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Statistical evaluation model for future business opportunities of SAAB AB

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Statistisk utvärderingsmodell av SAABs framtida affärsmöjligheter

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Sammanfattning

Den här uppsatsen genomför en statistisk analys av SAAB ABs vunna och förlorade affärer från dess försäljningsdata. Metoden som valdes är logistisk regressionsanalys och den är implementerad mot statistiskt signifikant och beroende data. Försäljningsdatan är uppdelad på olika produktområden så att varje produkt får sin egen analys. Resultatet av regressionsanalysen är sedan implementerad på olika länder som SAAB inte har försökt att sälja den undersökta produkten till. Detta ger sannolikheten för att genomföra en lyckad försäljning av en viss produkt till ett land. Dessa sannolikheter bildar sedan en ranking för de olika länderna för en specifik produkt. Rankingtabellerna är tänkta att användas som statistiskt underlag för SAABs anställda när de utvärderar potentiella framtida affärer.

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Abstract

This thesis conducts a statistical analysis of the won and lost sell data for SAAB AB. The method of choice is logistic regression analysis against believed and confirmed statistically significant dependable data. The sell data is split by different products so that each product gets an individual evaluation. The outcome of the regression analysis is then implemented on non-ventured markets for a specific product. This provide an implied probability of a successful sale of a product to different countries. These implied probabilities form a ranking of different countries for a specific product. The ranking tables are then supposed to be used as a statistical input for SAAB employees to use when evaluating potential future market gains.

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Gustav Hedén

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NOMENCLATURE

Notations

Symbol	*Description*
X1	Size of order in KSEK
X2	Dummy variable of NATO membership, 1 for members and 0 otherwise
X3	Gross domestic product over capita
X4	Total arms imports in M$ between the years 2000 and 2016
X5	Total arms import over total arms trade between the years 2000 and 2016
X6	Total defence spending over gross domestic product in the year 2015

Abbreviations

AIC	Akaike's Information Criteria
BIC	Bayesian Information Criteria
df	degrees of freedom

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1 INTRODUCTION

1.1 Background

SAAB AB is a large corporation with its main focus on exporting defence and security material all over the world. When SAAB has an intent of trying to sell a complex and expensive defence and security system there is a lot of investments in terms of marketing and worked hours for its employees for such a pursuit. It is therefore of interest for SAAB to investigate which sales they should work more or less on to increase their success rate and efficiency.

1.2 Purpose

The purpose of this report is to investigate if there are any statistical variables that sales done by SAAB AB have a dependence on. To investigate this multiple logistic regression analyses will be performed on SAAB's won and lost orders. When this is done one can use the outcome of the logistic regressions to test potential future countries whether or not SAAB are more or less likely to win a specific order based upon the historical orders and the statistically explanatory variables.

1.3 Delimitations

There are limitations to the logistic regression procedure done in this report. For instance will it always be variance in the estimations so therefore the results should be viewed as indicators and that the calculated numbers present a range and not the absolute truth. There is also a limitation as to what can be inserted into a logistic regression model. There will also always be an individual and unique component to a defence and security material trade. These unique circumstances can range from individual political and historical relations between nations to the value of a procurement of an individual nation.

1.4 Longer summary and tutorial

This report has conducted a statistical analysis on the won and lost orders by SAAB that has been reported into the LIME CRM system. The analysis done is called a logistic regression analysis and is explained in great detail in section 1.5. This regression analysis is done against perceived and later confirmed statistically explanatory variables X1 to X6 explained in the beginning of section 1.5 below and in the notations above.

The outcome of the logistic regression analysis is a mathematical model that can calculate the implied probability of a successful sale to different countries that have not yet been approached by SAAB for a specific product. These implied probabilities are presented in different tables in the appendix section of this report. Short explanations and conclusions of these tables are presented in section 3.1.

There are a few important facts that you should be aware of when looking at the tables in the appendix section.

First is to always check the degrees of freedom (df) since the lower degrees of freedom that a data set has, the larger the variance of the outcome will be. Notice that if there is a sharp divide between the implied probabilities in the table it is due to the fact that there are not many data points that have been analysed and therefore not put too much rely on the outcome in the table.

Second is to remember that there is variance in the estimates in the regression analysis so the outcome in the tables should be interpreted as approximates.

Thirdly is to understand that the implied probabilities are only based on the explanatory variables that have been used in the regression analysis. So for instance if there are strong data outside of the analysis that suggest that sales to a certain country is impossible to achieve then the calculated model should be rejected.

A practical example is that trying to sell large and complex naval systems to Country51 is impossible since their navy is not very large so therefore any implied probabilities on Country51 for larger naval products are irrelevant. Another example is if SAAB has a major competitor stationed in a certain country. Then the implied probabilities from the model to sell similar products as the competitor are irrelevant.

It is recommended that a person who only wants the results of the report to look up the desired table in the appendix and read the corresponding section in section 3.1. One should also understand that the results are a statistical perspective based on the explanatory variables X1 to X6 and that it should be treated as such. It would be irresponsible not to apply common sense when looking at the tables since there are almost certainly countries inserted there that are impossible to sell the product to for reasons that are outside of the calculations.

1.5 Method and theoretical background

The hypothesis of this thesis is that there are statistically explanatory variables that can predict sales done by SAAB. These hypothetically explanatory variables where chosen as follows:

X1 – size of order in KSEK was chosen as a potential explanatory variable since when trying to sell any product, it is reasonable to assume that the price has some sort of statistical influence on if the sell is successful or not.

X2 – dummy variable for NATO membership. This variable was chosen since SAAB sell a lot of its products within the defence and security sector. Therefore it is reasonable to assume that there is a statistical connection between a membership of the defence alliance NATO and whether or not SAAB are successful in selling defence and security products to that country.

X3 – gross domestic product over capita. It is reasonable to assume that countries with a higher gross domestic product over capita should be more interested in buying modern and expensive defence and security material.

X4 – total arms imports in M$ between the years 2000 and 2016. This one is obviously interesting since countries that have a larger arms import registered by SIPRI between the years 2000 and 2016 should have a greater demand for SAAB’s defence and security products.

X5 – total arms import over total arms trade between the years 2000 and 2016. This variable gives the ratio between a countrys´ imported and exported arms according to SIPRI. This could absolutely have a statisticalinfluence within SAAB’s sales of its defence and security products since countries with a higher import ratio could have a greater interest.

X6 – Total defence spending over gross domestic product in the year 2015. X6 is assumed to be a statistically explanatory variable since it is reasonable to assume that countries that spend more on their defence could be more interested in SAAB’s defence and security products.

The explanatory variables are then implemented with logistic regression against the won and lost orders from SAAB’s internal LIME CRM system.

1.5.1 Logistic regression

A logistic regression model assumes that the outcome is binary and takes the value 0 or 1. This means that the outcome, Y, can be viewed as a Bernoulli-distributed random variable as shown in (1) below.

$$Y \sim \mathrm{Be}\big(\sigma(\boldsymbol{x\beta})\big) \tag{1}$$

The variable $\boldsymbol{x}_i = [1 \quad x_{i1} \quad x_{i2} \quad \dots \quad x_{ik}]$ is the given independent data that is presumed to be dependent of the response variable Y and $\boldsymbol{\beta} = [\beta_0 \quad \beta_1 \quad \beta_2 \quad \dots \quad \beta_k]^{\boldsymbol{T}}$ is the unknown parameters that is calculated when implementing the logistic regression model.

$$\boldsymbol{x\beta} = \beta_0 + \beta_1 x_1 + \dots + \beta_k x_k \tag{2}$$

The logistic function is given in (3) as:

$$\sigma(z) = \frac{1}{1 + e^{-z}} \tag{3}$$

The probability mass function generated from (1) then becomes:

$$P_Y(y) = \sigma(\boldsymbol{x\beta})^y \big(1 - \sigma(\boldsymbol{x\beta})\big)^{1-y} \tag{4}$$

The name logistic regression is used because:

$$Ln\left(\frac{P_Y(y=1)}{P_Y(y=0)}\right) = Ln\left(\frac{\sigma(\boldsymbol{x\beta})}{1 - \sigma(\boldsymbol{x\beta})}\right) = Ln\left(\left(\frac{1}{1 + e^{-\boldsymbol{x\beta}}}\right)\left(\frac{1}{1 - \frac{1}{1 + e^{-\boldsymbol{x\beta}}}}\right)\right) \tag{5}$$
$$= Ln\left(\frac{1}{1 + e^{-\boldsymbol{x\beta}} - 1}\right) = \ \boldsymbol{x\beta}$$

The data to be analyzed is denoted as:

$$D = (\boldsymbol{x_i}, y_i)_{i=1}^{N} \tag{6}$$

Where each of the samples are interpreted as independent and identically distributed random variables with a Bernoulli distribution as described in (1) the likelihood function is given as:

$$L(D, \boldsymbol{\beta}) = \prod_{i=1}^{n} P_Y(y_i) = \prod_{i=1}^{n} \sigma(\boldsymbol{x_i\beta})^{y_i} \big(1 - \sigma(\boldsymbol{x_i\beta})\big)^{1-y_i} \tag{7}$$

And the corresponding log-likelihood function then becomes:

$$Ln\big(L(D, \boldsymbol{\beta})\big) = \sum_{i=1}^{n} y_i Ln\big(\sigma(\boldsymbol{x_i\beta})\big) + (1 - y_i) Ln\big(1 - \sigma(\boldsymbol{x_i\beta})\big) \tag{8}$$

The cost function is then defined in (9) as:

$$J(\boldsymbol{\beta}) \triangleq -\frac{1}{n}Ln\big(L(D,\boldsymbol{\beta})\big) = -\frac{1}{n}\sum_{i=1}^{n} y_i Ln\big(\sigma(\boldsymbol{x_i\beta})\big) + (1-y_i)Ln\big(1-\sigma(\boldsymbol{x_i\beta})\big) \quad (9)$$

Where the gradient of the cost function becomes:

$$\frac{\partial}{\partial \boldsymbol{\beta}}\big(J(\boldsymbol{\beta})\big) = \begin{pmatrix} \frac{\partial}{\partial \beta_0}\big(J(\beta_0)\big) \\ \cdots \\ \frac{\partial}{\partial \beta_k}\big(J(\beta_k)\big) \end{pmatrix}^T \quad (10)$$

A practical rewriting is then performed to simplify the cost function

$$h_i = \sigma(\boldsymbol{x_i\beta}) \quad (11)$$

$$J(\boldsymbol{\beta}) = -\frac{1}{n}\sum_{i=1}^{n} y_i Ln(h_i) + (1-y_i)Ln(1-h_i) \quad (12)$$

Hence the gradient of the cost function can be expressed as:

$$\frac{\partial}{\partial \boldsymbol{\beta}}\big(J(\boldsymbol{\beta})\big) = \left(\frac{\partial}{\partial h_i}\big(J(\boldsymbol{\beta})\big)\right) * \left(\frac{\partial}{\partial \boldsymbol{\beta}}(h_i)\right) \quad (13)$$

The first factor in (13) becomes:

$$\begin{aligned} \frac{\partial}{\partial h_i}\big(J(\boldsymbol{\beta})\big) &= \frac{\partial}{\partial h_i}\left(-\frac{1}{n}\sum_{i=1}^{n} y_i Ln(h_i) + (1-y_i)Ln(1-h_i)\right) \\ &= -\frac{1}{n}\left[\sum_{i=1}^{n} y_i \frac{1}{h_i} - (1-y_i)\frac{1}{1-h_i}\right] \end{aligned} \quad (14)$$

The second factor in (13) becomes:

$$\frac{\partial}{\partial \boldsymbol{\beta}}(h_i) = \sigma'(\boldsymbol{x_i\beta}) * \boldsymbol{x_i} \quad (15)$$

To get any further one needs the derivative of the logistic function, which is given as:

$$\frac{d}{dx}\sigma(x) = \frac{d}{dx}\left(\frac{1}{1+e^{-x}}\right) = \frac{-(1+e^{-x})'}{(1+e^{-x})^2} = \frac{e^{-x}}{(1+e^{-x})^2} \tag{16}$$

(16) can be further simplified to:

$$\frac{e^{-x}}{(1+e^{-x})^2} = \sigma(x)\frac{e^{-x}}{1+e^{-x}} = \sigma(x)\left(\frac{1+e^{-x}}{1+e^{-x}} - \frac{1}{1+e^{-x}}\right) = \sigma(x)\big(1-\sigma(x)\big) \tag{17}$$

So in conclusion we have

$$\frac{d}{dx}\sigma(x) = \sigma(x)\big(1-\sigma(x)\big) \tag{18}$$

Hence the second factor in (13) becomes:

$$\frac{\partial}{\partial \boldsymbol{\beta}}(h_i) = \sigma(\boldsymbol{x_i}\boldsymbol{\beta})\big(1-\sigma(\boldsymbol{x_i}\boldsymbol{\beta})\big) * \boldsymbol{x_i} = h_i(1-h_i) * \boldsymbol{x_i} \tag{19}$$

Now one can finally put the entire gradient of the cost function together and get that:

$$\begin{aligned}\frac{\partial}{\partial \boldsymbol{\beta}}\big(J(\boldsymbol{\beta})\big) &= \left(-\frac{1}{n}\left[\sum_{i=1}^{n} y_i\frac{1}{h_i} - (1-y_i)\frac{1}{1-h_i}\right]\right) * \left(h_i(1-h_i) * \boldsymbol{x_i}\right) \\ &= -\frac{1}{n}\left[\sum_{i=1}^{n}\left(y_i(1-h_i) - (1-y_i)h_i\right) * \boldsymbol{x_i}\right] \\ &= \frac{1}{n}\left[\sum_{i=1}^{n}(h_i - y_i) * \boldsymbol{x_i}\right]\end{aligned} \tag{20}$$

When one has both the cost function and the gradient of the cost function and can finally optimize it in for instance MATLAB using the function fminunc.

1.5.2 Likelihood ratio tests

A likelihood ratio test is something that one can apply if there is an interest of reducing a logistic model. If one suspects that a variable introduced in the initial logistic model is of no statistical significance, then applying a likelihood ratio test is one way of finding out if it is desirable to reduce the logistic model. This is done by using a regular likelihood ratio test where two times the log-likelihood is preferable since it has a chi-square distribution.

The full model can be represented as FM and the reduced model as RM. Then the likelihood ratio test will look like in (24) below.

$$LR = 2ln\left(\frac{L(FM)}{L(RM)}\right) = 2\big[ln\big(L(FM)\big) - ln\big(L(RM)\big)\big] \tag{21}$$

Hence will this follow a chi-square distribution with the degrees of freedom being the difference in the number of parameters between the two models. This means that if LR has a large value. Then the reduction of the model should not be performed.

From (13) we have derived the log-likelihood function which can instead be applied when y is represented as the total number of wins and n is the total number of observations. Then the log-likelihood of the reduced model becomes

$$ln\big(L(RM)\big) = yln(y) + (n-y)ln(n-y) - nln(n) \tag{22}$$

Then when this approach is used to the full model one gets that the likelihood ratio test becomes

$$\begin{aligned} LR = 2\Bigg(\sum_{i=1}^{n} y_i ln(p_i) + (n_i - y_i)ln(1-p_i) \\ - \big(yln(y) + (n-y)ln(n-y) - nln(n)\big)\Bigg) \end{aligned} \tag{23}$$

1.5.3 Goodness of fit testing

There are several ways of testing the goodness of fit for a logistic regression model. In this section the most common ones will be presented.

1.5.3.1 Chi-square and standardised Pearson test goodness of fit test

A chi-square (χ^2) test for categorical data is given as

$$\chi^2 = \sum \frac{(Expected - Observed)^2}{Expected} \tag{24}$$

Where Expected is the expected value of an observation and Observed is the observed value that is being tested. If there are more than one observation then one of course must sum all the observations to get the total χ^2 value. So referring to an observation as y and the expected value of an observation as $\hat{y}$, where $\hat{y} = \sigma\big(\boldsymbol{x}\boldsymbol{\hat{\beta}}\big)$ and $\boldsymbol{\hat{\beta}}$ is the maximum likelihood estimation of $\boldsymbol{\beta}$, note that $\hat{y_i} = \sigma\big(\boldsymbol{x_i}\boldsymbol{\hat{\beta}}\big)$, (24) then gives when there are n observation that the χ^2 value can be written as

$$\chi^2 = \sum_{i=1}^{n} \frac{(\hat{y_i} - y_i)^2}{\hat{y_i}} \tag{25}$$

Now the degrees of freedom for a χ^2 test is given as

$$df = (Number\ of\ rows - 1) * (Number\ of\ columns - 1) \tag{26}$$

Which in the case of a logistic regression analysis where the categorical data has two rows ($y \in \{0,1\}$) and n columns representing the total amount of observations. Hence the total degrees of freedom for a chi-square test of a logistic regression outcome is simply

$$df = (2-1) * (n-1) = n-1 \tag{27}$$

This procedure of conducting a chi-square test has been developed by Pearson into a standardized Pearson test, which is similar in the procedure but has the value of χ^2 estimated in (28).

$$\chi^2 = \sum_{i=1}^{n} \frac{(\widehat{y_i} - y_i)^2}{\widehat{y_i}(1-\widehat{y_i})} \tag{28}$$

So in conclusion the standardized Pearson test with $df = n-1$ is the preferred method of choice when testing the goodness of fit for a logistic regression. It is worth mentioning again that a small value of the chi-square value corresponding to large p-values is desired if the model should be considered of having a good goodness of fit.

It should be mentioned that if similar patterns emerge between covariates one should analyze each pattern individually. This means that if there is a pattern, J, then if J is close in numbers to the number of total observations, n, then this test does become weak.

1.5.3.2 Hosmer-Lemeshow test

This test is similar to the standardized Pearson test in the sense that it also uses the chi-square distribution to test the goodness of fit. The difference between them is that the Hosmer-Lemeshow test splits the data between wins and losses. This lowers the degrees of freedom to $df = g-2$ where g is the total number of observations looked into.

$$HL = \frac{(Expected\ wins - Observed\ wins)^2}{Expected\ wins} + \frac{(Expected\ losses - Observed\ losses)^2}{Expected\ losses} \tag{29}$$

The Hosmer-Lemeshow statistic presented in (29) can also be written in a more mathematically formal manner. This usually looks like

$$HL = \sum_{i=1}^{n} \frac{(O_i - N_i\widehat{y_i})^2}{N_j\widehat{y_i}(1-\widehat{y_i})} \tag{30}$$

Where O_i are the observed number of wins. N_j is the number of the specific group that are being looked into.

It is again worth reminding that a small value of HL will render a large p-value from the χ^2-distribution. This outcome is preferable since then the model has a good goodness of fit.

1.5.4 Model reduction control with AIC or BIC

The Akaike information criterion (AIC) presented by Akaike in 1973 is a test of a model that maximizes the expected entropy of the model. Entropy is a measure of expected information so therefore the AIC is a reduced log-likelihood measure. The definition of AIC is given in (31).

$$AIC = -2ln(L) + 2k \tag{31}$$

In (31) $ln(L)$ represent the log-likelihood function and k represents the number of parameters within the model. This means that when applying AIC onto a logistic regression analysis one needs the log-likelihood, which is also referred to as the deviance. The deviance is therefore given as

$$D = -2\sum_{i=1}^{n} y_i ln(\widehat{y_i}) + (1 - y_i)ln(1 - \widehat{y_i}) \tag{32}$$

Now (31) and (32) gives that the AIC for logistic regression can be written as

$$AIC = D + 2k \tag{33}$$

Then when one wants to investigate if there is a desire to reduce the model one should calculate the AIC value for both the full and the reduced model. The one with the lowest AIC-value should then be used since it is the best one.

Since AIC was introduced in 1973 there have been several other popular extensions of this practice. One of the most popular ones is the Bayesian information criteria (BIC) introduced by Schwartz in 1978. This is given as

$$BIC = D + kln(n) \tag{34}$$

Where n is the total number of observations. BIC is implemented in the same manner as AIC where the BIC-value is calculated for both the full and the reduced model and then the ones with the lowest BIC-value is the preferred choice.

1.5.5 Weakness of logistic regression

There are some weaknesses with logistic regression analysis. One is that if the sample size of the data of interest is below approximately 200 then the estimates will have an impactful bias. This is a natural problem that will occur many times in the results in this report since the sample size is below 200 most if the times. This problem is something one has to remember when drawing conclusions that there is a small sample size with an inherent bias as a result of it.

Skewed data sets are another problem that can occur within logistic regression. This is also something that will occur in some of the results. Skewed data sets means that a large number of the data points are either just a won or just a lost deal. If the data sets is too skewed, meaning that there is only one or two wins or losses and many more for the other one it should be rejected in the analysis since the outcome will be too misleading. Skewed data sets (or rare events in data) is something that has been looked into by King and Zeng (2001). They tested two methods where one is to insert a prior correction term from Bayes' formula. This for β_0 for instance becomes

$$\beta_{0,corrected} = \beta_0 - ln\left[\left(\frac{1-\tau}{\tau}\right)\left(\frac{\bar{y}}{1-\bar{y}}\right)\right] \tag{35}$$

Where τ represent the actual win probability. This term can be very hard to calculate exactly using additional data. Hence this method of using a probability prior in order to correct he estimates can be insufficient.

King and Zeng (2001) also tested a weighting procedure on the log-likelihood function (8) where (8) can be rewritten to

$$lnL_w(\boldsymbol{\beta}|\mathbf{y}) = \sum_{i=1}^{n} w_1 ln(p_i) + w_0 ln(1-p_i) = -\sum_{i=1}^{n} w_i ln\left(1 + e^{(1-2y_i)x_i\beta}\right) \tag{36}$$

Where $w_1 = \tau/\bar{y}$ and $w_0 = (1-\tau)/(1-\bar{y})$ and then one has that the general weights can be calculated as

$$w_i = w_1 y_i + w_0(1-y_i) \tag{37}$$

Now this weighting procedure does also have the same problem as the prior procedure had in that it requires τ in order to improve the model.

There can also be a problem with the fact that the maximum likelihood function is not defined when there is a complete separation of explanatory variables between wins and losses as can be seen in Figure 1 below where **x** is two-dimensional for graphical reasons. This problem is of course valid for multidimensional properties of **x**.

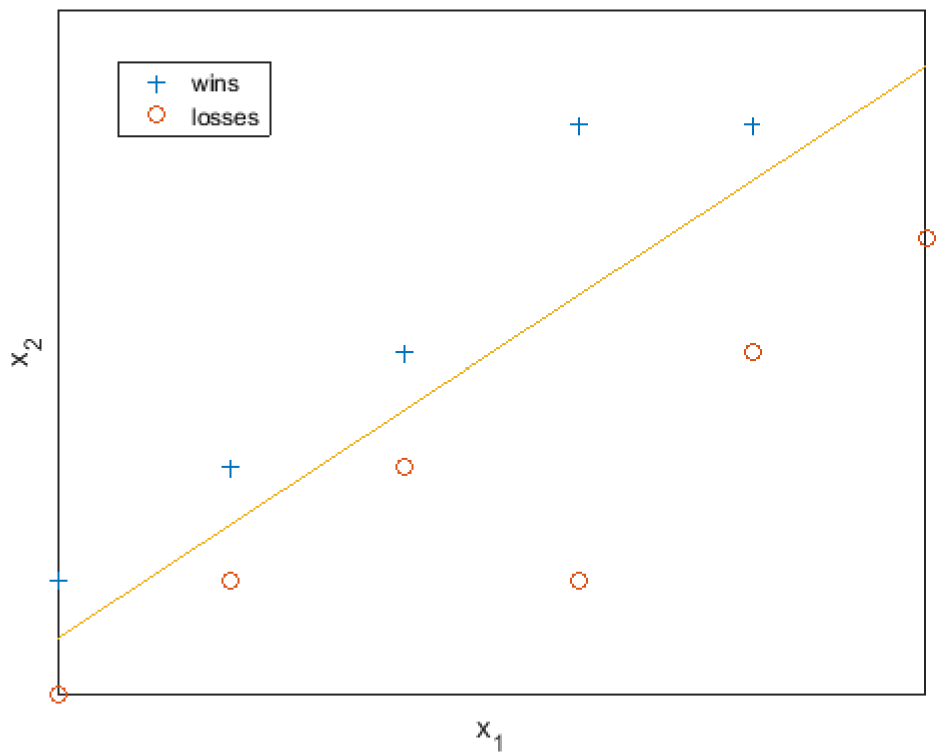


Figure 1. Complete separation between wins and losses

When there is a complete separation of explanatory variables the maximum likelihood is not defined. This phenomenon was is discussed by Albert and Anderson (1984) and a good empirical approach for detection this problem is if the solution yields a complete separation as well. That was that if the solution yield an implementation where the implied probabilities become either 1 or 0 then one must see this as an indicator of complete separation. This phenomenon is of course also more likely to occur if the sample size that is being modeled is rather small and also if the sample size is similar in size to the number of explanatory variables. When calculating this in practice it is good to use an optimizer that uses a stopping rule if the maximum likelihood becomes undefined. It was discovered during the work of the thesis that MATLABs fminunc does have this sort of stopping built into it. It was also discovered that Excels solver does not have this stopping mechanism built in. At least not by default.

The topic of complete and quasi-complete separation has also been extensively looked into by Allison (2008) using SAS. It looked into specific solutions when working in SAS, but it also concluded that using a penalized maximum likelihood function is a preferable solution when handling problems with separation.

1.5.6 Small sample size in logistic regression

There are a lot of research done on the implication of logistic regression on a small sample size. One is Rainey and McCaskey (2015) where they investigate bias in the estimated parameters in logistic regression with small sample sizes. What is found is that there is a significant bias on smaller sample sizes and that it gradually shrinks up until the sample size is about 200. They have implemented the regular maximum likelihood estimation and compared it to a penalized maximum likelihood developed by Firth (1993). The penalized maximum likelihood is just an implemented Jeffrey's invariant prior and it gave the equation

$$lnL^*(\boldsymbol{y}, \boldsymbol{\beta}) = \sum_{i=1}^{n} y_i ln(p_i) + (1 - y_i) ln(1 - p_i) + \frac{1}{2} log|I\beta| \qquad (38)$$

Which reduced the bias of the estimates.

This method was tested in this thesis as well but with a different outcome. The bias reduction achieved in Rainey and McCaskey (2015) was not evident for the sell-data from SAAB. Hence the penalized maximum likelihood method is omitted from the report and regular maximum likelihood was used instead.

2 RESULTS

2.1 Optimized logistic models

The constructed ranking tables for the corresponding results are presented in the appendix. Those tables are colored with green when the implied probability is above 0.9. Yellow when the implied probability is between 0.5 and 0.9 and red when the implied probability is below 0.5. This has no mathematical meaning. It is just a way for SAABs employees to easier visualize the implied probabilities.

The results presented in this section are the optimal models according to AIC and BIC.

2.1.1 Air and airborne solutions

Air and airborne solutions have three lost order and eight won orders. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=15.3073 and BIC=17.6946 for the full model and AIC=10.1424 and BIC=11.3361 for the reduced model. Hence the model was reduced to three explanatory variables. The Pearson chi-square value for the optimized model was 3.2922 with df=10 and that gives a p-value of 0.9737. The significant covariates are given in table A1 below:

Table 1. Air and Airborne solutions

Ln(X1)	The size of the order
X2	Dummy of NATO membership
X5	Imported arms over total arms trade since 2000

- List of explanatory variables for Air and airborne solutions.

2.1.2 Air Defence radar

Air defence radar have 14 lost order and 15 won orders. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=37.9426 and BIC=46.1464 for the full model and AIC=34.1177 and BIC=39.5869 for the reduced model. Hence the model was reduced to four explanatory variables. The Pearson chi-square value for the optimized model was 23.8576 with df=28 and that gives a p-value of 0.6891. The significant explanatory variables are given in table A2 below:

Table 2. Air defence radar

Ln(X1)	The size of the order
X2	Dummy of NATO membership
Ln(X3)	Gross domestic product over capita
X5	Imported arms over total arms trade since 2000

- List of explanatory variables for Air Defence radar.

2.1.3 Airborne ESM/ELINT

Airborne ESM/ELINT have lost orders to 6 different countries and won orders from four different countries. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=12.1853 and BIC=14.0008 for the full model and AIC=8.5080 and BIC=9.7183 for the reduced model. Hence the model was reduced to four explanatory variables. The Pearson chi-square value for the optimized model was 0.2659 with df=9 and that gives a p-value of 1. The significant covariates are given in table A3 below:

Table 3. Airborne ESM/ELINT

Ln(X1)	The size of the order
Ln(X3)	Gross domestic product over capita
Ln(X4)	Total arms imports in M$ between the years 2000 and 2016
X5	Imported arms over total arms trade since 2000

- List of explanatory variables for At4.

2.1.4 At4

At4 have lost orders to three different countries and won orders from eleven different countries. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=12.0259 and BIC=15.8603 for the full model and AIC=10.0266 and BIC=13.2218 for the reduced model. Hence the model was reduced to five explanatory variables. The Pearson chi-square value for the optimized model was 0.0133 with df=13 and that gives a p-value of 1. The significant explanatory variables are given in table A4 below:

Table 4. At4

Ln(X1)	The size of the order
X2	Dummy of NATO membership
Ln(X4)	Total arms imports in M$ between the years 2000 and 2016
X5	Imported arms over total arms trade since 2000
X6	Military spending over gross domestic product

- List of explanatory variables for At4.

2.1.5 CBRN

CBRN have lost orders to three different countries and won orders from nine different countries. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=12.0272 and BIC=15.4169 for the full model and AIC=6.1248 and BIC=7.2546 for the reduced model. Hence the model was reduced to two explanatory variables. The Pearson chi-square value for the optimized model was 1.3822 with df=12 and that gives a p-value of 0.9999. The significant covariates are given in table A5 below:

Table A5. CBRN

X2	Dummy of NATO membership
X5	Imported arms over total arms trade since 2000

- List of explanatory variables for CBRN.

2.1.6 CNS/ATC US NL

CSN/ATC US NL have lost orders to seven different countries and won orders from 17 different countries. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=41.1339 and BIC=51.8390 for the full model and AIC=37.4489 and BIC=44.5856 for the reduced model. Hence the model was reduced to four explanatory variables. The Pearson chi-square value for the optimized model was 30.4866 with df=43 and that gives a p-value of 0.9243. The significant covariates are given in table A6 below:

Table A6. CNS/ATC US NL

Ln(X1)	The size of the order

X2	Dummy of NATO membership
X5	Imported arms over total arms trade since 2000
X6	Military spending over gross domestic product

- List of explanatory variables for CNS/ATC US NL.

2.1.7 Component maintenance

Component maintenance have lost orders to 19 different countries and won orders from nine different countries. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=70.6655 and BIC=82.4872 for the full model and AIC=68.8576 and BIC=78.7090 for the reduced model. Hence the model was reduced to five explanatory variables. The Pearson chi-square value for the optimized model was 52.0529 with df=52 and that gives a p-value of 0.4719. The significant covariates are given in table A7 below:

Table A7. Component maintenance

X2	Dummy of NATO membership
Ln(X3)	Gross domestic product over capita
Ln(X4)	Total arms imports in M$ between the years 2000 and 2016
X5	Imported arms over total arms trade since 2000
X6	Military spending over gross domestic product

- List of explanatory variables for Component maintenance.

2.1.8 Counter measure despencer system

Counter measure despencer system have lost orders to four different countries and won orders from ten different countries. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=22.7105 and BIC=26.5448 for the full model and AIC=17.7708 and BIC=19.6879 for the reduced model. Hence the model was reduced to three explanatory variables. The Pearson chi-square value for the optimized model was 12.4269 with df=13 and that gives a p-value of 0.4930. The significant covariates are given in table 8 below:

Table 8. Counter measure despencer system

Ln(X1)	The size of the order
X2	Dummy of NATO membership
X5	Imported arms over total arms trade since 2000

- List of explanatory variables for Counter measure despencer system.

2.1.9 E & PS

E & PS have lost orders to three different countries and won orders from eleven different countries. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=22.7262 and BIC=26.9745 for the full model and AIC=18.7905 and BIC=21.6227 for the reduced model. Hence the model was reduced to four explanatory variables. The Pearson chi-square value for the optimized model was 9.4001 with df=14 and that gives a p-value of 0.8046. The significant covariates are given in table 9 below:

Table 9. E & PS

Ln(X1)	The size of the order
X2	Dummy of NATO membership
Ln(X3)	Gross domestic product over capita
X5	Imported arms over total arms trade since 2000

- List of explanatory variables for E & PS.

2.1.10 Flight control and actuation systems

Flight control and actuation systems should have every order treated as an independent event. It had 73 different won orders and 32 different lost ones. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=97.8783 and BIC=113.8589 for the full model and AIC=94.2145 and BIC=102.2048 for the reduced model. Hence the model was reduced to three explanatory variables. The Pearson chi-square value for the optimized model was 122.8526 with df=105 and that gives a p-value of 0.1124. The significant covariates are given in table 10 below:

Table 10. Flight control and actuation systems

Ln(X1)	The size of the order
Ln(X3)	Gross domestic product over capita
X5	Imported arms over total arms trade since 2000

- List of explanatory variables for Flight control and actuation systems.

2.1.11 Force on target

Force on target should have every order treated as an independent event. It had 55 different won orders and 63 different lost ones. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=152.3998 and BIC=169.0239 for the full model and AIC=147.5252 and BIC=155.8372 for the reduced model. Hence the model was reduced to three explanatory variables. The Pearson chi-square value for the optimized model was 123.9081 with df=117 and that gives a p-value of 0.3133. The significant covariates are given in table 11 below:

Table 11. Force on target

Ln(X1)	The size of the order
Ln(X3)	Gross domestic product over capita
X6	Military spending over gross domestic product

- List of explanatory variables for Force on target.

2.1.12 Integrated communication solutions

Integrated Communication solutions should have every order treated as an independent event. It had 91 different won orders and 54 different lost ones. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=171.1249 and BIC=188.9853 for the full model and AIC=169.5324 and BIC=184.4161 for the reduced model. Hence the model was reduced to five explanatory variables. The Pearson chi-square value for the optimized model was 154.2427 with df=144 and that gives a p-value of 0.2647. The significant covariates are given in table 12 below:

- Table 12. Integrated communications solutions.

Ln(X1)	The size of the order
X2	Dummy of NATO membership
Ln(X3)	Gross domestic product over capita
Ln(X4)	Total arms imports in M$ between the years 2000 and 2016
X5	Imported arms over total arms trade since 2000

- List of explanatory variables for integrated communication solution.

2.1.13 Integrated **self-protection system**

Integrated Communication solutions should have every order treated as an independent event. It had 23 different won orders and 38 different lost ones. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=88.5750 and BIC=101.2403 for the full model and AIC=88.9946 and BIC=90.3272 for the reduced model. Hence the model was reduced to three explanatory variables. The Pearson chi-square value for the optimized model was 60.7366 with df=60 and that gives a p-value of 0.4491. The significant covariates are given in table 13 below:

- Table 13. Integrated self-protection system

X2	Dummy of NATO membership
X5	Imported arms over total arms trade since 2000
X6	Military spending over gross domestic product

- List of explanatory variables for integrated self-protection system.

2.1.14 Land and naval support solution

Land and naval support solutions should have every order treated as an independent event. It had 315 different won orders and 68 different lost ones. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=326.3890 and BIC=350.0773 for the full model and AIC=320.4351 and BIC=332.2792 for the reduced model. Hence the model was reduced to three explanatory variables. The Pearson chi-square value for the optimized model was 363.3033 with df=382 and that gives a p-value of 0.7465. The significant covariates are given in table 13 below:

- Table 13. Land and naval support solution

Ln(X1)	The size of the order
X5	Imported arms over total arms trade since 2000
X6	Military spending over gross domestic product

- List of explanatory variables for land and naval support solution.

2.1.15 Land ESM/ELINT

Land ESM/ELINT have lost orders to 8 different countries and won orders from 2 different countries. Hence it has a large enough data set to be implemented into the logistic regression model. But the sample size should be considered small.

The logistic model had AIC=12.0000 and BIC=13.8155 for the full model and AIC=4.0244 and BIC=4.6296 for the reduced model. Hence the model was reduced to two explanatory variables. The Pearson chi-square value for the optimized model was 0.0122 with df=9 and that gives a p-value of 1. The significant covariates are given in table 14 below:

- Table 14. Land ESM/ELINT

Ln(X1)	The size of the order

X2	Dummy of NATO membership

- List of explanatory variables for land ESM/ELINT.

2.1.16 Land self-protection system

Land self-protection system should have every order treated as an independent event. It had 8 different won orders and 20 different lost ones. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=20.5282 and BIC=28.5214 for the full model and AIC=16.9981 and BIC=22.3269 for the reduced model. Hence the model was reduced to four explanatory variables. The Pearson chi-square value for the optimized model was 7.6123 with df=27 and that gives a p-value of 0.9999. The significant covariates are given in table 15 below:

- Table 15. Land self-protection system

Ln(X1)	The size of the order
X2	Dummy of NATO membership
Ln(X3)	Gross domestic product over capita
X6	Military spending over gross domestic product

- List of explanatory variables for land self protection system

2.1.17 Land solutions

Land solutions should have every order treated as an independent event. It had 115 different won orders and 11 different lost ones. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=36.9909 and BIC=54.0086 for the full model and AIC=33.3013 and BIC=38.9738 for the reduced model. Hence the model was reduced to two explanatory variables. The Pearson chi-square value for the optimized model was 96.8672 with df=125 and that gives a p-value of 0.9707. The covariates are given in table 16 below:

- Table 16. Land solutions

Ln(X1)	The size of the order
X5	Imported arms over total arms trade since 2000

- List of explanatory variables for land solutions.

2.1.18 Land vetronics systems

Land vetronics systems should have every order treated as an independent event. It had 67 different won orders and 15 different lost ones. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=83.3218 and BIC=97.7621 for the full model and AIC=78.9726 and BIC=86.1927 for the reduced model. Hence the model was reduced to three explanatory variables. The Pearson chi-square value for the optimized model was 93.4884 with df=81 and that gives a p-value of 0.1619. The significant covariates are given in table 17 below:

- Table 17. Land vetronics systems

X2	Dummy of NATO membership
Ln(X3)	Gross domestic product over capita
Ln(X4)	Total arms imports in M$ between the years 2000 and 2016

- List of explanatory variables for land vetronics systems.

2.1.19 Live simulations

Live simulations should have every order treated as an independent event. It had 145 different won orders and 32 different lost ones. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=142.4044 and BIC=161.4613 for the full model and AIC=138.8279 and BIC=151.5325 for the reduced model. Hence the model was reduced to three explanatory variables. The Pearson chi-square value for the optimized model was 185.4246 with df=176 and that gives a p-value of 0.2984. The significant covariates are given in table 18 below:

- Table 18. Live simulations

Ln(X1)	The size of the order
X2	Dummy of NATO membership
Ln(X4)	Total arms imports in M$ between the years 2000 and 2016
X5	Imported arms over total arms trade since 2000

- List of explanatory variables for live simulations.

2.1.20 Local situational awareness system

Local situational awareness system should have every order treated as an independent event. It had 7 different won orders and 6 different lost ones. This was spread over ten different countries. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=14.0145 and BIC=17.4042 for the full model and AIC=12.0345 and BIC=14.8593 for the reduced model. Hence the model was reduced to five explanatory variables. The Pearson chi-square value for the optimized model was 1.2797 with df=12 and that gives a p-value of 0.9999. The significant covariates are given in table 19 below:

- Table 19. Local situational awareness system

Ln(X1)	The size of the order
X2	Dummy of NATO membership
Ln(X3)	Gross domestic product over capita
Ln(X4)	Total arms imports in M$ between the years 2000 and 2016
X5	Imported arms over total arms trade since 2000

- List of explanatory variables for local situational awareness system.

2.1.21 Mobile camouflage

Mobile camouflage should have every order treated as an independent event. It had 60 different won orders and 5 different lost ones. Hence it has a large enough data set to be implemented into the logistic regression model.

It was not possible to find a combination of possible explanatory variables for the sales of mobile camouflage. This due to the fact that the chi-square test consistently got a p-value too close to zero to find any useable model.

2.1.22 Mortar systems

Mortar systems have lost orders to seven different countries and won orders from five different countries. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=12.0589 and BIC=14.9683 for the full model and AIC=8.0769 and BIC=10.0165 for the reduced model. Hence the model was reduced to four explanatory variables. The Pearson chi-square value for the optimized model was 0.0387 with df=11 and that gives a p-value of 1. The significant covariates are given in table A21 below:

Table 20. Mortar systems

Ln(X1)	The size of the order
X2	Dummy of NATO membership
Ln(X3)	Gross domestic product over capita
Ln(X4)	Total arms imports in M$ between the years 2000 and 2016

- List of explanatory variables for mortar systems.

2.1.23 Naval ESM/ELINT

Naval ESM/ELINT have lost orders to 17 different countries and won orders from ten different countries. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=46.7247 and BIC=56.8579 for the full model and AIC=42.7701 and BIC=49.5256 for the reduced model. Hence the model was reduced to four explanatory variables. The Pearson chi-square value for the optimized model was 45.6925 with df=39 and that gives a p-value of 0.2139. The significant covariates are given in table 22 below:

Table 21. Naval ESM/ELINT

Ln(X1)	The size of the order
X2	Dummy of NATO membership
Ln(X3)	Gross domestic product over capita
X5	Imported arms over total arms trade since 2000

- List of explanatory variables for naval ESM/ELINT.

2.1.24 Naval radar

Naval ESM/ELINT have lost orders to 17 different countries and won orders from 15 different countries. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=47.8919 and BIC=56.6863 for the full model and AIC=44.1227 and BIC=49.9857 for the reduced model. Hence the model was reduced to four explanatory variables. The Pearson chi-square value for the optimized model was 31.1253 with df=31 and that gives a p-value of 0.4599. The significant covariates are given in table 22 below:

- Table 22. Naval Radar

Ln(X1)	The size of the order
X2	Dummy of NATO membership
Ln(X4)	Total arms imports in M$ between the years 2000 and 2016
X5	Imported arms over total arms trade since 2000

- List of explanatory variables for naval radar.

2.1.25 Naval solutions

Naval solutions should have every lost order treated as an independent event. It has won orders from 19 different countries and lost 53 orders. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=90.7765 and BIC=104.6008 for the full model and AIC=84.7089 and BIC=87.0130 for the reduced model. Hence the model was reduced to one explanatory variable. The Pearson chi-square value for the optimized model was 74.0439 with df=73 and that gives a p-value of 0.4439. The significant covariates are given in table 23 below:

Table 23. Naval solutions

Ln(X3)	Gross domestic product over capita

- List of explanatory variables for naval solutions.

2.1.26 Operation center solution

Operation center solution have lost orders to 21 different countries and won orders from 11 different countries. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=42.8816 and BIC=51.6760 for the full model and AIC=38.2338 and BIC=41.1652 for the reduced model. Hence the model was reduced to three explanatory variables. The Pearson chi-square value for the optimized model was 33.1299 with df=31 and that gives a p-value of 0.3636. The significant covariates are given in table 24 below:

Table 24. Operation center solution

Ln(X1)	The size of the order
Ln(X4)	Total arms imports in M$ between the years 2000 and 2016

- List of explanatory variables for Operation center solution.

2.1.27 Radio monitoring systems

Radio monitoring systems have lost orders to 9 different countries and won orders from 22 different countries. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=40.2942 and BIC=48.8981 for the full model and AIC=35.9346 and BIC=40.2365 for the reduced model. Hence the model was reduced to three explanatory variables. The Pearson chi-square value for the optimized model was 27.7816 with df=30 and that gives a p-value of 0.5820. The significant covariates are given in table 25 below:

Table 25. Radio monitoring systems

Ln(X1)	The size of the order
X2	Dummy of NATO membership
X5	Imported arms over total arms trade since 2000

- List of explanatory variables for radio monitoring systems.

2.1.28 RBS 70

RBS 70 have lost orders to 13 different countries and won orders from 7 different countries. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=31.6901 and BIC=37.6645 for the full model and AIC=22.5930 and BIC=23.5887 for the reduced model. Hence the model was reduced to one explanatory variable. The Pearson chi-square value for the optimized model was 20.5930 with df=19 and that gives a p-value of 0.4080. The significant covariates are given in table 26 below:

Table 26. RBS 70

Ln(X1)	The size of the order

- List of explanatory variables for RBS 70.

Since RBS70 was best modelled from only the size of the order there is no need to make a table for different countries. It is enough to say that when the size of the order is 400MSEK then the p-value became 0.3787.

2.1.29 Regional aircraft support system

Regional aircraft support system have lost orders to 5 different countries and won orders from 12 different countries. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=21.5818 and BIC=26.5811 for the full model and AIC=19.8570 and BIC=24.0231 for the reduced model. Hence the model was reduced to five explanatory variables. The Pearson chi-square value for the optimized model was 10.2827 with df=16 and that gives a p-value of 0.8515. The significant covariates are given in table 27 below:

Table 27. Regional aircraft support system

Ln(X1)	The size of the order
X2	Dummy of NATO membership
Ln(X3)	Gross domestic product over capita
Ln(X4)	Total arms imports in M$ between the years 2000 and 2016
X5	Imported arms over total arms trade since 2000

- List of explanatory variables for regional aircraft support system.

2.1.30 Static camouflage

Static camouflage have lost orders to 8 different countries and won orders from 17 different countries. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=37.8088 and BIC=45.1221 for the full model and AIC=31.5096 and BIC=33.9474 for the reduced model. Hence the model was reduced to two explanatory variables. The Pearson chi-square value for the optimized model was 23.8524 with df=24 and that gives a p-value of 0.4701. The significant covariates are given in table 28 below:

Table 28. Static camouflage

X2	Dummy of NATO membership
Ln(X4)	Total arms imports in M$ between the years 2000 and 2016

- List of explanatory variables for static camouflage.

2.1.31 Training services

Training services have lost orders to 6 different countries and won orders from 17 different countries. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=28.4525 and BIC=35.2655 for the full model and AIC=23.4041 and BIC=26.8106 for the reduced model. Hence the model was reduced to three explanatory variables. The Pearson chi-square value for the optimized model was 15.0895 with df=22 and that gives a p-value of 0.8584. The significant covariates are given in table 29 below:

Table 29. Training services

X2	Dummy of NATO membership
Ln(X4)	Total arms imports in M$ between the years 2000 and 2016
X5	Imported arms over total arms trade since 2000

- List of explanatory variables for training services.

2.1.32 Underwater vehicles

Underwater vehicles have lost orders to 7 different countries and won orders from 3 different countries. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=12.0760 and BIC=13.8915 for the full model and AIC=6.8125 and BIC=7.7202 for the reduced model. Hence the model was reduced to three explanatory variables. The Pearson chi-square value for the optimized model was 0.4366 with df=9 and that gives a p-value of 1. The significant covariates are given in table 30 below:

Table 30. Underwater vehicles

Ln(X1)	The size of the order
X2	Dummy of NATO membership
Ln(X3)	Gross domestic product over capita

- List of explanatory variables for Underwater vehicles.

2.1.33 Weapon localization radar

Weapon localization radar have lost orders to 8 different countries and won orders from 10 different countries. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=30.9513 and BIC=36.2935 for the full model and AIC=25.9121 and BIC=27.6928 for the reduced model. Hence the model was reduced to two explanatory variables. The Pearson chi-square value for the optimized model was 18.0300 with df=17 and that gives a p-value of 0.3870. The significant covariates are given in table 31 below:

Table 31. Weapon localization radar

X2	Dummy of NATO membership
X5	Imported arms over total arms trade since 2000

- List of explanatory variables for weapon localization radar.

2.1.34 Virtual constructive and integration

Virtual constructive and integration have lost 45 orders and won orders from 15 different countries. Hence it has a large enough data set to be implemented into the logistic regression model.

The logistic model had AIC=70.4853 and BIC=83.0514 for the full model and AIC=64.8247 and BIC=71.1077 for the reduced model. Hence the model was reduced to three explanatory variables. The Pearson chi-square value for the optimized model was 59.0459 with df=59 and that gives a p-value of 0.4607. The significant covariates are given in table 32 below:

Table 32. Virtual constructive and integration

Ln(X1)	The size of the order
X2	Dummy of NATO membership
X5	Imported arms over total arms trade since 2000

- List of explanatory variables for virtual constructive and integration.

3 DISCUSSION AND CONCLUSIONS

3.1 Individual discussions

3.1.1 Air and airborne solutions

Air and airborne solutions have a small df of only 10. This means that the calculations from the logistic regression model will be not as certain as it would have been with a larger sample size. According to the structure of table A1 one can see a somewhat sharp division between zero and 1 within the implemented countries. This gives a hint that the data is most likely nearly separated. This means that somewhere in the three-dimensional space where the explanatory variables span a separation is most likely occurring.

Because of the small sample size one should be vary of relying too heavily on this model. But it can be used as an interesting statistic as to how the sales data have behaved statistically so far for SAAB.

So when evaluating potential future deals for air and airborne solutions it is recommended to use the explanatory statistics of X1, X2 and X5. This due to the fact that it was the preferred model by both AIC and BIC plus the fact that the Pearson chi-square test was statistically significant.

3.1.2 Air defence radar

Air defence radar have a relative small df of 28. This indicates that the calculations from the logistic regression model will be good and usable but one should always remember that the calculations are based on 29 different observations and therefore not perfect in any way. The structure of table A2 is relatively smooth so there is no indication of any separating explanatory variable within the model.

The Pearson chi-square test gives that the results are statistically significant. These four explanatory variables was preferred by both AIC and BIC so therefore is it the recommended model of choice.

3.1.3 Airborne ESM/ELINT

Airborne ESM/ELINT have a small df of only 9. This means that the calculations from the logistic regression model will be not as certain as it would have been with a larger sample size. According to the structure of table A3 one can see a somewhat sharp division between zero and 1 within the implemented countries. This gives a hint that the data is most likely nearly separated. This also means that somewhere in the four dimensional space spanned from the explanatory variables there is a nearly complete separation of the explanatory variables.

Because of the small sample size one should be vary of relying too heavily on this model. But it can be used as an interesting statistic as to how the sales data have behaved statistically so far for SAAB.

So when evaluating potential future deals for airborne ESM/ELINT it is recommended to use the explanatory statistics of X1, X3, X4 and X5. This due to the fact that it was the preferred model by both AIC and BIC. The Pearson chi-square test gives that the results are statistically significant.

3.1.4 At4

At4 has a small df of only 13. This means that the calculations from the logistic regression model will be not as certain as it would have been with a larger sample size. According to the structure of table A4 one can see a somewhat sharp division between zero and 1 within the implemented countries. This gives a hint that the data is most likely nearly separated. This also means that somewhere in the five dimensional space spanned from the explanatory variables there is a nearly complete separation of the explanatory variables.

Because of the small sample size one should be vary of relying too heavily on this model. But it can be used as an interesting statistic as to how the sales data have behaved statistically so far for SAAB.

So when looking into future potential deals for At4 it is recommended to use the explanatory variables X1, X2, X4, X5 and X6. This is because it was the preferred model by both AIC and BIC. The Pearson chi-square test gives that the results are statistically significant.

3.1.5 CBRN

CBRN has a small df of only 11. This means that the calculations from the logistic regression model will be not as certain as it would have been with a larger sample size. According to the structure of table A5 one can see a somewhat sharp division between zero and 1 within the implemented countries. This gives a hint that the data is most likely nearly separated. This also means that somewhere in the two dimensional space spanned from the explanatory variables there is a nearly complete separation of the explanatory variables.

Because of the small sample size one should be vary of relying too heavily on this model. But it can be used as an interesting statistic as to how the sales data have behaved statistically so far for SAAB.

So when evaluating potential future deals for CBRN it is recommended to use the explanatory statistics of X2 and X5. This due to the fact that it was the preferred model by both AIC and BIC. The Pearson chi-square test gives that the results are statistically significant.

3.1.6 CNS/ATC US NL

CNS/ATC US NL has a df of 43. This means that the model will not be as certain as it could have been with a larger sample size. The structure in table A6 indicates a smooth and wide distribution of implemented countries. This indicates that there is not a complete separation within the data.

AIC and BIC indicates that the preferred model is given by X1, X2, X5 and X6 The Pearson chi-square test gives that the results are statistically significant. This indicates that the CNS ATC US NL model could have an application when evaluating potential future markets.

3.1.7 Component maintenance

Component maintenance has a df of 52. The structure in table A7 indicates a smooth distribution between countries. This means that there is not a complete separation within the data.

AIC and BIC gives that the preferred model is given by X2, X3 X4, X5 and X6. The Pearson chi-square test gives that the results are statistically significant.

The model by the information above be implanted as a reference when investigating potential future markets but one should be aware of the fact that the df is 52 which is somewhat small.

3.1.8 Counter measure despencer system

Counter measure despencer system has a df of only 13. It does have a relative smooth but skewed distribution according to table A8 and therefore not likely a complete separation. But since the df is only 13 and still no complete separation between explanatory variables makes this model even weaker than the other products with a small sample size. So therefore should table A8 even though AIC and BIC combined with a statistically significant Pearson chi-square test, be considered weak and not very reliable.

In conclusion there are not much from the model that is recommended to be applied when investigating potential future markets.

3.1.9 E & PS

E & PS has a small df of only 14. The table A9 gives a smooth and wide distribution of the implemented countries different implied probabilities. This implies that there is no complete separation between the explanatory variables.

AIC and BIC prefers the model that is given by X1, X2, X3 and X5. The Pearson chi-square test gives that the results are statistically significant.

Since the df is as small as 14 one should be vary of relying too much on these calculations since there will be a bias in the estimates. But it can still be used as an interesting input in the strategical investigation into potential future markets for E & PS.

3.1.10 Flight control and actuation systems

Flight control and actuation systems have a df of 105. Table A10 gives a smooth and wide distribution of the implemented countries. This implies that there is no complete separation between the explanatory variables.

AIC and BIC prefers the model that is given by X1, X3 and X5. The Pearson chi-square test gives that the results are statistically significant.

Since the df is as large as 105 and that the Pearson chi-square test holds one can rely much more heavily on this model than those model with sample size numbers in the teens. So therefore one thing that stands out in table A10 is the preference for countries on the Arabian Peninsula. This is statistically significant compared to the other simulated countries and therefore something well worth looking into as to why SAAB has not attempted to sell flight control and actuation systems there since this logistic model strongly suggest that those countries would have a high success rate. It could be geo- or security-political reasons as to why that is but it is not something that is obvious to the author of this report.

3.1.11 Force on target

Force on target have a df of 117. Table A11 gives a smooth and wide distribution of implemented countries. Hence there is no apparent complete separation within the explanatory variables.

AIC and BIC prefers the model that is given by X1, X3 and X6. The Pearson chi-square test gives that the results are statistically significant.

Since the df is as large as 117 and the chi-square test holds one can draw more secure conclusions from table A11 than those other tests with much lower sample sizes. One interesting note is that X3 had a rather significant impact on the model which states that countries with higher gross domestic product over capita has a greater chance of buying force on target. It might seem as a redundant result but it is always good to have it confirmed. This is also one of the reasons why countries like Country51, Country57 and Country52 are more likely to buy Force on target than other countries. So in conclusion table A11 is well worth relying on when investigating the implied probabilities of a successful affair for a deal with force on target for 20M SEK.

3.1.12 Integrated communication solutions

Integrated communication solutions have a df of 144. Table A12 gives a smooth and wide distribution of implemented countries. Hence there is no apparent complete separation within the explanatory variables.

AIC and BIC prefers the model which is made of X1, X2, X3, X4 and X5. The Pearson chi-square test gives that the results are statistically significant.

Since the model has such a large df as 144 one can rely more on this one than those with a much smaller sample size. So the Table A12 is a good reference as to which countries are more or less likely to complete a sell to. For instance should SAAB be more interested in investigating potential sells of integrated communication solutions to Country75, Country48 or Country51 instead of countries like Country14, Country84 or Country39. To get the complete picture of the implied probabilities of a deal for 20M SEK one should simply just study table A12.

3.1.13 Integrated self-protection system

Integrated self-protection system has a df of 60. Table A13 gives a smooth and somewhat wide distribution of the implemented countries. Hence there is no apparent complete separation within the explanatory variables.

AIC and BIC prefers the model which is made of X2, X5 and X6. The Pearson chi-square test gives that the results are statistically significant.

Since the model has a relative large df of 60 one can somewhat rely on this model. Table A13 is therefore an interesting reference when investigating potential new markets but since the distribution is not that wide there are not that definitive conclusions to be drawn since Country70 is not even twice more likely to win an order from than Country78. This means that the results from table A13 indicates that there are not many concrete significant conclusions to be drawn for integrated self-protection system. But table A13 can still be use as a reference when investigation potential future markets.

3.1.14 Land and naval support solution

Land and naval support solution has a df of 382. Table A14 has a smooth and wide distribution of the implemented countries. It is therefore no apparent complete separation between the implemented countries.

AIC and BIC prefers the model that consists of X1, X5 and X6. The Pearson chi-square test gives that the results are statistically significant.

382 is a large df that gives a good statistical fit to the explanatory variables. Hence can table A14 be considered a good reference when evaluating future potential markets. Therefore should Country30, Country48 and the Country12 be considered with much more interest than the countries Country74, Country43 and Country14.

3.1.15 Land ESM/ELINT

Land EMS/ELINT has a small df of only 9. Table A15 has a sharp split between the implemented countries. It is therefore likely to be a complete split between the explanatory variables. Even though the Pearson chi-square test and the AIC and BIC gives a statistically valid model one must be vary of the fact that it is a very small sample size and therefore not rely too much on table A15. So in conclusion one should be sceptical of the outcome in table A15.

3.1.16 Land self-protection system

Land self-protection system has a df of 27. Table A16 is very interesting where Country23 is considered much more likely than any other country for a potential successful market expansion. The AIC and BIC combined with the Pearson chi-square test gives that the model is statistically significant. But since the df is only 27 there will be a bias in the estimates. Despite the weakness of the model it is recommended to at least investigate if it is possible to sell a land self-protection system to Country23.

In the original data it was obvious that there was a lot of lost orders with higher values above 100M SEK. This is problematic since there are several won orders in the smaller ranges. This implies that it would be more suitable to pursuit orders in the range of 50M SEK or smaller, as implemented in table A16, since the success rate was much higher there.

3.1.17 Land solutions

Land solutions has a df of 125. Table A17 has a smooth and wide distribution. The Pearson chi-square test gives that the results are statistically significant. Since the sample size is relatively large there can be a much larger significance put into the result in table A17. It is therefore just to recommend the best potential future Land solutions sales as Country16, Country52 and Country30. Then the countries that one should be aware of has a low chance of success are, for instance, Country29, Country49 and Country75.

3.1.18 Land Vetronics systems

Land vetronics systems has a df of 81. Table A18 has a smooth and wide but slightly skewed distribution. This indicates that any possible deal is more likely to succeed than to fail based on historical data. Since the df are reasonably high one can somewhat rely on this outcome but be aware of that the data is skewed. AIC and BIC combined with the Pearson chi-square test gives a statistically significant outcome.

Table A18 indicates that most countries are possible to sell land vetronics systems to. This is an important conclusion in and of itself since if one wonders if a potential deal with land vetronics systems will be successful or not the general conclusion is that most countries are. There are some more likely than others and a special mention to the African nations of Country54, Country46 and Country47 since they are very likely to succeed in a potential sell if there is an interest from them. It is also worth mentioning that countries on the Arabian Peninsula like Country74, Country75 and the Country7 are less likely to succeed in a potential sell.

3.1.19 Live simulations

Live simulations has a df of 176. The distribution in table A19 is smooth and wide. The Pearson chi-square test gives that the results are statistically significant. Since the sample size is rather large this result has a good reliability.

Table A19 gives a rather diverse mix of different good and less good countries for potential future market gains. So it is therefore just to conclude that the countries of Country48, Country51 and Country72 are statistically recommended countries to try and sell live simulations to if there are an interest from those countries. In the same manner one can conclude that the countries of Country14, Country49 and the Country7 are less likely to successfully sell live simulations to.

3.1.20 Local situational awareness system

Local situational awareness system has a df of 12. The distribution in Table A20 has a somewhat sharp split within it. This gives a hint that there is probably an almost complete split within the explanatory variables. Since the sample size within the model is so small one must take the results in Table A20 with caution since there is a significant bias within the model.

Table A20 can still be used as a recommendation to which countries are somewhat more or less likely to successfully sell local situational awareness systems to but it would be dangerous to rely too heavily on the outcome in table A20. This despite that the Pearson chi-square test gives that the outcome is statistically significant.

3.1.21 Mortar systems

Mortar systems has a df of 11. The distribution in table A21 is very sharply split within. This gives a clear indication that there is a complete separation of explanatory variables within the model. Since the sample size is so small this is not surprising. It is therefore not recommended to rely too much on the outcome in table A21 since it is very uncertain. But one can always say that the countries with an implied probability of success at one is mostly more likely to succeed than those with an implied probability of approximately zero.

The Pearson chi-square test gives that the model preferred by both AIC and BIC is statistically significant.

3.1.22 Naval ESM/ELINT

Naval ESM/ELINT has a df of 39. The distribution in table A22 is smooth and wide but somewhat skewed. The skewness is there because there are a lot more failed sales than there are successful ones. The Pearson chi-square test gives that the results are statistically significant.

Since the data has a df of 39 it can be relied more upon than those with a sample size in the teens. But that there is a bias within the model due to the sample size is something that one should be aware of. Despite this it is still reasonable that from table A22 draw the conclusion that good potential future markets for naval ESM/ELINT are Country16, Country56 and the Country73. Similarly one can draw the conclusion that the countries Country75, Country78 and Country35 are less likely to buy Naval ESM/ELINT products from SAAB.

3.1.23 Naval radar

Naval radar has a df of 31. The distribution in table A23 is smooth and wide but somewhat skewed. The Pearson chi-square test gives that the results in table A23 are statistically significant. Since the sample size is relatively small there will be some bias within the model. But the results from table A23 are still statistically significant and therefore one can conclude that the countries Country73, Country84 and Country49 are preferable when trying to expand the market of naval radar. By the same reasoning can it be concluded that the countries Country48, Country75 and Country76 are less likely to be successful in trying to sell naval radar to.

3.1.24 Naval solutions

Naval solutions has a df of 73. The distribution in table A24 is smooth and wide but skewed towards the lower end. The Pearson chi-square test gives that the results are statistically significant. Since the sample size is relatively large the variance in the estimates are reduced. However AIC and BIC wanted to remove all potentially explanatory variables except X3. This means that X3 alone was the best model for naval solutions, which is not ideal but it is applicable. So therefore the general conclusion from naval solution is that since β_3 was positive then countries with a high gross domestic product over capita are more likely to buy naval solutions from SAAB.

3.1.25 Operation center solution

Operation center solution has a df of 31. The distribution in Table A25 is smooth and wide and slightly skewed towards the lower end. Since the sample size is not too small one can rely on the outcome. The Pearson chi-square test gives that the results are statistically significant. AIC and BIC preferred the modelling by X1 and X4.

In conclusion one can say that the countries Country14, Country74 and the Country59 are preferable when looking for future market expansions for Operation center solutions. In the lower end of table A25 are, among others, the countries of Country48, Country51 and Country16 which therefore are not recommended to try and sell operation center solutions to.

3.1.26 Radio monitoring systems

Radio monitoring systems has a df of 30. Table A26 has a smooth and wide distribution. The Pearson chi-square test gives that the results are statistically significant. AIC and BIC gave that X1, X2 and X5 are statistically significant when analysing the sell data of radio monitoring systems.

When looking into potential future market gains for radio monitoring systems the countries Country56, Country43 and the Country73 are preferable and the countries of Country41, Country55 and Country44 are not very likely to be successful.

3.1.27 RBS 70

RBS 70 has a df of 19. Table A27 was optimized with AIC and BIC and it concluded that the selling of RBS 70 was best statistically explanatory on only the size of the order. Hence are the possible conclusions very limited and the analysis rather meaningless. The only real conclusion one can draw from this calculation is that it is easier to sell RSB 70 when the order size is small than when the order size is larger. But that is not very useful and somewhat obvious before the calculation.

3.1.28 Regional aircraft support system

Regional aircraft support system has a df of 16. Table A28 is smooth and wide and somewhat skewed towards the top. The Pearson chi-square test gives that the results are statistically significant. The problem it has is that the sample size is somewhat small. Especially since there are five significant explanatories and only a df of 19. This is too far away from the recommended ratio of ten times more data points than explanatories. Hence is the variance larger than for most other tables but one can still use the table as a reference and there are still some countries that are statistically more likely to be successful than others.

The countries of Country44, Country79 and Country16 are statistically more likely to be successful in a potential market gain for SAAB's regional aircraft support system. The countries of Country14, Country80 and Country40 are less likely to be successful in completing a sell for SAAB.

3.1.29 Static camouflage

Static camouflage has a df of 24. Table A29 is smooth and wide. The Pearson chi-square test gives that the results are statistically significant. AIC and BIC preferred X2 and X4 as explanatories. This all gives that the results in table A29 are somewhat reliable but one must always be aware of the fact that there is a variance connected to the estimates.

The recommended countries for potential future market gains are therefore Country84, Country73 and Country55. By the same reasoning are the countries of Country20, Country33 and Country51 less likely to be successful.

3.1.30 Training services

Training services has a df of 22. Table A30 has a smooth and wide distribution. The Pearson chi-square test gives that the results are statistically significant. AIC and BIC concluded that X2, X4 and X5 was the best explanatory variables for the model. Since the sample size is not very large one must be aware of the variance within the estimates.

The model is still good enough to draw conclusion from table A30. Hence are the countries that are preferable to try and sell Training services to Country72, Country4 and Country38. By the same reasoning are the countries Country43 and the Country59 less likely to buy training services from SAAB.

3.1.31 Underwater vehicles

Underwater vehicles has a df of 9. Table A31 has a somewhat sharp split within it so it is likely that there is a close to complete separation of explanatory variables. This is due to the low sample size. The Pearson chi-square test gives that the results are statistically significant. But since there is a low sample size one must be aware of significant bias of the estimates. So therefore should one not rely too much one the possible conclusion from table A31 but one can always say that countries that have a close to 1 in p-value has most likely a greater chance of success than those with a p-value close to zero.

3.1.32 Weapon localization radar

Weapon localization radar has a df of 17. Table A32 has a smooth and somewhat wide distribution. The Pearson chi-square test gives that the results are statistically significant. AIC and BIC concluded that the best statistical modelling for weapon localization radar is done with X2 and X5. Since the sample size is rather small one should be aware of possible statistical bias against the model.

Since there is no split within the data and that the data set is almost ten times the number of explanatories one can somewhat reasonably rely on the result. It is therefore recommended to try and sell weapon localization radars to NATO countries that export more defence systems than they import. It is therefore recommended to try and sell to Country16, Country56 and Country52. By the same reasoning is recommended to avoid the countries of Country25, Country71 and Country23.

3.1.33 Virtual constructive and integration

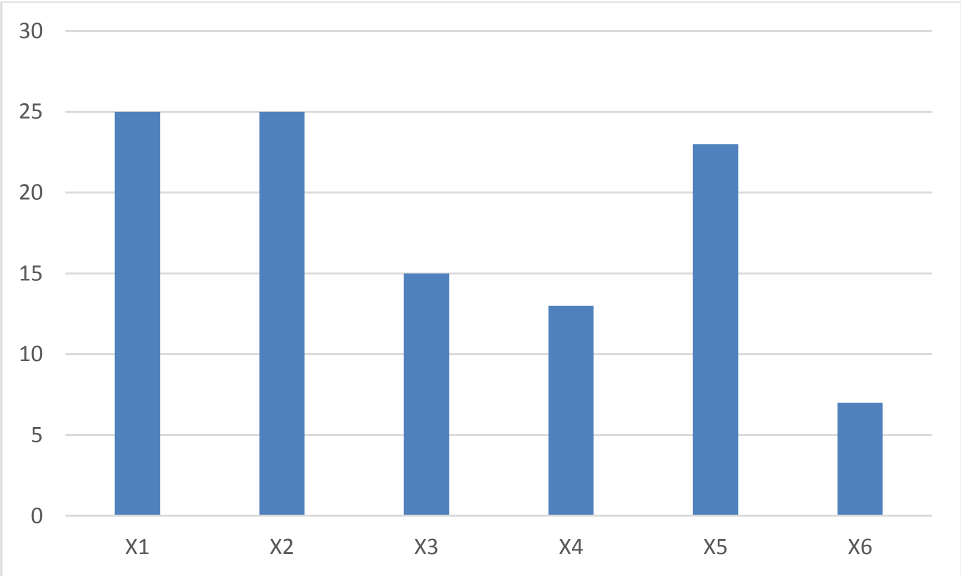
Virtual constructive and integration has a df of 59. Table A33 is smooth and skewed towards the lower end. The Pearson chi-square test gives that the results are statistically significant. AIC and BIC concluded that the best statistical modelling for weapon localization radar is done with X1, X2 and X5. Since the sample size is large enough one can somewhat rely on the results in table A33.

It is clear that Table A33 does not give any good countries to try and sell virtual constructive and integration to. This is due to the fact that there are a lot of lost orders for this specific product. But if one is to try and sell this despite the bad odds one should try and focus on the countries of Country43, Country17 and Country61. For the same reason one should avoid the countries of RCountry23ia, Country69 and Country66.

3.2 Conclusions

There are of course several conclusions that can be drawn from this master thesis. One is to look at how often the assumed explanatory variables actually where dependable. The result in table 3.2.1 clearly indicates that X1, size of the order, X2, NATO membership and X5, imported arms over total arms trade, are the most important statistics in general to look at when evaluating a potential sell for SAAB. Each Assumed explanatory variable are evaluated here below:

Table 3.2.1 Frequency of statistical dependency



- Table of how often X1 to X6 were statistically significant explanatory variables.

X1 – size of order in KSEK. This variable was as can be seen in table 3.2.1 statistically significant 25 out of 33 times. The general conclusion then becomes that X1 is a variable that SAAB in general should look into when evaluating an order. 21 out of the 25 has a negative sign. This means that 21 times was SAAB having it statistically significantly easier to win an order if it was a relatively smaller one. This leads to conclude that SAAB should focus more on smaller orders since they almost always are statistically more likely to succeed. Since this is so decisive this conclusion could be implemented on areas that are not analysed because of a small sample size and also new products yet to be launched to the market.

X2 – dummy variable for NATO membership. X2 according to table 3.2.1 was statistically significant 25 out of 33 times. This means that NATO membership is an important variable that SAAB should take into account when evaluating an order. 13 out of 25 times had X2 a positive sign. This means that 12 of 25 had a negative sign. The conclusion one should draw from this is that NATO membership is statistically important and has a different effects for different products. This means that one should be aware if NATO is a positive or negative statistic for a certain product. For new products one should therefore assume that NATO is statistically significant but make a thorough assessment weather it is a positive or negative effect.

X3 – gross domestic product over capita. X3 according to table 3.2.1 was statistically significant 15 of 33 times. 11 of those 15 had a positive sign and 4 has a negative sign. This means that there are in general easier to sell defence systems to countries with a higher gross domestic product over capita. But since this was only statistically significant 15 of 33 times one should be aware that this is not always the case. For new products one should therefore assume that it could be easier to sell the product to countries with a higher GDP/C but that it does not have to be the case.

X4 – total arms imports in M$ between the years 2000 and 2016. X4 was statistically significant 13 out of 33 times. 7 of those 13 was positive and 6 was negative. This means that it is not a statistically strong indicator to look at just total arms import of a country in order to statistically evaluate it. It is therefore recommended to in general use X5 instead.

X5 – total arms import over total arms trade between the years 2000 and 2016. X5 was according to table 3.2.1 statistically significant 25 out of the 33 times. It had a positive sign 10 times and a negative sign 13 times. This means that the ratio of the imported arms for a country over the total arms trade conducted by a country is in general statistically significant and something that one should take into account. If a country has a relatively large domestic defence industry it is therefore not necessarily a negative thing. This explain why SAAB has been relatively successful in selling products to countries like Country16 and the Country56 despite their relatively large domestic defence industries. For new products it is therefore recommended to assume that the relative import ratio of defence materials are statistically significant. But one should not assume that a large domestic defence industry is always a bad thing. It is therefore important for new products to be evaluated if they are more or less likely to be sold to countries with a relatively large domestic defence industry.

X6 – Total defence spending over gross domestic product in the year 2015. X6 was only statistically significant 7 of 33 times. 5 of those had a negative effect and 2 had a positive. From this one can conclude that a nation’s relative military budget does not have a strong statistical dependency most of the times. For new products it is therefore recommended not to look to much into different countries military budgets when evaluating potential sales. But it is never wrong if one is convinced that the relative military budget is statistically significant.

4 RECOMMENDATIONS AND FUTURE WORK

4.1 Recommendations

The recommendations that can be drawn from this thesis are many. One is to use these statistical evaluations in appendix A as an input when evaluating potential future markets. Another one is to apply the conclusions from section 3.2 on new products. Those recommends SAAB to put more effort in pursuing relatively smaller orders since they have a greater chance of success. Another recommendation is to evaluate each product if they are easier or harder to sell to a NATO country since it has been shown that one or the other is usually true. Then one should also investigate if a product is easier or harder to sell to a country with a relatively large domestic defence industry or not since it has been shown that statistically one or the other is usually true.

4.2 Future work

There are multiple potential future work that can be done in the area of statistical strategy evaluation for SAAB AB. One is to statistically look at the ISP (Inspektionen för strategista produkter) outcomes. There one should analyze the approvals and rejections from a statistical perspective so that SAAB can try and lower the amount of potential sells that ends up being stopped by ISP. The result of such an evaluation can then be evaluated at face value or with an implementation of the KEX investigation (KEX utredningen) of 2017.

Another potential future work is to apply the internal evaluations with a statistical analysis and conduct a similar evaluation of this thesis. Combining this future work with the evaluation of ISP combined with the results of this master-project would get a very good statistical evaluation for SAAB when it ventures into new markets.

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SAAB LIME CRM system

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APPENDIX A: SUPPLEMENTARY INFORMATION

A.1 Tables of predictions on countries

A.1.1 Air and airborne solutions

Table A1. Air and airborne solutions 5MSEK

Countries	P-values
1. Country51	1
2. Country43	1
3. Country16	1
4. Country52	1
5. Country17	1
6. Country76	1
7. Country64	1
8. Country12	0.9995
9. Country61	0.9804
10. Country30	0.9752
11. Country59	0.9661
12. Country39	0.8785
13. Country20	0.5658
14. Country35	0.0384
15. Country46	0.0276
16. Country40	0.0058
17. Country78	0.0039
18. Country31	0.0026
19. Country81	0.0025
20. Country72	0.0016
21. Country38	0.0013
22. Country7	0.0010
23. Country1	0.0010
24. Country14	0.0007
25. Country33	0.0006
26. Country13	0.0006
27. Country74	0.0006
28. Country29	0.0005
29. Country17	0.0005
30. Country75	0.0004
31. Country23	0.0004
32. Country25	0.0004
33. Country9	0.0004
34. Country4	0.0000
35. Country48	0.0000
36. Country37	0.0000
37. Country8	0.0000

β_0	β_1	β_2	β_5

113.3247	-5.7959	-37.2873	-71.7403

A.1.2 Air Defence radar

Table A2. Air Defence radar 500MSEK

Countries	P-values
1. Country43	0.6282
2. Country17	0.4246
3. Country12	0.3835
4. Country61	0.3441
5. Country6	0.3366
6. Country30	0.3295
7. Country13	0.3268
8. Country39	0.3178
9. Country81	0.3019
10. Country25	0.2972
11. Country72	0.2871
12. Country71	0.2745
13. Country38	0.2703
14. Country40	0.2635
15. Country9	0.2609
16. Country29	0.2520
17. Country27	0.2479
18. Country33	0.2264
19. Country57	0.1994
20. Country79	0.1987
21. Country8	0.1755
22. Country44	0.1500
23. Country28	0.1274
24. Country41	0.1095
25. Country84	0.1010
26. Country69	0.0845
27. Country5	0.0843
28. Country49	0.0804
29. Country66	0.0776

β_0	β_1	β_2	β_3	β_5
8.4929	-0.7641	-1.5728	0.6016	-2.4085

A.1.3 Airborne ESM/ELINT

Table A3. Airborne ESM/ELINT 30MSEK

Countries	P-values
1. Country49	1
2. Country29	1
3. Country40	1
4. Country7	1
5. Country35	1

A.1.4 At4

6. Country13	1
7. Country81	1
8. Country17	1
9. Country78	0.9996
10. Country71	0.9981
11. Country61	0.9904
12. Country2	0.8568
13. Country1	0.5073
14. Country55	0.0004
15. Country23	0.0001
16. Country33	0.0000
17. Country31	0.0000
18. Country41	0.0000
19. Country27	0.0000
20. Country46	0.0000
21. Country42	0.0000
22. Country43	0.0000
23. Country75	0.0000
24. Country72	0.0000
25. Country37	0.0000
26. Country76	0.0000
27. Country79	0.0000
28. Country44	0.0000
29. Country82	0.0000
30. Country73	0.0000
31. Country20	0.0000
32. Country69	0.0000
33. Country70	0.0000
34. Country28	0.0000
35. Country30	0.0000
36. Country62	0.0000
37. Country57	0.0000
38. Country4	0.0000
39. Country5	0.0000
40. Country8	0.0000
41. Country12	0.0000
42. Country38	0.0000
43. Country52	0.0000
44. Country51	0.0000
45. Country16	0.0000

β_0	β_1	β_3	β_4	β_5
-36.2771	**-43.8146**	**-21.0176**	**27.4334**	**106.9440**

A.1.4 At4

Table A4. At4 400MSEK

Countries	P-values
1. Country79	1
2. Country30	1
3. Country41	1
4. Country57	1
5. Country39	1
6. Country28	1
7. Country12	1
8. Country4	1
9. Country73	1
10. Country52	1
11. Country38	1
12. Country62	0.9998
13. Country13	0.0728
14. Country14	0.0659
15. Country40	0.0611
16. Country29	0.0344
17. Country25	0.0067
18. Country17	0.0037
19. Country61	0.0031
20. Country59	0.0022
21. Country2	0.0019
22. Country33	0.0004
23. Country20	0.0003
24. Country78	0.0002

β_0	β_1	β_2	β_4	β_5	β_6
1.6963	-4.0166	20.4122	2.0165	4.3375	-2.5876

A.1.5 CBRN

Table A5. CBRN 100MSEK

Countries	P-values
1. Country30	1
2. Country39	1
3. Country38	1
4. Country4	1
5. Country48	1
6. Country37	1
7. Country8	1
8. Country57	1
9. Country79	1
10. Country28	1
11. Country55	1
12. Country84	1
13. Country69	1

14. Country49	1
15. Country51	0.9996
16. Country43	0.9724
17. Country17	0.5218
18. Country61	0.0819
19. Country59	0.0730
20. Country20	0.0385
21. Country35	0.0183
22. Country2	0.0136
23. Country40	0.0121
24. Country78	0.0111
25. Country7	0.0083
26. Country14	0.0076
27. Country33	0.0075
28. Country13	0.0074
29. Country74	0.0073
30. Country75	0.0069

β_0	β_2	β_5
10.7422	26.5335	-15.7220

A.1.6 CNS/ATC US NL

Table A6. CNS/ATC US NL 50MSEK

Countries	P-values
1. Country23	1
2. Country74	1
3. Country7	0.9999
4. Country43	0.9997
5. Country9	0.9952
6. Country56	0.9904
7. Country78	0.9802
8. Country17	0.9702
9. Country59	0.9522
10. Country14	0.8940
11. Country81	0.8327
12. Country35	0.7610
13. Country29	0.7305
14. Country61	0.7210
15. Country51	0.7147
16. Country25	0.6916
17. Country2	0.6805
18. Country75	0.6751
19. Country17	0.6184
20. Country20	0.5845
21. Country31	0.5801
22. Country33	0.5648
23. Country84	0.5453

24. Country39	0.5267
25. Country13	0.4801
26. Country72	0.4624
27. Country55	0.4279
28. Country40	0.4201
29. Country62	0.3815
30. Country64	0.3671
31. Country46	0.3483
32. Country8	0.3413
33. Country79	0.2897
34. Country49	0.2862
35. Country66	0.2813
36. Country37	0.2805
37. Country38	0.2538
38. Country42	0.2463
39. Country30	0.2428
40. Country4	0.2377
41. Country57	0.1505
42. Country5	0.1480
43. Country28	0.1248
44. Country48	0.1184
45. Country69	0.1131
46. Country70	0.1041

β_0	β_1	β_2	β_5	β_6
5.6110	-0.5147	-1.9859	-1.6299	1.5452

A.1.7 Component maintenance

Table A7. Component maintenance, independent of order size

Countries	P-values
1. Country13	0.9035
2. Country71	0.8245
3. Country25	0.7721
4. Country40	0.7702
5. Country20	0.7259
6. Country6	0.7252
7. Country29	0.6971
8. Country78	0.6733
9. Country59	0.6611
10. Country2	0.6437
11. Country61	0.6221
12. Country79	0.5717
13. Country14	0.5325
14. Country48	0.4613
15. Country44	0.4584
16. Country33	0.4458
17. Country41	0.4302

18. Country30	0.4196
19. Country28	0.3752
20. Country12	0.3553
21. Country84	0.3517
22. Country4	0.3180
23. Country66	0.2139
24. Country27	0.2025
25. Country9	0.1913
26. Country8	0.1550
27. Country82	0.1310
28. Country64	0.0797
29. Country43	0.0576

β_0	β_2	β_3	β_4	β_5	β_6
-15.6449	**-1.3100**	**0.8286**	**0.3689**	**1.5538**	**-0.8698**

A.1.8 Counter measure despencer system

Table A8. Counter measure despencer system 150MSEK

Countries	P-values
1. Country84	0.9950
2. Country41	0.9946
3. Country55	0.9926
4. Country44	0.9921
5. Country79	0.9881
6. Country57	0.9854
7. Country8	0.9826
8. Country37	0.9798
9. Country48	0.9798
10. Country4	0.9786
11. Country71	0.9739
12. Country25	0.9739
13. Country75	0.9738
14. Country29	0.9736
15. Country74	0.9733
16. Country33	0.9732
17. Country14	0.9730
18. Country7	0.9724
19. Country72	0.9717
20. Country78	0.9702
21. Country38	0.9697
22. Country40	0.9695
23. Country2	0.9685
24. Country35	0.9658
25. Country20	0.9582
26. Country59	0.9500
27. Country61	0.9484
28. Country30	0.9449

29. Country12	0.9309
30. Country17	0.9021
31. Country16	0.8321
32. Country43	0.7794
33. Country63	0.4688

β_0	β_1	β_2	β_5
-11.7643	0.9268	2.1701	4.3356

A.1.9 E & PS

Table A9. E & PS 10MSEK

Countries	P-values
1. Country75	0.9794
2. Country78	0.9721
3. Country7	0.9674
4. Country74	0.9627
5. Country23	0.9584
6. Country35	0.9562
7. Country13	0.9544
8. Country25	0.9398
9. Country76	0.9355
10. Country81	0.9324
11. Country72	0.9240
12. Country71	0.9229
13. Country2	0.9122
14. Country9	0.9101
15. Country17	0.9061
16. Country43	0.8995
17. Country29	0.8989
18. Country68	0.8937
19. Country61	0.8911
20. Country40	0.8894
21. Country33	0.8611
22. Country17	0.8561
23. Country47	0.8505
24. Country14	0.8470
25. Country80	0.8218
26. Country48	0.6985
27. Country49	0.6787
28. Country57	0.6637
29. Country41	0.6514
30. Country37	0.6344
31. Country55	0.6228
32. Country28	0.6187
33. Country38	0.5982
34. Country4	0.5718
35. Country12	0.5539

36. Country39	0.5221
37. Country8	0.4998
38. Country64	0.4451
39. Country16	0.4420

β_0	β_1	β_2	β_3	β_5
0.7406	-0.7325	-1.9828	0.7237	1.3621

A.1.10 Flight control and actuation systems

Table A10. Flight Control and actuation systems 20MSEK

Countries	P-values
1. Country75	0.8960
2. Country7	0.7632
3. Country74	0.7036
4. Country79	0.6861
5. Country23	0.6491
6. Country48	0.6480
7. Country35	0.6452
8. Country13	0.6034
9. Country44	0.5876
10. Country57	0.5390
11. Country20	0.5291
12. Country76	0.5165
13. Country5	0.5104
14. Country37	0.4998
15. Country69	0.4814
16. Country62	0.4755
17. Country38	0.4549
18. Country25	0.4486
19. Country12	0.4342
20. Country70	0.4259
21. Country41	0.4248
22. Country28	0.3808
23. Country84	0.3764
24. Country4	0.3698
25. Country43	0.3618
26. Country72	0.3299
27. Country71	0.3167
28. Country2	0.2686
29. Country8	0.2281
30. Country61	0.2096
31. Country40	0.1745
32. Country33	0.1042

β_0	β_1	β_3	β_5
-7.3756	-0.9937	1.5302	1.3805

A.1.11 Force on target

Table A11. Force on target 10MSEK

	Countries	P-values
1.	Country65	0.7723
2.	Country51	0.6955
3.	Country57	0.6748
4.	Country13	0.6477
5.	Country28	0.6296
6.	Country52	0.6214
7.	Country4	0.6192
8.	Country76	0.5983
9.	Country72	0.5983
10.	Country40	0.5644
11.	Country39	0.5635
12.	Country25	0.5533
13.	Country17	0.5510
14.	Country49	0.5331
15.	Country2	0.5211
16.	Country55	0.5159
17.	Country61	0.5121
18.	Country81	0.4895
19.	Country29	0.4742
20.	Country84	0.4629
21.	Country59	0.4453
22.	Country78	0.4395
23.	Country63	0.3849
24.	Country80	0.2670
25.	Country47	0.2371
26.	Country9	0.2197
27.	Country21	0.1963
28.	Country43	0.1821
29.	Country23	0.0643

β_0	β_1	β_3	β_6
-0.2839	**-0.2528**	**0.3428**	**-0.4356**

A.1.12 Integrated communication solution

Table A12. Integrated communication solution 20MSEK

	Countries	P-values
1.	Country75	0.8529
2.	Country45	0.8094
3.	Country48	0.7025
4.	Country78	0.6511
5.	Country51	0.5974
6.	Country5	0.5873
7.	Country23	0.5685

8. Country62	0.5120
9. Country7	0.5100
10. Country69	0.4890
11. Country57	0.4653
12. Country70	0.4543
13. Country72	0.4320
14. Country13	0.4280
15. Country38	0.4163
16. Country35	0.4051
17. Country66	0.3843
18. Country28	0.3551
19. Country16	0.3081
20. Country68	0.2949
21. Country81	0.2898
22. Country41	0.2707
23. Country43	0.2691
24. Country8	0.2519
25. Country30	0.2012
26. Country55	0.1970
27. Country39	0.1931
28. Country33	0.1568
29. Country49	0.1533
30. Country47	0.1297
31. Country84	0.1278
32. Country9	0.1247
33. Country29	0.1021
34. Country14	0.0259

β_0	β_1	β_2	β_3	β_4	β_5
-2.1034	**-0.4618**	**-0.5846**	**1.4141**	**-0.4164**	**0.8112**

A.1.13 Integrated self-protection system

Table A13. Independent of order-size

Countries	P-values
1. Country70	0.5637
2. Country69	0.5603
3. Country28	0.5386
4. Country66	0.5290
5. Country49	0.5287
6. Country42	0.5198
7. Country48	0.5192
8. Country57	0.5184
9. Country62	0.5166
10. Country79	0.4991
11. Country37	0.4889
12. Country38	0.4838
13. Country72	0.4570

14. Country12	0.4465
15. Country64	0.4446
16. Country39	0.4392
17. Country20	0.4346
18. Country75	0.4339
19. Country2	0.4292
20. Country35	0.4163
21. Country81	0.4075
22. Country76	0.3967
23. Country82	0.3662
24. Country17	0.3590
25. Country78	0.3457
26. Country47	0.3449
27. Country7	0.2155
28. Country43	0.2133

β_0	β_2	β_5	β_6
-0.5591	**0.4200**	**0.5571**	**-0.1758**

A.1.13 Land and naval support solution.

Table A13. Land and naval support solution 40MSEK

Countries	P-values
1. Country30	0.5728
2. Country48	0.5646
3. Country64	0.5636
4. Country12	0.5346
5. Country16	0.5148
6. Country4	0.5041
7. Country46	0.4917
8. Country28	0.4881
9. Country37	0.4822
10. Country63	0.4714
11. Country40	0.4612
12. Country8	0.4495
13. Country70	0.4377
14. Country20	0.4338
15. Country69	0.4335
16. Country44	0.4279
17. Country41	0.4189
18. Country61	0.4035
19. Country2	0.3821
20. Country75	0.3709
21. Country25	0.3652
22. Country55	0.3609
23. Country35	0.3586
24. Country29	0.3524

25. Country49	0.3467
26. Country62	0.3168
27. Country84	0.3034
28. Country14	0.2779
29. Country80	0.2202
30. Country9	0.1236
31. Country43	0.1064
32. Country74	0.0257

β_0	β_1	β_5	β_6
5.9349	-0.4705	-0.7578	-0.4799

A.1.14 Land ESM/ELINT

Table A14. Land ESM/ELINT 100MSEK

Countries	P-values
1. Country64	0.9995
2. Country69	0.9995
3. Country70	0.9995
4. Country48	0.9995
5. Country28	0.9995
6. Country62	0.9995
7. Country44	0.9995
8. Country4	0.9995
9. Country66	0.9995
10. Country38	0.9995
11. Country57	0.9995
12. Country41	0.9995
13. Country30	0.9995
14. Country16	0.9995
15. Country12	0.9995
16. Country52	0.9995
17. Country37	0.9995
18. Country79	0.9995
19. Country39	0.9995
20. Country49	0.9995
21. Country73	0.0000
22. Country33	0.0000
23. Country17	0.0000
24. Country40	0.0000
25. Country56	0.0000
26. Country76	0.0000
27. Country13	0.0000
28. Country75	0.0000
29. Country25	0.0000
30. Country81	0.0000

β_0	β_1	β_2

-501.8417	37.7152	75.1759

A.1.15 Land self-protection system

Table A15. Land self-protection system 50MSEK

Countries	P-values
1. Country23	0.9653
2. Country47	0.3543
3. Country80	0.3336
4. Country8	0.1286
5. Country55	0.0801
6. Country49	0.0574
7. Country14	0.0125
8. Country41	0.0092
9. Country39	0.0073
10. Country70	0.0059
11. Country5	0.0034
12. Country28	0.0029
13. Country69	0.0026
14. Country4	0.0020
15. Country30	0.0006
16. Country44	0.0005
17. Country52	0.0005
18. Country37	0.0004
19. Country57	0.0000
20. Country79	0.0000

β_0	β_1	β_2	β_3	β_6
85.7368	-3.9351	12.5439	-6.2831	3.2191

A.1.16 Land solutions

Table A16. 50 MSEK

Countries	P-values
1. Country16	0.9842
2. Country52	0.9783
3. Country30	0.9033
4. Country39	0.8888
5. Country43	0.7914
6. Country38	0.7826
7. Country4	0.6765
8. Country48	0.6555
9. Country8	0.6027
10. Country57	0.5339
11. Country28	0.2949
12. Country61	0.2337
13. Country42	0.2300
14. Country59	0.2245

15. Country41	0.2001
16. Country84	0.1806
17. Country20	0.1787
18. Country35	0.1362
19. Country2	0.1220
20. Country40	0.1167
21. Country72	0.1049
22. Country7	0.1011
23. Country14	0.0980
24. Country33	0.0972
25. Country13	0.0970
26. Country66	0.0969
27. Country74	0.0964
28. Country29	0.0952
29. Country49	0.0945
30. Country75	0.0943

β_0	β_1	β_5
14.5797	-0.9445	-6.6283

A.1.17 Land vetronics systems

Table A17. Land vetronics systems, independent of the size of order.

Countries	P-values
1. Country54	0.9989
2. Country46	0.9984
3. Country47	0.9949
4. Country33	0.9942
5. Country64	0.9831
6. Country72	0.9768
7. Country8	0.9737
8. Country66	0.9732
9. Country70	0.9721
10. Country5	0.9702
11. Country62	0.9678
12. Country40	0.9677
13. Country2	0.9633
14. Country14	0.9616
15. Country71	0.9549
16. Country28	0.9536
17. Country29	0.9471
18. Country42	0.9471
19. Country20	0.9366
20. Country9	0.9300
21. Country4	0.9219
22. Country41	0.9079
23. Country25	0.8999

24. Country38	0.8851
25. Country48	0.8820
26. Country55	0.8777
27. Country57	0.8700
28. Country51	0.8535
29. Country23	0.8315
30. Country30	0.8308
31. Country43	0.8165
32. Country13	0.7864
33. Country59	0.7269
34. Country35	0.6646
35. Country74	0.5940
36. Country75	0.5276
37. Country7	0.5184

β_0	β_2	β_3	β_4
29.5853	-0.1833	-1.5515	-0.5196

A.1.18 Live simulations

Table A18. Live simulations 200MSEK

Countries	P-values
1. Country64	0.9924
2. Country46	0.9684
3. Country48	0.9479
4. Country51	0.9444
5. Country72	0.9381
6. Country33	0.9266
7. Country70	0.9260
8. Country47	0.9176
9. Country66	0.9041
10. Country28	0.8648
11. Country38	0.8451
12. Country2	0.7784
13. Country21	0.7664
14. Country75	0.7652
15. Country71	0.7573
16. Country42	0.7061
17. Country25	0.6362
18. Country41	0.6132
19. Country43	0.5993
20. Country40	0.5908
21. Country30	0.5617
22. Country39	0.5031
23. Country37	0.4570
24. Country78	0.4364
25. Country29	0.3849
26. Country9	0.3709

27. Country35	0.3513
28. Country80	0.3475
29. Country59	0.3199
30. Country7	0.2970
31. Country49	0.1902
32. Country14	0.1401

β_0	β_1	β_2	β_4	β_5
30.3950	-0.4651	-0.9458	-1.0488	-0.8606

A.1.19 Local situational awareness system

Table A19. Local situational awareness system 50MSEK

Countries	P-values
1. Country51	1
2. Country64	1
3. Country82	1
4. Country20	1
5. Country72	1
6. Country46	1
7. Country75	1
8. Country33	1
9. Country76	1
10. Country47	1
11. Country48	0.9999
12. Country1	0.9994
13. Country2	0.9714
14. Country17	0.9707
15. Country43	0.8692
16. Country71	0.8687
17. Country21	0.6771
18. Country5	0.4123
19. Country61	0.0547
20. Country25	0.0079
21. Country81	0.0014
22. Country78	0.0003
23. Country62	0.0002
24. Country13	0.0001
25. Country70	0.0000
26. Country8	0.0000
27. Country69	0.0000
28. Country38	0.0000
29. Country40	0.0000
30. Country66	0.0000
31. Country35	0.0000
32. Country28	0.0000
33. Country4	0.0000
34. Country7	0.0000

35. Country59	0.0000
36. Country74	0.0000
37. Country9	0.0000
38. Country12	0.0000
39. Country29	0.0000
40. Country30	0.0000
41. Country42	0.0000
42. Country80	0.0000
43. Country41	0.0000
44. Country37	0.0000
45. Country55	0.0000
46. Country14	0.0000

β_0	β_1	β_2	β_3	β_4	β_5
408.3069	-6.8532	-56.7585	8.8408	-18.0640	-28.0255

A.1.21 Mortar systems

Table A21. Mortar systems 200MSEK

Countries	P-values
1. Country78	1
2. Country75	1
3. Country13	1
4. Country35	1
5. Country76	1
6. Country60	1
7. Country43	1
8. Country23	1
9. Country59	1
10. Country2	0.0004
11. Country61	0.0000
12. Country14	0.0000
13. Country72	0.0000
14. Country17	0.0000
15. Country74	0.0000
16. Country9	0.0000
17. Country79	0.0000
18. Country33	0.0000
19. Country49	0.0000
20. Country44	0.0000
21. Country12	0.0000
22. Country57	0.0000
23. Country84	0.0000
24. Country48	0.0000
25. Country73	0.0000
26. Country39	0.0000
27. Country52	0.0000

28. Country55	0.0000
29. Country56	0.0000
30. Country47	0.0000
31. Country28	0.0000
32. Country69	0.0000
33. Country62	0.0000
34. Country8	0.0000
35. Country64	0.0000

β_0	β_1	β_2	β_3	β_4
-690.2421	-16.8164	-71.4781	57.8757	13.6725

A.1.22 Naval ESM/ELINT

Table A22. Naval ESM/ELINT 100 MSEK

Countries	P-values
1. Country16	0.6541
2. Country64	0.6009
3. Country56	0.5873
4. Country30	0.5133
5. Country73	0.5025
6. Country12	0.4992
7. Country39	0.4981
8. Country8	0.4345
9. Country38	0.4016
10. Country4	0.3961
11. Country57	0.3023
12. Country48	0.2974
13. Country28	0.2925
14. Country55	0.2878
15. Country44	0.2369
16. Country66	0.2213
17. Country70	0.2081
18. Country51	0.2076
19. Country69	0.1977
20. Country62	0.1964
21. Country5	0.1886
22. Country46	0.1586
23. Country43	0.1563
24. Country47	0.1151
25. Country61	0.1082
26. Country76	0.0842
27. Country72	0.0694
28. Country71	0.0686
29. Country35	0.0481
30. Country74	0.0396
31. Country7	0.0361
32. Country78	0.0328

Countries	P-values
33. Country75	0.0251

β_0	β_1	β_2	β_3	β_5
15.1906	-0.8724	1.4414	-0.5511	-2.3285

A.1.23 Naval radar

Table A. 500 MSEK

Countries	P-values
1. Country73	0.5843
2. Country84	0.5433
3. Country49	0.5118
4. Country39	0.4849
5. Country12	0.4107
6. Country74	0.3446
7. Country7	0.3416
8. Country35	0.3190
9. Country43	0.3102
10. Country16	0.2690
11. Country41	0.2500
12. Country44	0.2198
13. Country13	0.2131
14. Country38	0.1978
15. Country61	0.1626
16. Country17	0.1625
17. Country76	0.1356
18. Country71	0.1125
19. Country75	0.1096
20. Country48	0.0854

β_0	β_1	β_2	β_4	β_5
-10.6833	-0.4881	0.9693	0.7300	-0.7895

A.1.24 Naval solutions

Table A24. Naval solutions independent of order size.

Countries	P-values
1. Country75	0.4246
2. Country48	0.3412
3. Country56	0.3174
4. Country74	0.3125
5. Country12	0.3027
6. Country35	0.2976
7. Country52	0.2956
8. Country38	0.2877
9. Country16	0.2804
10. Country39	0.2645
11. Country30	0.2632

12. Country43	0.2595
13. Country41	0.2382
14. Country55	0.2342
15. Country49	0.2300
16. Country84	0.2230
17. Country72	0.2018
18. Country29	0.1622
19. Country68	0.1588
20. Country47	0.1194

β_0	β_3
-7.0974	**0.5778**

A.1.25 Operation center solution

Table A25. Operation center solution 200MSEK

Countries	P-values
1. Country14	0.5720
2. Country74	0.4156
3. Country59	0.4134
4. Country7	0.4109
5. Country35	0.3774
6. Country78	0.3175
7. Country43	0.2861
8. Country13	0.2699
9. Country40	0.2334
10. Country39	0.2263
11. Country30	0.2015
12. Country61	0.1907
13. Country23	0.1591
14. Country71	0.1493
15. Country75	0.1457
16. Country2	0.1425
17. Country41	0.1364
18. Country4	0.0836
19. Country16	0.0835
20. Country51	0.0817
21. Country38	0.0790
22. Country28	0.0597
23. Country8	0.0511
24. Country66	0.0413
25. Country48	0.0343

β_0	β_1	β_4
-12.6445	**-0.3835**	**0.7195**

A.1.26 Radio monitoring systems

Table A26. Radio monitoring systems 100 MSEK

Countries	P-values
1. Country56	0.9541
2. Country43	0.9536
3. Country64	0.9157
4. Country73	0.8637
5. Country17	0.8603
6. Country30	0.8517
7. Country39	0.8348
8. Country38	0.7240
9. Country48	0.6084
10. Country37	0.6082
11. Country35	0.6008
12. Country8	0.5632
13. Country78	0.5580
14. Country81	0.5495
15. Country7	0.5328
16. Country1	0.5325
17. Country33	0.5237
18. Country75	0.5168
19. Country71	0.5157
20. Country44	0.3196
21. Country55	0.3009
22. Country41	0.2268
23. Country69	0.1299
24. Country66	0.1277
25. Country70	0.1244
26. Country45	0.1244
27. Country62	0.1244

β_0	β_1	β_2	β_5
11.0679	-0.4829	-2.0143	-5.4460

A.1.27 RBS 70

No need for a table of countries. When the size of the order was 400 MSEK then the p-value for all countries became 0.3787

Table A27. RBS 70 400 MSEK

β_0	β_1
8.7179	-0.7142

A.1.28 Regional aircraft support solution

Table A28. Regional aircraft support solution 100 MSEK

Countries	P-values
1. Country45	1
2. Country64	1

3. Country5	1
4. Country48	1
5. Country69	1
6. Country66	1
7. Country28	0.9998
8. Country57	0.9998
9. Country44	0.9997
10. Country8	0.9996
11. Country4	0.9994
12. Country75	0.9993
13. Country79	0.9991
14. Country16	0.9987
15. Country41	0.9984
16. Country12	0.9959
17. Country72	0.9951
18. Country37	0.9938
19. Country23	0.9866
20. Country30	0.9849
21. Country39	0.9792
22. Country76	0.9701
23. Country78	0.9642
24. Country49	0.9574
25. Country33	0.9265
26. Country84	0.9246
27. Country71	0.8969
28. Country25	0.8794
29. Country47	0.8787
30. Country2	0.8703
31. Country7	0.8207
32. Country17	0.8056
33. Country74	0.7211
34. Country35	0.7157
35. Country61	0.5739
36. Country43	0.4729
37. Country17	0.4592
38. Country59	0.3913
39. Country40	0.3193
40. Country9	0.1548
41. Country29	0.1146
42. Country80	0.0088
43. Country14	0.0017

β_0	β_1	β_2	β_3	β_4	β_5
2.0148	**1.4026**	**3.2648**	**2.6004**	**-2.0512**	**2.8267**

A.1.29 Static camouflage

Table A29. Static camouflage 50 MSEK

	Countries	P-values
	1. Country84	0.9469
	2. Country49	0.9459
	3. Country73	0.9386
	4. Country55	0.9232
	5. Country30	0.9212
	6. Country12	0.9127
	7. Country41	0.9013
	8. Country44	0.8898
	9. Country42	0.8879
	10. Country4	0.8724
	11. Country38	0.8687
	12. Country28	0.8497
	13. Country8	0.8382
	14. Country48	0.8061
	15. Country14	0.7542
	16. Country74	0.6876
	17. Country59	0.6866
	18. Country35	0.6692
	19. Country29	0.6533
	20. Country78	0.6377
	21. Country43	0.6193
	22. Country40	0.5846
	23. Country61	0.5515
	24. Country71	0.5129
	25. Country75	0.5091
	26. Country2	0.5057
	27. Country51	0.4240
	28. Country47	0.3996
	29. Country33	0.3890
	30. Country20	0.3890

β_0	β_2	β_4
-8.1621	**2.2154**	**0.3792**

A.1.30 Training services

Table A30. Training services 300 MSEK

	Countries	P-values
	1. Country64	0.9999
	2. Country48	0.9996
	3. Country28	0.9995
	4. Country8	0.9991
	5. Country42	0.9983
	6. Country72	0.9981
	7. Country33	0.9976
	8. Country41	0.9971
	9. Country4	0.9959

10. Country20	0.9959
11. Country38	0.9947
12. Country55	0.9847
13. Country75	0.9777
14. Country17	0.9764
15. Country71	0.9761
16. Country2	0.9738
17. Country23	0.9714
18. Country49	0.9697
19. Country84	0.9417
20. Country25	0.9386
21. Country37	0.9368
22. Country40	0.8962
23. Country13	0.8628
24. Country30	0.8582
25. Country39	0.8261
26. Country78	0.7565
27. Country51	0.7525
28. Country29	0.7241
29. Country9	0.7068
30. Country35	0.5768
31. Country7	0.5571
32. Country59	0.3673
33. Country43	0.2349

β_0	β_2	β_4	β_5
37.0680	2.5491	-1.7819	5.2429

A.1.31 Underwater vehicle

Table A31. Underwater vehicle 100 MSEK

Countries	P-values
1. Country75	1
2. Country79	1
3. Country48	1
4. Country12	1
5. Country52	1
6. Country44	1
7. Country57	1
8. Country37	1
9. Country78	1
10. Country38	1
11. Country39	1
12. Country30	1
13. Country7	1
14. Country5	1
15. Country64	1
16. Country51	1

17. Country69	0.9998
18. Country62	0.9995
19. Country41	0.9992
20. Country74	0.9989
21. Country28	0.9924
22. Country49	0.9724
23. Country70	0.8657
24. Country35	0.8066
25. Country23	0.3495
26. Country66	0.0303
27. Country42	0.0115
28. Country76	0.0059
29. Country13	0.0023
30. Country8	0.0002
31. Country20	0.0000
32. Country43	0.0000
33. Country25	0.0000
34. Country72	0.0000
35. Country71	0.0000
36. Country2	0.0000

β_0	β_1	β_2	β_3
-503.2106	2.0878	29.0682	44.5103

A.1.32 Weapon localization radar

Table A32. Weapon localization radar. Independent of order size.

Countries	P-values
1. Country16	0.8529
2. Country52	0.8453
3. Country56	0.8452
4. Country64	0.8256
5. Country12	0.8147
6. Country38	0.7758
7. Country48	0.7551
8. Country37	0.7551
9. Country8	0.7475
10. Country57	0.7377
11. Country44	0.7032
12. Country28	0.7010
13. Country55	0.6992
14. Country42	0.6881
15. Country41	0.6811
16. Country84	0.6761
17. Country66	0.6470
18. Country5	0.6455
19. Country70	0.6455
20. Country62	0.6455

21. Country51	0.5826
22. Country43	0.5013
23. Country17	0.4354
24. Country76	0.4246
25. Country61	0.3892
26. Country20	0.3748
27. Country35	0.3612
28. Country40	0.3538
29. Country81	0.3506
30. Country72	0.3489
31. Country7	0.3472
32. Country14	0.3458
33. Country33	0.3454
34. Country13	0.3453
35. Country74	0.3451
36. Country23	0.3438
37. Country71	0.3438
38. Country25	0.3438

β_0	β_2	β_5
0.5529	**1.2457**	**-1.1992**

A.1.33 Virtual constructive and integration

Table A33. Virtual contructive and integraton 50 MSEK

Countries	P-values
1. Country43	0.1550
2. Country17	0.1205
3. Country61	0.0999
4. Country59	0.0989
5. Country35	0.0886
6. Country46	0.0881
7. Country2	0.0866
8. Country40	0.0858
9. Country78	0.0853
10. Country72	0.0840
11. Country7	0.0834
12. Country33	0.0827
13. Country29	0.0823
14. Country71	0.0821
15. Country9	0.0821
16. Country64	0.0756
17. Country30	0.0655
18. Country38	0.0547
19. Country48	0.0485
20. Country37	0.0485
21. Country8	0.0465
22. Country44	0.0367

23. Country28	0.0363
24. Country55	0.0360
25. Country42	0.0340
26. Country69	0.0281
27. Country66	0.0279
28. Country49	0.0578
29. Country70	0.0277
30. Country62	0.0277

β_0	β_1	β_2	β_5
6.4653	**-0.6984**	**-1.1428**	**-1.3227**

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