of a given period. From discussions on the topic of assortment choice with the retailer's team, it became clear that important changes on the desired assortment is not common, and never generalized trough out the families. Between 15 and 30 product families where completely reworked each year by the product managers, never more than two or three per month. And the implementation is done store by store, with no central coordination. It can take months to have the new family implemented in all stores. It is obvious that new items enter and leave the retailer catalog every week (in average 500 new items created every week), but these movements are spread throughout product families. If a major reduction in the number of items with stock is perceived, chances are the replenishment process suffered from a major impact.

The equation applied to calculate the SC in store availability rate for a supply chain on a given period can be seen bellow (equation 13):

$$Y\_avail_{t1}^{t0} = \frac{1}{n} \sum_{location=1\ to\ n} \frac{items_{location}^{t1}}{items_{location}^{t0}}$$

Where,

a) $Y\_avail_{t1}^{t0}$ is the In store availability rate calculated for one SC in the period between t0 and t1;
b) t0,t1 are the beginning and the end of the period;
c) location represents all locations within the SC;
d) n is the total number of locations within the SC;
e) $items_{location}^{t1}$ is the number of items with stock at location in t1;
f) $items_{location}^{t0}$ is the number of items with stock at location in t0;

Before applying equation 6 to calculate the scores, a set of steps was taken to prepare the data:

a) extract and consolidate stock positions from both ERPs for the dates of interest (2017-03-22, 2017-04-21, 2017-05-21, 2017-06-20, 2018-03-22, 2018-04-21, 2018-05-21, 2018-06-20);
b) aggregate date by product family excluding imported items;

For the 2x2 factorial design, a last step was necessary. Y_avail scores calculated for O1, O2, O3 and O4 observations were combined to define the Y_avail of SCs in each condition. Conditions with no influence of the 2018 strike calculated Y_avail as O2-O1. Those under the 2018 strike influence calculated Y_avail as O4-O3.

Data from product master data and inventory was used to calculate the variable. Table 6 shows the summary statistics for In store availability rate by observation:

Y_avail	O1	O2	O3	O4
count	963,00	969,00	983,00	969,00
mean	1,02	1,03	1,02	1,03
std	0,07	0,13	0,07	0,13
min	0,66	0,50	0,70	0,50
25%	0,99	1,00	0,99	1,00
50%	1,00	1,01	1,00	1,01
75%	1,03	1,04	1,03	1,04
max	2,00	4,18	1,86	4,18

Table 6 - summary statistics for In store availability rate treatment and comparison groups

Even thou catalog evolution tends to be equally spread over product families and months, some exceptions can generate outliers for this variable. When a complete product family renewal takes place, the product family can have a drastic change on the number of items available at the store. It is not uncommon for the product manager to merge or split product families, causing some extreme values for this variable.

3.4.2 Client order on time delivery

One of the main improvements of the new ERP system is its ability to store the client order real delivery date. The new process obliges carriers to confirm the delivery conclusion

via EDI in order to get paid. In the old ERP, only the invoice date was available and used as a proxy for the shipment date. Carriers would send each store a physical proof of delivery once a week as part of the payment process. In this setting, an order is considered to be on time if it is invoiced at least two days before the promise date. Using the delivery date from the new ERP would create a threat to both internal validity (instrumentation differences) and construct validity (outcome definition). As a compromise, delivered date will be considered in both systems as the invoice date plus two days. As an order can contain products from multiple SCs, line orders and not orders were used to calculate the rate.

The equation applied to calculate the SC On time client order delivery rate can be seen bellow (equation 14):

$$Y\_ot\_rate_{period} = \frac{ot\_lines_{period}}{lines_{period}}$$

Where,

a) $Y\_ot\_rate_{period}$ is the percentage of line orders delivered on time for the supply chain during the period for all locations;
b) ot_lines_{period} number of line orders delivered on time for the supply chain during the period for all locations;
c) $lines_{period}$ number of line orders delivered on time for the supply chain during the period for all locations;

Before applying equation 7 to calculate the scores, a set of steps was taken to prepare the data:

a) extract and consolidate client order data from both ERPs where invoice dates are within the periods of interest (2017-03-22 and 2017-04-21; 2017-05-21 and 2017-06-20;2018-03-22 and 2018-04-21;2018-05-21 and 2018-06-20);
b) calculate delivery date as invoice date plus two days;
c) aggregate date by product family excluding imported items;
d) tag client orders as on time when delivery date is equal or prior to promise date;

For the 2x2 factorial design, a last step was necessary. Y_ot_rate scores calculated for O1, O2, O3 and O4 observations were combined to define the Y_ot_rate of SCs in each condition. Conditions with no influence of the 2018 strike calculated Y_ot_rate as O2-O1. Those under the 2018 strike influence calculated Y_ot_rate as O4-O3.

Data from product master data and client orders was used to calculate the variable. Table 7 shows the summary statistics for client order on time rate by observation:

Y_ot_rate	O1	O2	O3	O4
count	699,00	695,00	698,00	689,00
mean	0,91	0,93	0,89	0,88
std	0,15	0,12	0,16	0,19
min	0,00	0,00	0,00	0,00
25%	0,88	0,90	0,83	0,83
50%	0,96	0,97	0,93	0,92
75%	1,00	1,00	1,00	1,00
max	1,00	1,00	1,00	1,00

Table 7 - Summary statistics for client order on time rate treatment and comparison groups

It is important to note that supply chains with few client orders are in risk of having extreme values for this variable. With few orders, the impact of missing one deadline can be enormous, driving the score to zero. The opposite is also true. One can expect some outliers in Y_ot_rate from generate by the small population of orders per SC.

3.4.3 SC complexity

From Craighead (Craighead et al., 2007), SC complexity can be calculated as the total number of nodes and links between nodes. Deliveries were used as proxies to links, i.e. two nodes are linked if at least one order was delivered from one of them to the other. The direction of the flow is not taken into account. A node is considered to be part of a supply chain if it participates in at least one delivery containing items from the SC product family.

Equation 15 uses the previous definition to calculate SC complexity:

$$X\_complexity = nodes + links$$

Where,

a) $X\_complexity$ is the score for SC complexity;
b) $nodes$ is the number of nodes that participated in at least one delivery containing items from the SC product family;
c) $links$ is the number of connected nodes in the SC. Two nodes are linked if at least one order was delivered from one of them to the other, no matter in which direction;

Data from product master data, purchase order, transfer order and client order were used to calculate the variable. Table 8 shows the summary statistics for SC complexity by observation:

X_complexity	O2	O4
count	934,00	934,00
mean	554,66	538,19
std	2744,63	2822,42
min	0,00	0,00
25%	85,00	85,00
50%	133,00	127,50
75%	248,75	233,75
max	51935,00	53088,00

Table 8 - summary statistics for SC complexity treatment and comparison groups

For the 2x2 factorial design, SCs were classified into low and high SC complexity. SCs with above average SC complexity score were classified as high, and those below as low. No outliers were excluded from the 2x2 factorial design.

Client locations represent 98,7% of all locations and are 10^5 times more common than suppliers, DCs or stores. That is the reason why supply chains with many client deliveries can show as outliers on this variable.

3.4.4 SC node criticality

Node centrality can be used as a proxy for node criticality (Lebichot & Saerens, 2017), and edge connection (EC) is one of many possible ways to measure node centrality. It is the sum of all link weights arriving and departing from each node (Lebichot & Saerens, 2017). The higher the EC the higher the importance of the node to the network. For this research, a node is deemed critical if its EC is above the network average. From Craighead (2007), the number of critical nodes is an indicator of SC criticality. To be able to compare supply chains that differ widely in their total number of nodes, a ration between the number of critical nodes and the number of total nodes will be used in the operationalization of the variable. Client nodes must be excluded from the analysis, or their extremely low EC would skew the ECs' distribution.

Node EC within a SC can be calculated using equation 16:

$$EC_{node} = inward_{node} + outward_{node}$$

Where,

a) EC_{node} is the score for node EC;
b) $inward_{node}$ is the total quantity received by the node during the period of interest;
c) $outward_{node}$ is the total quantity shipped by the node during the period of interest.

The average SC EC can be calculated using equation 17:

$$\overline{EC}_{SC} = \frac{1}{n} \sum_{node=1\ to\ n} inward_{node} + outward_{node}$$

Where,

a) $\overline{EC}_{SC}$ is the average SC EC;
b) $node$ represents all nodes within the SC;

The equation to calculate SC Node Criticality can be seen bellow (equation 18):

$$X\_criticality = \frac{critical\_nodes}{nodes}$$

Where,

c) $X\_criticality$ is the score of the SC criticality;
d) $critical\_nodes$ is the number of nodes with EC above the SC average;
e) $nodes$ is the total number of nodes in the SC.

Before applying the equations 8 until 10 to calculate the scores, a set of steps was taken to prepare the data:

a) extract and consolidate purchase, transfer and client order data from both ERP plus the BI system. Data extraction was restricted to orders with delivery date in the period of interest (20/02/2017 - 21/05/2017; 20/02/2018 - 21/05/2018);
b) aggregate data by product family excluding imported items;
c) exclude client locations;
d) for stores, calculate the expected in store sales quantity by observation, location, and product family as total income quantity minus total outcome quantity, and sum it into outward quantity.

For the 2x2 factorial design, SCs were classified into low and high SC node criticality. SCs with above average SC node criticality score were classified as high, and those below as low. No outliers were excluded from the 2x2 factorial design.

Data from product master data, purchase orders and transfer orders were used to calculate the variable. Table 9 shows the summary statistics for SC node criticality by observation:

X_criticality	O2	O4
count	934,00	934,00
mean	0,20	0,19
std	0,09	0,08
min	0,00	0,00
25%	0,15	0,15
50%	0,20	0,19
75%	0,25	0,23
max	0,75	0,67

Table 9 - summary statistics for SC node criticality treatment and comparison groups

3.4.5 SC density

From Craighead(2007), SC Density is the average distance among all nodes from a SC network. Distances can be calculated using the geodesic model. A geodesic is the shortest path between two location at the earth surface, when the planet is seen as an ellipsoid (Karney, 2013). This research used the geopy package for Python which implements the algorithm defined by Karney (2013). To use the model, all locations had to be geocoded, i.e., identified by their geographic coordinates of latitude and longitude. This was achieved by geocoding the locations' postal codes with the help of a proprietary data base sold by qualocep.com. Only 32 locations could not have their geo-coordinates defined and where excluded from the analysis.

With the computation capabilities and time available to the research, the number of locations had to be reduced. After discussing with the retailer's transport manager, client locations were ignored for the calculation of SC density. Client locations represent 99% of the more than one hundred thousand locations, but almost all home deliveries occur on a short radio around the store or regional DC. Because of their sheer number, client locations would obfuscate long supply chains.

Equation 19 can be used to calculate SC density:

$$X\_density = \frac{\sum distance_{ab}}{C_2^n}$$

Where,

a) $X\_density$ is the score for SC density;
b) $distance_{ab}$ is the distance between the pair of nodes ab of the SC;
c) $\sum distance_{ab}$ is the sum of the distances between each combination of two nodes form the SC;

d) C_2^n is the number of possible combinations of 2 nodes from the SC;

e) n is the total number of nodes in the SC;

Before applying equation 11 to calculate scores, a set of steps was taken to prepare the data:

a) extract and consolidate purchase, transfer and client order data from both ERP plus the BI system. Data extraction was restricted to orders with delivery date in the period of interest (20/02/2017 - 21/05/2017; 20/02/2018 - 21/05/2018);

b) aggregate data by product family excluding imported items;

c) exclude client locations;

For the 2x2 factorial design, SCs were classified into low and high SC density. SCs with above average SC density score were classified as high, and those below as low. No outliers were excluded from the 2x2 factorial design.

Data from product master data, geocoordinates, client orders, purchase orders, transfer orders, location master data was used to calculate the variable. Table 10 shows the summary statistics for SC node criticality by observation:

X_density	**O2**	**O4**
count	896,00	907,00
mean	697,02	695,23
std	144,54	159,17
min	5,34	2,27
25%	678,96	677,88
50%	710,37	711,75
75%	742,88	749,47
max	1574,77	2296,35

Table 10 - summary statistics for SC node criticality treatment and comparison groups

The formulae to calculate SC density uses a cartesian product to relate each node of the SC to every other node. Nodes distant from the others will have a disproportionate impact at the average SC distance, and in consequence at the SC density. This was the origin of some outliers found at the data.

3.4.6 Confounding variables

A confounding is anything that varies across the treatment and comparison conditions (Reichardt, 2019). In their empirical paper about SCVD, Wagner & Bode (2006) indicated firm size as a potential confounding and used the number of employees of each firm to operationalize

it. Hendricks & Singhal (2008) also identified firm size, measured by the firm turnover, as an influence on the impact of SC risk on firms. Number of employees and turnover for each SC node would be needed in order to calculate the SC size using one of the aforementioned proxies. Due to the limitations around data acquisition outside the limits of the retailer's ERP, different proxies for size had to be used instead. Total number of distinct items and total quantity passing through the SC were chosen to isolate SC size effects on this research. Both measures approximate the amount of work performed by each SC.

As with all covariates, the confounding cannot be affected by the treatment. In our case they represent stable properties of the unit of analysis. We used date between post-test minus 30 days and post-test minus 120 days to calculate the scores. See below the equations used to operationalize each of the two confounding variables.

Equation 20:

$$C\_items = \ count\ distinct\ (Items)$$

Where,

a) C_items is the score for the number of distinct items managed by the SC;
b) $Items$ is the set of all items from a product family that appeared in the any type of order;
c) $count\ distinct$ is a function that drop all duplicates and then count the remaining elements of the set.

Equation 21:

$$C\_quantity = \sum_{line=1}^{n} quantity_{line}$$

Where,

a) $C\_quantity$ is the score for the total quantity managed by the SC;
b) $line$ represent a single line from any order type;
c) $quantity_{line}$ is the quantity for a single line order of any type;
d) n is the total number of line orders for a product family;

Data from product master data, purchase orders, transfer orders and client orders were used to compute both variables. To use quantity and number of items as proxies for size has the generation of outliers as side effects. Some Supply Chains have a preponderance of cheap items usually sold in big quantities (e.g. nails). The difference in managed quantity between those

SCs and the rest can go as far as 8 million units. Something alike occurs with the number of items. There are SCs where many variations of the same product are needed (e.g. sockets), exploding the total number of items.

4 Data analysis

This section will explain all steps undertaken to analyze the scores calculated using the rules and formulas defined in the methodology section. First, the results of tests and ensuing treatments around regression pre-requisites are described. Later, the results on both non-equivalent groups and 2x2 factorial designs are presented.

4.1 Statistical tests and analysis

Scores for both groups in all variables were gathered into one table. Each line of the table represents one unit of observation, i.e. a SC. Each column represents one of the variables, plus the dummy variable indicating the group. In total, 1992 observations have been collected. Table 11 shows some basic statistics for reference. Y2 stands for post-test and Y1 for the pre-test scores on the dependent variables.

	X_complexity	X_critical	X_density	C_nbitems	C_quantity_un	Y1_avail	Y2_avail	Y1_ot_rate	Y2_ot_rate
count	1868,000	1868,000	1803,000	1811,000	1811,000	1946,000	1938,000	1397,000	1384,000
mean	546,424	0,198	696,118	55,920	123185,254	1,018	1,027	0,897	0,903
std	2783,065	0,084	152,036	92,464	484566,437	0,071	0,125	0,159	0,160
min	0,000	0,000	2,274	1,000	2,000	0,663	0,500	0,000	0,000
25%	85,000	0,151	678,271	8,000	3319,500	0,991	0,997	0,854	0,870
50%	129,500	0,190	711,082	26,000	18372,000	1,003	1,011	0,944	0,956
75%	239,250	0,241	746,319	65,000	76535,000	1,027	1,036	1,000	1,000
max	53088,000	0,750	2296,350	1349,000	7988911,000	2,000	4,175	1,000	1,000

Table 11 - Basic statistics for all variables, treatment and comparison groups

For the non-equivalent group design, an outlier's analysis using the rule of 3 standard deviations from the mean was performed in each variable. The identified outliers were always a function of variable operationalization, not bad data. After outliers' removal, 1820 observations remained in the database. The number of observations available in each group can be seen at table 14. For both variables, the number of participants were evenly distributed among groups. Outliers were removed from all variables using the 3 standard deviations rule, except for Y2_ot_rate. Y2_ot_rate outliers were concentrated on the lower service level side and could be a treatment effect. Table 12 shows the number of outliers found by variable.

Variable	Nb of outliers
X_critical	22
X_complexity	18
X_density	62
C_items	36
C_quantity	19
Y_avail (pre-treatment)	34
Y_avail (post-treatment)	20
Y_ot_rate (pre-treatment)	27
Y_ot_rate (post-treatment)	27

Table 12 – Number of outliers identified per variable.

The next step was to plot each factor and confounding variable against each dependent variable using scatter plots. The results can be seen in figure 20. For most pairs, no pattern is clearly defined. Logarithmic and exponential transformations were tested in all variables to check for the emergence of a clear pattern, with no improvement.

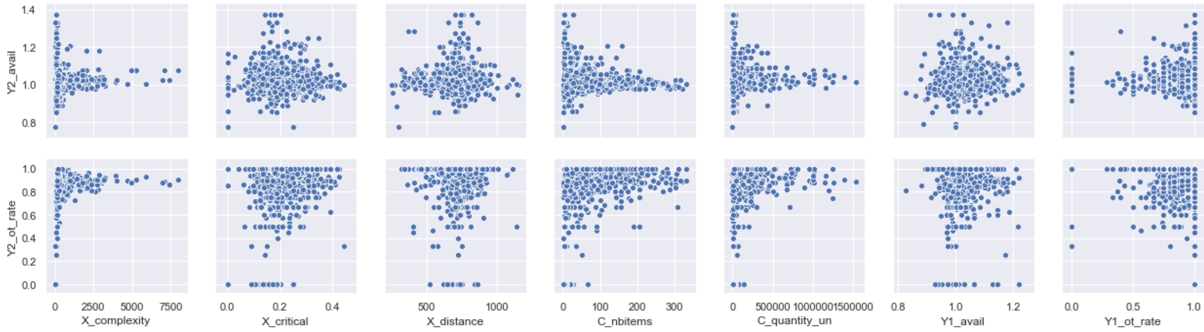

Figure 20 – Scatter plots of factor and confounding variable against each dependent variable

Multicollinearity was checked using Pearson's product moment correlation coefficient (PMCC) (Saunders et al., 2015). The resulting correlation coefficient matrix is represented in figure 21. No pair exceeded 0,470, far below the 0,7 limit, and thus no variables has been discarded.

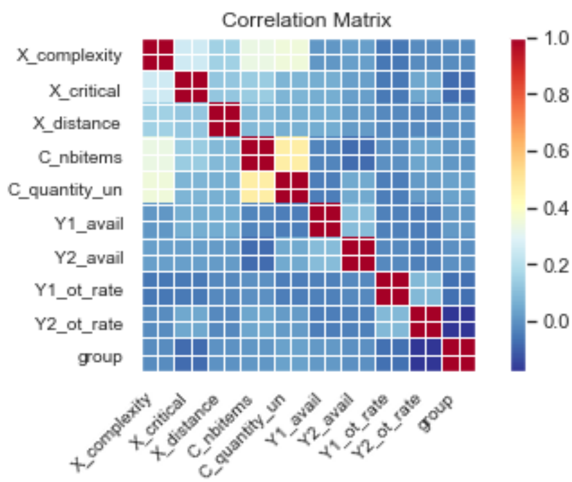

Figure 21 – correlation coefficient matrix

Histograms for each variable (figure 22) showed they do not follow a normal distribution. Moreover, with the number of observations close to two thousand, it seems

plausible to assume the central limit would allow for unbiased parameters estimation. In any case, bootstrapping was used during model fitting.

Variance on Y2_avail was found to be equal between comparison and treatment groups. In contrast, Y2_ot_rate did not pass Levene test based on the mean - $F(1,1279)=44{,}081$, $p=0{,}000$. The difference in variance is significant (see table 13). The results are somewhat surprising. One could expect that during a disturbance not only the SC performance level (its mean) would be affected, but also that teams would have a hard time to keep it stable, increasing its amplitude and variation (variance). It did not happen to Y2_avail. Figures 23 shows the boxplots for Y2_of_rate where it can be seen both a variance increase and mean reduction between both groups.

In fact, no relevant difference is found in the mean of the post-test measure for Y_avail between comparison and treatment groups. The bootstrapped confidence intervals of the means overlap, suggesting they could come from the same population (see table 14). An independent sample t-test also supported this conclusion ($t=-0{,}772$; $p=0{,}440$). For Y_ot_rate, on the other hand, the confidence intervals of the means do not overlap. The groups have a statistically significant difference on their means. The independent sample t-test support this affirmation with $t=6{,}481$, $p=0{,}000$. Both t-statistics reported are robust to heteroscedasticity. When bootstrapped, p values and confidence intervals changed slightly, but their interpretation remained the same. Y2_avail shows no indication of a treatment effect.

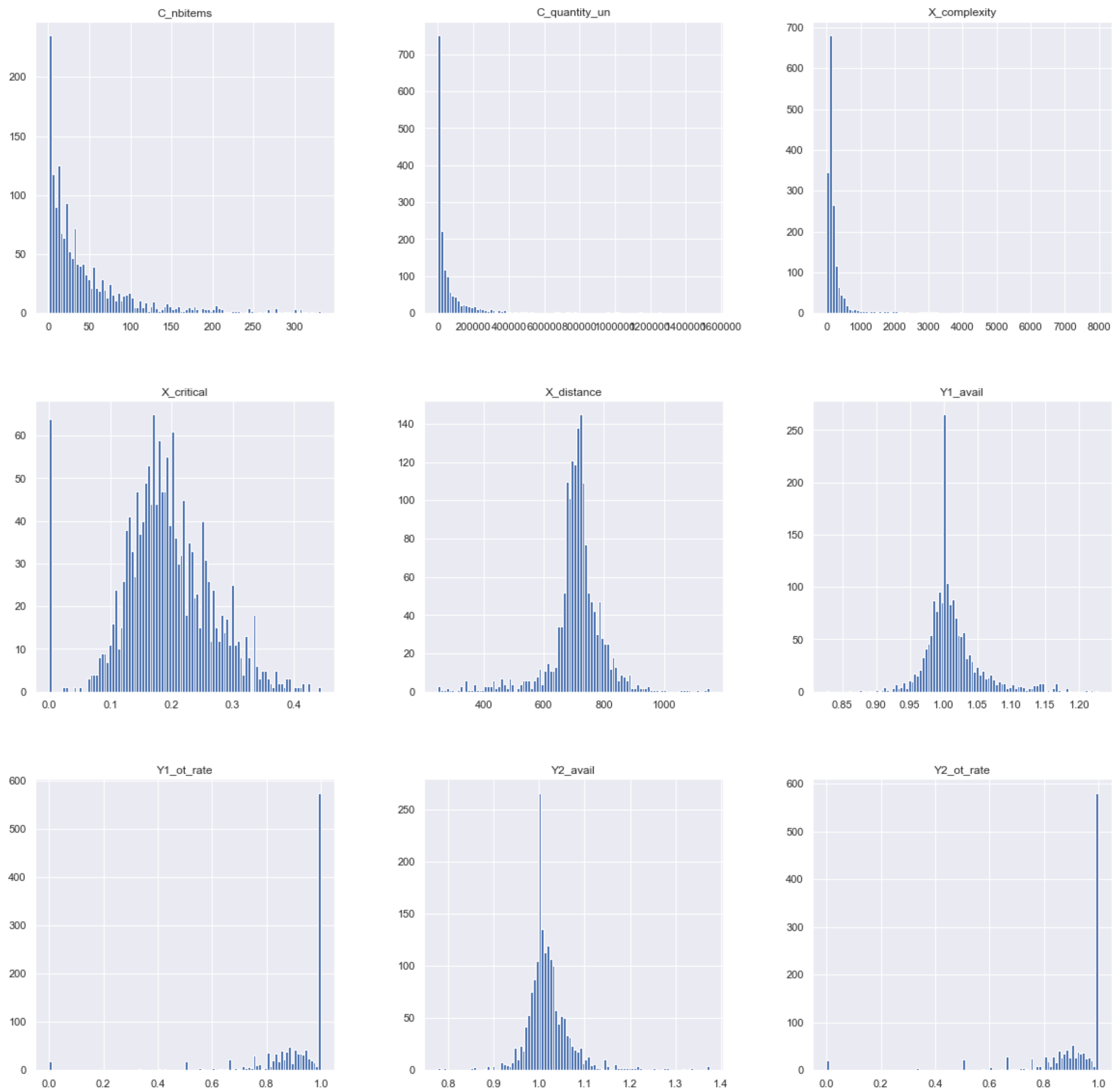

Figure 22 – Histograms for each variable

Test of Homogeneity of Variance

		Levene Statistic	df1	df2	Sig.
Y2_avail	Based on Mean	,182	1	1778	,669
	Based on Median	,132	1	1778	,716
	Based on Median and with adjusted df	,132	1	1772,163	,716
	Based on trimmed mean	,145	1	1778	,704
Y2_ot_rate	Based on Mean	53,679	1	1279	,000
	Based on Median	44,081	1	1279	,000
	Based on Median and with adjusted df	44,081	1	1129,238	,000
	Based on trimmed mean	46,580	1	1279	,000

Table 13 – Test of homogeneity of variance for dependent variables

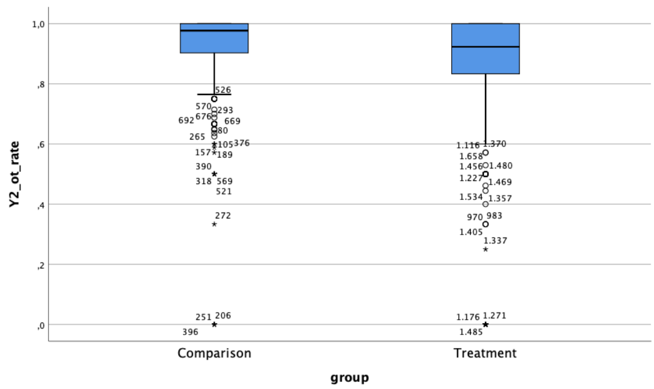

Figure 23 – Y2_of_rate box plot by group

Post-test scores	group			Bias	Std. Error	BCa 95% Confidence Interval	
						Lower	Upper
Y2_avail	Comparison	N	888,000				
		Mean	1,020	0,000	0,002	1,020	1,030
		Std. Deviation	0,050	0,000	0,003	0,044	0,057
	Treatment	N	892,000				
		Mean	1,020	0,000	0,000	1,020	1,020
		Std. Deviation	0,054	0,000	0,004	0,046	0,062
Y2_ot_rate	Comparison	N	646,000				
		Mean	0,930	0,000	0,005	0,920	0,940
		Std. Deviation	0,120	-0,001	0,012	0,097	0,141
	Treatment	N	635,000				
		Mean	0,870	0,000	0,010	0,860	0,890
		Std. Deviation	0,192	0,000	0,012	0,167	0,217

Table 14 – Between groups mean comparison

The Independent Sample T-test was also performed to check the independence between treatment and each covariate (Field, 2017). X_critical and Y1_of_rate presented statically significant differences in the group means even when bootstrapped (see table 15). At any rate, the differences found have a ratio between mean difference and standard deviation at 0,258 for X_critical and 0,133 for Y1_of_rate (Reichardt, 2019). There is enough overlap between the values in both groups to support ANCOVA mathematical matching (Reichardt, 2019).

Equality of Means t-test	Mean Difference	Bias	Std. Error	Sig. (2-tailed)	BCa 95% Confidence Interval	
					Lower	Upper
X_complexity	14,314	-2,944	37,007	0,689	-60,184	82,351
X_critical	0,017	0,000	0,004	0,001	0,010	0,023
X_distance	-0,645	-0,068	4,583	0,893	-9,339	8,529
C_nbitems	-1,597	-0,151	3,232	0,592	-8,128	4,580
C_quantity_un	-14531,173	37,508	9791,508	0,134	-34118,348	3765,102
Y1_avail	-0,001	0,000	0,002	0,653	-0,006	0,003
Y1_ot_rate	0,021	-0,001	0,009	0,022	0,005	0,037

Table 15 – Between groups mean differences

4.2 Non-equivalent groups design results

Two ANCOVA models were fitted using OLS method, one for each dependent variable following equations 4 and 5. Table 16 shows the parameters estimates for the regression model having Y2_avail as dependent variable. The model used robust parameters estimates to account for any heteroscedasticity in the residuals. Groups have almost the same number of observations, and a total of 1626 observations were available after deleting rows with missing data. The Wald-statistic of the model reports $F(13,1612)=6{,}959$, $p=0{,}000$, and the adjusted R-squared 0,019 (Wooldridge, 2013). The model is statistically significant but explains only a small fraction of the variability presented in Y2_avail. The maximum VIF statistic is 1,360, and the average is VIF 1,183, reinforcing the previous conclusion of no multicollinearity in the model. No difference was found in the group means adjusted for covariates (bootstrapped; mean comparison = mean treatment = 1,023; standard error 0,002). Plotting standardized predicted values against the standardized residual (figure 24) confirmed heteroscedasticity of residuals, and linearity.

Y_avail ANCOVA OLS Robust Parameters Estimation (HC3)	B	Robust Std. Errora	t	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound	Partial Eta Squared	Observed Powerc
Intercept	1,02E+00	0,002	547,490	0,000	1,019	1,026	0,995	1,000
[group=0]	-9,35E-05	0,003	-0,036	0,971	-0,005	0,005	0,000	0,050
X_complexity_centered	2,25E-06	0,000	0,937	0,349	0,000	0,000	0,001	0,155
X_critical_centered	3,00E-03	0,031	0,105	0,916	-0,057	0,063	0,000	0,051
X_distance_centered	2,24E-05	0,000	0,853	0,394	0,000	0,000	0,000	0,136
C_nbitems_centered	0,00E+00	0,000	-4,619	0,000	0,000	0,000	0,013	0,996
C_quantity_un_centered	3,53E-08	0,000	4,712	0,000	0,000	0,000	0,014	0,997
Y1_avail_centered	4,40E-02	0,061	0,716	0,474	-0,076	0,163	0,000	0,110
[group=0] * C_nbitems_centered	-1,01E-05	0,000	-0,278	0,781	0,000	0,000	0,000	0,059
[group=0] * C_quantity_un_centered	-1,37E-09	0,000	-0,114	0,909	0,000	0,000	0,000	0,051
[group=0] * X_complexity_centered	8,60E-07	0,000	0,247	0,805	0,000	0,000	0,000	0,057
[group=0] * X_critical_centered	-1,40E-02	0,040	-0,346	0,729	-0,092	0,064	0,000	0,064
[group=0] * X_distance_centered	-2,54E-05	0,000	-0,763	0,445	0,000	0,000	0,000	0,119
[group=0] * Y1_avail_centered	1,08E-01	0,080	1,351	0,177	-0,049	0,265	0,001	0,272

Table 16 – ANCOVA Y_avail OLS with robust parameter estimates

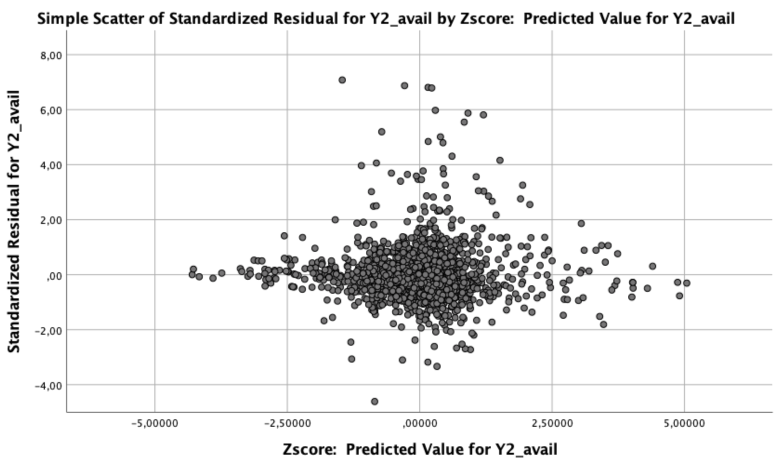

Figure 24 – Y2_avail ZPRE vs ZRES scatterplot

No treatment effect nor any interaction between the treatment and the covariates was found to be statistically significant. Although C_nbitems_centered (B=0,00E+00; t=-4,619; p=0,000) and C_quantity_centered (B=3,53E-08; t=4,712; p=0,000) both are statistically significant, the effect sizes calculated using Partial ETA Squared are both small, 0,013 and 0,014 respectively. Together they explain only 2,7% of the variability in Y2_avail, not already explained by another variable (Field, 2017). The same model was fit using bootstrapping with similar results, and an even small Partial ETA Squared for C_nbitems_centered and C_quantity_centered. Under the lights of these results, hypothesis 1A, 2A and 3A were refused.

Table 17 shows the parameters estimates for the regression model having Y2_ot_rate as dependent variable. Again, OLS and Robust Parameter Estimates HC3 methods have been used. The model Wald-statistic reports F(13,1176)=11,84, p=0,000, and the adjusted R-squared 0,049 (Wooldridge, 2013). The model is statistically significant but explains only a small fraction of the variability presented in Y2_ot_rate. The maximum VIF was found to be 1,320 and the average VIF is 1,148, reinforcing the previous conclusion of no multicollinearity in the model. Plotting standardized predicted values o Y2_avail against the standardized residual (figure 25) confirmed heteroscedasticity, but non-linearity remains unclear.

Y_ot_rate ANCOVA OLS Robust Parameters Estimation	B	Robust Std. Error	t	Sig.	95% Confidence Interval		Partial Eta Squared	Observed Powerc
					Lower Bound	Upper Bound		
Intercept	8,70E-01	0,009	98,076	0,000	0,853	0,888	0,892	1,000
[group=0]	6,60E-02	0,010	6,501	0,000	0,046	0,086	0,035	1,000
X_complexity_centered	-3,75E-06	0,000	-0,793	0,428	0,000	0,000	0,001	0,124
X_critical_centered	1,58E-01	0,137	1,159	0,247	-0,110	0,427	0,001	0,212
X_distance_centered	-3,11E-05	0,000	-0,244	0,807	0,000	0,000	0,000	0,057
C_nbitems_centered	0,00E+00	0,000	2,153	0,032	0,000	0,000	0,004	0,576
C_quantity_un_centered	9,44E-09	0,000	0,454	0,650	0,000	0,000	0,000	0,074
Y1_ot_rate_centered	1,01E-01	0,063	1,586	0,113	-0,024	0,225	0,002	0,354
[group=0] * C_nbitems_centered	0,00E+00	0,000	-1,610	0,108	0,000	0,000	0,002	0,363
[group=0] * C_quantity_un_centere	1,85E-08	0,000	0,676	0,499	0,000	0,000	0,000	0,104
[group=0] * X_complexity_centerec	-4,94E-06	0,000	-0,902	0,367	0,000	0,000	0,001	0,147
[group=0] * X_critical_centered	-2,69E-01	0,151	-1,785	0,075	-0,566	0,027	0,003	0,430
[group=0] * X_distance_centered	-3,92E-06	0,000	-0,029	0,977	0,000	0,000	0,000	0,050
[group=0] * Y1_ot_rate_centered	-3,60E-02	0,080	-0,453	0,651	-0,193	0,121	0,000	0,074

Table 17 – ANCOVA Y_ot_rate OLS with robust parameter estimates

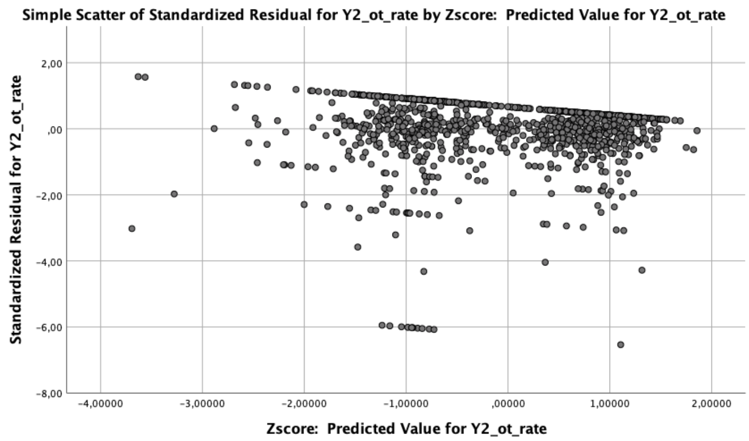

Figure 25 – Y2_ot_rate ZPRE vs ZRES scatterplot

The treatment effect was found to be statistically significant in this case. The difference in means between groups is of 0,060, with the comparison group presenting a mean (0,935) considerably inferior to the treatment group (0,875) already adjusted to the covariates effect. Although C_nbitems_centered (B=0,00E+00; t=2,153; p=0,032) also appeared as statistically significant in the model, the effect size is very small (Partial ETA Squared = 0,004). The same model was fit using bootstrapping and offered similar results. No interaction between treatment and covariate was found to be significant. Under the lights of these results, hypothesis 1B, 2B and 3B were refused.

4.3 2x2 Factorial design

Six ANOVA models were fitted using OLS method, one for each combination of the 2 independent variables and 3 SC characteristics following equations 8 to 13. The models used robust parameters estimates to account for any heteroscedasticity in the residuals.

On the 3 models related to Y_avail, groups were balanced between yes and no for the 2018 Strike factor, but not for the SC characteristic level factor. Table 18 shows the number of participants in each condition for the 3 experiments, together with its mean and standard deviation. The F statistic of each model can be seen on table 19. None passed the test of significance. The same is true for the t-test on parameters estimation presented in table 20. Under the lights of these results, hypothesis 1A, 2A and 3A were refused.

Y_avail - Descriptive Statistics				
X_complexity				
2018 Strike	**Characteristic**	**Mean**	**Std. Deviation**	**N**
No	Low	0,0137	0,14045	806
No	High	-0,0013	0,08647	99
No	Total	0,0121	0,13564	905
Yes	Low	0,0103	0,14469	818
Yes	High	0,0108	0,07826	94
Yes	Total	0,0103	0,13929	912
Total	Low	0,012	0,14257	1624
Total	High	0,0046	0,08258	193
Total	Total	0,0112	0,13745	1817
X_density				
2018 Strike	**Characteristic**	**Mean**	**Std. Deviation**	**N**
No	Low	0,0231	0,19697	334
No	High	0,0055	0,07963	556
No	Total	0,0121	0,13625	890
Yes	Low	0,015	0,20835	312
Yes	High	0,0074	0,08393	573
Yes	Total	0,0101	0,14087	885
Total	Low	0,0192	0,20243	646
Total	High	0,0064	0,08181	1129
Total	Total	0,0111	0,13854	1775
X_critical				
2018 Strike	**Characteristic**	**Mean**	**Std. Deviation**	**N**
No	Low	0,0242	0,17532	453
No	High	-0,0001	0,07601	452
No	Total	0,0121	0,13564	905
Yes	Low	0,0112	0,15999	551
Yes	High	0,009	0,09994	361
Yes	Total	0,0103	0,13929	912
Total	Low	0,0171	0,16712	1004
Total	High	0,0039	0,08751	813
Total	Total	0,0112	0,13745	1817

Table 18 – Basic statistics for each condition in Y_avail ANOVA models

Y_avail	F	Sig.
X_complexity	0,377	0,769
X_density	1,365	0,252
X_critical	2,408	0,065

Table 19 – F statistic for Y_avail ANOVA models

Y_avail ANOVA OLS Robust Parameters Estimation (HC3)	B	Robust Std. Errora	t	Sig.	95% Confidence Interval		Noncent. Parameter	Observed Powerc
					Lower Bound	Upper Bound		
X_complexity								
Intercept	0,011	0,008	1,327	0,185	-0,005	0,027	1,327	0,264
2018 Strike = No	-0,012	0,012	-1,015	0,31	-0,035	0,011	1,015	0,174
[X_complexity_level= Low]	0	0,01	-0,052	0,959	-0,019	0,018	0,052	0,05
[2018 Strike = No] * [X_complexity_level=Low]	0,016	0,014	1,122	0,262	-0,012	0,043	1,122	0,202
X_density								
Intercept	0,007	0,004	2,096	0,036	0	0,014	2,096	0,554
2018 Strike = No	-0,002	0,005	-0,384	0,701	-0,011	0,008	0,384	0,067
[X_density_level= Low]	0,008	0,012	0,62	0,536	-0,017	0,032	0,62	0,095
[2018 Strike = No] * [X_density_level=Low]	0,01	0,017	0,598	0,55	-0,023	0,043	0,598	0,092
X_critical								
Intercept	0,009	0,005	1,709	0,088	-0,001	0,019	1,709	0,401
2018 Strike = No	-0,009	0,006	-1,427	0,154	-0,022	0,003	1,427	0,297
[X_critical_level= Low]	0,002	0,009	0,255	0,799	-0,015	0,019	0,255	0,057
[2018 Strike = No] * [X_critical_level=Low]	0,022	0,012	1,776	0,076	-0,002	0,047	1,776	0,427

Table 20 – ANOVA models for Y_avail fit with OLS and robust parameter estimates

On the 3 models related to Y_ot_rate, groups were balanced between yes and no for the 2018 Strike factor, but not for the SC characteristic level factor. Table 21 shows the number of participants in each condition for the 3 experiments, together with its mean and standard deviation. The F statistic of each model can be seen on table 22. The models for X_complexity and X_critical were significant. However, only the interaction between X_complexity and the 2018 Strike passed the t-test, as can be seen on table 23 that presents the models parameters estimation. Under the lights of these results, hypotheses 1B and 2B were refused. Only hypothesis 3B was accepted.

Y_ot_rate - Descriptive Statistics				
X_complexity				
2018 Strike	**Characteristic**	**Mean**	**Std. Deviation**	**N**
No	Low	0,0224	0,17939	544
No	High	0,0192	0,03669	99
No	Total	0,0219	0,1656	643
Yes	Low	-0,013	0,24222	535
Yes	High	0,0149	0,05162	94
Yes	Total	-0,0088	0,22446	629
Total	Low	0,0049	0,21351	1079
Total	High	0,0171	0,04452	193
Total	Total	0,0067	0,19744	1272
X_density				
2018 Strike	**Characteristic**	**Mean**	**Std. Deviation**	**N**
No	Low	0,0237	0,15724	222
No	High	0,0214	0,17004	420
No	Total	0,0222	0,1656	642
Yes	Low	-0,0001	0,20537	199
Yes	High	-0,0106	0,22821	429
Yes	Total	-0,0073	0,22112	628
Total	Low	0,0125	0,18175	421
Total	High	0,0052	0,20206	849
Total	Total	0,0076	0,19552	1270
X_critical				
2018 Strike	**Characteristic**	**Mean**	**Std. Deviation**	**N**
No	Low	0,0203	0,19368	273
No	High	0,0231	0,14163	370
No	Total	0,0219	0,1656	643
Yes	Low	-0,0294	0,25626	345
Yes	High	0,0162	0,17559	284
Yes	Total	-0,0088	0,22446	629
Total	Low	-0,0075	0,23187	618
Total	High	0,0201	0,15719	654
Total	Total	0,0067	0,19744	1272

Table 21 – Basic statistics for each condition in Y_ot_rate ANOVA models

Y_ot_rate	F	Sig.
X_complexity	3,13	0,025
X_density	2,549	0,054
X_critical	5,416	0,001

Table 22 – F statistic for Y_ot_rate ANOVA models

Y_ot_rate ANOVA OLS Robust Parameters Estimation (HC3)	B	Robust Std. Errora	t	Sig.	95% Confidence Interval		Noncent. Parameter	Observed Powerc
					Lower Bound	Upper Bound		
X_complexity								
Intercept	0,015	0,005	2,781	0,006	0,004	0,025	2,781	0,794
2018 Strike = No	0,004	0,007	0,66	0,51	-0,008	0,017	0,66	0,101
[X_complexity_level= Low]	-0,028	0,012	-2,37	0,018	-0,051	-0,005	2,37	0,658
[2018 Strike = No] * [X_complexity_level=Low]	0,031	0,015	2,142	0,032	0,003	0,06	2,142	0,572
X_density								
Intercept	-0,011	0,011	-0,961	0,337	-0,032	0,011	0,961	0,16
2018 Strike = No	0,032	0,014	2,317	0,021	0,005	0,059	2,317	0,639
[X_density_level= Low]	0,011	0,018	0,576	0,565	-0,025	0,046	0,576	0,089
[2018 Strike = No] * [X_density_level=Low]	-0,008	0,023	-0,362	0,717	-0,053	0,036	0,362	0,065
X_critical								
Intercept	0,016	0,01	1,552	0,121	-0,004	0,037	1,552	0,341
2018 Strike = No	0,007	0,013	0,543	0,587	-0,018	0,032	0,543	0,084
[X_critical_level= Low]	-0,046	0,017	-2,636	0,008	-0,08	-0,012	2,636	0,75
[2018 Strike = No] * [X_critical_level=Low]	0,043	0,022	1,93	0,054	-0,001	0,086	1,93	0,488

Table 23 – ANOVA models for Y_ot_rate fit with OLS and robust parameter estimates

5 Results discussion

The findings on each dependent variable is discussed in turn on the following text.

5.1 In Store Availability (Y_avail)

From the statistical analysis, it is safe to assume that nothing changed in the In-store availability rate as consequence of the 2018 Strike. This lack of effect could be attributed to a construct validity issue related to the treatment (Reichardt, 2019). Perhaps no shortage of transportation means impacted the observed supply chains during the 2018 Strike, and the treatment was ill defined. If that was true, the replenishment flow would not have been disrupted and this would explain the service level stability. After interviewing the retailer's operations director, this alternative explanation was ruled out. All DCs suffered from lack of volumes during the strike. He showed a photo of the XD site completely empty in the middle of the strike period. The site is never empty during normal operation and manages 55% of the total volume sold by the retailer.

A different explanation is the work of positive forces that counterbalance the negative impacts of a disturbance. This too could be interpreted as a threat to the construct validity of the treatment. Craighead et al. (2007) included in their model two mitigation capabilities that could have this effect: recovery and warning. The authors define recovery capability as "the interactions of supply chain entities and the corresponding coordination of supply chain resources to return the supply chain to a normal and planned level of product flow" (Craighead et al., 2007, page 144). Recovery capability is an unlikely explanation in our case for two reasons. First, collaboration is a main component of this capability and an antecedent of SC resilience in general (Scholten et al., 2014). The retailer had no collaboration program in place with suppliers or carriers in 2018, and the relationship with stores is more on the combative side. It is difficult if not impossible to coordinate a response to a disturbance with only commercial links in place. Second, flexibility would also be needed to allow the recovery capability to play its role. From the SC resilience literature, flexibility offers different options to SC actors when trying to circumvent difficulties created by the disturbance (Bradaschia & Pereira, 2016). The retailer and its main suppliers where heavily dependent upon fixed routes and truck services to move products for the lowest possible cost. No alternatives were readily available when the strike hit.

It leaves us with the warning capability defined by Craighead et al. (2007) as a combination of disturbance detection and the timely dissemination of relevant information through the SC. The retailer's transportation team was indeed informed about the strike movement days in advance. Few believed it was going to happen and no preparation was done. The low level of risk awareness and the low priority given by the management to SCRM can account for this reaction. Risk awareness has been cited as an important piece of SC resilience (Kleindorfer & Saad, 2005), demanding the implementation of policies and processes that insure continuous risk assessment and a risk management culture.

The different choices of time can also be a threat to construct validity (Reichardt, 2019) and account for the lack of effect. The delay between treatment administration and the observation of results is a size-of-effect factor (Reichardt, 2019). The design used in this research measures the treatment effect 30 days after its administration. The reason was explained at the methodology section, and is related to the disturbance lifecycle proposed by Sheffi & Rice (2005). The 30 days should encompass the first days after the disturbance before the full impact arrive, the bulk of the impact, and the initial recovery. With 10 days of disturbance and 17 days of lead time, 30 days seems to be a good enough window of time to assess treatment effect. The out of stock level reported by the client kept stable between April and June. Changing the time interval would have made no difference in our evaluation.

The most probable answer for the riddle on the missing treatment effect came from the retailer's commercial team. The director of the one of their stores volunteered the information that the number of clients visiting the store reduced considerably during the strike. The numbers confirmed: 5,69% fewer paying customers and 7,09% less sales, comparing 30 days before 21/05/2018 with 30 days after it. Prior to the strike the retailer was experiencing growth, so the fall in client flow was considerable. With less demand, the replenishment flow interruption was not enough to reduce In store availability. By the time clients came back to the stores, the physical flow has been reestablished to normality. The reduction on client flow worked quite similar to a placebo effect on a medical trial. It is a confound to the intended treatment and threatens the construct validity of the cause (Reichardt, 2019).

If it was possible for some SCs to have a positive effect of the disturbance, even an overall stability on In store availability could result from a combination of gains and losses among SCs. SCs with a lessened client flow could improve their In-store availability with the few receptions made during the disturbance time window. Others SCs would not lose clients, and their availability are to be depressed by the end of the period. Nonetheless, this scenario is not support by the data on hand. The Y2_avail mean could be the same between comparison

and treatment groups, but the polarization of scores in low availability and high availability should increase the variance on the treatment group. It was not the case. The variable passed lavene's test for homoscedasticity. The same reasoning applies to the covariates in the model. In sum, no main treatment effect and no interaction between treatment and SC characteristics was found to influence the In-store availability rate during the 2018 Strike.

Despite the previously unknown and unaccounted for reduction in client flow, the hypothesis delineated in section 2 are still valid, as they are not strictly dependent on the treatment middle effects. Stating differently, including a secondary dimension in the treatment (i.e. the client flow reduction) does not invalidate the hypothesis testing. The new treatment middle effect is composed of a shortage in trucks for cargo transportation and a reduction on the store client flow. Hypotheses 1A, 2A and 3A were refused in both quasi-experiment designs. The In-store availability rate was equally impacted by the 2018 Strike (null effect) no matter the level of SC density, SC complexity or SC node criticality of each Supply Chain.

This new treatment dimension (client flow) is an important finding. The entire research was constructed looking to the flow of products, from supplier to customer. The flow of customers to the stores and their impact on SC performance was never part of the setting, and, in the end, it greatly impacted the results. Based on this author limited knowledge of the literature on SCRM, this myopia seems to be shared by many researchers. The change in customer flow could also account for the difference in losses suffered by different sectors of the economy listed in table 24. It is possible that clients have different motivations to buy during a disturbance this size.

Industry	Losses in Billion Reais
Chicken and pigs	3
Bovines	8
Sugar	0,74
Milk	1
Wheat	0,225
Tobacco	0,672
Chemicals	9,5
Pharmaceuticals	1,6
Construction	3,8
Textile	1,8
Beverages	11,5
Services	27
Commercial airlines	0,45
Supermarkets	2,7

Table 24 – Losses per industry, adapted from Silva (2018)

5.2 Client order on time delivery rate (Y_ot_rate)

Based on the statistical analysis performed as part of the non-equivalent groups quasi-experiment, client order on time delivery rate was found to be negatively impacted by the 2018 Strike. The same effect was found in the 2x2 factorial design when SC density integrated the model as factor. The treatment effect, however, does not have the expected size. One possible reason is the impact of approximated data on the construct definition. From the methodology section, delivery date was approximated as invoice date plus two days. It is possible that some orders got to be invoiced on time, but did not leave the retailer store on the same day. In business-as-usual times such occurrences are so rare that the score is close enough to the truth. With a shortage of trucks during the strike, it is conceivable that invoiced orders piled up at the stores waiting for carriers. This is a construct validity threat of the outcome measurement, and it is probably masquerading the treatment effect.

The difference found between both groups at the scores on the pre-test of the non-equivalent group design could also be a threat to validity, but internal validity in this case. The treatment group started with a lower score, and this could account for at least part of the effect perceived in the post-test. However, the fact that the scores on the comparison group went up from pre-test to post-test, and down on treatment group reduce this probability. A t-test comparing the differences in each group (Y2_ot_rate – Y1_ot_rate) confirmed the difference in differences of 0,3655 (t=3,151;p=0,002).

Now that we established the reality of the treatment effect, the interactions between treatment and SC characteristics can be discussed. Only SC complexity interacted with the 2018 Strike to change the impact suffered by SCs in their ability to deliver client order on time. The interaction was found to be statistically significant (t=2,142, p=0,032) under the 2x2 factorial design. However, the influence was on the opposite direction to what has been initially hypothesized in H3B. SCs with low complexity had a greater impact than SCs with high complexity.

One possible explanation lies with the way the retailer organizes its home delivery operation and the product supply chains that support it. Home delivery is operationalized at regional DCs or stores, in what Chopra (2003) described as distributor storage with last mile delivery. This network configuration allows the retailer to offer a high service level to consumers, with a reduced lead time and exploiting the existing store facilities, in line with the benefits listed by Chopra (2003). Products are shipped to clients from the closest store or DC, and most part of the trips are short (less than 100 Km). The limit on trip distance is an economic

limitation. Client orders tend to be small in B2C business and there is a need for high concentration of deliveries on a geographic region to justify transportation costs (Lee & Whang, 2001). From the section that described the retailer business we know home delivery is requested by clients specially for heavy and bulky products. Supply chains that support heavy products tend to be local, as transportation costs can be prohibited even for store replenishment. In this way, local sourcing was developed in each city, increasing the SC complexity of the product SCs involved in heavy and bulky products. One can expect the truck shortage caused by the 2018 Strike to have a greater impact on long trips than on short ones. Under these circumstances, local and short supply chains delivering heavy and bulky products were to be less impacted on their ability to deliver client orders on time than long supply chains.

The missing interactions between SC node criticality, SC density and the 2018 Strike can be explained by the nature of the 2018 Truck drivers' strike. The strike was a country wide disturbance hitting all major cities and transportation arteries (economia.uol, 2018; Silva, 2018). Virtually all nodes of each SC were hindered because of it. Hypothesis 1B and 2B share the same hidden assumption: the disturbance is local, not global. To exemplify, see below the logical structure behind hypothesis 1B:

a) critical nodes bear an important part of the SC volume;
b) should a critical node fall, the impact on the SC would be considerable;
c) the higher the number of critical nodes, the higher the chance one of them is hit by a disturbance and fall;
d) the higher the number of critical nodes, the higher the SC vulnerability level;

Should all nodes from a SC be impacted by a disturbance, it is logic that the number of critical nodes no longer drives vulnerability. The same can be said for density. In other words, SC node criticality and SC density cannot be vulnerability drivers for disturbances that affects all SC nodes. This notion can be generalized to say that a SCVD is conditional on the disturbance properties. The same SC characteristic when confronted with two different disturbances can work as SCVD for one disturbance and have no effect on the second.

Perhaps a classification or taxonomy of disturbances based on their properties could enlighten us on the role of SC characteristics as SCVD. The classification of disturbances is part of the SCRM literature, and usually goes under the rubric of risk source. Ho et al. (2015) did a literature review on SCRM and proposed a three-level categorization of risk sources. The first level distinguishes between macro and micro-risks (Ho et al., 2015). Macro-risks are external high impact-low frequency disturbances (Ho et al., 2015). Micro-risks are low impact-

high frequency disturbances originated from the daily business activities (Ho et al., 2015). Macro-risks can be divided into man-made and natural (Van Wassenhove, 2006). Micro-risks are grouped into four sub-categories: demand, manufacturing, supply and infrastructure. Under each sub-category (Ho et al., 2015) classified different risk types, the last level of categorization. The authors continue their article matching the available literature covering different SCRM activities and mitigation strategies to each sub-category (Ho et al., 2015). An example is a list of articles referring to demand forecasting as a mitigation alternative to demand risk source.

Other risk source classifications have been proposed, focusing on different properties of the disturbance besides its origin. Van Wassenhove (2006) separates risk sources based on their onset speed: fast and slow onset. Jüttner & Maklan (2011) did not used speed to classify disturbances but identified velocity as an important property of risk events. As previously stated, by knowing the cause, scholars and managers hope to devise successful SC risk management strategies (Heckmann et al., 2015). The same approach could be used by researchers to propose a classification of disturbances based on their properties that allow the identification of the right SCVDs.

Coming back to the 2018 Truckers' strike, it can be classified as a macro-risk with a fast onset. The removal of an important asset as road transportation is a major risk source (Peck, 2005), and one that seems quite impossible to mitigate using only isolated SC resources (McKinnon, 2006). McKinnon (2006) concluded his paper about truck strikes in London with the following note:

"There would be little that individual companies could do to protect themselves against this very unlikely occurrence. Traditional business continuity techniques would provide only marginal relief. Responsibility for dealing with a crisis of this magnitude would primarily rest with government." (page 246).

The collaboration between private and public sectors to mitigate risks is being advocated and openly practiced for many years in US and Europe after September 11 (Voss & Williams, 2013). An example is the Customs-Trade Partnership Against Terrorism (C-TPAT), a certification program build in partnership between the US Department of Home Security and private firms (Voss & Williams, 2013). If collaboration was enough to strengthen firms and by consequence the US national security against terrorism, a similar cooperation can happen between the Brazilian government and the private sector to change the transportation landscape and reduce dependence on road transport.

Notwithstanding, the collaboration with government is not alone in the literature as a pathway to reduce SCV to macro-risks. Inventory positioned close to demand centers has been cited as an effective buffer (Stecke & Kumar, 2009). Resilience in general is also offered as a remedy to the overall risk exposition (Bradaschia & Pereira, 2016; Christopher & Peck, 2004; Jüttner & Maklan, 2011; Sheffi & Rice, 2005).

In sum, for the client order on time delivery rate, hypothesis 1B, 2B and 3B were refused in both quasi-experimental settings. The client order on time delivery rate was equally impacted by the 2018 Strike (negative impacted) no matter the level of SC density and SC node criticality of each Supply Chain. The client order on time delivery rate was more impacted by the 2018 Strike (negative impacted) for SCs with low SC complexity level than with high SC complexity.

5.3 Final considerations on the research findings

The hypotheses in this dissertation originated from the work of Craighead et al.(2007) published in Decision Sciences under the title "The Severity of Supply Chain Disruptions: Design Characteristics and Mitigation Capabilities". Craighead et al.(2007) used a three-phase qualitative design, in which each phase had different data source and collection methods. The authors were aiming at "the identification and definition of the various factors that could contribute to or could dampen the severity of supply chain disruptions. (Craighead et al., 2007, page 135)". It is a sound piece of research and, before our statistical analysis, odds seemed to be in favor that at least some of the hypotheses would be confirmed. At some level, they are almost common-sense for Supply Chain professionals and scholars. In any case, the data from the quasi-experiment performed did not support them. Our findings are valid to Brazilian specialty retailers with national coverage, considerable scale and diversified line of products, under the effect of a nationwide, all-encompassing disturbance, that reduces the cargo and passenger transportation service offerings during a time interval close to 10 days. At the same time, there are many different settings yet to be checked.

The two major research findings are repeated below:

a) The flow of clients toward the store during a disturbance is an important factor to determine disturbance impact on the SC.
b) Short supply chains seem to be less vulnerable to SC disturbances.
c) Not all SC characteristics can play the role of SCVD for all disturbances. Its role and effectiveness are conditional to the properties of the disturbance in question.

6 Conclusion

The aim of this dissertation was to assess in what measure supply chain characteristics drives the vulnerability of supply chains to disruptions, and which characteristics are more influential. The study focused on the impact of the 2018 Brazilian Truckers' Drivers Strike, into the performance of the product category supply chains from one home improvement retailer. The hypotheses to be tested were developed from the work of Craighead et al. (2007), and involved three SC characteristics of interest (SC density, SC complexity, SC node criticality) and two SC performance metrics (in store availability, on time client order delivery).

In accordance to the dissertation objectives, all product category supply chains that compose the assortment of a Brazilian home center have been identified. Each SC was mapped from the last point of stock on the supplier side to the point of retrieval by the client based on purchase and sales orders extracted from the retailer's ERP systems. The same data was used to calculate individual scores for the characteristics of SC complexity, SC density and SC node criticality. In store availability and on time client order delivery levels for each supply chain before and after the strike were also calculated. Finally, two quasi-experimental designs (non-equivalent group design, 2x2 factorial design) have been used to fit data from the retailer's ERP systems into two statistical modes (ANCOVA and ANOVA).

No evidence was found to support the dissertation hypotheses, and thus all six have been refused. For In store availability, no treatment effect could be detected. It is probable that the reduction on client flow during the strike was sufficient to zero the effect on availability. Client flow is as important to brick and mortar retailers as the product flow. For Client order on time delivery, the treatment effect was there, but only SC complexity influenced the outcome, and on the opposite direction. Heavy and bulky products tend to have local sourcing which increases the SC complexity, but shorten the SC which seems to reduce SCV. SC node criticality and SC density had no influence on the disturbance impact. One possible explanation to account for the missing interactions of SC density and SC node criticality with the treatment effect is the fact that the 2018 strike hit all nodes. SC density and SC node criticality should have an effect only if part of the SC is affected by the disturbance. The role of SCVD seems to be conditional on the properties of the disturbance.

From the empirical evidence, SC characteristics do drive SC vulnerability, as SC complexity was found to be influential on the impact suffered by SCs during disturbance. The current study offers three main theoretical contributions to the SCRM literature. First, it

introduced the concept of conditional SCVD. The ability of a SC characteristic to drive vulnerability do not depends solely on the SC characteristic level, but also on properties of the disturbance involved. As a second contribution, it identified the importance of analyzing client flows during disturbances when including customers and retailers in the research scope. On the third major contribution, SC complexity was established as SCVD for product supply chains and risks related to transportation networks.

On a lesser important note, the dissertation covers some gaps found in previous works. It takes the SC as unit of analysis, and not dyads. The distinction between SCVD - as SC characteristics - and SCRD - as SC practices or philosophies - have been further stressed and should help future works. Also, we went out to test the relationship between SCVD and SCV on a quantitative framework using real data from a firm ERP instead of surveys. The use of secondary data from ERPs can also be considered a methodological contribution, together with the application of a quasi-experiment method to the research.

The empirical contribution is related to the quasi-experiment result. Managers can use the case description and findings to better prepare for disruptions. Client flow and short supply chains are two main points that should be included in SCRM strategies and recovery plans, especially for retailers. And finally, SCs must lobby with governments to diversify the offer on transportation solutions as a risk mitigation strategy.

The study has several limitations. First, variable had to be compromised to comply with the limits of the available data. Second, the selection of SCVD did not take into account the properties of the disturbance. Third, the use of data from only one nexus firm to model the SCs. Fourth, only two experimental designs were used.

Many paths exist to continue this line of research. Future work can expand the range of SC characteristics tested for SCVD, expand the SC performance indicators or do a similar work with data from a different company. It is also possible to imagine a randomized experiment to check the effect of different levels of SCVD candidates and the SC performance without the presence of a disturbance. It is also possible to think on different statistical instruments and models (e.g.: Poisson regression) that could be more sensitive to signals that stayed hidden under the noise. A new line of inquiry just opened with the concept of conditional SCVD, and it is in need more theoretical development. A qualitative work with managers could dive into the properties of disturbances that would limit the effectiveness of SCVD, and perhaps generate a new risk source taxonomy.

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