Chapter 6

An application in the automotive industry

6.1 The business objective

This chapter presents a practical application of the methods presented in Chapters 1 and 2, as well as the resulting evaluations of the results obtained.

The case study in question concerns a large company operating within the automotive sector. Data pertaining to the survival of the vehicle or its components is of significant importance to various areas of the company. For instance, an understanding of the reliability of specific products enables a comparison to be made between the failure times declared by suppliers and the actual ones. Alternatively, the collection of data enables the testing of whether new or old components are breaking down at a higher rate, thus facilitating the implementation of recall campaigns.

In the present case, however, the vehicle survival analysis concerns the estimation of warranty contracts. In order to guarantee the quality of its products, the company in question offers a *basic warranty* service for a period of one or two years, depending on the object of coverage. The aforementioned covers are categorised into three macro-sectors: drive unit system, extra drive unit system, and brake and clutch wear.

The company offers services that extend the basic warranty. For this reason, these types of contracts are referred to as *extended warranties*. Therefore, for an initial *premium* (price), a warranty contract ensures the contractor free replacement of insured broken components of the vehicle. It is therefore prudent to consider this factor during the analysis, as the vehicles that will renew the contract are likely to be those most prone to breakage.
The company's objective is therefore to identify the so-called *fair price*, also known as *technical price*, which is the price that equates to the anticipated future costs associated with repairs included in the warranty contract.
It is of the utmost importance to ascertain the aforementioned *technical price* with the greatest possible degree of accuracy. To deviate from this amount could mean generating losses, even large ones, or providing a price that is too high for the customer and therefore not competitive on the market, respectively.

In terms of market of analysis, the company has an international character. However, for the sake of convenience, it divides the market areas into two parts. The company's core market is Canada, with Europe representing a secondary market area. This distinction is based on the fact that sales in Canada account for approximately 80% of all vehicles sold by the bus division. It is therefore prudent to direct particular attention to the largest market for the company.

It is worth noticing that the analysis presented in this work is specifically focused on vehicles fuelled by natural gas, which are primarily used for medium to long distances.

The objective of the present case study is to estimate the number of potential failures on components that are of particular interest for the company business management. In this instance, a survival analysis is conducted in order to fulfil the requirements of the business, which necessitates the utilisation of specific reliability indices, such as BE10 and the Median/Mean survival time, in order to provide technical reliability details during the bus sales phase.

The objective of the present case study is to estimate the number of potential failures on components that are of particular interest for the company's business management. This activity is functional to the technical price estimation since, on the one hand, estimating the expected number of failures implies a deep understanding of the vehicle behaviour, and on the other hand, estimating a mean cost for one failure helps deriving a total expected cost for a specific vehicle type.

6.2 Data understanding

In order to achieve this objective, it is necessary to formalise the various concepts mentioned above. Vehicles will be grouped by type of use, with each group designated as a *vehicle division*. This concept is based on the observation that not all buses are identical in composition or usage. Some vehicles are used exclusively within the city limits, while others are used for intercity travel. Each vehicle will then be divided into logical parts, called *defect codes*. The latter subdivision serves to narrow down the field of analysis for the detection of breakage. Also, each *defect code* is identified by a unique number, which is not arbitrary but rather the union of three triplets of numbers. These terms are employed to identify the component of the vehicle under consideration progressively finer. The first three digits of the code indicate the macro-component, while the second three indicate the individual 'group' of components that make up the macro-component. The last three digits of the code indicate the smallest logical part in the reference vehicle, which is typically a single component that is separate from other larger components. This logical part is designated by a *part number*. Each *defect code* is so comprised of a set of *part numbers* that are not logical components of the vehicle, but rather physical elements such as tyres, gears, gaskets, and so on.

It is also important to note that the data is biased towards those vehicles that were involved in at least one break-up event are available. A breakage event is referred to as a *claim* and may be conceptualised as a 'receipt' issued by one of the company's numerous workshops. Each receipt contains a list of interventions on

the vehicle in question. Each intervention may be of a variety of breakdown types, including the replacement of a specific part number that causes the vehicle to cease functioning and thus the claim, the replacement of a number of part numbers that are directly involved in the claim, or the repair of elements that prevent the vehicle from operating. The cost of each receipt may vary depending on the circumstances. A full replacement is clearly a more expensive option than simply fixing.
It is also pertinent to note that although the price of a component is fixed (fluctuations in the market value of the component aside), the final price of the claim is variable. This is attributable to a confluence of factors specific to the nature of the incident in question. For instance, replacing a component in one part of a vehicle may be more expensive than doing so in another, given the costliness of the process.

Furthermore, due to the method of data collection, the full list of all *defect codes* and their respective composition in terms of *part numbers* is not available in this study. The composition of a specific vehicle (*bus code*) is therefore assumed by means of the set of breakage events of similar vehicles (*bus division*).

It is now necessary to elucidate the conceptualisation of time for the duration of the bus guarantee contract. As anticipated, the bus is sold with a basic 24-month warranty contract. However, the warranty commences upon the utilisation of the bus, rather than upon its purchase. This is where the concept of *Month-in-Service (MIS)* arises. The *MIS* represents the month the vehicle is within its warranty contract. A *MIS* of 21, for instance, signifies that the vehicle is currently in its 21st month of warranty coverage. (Hence, still in Basic Warranty insurance-time) This concept will become increasingly important in the near future, as we begin to address the issue of censored vehicle life data.

Finally, the concept of time is also represented through a process known as the *production period*. The variable is constructed on a time axis of six months. Consequently, for each year, there will be two production periods.

In light of the aforementioned considerations, it is imperative to examine the content of the following datasets. The datasets provide a formalisation of the content described in the preceding pages.
The datasets in question are the ***inconvenient dataset*** and the ***fleet dataset***. As the name implies, the *inconvenient dataset* encompasses all vehicles that have been involved in at least one insurance claim. The dataset is comprised of a series of records, each of which contains a claim. The data set thus encompasses information pertaining to the vehicle in question, including the *vehicle division*, the *unique vehicle identifier*, the *defect code*, the *reference market* where the vehicle has an active warranty contract, the *part number* involved in the claim, the *target service* in the warranty contract, which covers the breakdown, the *mileage* covered up to that date, and finally the *cost* of the claim.

Vehicle division	Unique vehicle id	Defect code	Claim date	Part number	Target service	Distance covered	Reference market	Cost (€)
12561	11112972	501763111	20/11/2022	705500288168	81	79918.670	CANADA	490.32
12561	11335743	670311431	14/04/2023	705500991123	81	36880.530	CANADA	614.70
12561	11777185	501754753	04/08/2023	705500717833	81	55442.720	EUROPE	67.27
12561	11830934	764461084	19/09/2023	705501114612	81	57115.740	CANADA	10583.61
12561	11621073	502287234	28/11/2023	705500171400	32	92932.430	CANADA	349.13
12561	11957522	623868777	13/12/2023	705500446312	81	60178.200	EUROPE	8161.05

Table 6.1: An example of the inconvenient dataset. None of the information is real.

Conversely, the *fleet dataset* encompasses life data on each vehicle currently in use, irrespective of whether it has been involved in a claim. Each record in the dataset consists of a *MIS* of a warranty contract. Hence, it is possible to derive the distribution (i.e., the number) of vehicles in each *MIS* and *production period*, frequently used to split the *vehicle fleet* dataset. It comprises the following information: the *vehicle division*, the *unique vehicle identifier*, the *target service*, the *market*, the *mis*, the time at which the warranty starts, the *duration* of the warranty (in months).

Figure 6.1: Number of vehicles ('vehicle fleet' dataset) divided by production period and stratified per MIS.

Vehicle division	Unique vehicle id	Target service	Reference market	MIS	Date warranty start	Date warranty end	Warranty duration (months)
12561	11112972	81	CANADA	4	13/01/2024	13/01/2026	24
12561	11112972	81	CANADA	5	13/01/2024	13/01/2026	24
12561	11112972	81	CANADA	6	13/01/2024	13/01/2026	24
12561	11830934	81	EUROPE	1	20/02/2024	19/09/2028	48
12561	11830934	81	EUROPE	2	20/02/2024	19/09/2028	24
12561	11957522	32	CANADA	33	09/03/2024	13/12/2029	60

Table 6.2: An example of the fleet dataset. None of the information is real.

6.3 Data preparation

Imperative is at this stage of the analysis the concept of *top component* (or *top defect code*), which represent a *defect code* the cumulative relative cost of which is in the top 80% of total costs. This indicator thus serves to delineate which *defect codes* alone account for 80% of the total costs, thus narrowing the analysis.

Vehicle division	Defect code	Tot. cost (€)	Relative cost	Description
12561	206012	176,119.78	4.220	TRAVEL COSTS
12561	541024	163,222.10	4.118	TURBO CHARGER
12561	507222	153,934.48	2.953	AD-BLUE INDICATOR
12561	792328	144,521.72	2.652	LEVEL VALVES
12561	504871	139,591.34	2.592	PRESSURE SENSOR
12561	504830	135,882.12	2.475	CATALYZER

Table 6.3: An example table illustrating the first six top components (*defect codes*) within the *vehicle division* 12561. Only the data concerning "Relative cost" and "Description" are real.

The *defect codes* that will be considered are the TURBO CHARGER and the CATALYST. The rationale for this selection is as follows: the first item represents the *de facto* most expensive component in the cost items, (second only to *travel costs*, that are not included in the vehicle's components), while the second item symbolises a particularly important component for the company involved, given its strategic nature.

With regard to the part numbers, a review revealed that about 32% of the costs were attributed exclusively to the *part number* 'catalytic silencer' for the defect code 'TURBO CHARGER'.

Vehicle division	Part number	Tot. cost (€)	Relative cost	Description
12561	4395826026	323.22	71.319	CATALYTIC SILENCER
12561	8412092000	77.21	3.077	NOX SENSOR
12561	4839084033	864.11	2.706	DPF-PARTIC.FILT.
12561	5803840222	213.76	1.569	ELECTRICAL INJECTION
12561	5308390444	544.32	1.276	NH3 SENSOR
12561	4280592942	34.65	0.942	EXHAUST PIPE

Table 6.4: Illustrating the top part numbers for the *defect code* 'CATALYZER'. *vehicle division* 12561. Only the data concerning "Relative cost" and "Description" are real.

On the other hand, within the 'TURBO CHARGER', approximately 15% were attributed to the *part number* 'turbocharger'.

Vehicle division	Part number	Tot. cost (€)	Relative cost	Description
12561	4395826026	372.33	31.966	CATALYTIC SILENCER
12561	5836284040	57.21	15.503	TURBOCHARGER
12561	0853072010	110.22	5.214	ENGINE COMPLETE
12561	2497173028	99.43	3.431	SERVICE ENGINE
12561	8412092000	603.67	2.367	NOX SENSOR
12561	1398202840	543.91	1.647	PARAFLU HT CONC.

Table 6.5: Illustrating the top part numbers for the *defect code* 'TURBO CHARGER'. *vehicle division* 12561. Only the data concerning "Relative cost" and "Description" are real.

For the *part numbers*, the same rationale applies as for *defect codes*. The *part number* "catalytic silencer" is in itself a top component, while the "turbocharger" is a particularly strategic component for the business, such that it must be studied separately. The main interest of this thesis is thus performing a survival analysis on these two specific *part numbers*, with no constraints on the logical parts to which they belong, despite the fact that each *part number* could be utilised in virtually every logical component of the vehicle. Consequently, the potential failure modes could be significantly disparate. It is worth noting that this choice was also driven by the data shortage for the *part numbers* involved. By grouping the different *part numbers* without considering their point of 'origin', it is possible to perform a more comprehensive and accurate analysis, which is a fundamental objective for the customer given the importance and strategic nature of these components.
This final step also exemplifies another aspect of the analysis. Domain knowledge enables the transition from a layman's perspective of data to a functional one. In other words, the focus is not on the *part numbers* that break more frequently or those that are the most expensive. Instead, the focus is shifted to those parts that, in the context of the investigation, are of most interest at the present moment.

Therefore, the data preparation process then filters the data for the two *part numbers* in question and derives a useful dataset for the application of the survival models. In particular, two datasets will be generated - one for each *part number* - which will take the form of the following table:

Unique vehicle id	Km	Km at MIS + 12	Event	Contract market	MIS
47297492	162655.939	195187.126	0	1	60
71903821	605419.697	726503.636	0	0	60
31870701	460000.000	-	1	0	53
31870701	514851.067	890431.81	0	1	60
28401803	583595.920	700315.104	0	1	60

Table 6.6: Illustrating an example of the structure of the filtered dataset. Only data regarding the *mileage*, the *event* and the *MIS* are real.

The final dataset is structured in a manner that enables the tracking of vehicle deterioration and the recording of any instances of damage. When the $event = 0$, the observation is censored due to the conclusion of the contract, and the mileage represents the last known distance travelled. Conversely, when the $event = 1$, the mileage represents the distance at which the damage occurred.

Consequently, each record in the dataset represents a vehicle when $event = 0$, as $event = 1$ indicates a duplicate of the vehicle in question.

To illustrate, Table 6.6 presents the mentioned case in the a vehicle with a *Unique vehicle id* = 31870701. This vehicle exhibited a brake event at a mileage of 460,000 and *MIS* 53, resulting in an *event* value of 1. In this case, it is not necessary to project the mileage to one year, given that the warranty contract is still active. Subsequently, the contract ends at *MIS* 60, resulting in right-censored event values.

For the more advanced modeling technique in survival analysis, *reference market* as a covariate is used. It consists of a binary variable, taking on the value of 1 when the vehicle in question belongs to the most important market for the company (Canada). Conversely, a value of 0 indicates that the vehicle belongs to every other market. Overall, out 11266 events, 50 identified as breaking (event = 1) for the 'catalytic silencer' *part number*. Same story proportions apply for the 'turbocharger'.

6.4 Data modeling

This section of the thesis presents and analyses the results obtained from the three models addressed in Chapter 2. It is important to note that, due to the scarcity of breakage data, it was not possible to conduct a data validation phase. In fact, only 49 and 46 unique failures were available for each *part number*, compared to over 11,2666 and 11,2664 observations, respectively for 'catalytic silencer' and 'turbocharger'.
The lack of positive observations is a typical problem in survival analysis. In this case, split-sample model validation approaches tend to be avoided [13].

The objective for all three models was to predict the trend in survival probability one year ahead of the last available observation (current *mis* + 12). The one-year mileage in the future was calculated on the assumption of a linear mileage trend. Furthermore, the utilisation of a probability threshold was employed to delineate the evolution of the phenomenon of breakage as it undergoes change. The following models are based on the **catalytic silencer** and **turbocharger** *part numbers*.

6.4.1 Cox-PH

The first model tested was Cox proportional hazard. The results after training shows a concordance index with reasonable predictive ability for both elements. It is worth noting that, for this model as well as for subsequent models, it is calculated up to the last positive observation of 460 thousand and 510 thousand kilometres, respectively.
The impact of the variable contract market=1 (Canada) is significant in terms of the discriminatory power of the model, as revealed by the log-likelihood ratio test and the p-value.

	coef	exp(coef)	coef lower 95%	coef upper 95%	p	-log2(p)
Catalytic silencer	1.68	5.37	1.03	2.34	<0.005	20.93
Turbocharger	1.44	4.21	0.74	2.14	<0.005	14.17

Table 6.7: Summary results from the Cox-PH model

	C-index	AIC	ll-ratio test	-log2(p) of ll-ratio test
Catalytic silencer	0.64	616.11	30.44 on 1 df	24.79
Turbocharger	0.60	674.09	19.12 on 1 df	16.31

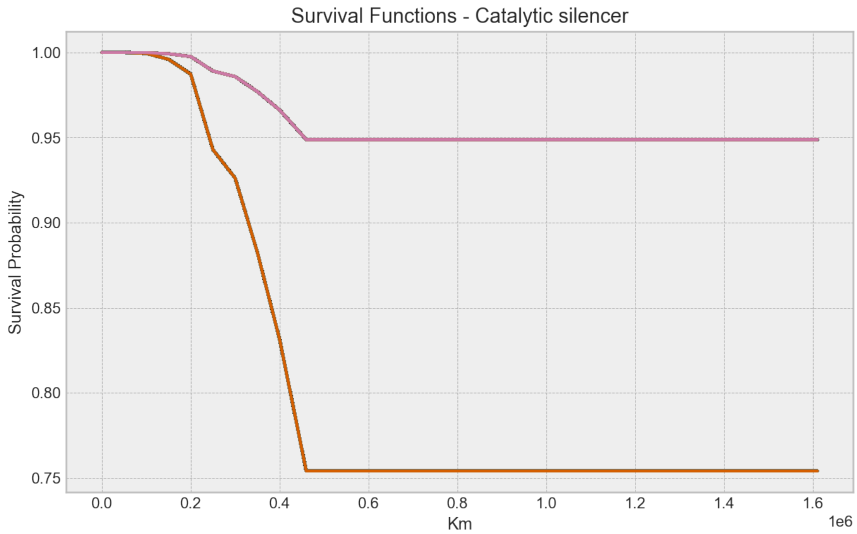
Table 6.8: C-index, partial AIC and log-lokeliood ratio test for the Cox-PH model

The log-likelihood ratio test tests compares the fit of the *null model* (a simpler model, in this case) with the fitted Cox-PH model, which includes the passed covariates (only 'contract_market' in this case). The Null Hypothesis (H0) assumes that the simpler model, which does not include the variable 'contract_market', fits the data as well as the model with 'contract_market'.
In contrast, the Alternative Hypothesis (H1) hypothesise that the full model provides a significantly better fit to the data than the simpler model. Degrees of Freedom (df) indicate the number of parameters being tested, which is 1 in this

case.

The results indicate that the *part number* ‘catalytic silencer’ is slightly more discriminatory than the ‘turbocharger’.

As for the survival curves, they show the following behaviour:



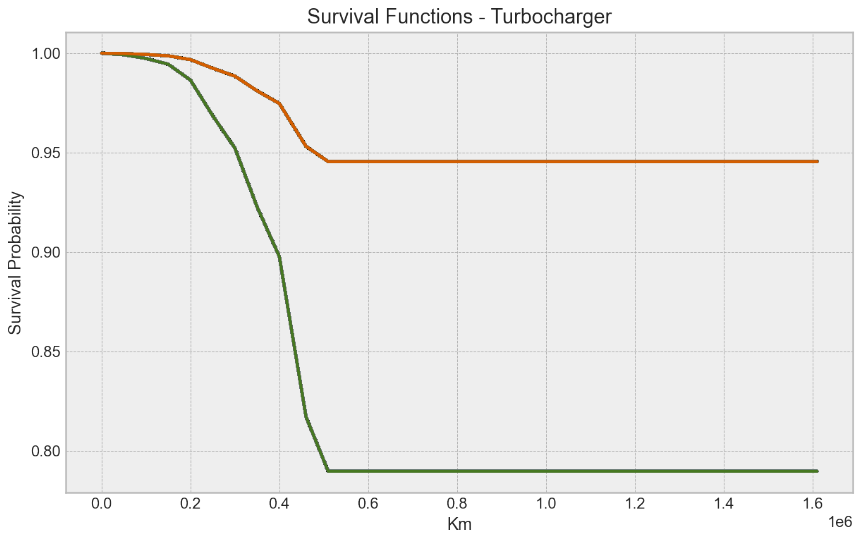


Figure 6.2: Survival curves for the Cox-PH model. No adjustments made. The steepest lines indicate the curve when the variable contract_market = 1

The flattening at 460,000 km and 510,000 km is evident from the curves. This is due to the fact that the last positive observation occurs at those mileages. The Cox-PH model is designed to maintain a constant survival probability in the absence of positive observations. In order to overcome this problem, a linear extrapolation of the data for each curve was performed, leading to the following result:

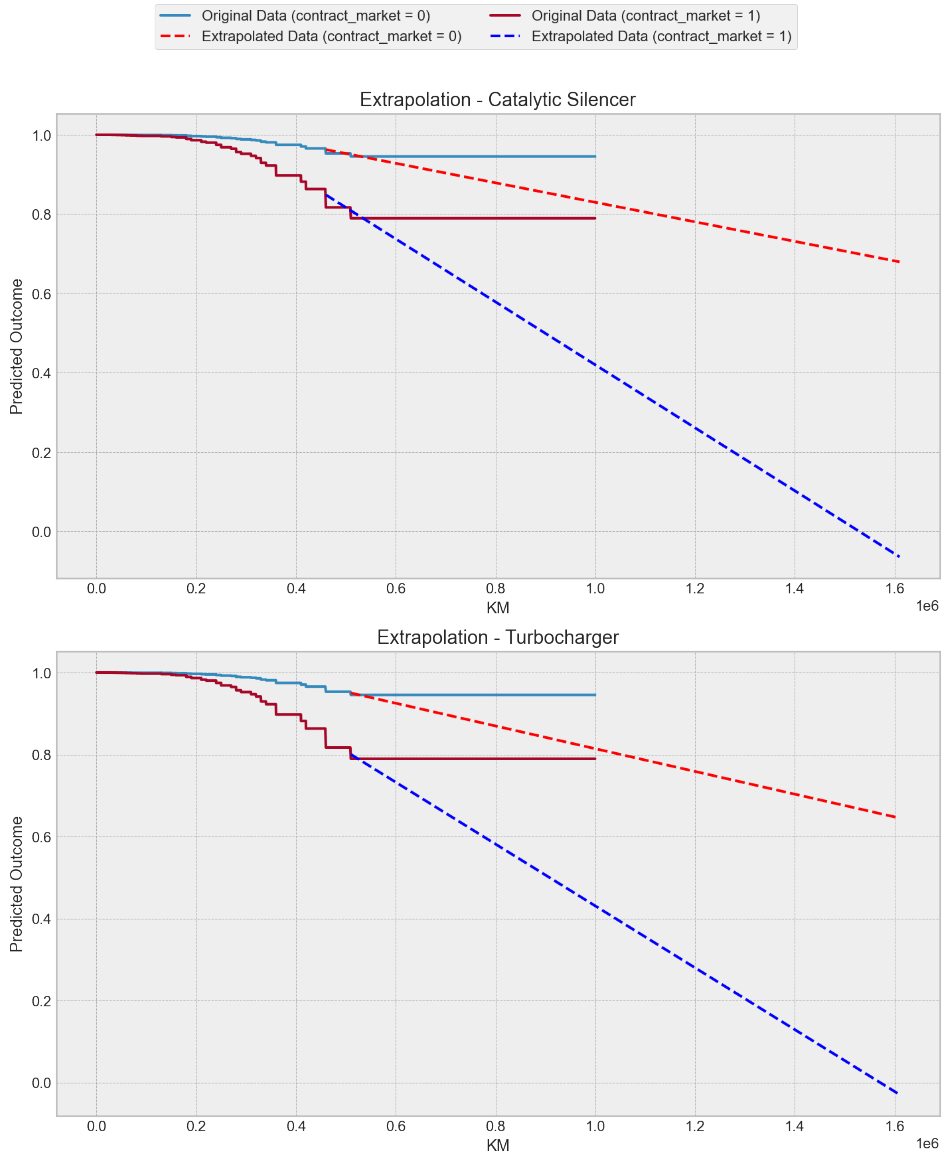


Figure 6.3: Extrapolated survival curves for the Cox-PH model

For both part numbers, the respective curves appear to be quite similar. With regard to the 'catalytic silencer', at the final mileage it reaches a survival probability of approximately 68%, whereas it reaches 0% approximately 50,000 kilometres earlier. A similar pattern is observed for the 'turbocharger', which at the final mileage reaches a survival probability of approximately 64.5%, while it reaches zero shortly before.

What, on the other hand, can be said about the assumption of a constant risk function? The python package *Lifelines* allows this assumption to be tested in an integrated way. The graph below shows the results:

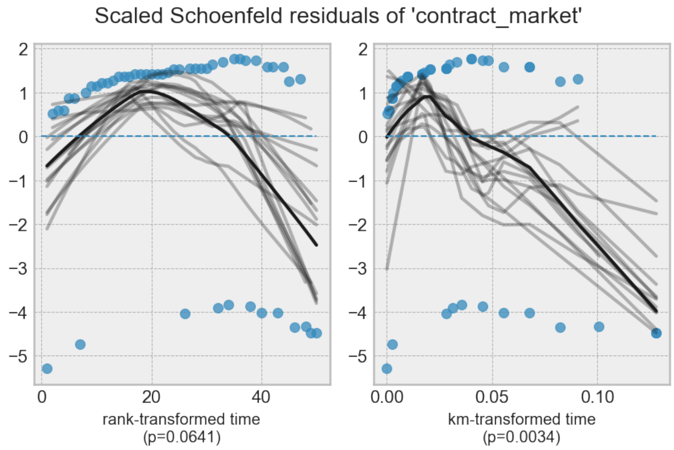


Figure 6.4: Graph showing the test for the proportional hazard assumption in the Cox-PH model - Catalytic silencer

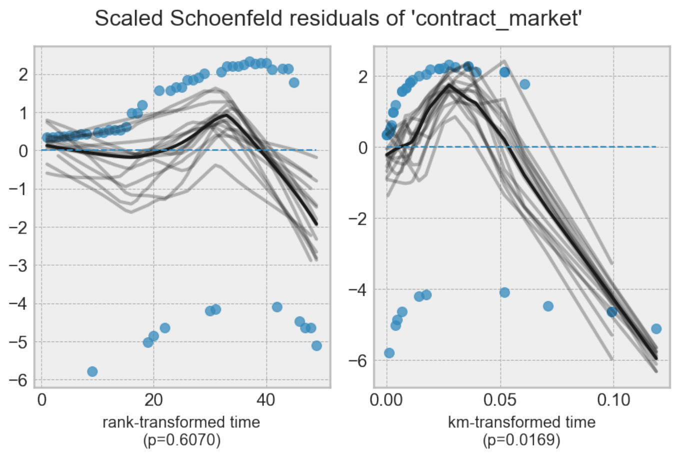


Figure 6.5: Graph showing the test for the proportional hazard assumption in the Cox-PH model - Turbocharger

Regarding the Figure 6.4, predictably, the time-transformed km (right) suggests a violation of the proportional hazards assumption (p-value < 0.05). This is due to the fact that, in this context, time clearly has a non-linear effect on the probability of failure. In fact, for the following component (but this can be found in the automotive field more generally), failures start to occur after some time. Additionally, the residuals exhibit a discernible pattern, suggesting that the effect of the covariate may vary over time.
However, the rank-transformed time plot (left) shows a p-value slightly above the 0.05 threshold, indicating a possible but not conclusive violation.

Conversely, Figure 6.5 illustrates in the left plot a p-value above the conventional significance level of 0.05, which provides no evidence against the proportional hazard assumption in the rank-transformed time. With regard to the residuals, it appears that they oscillate around the horizontal line at zero, exhibiting no discernible trend. With regard to the plot on the right, as with the 'catalytic silencer', the p-value is below 0.05, which suggests that the proportional hazard assumption may be violated for the KM-transformed time.

In summary, there is no compelling evidence to suggest that the proportional hazard assumption is not valid based on the rank-transformed time plot. However, there is evidence to suggest that the assumption may be violated based on the KM-transformed time plot.

With regard to the breaking thresholds, the results can be seen in the table below:

	Threshold 80%	70%	60%	50%	40%	30%	20%
Catalytic Silencer	86	41	32	20	17	14	11
Turbocharger	46	37	25	17	14	13	8

Table 6.9: A table displaying the number of failures per probability threshold for the Cox-PH model, 'catalytic silencer' and 'turbocharger'.

6.4.2 Log-Logistic AFT

The second model that was subjected to examination was the AFT. In particular, the underlying Log-Logistic distribution was selected on the grounds of their lower AIC compared to the Weibull, Exponential and LogNormal distributions. Furthermore, the variable 'contract_market' is demonstrated to be of particular significance in this model, as evidenced by the log-likelihood ratio test and the p-value.

	C-index	AIC	ll-ratio test	-log2(p) of ll-ratio test
Catalytic silencer	0.64	1650.07	18.47 on 1 df	15.82
Turbocharger	0.60	1686.13	13.86 on 1 df	12.31

Table 6.10: C-index, partial AIC and log-lokeliood ratio test for the AFT model

For the 'catalytic silencer', the median survival mileage was found to be 771,645, while the average survival mileage 908,261. Conversely, for the *part number* 'turbocharger', the median survival mileage was found to be X, while the average survival mileage was Y.

In interpreting the results, it is important to note that the *lifelines* package defines the relationship between two survival functions as $S_a(t) = \frac{S_b(t)}{\lambda}$. The accelerated factor is then defined as the reciprocal of what is defined in (4.3). Consequently, the interpretation of the coefficients is reversed: negative coefficients will accelerate the event time, thereby reducing the mean/median survival time. The impact of the variable *contract_market*=1 (Canada) is of significant value in terms of discriminatory efficacy for the model, as evidenced by the log-likelihood ratio test. Furthermore, the concordance index of 0.64 and 0.60 indicates that the predictive ability of the model is moderate.

After fitting, it is possible to plot what the survival curves look like when a single covariate is varied, holding everything else constant. This is useful to understand the effect of a feature, given the model:

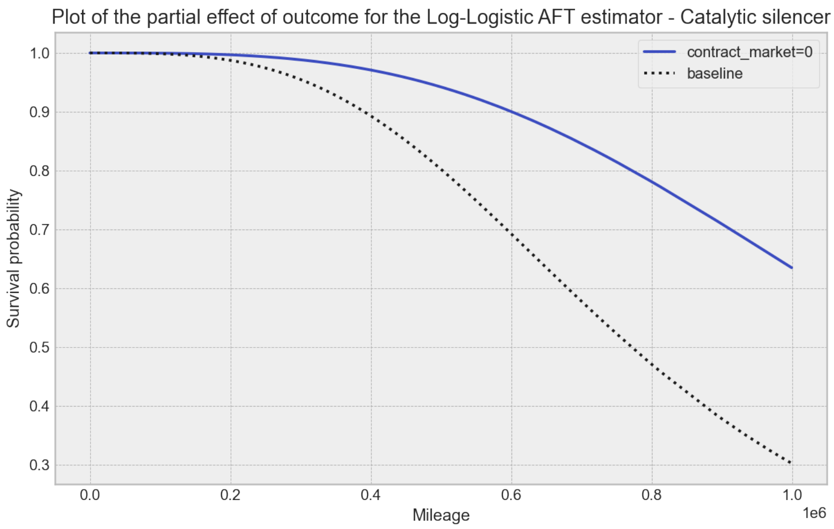


Figure 6.6: Partial effect of outcome for the contract_market feature - Catalytic silencer

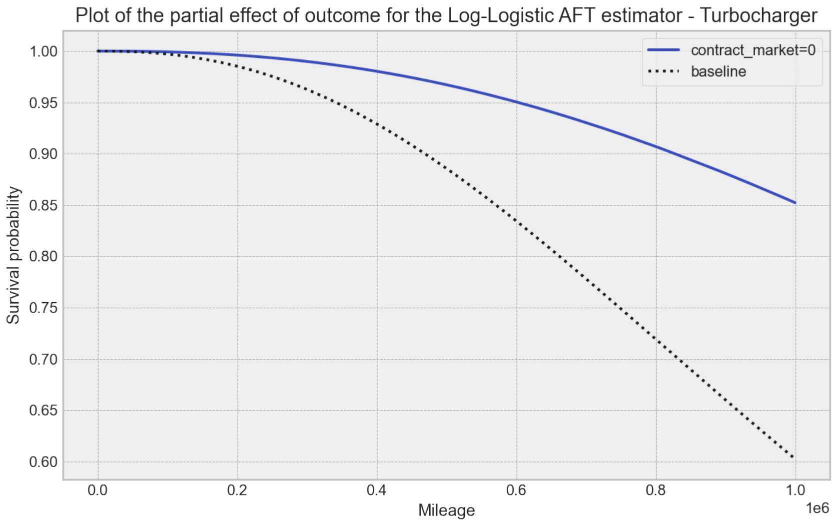


Figure 6.7: Partial effect of outcome for the contract_market feature - Turbocharger

Figure 6.6 and Figure 6.7 allow to visualise what was said earlier about the effect of the variable 'contract_market'. When this is equal to 1, the survival curve falls faster. This effect is more pronounced for the *part number* 'catalytic silencer', which at one million kilometres reaches a survival probability of approximately 0.30 when the reference market is Canada, while the 'turbocharger' remains on a relatively high survival probability of 0.6.

This behaviour is attributable, although not exclusively, to the structure of the data set. When considering the 'catalytic silencer', buses in Canada account for 74% of the total number of breakdowns. (Even though in relative terms, they account for 80% of all vehicles).

Event	Contract market	Number of vehicles
0	0	2249
	1	8967
1	0	12
	1	34

Table 6.11: Table displaying the number of vehicles by *event* and *contract market* - Catalytic silencer

Conversely, an analysis of the *part number* 'turbocharger' reveals that buses account for approximately 77.6% of the total number of failures in the main market.

The graphs below display the survival functions up to the mileage twelve months in the future in respect of the largest observation. For the 'catalytic silencer', it can be seen that the survival function for the Canadian market is up to 8.7%, while for the European is up to approximately 28%. The pattern observed for the 'turbocharger' is consistent with that observed previously. It is therefore reasonable to conclude that the probability of survival for this component is also high, reaching a minimum of 33.4% for the Canadian market.

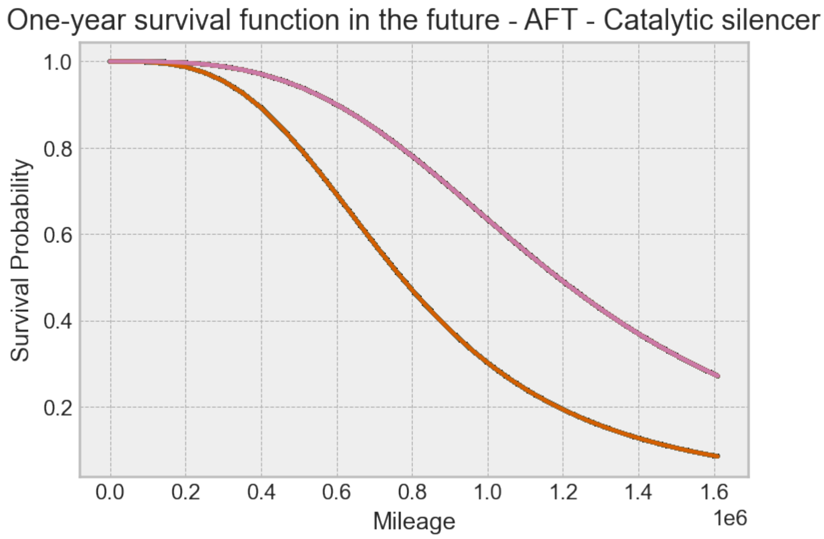


Figure 6.8: One-year Survival functions in the future - Catalytic silencer

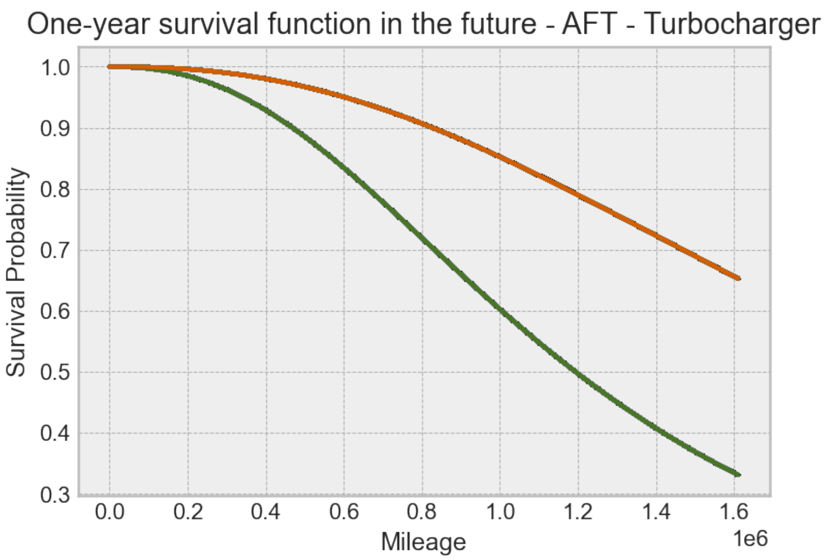


Figure 6.9: One-year Survival functions in the future - Turbocharger

Event	Contract market	Number of buses
0	0	2249
	1	8966
1	0	11
	1	38

Table 6.12: Table displaying the number of vehicles by *event* and *contract market* - Turbocharger

From these survival functions, it is then possible to derive the survival probability of each bus by linear interpolation.

By setting a threshold below which the component is considered broken, it is possible to observe how the failure numbers change:

	Threshold 80%	70%	60%	50%	40%	30%	20%
Catalytic Silencer	53	42	33	25	18	15	13
Turbocharger	33	20	14	12	4	-	-

Table 6.13: A table displaying the number of failures per probability threshold for the AFT model, 'catalytic silencer' and 'turbocharger'.

It is clear that the more one moves towards a 'conservative' approach, the more failures will be experienced. Conversely, the more one leans towards a guarantee-based approach, the fewer failures will manifest. The aforementioned differences in survival are reflected in this table, with the 'turbocharger' consistently demonstrating a survival probability of at least 30%.

6.4.3 XGBSE

Moving on to analyse the performance of the XGBSE model, specifically in its *debiased* version, a clarification is in order. As with the Cox-PH model, this family of models tends to suffer from a lack of positive observations (event = 1). In this case, the curve is flattened, unlike the AFT which, due to its different nature (the presence of an underlying distribution), naturally tends towards 0. The graph below shows the four survival curves:

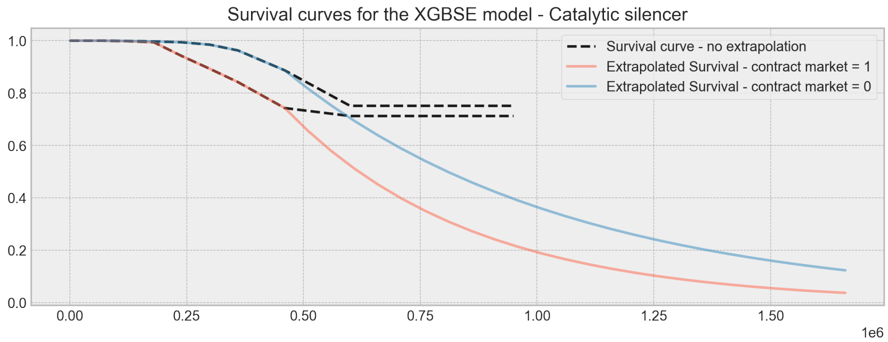


Figure 6.10: Survival curves (extrapolated) for the xgbse model - Catalytic silencer

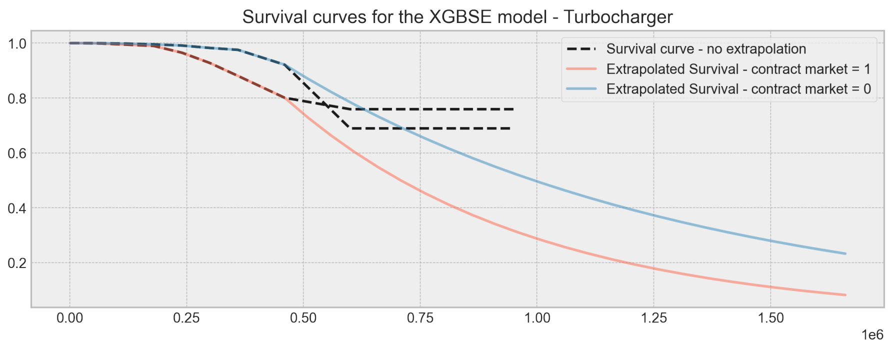


Figure 6.11: Survival curves (extrapolated) for the xgbse model - Turbocharger

With regards to the 'catalytic silencer' *part number*, as can be seen in Figure 6.10, the two dotted black curves curves flatten out completely at the last positive observation of 460,000 kilometres. The other two curves, the one in pink and the one in blue, show the extrapolation of the survival curves from the last observation to twelve months in the future. In contrast to previous models, the XGBSE exhibits a more pronounced inclination towards steeper survival curves for the European market, with a value of 0.123 at the last mileage.
In terms of performance evaluation, in this model the concordance index shows a slightly higher performance than the previous Log-Logistic AFT, with a value of 0.649.

Conversely, for the 'turbocharger' *part number*, a contrasting pattern emerges when examining the survival curves, in contrast to the previous models. As illustrated in Figure 6.11, the curve representing the European market becomes steeper than that of the Canadian market at the last available observation (510,000 km), and then stabilises around 0.7. This is shown by the dotted lines, which may mean that for the European market, the events (failures) occur more frequently compared to the other group. In contrast, extrapolation reveals that the aforementioned dynamics are maintained, with the survival curve exhibiting a steeper slope when contract_market = 1. With regard to performance evaluation, the concordance index registered a value of 0.604.

To test this hypothesis, it is possible to filter the two different datasets on the basis of the positive events and a mileage between, for example, 300,000 and 650,000 kilometres for both values of the covariates. The results are shown in the tables below:

Contract market	Unique vehicle id	Km	Event	MIS
0	11802498	360000	1	52
0	13583069	420000	1	43
0	11788777	460000	1	53
0	11943290	460000	1	47
0	11820439	510000	1	60

Table 6.14: Table showing all observations for the 'turbocharger' dataset, where event = 1, contract market = 0 and mileage is between 300,000 and 650,000 kilometres.

Contract market	Unique vehicle id	Km	Event	MIS
1	89723813	310000	1	61
1	12090432	320000	1	48
1	32013193	330000	1	49
1	11208391	330000	1	57
1	11440155	340000	1	51
1	28310130	360000	1	46
1	11201122	360000	1	51
1	11322393	410000	1	53

Table 6.15: Table showing all observations for the 'turbocharger' dataset, where event = 1, contract market = 1 and mileage is between 300,000 and 650,000 kilometres.

As can be seen from Table 6.14 and Table 6.15, there are several breaks in the observations close to 300,000 km, with the filter for the Canadian market. Therefore, as shown in Figure 6.11, there is a decrease near these values. However, in the observations close to the intersection of the curves, there are definitely more observations for the European market, which explains the faster descent.
Thereafter, the curves tend to stabilise and extrapolation assigns a higher risk to the Canadian market.

As far as the break thresholds are concerned, it can be seen that they show higher values than the AFT due to the greater slope of the curves.

	Threshold 80%	70%	60%	50%	40%	30%	20%
Catalytic Silencer	330	139	79	45	29	19	15
Turbocharger	105	66	41	25	17	14	5

Table 6.16: A table displaying the number of failures per probability threshold for the XGBSE model, 'catalytic silencer' and 'turbocharger' as *part numbers*.

The greater slope of the curves for the 'catalytic silencer' is clearly reflected in the number of expected failures per threshold.