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Crew Safety in Shipping

An in-depth study towards the determinants of injury severity onboard offshore construction vessels

by

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Acknowledgements

In my two years of MEL I met approximately 70 students from all over the world. From them, I was at least asked 40 times why I decided to study MEL after graduating from the master Health Economics, Policy and Law. If the response to my answers – including a thousand arguments ranging from “I prefer the mentality of the maritime sector” to “I made a mistake that lasted 4 years” – would be sketched in a comic book, you could have literally seen the question marks that appeared above the heads of my classmates. So when I was asked again by my South African friend Gerhard Dekker, I did my usual effort and finally said: “Well, my mom is a nurse, my dad a shipbroker, and I guess I’m just a bit of both”. The response I got was: “Really? That’s great!” From then on, what I did made perfect sense.

First of all I would therefore like to thank my parents, for (financially) supporting my 6 year ‘unusual’ journey through the Erasmus University and believing in my ‘bit-of-both’ strategy. Second, a big “thank you” to Michele Acciaro, who did not hesitate for a second to accept me as a thesis student and has been incredibly dedicated ever since. Third, I would like to thank all MEL students, for the lessons I learned and the stories that were told. Fourth, my friends deserve some credits, for listening to my chatter about cataract surgeries without having a clue what I was talking about. But also for giving their full attention during my stories about LTI’s without having, again, a clue about what I was saying. Above all, I guess that I would like to thank the Rotterdam Eye Hospital for keeping an unsatisfied post-master maritime economics student employed, and Allseas Engineering B.V. for hiring a graduated health care manager.

The biggest lesson for me was that combining two worlds is always possible when someone offers you a platform and you offer them your best efforts. MEL provided my platform for combining healthcare and shipping. Due to their open mind, I was able to write this thesis.

Thank you MEL, thank you all,

Lieke (C. E.) de Korte, MSc

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Abstract

Background: Considering that over 90 percent of the world trade is transported by means of ocean transportation, the dangers in the maritime industry potentially affect many stakeholders. It is because of this, that overall safety became an increasingly important topic in the maritime sector. Enhancing safety onboard is not only important for the vessel's crew, but also in terms of financial and fiscal drivers from the industry – often ships are chartered on the strength of their safety performance. Due to a changing view – from technical to human failures – the safety of seafarers slowly found its way to the spotlights. One may safely argue that, once proved feasible, a method of achieving acceptable crew safety performance outcomes in a cost-efficient way will be easily adopted by ship owning companies. To achieve cost-effectiveness however, one should not only look at crew safety performance outcomes but also be aware of the determinants contributing to these outcomes so that investments can be strategically made.

Purpose: This study focuses on the latter issue and attempts to define the variables that influence the distribution of injury – in terms of severity – for a ship owning company operating in the 'safety aware' offshore sector. Hereby, the main goal was to develop a model explaining the distribution of injuries among crew members, so that investment post may be defined on the road to cost-efficient crew safety management.

Methods: The study mainly uses quantitative methods. An in-depth company study was conducted, analyzing data provided by a Swiss based ship owning company with its main office located in The Netherlands. The database was provided by the company. Four injury levels were included in the study as dependent variables: first aid (n = 736), medical treatment (n = 98), restricted work (n = 13) and lost time injury (n = 23). Since the injury levels are ascending from first aid case – minor injury – to lost time injury – major injury, an ordinal logistic regression model was used in the first attempt. Later, a generalized ordinal logistic regression model was added to study the individual effects of the included independent variables.

Results: Concluding evidence was found for eight of the eleven formulated hypotheses. A larger number of construction sites, cold weather conditions, and operating in areas near developing or less than developed countries had a negative impact on crew safety performance. Strict safety regulations had a positive effect. The more recent years were associated with a higher distribution of severe injuries. The more exposed construction crew appeared to be less prone to severe injuries, whereas reported injuries for the technical crew were relatively severe.

Implications for practice: It is in reducing the gap between science and practice that the most valuable solutions for improving crew safety performance may be found. One should keep this in mind when conducting further research in this field with the ultimate purpose of saving lives and always pursue to translate scientific findings into workable solutions for practice.

Keywords: *Maritime safety, Crew safety performance, Injury severity distribution, Ordinal logit model, Generalized ordinal logit model, Offshore construction*

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List of Abbreviations

ALARP	As Low As Reasonably Practicable
BSC	Balanced Scorecard
CSR	Corporate Social Responsibility
FAID	First Aid
FAT	Fatality
Gologit	Generalized ordinal logistic regression model
ILO	International Labour Organization
IMO	International Maritime Organization
ISM	International Safety Management Code
KPI	Key Performance Indicator
LTI	Lost Time Injury
MLC	Maritime Labour Convention
MTC	Medical Treatment Case
NM	Near Miss
Ologit	Ordinal Logistic regression model
PI	Performance Indicator
QHSE	Quality, Health, Safety and Environment
RWC	Restricted Work Case
SOLAS	International Convention for the Safety of Life at Sea
STCW	Standards of Training, Certification and Watchkeeping

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1. Introduction

“Shipping is perhaps the most international of all the world’s great industries and one of the most dangerous” (Hetherington et al., 2006, p. 401).

About ninety percent of world trade is transported overseas by ocean going vessels (IMO, 2013). The total active crew number sailing onboard the world merchant fleet was estimated by the European Commission (2011) to be 1,371,000. Vessels however, do not solely play a large role in the movement of goods, they are used for many other purposes that are often underexposed to the public – the most important being offshore supply and construction activities. No estimates were published so far, but the crew onboard these offshore supply and construction vessels is extensive and can reach up to 600 individuals per vessel (Vermeer, Sanders & Oreel, 2013).

The maritime environment is known to be among the harshest in the world (Deacon et al., 2010). Partly because working onboard of vessels is simply said a ‘tough job’, but even more due to the fact that small incidents can lead to devastating consequences for both the environment and human life (Hetherington, 2006). The latter has made the interference of quality, health, environment and safety officers increasingly important within the industry (Bouter, 2013). Keeping track of occurring incidents by developing safety standards may provide lessons to learn for ship-owning companies. Eventually, reducing the number of incidents and accidents may even increase onboard efficiency and save some money (Wang, 2000; 2001; 2006).

1.1 Background

It is because of a changing view – from technical failures to human failures – that the safety of seafarers slowly found its way to the spotlights (Mearns et al., 2003). Furthermore, it is suggested that it is far less expensive to change human behavior than it is to redesign a vessel for safety reasons contributed to the current focus on crew safety (Talley, 1999). The reason of increased investments in safety projects seems to be twofold: Enhancing safety is important for the vessel’s crew and in terms of financial and fiscal drivers from the industry – ships are nowadays often chartered on the strength of their safety performance (Hetherington, 2006).

1.1.1 Enhancing safety in the light of corporate social responsibility

Enhancing safety is first and foremost important to guarantee a working environment onboard in which all feasible measures to reduce incidents are taken (Vermeer, Oreel & Sanders, 2013). Stating this, one may conclude that safety in shipping links closely to corporate social responsibility (CSR), a recent trend spot in hazardous industries such as the maritime sector (Fafaliou et al., 2006). CSR is addressed in terms of a number of variables such as employees’ satisfaction, corporate efficiency, social welfare and social accountability of leading staff (Fafaliou et al., 2006). To assess whether or not such high standards are achieved in shipping, these concepts should be translated into quantitative statements. As such, as the importance of safety on board increases, ship-owning companies require a measurable concept of crew safety performance, resulting in so called ‘determinants of safety’ to find their way into the maritime sector (Cox & Cheyne, 2000; Rotblum, 2000; O’Neil, 2003; Thai, 2008, Bjerkan, 2010). One strategy to avoid incidents is to be continuously vigilant through the use of performance indicators directed at safety issues (Øien et al., 2011a). Safety in shipping is nowadays starting to be more and more based on the prospects and outcomes of such performance indicators, which are measurable representations of an aspect of reality (Øien et al., 2011a). Based on those safety determinants, ship-owning companies developed performance indicators (PIs) and their optimal crew safety ‘key’ outcomes (KPIs). By keeping constant vigil to determine potential weaknesses in their safety systems, ship-owning companies strived towards minimizing risk (Mearns & Håvold, 2003).

1.1.2 Enhancing safety for financial reasons

Since recently, safety in shipping is not considered to be beneficial for onboard crew only. Some major and multiple minor disasters have attracted the attention of the media and several non-profit organizations towards the maritime industry, making the occurrence of accidents not only more transparent, but also more expensive as vessels with low safety standards are no longer chartered (Wang, 2001; Hetherington, 2006). Slowly, companies began to realize that increasing safety standards onboard may lead to financial and competitive advantages. However, safety in shipping has a price (Fafaliou et al., 2006). Overall, there is a general agreement that the risk of incidents should be reduced to levels that are ‘as low as reasonably practicable’, or ALARP (Wang, 2002). This concept however has not yet advanced beyond its developmental stage (Guldenmond, 2000), for despite the increase focus on safety, not a single article directed at maritime research focuses on the question of ‘how safe is safe enough’. In other words, were lies the balance between the costs of accidents and the expenses for a safer onboard environment? An answer to this question may lead to cost-efficient safety management in shipping, although it requires extensive study of incident determinants and incident severity before anything reasonable can be concluded.

For merchant shipping, more and more companies are found to track PIs, although the underlying ‘system’ is often an unstructured excel sheet (Stolk, 2013; Van Rijsinge, 2013). Looking at the offshore sector – which may be considered merchant shipping’s big brother in terms of safety performance (Vermeer, Oreel & Sanders, 2013) – one finds the requirements for safety to be exhausting and the (financial) consequences of injuries occurring harsh. Here too, data is limited to PI results. In other words, in shipping one measures outcomes, not causes. Some may say that the sector is assessed in reverse; we start at the end and somehow try to find the unmarked way to the beginning. Literature about the shipping sector directed at the occurrence of accidents and incidents is limited; few articles address the determinants of occurring injuries or their financial impact, none have considered the determinants of injury severity relevant so far. The latter is surprising given it is the severity of injuries that matters to the offshore construction industry and large oil and gas companies, who belong to the most important clientele of offshore ship owning companies.

1.2 Objective and definition of the research problem

It is therefore that this study attempts to define the variables that influence the distribution of injury – in terms of severity – for a ship owning company operating in the safety aware offshore sector. Hereby, the main goal is to develop a model explaining the distribution of injuries among crew members, so that investment post may be defined on the road to cost-efficient crew safety management. The objective of this study is thus to define the variables that influence the distribution of injury in terms of severity, instead of analyzing the variables responsible for the occurrence of those injuries – as has been done before by Talley (1999; 1999a; et al. 2005).

To achieve this, the following research question was adopted for this study: *"What are the variables that influence the crew related injury severity distribution in the company studied and what are the corresponding lessons for practice?"*

To study the severity distribution of injuries in the maritime world, one needs a dataset that contains information about such injuries. Although injuries occur quite often, they are still considered 'rare' when compared to non-occurrence of injuries (Westphal, 2013). The aim of this study was therefore very advanced and required a solid database containing a large variation of statistics. To maintain such a database containing more than solely outcome measures however, is no common practice in the maritime domain. In order to conduct the study, it was therefore decided to focus upon a single company able to provide sound injury severity data.

1.3 Methodological approach and data

An in-depth company study was conducted analyzing data provided by a Swiss based ship owning offshore company with its main office located in the Netherlands. Unlike comparable companies, the object of study was in the possession of a remarkably detailed database regarding the injuries occurring in the past 5 years, that is, 2009-2013. The research done was supported by eleven hypotheses that are further explained in chapter 3. Mainly quantitative methods were used to conduct the study, although some exploring interviews were held in the start-up phase. In addition to applying existing methodologies to a new problem, this study also contributes in a new direction by using advanced statistical methods rather than ordinary least squares regression. Six statistical models were developed, using both ordinal logistic regression and generalized ordinal logistic regression. Although logistic regression is often used in transport studies, ordinal logistic and generalized ordinal logistic regression models have not been applied before in the studies focusing on the maritime sector and are only seldom used in other fields of research. A detailed description of the methodology is provided in chapter 4.

1.4 Relevance and contribution of the study

Especially in the view of increasing importance of crew safety performance for both safety and financial reasons, the lack of theoretical investigation on the subject becomes obvious. In addition, the industry is increasingly looking for cost efficient safety management, but so far this is mainly based on outcome indicators. To achieve an improved regime at a decent price, one should start defining determinants of safety performance, more specifically factors that contribute to injury severity. Given the limited literature on crew safety performance and the somewhat straightforward research methods that were applied on the few quantitative studies, the contribution of this research is twofold: First and foremost, the identification of factors contributing to injury severity is a first step in the direction of cost-efficient crew safety performance that could potentially lay a foundation for a new type of research, as well as increase the focus within ship owning companies on the importance of recording detailed injury data. Second, in-depth analysis using advanced statistical methods may form an incentive for studies that are yet been published based on large data samples to reuse that valuable data and apply more dedicated methods; most importantly methods that focus on input rather than output factors and the use of statistical methods able to show relations of certain degrees of incidents and accidents rather than occurrence alone.

1.5 Outline

This thesis is structured as follows: The second chapter contains a literature review explaining the role of safety and crew safety performance in the shipping industry. It starts by explaining the very basics safety measures that are in place, such as the regulatory framework, and works its way to the advanced idea of improving crew safety performance by means of benchmarking initiatives. Chapter 3 describes the development of the conceptual framework considered suitable to study the distribution of injury severity for accidents occurring in the maritime sector. It also contains eleven hypotheses resulting from the literature study that was done. Chapter 4 provides the methodology approach of the study and introduces the statistical models that were used. In the fifth chapter, the quantitative data input to conduct research towards the key question is analyzed, the results of six statistical models are presented and the eleven hypotheses are answered. Chapter 6 contains a conclusion and discussion, interpreting the found results in a broader context. It also addresses the limitations of the study and defines areas for further research.

2. Literature review

In this chapter, the literature related to the topic of crew safety performance measurement is reviewed. Starting from the general concept of ‘safety in shipping’, this chapter continues towards the different views on crew safety performance to the use of measurement systems. Performance indicators, balance scorecards and the tool of benchmarking are discussed. Hereby, the chapter strives to cover the current status of indicator use, its pros and cons for ship owning companies and the proposed added value of a crew safety performance benchmarking initiative.

2.1 Safety in shipping; rules, regulations and legal instruments

“Shipping is perhaps the most international of all the world’s great industries and one of the most dangerous” (Hetherington, 2006, p. 401). Considering that over 90 percent of the world trade is transported by means of ocean transportation (IMO, 2013; Seaweb, 2013), the dangers in the maritime industry potentially affect many stakeholders. It is because of this, that overall safety became an important topic within the industry (Mearns et al., 2003; Darbra & Casal, 2004; IMO, 2013; Seaweb, 2013). The concept of ‘safety in shipping’ can be decomposed into many segments, including among others passenger-, environmental- cargo- and financial safety. Due to their importance, all of the previous topics related to maritime transportation are thoroughly studied (Talley, 1999; Wang, 2001).

When thinking of major accidents related to these shipping segments, examples often used are the Torrey Canyon (1967), the Herald of Free Enterprise (1987), the Exxon Valdez (1989), the Erika (1999), the Estonia (1994) or even the recent MOL containership (2013), most of them leading to new developments in the field of safety (Card, 1998). “It has always been accepted that the best way of improving safety at sea is by developing international regulations that are followed by most shipping nations” (Pun et al., 2003, p. 704).

2.1.1 Rules, regulations and legal instruments

The maritime safety regime is complex. The legal framework is created by three major international organizations; the United Nations, UN (1), the International Labour Organization, ILO (2) and the International Maritime Organization, IMO (3) and by country specific legislation (Knapp & Franses, 2010). Although relevant to mention, the UN delegates most maritime matters that have to be dealt with to the IMO. Furthermore, there are the rules of the flag states, port state control, the classification societies, P&I clubs, insurance companies, vetting bureaus, banks, ship operators and many other parties (Nunn, 1998; Payer, 1998; Smith, 1998; Knapp, 2004; Knapp & Franses, 2010). The most important legal instruments – the ISM code, the SOLAS, the STCW and the ILO convention – are briefly explained below.

The International Safety Management code, or ISM code, was introduced by the IMO. ISM is principally concerned with eliminating the uncertainties about responsibilities, improving communication and the flow of information and to set up clear procedures that should be used in case of emergency (Payer, 1998). The ISM code was made mandatory through the International Convention of Safety of Life at Sea, or SOLAS, signed in 1974. The SOLAS convention specifies the minimum standards of, among others, the operation of vessels. It is up to the flag state to ensure that a ship registered under its flag complies with these requirements (Knapp, 2004). In addition to the original SOLAS, the protocol of 1978 deals with several amendments for tanker vessels and port state control requirements (Knapp, 2004). The Standards of Training, Certification and Watchkeeping for Seafarers (STCW), signed in 1978, was the first internationally-agreed Convention to address the issue of minimum standards of competence for seafarers (IMO, 2013). The STCW Convention was revised and updated in 1995 in order to clarify the standards of competence required (IMO, 2013). The flag state is responsible for the implementation of the STCW, although the port state control can also act to ensure compliance (Knapp, 2004). The Merchant Shipping Minimum Standards Convention from the ILO applies to seafarers of foreign flagged vessels (Knapp, 2004). The convention is still in force, although the STCW convention replaces it in practice. The primary concern of the Merchant Shipping Convention is to ensure safe working and living conditions onboard the vessel (Knapp, 2004). Seafarers may direct their complaints regarding those conditions towards the port state control, who forwards the complaint to the flag state resulting in a detention of the vessel in serious cases (Knapp, 2004; Knapp & Franses, 2010). Lastly, the Maritime Labour Convention (MLC), in force since August 2013, embodies all up-to-date standards of existing international maritime labour Conventions and Recommendations, as well as the fundamental principles to be found in other international labour Conventions (MLC, 2006). The MLC applies, like the SOLAS and STCW, to all ships entering the harbors of port states, as well as to all flag states. In total, the MLC covers about 80 percent of the world shipping.

2.1.2 The role of classification societies on flag states

Next to the legislation, the classification societies provide the technical expertise during ship building and technical maintenance of the vessel (Payer, 1998; Smith, 1998; Knapp & Franses, 2010). In addition, they can be authorized to perform surveys on behalf of the flag states (Smith, 1998; Knapp & Franses, 2010). A flag state is the country where the vessel is registered, although one should keep in mind that there are various types of registration; open-, restrictive- and hybrid registries (Nieuwpoort & Meijnders, 1998; Knapp & Franses, 2010). In an open registry, the country of registry allows ownership and control of its vessels by non-citizens. Furthermore, access to the registry is easy. In a restrictive registry, the flag state upholds a policy of conferring nationality only on ships owned by nationals of that state. A hybrid registry can take any form between an open and restrictive registry (Mukherjee, 1993). The flag of the vessel represents the format that is responsible to transpose the international conventions into national legislation and to enforce it onboard ships sailing under that country's flag (Nieuwpoort & Meijnders, 1998; Knapp & Franses, 2010). Port state control can be described as the second line of defense, behind the flag state regulations (Knapp & Franses, 2010). Port state control, with the primary role of eliminating substandard vessels, is backed up by the industries solution to unsafe conditions; vetting inspections. The vetting inspections are in place to protect the cargo or product owners from legal claims in case of accidents (Knapp & Franses, 2010). In the end, the owner of the vessel –

the ship-owning company – has the responsibility to comply with the combined legal requirements.

Due to the many rules and regulations, the shipping and related offshore industry is expected to have a fairly good safety record (Knapp & Franses, 2010). However, maritime incidents and accidents never lose their potential to result in catastrophes (Hetherington, 2006). The large percentage of trade by and production at sea makes the catastrophes related to vessel accidents seem minor compared to what happens on other transport legs. However, the line of responsibility to comply with the legislative framework for safety is not completely clear in shipping, which complicates enforcement of the legal instruments (Knapp & Franses, 2010). Furthermore, the various inspection systems do reference each other but there is no cross-recognition, causing the whole setup to actually create legal 'loopholes' and the allowance for ship-owning companies to operate below the minimum safety standards, which may cause accidents and damage to human lives (Nieuwpoort & Meijnders, 1998; Knapp & Franses, 2010). In an environment that relies heavily on governmental policy or regulation to offset negative externalities like lack of safety, studies have found that the government and institutionary regulations tend to be less efficient than market innovation in achieving the intended goals (Card, 1998). Some authors nevertheless claim that the shipping industry is 'fairly safe' (Hetherington, 2006). However, all is relative.

2.2 Crew safety

Larsson & Lindquist (1992) showed that the mortality of seafarers in Sweden alone was 113 in 1984. This was nine times that of railway employees, and 147 times that of factory and shop employees (Håvold, 2005). Jensen (et al., 2004) also acknowledges seafaring as a high-risk occupation. The relative risk of mortality due to accidents on board found in his study was almost 24 times higher than for all workers in Great Britain. A Finnish study (Saarni, 1989) found that also for non-fatal injuries, the rate of accidents related to work on board Finnish ships was close to the rate of the whole working population of Finland: A finding similar to the study of Darbra and Casal (2004), who concluded that regarding accidents that occur in transport, a majority of 65 percent takes place on board of ocean going vessels. Tragic marine accidents have so far caused serious consequences including loss of lives, loss of property and damage to the environment (Wang, 2001). Loss of lives, especially human injuries, shall be the focus of this study.

Focusing on loss of lives only, "merchant and offshore related shipping is known to be an occupation with a high rate of fatal accidents caused by maritime disasters and occupational accidents" (Hansen et al., 2002, p. 85). One may therefore conclude that, irrespectively of the number of injuries or casualties in shipping, the maritime industry is among the harshest in the world (Deacon et al., 2010). Hereby, one should keep in mind that a vessel is a floating machinery space factory – especially when it concerns offshore vessels – often located far away from doctors and hospitals, with complex and dangerous machinery in a limited space. This indicates an inherent risk on board of the vessel. On top of that, a vessel is subject to the elements of a heavy sea and bad weather (Håvold, 2005); "Ship casualties like collisions, capsizing, fires/explosions and also personal accidents, homicide, suicide, and diseases can be added to the dangers for seafarers" (Håvold, 2005, p. 442), creating an indirect cause for the lack of a safe environment. It was already mentioned that incidents on board of vessels can lead to devastating consequences (Hetherington, 2006). Although there has been considerable interest in safety in many industries, little attention has been given – with the last few years as an exception – to safety in world's riskiest industries, shipping and offshore (Håvold, 2005). The latter may be a consequence of adopting the ISM code in 1998, heavily increasing focus on accidents and incidents in the maritime domain. Nowadays, accidents involving passengers, the environment or large quantities of cargo are exhaustively investigated (IMO, 2013). Although currently loss of cargo and environmental damage are commonly properly covered and dealt with (Talley, 1999), there is one specific topic of safety that has long remained out of scope: *crew safety*. Where property loss is coped with by insurers, the environment by global organizations and activists, crew injury however has long lacked interest (Hetherington, 2006). The main reason for this long lasting indifference is troubling but straightforward:

> *"While ship accident injury data collected by ship classification societies are sparse, ship (and cargo) damage data are extensive. The reason is clear: Ship classification societies are primarily concerned with safety of property as opposed to safety of crew at sea. Ships and their cargo are usually insured (requiring property damage data for processing insurance claims), while the lives of people on board are often not" (Goss et al., 1991 in Talley, 1999, p. 1366).*

The above quotation obviously originates from before the major conventions that emphasized the importance of safety onboard and brought the topic under attention of the public. However, it is not that long ago that this view was common practice. The traditional view of industrial accidents states that accidents are produced by both technological and individual human failures (Reason, 1990). The reductions of failures in shipping technology and shipbuilding have revealed the underlying influencing level of human error in accident causation (Hetherington, 2006). Due to this finding, the shift of safety focus has been driven from technical failures as the prime cause of accidents to organizational, managerial and human factors (Håvold, 2005). Although the exact percentage is unknown – the estimation lies between 15.9 percent (Darbra & Casal, 2004) and 49 percent (Hetherington, 2006) – accidents caused by human factors make a significant contribution (Darbra & Casal, 2004). Although, in the last decade, safety at sea has become an increasingly stressed topic (Wang, 2001), it appears that very little human factors research has been carried out within the maritime industry (Hetherington, 2006). This obviously has its impact on crew safety, since the ones that suffer from incidents and accidents on board of sea going vessels are the seafarers themselves.

2.3 Crew safety performance and investments

It is because of the changing view – from technical failures to human failures – that the safety of seafarers slowly found its way to the spotlights (Mearns et al., 2003).

Furthermore, the incentive to shift towards the regulation of human actions and crew safety on board of vessels has been attributed to the fact that it is far less expensive to change human behavior than it is to redesign or rebuilt vessels for safety reasons (Talley, 1999). Therefore, ship owning companies are nowadays increasingly investing in safer work environments for their employed personnel (De Bruine, 2013; Bouter, 2013; Stolk, 2013; Vermeer, Sanders & Oreel, 2013). The reason for these investments seems to be twofold: Enhancing safety is not only important for the vessel's crew, but also in terms of financial and fiscal drivers form the industry – often ships are chartered on the strength of their safety performance (Hetherington, 2006). The concepts of 'safety' and 'performance' are closely related (Van Steen, 1996; Janicak, 2010). With safety being the absence of danger from which harm or loss may occur, performance is measured as the harm or loss that does occur (Van Steen, 1996). Performance improvements can thus be measured through the absence of failures, injuries and illnesses (Van Steen, 1996). Furthermore, reducing the severity of injuries that do occur may also be seen as a form of safety performance improvement (IMO, 2013). As such, both the ship-owners and the shipping industry demand a measurable concept of safety performance, causing so called 'determinants of safety' to find their way into the sector (Talley, 1999; Cox & Cheyne, 2000; Flin et al., 2000; Rotblum, 2000; Hansen et al., 2002; Mearns et al., 2003; O'Neil, 2003; Darbra & Casal, 2004; Jensen et al., 2004; Hetherington, 2006; Thai, 2008; Celik, 2009; Bjerkan, 2010). In the literature, basically two major sides of human and crew safety performance for companies are highlighted: One side relates to behavioral issues, psychology, attitudes and culture (1), the other to cost-efficient safety management (2). Both are explained and discussed below.

2.3.1 Behavioral psychology

The behavioral side of crew safety performance relates to the fact that researchers (Brown, Willis & Prussia, 2000; Dwyer and Raftery, 1991) have increasingly recognized that industrial accidents are caused by an interaction between factors in the social and physical environments, that is, characteristics of the individual as well as technical forces (Bjerkan, 2010). Subsequent to recognition, a lot of research has been done towards measuring attitude, culture, social aspects and behavior related to safety culture and performance in many industries (Zohar, 1980; Rundmo, 1992, 1998; Lee, 1993; Coyle et al., 1995; March et al., 1998; Mearns et al., 2000; Flin et al., 1996; Flin et al., 2000; Glendon & Litherland, 2001; Seo et al., 2004; Cooper & Philips, 2004; Mearns & Yule, 2009; Bjerkan, 2010). Although "it is recognized that accidents are caused by an interacting system of social, cultural and technical forces" (Bjerkan, 2010, p. 470), Håvold (2000) found that no safety culture or safety performance research related to the maritime sector has been reported up till the year 2000. Similarly, Hansen (et al., 2002) concluded that despite some international concern about the problem, few studies covered the aspect of fatal and non-fatal injuries on board of cargo carrying ships.

During the last decade the lack of research diminished, as some authors start to focus their studies on safety performance in the maritime industry (Talley, 1999; Mearns et al., 2001, 2003; Mearns & Håvold, 2003; Hetherington, 2006), although some of these studies focus on the offshore sector, they mainly discuss the environment on offshore platforms instead of vessels. Nevertheless, the outcome of, among others, these studies, seems to have led to a different attitude towards safety performance within companies: "We have moved from a culture of blaming and shaming towards a culture of constructive criticism" (Vermeer, Sanders & Oreel, 2013). Based on the behavioral psychology crew safety related literature, a number of different measurement instruments have been developed by industrial psychologists (Flin et al., 2000). Although behavior has proven to be an important indication of safety performance, one should not forget the cost-efficiency side of safety investments (Warburto, 2005).

2.3.2 Cost-efficiency (ALARP)

Although the main focus in academic research to crew safety performance is directed at behavioral psychology, there is little doubt that accidents can also influence an organization's present and future competitive success (Mearns & Håvold, 2003; Håvold, 2005). Incidents and accidents may actually account for as much as 37 percent of annualized profits for a transport company (Mearns & Håvold, 2003). Furthermore, injuries and fatalities of crew members alone turned out to be equally expensive to the total added costs of spills and property damages, even though injuries are far less like to occur (Card, 1998). Many people, and companies for that matter, do not realize how expensive accidents are (Mearns & Håvold, 2003). Of course, an increase in safety on board may require additional investments and therefore result in an increase in costs. However, in the long term, increasing safety and the crew safety performance level will decrease overall costs for the ship-owning company due to accident prevention (Konsta & Plomaritou, 2012). Behavioral psychology is the current direction taken by ship-owning companies in their crew safety management approach, although the real value lies with the reduction of safety – or rather the lack of it – related costs.

Due to this cost incentive, some authors argue for cost-effectiveness reasons to increase onboard safety performance, next to the mere behavioral approach of 'keeping the crew safe' (Wang, 2000, 2001a, 2001b; Aven & Vinnem, 2005; Fafaliou et al., 2006): "We believe that we can do better if cost-effectiveness (in the wide sense) is the ruling thinking" (Aven & Vinnem, 2005, p. 16). Authors that argue for cost-effectiveness as a leading catalyst recurrently refer to the ALARP principle. By reducing safety to ALARP level – 'as low as reasonably practicable' – crew safety performance is included as an outcome parameter (Wang, 2000) and plotted against the investments that contributed to the resulting level of crew safety (Wang, 2000). According to Wang, using the ALARP principle, the major objective of "reducing risk to a minimal level within economic constraints in order to achieve cost savings" (Wang, 2002, p. 93) is then fulfilled. Taking the economic constraint into account, the ALARP strategy may thus not lead to the highest possible level of safety. Instead, it finds a safety performance level that is cost-efficient (Wang, 2000, 2001a, 2001b). This may be an interesting angle of incidence for the shipping industry that is always looking at ways to increase profit margin and lower expenses (Fafaliou et al., 2006) although nowadays constraint by a required minimum level of crew safety performance (Hetherington, 2006). Further reference to the ALARP principle is made in subsection 2.6.1How safe is "safe enough", a comparison with healthcare.

2.4 Measuring systems and safety assessment (KPIs)

Including crew safety performance as a parameter of success, from either a behavioral or economic standpoint, requires a tool with the ability of measuring safety performance. Performance measurement is not new in the management world (Neely, 1998). In fact, there are seven reasons why performance measurement is nowadays extensively used: the changing nature of work, increasing competition, specific improvement initiatives, national and international quality awards, changing organizational roles, changing external demands, and the power of information technology (Neely, 1998). Not all of them apply directly at shipping, although increasing competition and changing external demands can be seen as two main incentives for improving crew safety performance on board (Konsta & Plomaritou, 2012).

2.4.1 The use of key performance indicators for safety assessment

One strategy to avoid incidents is to be continuously vigilant through the use of performance indicators directed at safety issues (Øien et al., 2011a). Safety onboard is nowadays starting to be more and more based on the prospects and outcomes of such performance indicators, which are measurable representations of an aspect of reality (Øien et al., 2011a). Nevertheless, measuring crew safety performance is in its infancy, since crew safety onboard was long overlooked (Hetherington, 2006). There is, for example, no standardized accident reporting system in the maritime domain (Hetherington, 2006). However, the development of safety measurement systems in other, non-shipping, industries is a topic with high attention – Safety Science, volume 47 issue 4, April 2009 devoted a whole edition to this topic (Vinnem, 2010). These measurement systems are based on so called key performance indicators (KPIs) and now slowly find their way into the maritime industry (Vinnem, 2010), making them an interesting object of study.

KPIs set a key performance level based on a selected indicator (Parmenter, 2010). Those key performance levels are based on both the industries allowances and the past performance of the ship-owning company (Bouter, 2013). As such, the KPI for fatal accidents is obviously zero, where the KPI for lost time injuries may be set at any level accepted by the company or industry (Bouter, 2013; Vermeer, Sanders & Oreel, 2013). According to Konsta and Plomaritou (2012, p. 146): “Shipping, being characterized as a highly competitive industry, makes the use of performance indicators extremely important. Consequently it is very important to closely monitor the performance implications of the adopted competitive strategies”. This statement again shows the fiscal and competitive importance for ship-owning companies of keeping their crew safety performance up to a decent level. Under the guise of “one cannot manage what is not measured” (Sink & Tuttle, 1989 in Chan & Qi, 2003, p. 180), it may be concluded that without a proper set of (key) performance indicators, improvement of the overall crew safety performance level is hard to achieve. In the world of safety measurement systems however, the discussion of what type of indicators are best for improvement of safety performance continues (Safety Science, Vol. 47, No 4). The two main players on the field are the prospective and retrospective KPIs, commonly referred to as ‘leading’ and ‘lagging’ indicators (Dyreborg, 2009). Leading performance indicators are prospective and “indicate the performance of the key work processes, culture and behavior, or the working of protective barriers between hazards and harms that are believed to control unwanted outcomes" (Dyreborg, 2009, p. 475), whereas lagging performance indicators are retrospective measures based on "incidents that are determined as unwanted outcomes" (Dyreborg, 2009). Before introducing any further theory on the topic of crew safety performance, it is important to understand the measurement systems that are in place and the KPI methods – either leading or lagging indicators – on which they are based. The pros and cons of both types of indicators and their current practical use are discussed below, as well as the drawbacks that should be taken into account.

2.4.2 Lagging indicators

Lagging indicators, commonly referred to as 'outcome indicators' due to their retrospective nature, capture the outcomes in terms of safety performance after an event has occurred (Dyreborg, 2009). Lagging indicators hereby have the feature of capturing results based on the exiting situation (Dyreborg, 2009); making them very suitable for safety assessment in the economic, cost-effective, sense (Wang, 2006). For, as Wang (2006, p. 14) argues: "To conduct cost-benefit assessment, it is required to set a base that can be used as a reference for comparisons where a base reflects the existing situation, that is, what actually happens rather than what is supposed to happen". Hereby, lagging indicators are suitable for measuring solid quantitative measures such as investment rates, fatalities and injury data (Wang, 2006, Øien et al., 2011a). They should thus be more than able to cover sufficient data for a cost-effective or ALARP approach to crew safety performance.

Nevertheless, in the literature, there has been a movement away from lagging measures of safety performance based on retrospective data towards leading, or predictive, assessment of the safety performance level of a worksite (Flin et al., 2000). For realizing crew safety improvements, "it makes a big difference whether we try to predict the possibility of having a major accident 'tomorrow', including all possible causes, or if we 'only' try to establish the causes after-the-event in retrospect (Øien et al., 2011a, p. 150). The former is accomplished by the use of leading – prospective – rather than lagging indicators.

2.4.3 Leading indicators

The previous paragraph associated lagging indicators with cost-effective measures of crew safety performance. Studying Dyreborg's (2009, p. 475) definition – "key work processes, culture and behavior" – of leading indicators, one might consider them related to the behavioral psychology approach of crew safety performance discussed in paragraph 2.3.1. The advantage of leading indicators is that they can prevent accidents from happening due to their prospective nature (Dyreborg, 2009). Because of this, the overall conclusion seems to be that a good set of leading safety performance indicators will certainly improve any crew safety management system. However, there are doubts whether they will help ship-owning companies to develop innovative crew safety strategies with great potential for the future (Zwetsloot, 2009). The major reason for this doubt is briefly summarized by Flin (et al., 2000, p. 189): "The real test of safety climate measures is validity, in terms of their power to reveal the level of site safety". Meaning that, if an indicator is leading in the true sense of the word, that indicator should demonstrate a valid and reliable relationship with the outcome of a lagging indicator down the line (Mearns, 2009). It is because of this validity requirement that collecting and sharing data based on leading KPIs has – so far – not resulted in any added value for ship-owning companies; there are simply too much leading indicator drawbacks.

First, there is the concern of leading indicators and their correlation with safety outcomes (Wang 2000, 2002, 2006). There seems to be an implicit assumption that leading performance indicators capture the direct origin of the lagging indicator outcome (Mearns, 2009). “However, safety performance is a complex phenomenon operating at many different levels and therefore cause and effect relationships are very difficult to establish and verify” (Mearns, 2009, p. 491). Consequently, Rotblum (2000, p. 1) argues: “Here is the most important point: every human error that was made was determined to be a necessary condition for the accident. That means that if just one of those human errors had not occurred, the chain of events would have been broken, and the accidents would not have happened”. Accidents related to human safety on board are by their nature due to a particular set of complex circumstances or events coming together in a particular point in time (Mearns, 2009). Therefore, simple cause-effect relationships between leading and lagging indicators are not easy to delineate, which affects the predictive added value of a leading indicator in the negative sense (Rotblum, 2000; Mearns, 2009; Øien et al., 2011a, 2011b). In conclusion, a company could – and should – never manage and collect the data required for all possible events that might lead to an accident. Second, leading indicators lack the ability of capturing the right measures representing safety performance in terms of cost-efficiency: “The cost incurred in the safety improvement with a design and operation is usually affected by many factors that often have large uncertainties of estimation” (Wang, 2006, p. 9). A third argument against the use of leading indicators is the mere fact that the shipping industry is complex and the complexity lies in its high cyclicality, volatility and unpredictability (Konsta & Plomaritou, 2012). Unpredictability in the industry itself would never allow for leading indicator development due to the resulting unreliable correlation between leading indicators and their safety outcomes (Wang, 2006). In other words: “It should be noted that the application of numerical risk criteria may not always be appropriate because of uncertainties in inputs” (Wang, 2006, p. 7). Fourth, one should keep in mind that a major obstacle to the assessment of organizational determinants – such as behavioral effects on crew safety performance – is that these accidents are quite rare and that therefore, developing a direct leading measure of safety is hardly possible (Øien et al., 2011a).

One should not deny that sound leading indicators have the ability of lifting the crew safety performance on board to a higher level. However, since both developing leading indicators and proving their validity is not done so far, working with lagging indicator outcomes is highly preferred. From the lagging indicator outcomes, ship-owning companies can react to the possible processes withholding improvement in human safety performance. As such, working bottom-up rather than top-down may in the end affect the leading processes requiring attention (Øien et al., 2011b).

2.4.4 Indicator drawbacks

Although extensively used in many industries, and increasingly developed for the maritime industry, indicators and their related KPIs have drawbacks that one should be aware of. First, one should keep in mind that what gets measured becomes important and, consequently, what does not get measured may become insignificant (Zwetsloot, 2009). The introduction of pre-determined criteria, or KPIs, may give the wrong focus; meeting these criteria rather than obtaining overall good and cost-effective measures may become more important (Aven & Vinnem, 2005). Furthermore, seemingly contradictive to the statement of (Sink & Tuttle, 1989 in Chan & Qi, 2003, p. 180), Hudson (2009, p. 484) argues “what gets measured gets managed […]. Having ineffective indicators may lead to measurement of the figures, instead of the issues under consideration”. However, having no indicators at all leads to having no attention paid at tall to the level of crew safety performance (Hudson, 2009). Second, it is important to realize that indicators and their related KPIs do not necessarily represent reality, but that they are an attempt to reflect the current situation in the form of multiple and different forms of data. In other words, they are just indicators (Mearns, 2009). Indicators thus only measure what they are designed for to measure. Despite this commonly known limitation, indicators have been abused in many different settings. “By abused, we mean that indicators on personal safety have been used as a measure of ‘system safety’ or risk of major accidents” (Øien et al., 2011b). When measuring crew safety performance by the use of indicators, one should keep in mind that the results do not represent reality, but an oversimplified and sometimes even counterproductive – when based on cost-reduction indicators – reflection of reality (Acciaro & Liu, working paper A). Third, indicators and their related KPIs should never be seen as the only way for assessing crew safety performance (Øien et al., 2011b). Although in many industries, they have proven to be a good starting point (Safety Science, Vol. 47 No 4, 2009; Øien et al., 2011b). Keeping these indicator drawbacks in the back of the head, one should be able to develop sound indicators and KPIs for the measurement of crew safety performance in the maritime sector, to the benefit of ship-owning companies and their employed crews.

2.5 Balanced Score Cards

There is no such thing as “zero risk”, although by keeping constant vigil to determine potential weaknesses in their safety systems, organizations may strive towards minimizing risk (Mearns & Håvold, 2003). The Health and Safety Executive therefore recommends the use of balance scorecards to support the process of monitoring safety measures (Kaplan & Norton, 1996; HSE, 2001). Balance scorecards, or BSCs, consist of combined KPIs and their related indicator definitions that together reflect the concept of the determinant to measure; crew safety performance (Mearns et al., 2003). Indicators related to crew safety performance can thus be integrated as KPIs into organizational performance measurement systems like a BSC (Håvold, 2005). As such, “a BSC is designed to capture the firm’s desired business strategy and to include the drivers on performance on all areas important to the business” (Mearns & Håvold, 2003, p. 409). Meaning that, if crew safety performance is an important area, it should be included as a driver in the scorecard (Mearns & Håvold, 2003).

Since KPIs are the tools for improvement of crew safety performance, ship owning companies should acknowledge the importance of one common set of KPIs – a BSC – and implement them systematically and methodologically (Konsta & Plomaritou, 2012). A well-structured BSC requires, according to Vinnem (2010), ten criteria: The BSC should: Contain a combination of leading and lagging indicators (1); be related to easily observable performance (2); contain intuitive indicators (3); not require complex calculations (4); reflect accident mechanisms (5); be sensitive to change (6); be able to show trends (7); be robust to manipulation (8); be valid for major accident risk (9); not be influenced by campaigns that give conflicting signals (10). These are the ten criteria that should be addressed when reviewing current use of indicators or new proposals (Vinnem, 2010). One should realize that these are the ideal BSC circumstances (Vinnem, 2010), although they might not all be feasible in practice – such as the requirement for leading indicators (Rotblum, 2000; Wang, 2002, 2006; Mearns, 2009; Konsta & Plomaritou, 2012).

In the process towards improvement, it is important to acknowledge that realizing a crew safety related BSC is not an end in itself, but a vital tool to improve both short-term and long term occupational safety if it is implemented and followed up continuously (Mearns & Håvold, 2003). Summarizing the above sections, it was found that safety management is becoming increasingly important for ship owning companies. The reason for this is very straightforward; unsafe vessels are no longer accepted by the dominating customers and unsafe vessels are therefore expensive to manage. By monitoring their crew safety performance, companies now try to prescribe the right medicine to improve safety (Håvold, 2005). There is, not surprisingly, only so much one you can learn from the annual safety performance sheet. Besides evaluating the annual performance on the field of crew safety, comparing previous crew safety performance results to current outcomes could contribute to increased levels of safety and an internal learning process (Wijnolst & Wergeland, 2009). What makes it difficult is that individual vessels are acting as closed social milieus (Håvold, 2005). The resulting lack of transparency – not only between companies, but also within a company – often prevents the crew safety performance learning curve to finalize. It is in the ‘opening up’ of the sector and its individuals where the profit lies: The low hanging fruit of crew safety.

2.6 How safe is “safe enough”?

Quality in shipping – crew safety being an element of it – has a price, a mere fact that resulted in the maritime industry to be long responsive instead of proactive when it came to improved crew safety standards (Fafaliou et al., 2006). However, “new competitive pressures on business performance […] have challenged the old strategic management orientation to achievement of goals related to profits only” (Fafaliou et al., 2006, p. 412; Thai, 2008). Nowadays, crew safety in onboard becomes increasingly important to the success and competitiveness of ship-owning companies (Mearns & Håvold, 2003; Fafaliou et al., 2006; Thai, 2008; Lu et al., 2009). This growing interest redirects parts of the companies’ budgets to the safety management department. The literature is quite unanimous about the fact that investments in safety programs can be an inexpensive yet effective way to improve safety performance levels in an organization and onboard of vessels (Sawacha et al., 1999; Guldenmond, 2000; Mearns et al., 2003; Brady, 2007; Lutchman et al., 2012). However, “the only area of disagreement – and it is a big one – is how incentive programs should be structured to do the most good” (Brady, 2007, p. 43). Also, the validity of including safety measures in a cost-efficiency study is questioned: “While the importance of the concept of safety is stressed by most authors, very few have attempted to support their claim by reporting an indication of its construct validity or predictive validity […]. Basically, this means that the concept still has not advanced beyond its first developmental stages" (Guldenmond, 2000, p. 216). As such, despite the increase expenses on safety, not a single article directed at the maritime sector focuses on the obvious question of "how safe is safe enough?"

2.6.1 How safe is "safe enough", a comparison with healthcare

A sector in which safety performance has played a major role for quite some time already, is healthcare (Räsänen et al., 2006). Like ship-owning companies, hospitals have a financial, competitive and a social incentive to 'do good' (Boot & Knapen, 2005; Porter & Teisberg, 2006). Unlike the maritime industry however, the research directed at quality of care – patient safety being a major element of it – is extensive (Berg, 1997; Epstein, 1995; Freeman, 2002; Berg et al., 2005; Wait & Nolte, 2005; Porter & Teisberg, 2006; Basu et al., 2010). Awareness of errors in healthcare has skyrocketed in recent years and as a result huge resources have been mobilized to measure and reduce the risk (Warburto, 2005). Warburto (2005) is one of the authors who devoted an article to the question of "how safe is safe enough?", since he found out that the cost-effectiveness of most proposed improvements in the field of patient safety remained unknown despite the major investments done. "Unless we collect information of cost-effectiveness, and use it to prioritize both improvement initiative and new safety research, society will not gain the maximum return (in terms of safety) for whatever resources are put into error reduction" (Warburton, 2005, p. 226). The basic nature of patient safety and crew safety is in essence the same. For a difference, one should look at the context of both safety performance levels. Where healthcare and thus its safety level is a public good – for as far as injuries are reported to the public – safety onboard of vessels is mainly a private good.

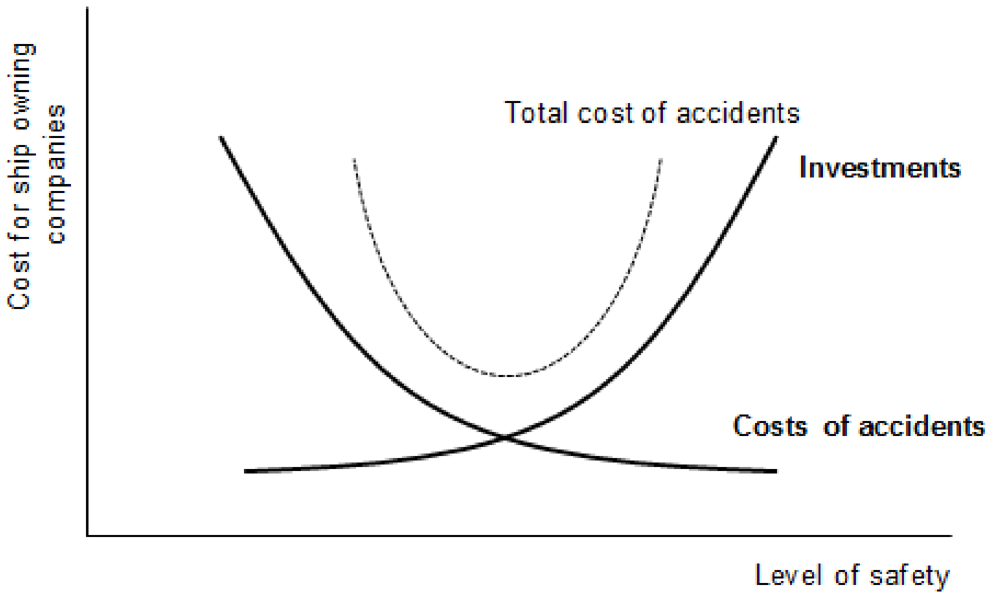

Figure 2.1, Optimum investment in safety (Source: Warburton, 2005)

Therefore, gaining a maximum return in terms of crew safety for the investments that are put into it is of even higher significant importance for the overall success of a ship-owning company (Wang, 2000; Wang, 2002) than it would be for a hospital. Simply said: one should be searching for the largest return of investment in terms of an adequate crew safety performance level. However, a higher level of crew safety does not always indicate a positive development: "Holding perfection as an ideal is inspiring and perhaps necessary to discourage complacency, but there can be great harm in trying to achieve it, because near-perfection often imposes near-infinite costs (Warburton, 2005, p. 224).

Starting from this standpoint, one may assume there exists a certain 'optimum' level of human safety at the point where the sum of accident costs and safety investments is lowest (Warburton, 2005; Figure 2.1). It is precisely this optimum that ship-owning companies should strive towards; the point that impersonates the ALARP-principle. The goal of minimizing the total costs and locating this ALARP optimum however, requires information of on both costs and effects of specific safety improvements (Warburton, 2005). This is where the indicators, related KPIs and combined BSC structures enter the picture.

2.7 Benchmarking crew safety performance

One of the most important goals of crew safety performance measurement is to stimulate discussion and improvement through the assessment process (Cox & Cheyne, 2000). Here, the most successful company is the one that performs better in the field of crew safety compared to its competitor (Konsta & Plomaritou, 2000). Above was argued that a safety assessment should not remain at evaluating annual outcomes, since much more can be learned from comparing the safety performance levels over the years (Konsta & Plomaritou, 2012). Besides, a company might be able to improve its crew safety level without increasing the level of investments based on the lessons learned from past years (Mearns & Håvold, 2003). The question that remains is: How is success of a ship-owning company measured in order to compare results? This is where the concept of benchmarking comes in.

2.7.1 The academic view on benchmarking

Looking exclusively at the noun of benchmarking, its meaning is: "A predefined position, used as a reference point for taking measure against" (Andersen, 1999, p. 1). The part where benchmarking is described as 'a reference point' may have led to the association with external benchmarking as being a tool for improvement, as stated by Bhutta and Huq (1999, p. 255): "Benchmarking is first and foremost a tool for improvement, achieved through comparison with other organizations as the best within an area". The comparison between organizations results in defining a best practicing company, indicating another goal of external benchmarking: "Benchmarking is the systematic search for best practices that leads to superior performance" (Lema & Price, 1995, p. 28). Based on many of such definitions, Andersen (1999) identified the leading components of benchmarking – measurement of performance levels (1), comparison of performance and processes (2), learning from benchmark partners (3) and changing or improving processes based on benchmark results (4) – and included them in a single overarching definition. According to him, benchmarking is "the process of continuously measuring and comparing one's business processes against comparable processes in leading organizations to obtain information that will help the organization identify and implement improvements" (Andersen, 1999, p. 2). External benchmarking may lead to the definition of best practices in the maritime sector and provoke a joined incentive to do better. Furthermore, it might help a company to internally increase its level of crew safety onboard. However, an important step prior to external benchmarking is internal benchmarking, that is, to collect, analyze, compare and react upon data that is available within a certain company.

In the literature, benchmarking is presented a powerful tool to understand and create a strong stimulus for innovation in the field of safety performance (Wijnolst & Wergeland, 2009). Multiple studies are yet performed that include several human, or crew, safety measures that were expected to be comparable (Fuller, 2001; Mearns et al., 2001; Mearns et al., 2003; Mearns & Håvold, 2003; Håvold, 2005; Skogdalen & Vinnem, 2011). Although the academic world encourages benchmarking, the process should be handled with care (Flin et al., 2000; Groeneweg & Weerheym, 2010). For in the end, it is not the information structure itself that is important, but the activities it generates (Zwetsloot, 2009). Nevertheless, benchmarking is seen as the future of safety – and therefore crew safety – assessment (Fuller & Vassie, 2001; Håvold, 2005). "A move towards excellence is accelerated by the adoption of a continuous improvement philosophy that is supported by the process of benchmarking" (Fuller & Vassie, 2001, p. 414). Meaning that ship owning companies could, and should, use indicators to benchmark performance between organizational units like vessels (Håvold, 2005). Companies should thus not only develop indicators in order to evaluate and get feedback on their human safety performance, but also benchmark their overall onboard crew safety level against past outcomes (Konsta & Plomaritou, 2012). Eventually, benchmarking may even be a tool to compare results between competitors and profit from their knowledge of how to achieve higher safety levels (Konsta & Plomaritou, 2012).

2.7.2 Benchmarking and crew safety assessment

Hence, although benchmarking proofed to be a useful tool in many industries so far, implementing such an initiative for crew safety assessment of ship owning companies to achieve better safety standards requires extensive study (Mearns & Håvold, 2003; Pun et al., 2003; Wang, 2006). To achieve such a benchmark initiative, first safety assessment techniques such as BSCs, KPIs and indicators should be further studied and the criteria for their effective use need to be established in crew safety assessment (Wang, 2006). Second, to conduct cost-efficiency assessment, it is required to set a sound base case reflecting the existing level of crew safety performance that can be used as a reference for comparisons (Wang, 2006). Third, a crucial requirement is that the indicators and KPIs used in such BSCs with the purpose of benchmarking should be nationally valid and tailor made for the maritime industry. As such, selecting, measuring and managing the right indicators for ship-owning companies using crew safety performance benchmarking activity is where the major future challenge lies for ship-owning companies (Mearns & Håvold, 2003; Pun et al., 2003; Wang, 2006). Fourth, and probably most important for the industry, the relation between the investments in crew safety projects and the resulting crew safety performance level should be studied. In other words: how much of the investments (input) are converted into enhanced crew safety performance levels (output).

2.8 *Towards benchmarking and cost efficient crew safety performance*

One may safely argue that, once proved feasible, the method of achieving acceptable crew safety performance outcomes in a cost-efficient way by benchmarking past safety outcomes will be easily adopted by ship owning companies. Although the academically acclaimed tool of benchmarking has proved its worth many times in achieving cost-efficiency, its process seems to skip a significant part in the case of crew safety: To achieve cost-efficiency, a ship owning company should have knowledge about where to invest. In other words, benchmarking crew safety performance outcomes is only useful when the results link back to a defined process and, on top of that, a certain company structure. That is, the determinants that affect the crew safety performance level have to be known (Talley, 1999; Talley, Jin & Kite-Powell, 2005).

The academic foundation for research concerning crew safety determinants is constructed by Talley, who studied all marine accidents and incidents over the period 1991-2001 (Talley, Jin & Kite-Powel, 2005) and published several articles about this. Talley (2009) found that whether or not injuries and accidents occurred on a vessel was a function of ship characteristics, ship type, ship operation phase, ship location and weather and visibility conditions. Based on such findings, the IMO is now aware of the fact that older vessels, vessels that are moored or docked, tankers and vessels that often sail in rough seas are more likely to deal with injured crew members or vessel accidents (Talley, 2009). However, although some research has been done on this field (Mearns et al., 2003; Talley, 2009), ship owning companies have no access to a list of determinants that may affect their crew safety performance levels other than the industry basics that authors like Talley provide. In other words, they have their outcomes, but miss their process variables. By lacking these determinants, investment decisions within ship owning companies are still based upon what is *expected* to have an effect on crew safety performance, rather than what is *known* to influence performance levels (Vermeer, Sanders & Oreel, 2013). To achieve cost-effectiveness however, one should not only benchmark crew safety performance outcomes but also be aware of the determinants resulting in these outcomes so that investments can be strategically done. Besides, one should not only investigate which determinants affect the occurrence of injury alone, but also the severity of the injury.

This study focuses on the latter issues and attempts to define the variables that influence the distribution of injury – in terms of severity – for a ship owning company operating in the ‘safety aware’ offshore sector. Hereby, the main goal was to develop a model explaining the distribution of injuries among crew members, so that investment post may be defined on the road to cost-efficient crew safety management. However, to study the severity distribution of injuries in the maritime world, one needs a dataset that contains information about such injuries. Although injuries occur quite often, they are still considered ‘rare’ when compared to non-occurrence of injuries (Westphal, 2013). To overcome this problem, several articles about the analysis of rare-events data were studied.

2.9 Analysis of rare event injury data

Rare events, described by King and Zeng (2001) as “dozens to thousands of times fewer ones than zeroes” (p. 138) are associated with and researched mainly in medical studies (King & Zeng, 2001; Westphal, 2013). Although well known in medical research, only two studies containing similar analysis could be found in scientific maritime papers. Talley (1999; 1999a), together with Jin and Kite-Powell (2005), performed multiple studies towards the determinants of ship accidents. Two particular studies (Talley, 1999; Talley, Jin & Kite-Powell, 2005), focused on the determinants of crew injuries. Using a simple OLS regression model, Talley (1999) studied fatal and non-fatal accidents occurring in the maritime sector for the years 1981-1991. One of the conclusions was that ship accidents combined with crew injuries are infrequent and if injuries do occur, they are small in number. This combination made the use of OLS regression inappropriate (Talley, 1999). Their study continued with a Poisson regression, assuming that the mean and variance of the observations of the dependent variable were equal. Considering this shortcoming, Talley (p. 1369) finally argues that negative binominal regression could be a solution for rare events data. In 2005, Talley, Jin and Kite-Powell published a similar article studying crew injuries over a period of 1991-2001. Here, the same statistical method was used resulting in similar findings, which were categorized per vessel type. Although some effects proved to be significant, none of the estimates was truly outspoken (Talley, Jin & Kite-Powell, 2005, p. 272). In the discussed articles, the occurrence of maritime accidents was studied, striving to define the variables associated with higher probabilities for accidents.

Looking beyond the maritime sector, one study researching injury severity was found (Yamamoto et al., 2008). However, the main focus of this article was on underreporting of accidents rather than the distribution of injuries. Despite this, an important finding of the study of Yamamoto (et al., 2008) was that due to underreporting of traffic incidents with lower injury severities, accident data can be regarded as outcome-based samples with unknown population shares of the injury severity. That is, outcome-based samples result in biased parameters which “skew the inferences on the effect of key safety variables” (Yamamoto et al., 2008, p. 1320): An important finding to take into account when studying injury severity in the maritime domain.

All in all, rare events have proven difficult to explain and predict: “Most popular statistical procedures, such as logistic regression, can sharply underestimate the probability of rare events, and commonly used data collection strategies are grossly inefficient” (King & Zeng, 2001, p. 138). The objective of this study – to define the variables that influence the distribution of injury in terms of severity, instead of analyzing the variables responsible for the occurrence of those injuries – is therefore very advanced and requires a solid database containing a large variation of statistics. To maintain such a database however, is no common practice in the maritime domain.

Concluding the literature review, the next section continues with the development of a conceptual framework suitable to study the determinants that affect the distribution of injury severity for accidents occurring in the maritime sector. The result of chapter

3 will eventually provide statistical input to conduct research towards our key question: *“What are the variables that influence the crew related injury severity distribution in the company studied and what are the corresponding lessons for practice?”*

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3. Conceptual Framework

The third chapter contains the conceptual framework of this study. Prior to the presentation of the conceptual model, the scope of the study is addressed in subsection 3.1. The variables that are, by the literature, considered to have an influence on crew safety performance levels are discussed in subsection 3.2, together with their measurable components. Finally, the key hypothesis and conceptual model are presented, serving as the conceptual framework for this study.

3.1 Scope of the study

The literature review previously introduced the direction of this study. For the construction of the conceptual model and methodological approach, the scope of the research shall now be defined. To be feasible for study, the participating company had to fulfill two main requirements: The company had to be ship-owning and in the possession of at least two vessels (1) and the company had to be far advanced in the collection of crew safety performance measures (2).

3.1.1 Ship owning arguments

The relevance and importance of crew safety performance is, obviously, not limited to ship owning companies alone (Haralambides, 1998). Nevertheless the choice for a ship owning company was made based upon the direct financial consequences for ship owning companies related to their crew safety levels (Hetherington, 2006). Simply said: “No safety, no client, and no shipment” (Van Rijsinge, 2013; Stolk, 2013; Vermeer, Oreel & Sanders, 2013). For ship owning companies, well maintained safety standards are not solely a legal obligation. Crew safety standards demanded by customers of ship owning companies often require higher levels of safety compared to the minimum legal standards, resulting in direct commercial and financial consequences when requirements are not met (Hetherington, 2006). Even though ship management may be outsourced to a management company, the ship owner remains responsible for the quality of the vessel in the end (Bouter, 2013). Next to the financial consequence, the choice to study a ship owning company was also based upon the interdependent effect of crew safety standards among companies. Due to the commercial and financial consequences, crew safety standards of accompany are also related to that company’s competitiveness in the sector (Hetherington, 2006). Meaning that, if several ship companies increase their safety standards, the remaining competitors can be expected to do the same for the sake of their competitive market share (Vermeer, Sanders & Oreel, 2013). Although several companies are still listed as ‘ship owning’, they are not automatically ‘asset owning’. The previous arguments indicate the reason why participants to the study had to be in the possession of at least one vessel.

3.1.2 Performance measurement

Next to being ship owning, the participating company had to collect crew safety performance measures. The reason for this requirement is quite straightforward: without the ability to show results, studying the company would not result in any additional value of the research.

3.2 Determinants of crew safety performance

In the relation to crew safety performance levels, the literature review identified several issues considered relevant for the study which determinants influence crew safety. This paragraph is directed at the explanation of these relevant variables and how they are interrelated with each other. We start by defining a measurable dependent variable of crew safety performance and continue from there to the independent variables. The independent variables influencing crew safety performance can be roughly classified into five categories: focus on safety (1), rules and regulations (2), vessel characteristics (3), individual factors (4) and context factors (5). The sections below address these categories. Variables are provided with names for analysis, which are indicated in brackets.

3.2.1 Crew safety performance

Crew safety performance is included as the dependent variable in the model. The basic concept of crew safety performance was explained in the literature review, as well as the difference between leading and lagging indicators, the know-how of measuring crew safety performance within ship owning companies can be introduced. However, the literature lacks information about indicators required to assess crew safety performance. Therefore, exploring interviews (n = 5) with ship owning companies operating in different segments were used to obtain relevant KPIs. Nine different KPIs were found, of which five were used and considered important by all interviewees (Bouter, 2013; De Bruine, 2013; Stolk, 2013; Van Rijsinge, 2013; Vermeer, Sanders & Oreel, 2013): *Fatalities* (1), *lost time injuries*, or *LTIs* (2), *restricted work cases* (3), *medical treatment cases* (4) and *first aid cases* (5). All five KPIs are explained briefly (Lee, 2010).

1. Fatality: A work-related accident resulting in the dead of a crew member.
2. LTI: A work-related injury or illness that results in the crew member not being able to work on a subsequent scheduled workday or shift.
3. Restricted work case: A work-related injury or illness that results in limitations on work activity that prevents a crew member from doing any task of his/her normal job or from doing all of his/her job for any part of the day.
4. Medical treatment case: A work-related injury or illness that calls for medication, treatment, or medical check that is normally administered by a healthcare professional and goes beyond a first aid case. Hereby, a medical treatment case does not result in lost time form work beyond the date of the injury.
5. First aid case: A minor work-related injury or illness that calls for only simple treatment and does not call for follow-up treatment by a healthcare professional. Hereby, a first aid case does not result in lost time from work or work restrictions.

This study includes both the number of injuries that occurred, as well as the distribution of injuries among the KPI levels explained above. Although the above definitions seem very clear, a lot of different interpretations are found when studying the KPIs used in practice. For example, some companies considered 24 hours of lost work time a LTI, whereas other companies considered a lost shift of eight hours (Bouter, 2013; Stolk, 2013), or twelve hours (Vermeer, Oreel & Sanders, 2013) a LTI. This highlights the fact that the use of KPIs indeed has drawbacks when they are used for external benchmarking purposes, as explained before in the literature review. By studying the safety process in a single company, this important drawback is eliminated.

Another limitation related to the KPI outcomes relates to their mutual relation to each other, in other words; their relative weight. The literature deliberating on this topic is limited. Wang (2001; 2006) introduces the Cost of Unit Risk Reduction (CURR). The CURR uses a mutual indicator weight where 50 minor injuries are equivalent to 10 serious injuries or to 1 life. Hereby, Wang (2001) is the only author who came up with a crew safety indicator weight. For this research, this means that the crew safety performance outcomes, classified in the categories mentioned above, cannot be combined into a single value. Therefore, the outcome levels are ordinal and may not be considered interval. This, of course, influences the statistic model that is used for this study.

3.2.2 Rules and regulations

In the literature, the presence of safety regulations is considered to have a positive influence on safety performance (Laurence, 2005; Knapp & Franses, 2009). However, to have more rules and regulations is not always better; too many regulations can lead to confusion among workers, resulting in lower safety performance outcomes (Laurence, 2005). According to Chaturvedi (2005), the diversity in safety and investments in safety projects can be represented by three developmental stages: “Stage 1 where safety is compliance driven and based on rules and regulations, Stage 2 where safety performance becomes organization’s goal, and Stage 3 where safety is a continuing process of improvement where everyone can contribute” (Chaturvedi, 2005, p. 432). These stages indicate that crew safety performance in the maritime industry is in currently in the first stage and moving towards the second stage. Rules and regulations should always be addressed in combination with the vessel type, since ship specific rules may differ (Oldham, 1998; Wang, 2001). As such, many studies differentiate between five categories of vessel types (Munro-Smith, 1975; Talley, 1999; Knapp, 2004): Container vessels (1), bulk vessels (2), tanker vessels (3), general cargo vessels (4) and specialty vessels (5). The distinction is often made, for example, due to the fact that tanker vessels are subject to lower levels of crew safety performance compared to bulk and container vessels (Talley, 1999).

For this study, a single offshore related ship owning company was studied with all vessels registered under the Panamanian flag. Besides, all vessels were either pipelaying vessels or vessels supporting the pipelay process. As such, applicable rules and regulations were similar for all vessels. Including a variable for the vessel type in the statistic model would therefore cover the differences in rules and regulations if any. However, the area in which the vessel operates may have an influence on the compliance to the existing safety rules and regulations. Therefore, some context variables were controlled for, of which the operating area (*Area*) and the strictness of safety regulations (*Safety_reg*) are two. These are discussed in detail in subsection 3.2.6.

Hypothesis 1: *“The presence of strict safety regulations is positively correlated with crew safety performance levels.”*

3.2.3 Focus on safety

According to Talley (1999), the number of crew injured and the severity of the injuries in a ship accident depends, among others, upon injury-prevention and effort. ‘Focus on safety’ is used as an independent variable in this study. ‘Focus on safety’ is mostly interpret as the ‘safety climate’ and related ‘safety culture’ of an organization (Guldenmond, 2000; Mearns et al., 2003), defined as: “that assembly of characteristics and attitudes in organizations and individuals, which establishes that, as an over-riding priority, safety issues receives the attention warranted by their significance” (IAEA, 1986). Safety culture is important because is forms the context in which safety attitudes develop and persist and safety behaviors are promoted (Zohar, 1980). Variables related to ‘organizational policy’ are the most dominant group of factors influencing safety performance (Sawacha et al., 1999). According to Lutchman (et al., 2012), the key to world class safety performance and the establishment of a strong safety climate, is leadership. “World-class safety system performance or status may be defined as an organization with demonstrated exceptional and industry-leading safety performance that is supported by the right personnel, in the right roles, for stewarding safety” (Lutchman et al., 2012, p. 31). Next to the right personnel, the effect of leadership on safety performance levels is very profound with a clear safety vision (Lutchman et al., 2012). The study of Sawacha (et al., 1999) also found several organizational variables positively correlating with safety performance levels: Safety committee policy (1), talk by the management on safety (2) and safety poster display (3).

The literature is quite unanimous about the fact that a safety incentive program focusing on safety behavior and safety-related activities, directed by a strong inter-organizational management, can be an inexpensive yet effective way to improve safety performance levels in an organization and on board of vessels (Sawacha et al., 1999; Guldenmond, 2000; Mearns et al., 2003; Brady, 2007; Lutchman et al., 2012). However, “the only area of disagreement – and it’s a big one – is how incentive programs should be structured to do the most good” (Brady, 2007, p. 43). Also, the validity of including a ‘safety climate’ or ‘safety culture’ variable in studies is questioned: “While the importance of the concept of safety climate or culture is stressed by most authors, very few have attempted to support their claim by reporting an indication of its construct validity or predictive validity […]. Basically, this means that the concept still has not advanced beyond its first developmental stages” (Guldenmond, 2000, p. 216). To include a variable covering the ‘focus on safety’ is therefore difficult and requires indirect variables to be included that are measurable and quantifiable. Measurable components of safety management are the existence of a set-aside safety department, the introduction of safety programs, the number of quality, health, safety and environment (Q-HSE) managers and engineers working for the company and the number of Q-HSE managers assigned to a single vessel.

1. Safety department: The expectation is that the presence of a set-aside department fully directed at quality, health, safety and environmental issues is positively correlated with the crew safety performance level.
2. Safety programs: The expectation is that the introduction of a safety program is positively correlated with the crew safety performance level.
3. Number of Q-HSE: The expectation is that the number of Q-HSE managers and engineers working for the company – in other words the

Q-HSE rate – is positively correlated with the crew safety performance level. That is, the higher the Q-HSE rate, the higher the crew safety performance level.
4. Q-HSE per vessel: The expectation is that with every vessel having a dedicated Q-HSE manager or engineer, the crew safety performance level is positively influenced.

Overall, the expectation for this study is that the organizational focus on safety positively influences the crew safety performance level. That is, the injuries that occur are expected to be categorized in the lower segments of an injury severity distribution. The safety department was present during all years (2009-2013) of study, therefore this variable was in the end not included in the model. For the other variables, the expectation is that they are heavily correlated with one another. A large safety program was launched in 2009, attempting to reduce both the frequency of injuries as well as their severity. Therefore, the year in which injuries occurred (*Year*) was taken into account. Furthermore, the number of Q-HSE personnel (*QHSE*) and the number QHSE rate per vessel were (*QHSE_rate*) were included as variables for 'focus on safety'.

Hypothesis 2: *"Due to the increasing focus on safety, the more recent years are associated with higher crew safety performance levels".*

3.2.4 Vessel characteristics

The number of injuries that occur and their distribution depends on the characteristics of the vessel (Talley, 1999; 2009; Talley, Jin & Kite-Powell, 2005). Four main general characteristics that are often used in studies are the vessel type (*Pipelay*), the number of crew onboard (*Crewnr*), the vessel size (*Vessel_size*) and the vessel age (*Vessel_age*). The relevance of vessel type was explained in paragraph 3.2.2, where it was stated that relatively more accidents occurred on tanker vessels. Since the vessels included in this study are all but one of the same type – offshore pipelaying vessels – ship type is controlled for in the model by making a distinction between pipelay vessels ($n = 4$) and a non-pipelay vessel ($n = 1$). Second, the number of injuries depends, of course, upon the number of people that could potentially get injured (Talley, 2009). The number of crew onboard a vessel differs with the size and the age of the ship (Talley, 1999). Vessel size is supposed to have a non-negative effect on the number of crew onboard, since larger ships do not necessarily require a larger crew (Talley, 1999). However, this does not account for offshore related pipelaying vessels which require a larger crew due to the fact that they are manufacturing pipelines within the hull of the vessel (Vermeer, Oreel & Sanders, 2013). The age of the ship is positively related to the number of crew members onboard and proved to have a negative influence on the number of injuries that occurred (Talley, 1999). Although this relation is mainly studied to indicate the effect of the number of crew aboard towards the total number of injuries, it is also interesting to know how this affects the injury severity distribution. The four main vessel characteristics differ for each vessel included in this study. However, since each vessel has its own characteristics, controlling for each vessel covers all of the variables that are mentioned above. The vessel on which the injury occurred (*Ship*) on is therefore included as an independent variable in this study.

Next to the general vessel characteristics, controlling for company specific vessel characteristics was required. Three variables were considered relevant. Due to the reporting of a relatively high number of injuries occurring at the welding stations onboard, the number of welding stations (*Weld*) was included. The same accounts for the coating stations (*Coat*). Those two variables were then combined, indicating the number of construction places onboard the vessel (*Constr_place*). Furthermore, heavier material handling was considered to expose a higher risk of more severe injuries. Therefore, the vessels' maximum pipe size (in inches) was also taken into account (*Max_pipesize*).

Hypothesis 3: *"The number of crew members onboard, that increases with vessel size, is negatively correlated with crew safety performance levels."*

Hypothesis 4: *"The age of the vessel is negatively correlated with crew safety performance levels."*

Hypothesis 5: *"The number of welding and coating stations are negatively correlated with crew safety performance levels".*

Hypothesis 6: *"Vessels capable of handling larger maximum pipe sizes are associated with lower crew safety performance levels".*

3.2.5 Individual factors

According to Hetherington (2006), several individual factors that influence injury occurrence can be thought of. Nationality, stress, age, sex, fatigue, health, situation awareness and communication are considered to be the main contributors. Whether they also influence the severity of an injury is unknown so far. Unfortunately, personal characteristics of the injured persons in the dataset could not be included in this study, due to legal confidentiality reasons. However, on the company's request, job specifications were taken into account to study whether some jobs – considered to have a severe injury potential – in fact showed different injury distribution patterns. For the construction crew on board, welders and welder helpers (*Wldr*), spacers (*Spcr*) and riggers (*Rggr*) were considered a high potential group. For the technical crew, mechanics (*Mchnc*) and engineers (*Engnr*) were included. Using these specifications as input, two high potential function groups were created: $Function\_Constr = Wldr + Spcr + Rggr$ (1), and $Function\_Techn = Engnr + Mchnc$ (2). The variables were tested both individually and in their function groups.

Next to these function related variables, the rank of the injured person (*Rank*) was also included in the model. According to the company, crew members with a higher rank were less exposed to high potential injury situations.

Hypothesis 7: *"The combined construction function group of welders, spacers and riggers is negatively correlated with crew safety performance levels".*

Hypothesis 8: *"The combined technical function group of mechanics and engineers is negatively correlated with crew safety performance levels".*

Hypothesis 9: *"A higher rank among the vessel's crew is positively correlated with crew safety performance levels".*

3.2.6 Context factors

The compliance to safety regulation (*Safety_reg*) was discussed in subsection 3.2.2 and was included in the model as a context factor relating to hypothesis 1. The compliance to safety regulation was based upon the project number and the area (*Area*) in which the vessel was operating. Hence, it is assumed that the variable area and the compliance to safety regulation are to some extent interrelated and should therefore be carefully dealt with when used together in a statistical model. Six different geographical areas of operation were distinguished in the model: Asia, Australia, Africa, South America, North America and Europe, representing the global continents. The literature suggest that for developing and less than developed areas, safety performance may be lower compared to areas of operation surrounding developed countries (Koehn, Kothari & Pan, 1995).

A second context factor that may be considered relevant is the weather condition during vessel operations. According to Wang (2002), Håvold (2005) and Antão & Soares (2008), conditions such as fog, high winds, waves and cold and are associated with the occurrence of injuries. Unfortunately, information about most weather conditions – except for cold (*Cold*) – could not be obtained. Some operations of the company are taking place in areas with a possibility of cold weather conditions. The crew is therefore being exposed to hazard associated with these cold conditions. Cold weather can, without proper protection, severely affect the performance and safety of crew members (Enander, 1984; Parsons, 2003; Sillitoe et al., 2010). Therefore, the variable *Cold* was included to be tested in this study.

Hypothesis 10: *"Operating in waters surrounding developing and less than developed countries negatively correlates with crew safety performance levels".*

Hypothesis 11: *"Cold weather conditions are negatively correlated with crew safety performance levels".*

3.2.7 Commercial factors

In the literature review, it was said more than once that commercial factors, such as customer pressure, also play a role in the increased focus on safety performance. Hetherington (2006) emphasized the impact of high safety performance levels on the chartering of vessels, as did several interviewees (Vermeer, Oreel & Sanders, 2013). However, since this study takes only one company into account, the so called 'commercial' pressure is the same for all vessels. Furthermore, customer pressure is related to the importance of safety performance for the company and may only indirectly influence the injury severity of occurring incidents. As such, commercial factors are considered out of scope for this particular study, although the external pressure on safety performance may never be seen as irrelevant.

3.3 Conceptual model

All of the relevant variables were included in the conceptual model below (Figure 3.1). From the figure, one can derive that the expectation is that the crew safety performance level depends on the rules and regulations, the vessel characteristics, the focus on safety, individual factors and context variables.

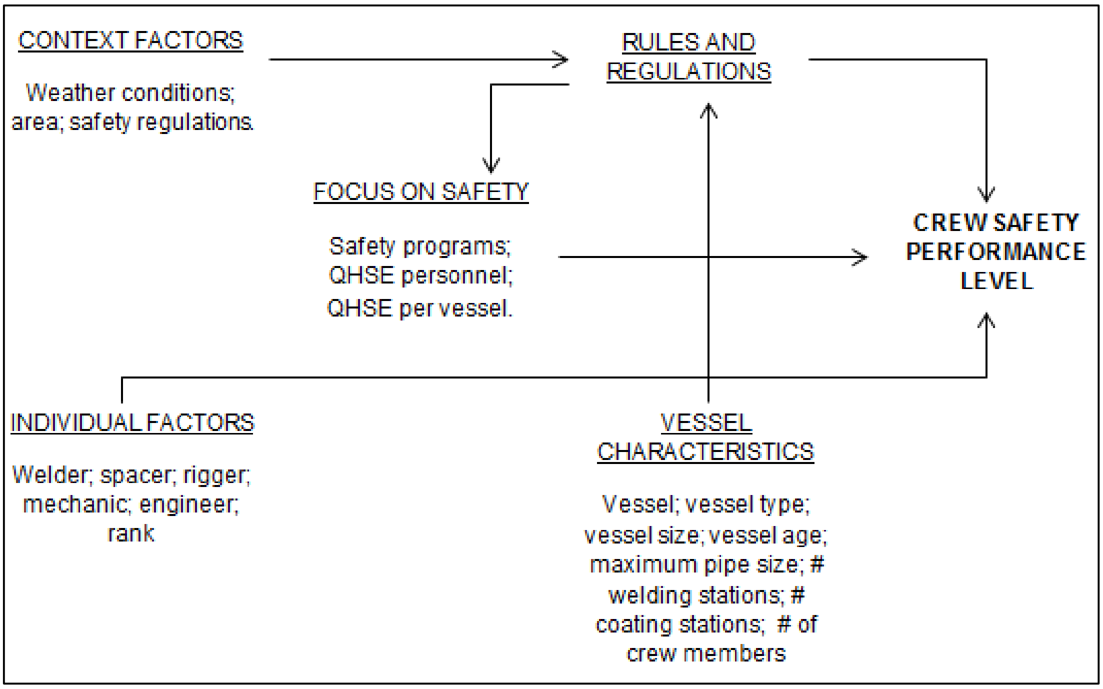

Figure 3.1, Conceptual Model (Source: Author)

The conceptual model above corresponds to the formulas in Table 3.1 below, containing the variable names that were statistically tested for this study.

Table 3.1, Corresponding Formula's (Source: Author)

$$Crew\ Safey\ Performance = G[Rules; Vessel\ Characteristics; Focus\ on\ Safety; Individual\ Factors; Context\ Factors]$$ **[3.1]**

$$Vessel\ Characteristics = h_1(Ship; Pipelay; Vessel\_size; Vessel\_age; Max\_pipesize; Weld; Coat; Crewnr) = h_1(Ship; Pipelay; Vessel\_size; Vessel\_age; Max\_pipesize; Constr\_place; Crewnr)$$ **[3.2]**

$$Focus\ on\ safety = h_2(Year; QHSE\_rate; QHSE\_vessel)$$ **[3.3]**

$$Individual\ factors = h_3(Wldr; Spcr; Rggr; Mchnc; Engnr; Rank) = h_3(Function\_Constr; Function\_Techn; Rank)$$ **[3.4]**

$$Context\ factors = h_4(Cold, Area; Safety\_reg)$$ **[3.5]**

Table 3.2 summarizes the variables that were taken into account, their corresponding name in the statistical models and the variable type, which was either dummy or string. The model highlighted in this chapter provides the input for the statistical tests of this study. The methodology for these tests is further explained in chapter 4.

Table 3.2, Input Variables (Source: Author)

	Variable	**Model**	**Data**	**Type**
1.	Vessel	*Ship*	Qualitative	Nominal
2.	Vessel type	*Pipelay*	Qualitative	Nominal
3.	Vessel age	*Vessel_age*	Quantitative	Interval
4.	Vessel size	*Vessel_size*	Quantitative	Interval
5.	Maximum pipesize	*Max_pipesize*	Quantitative	Interval
6.	No. of welding stations	*Weld*	Quantitative	Interval
7.	No. of coating stations	*Coat*	Quantitative	Interval
8.	No. of crew onboard	*Crewnr*	Quantitative	Interval
9.	Year	*Year*	Quantitative	Interval
10.	No. QHSE personnel	*QHSE*	Quantitative	Interval
11.	QHSE per vessel rate	*QHSE_rate*	Quantitative	Interval
12.	Welder	*Wldr*	Qualitative	Nominal
13.	Spacer	*Spcr*	Qualitative	Nominal
14.	Rigger	*Rggr*	Qualitative	Nominal
15.	Mechanic	*Mchnc*	Qualitative	Nominal
16.	Engineer	*Engnr*	Qualitative	Nominal
17.	Construction function group	*Function_Constr*	Qualitative	Nominal
18.	Technical function group	*Function_Techn*	Qualitative	Nominal
19.	Rank	*Rank*	Qualitative	Ordinal
20.	Compliance to safety regulations	*Safety_reg*	Qualitative	Ordinal
21.	Area of operation	*Area*	Qualitative	Ordinal
22.	Weather conditions	*Cold*	Qualitative	Nominal

Now that all variables are specified, the statistical methods that were used have to be explained. Chapter 4, containing the study's methodology is dedicated to discuss the research design, research method, data collection techniques, the quantitative model used and corresponding limitations of this strategy. Furthermore, a brief introduction of the case company is provided.

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4. Methodology

This chapter describes and justifies the research design, research method and data collection techniques used for the purpose of answering the formulated key question. The study mainly uses quantitative methods. An in-depth company study was conducted, analyzing data provided by a Swiss based ship owning company with its main office located in The Netherlands. Prior to this chapter, one main research objective was formulated: To define the variables that influence the distribution of injury – in terms of severity – for a ship owning company operating in the offshore sector. Hereby, the main goal was to develop a model explaining the distribution of injuries among crew members, so that investment post may be defined on the road to cost-efficient crew safety management.

Section 4.1contains a justification for the research design and provides the approach that was taken in the study. The research method, as well as the introduction of the case company is given in section 4.2. Section 4.3 introduces the statistical models that were used. The limitations of the methodology are given in section 4.4.

4.1 Research Design

This study mainly uses quantitative methods. "The major purpose of quantitative research is to make valid and objective descriptions on phenomena" (Taylor, 2005). Hereby, the researcher attempts to show how these phenomena can be controlled by manipulating the variables in a dataset (Taylor, 2005). To what extent this is possible, depends on the quality of the input data (Taylor, 2005). As discussed in section 2.9, analyzing injury data is associated with rare event analysis, since the probability that an injury occurs is much smaller than the opposite probability of non-occurrence (King & Zeng, 2001). The few studies that were conducted in this field all used ordinary least squares (OLS) regression and Poisson regression methods. Although some interesting results were found, many variable estimates did not show significant effects. We expect the rare event characteristic of injuries being somewhat responsible for those outcomes. As mentioned before, rare events data should be handled with care, and often common statistical methods are inadequate of finding reliable evidence (King & Zeng, 2001).

On the one hand, this is why it was decided that studying the occurrence of injuries alone could best be left for authors in the possession of large datasets including multiple company data. On the other hand, those studies are done more often compared to what we try to accomplish in this study. The data that was made available to us provided the opportunity to study the distribution of injury severity rather than the occurrence of injury alone; a research design and methodology that was not tried before in maritime science. We had to come up with a sound research approach, of which an overview, in ten steps, is given in subsection 4.1.1.

4.1.1 *Approach*

1. The first step was to study the literature regarding crew safety, crew safety performance measurement, the use of KPIs, investments in crew safety projects and the value of benchmarking. Based on the literature, eleven hypotheses were developed.
2. The second step was to schedule five exploring interviews with the Q-HSE managers (*n = 7*) of five ship owning companies operating in different sectors. All interviewees were asked for the level and importance of crew safety performance, investments and safety projects of their companies and the added value of benchmarking. Crew safety KPIs were collected for all participating companies.
3. The third step was to develop a conceptual framework based on the literature and the exploring interviews, modeling all relevant variables in the scope of the research.
4. The fourth step was to select a feasible company for the in-depth study. The participant had to fulfill the requirements of being a ship-owning company in the possession of at least two vessels (1), sailing under the same flag (2) and extensively collecting data on crew safety performance (3).
5. The fifth step was to analyze the available data for the year 2009-2013. The data was then for each year categorized according to the commonly used crew safety KPIs; fatalities (FAT), lost time injuries (LTI), restricted work cases (RWC), medical treatment cases (MTC) and first aid cases (FAID).
6. The sixth step was to run several *(n = 3)* ordinal logistic regression, also known as a proportional odds regression, on SPSS and assess the effect of the independent variables on the distribution of the injuries in four ordered levels.
7. The seventh step was to run several *(n = 3)* generalized ordinal logistic regression in STATA – due to unavailability of the model in SPSS – and assess the effect of the independent variables on the distribution of the injuries in four ordered levels. The ordinal logistic regression model was also repeated in STATA, for the sake of uniformity.
8. The eight step was to analyze the regression results, discuss the differences between ordinal logistic regression modeling and generalized ordinal logistic regression modeling, and to answer the formulated hypotheses.
9. The ninth step was to write a sound conclusion to the study, containing a discussion that both addressed the scientific and practical contributions of the results.
10. The tenth step was to address the limitations of the research and research methodology, as well as the implications for practice.

4.2 *Research Method*

Despite the lack of information on the topic, the concerning maritime sector appeared to be interested when QHSE managers (*n = 7*) were asked for their opinion during five exploring interviews in ship owning companies operating in different segments. The topic of crew safety performance was stressed to be highly important for the economic welfare of ship owning companies and to become even more so in the near future. However, transparency and willingness of sharing sensitive injury and investment data appeared to be bottlenecks in the research towards the variables contributing to the distribution of injury severity (Prins, 2013). Although the safety of the maritime sector is emerging, injury severity was not researched before. Therefore, it was decided to conduct an in-depth analysis of injury data provided by a single case company with many years of experience and an adequate injury data log. Furthermore, the company had to be representative for the industry. To strengthen the added value of the results, it was agreed to select a company that could be considered a ‘best case’, or benchmark, example for the industry. By being representative for the rest of the sector, general remarks on the results of this study could be made. Such a company was not easily found, due to the requirements that it had to fulfil to be fit for this study. These requirements were addressed in the previous chapter and are discussed in relation with the case company in subsection 4.2.1.

4.2.1 Case context – Ship owning company

This paragraph provides some general information and about the participating case company, from here on referred to as ‘the company’. The Swiss-based company, a global leader in offshore pipeline installation and subsea construction, was founded in 1985 and has its main office located in Delft, The Netherlands. Despite the economic crisis, the company has experienced a staff expansion of about 200% over the last five years. The company owns a fleet of six offshore vessels that all sail under Panamanian flag, of which one is currently under construction. Each vessel – referred to as V_x, with x indicating the vessel number – is briefly described below:

Vessel 1 (V_1): Operational since December 2007, the vessel is optimized for the execution of small to large diameter pipeline projects of any length in all water depths, and for associated work such as the installation of risers and subsea protection frames. V_1 is 217 meter long (Lpp), has a breadth of 32 meters and a maximum speed of 16 knots. V_1 has a pipe hold capacity of 14,000 tons and accommodates a crew of 270 people.

Vessel 2 (V_2): Operational since 2005, V_2 is a versatile vessel optimized for pipeline trenching, the flooding, gauging and testing of pipelines, offshore lifts and installation of subsea structures, survey activities and other operations in support of the company’s pipelaying vessels.V_2 is 117 meter long (Lpp), has a breadth of 20 meters and a maximum speed of 11 knots. V_2 has one crane for general purposes (26 tons) and accommodates a crew of 72 people.

Vessel 3 (V_3): Operational since 1986 Year, V_3 is a versatile vessel optimized for the execution of small and medium diameter pipeline projects of any length in unlimited water depths, and for associated work such as the installation of risers and subsea protection frames. V_3 is 150 meter long (Lpp), has a breadth of 25.8 meter and a maximum speed of 16 knots. V_3 has a pipe hold capacity of 8,200 tons and accommodates a crew of 230 people.

Vessel 4 (V_4): Operational since 1998, V_4 is the largest pipelaying vessel in the world and has set new standards in the pipelaying industry. V_4 is optimized for laying medium and large diameter pipelines at high speed, making her a highly competitive vessel. V_4 is 249 meter long (Lpp), has a breadth of 41 meter and a maximum speed of 13.5 knots. V_4 has a pipe hold capacity of 22,000 tons and accommodates a crew of 420 people.

Vessel 5 (V_5): Purchased in 1997 and converted for pipelaying in 2002, V_5 is a flat-bottom, anchored barge for shallow water offshore construction activities that operates in shallow waters worldwide. V_5 supports the company's fleet but can also be contracted independently for pipelaying up to a water depth of 150 meters. V_5 is 111 long (Lpp), has a breadth of 27 meter and a deck cargo capacity of 10 tons per square meter. V_5 accommodates a crew of 144 people.

Vessel 6 (V_6): Currently under construction in Korea with an expected delivery in the second half of 2014, ready for offshore operations at the end of 2014. When built, V_6 will be world's largest pipelay vessel, although its main function will be the decommissioning of platform topsides and jackets. When finished, V_6 will have a length of 370 meter (Lpp), a breadth of 124 meter and a maximum speed of 14 knots. V_6 will have a pipe cargo capacity of 27,000 tons on deck and will accommodate 571 people.

4.2.2 Case context – crew safety performance measures

Next to the requirement of being a ship owning company, the company also fulfills the requirement of collecting crew safety performance measures. Starting in 2005, the company has logged every notified human injury, environmental spill, damage, equipment malfunction and loss of position that occurred. The company upholds the following definition for an incident:

> *"An unforeseen event which causes or has the potential to cause injury or death, negative impacts on the environment, damage to equipment / assets or impact on company reputation".*

For human injury the company distinguishes among six crew safety KPIs: Fatalities (1), lost time injuries, or LTIs (2), restricted work cases (3), medical treatment cases (4), first aid cases (5) and near misses (6). The latter refers to situations that could potentially have gone wrong, resulting in one of the other outcomes. The definitions corresponding to these crew safety KPIs shall be introduced.

1. Fatality: An incident resulting in the death of a person.
2. LTI: Any work-related injury or illness which results in the injured or ill person being away from his/her regular work at least one normal shift after the shift on which the injury occurred and the person is unable to perform restricted work. If the loss of time is only due to logistics e.g. to fly injured or ill persons to the shore for X-rays then the injury will not be classified as an LTI.
3. Restricted work case: Any work-related injury or illness where the injured or ill person only works partial days or is restricted from his or her "routine functions". Routine functions are defined as work activities the employee regularly performs at least once weekly.
4. Medical treatment case: A work-related injury or illness resulting in a medical treatment more than first aid.
5. First aid case: A work-related injury resulting in a first aid treatment.

6. Near miss: An event with no actual consequences but which, under slightly different conditions, could have resulted in an injury to personnel, negative effect to the environment or equipment damage.

The definitions used by the company appear to be similar to the ones that were introduced in the literature review of this thesis. Additionally, for each near miss that occurred, the company registered a potential outcome since 2011. However, the potential outcome of "serious injury", defined as "a near miss where the potential outcome of the incident would have required professional medical care, or would have resulted in a fatality", was not included in the study due to inconsistency of reporting near misses.

4.2.3 Additional reasons for selecting the company as subject for study

Next to what was argued above, several additional reasons can be mentioned for using the company as a subject of study. First, the amount of crew members is very relevant: Considering the above, it becomes clear that the company currently manages a total of 1,136 onboard crew members ($V_1 + V_2 + V_3 + V_4 + V_5$). Adding the crew of V_6, a total number of 1707 will be reached by the end of 2014. A total that equals, on average, the crew of more than a 100 merchant vessels (Van Rijsinge 2013; Vermeer, Sanders & Oreel, 2013). Note that this number refers to the onboard crew only. For each crew member onboard a vessel, the company has 1.5-2.0 additional crew members ashore, resulting in a total crew of about 2,000 seafarers that could potentially be harmed. Second, the company has a large department focusing on health, safety and environment on their vessels: The extensive number of crew members – next to the overall growing importance of crew safety performance for competitive reasons – creates a strong incentive for the company to strictly manage and improve their safety standards. The company therefore has a team of 7 Q-HSE engineers and 2 QA engineers. Third, the company's vessels are used for offshore purposes. According to the literature (Mearns & Håvold, 2003; Håvold, 2005) the offshore oil and gas industry is more advanced than merchant shipping when it comes to crew safety performance management. Due to the fact that the company's vessels are contracted by the offshore Oil and Gas Industry, the company is required to meet their standards of safety. Therefore, a benchmarking study like this could best be executed with an offshore operating ship owning company.

4.3 Quantitative model used

The database was provided by the company. Above, six possible outcome injury levels were introduced: near miss (1), first aid (2), medical treatment (3), restricted work (4), lost time injury (5) and fatality (6). However, when analyzing the available data, only four levels remained: first aid (n = 736), medical treatment (n = 98), restricted work (n = 13) and lost time injury (n = 23). This data was included in the statistical model used for the study. Since the injury levels are ascending from first aid case (FAID) – minor injury – to lost time injury (LTI) – major injury, an ordinal logistic regression model was used in the first attempt. Later, a generalized ordinal logistic regression model was added to study the individual effects of the included independent variables. Logistic regression, ordinal logistic regression being a variant of it, is used for predicting the outcome of a binary or categorical dependent variable, based on one or more predictor variables. The term ‘logistic regression’ is used to refer to a problem in which the dependent variable has two – and thus binary – outcome categories. Problems with more than two categories are referred to as multinomial logistic regression or, in our case, when the multiple outcome categories are ordered, as ordinal logistic regression (Field, 2009).

4.3.1 Analysis of ordinal data

In the literature review, the research of Talley (1999; 1999a; 2009) was taken into account for it was one of the few studies focusing on injury occurrence in the maritime industry. Talley used a Poisson regression approach. However, when dependent variables are measured on an ordinal scale, there are many options for their analysis. These include (Menard, 2002):

- Treating the variable as though it were continuous. Selecting this option would result in the use of an OLS regression model or another technique feasible to handle continuous variables. Although this is widely done since it is probably the easiest approach, it does not adequately capture the different outcome categories.
- Ignoring the ordinality of the outcome variable and treating it as nominal. This results in the use of multinominal logit techniques. The key problem with this method is a loss of efficiency. By ignoring the fact that the categories are ordered, one fails to use information available by assuming that the categories are fully independent. As a consequence, one may estimate more parameters than necessary, hereby increasing the risk of getting insignificant results.
- Treating the variable as though it were measured on a true ordinal scale but not expecting that they reflect crude measurement of some underlying continuous variable.
- Treating the variable as though it were measured on an ordinal scale, but expecting the ordinal scale to represent crude measurement of an underlying interval/ratio scale. This type of interpretation links best to this study, and ordinal logistic regression models are mainly used in these cases.

Considering the above, an ordinal approach of the data is expected to provide the most valuable results. In an ordinal logistic regression model, or ordered logit model, there is an observed ordinal variable, Y. Y in turn, is a function of another variable, Y^*, that is not measured. Y^* is a continuous unmeasured latent variable whose values determine what the observed ordinal variable Y equals. The continuous latent variable Y^* has various threshold points. In other words, the four injury levels in this study represent the threshold points of Y^* ($M = 4$), resulting from a reporting system were the continuous variable Y^* is the occurring injury. When $M = 4$:

Table 4.1, Study specific ordinal logistic regression model (Source: Author)

General ologit model	**Study specific ologit model**
$Y_i = 1\ if\ Y_i^*\ is\ \leq k_1$	$Y_i = FAID\ if\ Y_i^*\ is\ \leq k_{MTC}$
$Y_i = 2\ if\ k_1 \leq Y_i^* \leq k_2$	$Y_i = MTC\ if\ k_{MTC} \leq Y_i^* \leq k_{RWC}$
$Y_i = 3\ if\ k_2 \leq Y_i^* \leq k_3$	$Y_i = RWC\ if\ k_{RWC} \leq Y_i^* \leq k_{LTI}$
$Y_i = 4\ if\ Y_i^*\ is\ \geq k_3$	$Y_i = LTI\ if\ Y_i^*\ is\ \geq k_{LTI}$

Put in another way, one can think of Y as being a collapsed version of Y*, e.g. Y* can take on an infinite range of values – from no injury to death in this study – which might then be collapsed into 5 categories of Y: first aid, medical treatment, restricted work case, lost time injury and fatality.

4.3.2 Ordinal logistic regression model

In an ordinal logistic regression model, the outcome variable has – as a variant on the common binary logistic regression model with two possible outcomes – more than two outcome levels that are ordered (Liu & Koirala, 2012), as shown above. It estimates the probability being at or below a specific injury level given a collection of explanatory variables (Liu & Koirala, 2012). The ordinal logistic regression model can be expressed as follows in the logit form (Williams, 2006):

$$P(Y_i > j) = g(X_\beta) = \frac{\exp(\alpha_j + X_i\beta)}{1 + [\exp(\alpha_j + X_i\beta)]}\ ,\ j = 1, 2, \dots, M-1 \qquad \textbf{(1)}$$

When there are *j* categories (*M* = *j*), the proportional odds model estimates *j*-1 cut points (Liu & Koirala, 2012). This proportional odds model assumes that the logit coefficients of any predictor are independent of categories. In other words, the coefficients for the underlying binary models are the same across all cutpoints (Liu & Koirala, 2012). To estimate the odds of being at or below the j^{th} injury category, the proportional odds model can be written in the following form:

$$\begin{aligned} &P(Y = FAID) = 1 - g(X\beta_{FAID}) \qquad \textbf{(2)} \\ &P(Y = MTC) = g(X\beta_{FAID}) - g(X\beta_{MTC}) \\ &P(Y = RWC) = g(X\beta_{MTC}) - g(X\beta_{RWC}) \\ &P(Y = LTI) = g(X\beta_{RWC}) \end{aligned}$$

This model thus predicts the cumulative logits across *j*-1 injury response categories. In this study, four injury categories were analyzed, resulting in three (3) response categories. As mentioned before, the ordered logistic regression model as presented above assumes that the coefficients for each independent variable are the same across all outcome levels (Williams, 2006). Although this is assumed to be so for the case of injuries,

4.3.3 Generalized ordinal logistic regression model

The generalized ordinal logistic regression model extends the ordinal logistic regression, or proportional odds model, by relaxing the proportional odds assumption (Liu & Koirala, 2012). That is, the generalized ordinal logistic regression model does not assume that all the beta-coefficients are the same across the different outcome levels. In this model, if the proportional odds assumption is violated by a certain predictor, then its effect can be estimated freely across different categories of the dependent injury variables (Liu & Koirala, 2012). The generalized ordinal logistic regression can be expressed as (Williams, 2006):

$$P(Y_i > j) = g\left(X\beta_j\right) = \frac{\exp(\alpha_j + X_i\beta_j)}{1 - \left[\exp\left(\alpha_j + X_i\beta_j\right)\right]} \, , j = 1, 2, \dots, M - 1 \quad \textbf{(3)}$$

And can be rewritten in the following form:

$$\begin{aligned} &P(Y_i = FAID) = 1 - g(X_i\beta_{FAID}) \quad \textbf{(4)} \\ &P(Y_i = MTC) = g(X_i\beta_{FAID}) - g(X_i\beta_{MTC}) \\ &P(Y_i = RWC) = g(X_i\beta_{MTC}) - g(X_i\beta_{RWC}) \\ &P(Y_i = LTI) = g(X_i\beta_{RWC}) \end{aligned}$$

This model estimates the odds of being beyond a certain category relative to being at or below that category. A positive logit coefficient generally indicates that an individual is more likely to be in a higher injury category as opposed to a lower injury category (Liu & Koirala, 2012). In the generalized ordinal logistic regression model, all of the effects of the explanatory variables are allowed to vary across each of the cutpoints. If some of these effects, or coefficients, are found to be stable, they can be constrained to be equal across all injury levels as they are in the ordinal logistic regression, or proportional odds, model (Liu & Koirala, 2012). Using both models, a partial ordinal logistic regression model, also known as partial proportional odds model, can be developed (Williams, 2010).

4.4 Limitations of the methodology

Even though the methodology of this study was thoroughly set-up and thought over, one must be critical and mention possible limitations beforehand. Four methodological limitations were found. Below they are explained in more detail, together with the solutions that were put in place to minimize their effect on the results of this study.

First, the main limitation of the ologit model is the assumption of an equal effect of the included coefficients for all levels of Y. This limitation was captured by including gologit estimations for all ologit models, for they are not constraint to the parallel lines assumption. A second limitation that should be taken into account however, is the limited number of severe injuries included in the database. Although this may be judged as a fortunate phenomenon on company-level, it has some consequences for the models that cannot easily be resolved. The solution would be to include additional data which is, unfortunately, not yet available. Third, the statistical method used does not take into account the possibility that minor injuries in itself may be an explaining factor of more severe injuries. In other words, the fact that a person got injured in the first place – a 0-1 relation in which 0 means no injury and 1 means injury – might contribute to the severity of the injury. For a model, this would mean that the outcome at the level of $P(Y_i = FAID)$ should be included as an independent variable, or $X_i\beta_j$, at the outcome level of $P(Y_i = MTC)$, and so on. Such a possibility can be caught in a multilevel or hierarchical statistical analysis. Although tests were performed to assess the feasibility of such a model, no proof of a hierarchical relation was found. Fourth, of the five vessels that were taken into account in the analysis, only one of the vessels was a non-pipelaying vessel (V_2). Although the expectation is that this would not hinder the statistical testing, it may cause a small bias in the results of the study.

Now the methodology of the study is explained in detail, we continue to the results that were found by conducting several statistical analyses. The next chapter contains information on the descriptive statistics, the statistical outcomes of three ologit and three gologit models and an overview of the hypotheses developed in chapter 3 and their corresponding outcomes.

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5. Results

The severity of occurring injuries became an increasingly important indicator for the general quality assessment of ship owning companies (Hetherington, 2006). This makes the analysis of variables that contribute to a company's severity distribution of injuries more and more important. In the previous chapter, the methodology of this study was described in detail. This chapter quantifies how the factors discussed in chapter 3 contribute to the injury category, ranging from a first aid case to a fatality.

Section 5.1 contains the descriptive statistics of the dataset that was analyzed. Graphs are provided to increase the visibility of potential injury trends. The first statistical models, being ordinal logistic regression models, are given in section 5.2. The second statistical models, being general ordinal logistic regression models, are provided in section 5.3. All models are followed by an in-depth analysis of the variables included, the feasibility of the model and the model's fit. Finally, section 5.4 gives an overview of which of the hypotheses formulated in chapter 3 were supported by the statistical models.

5.1 Descriptive statistics

During the year 2009-2013, many notifications of incidents were reported to the company's QHSE department. Out of those reports, 870 concerned an actual incident that occurred onboard a vessel. For each notification, the actual incident as well as the potential incident that could have occurred was reported. The latter is not mandatory but often required by the company's clients. Furthermore, the company logs the following data for each incident: The vessel (a), the date and time of the incident (b), the client (c), the project number (d), the geographic area (e), the location on the vessel (f), a brief description of the incident (g), the actions that were taken to prevent for the incident occurring again (h), and the function of the injured person (i). Based on this information, the statistical analysis was done.

First, the injuries were classified in six categories: fatalities (1), lost time injuries (2), restricted work cases (3), medical treatment cases (4), first aid cases (5) and near misses with the potential to result in serious injury (6). An overview is given in Table 5.1 below, with near misses not included since they are no actual injuries. From Table 5.1, one derives a declining number of total injury occurrences. However, although the same decline is applicable to each injury category, such a trend is not visible for the distribution of injury severity.

Table 5.1, Injury severity distribution (Source: Author)

	2009	2010	2011	2012	2013	**Total**
Fatality	0	0	0	0	0	0
Lost Time Injury	11	4	2	4	2	23
Restricted Work Case	2	3	4	4	0	13
Medical Treatment Case	29	16	15	21	17	98
First Aid Case	312	145	131	99	49	736
Total	354	168	152	128	68	**870**

Table 5.1 was transformed in figure 5.1 below to provide a visual overview. In the graph it is clearly visible that the number of injuries decreased over the years. However, the injury severity distribution shows that more severe injuries play a larger role in the more recent years.

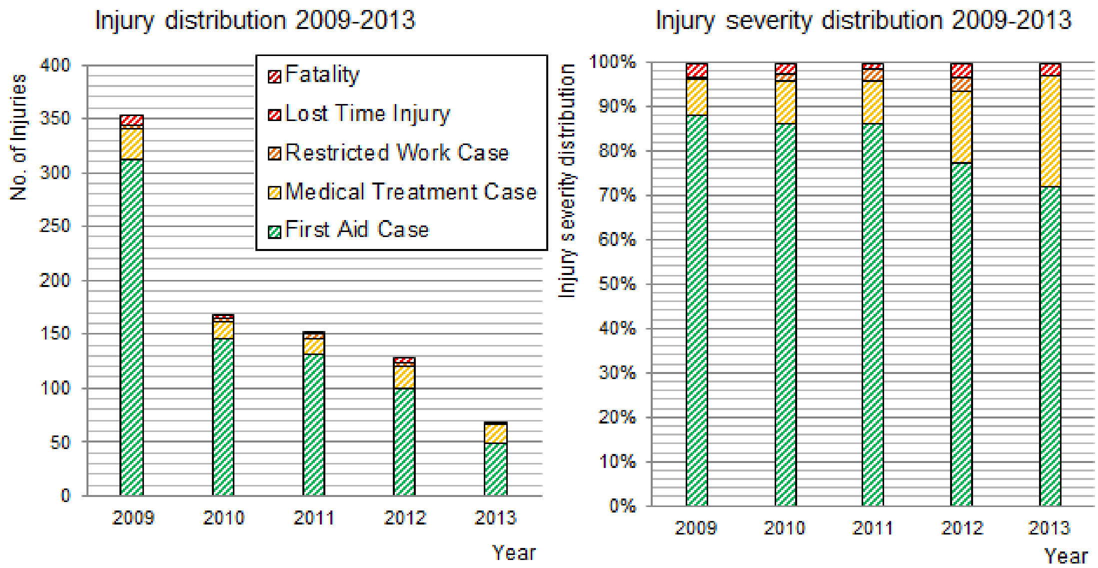

Figure 5.1, Number of injuries and injury severity distribution (Source: Author)

Using STATA, numerous regressions were run to study the interdependencies and effect of the variables on the injury category outcomes and to test the hypotheses formulated in chapter 2. Only the models (*n = 8*) relevant for answering the key question and corresponding hypothesis are discussed below. Before we continue to a detailed description, the descriptive statistics of the most important variables are shown in Table 5.2.

Table 5.2, Descriptive Statistics (Source: Author)

Variable	N	Min	Max	Mean	Std. Deviation
Ship	870	1	5	2.606	1.405
Vessel_age	870	1986	2008	2000.166	8.138
Crewnr	870	72	420	276.462	104.686
Max_pipesize	870	28	60	53.005	13.234
Weld	870	0	11	6.991	3.155
Coat	870	0	4	2.866	1.151
Constr_place	870	0	15	9.856	4.272
Function_Constr	853	0	1	.472	.410
Function_Tech	853	0	1	.097	.296
Area	870	1	6	3.753	1.605
Safety_reg	870	0	1	.699	.459
Cold	870	0	1	.129	.335
Year	870	2009	2013	2010.297	1.337

As mentioned before, two main statistical tests are used: Ordinal logistic regression and generalized ordinal logistic regression. Four models are described in detail for each of these tests, the latter model specifying differences in variable effects that might not show in the first ordinal logistic regression model.

5.2 *Ordinal logistic regression: Model I, Model II and Model III*

Logistic regression knows multiple variants, one of them being ordinal logistic regression. Ordinal logistic regression, or *ologit*, analyses the effect of a certain number of input variables on the distribution between three or more outcome categories. Here, the effect – β coefficients – of all input variables is assumed to be similar for all outcome categories. More information about the actual contents of an ologit model can be found in the methodology under subsection 4.3.1.

In subsections 5.2.1 - 5.2.3, three different ologit models are analyzed:

1. **Model I**: Ordinal logistic regression model with four independent categories ($j = 4$). These are first aid cases ($Y = 1; n = 736$), medical treatment cases ($Y = 2; n = 98$), restricted work cases ($Y = 3; n = 13$) and lost time injuries ($Y = 4; n = 23$). Input variables are *Cold*, *Safety_reg*, *Function_Constr*, *Function_Tech*, *Coat*, *Weld* and *Year*.

2. **Model II**: Ordinal logistic regression model with four independent categories (j = 4). Input variables were *Area*, *Cold*, *Max_pipesize*, *Function_Constr*, *Function_Tech* and *Year*.

3. **Model III**: Ordinal logistic regression model with four independent categories (*j = 4*). Input variables were *Cold*, *Crewnr*, *Max_pipesize*, *Safety_reg*, *Function_Constr*, *Function_Tech*, *Constr_place* and *Year*.

The results of these models are given below. In subsection 5.2.4, the conclusions of the statistical analysis of all three ordinal logistic regression models are summarized.

5.2.1 Model I

Model I was an ologit model containing four threshold categories (j = 4) and seven (*n = 7*) input variables. This model was mainly included in the overview to show the difference between the statistical tests of ordered logistic regression and generalized ordered logistic regression. Subsection 5.2.4 contains a discussion about this topic. The variables *Cold*, *Safety_reg*, *Function_Constr* and *Year* were found to be significant. For Cold, we found a positive effect indicating that cold weather conditions are likely to cause more severe injuries. Safety_reg showed a negative effect, proving that more strict safety regulation reduced the severity of injuries that occur. *Function_Constr* showed a negative influence on the injury severity, indicating that injuries associated with welders, spacers and riggers prove to be mainly minor FAID injuries. For *Year*, a positive relation was found, indicating that recent years were associated with more severe injuries. Model I passed the parallel lines assumption for all variables but *Function_Tech*, indicating that the β-coefficients are the same for each injury outcome level *j*. The models fit is disappointing, with an R-squared of 3.98%.

5.2.2 Model II

Model II was an ologit model containing four threshold categories (j = 4) and six (*n = 6*) input variables. For this model, the variables *Area*, *Cold*, *Year* and *Function* proved to be significant. Here, we found the higher categories of *Area*, being the European Union and the United States, to be negatively influencing the higher injury categories. *Cold* was positively related with higher injury categories, indicating that cold weather conditions indeed influence the occurrence of more severe injuries. For *Function_Constr*, combining the professions of welder, spacer and rigger, we found a negative effect, meaning that these employees mostly suffer from minor FAID injuries. However, for *Function_Tech*, combining the professions of mechanic and engineer, a positive effect was found, indicating that when employees of this kind get injured, those injuries are more likely to be severe. *Year* was positively related with higher injury categories, which we found interesting due to increasing interest on safe behavior within the company. Model II passed the parallel lines assumption for all variables. The R-square improved compared to Model I, being 5.50%.

5.2.3 Model III

Model III was an ologit model containing four threshold categories (j = 4) and eight (*n = 8*) input variables. Here, the variables *Cold*, *Safety_reg*, *Function_Constr*, *Function_Tech* and *Year* were found to be significant. Cold showed a similar positive estimate, as was found in Model II. For *Safety_reg*, we found a negative relation, indicating that operating in areas with strict safety rules and regulations in place, the injuries indeed proved to be less severe. A hopeful finding that seems to prove both the benefit and use of safety rules and regulations for the decrease in injury severity. For both *Function_Constr* and *Function_Tech* the model resulted in similar estimates compared to Model II. Year again showed the positive estimate which was found in Model I and Model II before. The parallel lines assumption was passed for all variables. However, the R-square was slightly lower compared to Model II, with a value of 4.84%.

5.2.4 Conclusions ordinal logistic regression models

For Model I, Model II and Model III, several significant effects were found, although the R-squared of all ologit models remained low. The latter is not surprising, since the models deal with injuries and injuries are considered to be largely dependent on random chance. However, the R-squared should not be so low that it stays around the general error margin, which seems to be the case for Model I. Furthermore, almost all estimates could be placed in a continuum reaching from -1.00 to 1.00, showing no strong positive or negative effects on injury severity distribution.

Looking back at the literature, the ologit model appears to be the most commonly used logistic regression model for ordinal response because of two reasons (Bender & Grouven, 1997): One, it has the feature that the effect of a covariate on injury outcome *Y* can be quantified by a single regression coefficient, and hence calculation of one common odds ratio is possible, making presentation of results short and simple. Two, an ologit regression can be run in all available statistical software. Considering this in combination with injury severity distributions, we are of the opinion that precisely the regression coefficient for all injury categories are important to know, for practical solutions should be based on real values rather than averages. In conclusion, we argue that ordinal logistic regression models are too modest to use in injury severity distribution analysis. Although we are able to learn from their effects, more in-depth analysis is required to translate the estimates in initiatives that can be used in practice. Subsection 5.3 contains three generalized ordinal logistic regression models trying to achieve this practical feasibility, by using the exact same variables that were used in Model I – Model III in a different statistical test.

5.3 Generalized ordinal logistic regression: Model IV, Model V and Model VI

Generalized ordinal logistic regression, or *gologit*, is similar to an ologit model, with the only difference being that the effect of all input variables may differ for each outcome category. This is quite relevant in the case of an injury severity distribution, for although an injury is an injury, the contributing causes might have a different impact on each category. More information about the actual contents of a gologit model can be found in the methodology under subsection 4.3.3.

In subsections 5.3.1 - 5.3.3, three different gologit models are analysed:

1. **<u>Model IV</u>**: Generalized ordinal logistic regression model with four independent categories ($j = 4$). These are first aid cases ($Y = 1; n = 736$), medical treatment cases ($Y = 2; n = 98$), restricted work cases ($Y = 3; n = 13$) and lost time injuries ($Y = 4; n = 23$). Input variables are *Cold*, *Safety_reg*, *Function_Constr*, *Function_Tech*, *Coat*, *Weld* and *Year*.

2. **Model V**: Generalized ordinal logistic regression model with four independent categories (*j = 4*). Input variables were *Area*, *Cold*, *Max_pipesize*, *Function_Constr*, *Function_Tech* and *Year*.

3. **Model VI**: Generalized ordinal logistic regression model with four independent categories (*j = 4*). Input variables were *Cold*, *Crewnr*, *Max_pipesize*, *Safety_reg*, *Function_Constr*, *Function_Tech*, *Constr_place* and *Year*.

The results of these models are given below. In subsection 5.3.4, the conclusions of the statistical analysis of all three general ordinal logistic regression models are summarized.

5.3.1 Model IV

Model IV was a gologit model containing four threshold categories (j = 4) and seven (n = 7) input variables. This model was mainly included in the overview to show the difference between the statistical tests of generalized ordered logistic regression and ordered logistic regression. The latter represented by Model I. An overview of the model results can be found in Table 5.3. For the first category, representing medical treatment cases (MTCs), the variables *Cold*, *Safety_reg*, *Function_Constr*, *Weld* and *Year* showed a significant effect. An interesting finding clearly showing the difference between ologit and gologit models, for in Model I only two variables – *Function_Constr* and *Year* – were found to be significant. For cold, the estimate was 1.016, a positive estimate indicating that in cold weather, medical treatment injuries were 1.016 times more likely to occur compared to the other injury categories of first aid cases, restricted work cases and lost time injuries. For the higher injury category of RWCs, we found the *Cold* estimate to increase to 1.566 ($p < 0.01$), supporting the argument that cold weather conditions contribute to the severity of injuries. The *Safety_reg* variable was only found significant ($p < 0.05$) on the MTC injury category, showing a negative estimate of -.524. From this, we derive that for areas in which more strict safety regulations are in place, less severe injuries indeed occur. We reasoned similarly in Model III. *Function_Constr* showed a negative estimate for the MTC category, which remained negative for the two highest injury categories. With an estimate of -2.161 ($p < 0.05$) it is clearly proven that welders, spacers and riggers – whom we expected to suffer from more severe injuries due to their exposed job – cannot be associated with major injuries. For *Function_Tech*, a positive significant effect was found for the higher injury categories RWC and LTI. For the LTI category, the positive estimate increased to a value of 2.211, meaning that the combined functions of mechanic and engineer were over two times more likely to suffer from severe injuries. The variable *Weld* shows an interesting effect. For injury categories MTC and RWC, we found a negative effect of -.190 ($p < 0.10$) and -.534 ($p < 0.05$) respectively. However, for the severe LTI category this turned into a positive estimate of .825 ($p < 0.05$). For this model, we may thus assume that more welding stations onboard the vessel are associated with more minor FAID injuries and severe LTIs, and less with medium MTCs and less-severe RWCs. Lastly, a significant ($p < 0.01$) effect for *Year* was found on the MTC level, showing a positive estimate of .209 – like in Model I – from which we may assume that the more recent years are associated with a slight increase in injury severity distribution. For Model IV, an R-squared of 8.11% was found, which is significantly higher compared to the ologit Model I using the same input variables.

5.3.2 Model V

Model V was a gologit model containing four threshold categories (*j = 4*) and five (*n = 6*) input variables. Hereby, Model VI copies Model II, although the statistic test was generalized. For the MTC injury category at the first threshold (*Injury = 1*), all variables but *Function_Tech* proved to be significant. However, for the RWC injury category (*Injury = 2*) these effects are less present, probably due to the small number of restricted work cases present in the sample (*n = 13*). For the LTI category (Injury = 3), three significant effects were found. For the higher categories of *Area*, we found a positive effect on the occurrences of severe LTIs, indicating that operating in the European Union or North America contributes to a higher risk of LTIs. However, Area showed a negative relation for MTCs, indicating that injuries requiring minor medical care were more likely to occur when operating in Asia and Australia. Studying the *Cold* variable, we found that cold weather conditions have a positive influence on the occurrence of injuries that require medical care – that is, MTC, RWCs and LTIs – with an exemption for LTIs, for which the effect is found to be non-significant. Although negatively influencing the occurrence of MTC and RWC injuries, *Max_pipesize* does have a positive influence on the occurrence of the severe LTIs. This indicates that the injuries associated with larger pipe sizes are mainly minor FAID injuries and severe LTIs. Interestingly enough, a similar effect was found for *Function_Constr*. Despite the large number of injuries that welders, spacers and riggers are responsible for, we found a strong negative estimate for both MTCs and LTIs, meaning that the injuries they suffer are mainly minor FAID injuries. The variable *Year* was only found to be significant for MTCs, were it showed a positive effect. Surprisingly so, since a negative effect was expected due to the large safety campaign launched in 2009 by the company. The R-squared of this model appeared to be 11.09%.

5.3.3 Model VI

Model VI was a gologit model containing four threshold categories (j = 4) and eight (n = 8) input variables. Again, a significant effect was found for *Cold*, *Safety_reg*, *Function_Constr*, *Function_Tech* and *Year*. *Cold* showed a significant and positive estimate for all injury categories, with a value of 3.512 for the LTI category. This emphasises again the effect of cold weather conditions on injury distribution and shows why cold weather is, and had to be, avoided by the company when it comes to safety performance standards. For *Safety_reg*, we found an interesting estimate that was negative for the MTC and RWC category with values of -.659 and -1.039 respectively, but positive with a value of 3.577 for severe LTIs. This estimate points towards a situation with more strict safety rules and regulations increase the likelihood of more severe injuries. A strange finding that did not occur in Model IV, but which may be explained by strict safety regulations increasing the reporting activity of the vessels. Subsection 5.3.4 further addresses this issue. For *Function_Constr* and *Function_Tech* the results were comparable with Model IV and Model V, although a significant and positive effect of .844 ($p < 0.10$) was found for *Function_Constr* in the RWC category. The other two gologit models showed the same effect, although not significant. The variable *Year* again showed a positive estimate for the MTC category, but no significant effects were found for the higher categories of RWC and LTI. Unlike we expected, no significant effect was found for *Crewnr*, pointing out that the number of crew members on board did not have an effect on the injury severity distribution. Furthermore, unlike Model V, the model did not show a significant effect for *Max_pipesize*. The R-squared of this model was 12.74%. Despite being the highest of all models, we prefer Model V on which a stronger argument can be based due to its many significant effects.

5.3.4 Conclusions generalized ordinal logistic regression models

In subsection 5.2.4, it was argued that the ologit model resulted in estimates that we considered too modest for practical usage. This argument was supported by the results of the gologit models, which provided estimates ranching from -4.00 to 4.00 rather than -1.00 to 1.00. A good example is the difference between Model I and Model IV, each containing the same input variables. In Model 1, an estimate of -.481 was given for *Function_Constr*, whereas in Model IV, the LTI category produced an estimate of -2.161. The latter statistic might offer an incentive for the company to switch its safety focus to mechanics and engineers – combined in *Function_Tech* with estimates of 2.211 for Model IV on the LTI category – rather than on welders, spacers and riggers who appear to be relatively safe from severe injuries.

Some other interesting results were found, one of them for the variable *Safety_reg*. When Model IV is compared to Model VI, both models provide a negative estimate for injury categories MTC and RWC. However, for injury category LTI, Model IV produces an estimate of -.526 whereas Model VI produces an estimate of 3.577. Only the latter was significant ($p < 0.01$). The estimate of Model IV seems more logical, but since Model VI's statistic is significant, we should take this strong positive estimate seriously. In subsection 5.3.3, we raised the argument that this effect resulted from increased reporting activity on the vessels. To support this argument, the raw data was studied and it was found that Australian and Dutch waters together were responsible for over $^1/_3$ of the reported LTIs. Australia is known for its incredibly strict safety regime, which may have resulted in reporting either more injuries, or reporting the occurring injuries as more severe. Interestingly enough, the company's QHSE engineers argue the opposite; the downgrading of occurring injuries under strict safety regimes such as in Australia (Haye-Geervliet, 2014). For the Netherlands, the reason might be more obvious; onshore safety officers are simply geographically closer to their vessels, able to partly monitoring them physically and via telephone rather than through official incident notifications.

In the literature, our argument regarding practical feasibility is backed up by Williams (2006), who state that gologit2 – the STATA command for a gologit model – can "fit models that are less restrictive than the parallel-lines models fitted by ologit but more parsimonious and interpretable than those fitted by a nonordinal method, such as multinominal logistic regression" (p. 58). For injury severity distribution analysis, we therefore consider generalized ordered logistic regression to be superior over ordinal logistic regression. Based on the results we found in the three gologit models, the hypothesis formulated earlier were tested and answered.

5.4 Multicollinearity

Multicollinearity of the models was tested using the Collin statistic. The Collin statistic produces variance inflation factors (VIF) for each variable. As a rule of thumb a variable whose VIF value is above 10 may merit further investigation. The tolerance level, defined as 1/VIF is used to check the degree of collinearity. Here, a tolerance value below 0.1 is comparable to a VIF of 10 or above (Statistical Consulting Group, 2014). We found quite stable results, although some cases of multicollinearity were found. The most relevant results for the ologit models are summarized in the tables below. More details regarding the Collin statistic can be found in Appendix II – IV.

Table 5.3, Multicollinearity testing (Source: Author)

	Model I and VI		Model II and V		Model III and VI	
Variable	**VIF**	**Tol.**	**VIF**	**Tol.**	**VIF**	**Tol.**
Area			1.35	.740		
Cold	1.20	.835	1.20	.833	1.24	.808
Crewnr					80.37	.012
Max_pipesize			1.16	.861	2.20	.455
Safety_reg	1.13	.887			1.14	.877
Function_Constr	1.14	.876	1.13	.887	1.13	.887
Function_Tech	1.12	.897	1.11	.901	1.11	.901
Coat	14.07	.071				
Weld	14.39	.070				
Constr_place					73.61	.014
Year	1.04	.965	1.11	.9017	1.07	.933
Mean VIF	4.87		1.18		20.23	

From the tables above, two cases of multicollinearity can be defined. First, as can be interpret from the tolerance values in Model I, *Weld* and *Coat* proved to be interrelated. This is not very surprising, since the number of welding stations on a vessel partly explains the amount of coating stations. Here, the more welding stations are present, the more coating stations are most likely present on the vessel. Second, the variable *Crewnr*, included in Model III and Model VI, correlates with the other variables in the model. This is most likely because the number of crew members onboard is directly associated with the vessel, as is the number of construction places onboard. Therefore one may expect a high VIF value for the variable *Constr_place*, which is indeed found in the model. Due to these indications of multicollinearity, the mean VIF value of Model III and Model VI is 20.23, which requires further investigation on the stability of these models. Overall, Model II and Model V appear to be the best models in terms of non-collinearity. A point emphasized by the low mean VIF statistic, with a value of 1.18 only.

5.4.1 Effects of multicollinearity

The danger of multicollinearity between the variables of a model is that regression coefficients are imprecisely estimated. Furthermore, slight fluctuations in correlation and adding or dropping cases may lead to large differences in regression coefficients. Also, multicollinearity may increase the standard error of coefficients, thereby reducing the significance of the variables included in the model (Hamilton, 2009). Keeping this in mind, one may conclude Model I, Model II, Model IV and Model V to be suitable with regard to the multicollinearity threat. Model III and Model VI require some extra attention on this topic.

5.5 Hypothesis testing overview

In chapter 2, eleven hypotheses were formulated, each of which was tested by the various models explained above. This section gives an overview of which of these hypotheses were supported, rejected or inconclusive. Table 5.3 summarizes the β-coefficients as presented earlier in section 5.2. Table 5.4 summarizes the β-coefficients as presented earlier in section 5.3. The table distinguishes among p-values of <*0.01* (green), <*0.05* (blue) and <*0.10* (red) percent level. For Model I, Model II and Model III, the parallel lines assumption was tested. The R-squared was reported for all models. Furthermore, we tested for multicollinearity.

Table 5.4, Ordinal Logistic Regression Models (Source: Author)

		Model I		Model II		Model III	
	Variable	**Est.**	**SE**	**Est.**	**SE**	**Est.**	**SE**
Threshold	[Injury = 1,00]						
	[Injury = 2,00]	421.226	138.811	624.207	157.111	531.161	153.488
	[Injury = 3,00]	422.692	138.815	625.718	157.118	532.663	153.495
	[Injury = 4,00]	423.158	138.815	626.1263	157.118	533.071	153.495
Location	Area			-.245	.077		
	Cold	1.059	.278	1.185	.301	1.003	.297
	Crewnr					-.007	.011
	Max_pipesize			-.012	.008	-.008	.011
	Safety_reg	-.542	.222			-.527	.246
	Function_Constr	-.481	.213	-.405	.225	-.410	.224
	Function_Tech	.442	.295	.645	.326	.6344	.325
	Coat	.446	.310				
	Weld	-.185	.115				
	Constr_place					.190	.311
	Year	.193	.070	.310	.078	.264	.076
	Constant	389.83		624.207		531.16	
	R-squared	*0.0398*		*0.0550*		*0.0484*	
	Parallel lines	Passed		Passed		Passed	

The table above summarizes the most important information from all ologit models. In an ologit model however, the coefficients alone are of difficult interpretation. To interpret the coefficients, the marginal effects were estimated by means of the mfx2 statistic. The results of this test are summarized in Table 5.5 below. A more detailed overview of the marginal effects was included in Appendix II – IV. Next to the marginal effects, the mfx2 statistic calculates the probabilities for all injury categories. Table 5.7 contains an overview of the probabilities for all models that were tested.

Table 5.5, Marginal effects for Model I, Model II and Model III (Source: Author)

	Model I	Model II	Model III
Variable	**% change in odds**	**% change in odds**	**% change in odds**
Area		-21.7	
Cold	188.3	227.0	172.7
Crewnr			-.7
Max_pipesize		-1.2	-.8
Safety_reg	-41.8		-41.0
Function_Constr	-38.2	-33.3	-33.6
Function_Tech	55.7	90.5	88.6
Coat	56.1		
Weld	-16.9		
Constr_place			20.9
Year	21.3	36.4	30.2

The Brant statistic was used to test the parallel lines assumption for Model I, Model II and Model III. The details of the Brant test are included in Appendix II – IV. All models appeared to fulfill the parallel lines assumption. That is, that the parameters are constant over all threshold values of an injury. However, passing the parallel lines test does not necessarily mean that there is no actual deviance between the threshold levels (Kim, 2003), providing an argument for statistically testing generalized ordinal logistic regression models (Table 5.4). The latter assumes that the effects of the β-coefficients may differ for each threshold value. Indeed, the gologit results were far more meaningful compared to the ologit models, which only showed modest estimates and lower R-squared values..

Table 5.6, Generalized Ordinal Logistic Regression Models (Source: Author)

		Model IV		Model V		Model VI	
	Variable	**Est.**	**SE**	**Est.**	**SE**	**Est.**	**SE**
[Injury = MTC]	Area			-.266	.078		
	Cold	1.016	0.284	1.207	.307	.969	.311
	Crewnr					-.003	.012
	Max_pipesize			-.014	.008	-.016	.012
	Safety_reg	-.524	.224			-.659	.253
	Function_Constr	-.486	.214	-.394	.228	-.398	.227
	Function_Tech	.232	.307	.363	.349	.337	.350
	Coat	.440	.313				
	Weld	-.190	.117				
	Constr_place					.072	.317
	Year	.206	.071	.315	.080	.275	.079
[Injury = RWC]	Area			-.250	.163		
	Cold	1.566	.507	1.324	.562	1.638	.642
	Crew_nr					-.015	.022
	Max_pipesize			-.032	.016	-.024	.023
	Safety_reg	-.620	.412			-1.039	.491
	Function_Constr	.496	.415	.751	.488	.844	.487
	Function_Tech	1.258	.521	1.507	.619	1.768	.639
	Coat	1.181	.587				
	Weld	-.534	.228				
	Constr_place					.317	.561
	Year	.039	.129	-.032	.164	-.045	.163
[Injury = LTI]	Area			.822	.297		
	Cold	1.376	.859	.138	.904	3.512	1.228
	Crewnr					-.432	18.735
	Max_pipesize			.078	.035	.340	5.855
	Safety_reg	-.526	.786			3.577	1.126
	Function_Constr	-2.161	.897	-3.562	.989	-.952	.873
	Function_Tech	2.211	.775	1.332	1.080	1.333	1.199
	Coat	-1.585	.992				
	Weld	.825	.404				
	Constr_place					12.41	632.147
	Year	.332	.304	.232	.211	.375	.284
	R-squared	*0.0811*		*0.1109*		*0.1274*	

The mfx2 statistic that was used for the ologit model was also found suitable for the gologit models. The probabilities were thus estimated using the mfx2 statistic. However, to be sure of the probabilities, the margins statistic was additionally used as a backup. Both the margins statistic and the mfx2 statistic require, for a gologit model, all variables to be defined separately, leaving an infinite number of possibilities (Park, 2009). For the benefit of this study it was therefore decided to use the mean values of all included variables and estimate the probabilities based on these mean values. Afterwards, the same probabilities were estimated, now including the ‘worst case scenario’ values for the values that showed significant estimates (Cold*, Safety_reg, Function_Constr, Function_Tech* and *Year*). Table 5.7 summarizes the outcomes for all models. Here, we find that for all models estimated with the mean values (*Margin μ* in Table 5.7) for all included variables, the probability of ending up in the first aid category (Injury = 1) lies between approximately 86 and 87 percent. For the medical treatment category, the estimated probability lies between 10 and 11 percent. For restricted work cases, a small probability of between zero and 2 percent was estimated, whereas for the most severe category of lost time injuries an approximate probability between 1 and 3 percent was found. However, if the worst case scenario values (*Margin adj.* in Table 5.7) are used for the variables that were found significant, the probabilities change drastically: The probability on a minor injury (FAID) decreases, whereas the probability of a major LTI injury increases significantly. The outcome for restricted work cases (*Injury = 3*) shows unlikely negative values, which was assumed to be the result of the small amount of injuries reported on this severity level. Nevertheless, the differences in margins seem to state a clear case. Additional information, as well as the complete results of the margin statistic, can be found in Appendix V-VII.

Table 5.7, Estimated probabilities for all Models (Source: Author)

	Model I and IV		Model II and V		Model III and VI	
	Margin μ	**Margin adj.**	**Margin μ**	**Margin adj.**	**Margin μ**	**Margin adj.**
[Injury = 1]	.859	.395	.871	.378	.873	.348
[Injury = 2]	.110	.247	.100	.427	.104	.275
[Injury = 3]	.014	-.404	.000	-.360	.016	-.055
[Injury = 4]	.017	.762	.028	.555	.007	.432

Even though Model I, Model II and Model III passed the parallel lines assumption, the effects – β-coefficients – appeared to differ significantly for each of the threshold categories, ranging for example from -.659 to 3.577 in case of *Safety_reg* in Model VI. Furthermore, one finds the p-values of most input variables to be different for each threshold injury category. Note that all models passed the log-likelihood test and the Pearson Chi-Square test, indicating that the models as a whole fit significantly better than an empty model with no predictors. Using Table 5.3 and 5.4 as input, we may now continue to answer the hypotheses that were formulated in chapter 3. Table 5.5 below gives an overview of the hypotheses and their respective outcomes.

Table 5.8, Hypotheses outcomes (Source: Author)

1.	The presence of strict safety regulations is positively correlated with crew safety performance levels.	*Partly supported*
2.	Due to the increasing focus on safety, the more recent years are associated with higher crew safety performance levels.	*Rejected*
3.	The number of crew members onboard, that increases vessel size, is negatively correlated with crew safety performance levels.	*Inconclusive*
4.	The age of the vessel is negatively correlated with crew safety performance levels.	*Inconclusive*
5.	The number of welding and coating stations are negatively correlated with crew safety performance levels.	*Partly supported*
6.	Vessels capable of handling larger maximum pipe sizes are associated with lower crew safety performance levels.	*Supported*
7.	The more exposed combined function group of welders, spacers and riggers is negatively correlated with crew safety performance levels.	*Rejected*
8.	The more exposed combined technical function group of mechanics and engineers is negatively correlated with crew safety performance levels.	*Supported*
9.	A higher rank among the vessel's crew is positively correlated with crew safety performance levels.	*Inconclusive*
10.	Operating in waters surrounding developing and less than developed countries negatively correlates with crew safety performance levels.	*Partly supported*
11.	Cold weather conditions are negatively correlated with crew safety performance levels.	*Supported*

5.5.1 Conclusions on the defined hypotheses

Of the eleven hypothesis, Model IV, Model V and Model VI found supporting evidence for six of them. Surprisingly so, two of the hypothesis had to be rejected based on the Models' results. For three hypotheses, no evidence was found and the hypothesis testing thus remained inconclusive. For hypothesis 1, supporting evidence was found for the injury categories MTC and RWC. For the LTI category however, we found contradicting evidence suggesting that more strict regulatory safety regimes contributed to more severe injuries. Several possibilities leading to this outcome were discussed in subsection 5.3.4. The second hypothesis argued that due to an increased focus on safety, recent years had to be associated with higher levels of crew safety performance. That is, an injury distribution in which the more severe injuries played a less significant role. However, all three gologit models suggested the opposite: For the more recent years, severe injuries requiring medical attention occupied a larger percent of the injury distribution, although the total number of injuries that occurred reduced (see Figure 5.1). Hypothesis 3 and hypothesis 4, suggesting that the number of crew members on board and the vessel age were negatively correlated with crew safety performance levels, remained inconclusive. Hypothesis 5 was partly supported by Model IV, in which a significant negative estimate was found for injury categories MTC and RWC, whereas this correlation turned positive for the severe LTI category. Hypothesis 6, assuming a larger pipe size contributed negatively to crew safety performance levels was supported by Model V, although the effect was only minor and turned, like *Weld* in Model IV, slightly positive for the LTI category. Hypothesis 7 and hypothesis 8 referred to the combined function categories of welder, spacer and rigger (hypothesis 7) and mechanic and engineer (hypothesis 8). It was assumed beforehand that due to their exposing occupation onboard the vessel, these two function categories would show a negative estimate with respect to crew safety performance levels. Although evidence supported this assumption for mechanics and engineers, it was found that welders, spacers and riggers in fact suffered less from severe injuries requiring any sort of medical attention. No evidence was found for hypothesis 9, assuming that higher ranked crew suffered less severe injuries. Hypothesis 10 was partly supported, for in Model V a negative estimate was found for injury category MTC and RWC, but this estimate turned positive for the LTI category. Lastly, cold weather conditions proved to be negatively influencing crew safety performance levels, supporting the assumption of hypothesis 11. Having answered all formulated hypotheses, it is of utmost importance to note that the significance of the coefficients as discussed above only holds within the models that were specified. Meaning that when new models are developed, their coefficients will change accordingly.

The above concludes the results of this study and the associated hypothesis testing. The statistic models of both types – ologit and gologit – provide enough food for thought. The next chapter is therefore dedicated to a thorough discussion on the topic. Furthermore, it provides a conclusion on the formulated key question and addresses the limitations of our research.

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6. Conclusion and Discussion

Concluding the study, this chapter is divided into four sections. Section 6.1contains a conclusion on the key question and a brief discussion on the research topic. Section 6.2addresses the limitations of the research. In section 6.3, the areas for expansion and possibilities for further study for the academic world are provided, whereas section 6.4 contains topics for further study in practice. We end with a general conclusion emphasizing the gap between science and practice in the field of crew safety performance.

6.1 Conclusion and Discussion

The objective of this study was to find the determinants that influence the distribution of injuries – in terms of severity – for a ship owning company operating in the safety aware offshore sector. Hereby, the main goal was to develop a model explaining the distribution of injuries among crew members, so that investment posts may be defined for further study towards cost-efficient crew safety management. For this, we wielded the following key question: *"What are the variables that influence the crew related injury severity distribution in the company studied and what are the corresponding lessons for practice?"*

Eleven hypotheses were developed to support the research methodology. The research question was explored by means of six quantitative models using two slightly different statistical approaches and testing a total of 22 variables. An in-depth study including a single ship owning company was conducted. The company selected was found to be very representative for the sector with the advantage of having crew safety performance information available. The company of choice employed over a thousand crew members and had a detailed record of the injuries occurring in the years 2009-2013. Being a 'best case scenario' – or benchmark – case in the offshore sector, the assumption was made that general findings of this study may to a large extent be applicable to other companies in the sector.

Among the major findings of this study is that a relation might exists between crew safety performance of the company and the strictness of external safety regulations put in place; the area of operation; the number of construction sites on the offshore vessels; cold weather conditions; the more recent years of safety data collection; the technical crew onboard the vessel and the construction crew onboard the vessel. Contradicting the investigators expectations, the more exposed construction crew was associated with less severe injuries. Furthermore, the increased focus on safety did not seem to contribute to a shift in the severity of injuries occurring, although it significantly lowered the absolute number of injuries. The interesting fact about the variables for which a relation was found, is that they are not company specific. These factors are known and dealt with throughout the whole offshore sector and as such may prove important to take into account when assessing crew safety performance. Next to these major findings, the use of statistical modeling using ordinal and generalized ordinal logistic regression techniques proved to be very suitable for this type of study. Research to accidents in the maritime and offshore sector is limited, and most quantitative research so far is based upon either ordinary least squares (OLS) regression or binary logistic regression models. More advance statistical models may not be thought of as 'better' simply for the fact that they are more difficult to use. However, although the total amount of studies done towards maritime safety are very limited, each of the studies done used rather large databases suitable for publishing more than one paper (Talley, 1999; 1999a; Knapp; 2004; Talley et al., 2005; Havold, 2005; Wang, 2000; 2001; 2002; 2006). To apply more advanced statistics might provide valuable additional results on crew safety performance and its determinants.

The objective of this study as well as its results may be translated into a broader and more general perspective. Even though focusing on a single company, the company was picked such that it was representative – in safety terms even leading – for the offshore supply sector. In the available literature, the importance of the topic was mentioned several times, although in-depth data analysis of injury distribution was not carried out before. Nevertheless, Hetherington (2006) argued that companies are increasingly judged upon their crew safety performance and their vessels are chartered only if they perform properly. Mearns and Havold (2003) wondered about the effect comparing data might have on crew safety levels without investing large amounts into it. Lutchman (et al., 2012) emphasized the effect of leadership on safety performance levels and encouraged companies to develop a clear safety vision. The literature review of this study contains many similar statements and considers multiple fields of impact. Let it be very clear then, that improving crew safety performance is not about safety alone. It is about prestige, leadership, economics and even marketing. Crew safety is no longer the topic to ignore, for the consequences are simply too extensive and expensive. By performing this study, the investigators aimed in contributing to this emerging field of research – of which the effect is further outstretched than often thought – and define determinants of safety through which higher levels of safety could be achieved. To conclude, one may say that research towards the offshore sector is emerging. However, the literature that is currently available is limited, even despite the fact that the requirements for vessel operating in the offshore environment are far stricter compared to merchant shipping. Therefore, the results of this study may be judged as a valuable contribution to, among others, the field of crew safety performance in the offshore industry and there are many possibilities for further research. Here, we should emphasize the fact that the interest of science and practice towards this topic may lie far apart.

6.2 Limitations of the study

Even though this study was thoroughly set-up, one must be critical in the assessment of its potential limitations. For the methodological limitations we refer to section 4.4, in which the limitation of the parallel lines assumption, the limited number of severe injuries included in the study and the probability of a multilevel structure within the data were already discussed. Next to these methodological limitations, four additional limitations are discussed below.

First, during the exploring interviews that were held in the starting phase of the study, several different perceptions were found on what should be reported as a lost time injury, restricted work case, medical treatment case or first aid case. The only definition that seemed clear to every company that was interviewed was that of a fatality. This phenomenon partly contributed to the decision to study a single company rather than compare multiple companies in slightly different sectors, for the effect of divergent definitions on the results of the study were considered too high. However, within the company of study, several injuries were reported as severe – say, a RWC – in the first instance and then later toned down to an MTC, or vice versa. It is important to take into account that even for a single company, the line between the distribution categories is very thin and may probably not be considered a line at all. The grey area appears to be wider in the top categories, where the injuries are more severe. Given the relatively small sample of severe injuries in these upper categories, a slight change may have its effect on the results of the statistical analysis. Especially the ologit model could provide variable results, since it uses averages per included indicator. In our study, we tried to counteract the possibility of data ending up in the wrong category by closely studying the description of each injury recorded in the database. For further study, we recommend researchers to do the same.

Second, this study is based upon so called ‘work-related injuries’, a concept that the industry came up with and means so much as an injury that occurs when the person is at a place for the purpose of working. For offshore situations, this means that injuries occurring during the time an individual is working his shift are reported as relevant. However, injuries that occur when the person is off-shift are not included in the database. This principle is adopted throughout the industry in slightly different ways – some companies include the traveling to work as being on-shift, others do not. Despite the fact that this distinction is considered common practice, it is a little odd in a way that the factor ‘time’ contributes significantly to the results of reporting. Weigh in mind the case of a welder falling from a stairs at 08:00 hours when he just started his shift, and the same welder falling from the same stairs at 20:00 hours when he just finished his daily work. If in the example both incidents result in a broken wrist, only the first one is reported as an LTI whereas the second one does not end up in the database, for it is not considered work-related. This emphasizes how time contributes to recordings and, in an indirect way, how recordings in the database that was used for this study may not blindly be judged as a reflection of reality.

Third, alike every study using pre-existing data, there was no control on the method the data was collected. As such, we were unable to counteract non-reporting – not reporting injuries that did occur – and misreporting – underestimating or exaggerating injuries that did occur. Fortunately, every reported injury was accommodated with a short description of the event, providing the opportunity to correct for misreporting to a large extent. However, non-reporting could not be prevented. Although the company was convinced it brought non-reporting back to a minimum, we are unable to guarantee the actual effect on the data and study results.

Finally, though the choice of studying a single company was heavily defended so far, some may still regard it a limitation of the research. This is partly agreed. Due to the fact that the topic of study is unexplored so far by the academic world, the choice of a single company in-depth study is a safe one for it is not subject to unknown differences in the industry that may significantly bias results. However, we also find the lack of comparability limiting the extent to which we may draw generalized conclusions. Therefore, we highly recommend further study on the topic. Section 6.3 and 6.4 contain our ideas for further study and areas of expansion that could be explored in order to increase knowledge regarding the topic of crew safety performance. The study we performed should be considered a starting point of crew safety research rather than a concluding chapter. It is due to this that many areas for expansion can be defined. Here, a distinction between theory and practice should be made, for the objectives and interests of both worlds may lie far apart.

6.3 Areas for expansion and further study for academia

For the academic world, it might be interesting to focus on one of the limitations mentioned above and study the relation between reporting incidents and the actions taken upon occurring injuries. Nowadays, most clients demand extensive report of even minor injuries. Throughout this study, it was often stressed that due to this increasing demand per injury, onboard investigators chose not to report minor injuries at all. This may explain the significant drop in reported first aid cases, from 312 in 2009 to only 49 in 2013. It might be that the requirement of reporting all that happens onboard actually contradicts the aim of complete transparency when it comes to minor injuries. A negative development, since it is the near miss and minor injury category that may point towards severe malfunctions in safety management.

On the other hand, one might state that due to recent developments, the focus on safety is exaggerated and the offshore industry attaches far too much importance to injury investigation. Building on the example in section 6.2, a man falling of the stairs at home breaking his wrist is considered an unfortunate event, while the same man tripping and tumbling down an onboard fire escape breaking his wrist is considered an LTI and is thus subject to extensive on-site investigation. In this light, one should reassess if is it really necessary to explain, classify and research all that occurs onboard, just because the maritime sector – especially the offshore world – in itself is judged as 'unsafe'. Then, an interesting study could be conducted towards the economic feasibility of extensive injury investigation. It is well known that injuries are expensive, even when only direct costs are taken into account (Hetherington, 2006). But measures taken to counteract the occurrence of those injuries are not for free either. This brings us back to the ALARP principle; the number of injuries should be 'as low as reasonably practicable'. Although the ALARP principle concerns a concept that is clearly defined, no research has yet been done towards the crossing of the two lines (see Figure 2.1). That is, crew safety and associated costs. Here, the Dutch healthcare sector can be set as an example, for cost-efficiency of medical treatment is exhaustively studied in The Netherlands (Barendregt et al., 1997; Meerding et al., 2005; Schut & Van de Ven, 2005).

Consequently, considering the economic component of safety performance relevant, one arrives at the question that is buried deep and often ignored; what is the value of a human life? In health economics, we are no longer ashamed of rationing and assessing the price of lives (Schut & Van de Ven, 2005). The common understanding is that lives have to be sacrificed in order to safe many others. Some attempts towards assessing the costs to avert fatalities are conducted that might be applicable on the offshore sector (Wang, 2002). However, none of those register what may be accounted for as ‘safety improvement costs’. For example, the restructuring of a vessels hold may be seen as an investment in safety as well as in production speed (Haye-Geervliet, 2014). Mention the value of a life in the offshore sector, and you will find this to be a monstrous topic. Although the offshore sector still upholds an admiring combative attitude, it may nevertheless walk hand in hand with outraging costs.

6.4 Areas of expansion and further study for practice

For practice, several areas of expansion come to mind. First, the technical function group appeared to be most prone to severe injuries. For practical reasons, it may be relevant to examine why the disciplines included in this group – technicians and mechanics – often belong to the victims. This could be resolved in a sub-study using both personal and job-specific data in a similar ordinal logistic regression model. Second, and considered most relevant by the company studied, one might continue with an in-depth study to find out whether the occurring injuries are related to routine or non-routine jobs. In other words, a hypothesis could be that severe injuries may be related with non-routine jobs and therefore with aspects related to non-routine jobs such as training, time pressure, incorrect tools, etc. If this appears to be so, practical solutions can be put in place. One may for example think of additional training or improved procedures. However, if no such relation between severe injuries and non-routine jobs is found, it is most likely the human factor, in terms of behavior, heavily contributes to the injury severity distribution. The latter likely means that the solution for safer performance lies in creating awareness and thus provides an incentive for the behavioral psychological approach, as was described in chapter 2. The question that remains then is to what extent we can prevent severe injuries from happening and even if we can, at what expense.

In order to prevent injuries from happening, offshore companies are known to publish a lot of safety material, such as monthly incident reports, safety flashes, rules, posters and many more. For practice, a third area of relevance for further research is therefore whether the safety information and educative material put in place in fact contributes to both the frequency of injury occurrence and severity. This would be a rather qualitative study, but of great value to QHSE engineers who develop and manage safety information.

Finally, on a more theoretical path, most valuable would be a study including more offshore companies. Although there are limitations to this type of research – as discussed in section 6.2 – comparing several companies and assess whether the same problems are conquered would be both very interesting and tremendously valuable. However, offshore companies are located in a for-profit and competitive environment, which makes a comparison unlikely in the short term. Of course, the IMCA set up some initiatives and publishes an annual safety report (IMCA, 2013). However, these reports include mainly outcome indicators whereas the knowledge and comparison of business processes would be more valuable. All that we just mentioned is knowledge that would come forward in a benchmarking process. The road to increased crew safety performance by means of benchmarking however seems quite long at this point.

To summarize, a variety of issues are still open to discussion. In particular, the areas of research that should be further explored are:

- The impact of work related and non-work related injuries on the injury severity distribution;
- The effect of routine and non-routine work related injuries on the injury severity distribution;
- The relation between cost-efficiency and crew safety performance in terms of ALARP investments;
- The feasibility of working with benchmark studies comparing both outcomes and business processes in the field of maritime safety.

Finally, we would like to state the following: When starting this study, we came across a quote in one of the company's so called 'Safety Flashes', used for creating safety awareness among the crew.

> *"Statistics are like a lamppost to the drunken man; they are more for leaning on than illumination" (Lang, 1903).*

The above brought us back to reality and made it very clear that when it comes to crew safety performance, we deal with reality rather than idiot-proof overly calculated models. More explicitly, QHSE engineers deal in and are responsible for human lives. One should keep in mind that statistical assumptions concern the very first step towards workable solutions for practice and may never be judged as anything in excess of this. Therefore, as a final personal note, we would like to emphasize that it is in reducing the gap between science and practice that the most valuable solutions for improving crew safety performance may be found. One should keep this in mind when conducting further research in this field with the ultimate purpose of saving lives and always pursue to translate scientific findings into workable solutions for practice.

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Appendices

Appendix I: Descriptive Statistics

Injury 4 levels	Freq.	Percent	Cum.
1	736	84.60	84.60
2	98	11.26	95.86
3	13	1.49	97.36
4	23	2.64	100.00
Total	870	100.00	

Injury 4 levels	Year 2009	2010	2011	2012	2013	Total
1	312	145	131	99	49	736
2	29	16	15	21	17	98
3	2	3	4	4	0	13
4	11	4	2	4	2	23
Total	354	168	152	128	68	870

```
. summarize Ship
```

Variable	Obs	Mean	Std. Dev.	Min	Max
Ship	870	1.605747	1.405141	0	4

```
. summarize Vessel_age
```

Variable	Obs	Mean	Std. Dev.	Min	Max
Vessel_age	870	2000.166	8.138485	1986	2008

```
. summarize Crewnr
```

Variable	Obs	Mean	Std. Dev.	Min	Max
Crewnr	870	276.4621	104.6859	72	420

```
. summarize Max_pipesize
```

Variable	Obs	Mean	Std. Dev.	Min	Max
Max_pipesize	796	53.00503	13.23365	28	60

```
. summarize Weld
```

Variable	Obs	Mean	Std. Dev.	Min	Max
Weld	870	6.990805	3.154613	0	11

. summarize Coat

Variable	Obs	Mean	Std. Dev.	Min	Max
Coat	870	2.865517	1.151007	0	4

. summarize Constr_place

Variable	Obs	Mean	Std. Dev.	Min	Max
Constr_place	870	9.856322	4.271704	0	15

. summarize Function_Constr

Variable	Obs	Mean	Std. Dev.	Min	Max
Function_C~r	853	.4724502	.4995333	0	1

. summarize Function_Tech

Variable	Obs	Mean	Std. Dev.	Min	Max
Function_T~h	870	.0965517	.2955163	0	1

. summarize Area

Variable	Obs	Mean	Std. Dev.	Min	Max
Area	870	3.752874	1.60475	1	6

. summarize Safety_reg

Variable	Obs	Mean	Std. Dev.	Min	Max
Safety_reg	870	.6988506	.4590214	0	1

. summarize Cold

Variable	Obs	Mean	Std. Dev.	Min	Max
Cold	870	.1287356	.3350997	0	1

. summarize Year

Variable	Obs	Mean	Std. Dev.	Min	Max
Year	870	2010.297	1.33704	2009	2013

Appendix II: Statistical testing – OLOGIT Model I

```
. ologit Injury Cold Safety_reg Function_Constr Function_Tech Coat Weld Year

Iteration 0:   log likelihood = -472.42206
Iteration 1:   log likelihood =  -454.6157
Iteration 2:   log likelihood =  -453.6319
Iteration 3:   log likelihood = -453.63008
Iteration 4:   log likelihood = -453.63008

Ordered logistic regression                       Number of obs   =        853
                                                  LR chi2(7)      =      37.58
                                                  Prob > chi2     =     0.0000
Log likelihood = -453.63008                       Pseudo R2       =     0.0398
```

Injury	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Cold	1.058894	.2784157	3.80	0.000	.5132094	1.604579
Safety_reg	-.542105	.2223552	-2.44	0.015	-.9779132	-.1062968
Function_Constr	-.4810715	.2128952	-2.26	0.024	-.8983383	-.0638046
Function_Tech	.4424432	.2947854	1.50	0.133	-.1353256	1.020212
Coat	.4456453	.3100934	1.44	0.151	-.1621266	1.053417
Weld	-.1849721	.1150491	-1.61	0.108	-.4104642	.04052
Year	.1932455	.0702784	2.75	0.006	.0555024	.3309885
/cut1	389.8392	141.2993			112.8977	666.7807
/cut2	391.3221	141.3037			114.372	668.2722
/cut3	391.7907	141.3037			114.8406	668.7408

Testing the parallel lines assumption

```
. brant

Brant Test of Parallel Regression Assumption
```

Variable	chi2	p>chi2	df
All	31.91	0.004	14
Cold	0.61	0.736	2
Safety_reg	1.51	0.470	2
Function_C~r	6.31	0.043	2
Function_T~h	8.98	0.011	2
Coat	0.46	0.795	2
Weld	0.41	0.815	2
Year	5.27	0.072	2

```
A significant test statistic provides evidence that the parallel
regression assumption has been violated.
```

Obtaining the odds ratios

```
. listcoef, help

ologit (N=853): Factor Change in Odds

  Odds of: >m vs <=m
```

Injury	b	z	P>|z|	e^b	e^bStdX	SDofX
Cold	1.05889	3.803	0.000	2.8832	1.4302	0.3379
Safety_reg	-0.54211	-2.438	0.015	0.5815	0.7786	0.4616
Function_C~r	-0.48107	-2.260	0.024	0.6181	0.7864	0.4995
Function_T~h	0.44244	1.501	0.133	1.5565	1.1410	0.2981
Coat	0.44565	1.437	0.151	1.5615	1.6786	1.1623
Weld	-0.18497	-1.608	0.108	0.8311	0.5547	3.1859
Year	0.19325	2.750	0.006	1.2132	1.2950	1.3376

```
       b = raw coefficient
       z = z-score for test of b=0
   P>|z| = p-value for z-test
     e^b = exp(b) = factor change in odds for unit increase in X
 e^bStdX = exp(b*SD of X) = change in odds for SD increase in X
   SDofX = standard deviation of X


. listcoef, help percent

ologit (N=853): Percentage Change in Odds

  Odds of: >m vs <=m
```

Injury	b	z	P>|z|	%	%StdX	SDofX
Cold	1.05889	3.803	0.000	188.3	43.0	0.3379
Safety_reg	-0.54211	-2.438	0.015	-41.8	-22.1	0.4616
Function_C~r	-0.48107	-2.260	0.024	-38.2	-21.4	0.4995
Function_T~h	0.44244	1.501	0.133	55.7	14.1	0.2981
Coat	0.44565	1.437	0.151	56.1	67.9	1.1623
Weld	-0.18497	-1.608	0.108	-16.9	-44.5	3.1859
Year	0.19325	2.750	0.006	21.3	29.5	1.3376

```
       b = raw coefficient
       z = z-score for test of b=0
   P>|z| = p-value for z-test
       % = percent change in odds for unit increase in X
   %StdX = percent change in odds for SD increase in X
   SDofX = standard deviation of X
```

Testing for multicollinearity

```
. collin Cold Safety_reg Function_Constr Function_Tech Coat Weld Year
(obs=853)

  Collinearity Diagnostics

                        SQRT                   R-
  Variable      VIF     VIF    Tolerance    Squared
----------------------------------------------------
      Cold      1.20    1.09    0.8350      0.1650
Safety_reg      1.13    1.06    0.8870      0.1130
Function_Constr      1.14    1.07    0.8775      0.1225
Function_Tech      1.12    1.06    0.8968      0.1032
      Coat     14.07    3.75    0.0711      0.9289
      Weld     14.39    3.79    0.0695      0.9305
      Year      1.04    1.02    0.9647      0.0353
----------------------------------------------------
  Mean VIF      4.87

                           Cond
        Eigenval          Index
---------------------------------
    1     5.3706          1.0000
    2     0.9997          2.3178
    3     0.8331          2.5391
    4     0.3865          3.7277
    5     0.2736          4.4305
    6     0.1310          6.4037
    7     0.0056         31.0506
    8     0.0000       5018.0179
---------------------------------
 Condition Number       5018.0179
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix)     0.0540
```

Appendix III: Statistical testing – OLOGIT Model II

```
. ologit Injury Area Cold Max_pipesize Function_Constr Function_Tech Year

Iteration 0:   log likelihood = -416.69012
Iteration 1:   log likelihood = -395.86047
Iteration 2:   log likelihood = -393.76945
Iteration 3:   log likelihood = -393.76176
Iteration 4:   log likelihood = -393.76176

Ordered logistic regression                       Number of obs   =        779
                                                  LR chi2(6)      =      45.86
                                                  Prob > chi2     =     0.0000
Log likelihood = -393.76176                       Pseudo R2       =     0.0550
```

Injury	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Area	-.2450883	.0771997	-3.17	0.001	-.396397	-.0937796
Cold	1.184696	.300826	3.94	0.000	.595088	1.774304
Max_pipesize	-.0116095	.007813	-1.49	0.137	-.0269226	.0037037
Function_Constr	-.4051199	.225185	-1.80	0.072	-.8464744	.0362345
Function_Tech	.6446131	.3263565	1.98	0.048	.0049662	1.28426
Year	.3103355	.0781551	3.97	0.000	.1571543	.4635167
/cut1	624.207	157.1109			316.2753	932.1388
/cut2	625.7178	157.1178			317.7725	933.663
/cut3	626.1263	157.118			318.1808	934.0719

Testing the parallel lines assumption

```
. brant

Brant Test of Parallel Regression Assumption
```

Variable	chi2	p>chi2	df
All	17.00	0.150	12
Area	1.27	0.531	2
Cold	0.24	0.888	2
Max_pipesize	0.60	0.743	2
Function_C~r	6.00	0.050	2
Function_T~h	6.68	0.035	2
Year	4.89	0.087	2

```
A significant test statistic provides evidence that the parallel
regression assumption has been violated.
```

Obtaining the odds ratios

```
. listcoef, help

ologit (N=779): Factor Change in Odds

  Odds of: >m vs <=m
```

Injury	b	z	P>|z|	e^b	e^bStdX	SDofX
Area	-0.24509	-3.175	0.001	0.7826	0.6765	1.5946
Cold	1.18470	3.938	0.000	3.2697	1.4917	0.3375
Max_pipesize	-0.01161	-1.486	0.137	0.9885	0.8566	13.3366
Function_C~r	-0.40512	-1.799	0.072	0.6669	0.8165	0.5003
Function_T~h	0.64461	1.975	0.048	1.9052	1.1968	0.2786
Year	0.31034	3.971	0.000	1.3639	1.5093	1.3265

```
       b = raw coefficient
       z = z-score for test of b=0
   P>|z| = p-value for z-test
     e^b = exp(b) = factor change in odds for unit increase in X
 e^bStdX = exp(b*SD of X) = change in odds for SD increase in X
   SDofX = standard deviation of X

. listcoef, help percent

ologit (N=779): Percentage Change in Odds

  Odds of: >m vs <=m
```

Injury	b	z	P>|z|	%	%StdX	SDofX
Area	-0.24509	-3.175	0.001	-21.7	-32.3	1.5946
Cold	1.18470	3.938	0.000	227.0	49.2	0.3375
Max_pipesize	-0.01161	-1.486	0.137	-1.2	-14.3	13.3366
Function_C~r	-0.40512	-1.799	0.072	-33.3	-18.3	0.5003
Function_T~h	0.64461	1.975	0.048	90.5	19.7	0.2786
Year	0.31034	3.971	0.000	36.4	50.9	1.3265

```
       b = raw coefficient
       z = z-score for test of b=0
   P>|z| = p-value for z-test
       % = percent change in odds for unit increase in X
   %StdX = percent change in odds for SD increase in X
   SDofX = standard deviation of X
```

Testing for multicollinearity

```
. collin Area Cold Max_pipesize Function_Constr Function_Tech Year
(obs=779)

  Collinearity Diagnostics

                        SQRT                   R-
  Variable      VIF     VIF    Tolerance    Squared
----------------------------------------------------
      Area      1.35    1.16    0.7392      0.2608
      Cold      1.20    1.10    0.8329      0.1671
Max_pipesize      1.16    1.08    0.8612      0.1388
Function_Constr      1.13    1.06    0.8871      0.1129
Function_Tech      1.11    1.05    0.9010      0.0990
      Year      1.11    1.05    0.9017      0.0983
----------------------------------------------------
  Mean VIF      1.18

                           Cond
        Eigenval          Index
---------------------------------
    1     4.6626          1.0000
    2     0.9981          2.1613
    3     0.8336          2.3650
    4     0.3498          3.6510
    5     0.1274          6.0494
    6     0.0284         12.8097
    7     0.0000       4874.8986
---------------------------------
 Condition Number       4874.8986
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix)     0.6293
```

Appendix IV: Statistical testing – OLOGIT Model III

```
. ologit Injury Cold Crewnr Max_pipesize Safety_reg Function_Constr Function_Tech Constr_place Year

Iteration 0:   log likelihood = -416.69012
Iteration 1:   log likelihood = -398.01372
Iteration 2:   log likelihood = -396.50717
Iteration 3:   log likelihood = -396.50264
Iteration 4:   log likelihood = -396.50264

Ordered logistic regression                       Number of obs   =        779
                                                  LR chi2(8)      =      40.37
                                                  Prob > chi2     =     0.0000
Log likelihood = -396.50264                       Pseudo R2       =     0.0484
```

Injury	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Cold	1.003313	.2974894	3.37	0.001	.4202443	1.586381
Crewnr	-.0073301	.0114396	-0.64	0.522	-.0297513	.015091
Max_pipesize	-.0082293	.0114964	-0.72	0.474	-.0307617	.0143032
Safety_reg	-.5270576	.2463811	-2.14	0.032	-1.009956	-.0441595
Function_Constr	-.4099222	.2237651	-1.83	0.067	-.8484938	.0286494
Function_Tech	.6344002	.3245863	1.95	0.051	-.0017772	1.270578
Constr_place	.1901514	.3108287	0.61	0.541	-.4190615	.7993644
Year	.2637627	.0763853	3.45	0.001	.1140502	.4134752
/cut1	531.1608	153.4884			230.3291	831.9924
/cut2	532.6625	153.4947			231.8184	833.5066
/cut3	533.0705	153.4948			232.2262	833.9149

Testing the parallel lines assumption

```
. brant

Brant Test of Parallel Regression Assumption
```

Variable	chi2	p>chi2	df
All	19.70	0.234	16
Cold	1.39	0.500	2
Crewnr	0.88	0.645	2
Max_pipesize	1.17	0.556	2
Safety_reg	2.25	0.325	2
Function_C~r	5.58	0.061	2
Function_T~h	7.04	0.030	2
Constr_place	0.60	0.740	2
Year	5.71	0.058	2

```
A significant test statistic provides evidence that the parallel
regression assumption has been violated.
```

Obtaining the odds ratios

```
. listcoef, help

ologit (N=779): Factor Change in Odds

  Odds of: >m vs <=m
```

Injury	b	z	P>|z|	e^b	e^bStdX	SDofX
Cold	1.00331	3.373	0.001	2.7273	1.4031	0.3375
Crewnr	-0.00733	-0.641	0.522	0.9927	0.5217	88.7725
Max_pipesize	-0.00823	-0.716	0.474	0.9918	0.8961	13.3366
Safety_reg	-0.52706	-2.139	0.032	0.5903	0.7867	0.4553
Function_C~r	-0.40992	-1.832	0.067	0.6637	0.8146	0.5003
Function_T~h	0.63440	1.954	0.051	1.8859	1.1934	0.2786
Constr_place	0.19015	0.612	0.541	1.2094	1.8392	3.2046
Year	0.26376	3.453	0.001	1.3018	1.4189	1.3265

```
       b = raw coefficient
       z = z-score for test of b=0
   P>|z| = p-value for z-test
     e^b = exp(b) = factor change in odds for unit increase in X
 e^bStdX = exp(b*SD of X) = change in odds for SD increase in X
   SDofX = standard deviation of X

. listcoef, help percent

ologit (N=779): Percentage Change in Odds

  Odds of: >m vs <=m
```

Injury	b	z	P>|z|	%	%StdX	SDofX
Cold	1.00331	3.373	0.001	172.7	40.3	0.3375
Crewnr	-0.00733	-0.641	0.522	-0.7	-47.8	88.7725
Max_pipesize	-0.00823	-0.716	0.474	-0.8	-10.4	13.3366
Safety_reg	-0.52706	-2.139	0.032	-41.0	-21.3	0.4553
Function_C~r	-0.40992	-1.832	0.067	-33.6	-18.5	0.5003
Function_T~h	0.63440	1.954	0.051	88.6	19.3	0.2786
Constr_place	0.19015	0.612	0.541	20.9	83.9	3.2046
Year	0.26376	3.453	0.001	30.2	41.9	1.3265

```
       b = raw coefficient
       z = z-score for test of b=0
   P>|z| = p-value for z-test
       % = percent change in odds for unit increase in X
   %StdX = percent change in odds for SD increase in X
   SDofX = standard deviation of X
```

Testing for multicollinearity

Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R-Squared
Cold	1.24	1.11	0.8080	0.1920
ear Crewnr	80.37	8.96	0.0124	0.9876
Max_pipesize	2.20	1.48	0.4552	0.5448
Safety_reg	1.14	1.07	0.8770	0.1230
Function_Constr	1.13	1.06	0.8872	0.1128
Function_Tech	1.11	1.05	0.9007	0.0993
Constr_place	73.61	8.58	0.0136	0.9864
Year	1.07	1.04	0.9332	0.0668

Mean VIF 20.23

	Eigenval	Cond Index
1	6.4112	1.0000
2	0.9988	2.5336
3	0.8355	2.7701
4	0.3741	4.1398
5	0.2711	4.8634
6	0.0745	9.2740
7	0.0343	13.6648
8	0.0005	110.1976
9	0.0000	5619.7453

Condition Number 5619.7453

Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)

Det(correlation matrix) 0.0074

Appendix V: Statistical testing – GOLOGIT Model IV

```
. gologit2 Injury Cold Safety_reg Function_Constr Function_Tech Coat Weld Year

Generalized Ordered Logit Estimates               Number of obs   =        853
                                                  LR chi2(21)     =      76.64
                                                  Prob > chi2     =     0.0000
Log likelihood = -434.10133                       Pseudo R2       =     0.0811
```

Injury	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						
Cold	1.015538	.2839608	3.58	0.000	.458985	1.572091
Safety_reg	-.5242657	.2241049	-2.34	0.019	-.9635033	-.0850281
Function_Constr	-.4864203	.2142679	-2.27	0.023	-.9063776	-.0664631
Function_Tech	.2324008	.3072966	0.76	0.449	-.3698896	.8346911
Coat	.4397744	.3131409	1.40	0.160	-.1739705	1.053519
Weld	-.1902363	.1166418	-1.63	0.103	-.41885	.0383774
Year	.2064836	.0708466	2.91	0.004	.0676269	.3453404
_cons	-416.3975	142.4409	-2.92	0.003	-695.5765	-137.2184
2						
Cold	1.565793	.5074408	3.09	0.002	.571227	2.560358
Safety_reg	-.6201409	.4121871	-1.50	0.132	-1.428013	.1877309
Function_Constr	.4963601	.4148376	1.20	0.231	-.3167067	1.309427
Function_Tech	1.258394	.5209954	2.42	0.016	.2372615	2.279526
Coat	1.180637	.5868775	2.01	0.044	.0303784	2.330896
Weld	-.5338999	.2278165	-2.34	0.019	-.980412	-.0873878
Year	.0389882	.128918	0.30	0.762	-.2136866	.2916629
_cons	-81.58451	259.0913	-0.31	0.753	-589.3941	426.2251
3						
Cold	1.376321	.8594699	1.60	0.109	-.3082092	3.060851
Safety_reg	-.5255231	.7862495	-0.67	0.504	-2.066544	1.015498
Function_Constr	-2.160563	.8971902	-2.41	0.016	-3.919023	-.4021023
Function_Tech	2.211374	.7748887	2.85	0.004	.6926202	3.730128
Coat	-1.585321	.9919389	-1.60	0.110	-3.529486	.3588433
Weld	.8254603	.4044562	2.04	0.041	.0327408	1.61818
Year	.3322672	.3039369	1.09	0.274	-.2634381	.9279725
_cons	-672.2581	611.008	-1.10	0.271	-1869.812	525.2956

Obtaining marginal effects and probabilities – .mfx2 command

```
. mfx2

Frequencies for Injury...
```

Injury 4 levels	Freq.	Percent	Cum.
1	719	84.29	84.29
2	98	11.49	95.78
3	13	1.52	97.30
4	23	2.70	100.00
Total	853	100.00	

```
Computing marginal effects after gologit2 for Injury == 1...

Marginal effects after gologit2
      y  = Pr(Injury==1) (predict, o(1))
         =  .85893502
```

variable	dy/dx	Std. Err.	z	P>|z|	[95% C.I.	]	X
Cold*	-.1584191	.05324	-2.98	0.003	-.26277	-.054068	.131301
Safety~g*	.0683873	.031	2.21	0.027	.007623	.129151	.692849
Functi~r*	.0585315	.02537	2.31	0.021	.008799	.108264	.47245
Functi~h*	-.0300925	.04239	-0.71	0.478	-.113173	.052988	.098476
Coat	-.0532855	.03781	-1.41	0.159	-.127401	.02083	2.86284
Weld	.0230501	.01407	1.64	0.101	-.004536	.050637	6.99062
Year	-.0250187	.00847	-2.95	0.003	-.041622	-.008415	2010.32

```
(*) dy/dx is for discrete change of dummy variable from 0 to 1

Computing marginal effects after gologit2 for Injury == 2...

Marginal effects after gologit2
      y  = Pr(Injury==2) (predict, o(2))
         =  .10950176
```

variable	dy/dx	Std. Err.	z	P>|z|	[95% C.I.	]	X
Cold*	.0715719	.05	1.43	0.152	-.026422	.169565	.131301
Safety~g*	-.0469235	.02721	-1.72	0.085	-.100247	.0064	.692849
Functi~r*	-.0740279	.0227	-3.26	0.001	-.118527	-.029529	.47245
Functi~h*	-.0339398	.03969	-0.86	0.392	-.111724	.043845	.098476
Coat	.017197	.03368	0.51	0.610	-.048813	.083207	2.86284
Weld	-.0067304	.01263	-0.53	0.594	-.031494	.018033	6.99062
Year	.023827	.00751	3.17	0.002	.009107	.038547	2010.32

```
(*) dy/dx is for discrete change of dummy variable from 0 to 1
```

```
Marginal effects after gologit2
      y  = Pr(Injury==3) (predict, o(3))
         =  .01440962
```

variable	dy/dx	Std. Err.	z	P>|z|	[95% C.I.]		X
Cold*	.0466604	.04602	1.01	0.311	-.043536	.136857	.131301
Safety~g*	-.0115945	.01805	-0.64	0.521	-.046971	.023782	.692849
Functi~r*	.0561439	.01912	2.94	0.003	.018665	.093622	.47245
Functi~h*	-.0357089	.06753	-0.53	0.597	-.16806	.096642	.098476
Coat	.062816	.01843	3.41	0.001	.026689	.098943	2.86284
Weld	-.0302364	.00829	-3.65	0.000	-.046475	-.013998	6.99062
Year	-.0044101	.00641	-0.69	0.491	-.016974	.008154	2010.32

(*) dy/dx is for discrete change of dummy variable from 0 to 1

```
Marginal effects after gologit2
      y  = Pr(Injury==4) (predict, o(4))
         =  .0171536
```

variable	dy/dx	Std. Err.	z	P>|z|	[95% C.I.]		X
Cold*	.0401868	.0401	1.00	0.316	-.038401	.118774	.131301
Safety~g*	-.0098693	.01736	-0.57	0.570	-.043893	.024154	.692849
Functi~r*	-.0406476	.01971	-2.06	0.039	-.079276	-.002019	.47245
Functi~h*	.0997413	.06817	1.46	0.143	-.033865	.233347	.098476
Coat	-.0267275	.017	-1.57	0.116	-.060056	.006601	2.86284
Weld	.0139167	.00724	1.92	0.055	-.000274	.028107	6.99062
Year	.0056018	.00573	0.98	0.328	-.005634	.016838	2010.32

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Obtaining marginal effects and probabilities – .margins command

```
. margins, predict(outcome(1)) atmeans
Warning: cannot perform check for estimable functions.

Adjusted predictions                              Number of obs   =        853
Model VCE    : OIM

Expression   : Pr(Injury==1), predict(outcome(1))
at           : Cold            =    .1313013 (mean)
               Safety_reg      =    .6928488 (mean)
               Function_C~r    =    .4724502 (mean)
               Function_T~h    =     .098476 (mean)
               Coat            =    2.862837 (mean)
               Weld            =    6.990621 (mean)
               Year            =    2010.322 (mean)
```

	Margin	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
_cons	.8589351	.012535	68.52	0.000	.8343669	.8835033

```
. margins, predict(outcome(2)) atmeans
Warning: cannot perform check for estimable functions.

Adjusted predictions                              Number of obs   =        853
Model VCE     : OIM

Expression    : Pr(Injury==2), predict(outcome(2))
at            : Cold            =     .1313013 (mean)
                Safety_reg      =     .6928488 (mean)
                Function_C~r    =     .4724502 (mean)
                Function_T~h    =      .098476 (mean)
                Coat            =     2.862837 (mean)
                Weld            =     6.990621 (mean)
                Year            =     2010.322 (mean)

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |   .1095017   .0112877     9.70   0.000     .0873782    .1316252
------------------------------------------------------------------------------

. margins, predict(outcome(3)) atmeans
Warning: cannot perform check for estimable functions.

Adjusted predictions                              Number of obs   =        853
Model VCE     : OIM

Expression    : Pr(Injury==3), predict(outcome(3))
at            : Cold            =     .1313013 (mean)
                Safety_reg      =     .6928488 (mean)
                Function_C~r    =     .4724502 (mean)
                Function_T~h    =      .098476 (mean)
                Coat            =     2.862837 (mean)
                Weld            =     6.990621 (mean)
                Year            =     2010.322 (mean)

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |   .0144096   .0044789     3.22   0.001     .0056312     .023188
------------------------------------------------------------------------------
```

```
. margins, predict(outcome(4)) atmeans
Warning: cannot perform check for estimable functions.

Adjusted predictions                              Number of obs   =        853
Model VCE    : OIM

Expression   : Pr(Injury==4), predict(outcome(4))
at           : Cold            =     .1313013 (mean)
               Safety_reg      =     .6928488 (mean)
               Function_C~r    =     .4724502 (mean)
               Function_T~h    =      .098476 (mean)
               Coat            =     2.862837 (mean)
               Weld            =     6.990621 (mean)
               Year            =     2010.322 (mean)

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |   .0171536    .005044     3.40   0.001     .0072675    .0270396
------------------------------------------------------------------------------


. margins, at(Cold=1 Function_Constr=0 Function_Tech=1 Year=2013 Safety_reg=0) predict(outcome(1))
Warning: cannot perform check for estimable functions.

Predictive margins                                Number of obs   =        853
Model VCE    : OIM

Expression   : Pr(Injury==1), predict(outcome(1))
at           : Cold            =           1
               Safety_reg      =           0
               Function_C~r    =           0
               Function_T~h    =           1
               Year            =        2013

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |    .394663   .1068699     3.69   0.000     .1852018    .6041241
------------------------------------------------------------------------------

. margins, at(Cold=1 Function_Constr=0 Function_Tech=1 Year=2013 Safety_reg=0) predict(outcome(2))
Warning: cannot perform check for estimable functions.

Predictive margins                                Number of obs   =        853
Model VCE    : OIM

Expression   : Pr(Injury==2), predict(outcome(2))
at           : Cold            =           1
               Safety_reg      =           0
               Function_C~r    =           0
               Function_T~h    =           1
               Year            =        2013

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |   .2473882   .1620537     1.53   0.127    -.0702313    .5650077
------------------------------------------------------------------------------
```

```
. margins, at(Cold=1 Function_Constr=0 Function_Tech=1 Year=2013 Safety_reg=0) predict(outcome(3))
Warning: cannot perform check for estimable functions.

Predictive margins                              Number of obs     =        853
Model VCE    : OIM

Expression   : Pr(Injury==3), predict(outcome(3))
at           : Cold            =           1
               Safety_reg      =           0
               Function_C~r    =           0
               Function_T~h    =           1
               Year            =        2013

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |  -.4043502   .2279853    -1.77   0.076    -.8511932    .0424927
------------------------------------------------------------------------------

. margins, at(Cold=1 Function_Constr=0 Function_Tech=1 Year=2013 Safety_reg=0) predict(outcome(4))
Warning: cannot perform check for estimable functions.

Predictive margins                              Number of obs     =        853
Model VCE    : OIM

Expression   : Pr(Injury==4), predict(outcome(4))
at           : Cold            =           1
               Safety_reg      =           0
               Function_C~r    =           0
               Function_T~h    =           1
               Year            =        2013

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |   .7622991   .2325829     3.28   0.001     .3064449    1.218153
------------------------------------------------------------------------------
```

Testing for multicollinearity

```
. collin Cold Safety_reg Function_Constr Function_Tech Coat Weld Year
(obs=853)

  Collinearity Diagnostics

                        SQRT                   R-
  Variable      VIF     VIF    Tolerance    Squared
----------------------------------------------------
      Cold      1.20    1.09    0.8350      0.1650
Safety_reg      1.13    1.06    0.8870      0.1130
Function_Constr      1.14    1.07    0.8775      0.1225
Function_Tech      1.12    1.06    0.8968      0.1032
      Coat     14.07    3.75    0.0711      0.9289
      Weld     14.39    3.79    0.0695      0.9305
      Year      1.04    1.02    0.9647      0.0353
----------------------------------------------------
  Mean VIF      4.87

                           Cond
        Eigenval          Index
---------------------------------
    1     5.3706          1.0000
    2     0.9997          2.3178
    3     0.8331          2.5391
    4     0.3865          3.7277
    5     0.2736          4.4305
    6     0.1310          6.4037
    7     0.0056         31.0506
    8     0.0000       5018.0179
---------------------------------
 Condition Number        5018.0179
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix)     0.0540
```

Appendix VI: Statistical testing – GOLOGIT Model V

```
. gologit2 Injury Area Cold Max_pipesize Function_Constr Function_Tech Year

Generalized Ordered Logit Estimates               Number of obs   =        779
                                                  LR chi2(18)     =      92.46
                                                  Prob > chi2     =     0.0000
Log likelihood = -370.46261                       Pseudo R2       =     0.1109
```

Injury	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						
Area	-.2662772	.078385	-3.40	0.001	-.4199089	-.1126455
Cold	1.206904	.3070502	3.93	0.000	.6050965	1.808711
Max_pipesize	-.013901	.0079432	-1.75	0.080	-.0294694	.0016675
Function_Constr	-.3939139	.2278754	-1.73	0.084	-.8405414	.0527137
Function_Tech	.3630194	.3489818	1.04	0.298	-.3209723	1.047011
Year	.315431	.0795873	3.96	0.000	.1594427	.4714192
_cons	-634.2632	159.9881	-3.96	0.000	-947.8341	-320.6924
2						
Area	-.2500961	.1627233	-1.54	0.124	-.5690278	.0688356
Cold	1.32422	.5620639	2.36	0.018	.222595	2.425845
Max_pipesize	-.0321131	.0158591	-2.02	0.043	-.0631964	-.0010298
Function_Constr	.7509907	.4884187	1.54	0.124	-.2062924	1.708274
Function_Tech	1.507412	.6190203	2.44	0.015	.2941545	2.72067
Year	-.0320122	.163632	-0.20	0.845	-.3527249	.2887006
_cons	62.76541	328.9882	0.19	0.849	-582.0397	707.5705
3						
Area	.8222908	.2966672	2.77	0.006	.2408338	1.403748
Cold	.1380391	.9035153	0.15	0.879	-1.632818	1.908896
Max_pipesize	.077735	.035113	2.21	0.027	.0089147	.1465552
Function_Constr	-3.562044	.9888594	-3.60	0.000	-5.500172	-1.623915
Function_Tech	1.332288	1.079717	1.23	0.217	-.7839182	3.448493
Year	.2322741	.2110256	1.10	0.271	-.1813285	.6458767
_cons	-476.0422	424.0239	-1.12	0.262	-1307.114	355.0294

Obtaining marginal effects and probabilities – .mfx2 command

```
. mfx2

Frequencies for Injury...
```

Injury 4 levels	Freq.	Percent	Cum.
1	662	84.98	84.98
2	86	11.04	96.02
3	10	1.28	97.30
4	21	2.70	100.00
Total	779	100.00	

```
Computing marginal effects after gologit2 for Injury == 1...


Marginal effects after gologit2
      y  = Pr(Injury==1) (predict, o(1))
         =  .87162942
```

variable	dy/dx	Std. Err.	z	P>|z|	[95% C.I.	]	X
Area	.0297942	.00854	3.49	0.000	.013051	.046538	3.80103
Cold*	-.1842669	.05793	-3.18	0.001	-.297811	-.070723	.130937
Max_pi~e	.0015554	.00089	1.74	0.082	-.000196	.003307	52.8524
Functi~r*	.0442267	.02553	1.73	0.083	-.00582	.094273	.504493
Functi~h*	-.0453772	.04834	-0.94	0.348	-.140129	.049375	.084724
Year	-.0352941	.00868	-4.07	0.000	-.052298	-.01829	2010.28

```
(*) dy/dx is for discrete change of dummy variable from 0 to 1

Computing marginal effects after gologit2 for Injury == 2...


Marginal effects after gologit2
      y  = Pr(Injury==2) (predict, o(2))
         =  .10060727
```

variable	dy/dx	Std. Err.	z	P>|z|	[95% C.I.	]	X
Area	-.0230435	.00773	-2.98	0.003	-.038195	-.007892	3.80103
Cold*	.124926	.05208	2.40	0.016	.022855	.226997	.130937
Max_pi~e	-.0006886	.00082	-0.84	0.401	-.002296	.000918	52.8524
Functi~r*	-.0648324	.0237	-2.74	0.006	-.111282	-.018383	.504493
Functi~h*	-.032016	.04957	-0.65	0.518	-.129168	.065136	.084724
Year	.0361582	.008	4.52	0.000	.020474	.051842	2010.28

```
(*) dy/dx is for discrete change of dummy variable from 0 to 1

Computing marginal effects after gologit2 for Injury == 3...


Marginal effects after gologit2
      y  = Pr(Injury==3) (predict, o(3))
         = -.00047894
```

variable	dy/dx	Std. Err.	z	P>|z|	[95% C.I.	]	X
Area	-.0293182	.01167	-2.51	0.012	-.052186	-.00645	3.80103
Cold*	.0553636	.03316	1.67	0.095	-.009625	.120352	.130937
Max_pi~e	-.0030002	.00111	-2.71	0.007	-.005166	-.000834	52.8524
Functi~r*	.164808	.08403	1.96	0.050	.00011	.329506	.504493
Functi~h*	.0131256	.07957	0.16	0.869	-.142832	.169083	.084724
Year	-.0072388	.00719	-1.01	0.314	-.021333	.006855	2010.28

```
(*) dy/dx is for discrete change of dummy variable from 0 to 1
```

```
Computing marginal effects after gologit2 for Injury == 4...

Marginal effects after gologit2
      y  = Pr(Injury==4) (predict, o(4))
         =  .02824226
```

variable	dy/dx	Std. Err.	z	P>|z|	[95% C.I.	]	X
Area	.0225675	.01229	1.84	0.066	-.001512	.046647	3.80103
Cold*	.0039773	.02674	0.15	0.882	-.04844	.056395	.130937
Max_pi~e	.0021334	.00092	2.32	0.020	.000332	.003934	52.8524
Functi~r*	-.1442023	.08481	-1.70	0.089	-.310434	.022029	.504493
Functi~h*	.0642677	.07379	0.87	0.384	-.080358	.208893	.084724
Year	.0063747	.00646	0.99	0.324	-.006281	.01903	2010.28

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Obtaining marginal effects and probabilities – .margins command

```
. margins, predict(outcome(1)) atmeans
Warning: cannot perform check for estimable functions.

Adjusted predictions                              Number of obs   =        779
Model VCE    : OIM

Expression   : Pr(Injury==1), predict(outcome(1))
at           : Area            =    3.801027 (mean)
               Cold            =    .1309371 (mean)
               Max_pipesize    =    52.85237 (mean)
               Function_C~r    =    .5044929 (mean)
               Function_T~h    =     .084724 (mean)
               Year            =     2010.28 (mean)
```

	Margin	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
_cons	.8716316	.0127767	68.22	0.000	.8465897	.8966734

```
. margins, predict(outcome(2)) atmeans
Warning: cannot perform check for estimable functions.

Adjusted predictions                              Number of obs   =        779
Model VCE    : OIM

Expression   : Pr(Injury==2), predict(outcome(2))
at           : Area            =    3.801027 (mean)
               Cold            =    .1309371 (mean)
               Max_pipesize    =    52.85237 (mean)
               Function_C~r    =    .5044929 (mean)
               Function_T~h    =     .084724 (mean)
               Year            =     2010.28 (mean)

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |   .1006051    .011563     8.70   0.000      .077942    .1232681
------------------------------------------------------------------------------

. margins, predict(outcome(3)) atmeans
Warning: cannot perform check for estimable functions.

Adjusted predictions                              Number of obs   =        779
Model VCE    : OIM

Expression   : Pr(Injury==3), predict(outcome(3))
at           : Area            =    3.801027 (mean)
               Cold            =    .1309371 (mean)
               Max_pipesize    =    52.85237 (mean)
               Function_C~r    =    .5044929 (mean)
               Function_T~h    =     .084724 (mean)
               Year            =     2010.28 (mean)

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |  -.0004785    .0070969    -0.07   0.946    -.0143882    .0134312
------------------------------------------------------------------------------
```

```
. margins, predict(outcome(4)) atmeans
Warning: cannot perform check for estimable functions.

Adjusted predictions                              Number of obs   =        779
Model VCE    : OIM

Expression   : Pr(Injury==4), predict(outcome(4))
at           : Area            =     3.801027 (mean)
               Cold            =     .1309371 (mean)
               Max_pipesize    =     52.85237 (mean)
               Function_C~r    =     .5044929 (mean)
               Function_T~h    =      .084724 (mean)
               Year            =      2010.28 (mean)

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |   .0282419   .0091073     3.10   0.002     .0103919    .0460918
------------------------------------------------------------------------------

. margins, at(Cold=1 Function_Constr=0 Function_Tech=1 Year=2013) predict(outcome(1))
Warning: cannot perform check for estimable functions.

Predictive margins                                Number of obs   =        779
Model VCE    : OIM

Expression   : Pr(Injury==1), predict(outcome(1))
at           : Cold            =            1
               Function_C~r    =            0
               Function_T~h    =            1
               Year            =         2013

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |   .3777946   .0991936     3.81   0.000     .1833788    .5722104
------------------------------------------------------------------------------

. margins, at(Cold=1 Function_Constr=0 Function_Tech=1 Year=2013) predict(outcome(2))
Warning: cannot perform check for estimable functions.

Predictive margins                                Number of obs   =        779
Model VCE    : OIM

Expression   : Pr(Injury==2), predict(outcome(2))
at           : Cold            =            1
               Function_C~r    =            0
               Function_T~h    =            1
               Year            =         2013

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |   .4270447   .1273214     3.35   0.001     .1774994      .67659
------------------------------------------------------------------------------
```

```
. margins, at(Cold=1 Function_Constr=0 Function_Tech=1 Year=2013) predict(outcome(3))
Warning: cannot perform check for estimable functions.

Predictive margins                              Number of obs     =        779
Model VCE    : OIM

Expression   : Pr(Injury==3), predict(outcome(3))
at           : Cold            =           1
               Function_C~r    =           0
               Function_T~h    =           1
               Year            =        2013

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |  -.3595728   .1591599    -2.26   0.024    -.6715205   -.0476251
------------------------------------------------------------------------------

. margins, at(Cold=1 Function_Constr=0 Function_Tech=1 Year=2013) predict(outcome(4))
Warning: cannot perform check for estimable functions.

Predictive margins                              Number of obs     =        779
Model VCE    : OIM

Expression   : Pr(Injury==4), predict(outcome(4))
at           : Cold            =           1
               Function_C~r    =           0
               Function_T~h    =           1
               Year            =        2013

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |   .5547335   .1948409     2.85   0.004     .1728523    .9366147
------------------------------------------------------------------------------
```

Testing for multicollinearity

```
. collin Area Cold Max_pipesize Function_Constr Function_Tech Year
(obs=779)

  Collinearity Diagnostics

                        SQRT                   R-
  Variable      VIF     VIF    Tolerance    Squared
----------------------------------------------------
      Area      1.35    1.16    0.7392      0.2608
      Cold      1.20    1.10    0.8329      0.1671
Max_pipesize      1.16    1.08    0.8612      0.1388
Function_Constr      1.13    1.06    0.8871      0.1129
Function_Tech      1.11    1.05    0.9010      0.0990
      Year      1.11    1.05    0.9017      0.0983
----------------------------------------------------
  Mean VIF      1.18

                           Cond
        Eigenval          Index
---------------------------------
    1     4.6626          1.0000
    2     0.9981          2.1613
    3     0.8336          2.3650
    4     0.3498          3.6510
    5     0.1274          6.0494
    6     0.0284         12.8097
    7     0.0000       4874.8986
---------------------------------
 Condition Number       4874.8986
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix)    0.6293
```

Appendix VII: Statistical testing – GOLOGIT Model VI

```
. gologit2 Injury Cold Crewnr Max_pipesize Safety_reg Function_Constr Function_Tech Constr_place Year

Generalized Ordered Logit Estimates                Number of obs   =        779
                                                   LR chi2(24)     =     106.19
                                                   Prob > chi2     =     0.0000
Log likelihood = -363.59549                        Pseudo R2       =     0.1274
```

Injury	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
1						
Cold	.9693527	.3105897	3.12	0.002	.3606081	1.578097
Crewnr	-.0026816	.0117209	-0.23	0.819	-.0256541	.020291
Max_pipesize	-.0156795	.011964	-1.31	0.190	-.0391285	.0077695
Safety_reg	-.658611	.2527102	-2.61	0.009	-1.153914	-.1633081
Function_Constr	-.3979164	.2270546	-1.75	0.080	-.8429353	.0471025
Function_Tech	.3368864	.3502885	0.96	0.336	-.3496664	1.023439
Constr_place	.0722149	.317186	0.23	0.820	-.5494583	.6938881
Year	.2749704	.0791398	3.47	0.001	.1198593	.4300814
_cons	-553.3425	159.0139	-3.48	0.001	-865.004	-241.681
2						
Cold	1.637662	.6418521	2.55	0.011	.3796553	2.895669
Crewnr	-.0151123	.0217323	-0.70	0.487	-.0577069	.0274823
Max_pipesize	-.0235265	.0226441	-1.04	0.299	-.0679081	.020855
Safety_reg	-1.038754	.4909836	-2.12	0.034	-2.001064	-.0764436
Function_Constr	.8445153	.4874779	1.73	0.083	-.1109239	1.799955
Function_Tech	1.767586	.6393032	2.76	0.006	.5145752	3.020598
Constr_place	.3169511	.5613431	0.56	0.572	-.7832611	1.417163
Year	-.0448747	.1628391	-0.28	0.783	-.3640335	.2742841
_cons	88.68425	327.382	0.27	0.786	-552.9727	730.3412
3						
Cold	3.51159	1.227554	2.86	0.004	1.105629	5.917551
Crewnr	-.4366734	21.07159	-0.02	0.983	-41.73623	40.86288
Max_pipesize	.341599	6.585136	0.05	0.959	-12.56503	13.24823
Safety_reg	3.576781	1.125613	3.18	0.001	1.37062	5.782942
Function_Constr	-.9518767	.873013	-1.09	0.276	-2.662951	.7591974
Function_Tech	1.332572	1.199227	1.11	0.266	-1.017869	3.683013
Constr_place	12.41021	632.1468	0.02	0.984	-1226.575	1251.395
Year	.374607	.2841051	1.32	0.187	-.1822288	.9314428
_cons	-783.323	1175.05	-0.67	0.505	-3086.378	1519.732

Obtain marginal effects and probabilities – .mfx2 command

```
. mfx2

Frequencies for Injury...
```

Injury 4 levels	Freq.	Percent	Cum.
1	662	84.98	84.98
2	86	11.04	96.02
3	10	1.28	97.30
4	21	2.70	100.00
Total	779	100.00	

```
Computing marginal effects after gologit2 for Injury == 1...

Marginal effects after gologit2
      y  = Pr(Injury==1) (predict, o(1))
         =  .87320329
```

variable	dy/dx	Std. Err.	z	P>|z|	[95% C.I.	]	X
Cold*	-.1387579	.05397	-2.57	0.010	-.244542	-.032973	.130937
Crewnr	.0002969	.0013	0.23	0.819	-.002247	.002841	296.026
Max_pi~e	.001736	.00132	1.32	0.187	-.000842	.004314	52.8524
Safety~g*	.0809528	.03353	2.41	0.016	.015244	.146662	.707317
Functi~r*	.0442128	.0252	1.75	0.079	-.005169	.093594	.504493
Functi~h*	-.041364	.04737	-0.87	0.383	-.134207	.051479	.084724
Constr~e	-.0079956	.03511	-0.23	0.820	-.076817	.060826	10.7895
Year	-.0304445	.0086	-3.54	0.000	-.047296	-.013594	2010.28

```
(*) dy/dx is for discrete change of dummy variable from 0 to 1

Computing marginal effects after gologit2 for Injury == 2...

Marginal effects after gologit2
      y  = Pr(Injury==2) (predict, o(2))
         =  .10422537
```

variable	dy/dx	Std. Err.	z	P>|z|	[95% C.I.	]	X
Cold*	.0695897	.05393	1.29	0.197	-.036118	.175297	.130937
Crewnr	.0000365	.00114	0.03	0.974	-.002189	.002262	296.026
Max_pi~e	-.001217	.00117	-1.04	0.300	-.003518	.001084	52.8524
Safety~g*	-.0517716	.02932	-1.77	0.077	-.109241	.005698	.707317
Functi~r*	-.0632578	.02317	-2.73	0.006	-.10868	-.017836	.504493
Functi~h*	-.0434352	.0509	-0.85	0.393	-.143188	.056317	.084724
Constr~e	.001003	.03046	0.03	0.974	-.058704	.06071	10.7895
Year	.0314345	.0082	3.83	0.000	.015364	.047505	2010.28

```
(*) dy/dx is for discrete change of dummy variable from 0 to 1
```

Computing marginal effects after gologit2 for Injury == 3...

Marginal effects after gologit2
y = Pr(Injury==3) (predict, o(3))
= .0155261

variable	dy/dx	Std. Err.	z	P>|z|	[95% C.I.	]	X
Cold*	-.0568722	10.511	-0.01	0.996	-20.6588	20.5451	.130937
Crewnr	.0027214	.14277	0.02	0.985	-.277112	.282554	296.026
Max_pi~e	-.0029087	.18112	-0.02	0.987	-.357893	.352075	52.8524
Safety~g*	-.0484281	1.81775	-0.03	0.979	-3.61115	3.51429	.707317
Functi~r*	.0259762	.65777	0.04	0.968	-1.26323	1.31518	.504493
Functi~h*	.0676357	1.60627	0.04	0.966	-3.08059	3.21586	.084724
Constr~e	-.0798243	3.84313	-0.02	0.983	-7.61222	7.45257	10.7895
Year	-.0036106	.2486	-0.01	0.988	-.490867	.483646	2010.28

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Computing marginal effects after gologit2 for Injury == 4...

Marginal effects after gologit2
y = Pr(Injury==4) (predict, o(4))
= .00704523

variable	dy/dx	Std. Err.	z	P>|z|	[95% C.I.	]	X
Cold*	.1260404	10.511	0.01	0.990	-20.476	20.7281	.130937
Crewnr	-.0030548	.14385	-0.02	0.983	-.285	.27889	296.026
Max_pi~e	.0023897	.18117	0.01	0.989	-.352694	.357474	52.8524
Safety~g*	.0192468	1.81769	0.01	0.992	-3.54335	3.58185	.707317
Functi~r*	-.0069312	.65772	-0.01	0.992	-1.29603	1.28217	.504493
Functi~h*	.0171635	1.60558	0.01	0.991	-3.12972	3.16405	.084724
Constr~e	.0868168	3.86643	0.02	0.982	-7.49124	7.66488	10.7895
Year	.0026206	.24909	0.01	0.992	-.485583	.490825	2010.28

(*) dy/dx is for discrete change of dummy variable from 0 to 1

Obtaining marginal effects and probabilities – .margins command

```
. margins, predict(outcome(1)) atmeans
Warning: cannot perform check for estimable functions.

Adjusted predictions                              Number of obs   =        779
Model VCE    : OIM

Expression   : Pr(Injury==1), predict(outcome(1))
at           : Cold            =    .1309371 (mean)
               Crewnr          =    296.0257 (mean)
               Max_pipesize    =    52.85237 (mean)
               Safety_reg      =    .7073171 (mean)
               Function_C~r    =    .5044929 (mean)
               Function_T~h    =     .084724 (mean)
               Constr_place    =    10.78947 (mean)
               Year            =     2010.28 (mean)
```

	Margin	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
_cons	.8732051	.0127537	68.47	0.000	.8482083	.8982019

```
. margins, predict(outcome(2)) atmeans
Warning: cannot perform check for estimable functions.

Adjusted predictions                              Number of obs   =        779
Model VCE    : OIM

Expression   : Pr(Injury==2), predict(outcome(2))
at           : Cold            =    .1309371 (mean)
               Crewnr          =    296.0257 (mean)
               Max_pipesize    =    52.85237 (mean)
               Safety_reg      =    .7073171 (mean)
               Function_C~r    =    .5044929 (mean)
               Function_T~h    =     .084724 (mean)
               Constr_place    =    10.78947 (mean)
               Year            =     2010.28 (mean)
```

	Margin	Delta-method Std. Err.	z	P>|z|	[95% Conf.	Interval]
_cons	.1042235	.011721	8.89	0.000	.0812508	.1271962

```
. margins, predict(outcome(3)) atmeans
Warning: cannot perform check for estimable functions.

Adjusted predictions                              Number of obs   =        779
Model VCE    : OIM

Expression   : Pr(Injury==3), predict(outcome(3))
at           : Cold            =    .1309371 (mean)
               Crewnr          =    296.0257 (mean)
               Max_pipesize    =    52.85237 (mean)
               Safety_reg      =    .7073171 (mean)
               Function_C~r    =    .5044929 (mean)
               Function_T~h    =     .084724 (mean)
               Constr_place    =    10.78947 (mean)
               Year            =     2010.28 (mean)

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |   .0155263    .674405     0.02   0.982    -1.306283    1.337336
------------------------------------------------------------------------------

. margins, predict(outcome(4)) atmeans
Warning: cannot perform check for estimable functions.

Adjusted predictions                              Number of obs   =        779
Model VCE    : OIM

Expression   : Pr(Injury==4), predict(outcome(4))
at           : Cold            =    .1309371 (mean)
               Crewnr          =    296.0257 (mean)
               Max_pipesize    =    52.85237 (mean)
               Safety_reg      =    .7073171 (mean)
               Function_C~r    =    .5044929 (mean)
               Function_T~h    =     .084724 (mean)
               Constr_place    =    10.78947 (mean)
               Year            =     2010.28 (mean)

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |   .0070451   .6743939     0.01   0.992    -1.314743    1.328833
------------------------------------------------------------------------------
```

```
. margins, at(Cold=1 Function_Constr=0 Function_Tech=1 Safety_reg=0 Year=2013) predict(outcome(1))
Warning: cannot perform check for estimable functions.

Predictive margins                              Number of obs     =        779
Model VCE    : OIM

Expression   : Pr(Injury==1), predict(outcome(1))
at           : Cold            =           1
               Safety_reg      =           0
               Function_C~r    =           0
               Function_T~h    =           1
               Year            =        2013

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |   .3483354   .1148931     3.03   0.002     .1231491    .5735217
------------------------------------------------------------------------------

. margins, at(Cold=1 Function_Constr=0 Function_Tech=1 Safety_reg=0 Year=2013) predict(outcome(2))
Warning: cannot perform check for estimable functions.

Predictive margins                              Number of obs     =        779
Model VCE    : OIM

Expression   : Pr(Injury==2), predict(outcome(2))
at           : Cold            =           1
               Safety_reg      =           0
               Function_C~r    =           0
               Function_T~h    =           1
               Year            =        2013

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |   .2749165   .1994455     1.38   0.168    -.1159895    .6658225
------------------------------------------------------------------------------

. margins, at(Cold=1 Function_Constr=0 Function_Tech=1 Safety_reg=0 Year=2013) predict(outcome(3))
Warning: cannot perform check for estimable functions.

Predictive margins                              Number of obs     =        779
Model VCE    : OIM

Expression   : Pr(Injury==3), predict(outcome(3))
at           : Cold            =           1
               Safety_reg      =           0
               Function_C~r    =           0
               Function_T~h    =           1
               Year            =        2013

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |  -.0549748   .2469779    -0.22   0.824    -.5390426     .429093
------------------------------------------------------------------------------
```

```
. margins, at(Cold=1 Function_Constr=0 Function_Tech=1 Safety_reg=0 Year=2013) predict(outcome(4))
Warning: cannot perform check for estimable functions.

Predictive margins                              Number of obs   =        779
Model VCE    : OIM

Expression   : Pr(Injury==4), predict(outcome(4))
at           : Cold            =           1
               Safety_reg      =           0
               Function_C~r    =           0
               Function_T~h    =           1
               Year            =        2013

------------------------------------------------------------------------------
             |            Delta-method
             |     Margin   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _cons |   .4317229   .1799019     2.40   0.016     .0791217    .7843242
------------------------------------------------------------------------------
```

Testing for multicollinearity

```
  Collinearity Diagnostics

                        SQRT                   R-
  Variable      VIF     VIF    Tolerance    Squared
----------------------------------------------------
      Cold      1.24    1.11    0.8080      0.1920
ar    Crewnr   80.37    8.96    0.0124      0.9876
Max_pipesize      2.20    1.48    0.4552      0.5448
Safety_reg      1.14    1.07    0.8770      0.1230
Function_Constr      1.13    1.06    0.8872      0.1128
Function_Tech      1.11    1.05    0.9007      0.0993
Constr_place     73.61    8.58    0.0136      0.9864
      Year      1.07    1.04    0.9332      0.0668
----------------------------------------------------
  Mean VIF     20.23

                           Cond
        Eigenval          Index
---------------------------------
    1     6.4112          1.0000
    2     0.9988          2.5336
    3     0.8355          2.7701
    4     0.3741          4.1398
    5     0.2711          4.8634
    6     0.0745          9.2740
    7     0.0343         13.6648
    8     0.0005        110.1976
    9     0.0000       5619.7453
---------------------------------
 Condition Number       5619.7453
 Eigenvalues & Cond Index computed from scaled raw sscp (w/ intercept)
 Det(correlation matrix)     0.0074
```