Full Report

Experience Data Quality

How to Clean and Validate Your Data

SOCIETY OF ACTUARIES A.S.A. 1889 A.I.A. 1909 1949

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Acknowledgement

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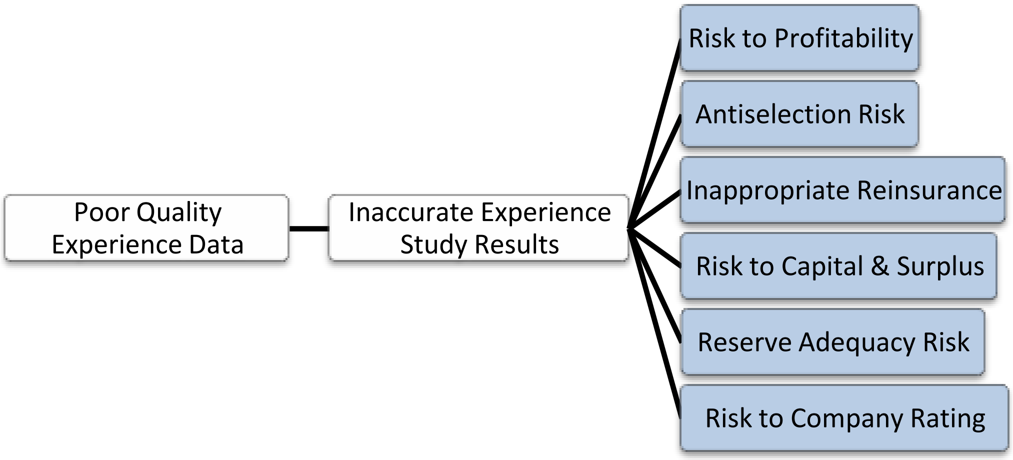
Introduction

In the current economic environment, having high quality data is essential for a competitive edge. Poor quality data is an issue in all industries. The Data Warehouse Institute estimated that data quality problems cost U.S. businesses over $600 billion a year.   Specifically for life insurers, the quality of data used in experience studies is the primary focus of this paper. Industry experience studies are resources life insurers use to manage and monitor their blocks of businesses. However, current voluntary submissions to the Individual Life Experience Committee of the SOA (ILEC) annual experience study data calls continue to be inconsistent. This leads to delays, reduced analysis, and possible data compromises in the reported results. With the principle-based reserving approach of the NAIC , it is likely that mandatory experience reporting will be required. Unlike the ILEC data submissions, the responsibility for high quality data in the NAIC data submissions will be on the life insurers.

The purpose of this paper is to provide an overview of the data cleansing and validation role specific to the life insurance experience study process. Very little has been written about data cleansing and validation specifically for data used in the life insurance experience study. Discussions in this paper will include common data errors, likely causes of these errors, methods for detecting these errors, and possible solutions. While the examples and techniques are focused on life insurance, most can be easily translated for use with other insurance products. This can be used as reference material for actuaries and analysts involved in experience studies.

It is first important to understand the impact of poor data quality and the value of good quality data. Data quality problems specific to the experience study process are harder to measure. Using inaccurate experience results could lead to bad pricing and product design, which leads directly to profitability risk and possible capital and surplus strain. This could also lead to reserve adequacy issues down the road. For many companies, a significant decline in sales due to over pricing could lead to solvency issues.

Figure 1: Implications of Poor Quality Experience Data


Poor Quality Experience Data
Inaccurate Experience Study Results
Risk to Profitability
Antiselection Risk
Inappropriate Reinsurance
Risk to Capital & Surplus
Reserve Adequacy Risk
Risk to Company Rating

While mispricing can be seen immediately through sales results, other consequences of poor experience data occur much later. For example, different aspects of valuation such as risk based capital, DAC, and tax reserves depend heavily on experience projections. Using inaccurate experience study results for these projections could lead to considerable changes in reserves, decline in capital and surplus, and possible downgrades to the company's financial ratings. Misunderstanding or not knowing the true experience of a block of business can also lead to inappropriate reinsurance decisions.

It is because of the seriousness of these implications that the role of data cleansing and validation is vital to the life insurance experience study process. And because of the magnitude of the costs due to data quality problems, several data management and data quality tools exist in the current marketplace.

While many of these data management and data quality tools have the ability to provide high quality data in general, they are not as well suited to life insurance experience study data. This is mainly due to the uniqueness of experience study data, with wide variations in acceptable values and outliers.

One tool that has been created specifically for use with life insurance experience study data is the SOA Data Quality Tool. The SOA Data Quality Tool software was created to specifically detect many of the common data errors found in experience studies, described in later sections. It also provides different views of the data to allow a knowledgeable analyst to visually detect the more complex errors. However, this tool is limited to the data collected utilizing the VM-51 format.

Software of any kind should be considered an aid to data cleansing and validation. It is not meant to be a replacement for analysts and actuaries.   Whether a system is purchased or built in-house, the need for a well trained and knowledgeable analyst or actuary to review the data is crucial.

1. Relevance and Source of the Data

The first steps to quality data are to know the source of the data and how the data will be used. Data source is particularly important with inter/intra-company studies as data formats are more likely to vary from source to source. Because a poor quality data source will require more time and resources to resolve data issues, creating and using a good quality source should be the primary goal. When data errors are found to be contained within the data source, it is generally recommended that corrections be made to the data source. However, corporate guidelines should take precedence as there may be other parties who feel that the source admin systems should be the system of record even, if the data is incorrect. Because of this, other options are discussed in later chapters and sections.

The relevance of the data is equally important. Time and resources spent compiling the data and resolving data issues would have been wasted if the data were not used for the experience study. An example would be collecting premium payment patterns for a standard mortality study. While premium payment pattern data would be beneficial in a universal life premium persistency study, it is not likely to be used in a mortality study. In addition to unused data fields, there is also the possibility that the results of the entire study are obsolete or outdated. Special attention should be given to the time horizon of the experience data as well as the time frame of the data cleansing, validation and analysis.

2. Data Cleansing

The objective of data cleansing is to have valid and accurate data. Data validity is the foundation for data cleansing and validation. Without valid data, all other data cleansing and validation would be a waste of time. For example, if a house is constructed on a deficient concrete slab, at some point the foundation will crumble causing the construction to collapse. The same is true for this first and most basic step in data cleansing – data validity.

Data validity checks are needed to provide a solid basis for all other data cleansing and validation checks. While it is possible to detect data validity errors within other aspects of data cleansing and validation, the time and effort are better spent focused on finding and correcting common data validity errors first before moving on to more complex data checks. However, before digging into definitions and examples of data validity and accuracy errors, it is helpful to understand how some errors come about.

2.1 Causes of Data Errors

Data validity errors are more common and widespread than data accuracy errors. They are also more frequent in inter/intra-company studies. Both of these types of errors can occur in all records throughout the data for a specific field (***field error***) or for certain records in specific fields (***value error***). In many instances, they are caused by data entry errors when policy information is initially entered into the source data. In other instances, a specific data field may not have been stored in the source data or was lost during system migrations. Another common cause is that the error occurred when collecting the data from the source data.

Frequently, data entry error is to blame for the data validity and accuracy errors within the source data. For many companies with legacy systems, some fields were never collected initially, entered incorrectly, or were lost or changed during system migrations. The occasional data entry errors will likely produce errors with a random pattern, while the other causes will likely produce errors in blocks of records or a number of consecutive records.

Other incidences of data validity and accuracy errors occur during data compiling, when the wrong field is pulled out of the source data. An example of this would be pulling a character field from the system to use as a numeric field within the experience data. While the character field may contain accurate data, translating them into a numeric value may leave a significant portion of records with errors. Because of the numerous fields within most data sources and experience study data, it is easy to mix up the necessary fields and the order of the fields. This cause is especially common in inter/intra-company studies where multiple data sources are used. Even for intra-company studies, it is unlikely that data sources are identical. Multiple data sources increase the chances of data validity and accuracy errors caused when collecting data for the experience study.

With understanding of various causes of data errors, the first step in data cleansing is to identify the errors within the policy data. Sections 2.2 and 2.3 define data validity and data accuracy errors, respectively. Once the errors are defined and understood, section 2.4 discusses various techniques to identify these errors within the policy data.

2.2 Defining Data Validity Errors

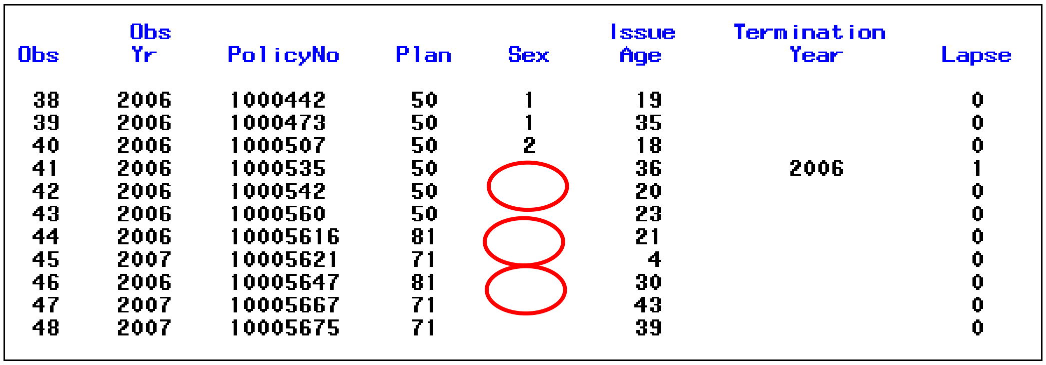
As stated before, data validity errors are more common and widespread than data accuracy errors. Three general types of data validity errors are discussed in the subsections below: missing value, data format, and coding errors.

2.2.1 Missing Value Errors

Depending on the specific field, end result analysis, and the programming for the analysis, some fields will have legitimate missing values. These are not considered invalid data and are ignored in this paper.

Before attempting to find the missing value errors, it is important to understand what is considered an error within the data. The first step is to understand how the analysis programs are set up. For example, can the program handle a blank/null value in a numeric, character, and date field? If no, then all missing field values are considered errors.

The example below focuses on the gender field. Depending on the circumstances, a blank/null value could be a valid value. For example, unisex policies may not be coded in this field. However, the analyst must be aware that the missing values may lead to an issue if the results are to be compared with only male and female mortality experience tables.



```
         Obs                                        Issue   Termination
Obs      Yr      PolicyNo    Plan     Sex          Age        Year         Lapse

 38     2006     1000442      50       1            19                       0
 39     2006     1000473      50       1            35                       0
 40     2006     1000507      50       2            18                       0
 41     2006     1000535      50                    36        2006           1
 42     2006     1000542      50                    20                       0
 43     2006     1000560      50                    23                       0
 44     2006     10005616     81                    21                       0
 45     2007     10005621     71                     4                       0
 46     2006     10005647     81                    30                       0
 47     2007     10005667     71                    43                       0
 48     2007     10005675     71                    39                       0
```

If the programming can handle blank/null values, then the next step is to identify and list which fields should not have missing values, in some cases listing fields that *are* allowed missing values could result in a shorter list. To create this missing field list, one must have knowledge of what analysis will be done in the study. At a minimum, the basic info about the insured is required. This would include fields such as policy number or unique identifying number, date of birth, gender, and face amount. In addition other fields should be added to the list if they are to be included in the experience study. For example, the issue date field should be added to the list if analysis of experience by issue age is planned. If experience by underwriting type is desired then the underwriting type field should be included within the list.

The fields mentioned so far are standard to most policies. There are fields tied to specific policies that may have legitimate missing values for a good portion of the data. These missing value errors are typically contingent on other fields. It is not recommended that these be added to the missing value field list as it would likely mean more time shifting through the legitimate missing values than finding missing value errors. These types of errors are discussed in the data accuracy section.

2.2.2 Data Format Errors

The first step in understanding data format errors is to know the source data and what is to be collected for the experience study. Oftentimes, variations within different data sources can cause problems. These errors can also easily occur during system migrations or conversions. For example, data source 1 may store a field as a numeric while data source 2 uses a character or string format for the same field. Combining the two for the experience study would cause a data format error due to the inconsistency. This situation can also occur for fields containing both numeric and character values.

With string and character formats, a value of 1 is not necessarily the same as a value of 01. But with a numeric format, both values would be equivalent. These discrepancies become a setback during the analysis phase and are better off processed during the early data cleansing phase.

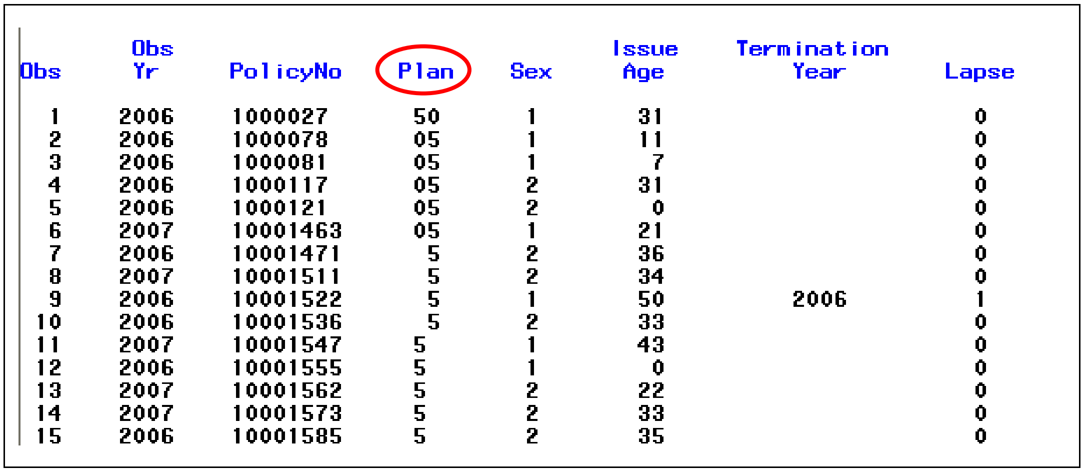
Another common data format error is with date fields, such as date of birth, issue date, and termination date. Different data sources may use different variations of date formats from one another, making it difficult to compile experience data by month or year. Using consistent date formats, like DD-MM-YY or MM-DD-YY, for example, would eliminate the discrepancies. There is also a preference to using the YYYYMMDD as it can be more effortlessly sorted numerically.

2.2.3 Coding Errors

Coding errors, also called mapping or translation errors, occur when a field value is not an accepted value for the field. The definition encompasses missing value and data format errors. However, since the paper has addressed these errors already , this section will focus on other coding errors.

The common example is that a field is defined to have a number of stated values, but contain more than those values. The gender field is defined as 1, 2, and 3 for male, female, and unisex. Any values other than 1, 2, or 3 would constitute coding errors.

Taking the prior example from data format errors, for the two-character field the values '1 ', ' 1', and '01' are considered different values. The first value contains a '1' followed by a blank space, while the second value starts with a blank space followed by '1'. The third value uses '0' to fill in the blank space before the '1'. It may be the case that only ' 1' (blank space followed by '1') is an acceptable value for this field. This is not considered a data format error because the field is defined as a two-character field and values within the field are two characters. However, this is a coding error because not all values within this field are accepted values.



```
          Obs                                   Issue    Termination
Obs        Yr    PolicyNo     Plan      Sex      Age        Year        Lapse

  1      2006    1000027       50        1        31                      0
  2      2006    1000078       05        1        11                      0
  3      2006    1000081       05        1         7                      0
  4      2006    1000117       05        2        31                      0
  5      2006    1000121       05        2         0                      0
  6      2007    10001463      05        1        21                      0
  7      2006    10001471       5        2        36                      0
  8      2007    10001511       5        2        34                      0
  9      2006    10001522       5        1        50        2006          1
 10      2006    10001536       5        2        33                      0
 11      2007    10001547      5         1        43                      0
 12      2006    10001555      5         1         0                      0
 13      2007    10001562      5         2        22                      0
 14      2007    10001573      5         2        33                      0
 15      2006    10001585      5         2        35                      0
```

There are also more complex coding errors that involve more than one field. In the case of termination date, the error is tied to whether or not the policy is terminated. If the policy is inforce, a date value within the termination date field is considered a coding error. Depending on how the analysis program is set up, acceptable values may be a blank or a pre-assigned value to denote a blank.

Coding errors also occur in date fields. Incorrect dates such as 9/31 or 2/29 (in a non-leap year) are considered coding errors. Depending on the type of software used in the source and data compiling, this may be easily detected.

2.3 Defining Data Accuracy Errors

Even if data pass the data validity error checks, it is still possible to have inaccurate data. A thorough data cleansing includes both data validity and data accuracy checks. Data accuracy in this context relates to data errors outside of data validity errors. This step essentially goes over the data with a “fine-toothed comb”. While it is possible to find data validity errors in this step, the process is not recommended due to the additional time and resources needed for data accuracy checks.

Data inaccuracies are more complicated than invalid data but are also less frequent; however, it does require more knowledge of the data and how the data will be used. Examples of common accuracy errors include experience period error, other missing value errors, and relationship of numeric field errors, described below.

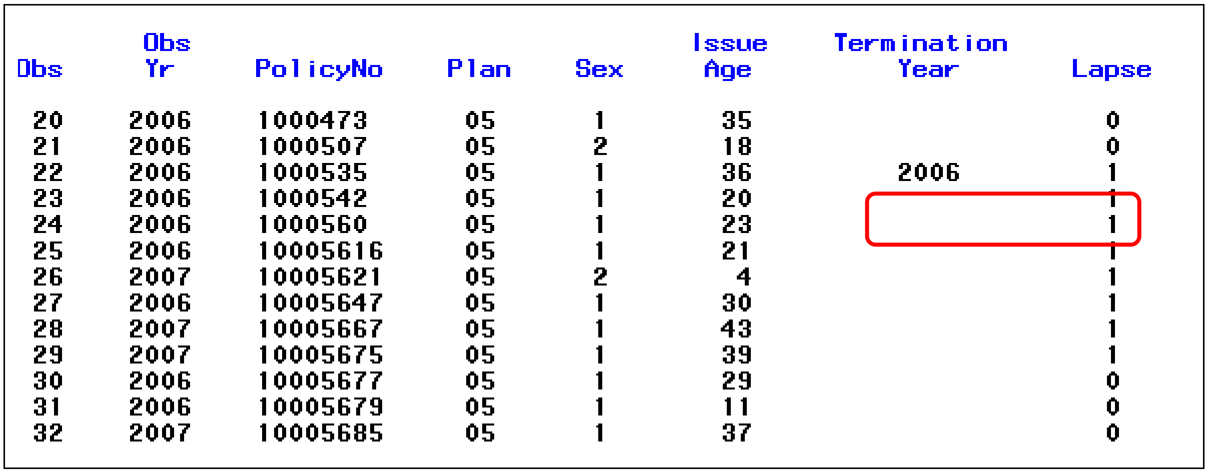
2.3.1 Experience Period Error

One common error is data outside of the experience period. While the records may contain valid data, any policy not within the experience period is considered inaccurate. This includes policies issued after the experience period and terminations not within the experience period. For example, if the experience study is for 2009-2010, all policies issued after 2010, terminated before 2009, and terminated after 2010 are considered errors.

A subset of this error is with observation years and when each inforce policy has a record for each observation year.   Using the prior example, records with an observation year of 2009 should not contain policies with issue year 2010 or termination date in 2010.

2.3.2 Other Missing Value Error

For missing value errors, a list of identified fields that should not have missing values should have been created (see section 2.2.1.). For those not on this list, some records with missing values are considered data accuracy errors.   A common error is the policy status and additional termination information that are necessary for experience studies. Fields used for additional termination information contain legitimate missing values. A termination date is expected only for terminated policies, whereas inforce policies will have legitimate missing values for termination date. Therefore, only terminated policies should be checked for missing values in this field. Possible solutions for this error are discussed in section 3.5, a specific solution for this is discussed in example 2 of section 3.5.4.



```
        Obs                                         Issue    Termination
Obs     Yr       PolicyNo     Plan     Sex     Age         Year         Lapse

 20     2006     1000473       05       1       35                        0
 21     2006     1000507       05       2       18                        0
 22     2006     1000535       05       1       36         2006           1
 23     2006     1000542       05       1       20                        1
 24     2006     1000560       05       1       23                        1
 25     2006     10005616      05       1       21                        1
 26     2007     10005621      05       2        4                        1
 27     2006     10005647      05       1       30                        1
 28     2007     10005667      05       1       43                        1
 29     2007     10005675      05       1       39                        1
 30     2006     10005677      05       1       29                        0
 31     2006     10005679      05       1       11                        0
 32     2007     10005685      05       1       37                        0
```

Another example of this is the death benefit option field. This field is used only for universal and variable universal life policies and will have legitimate missing values for term and whole life policies. If most of the policies are UL or VUL, then it is more beneficial to add this field within the missing value field list.

2.3.3 Relationship of Numeric Field Error

Many of the numeric fields in the experience data have ties to other numeric fields, much like observation year, experience year, issue year, and termination year within the experience period error. Other examples of these types of errors are listed below.

- Example 1: Face amount and cash value. Within individual life experience data, the cash value of a policy should always be less than the face amount of the policy.
- Example 2: Face amount and premium. Similar to Example 1, the premium paid at any one point or in total should always be less than the face amount of the policy.

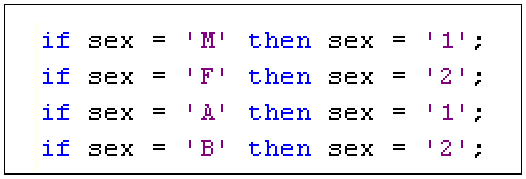
- Example 3: Issue age and attained age. Issue age should normally be less than or equal to attained age.

2.4 Detection Techniques

There are several ways to find valid data errors. The main constraints are time and resources in exchange for a higher portion of valid data. With the advanced computing power that is widely available, more detection and corrections can be automated.   Automation can greatly reduce the analyst's time constraints. For larger volumes of data, hardware computing time and resources could become significant. This is unlikely to be an issue for most companies, but inter/intra-company studies with tens or hundreds of millions of records could take hours to pick through.

2.4.1 Automation

Automating the detection of valid data errors is straightforward. It is time consuming to initialize, but once completed only minimal maintenance is needed. For each field on the list, programming may be put in place to detect valid data errors and apply solutions. The solutions should be manually approved prior to automation.



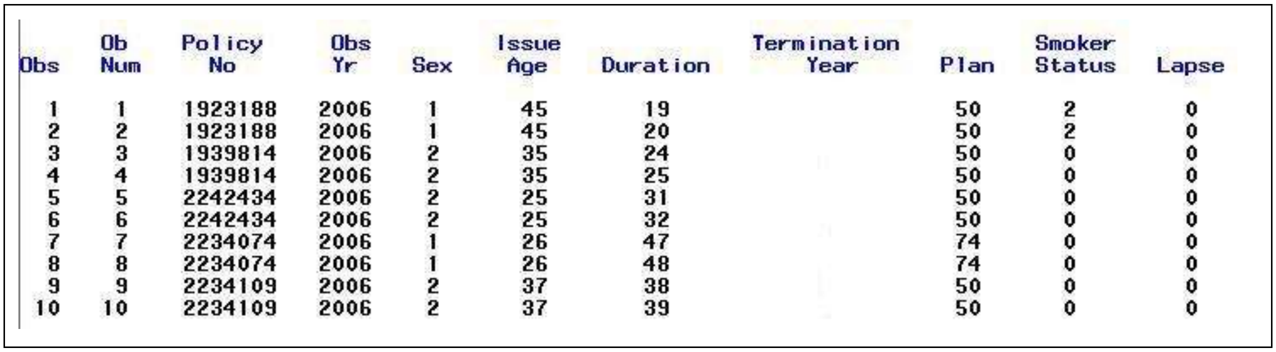
```
if sex = 'M' then sex = '1';
if sex = 'F' then sex = '2';
if sex = 'A' then sex = '1';
if sex = 'B' then sex = '2';
```

In cases where data fields being used for the experience study are uncertain and changing, it may not be worth the time and effort to program automated checks. This situation would have to depend solely on techniques with an analyst's review. Whether the automated program is minimal or thorough, an analyst should still review the data.

2.4.2 100 Records

One of the simplest techniques is to grab 100 consecutive records and visually inspect them for errors. This is the quickest and easiest way to detect valid data errors where an entire field is incorrect. This approach also uses consecutive records to more efficiently detect block errors. While this is a very effective technique in detecting large scale errors and errors within the 100 records, it is not an effective technique at detection errors within the data as a whole.

An example of this would be policies issued in 1990 with an administrative system that did not retain each policy's distribution channel. Unless the data were sorted, this block of business was added to the experience data together and consecutive records will have missing values in the distribution channel field. The number of records is somewhat arbitrary. A smaller set is likely to miss blocks of records with similar errors, while a larger set could become difficult for the analyst to review.



```
      Ob    Policy     Obs           Issue                Termination          Smoker
Obs   Num     No        Yr    Sex     Age     Duration       Year        Plan  Status   Lapse

  1     1   1923188   2006     1       45        19                       50     2        0
  2     2   1923188   2006     1       45        20                       50     2        0
  3     3   1939814   2006     2       35        24                       50     0        0
  4     4   1939814   2006     2       35        25                       50     0        0
  5     5   2242434   2006     2       25        31                       50     0        0
  6     6   2242434   2006     2       25        32                       50     0        0
  7     7   2234074   2006     1       26        47                       74     0        0
  8     8   2234074   2006     1       26        48                       74     0        0
  9     9   2234109   2006     2       37        38                       50     0        0
 10    10   2234109   2006     2       37        39                       50     0        0
```

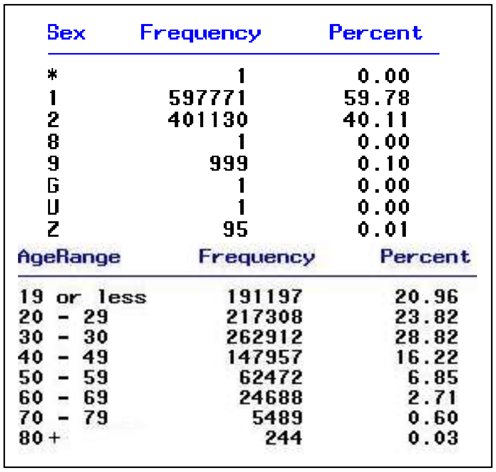
This method's starting point can be chosen arbitrarily. In some cases it may be beneficial to have additional filters. With the previous example, because of the extra information stored on separate accounts for variable universal life policies, data were incorrectly collected for annual premium, causing the null values within this field. Reviewing the 100 records may show a few records with missing values in the annual premium field. However, filtering for only variable universal life policies, it becomes clear that this is a widespread error.

This is a very effective technique in detecting errors within the 100 records; however, it is not an effective technique at detecting errors within the data set as a whole. This technique must be repeated several times, depending on the size of the data set, to be truly effective, but quickly becomes time consuming. Even with several iterations, the probability of finding random data entry errors is low. There is also the added probability of human error when reviewing the 100 records with each iteration.

2.4.3 Frequency Distribution

For reasonable sized data sets, the use of frequency tables, whether this is a straight numeric table or graphed, is a practical and thorough approach. Running a summary report of record counts by field values allows for a relatively quick visual check for valid data errors. Note that these reports are fairly uncomplicated for fields with discrete and limited values. An example of such a field is gender, where the number of distinct values is likely under 10.

But for fields with indiscrete or limitless values, such as face amount and premium, a basic frequency table would be cumbersome. For these types of fields, bands and ranges are recommended for quicker error detection.



```
 Sex      Frequency       Percent
 *                1          0.00
 1           597771         59.78
 2           401130         40.11
 8                1          0.00
 9              999          0.10
 G                1          0.00
 U                1          0.00
 Z               95          0.01
AgeRange         Frequency        Percent
19 or less          191197          20.96
20 - 29             217308          23.82
30 - 30             262912          28.82
40 - 49             147957          16.22
50 - 59              62472           6.85
60 - 69              24688           2.71
70 - 79               5489           0.60
80+                    244           0.03
```

The frequency table technique can also be used with larger volume data and inter/intra-company studies; however, the analyst must weigh the trade-off between precision versus time and resources.

2.4.4 Sampling

For larger volume data, an alternative method is to apply detecting techniques to a sample of the experience data. This technique can also be applied to a smaller volume of data, but is unlikely to increase the percentage of valid data for the additional time and resources spent. Appropriate sample size and sampling techniques are described in more detail in the Appendix section. Sampling methods discussed in the appendix include simple random sampling, stratification, systemic and cluster sampling.

For individual company studies, sampling within categories should be considered. The most fundamental categorization is by product. Whether it's a simple two category split of term and permanent products or categorized by each individual product is up to the analyst. Keep in mind that the greater the number of categories, the higher the probability of error detection — but also the greater the use of resources and time.

Sampling: Intra-Company For intra-company studies, a similar decision must be made on how to sample. Sampling categories based on company should be considered for intra-company studies when there are multiple data sources, data of each subsidiary company is a reasonable size, and where some subsidiaries are closed blocks of business or purchased blocks. Categorizing by company allows the analyst to focus on one block of business at a time. This becomes particularly important when detecting other errors because more knowledge and understanding of the data is necessary.

In cases where subsidiary data are relatively small, categorizing by company is not recommended. This runs into the constraints trade-off with using sampling for smaller individual company data.

Sampling: Inter-Company Because of the variance in experience by company, it is vital to categorize by company, along with other subcategories, for inter-company studies. Inter-company experience data should rarely be treated as a whole for data cleansing and validation. Instead, each company's experience data should be cleansed and validated separately. This is also due to the differences in data source and data submission. The techniques mentioned above are all applicable. For larger volume data, sampling should be considered.

It may be argued that in this case the law of large numbers allows for a lesser percentage of valid data. However, the implications and use of the results should be heavily weighted when allocating resources to data validation and cleansing.

After identifying the appropriate records, a decision must be made whether to delete the records from the data, correct the error, or make other adjustments. In certain cases, correcting the error may not be feasible. However, for smaller data sets, removing the records from the policy data set may be an issue for the experience study in terms of credibility, exposure, and depth of analysis. In these situations, alternative solutions may be more suitable than removing the records. Solutions and examples are discussed in the next section.

2.5 Solutions

There are several ways to deal with data validity and accuracy errors. These solutions range from easy and convenient to accurate and time consuming. There are several things to keep in mind when deciding on what to do:

- Purpose of the study
- Volume of data and credibility of termination and exposure
- Specific group of data with errors and the number of policies with errors
- Ability to validate the correction
- Ability to provide an audit trail for explanation later
- Goal of future studies
- Potential use of the data for other purposes

In addition, the analyst must evaluate whether an error can be corrected and how much time and resources are needed. Much like the error detection techniques, more than one solution can be applied to the errors.

2.5.1 Deleting

The easiest and quickest solution would be to discard these policies from the study. The definition of discard is left to the discretion of the analyst and actuary. Policies with errors can be flagged and ignored for the study, or completely removed from the data. Flagging the policy allows the data to be potentially used for other purposes and is useful during reconciliation to other sources. However, removal of the policy from the data eliminates the potential that the error is included in the experience study.

If the error detection was automated, this solution would be a relatively simple process added into the automation. If the detection process was done by hand, then additional work is needed to discard these specific policies.

Deletion is an acceptable solution for valid data errors where the data cannot be corrected. For errors that can be corrected, the trade-off between precision versus time and resources comes into play.

For a small number of records with random data entry errors having no correlation, deletion may be an acceptable option. For larger volume data, deleting a number of records would not affect the termination and exposure credibility; but for smaller volume data, the experience could be significantly lessened.

For errors with correlation, deletion should be carefully gauged. Deletion of errors with correlation would directly impact the analysis of the experience study, biasing the results. In cases of older administrative systems that do not store the necessary information, the analyst should weigh the experience of the data. Oftentimes these are older blocks of business and may represent a significant portion of a company's mature experience.

2.5.2 Ignoring

An alternative to deletion is to ignore the error. This is just as easy and quick of a solution as deletion; however, more hands-on review and analysis is required before implementing. Unlike deletion where the entire policy would be discarded, this approach keeps the policy in place but ignores the specific field of the policy. Instead of looking at groups of records with similar errors, this approach looks at the number of errors within each record. If a record contains only one error, it may be worthwhile to use the ignoring approach rather than deleting. As with deleting, termination and exposure credibility is still an issue when applying this technique over correcting the error.

If analysis is planned for the smoker status field and several records have a missing value only for this field, it would be valuable to keep these records and ignore the error for smoker status. These policies will still contribute to the overall experience and other analysis. Additionally, the missing value can be

- Left blank - noting that these errors are accepted
- Replaced with a value not reflective of the field
- Flagged to be ignored for specific analysis

If smoker status includes the values 1 through 5 and the replacement approach is selected, a value should be chosen outside of the range so that these policies are not accidently included in the smoker analysis.

For records with few errors, ignoring those errors may benefit the overall study — although errors within critical fields should not be considered for this technique. Including records with missing termination status and ignoring the error would add no benefit to an experience study. Records with missing ages would be of little use for a mortality study but can still be beneficial in a lapse study.

For inter/intra-company studies and individual company studies where credibility is less of a concern, this solution is favored over deletion.

2.5.3 Correcting

The most precise and preferred technique is to correct the data. Some valid data errors are fairly simple and quick to correct. The most common of these tend to be errors that occur when compiling the data, such as grabbing incorrect fields or putting the fields in the wrong order.

Other common errors occur when dealing with multiple data sources and having to translate field values to a common value. For example, the gender field in admin system 1 is coded (M, F, U) while admin system 2 is assumed to be coded (male, female, unisex). However, admin system 2 also has codes (unisex-male, unisex-female). If these two codes were not anticipated, then the gender fields for these records are likely blanks.

2.5.4 Filling In

In some cases the error comes from the source and cannot be fixed. Rather than deleting or ignoring the error, another alternative is to try to decipher the true value by using other valid fields for the policy.

- Example 1: The error is in the smoker status field. If the nonsmoker preferred class contains valid data, it can be implied that the policy has nonsmoker status.
- Example 2: The error is a missing termination date for a terminated policy. The premium paid-to-date can be a reasonable substitute.

These examples are straightforward, but others may not be. It is recommended that an analyst with knowledge of the data use this technique rather than automating.

3. Data Validation

Data validation detects potential data errors not easily found in the data cleansing step and also assesses the soundness of the experience data as well as the study results. Data cleansing and data validation go hand in hand. If data cleansing is considered the foundation of a house, then data validation would be considered the framework of the house. It is possible to build a house without a foundation, but the result would be questionable. And without a framework, it would be difficult to build a house. The same is true for data cleansing and data validation. It is possible to omit data cleansing and go straight to data validation. The errors are likely to show up during the analysis phase. Omitting the data validation, on the other hand, is likely to produce questionable experience study results.

This chapter describes the three common phases of data validation: consistency, reasonability, and completeness.

3.1 Data Consistency

While data for other business may fluctuate significantly over different time periods, most data used for experience studies should be fairly consistent from study to study. This section discusses the appropriate time horizons, ways to compare the data to gauge data consistency, and longitudinal consistency.

3.1.1 Time Horizon

The time span chosen for the experience study depends mainly on the goals of the study. If the main goal of the study is to continuously trend lapse experience, one full policy year or two consecutive calendar years of data may be appropriate. In this case, products influenced by economic conditions can be easily seen in the trends. However, if the goal is to compare mortality experience to industry tables, then a greater time horizon would be more suitable.

The same applies to the frequency and timeliness of experience studies. For lapse (and possibly mortality) experience of new and rapidly selling products, annual or biennial studies when data becomes available is more applicable. When the goal is to compare original pricing assumptions to actual experience on a block of business, longer time periods with less frequent studies are suitable. Especially for shorter time horizons, the analyst must also keep in mind the volume of data.

3.1.2 Inconsistency

With the time horizon set, the next step is to gauge data consistency. There are several reasons data inconsistency would occur. The most common cause is incorrect data. While the data may have passed the data cleansing phase, it is still possible that certain records are incorrect. A simple example of this is when analyzing a specific block of business or a particular subsidiary. Inconsistency in the data compared with prior studies may indicate the wrong block of business or subsidiary. On the other hand, inconsistency could also signal changes in products and business plan.

In general, comparison should be made of the year-over-year change in the number of policies, face amount, and premium. Percentage change should be small, less than ±5%, unless there is reasonable cause. This is due to the greater portion of mature business consistency between studies, with the small changes due to termination offsetting new sales.   A larger percentage increase may be an indicator that inappropriate data have been included while a larger percentage decrease could indicate data are missing from the study. Reasonable causes for a larger percentage change range include a new product gaining market share, a change in business strategy, or a sell-off of a block of business. The lack of change may also be indicative of an issue.

Below are some examples of varying levels of comparison. Each can be used on its own or combined with others.

1. *Overall Totals* The most basic method is to compare data totals between studies. This method is quick and simple, but not thorough.
    a. If the data is a closed block of business then the totals should decline from study to study due to terminations. Increases would signal incorrect data.
    b. For younger companies with less mature experience, a greater percentage of fluctuation is expected. In this case, it is difficult to tell whether the inconsistency is natural or due to error.
    c. For inter/intra-company studies, this level of comparison should be used only when there is consistency in participating companies from study to study.
2. *By Product* This method requires more knowledge of the data by product line. Whether this is split by the main product lines (whole life, term, universal life, & variable life) or a more detailed split (10-yr term, 20-yr term, etc.), the analyst must be familiar with what is happening and what has happened to the business. This finer split also allows for better detection of incorrect data.
    a. A larger decline in whole life offsetting a larger increase in term may show consistency with overall totals comparison. However, a comparison by product line will tell a different story.
    b. Similar to the overall totals comparison, a discontinued product should trend a decline from study to study, while a newer product will show greater fluctuation.
3. *By Observation Year* In addition to comparing consistency between studies, it is also recommended that comparison be done within the current study when possible. For studies with a time horizon of more than one year, there should be consistency between observation years.
4. *By Company* For inter/intra-company studies, it is recommended that comparisons are done at the company level, due to the large volume of data. In addition, errors are more likely to hide within inter-company studies where contributing companies vary from study to study. Breaking out the comparison by company reduces the chances of such errors.

3.1.3 Longitudinal

Longitudinal data inconsistencies are more likely to occur in experience studies with longer time horizons or when shorter time horizon studies are compiled across time, as is true for the inter-company mortality study. These inconsistency errors can occur when changes are made to policies.

An example of this would be if a policy was reported as a death in late 2008, but was then reinstated two months later in 2009 as a false claim. Mortality study for experience year 2008 would show the policy has a claim; however, the mortality study for experience year 2009 would credit the policy as inforce. When the two studies were compiled into a larger mortality experience study, this specific policy would create a longitudinal data consistency error.

This type of error can be potentially time and resource consuming, particularly for inter/intra-company studies with large volumes of data to sift through. There are no simple techniques to detect these errors, but robust computer programming can flag potential policies with these errors. In cases where policy record identifiers are consistent, data sets can be merged and mapped through programming to eliminate errors. As with the other data errors, a knowledgeable analyst or actuary is necessary.

3.2. Data Reasonability

In some cases, it is hard to detect a data issue until the analysis begins. This is particularly true for larger volume of data such as inter/intra-company studies. Data reasonability refers to the reasonability of the data based on the experience results. As with data consistency, experience results should be expected to be somewhat consistent from study to study. Trends can form over time. Similar to data consistency, a comparison of the results from study to study will highlight potential data issues.

The most likely causes of reasonability errors are policies missing from the data, the data contain policies not within the scope of the experience study, and miscoded fields. The latter refers to miscoding, such as a policy coded as simplified issue when it should be a non-medical underwriting policy.

1. *Unexpected Spikes* Unexpected spikes in experience results are usually a good indicator of possible data issues. When results are graphed, these can be easily detected as the anomalies along a smoother trend. There are few expected spikes within experience results; the most common example would be shock lapse rates at the end of level premium term periods.
2. *Change in Experience* Any notable changes in experience should be analyzed in more detail. While an improvement in mortality is expected, a significant improvement may indicate potential issues in the termination cause field, unreported deaths, or missing terminated policies. There are cases where significant changes are due to changes in business strategy, such as the introduction of a policy retention program.
3. *Change in Trend* Shifts in trends are also a good indicator of possible data issues. First year lapse rates for whole life are typically the highest among all policy years. If results show that third year lapse rates exceed first year lapse rates, there could be a potential issue for whole life policies in the first duration and third duration.

4. *Trends in Data* Trends in particular parts of the data can also be an indicator of data issues. Specifically watch for fewer terminations near the end of the experience period. This may indicate late reporting and perhaps the data was extracted too soon.

As with other data errors, the analyst must make a decision whether to remove, ignore, or correct the data. In some cases it is difficult and time consuming to correct the data. Removing or ignoring may be the most efficient solution. However, the issues of data completeness and credibility become more likely problems.

3.3 Data Completeness and Credibility

Data completeness and data credibility go hand in hand where data completeness refers to the amount of accurate and available data for use in the experience analysis and data credibility refers to the data's ability to provide reliable and trustworthy results. A greater degree of data completeness implies the opportunity for a more extensive analysis of the experience results, as well as greater credibility. When applying solutions for data errors, the analyst should always keep this issue in mind. While it is easier to remove or ignore the error, not spending the time to correct a correctable error could lead to loss of analysis.

The problem with data completeness is a greater issue for inter/intra-company studies. Some data sets may not contain all required fields. In this case, a decision must be made whether to exclude various company experiences from particular results or remove the analysis altogether. A similar time and resource trade-off exists, but due to the voluntary nature of inter-company studies it is more difficult to acquire data corrections. On the other hand, because of the larger volume of data, there is less worry about credibility with inter-company studies.

Determining the level of data completeness is solely up to the actuary or analyst. Credibility for individual company and intra-company data however should be estimated with inter-company studies. For additional information about credibility please refer to: http://www.soa.org/research/research-projects/life-insurance/research-credibility-theory-pract.aspx

Appendix – Sampling Methods

How long would it take to carefully look through 4 million records and analyze the data? It is probably possible, yet, time consuming. This is when sampling methods come into play. While the amount of data is reduced, rather than a full population, analysts will want the data to be reflective of the full population being sampled so accurate analyses can be made. Random samples give a better representation of the population because every object or person, in a specific sampling frame, is given an equal opportunity to be picked for the subset. Analysts can also apply their conclusions from what they discover about the sample data to the whole population. It is vital that data are not biased in the subset, as making an analysis about the full population is what is intended.

The following sampling techniques will allow the sample to represent the population: simple random sampling, systematic sampling, stratified random sampling, and cluster sampling. However, one may be more effective or efficient than another—their results differ from case to case. Additionally, there are advantages and disadvantages to each of these methods.

A.1 Simple Random Sampling

Simple random sampling is the most straightforward method used in which every entity of the population has an equal chance to be selected for the sample. Data probably are easiest to collect in this method, but the steps need to be carefully followed because data can become erroneous very easily.

A.1.1 How to Gather the Data

An effective technique is a random number generator. Each entity of the population would be assigned a number while the random number generator would produce *n* numbers, where *n* equals the proper sample size associated with the sampling frame. For instance, if the data contain 100 records, records should be assigned numbers from 1 to 100. The random number generator should then generate the appropriate set of different random numbers. The numbers randomly picked should be matched up with the records that are assigned, and those are the records that will be used in the sample.

Additionally, many programming systems have random number generators, such as Excel, SAS, SPSS, Minitab, C++, and Java, to name a few. In fact, several of these systems have simple random sampling functions built in. Ho and Brancard used SAS programs for many of their calculations.

Before an analyst can begin a simple random sample (SRS) an effective sample size needs to be determined. The analyst must first determine an appropriate margin of error and confidence level, and then calculate the sample size by using other variables including the population size, proportion, and a z-score.

A.1.2 Assigning Variables

The margin of error and confidence level are very important because they help determine the measure of precision for a sample size. The most common margin of error used is 5 percent; however, anything less can be used. The most typical choices for a confidence level are 95% and 99%. The 95% confidence level is most commonly used — although a 99% confidence level will provide higher precision. Confidence levels between 95% and 99% can also be used. The reason why a larger confidence level is more commonly used is because the results are not far off from the true answer, or what would be determined from the whole population. A lower margin of error and a higher confidence level necessitate a large sample size, which can be costly; however, these results will ultimately lead to higher precision. This technique would support the initiative of choosing between time and resources as opposed to cost. The margin of error is also known as variable *d* and the confidence level is classified as α, the Greek symbol called alpha.

When calculating the sample size, the proportion (p) is very important because the sample should be a true illustration of the sampling space. Sometimes the proportion is unknown, so researchers tend to use a proportion of 50% (0.5); that way the sample sizes calculated will show a conservative number to be sampled. These sample sizes will provide the fewest samples needed to provide the best precision. If the proportion is known, it is most appropriate to use that in the formula.

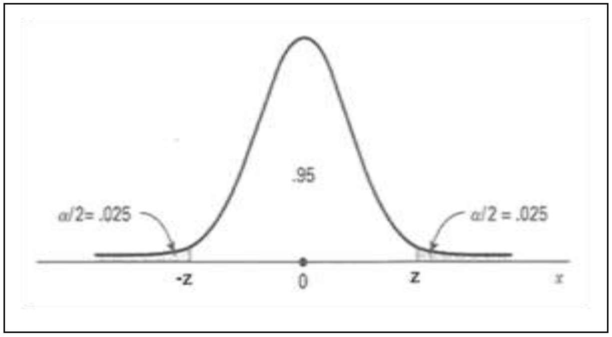
The last variable that needs to be found is the z-score (z). The z-score is calculated using the confidence level and a normal distribution statistics test. The most common confidence levels, 95% through 99%, can be found in *Table A*. If a different confidence level needs to be calculated, the following steps can be done:

Table A: Z-Score by Confidence Level

Confidence Level	95%	96%	97%	98%	99%
Z-score	1.96	2.06	2.17	2.33	2.576

1. If the confidence level is 95% ($0.95{=}\alpha$) and it is normally distributed, it is known that the tail ends equal $\frac{1-\alpha}{2} = 0.025$ each. See *Figure B: Normal Distribution With 95% Confidence* for a visual.

Figure B: Normal Distribution With 95% Confidence



2. The next step is to find the value of z. Normal distributions calculate the values from right to left and the area under the curve equals 1. So, the area of the left tail needs to be added to the 95%, ending up with an area of $0.95 + 0.025 = 0.975$ to the left of z. This area needs to be looked up in the z-score chart. The areas are listed in the main part of the table and the z-scores are listed in the first row and first column. Once the area [0.975] is found in the chart, this will match up to a certain z-score along the first column and first row. The z-score will be the sum of the row heading and column heading. So, 0.975 has 1.9 as its

row header and 0.06 as its column header (see *Table C*); therefore, $1.9 + 0.06 = 1.96$. The z-score for a 95% confidence level equals 1.96. The negative z-score equals the negative: -1.96.

Table C

z	…	0.05	0.06	0.07
…	…	…	…	…
1.8	…	0.9678	0.9686	0.9693
1.9	…	0.9744	0.975	0.9756
2.0	…	0.9798	0.9803	0.9808

Once all the variables are accounted for, they can be entered in the following two equations:

Variables		Formula 1	Formula 2
Margin of error	*d*	$n_0 = \frac{z^2pq}{d^2}$	$n_1 = \frac{n_0}{1+\frac{n_0}{N}}$
z-score	*z*		
Proportional variable	*p*		
$1 - p$	*q*		
Sample size 1	n_0		
Sample size 2	n_1		
Population	*N*		

Example:

Company XYZ would like to use the SRS method on its experience study data of 4 million policies. What sample size should be used to achieve a margin of error, *d*, of 3% with a confidence level of 95%?

Variables From Example	
d	.03
z	1.96
p	0.5
q	0.5
N	4,000,000

$$n_0 = \frac{z^2pq}{d^2} = \frac{(1.96)^2(0.5)(0.5)}{(0.03)^2} = 1{,}067 \text{ policies}$$

$$n_1 = \frac{n_0}{1+\frac{n_0}{N}} = \frac{1{,}067}{1+\frac{1{,}067}{4{,}000{,}000}} = 1{,}066.7 = 1{,}067 \text{ policies}$$

A.1.3 Recommended Sample Sizes

Table D was created by Ho and Brancard based on the formulas given above. It has been broken out by the two most common confidence levels — 95% and 99% — as well as margin of error. There are many population sizes to choose from; however, if the population being surveyed is not listed, the previous steps of this chapter should be used to determine the best sample size. Additionally, depending on the confidence level and margin of error used, a limit exists on the appropriate sample size for a certain population. For example, for a 95% confidence level with a 5% margin of error, a minimum sample size of 384 can be used for a population of 225,000 or greater. For a 99% confidence level with a 5% margin of error, a minimum sample size of 664 can be used for a population of 10 million or greater.

Table D: Sample Size by Population, Confidence Level, and Margin of Error (d)

	Confidence Level of 95%, z=1.96			Confidence Level of 99%, z=2.576		
Population Size (N)	***d=5%***	***d=3%***	***d=1%***	***d=5%***	***d=3%***	***d=1%***
250,000	384	1,063	9,249	662	1,830	15,557
500,000	384	1,065	9,423	663	1,837	16,057
1,000,000	384	1,066	9,513	663	1,840	16,319
5,000,000	384	1,067	9,586	663	1,843	16,535
10,000,000	384	1,067	9,595	664	1,843	16,562
50,000,000	384	1,067	9,602	664	1,843	16,584

Please note that while these recommended sample sizes have statistically high confidence intervals and low margins of error, they should not be used to replace the experience data for analysis purposes. To replace the experience data with a sample, a much larger sample size or the use of stratification sampling technique is recommended.

A.1.4 Confidence Interval

To finalize the SRS process, a confidence interval must be determined. The results, margin of error, and confidence level are needed for this. The interval should look like this: $results \pm d$, where the results are α (alpha) confident ($\alpha = 95\%, 99\%, etc$). Suppose 57% of a sample answered “yes” to a question and there is a 3% margin of error. 54% to 60% of the entire relevant population would have chosen “yes.” This can be said because SRS is used to be representative of the population being sampled. The confidence level, which measures the accuracy of a result, would then be applied to the interval. Therefore, the example above would be 95% accurate.

A.2 Systematic Random Sampling

Systematic sampling is a simplified form of random sampling. Similar to simple random sampling, this technique is used to pick a sample (*n*) from the sampling space. The sample is easily obtained by first selecting, at random, a number from the first *k* elements in the sampling space, which is ultimately known as a random start. After the starting point is determined, every *k*th entity will be chosen until the whole population has been sampled.

A.2.1 Drawing a Sample

To draw a sample systematically, the analyst must choose a 1-in-k sample. This can be determined very easily. Additionally, the sample size can be found using the same steps as in determining the sample size in simple random sampling. If the sampling space (population) is 1 million and the sample size is 1,066, then *k* must be less than or equal to $\frac{1,000,000}{1,066} = 938$; therefore, *k* must be less than or equal to $\frac{N}{n}$.

The analyst also has the option to change the starting point at the beginning and throughout the population. For instance, a number between 1 and 9 is randomly picked— 5 —that is where the 1-in-k sample will start until the sample size is achieved. Another variation is to choose a starting point by randomly selecting a number between 1 and 9. The 1-in-k sample will start there for a specified number of times and a new number will be randomly selected from the next 10 numbers. This will recur until the sample size is achieved. The randomness is important so results will encompass no or little bias.

A.3 Stratified Random Sampling

Stratified random sampling is an effective technique to use, but it can be complicated at first. Stratification is done by separating the population entities into separate groups, called strata, and then selecting a simple random sample or a systematic sample from each stratum. In fact, this method can show more precision than simple random sampling, but should be used only if the groups, or "strata," can be easily classified. There are two types of stratification: proportionate and nonproportionate, where proportionate is the more valuable method of the two. This method makes sure the sample size of each stratum is proportionate to the population size of each stratum. This section concentrates only on proportionate stratification.

A.3.1 Selecting the Strata

When running a stratified random sample, the analyst must first specify the strata wherein each sampling unit of the population can be placed. Perhaps the analyst is looking at the lapse rate on behalf of the Experience Study. There are 1 million policies for a specific company. The analyst can split the population into two strata: lapsed policies and in force policies.

First, the analyst will have to look at the full data set to determine the proportions of the full population. A frequency table can easily be programmed to look at the policies that lapsed versus the in force policies.

	Population	
	Frequency	Proportion
Lapsed Policies	18,816	1.88%
In Force Policies	981,184	98.12%
Total Policies	1,000,000	100%

In the table above, 1.88% of the sampling frame have lapsed policies and 98.12% have inforce policy. When figuring out how much to sample from each stratum, the sample sizes need to be proportionate. A sample size of at least 4,000 needs to be used if the sampling space is made up of 1 million entities. So, the proportions are applied to the sample size to determine how much of the sample goes to each stratum. The result: 1.88% of the sample should have policies that lapsed, which equals 75 policies and 98.12% of the sample should have in force policies, which equals 3,925 policies.

	Population		Proportionate Sample	
	Frequency	Proportion	Frequency	Proportion
Lapsed Policies	18,816	1.88%	75	1.88%
In Force Policies	981,184	98.12%	3,925	98.12%
Total Policies	1,000,000	100%	4,000	100%

The analyst could also break the Experience Study data down into strata based on gender (males and females), smoker status, duration of policy, and issue age; however, the latter two should be banded, like mentioned in the frequency distribution section. It is recommended that the number of strata defined should not exceed five. Importantly, simple random sampling or systematic sampling need to be performed on each stratum once the analyst calculates how many entities need to be pulled for the sample.

A.3.2 Recommended Sample Sizes

Ho and Brancard tested out different sample sizes based on a certain population size and recommend the following sample sizes in *table E*. Compared to Simple Random Sampling, the sample sizes to the associated sampling space, is significantly smaller using Stratification. This supports the advantage that precision can be achieved at a smaller cost. Note that the recommended sample sizes are meant to be used for basic experience study analysis where only 2 stratification classes are created. If additional fields are to be analyzed, it is recommended that additional stratification classes are added. In these cases, minimum sample sizes would increase.

Table E: Sample Size by Population

Population	Sample Size
50,000,000	9,375
40,000,000	8,000
10,000,000	7,250
1,000,000	4,000
500,000	3,500
100,000	649

A.4 Random Cluster

Random cluster samplings are used when a population is too large or naturally has clusters, also known as primary sampling units. This method differs from the other three because the groups are those being randomly selected, not the individuals. Unfortunately, this sampling method doesn't show the most precision compared to simple random sampling and stratification, but it is still substantial, especially when a budget exists. This method does show similarity to stratification, as both of them have subgroups of the population; however, the cluster sampling method includes all of the entities in a cluster (one-stage cluster), while the stratification method samples from each stratum.

This technique would be most appropriate to use if an analyst is looking at the number of life insurance policies from certain companies. The analyst could perform a random cluster sample by randomly selecting life insurance companies. For a one-stage cluster sample, the entities within these companies would be part of the sample, also known as the primary sampling units. For a two-stage cluster sample, the next step would be to randomly select a cluster of entities within the primary sampling units. These clusters would then be considered secondary sampling units.

A.5 Recommendations for Sampling Techniques

There are many types of sampling techniques, although, Ho and Brancard believe that the four mentioned sampling methods are the best choices for several reasons. Most importantly, these methods produce samples that are representative of the populations. Additionally, at least one of these methods is very attainable for a company's own needs. As mentioned throughout the different sections, advantages and disadvantages exist for each method. *Table F* was created to easily organize those analyses.

Table F: Advantages and Disadvantages of Sampling Methods

Method	Advantage	Disadvantage
Simple Random Sampling *Use if the population being used is fully up-to-date and time and money are not an issue.	• Easy to create the sample. • Every entity of the population has an equal chance of being selected for the sample. • Unbiased • Representative of the population	• The "list" must comprise the whole population being sampled. It may be hard to obtain the most current list. • It may be hard to go through a full list of entities, especially when the population is large. • This method could be very costly. • Need to use a certain sample size in order to obtain certain precision in results.
Systematic Sampling *Use if time and/or costs are limited. Although beware of hidden patterns when sample is collected.	• Simple technique ○ May be less complicated to create a program. • The population would be sampled uniformly.	• The 1-in-*k* method could follow a certain pattern in the population. ○ This could ultimately leave the sample biased and would not be representative of the population.
Stratified Random Sampling (Proportionate) *Use if proportions can be found from the main sampling frame and apply them to the sample. Also use if strata can be easily defined. Ho, Brancard prefer this method if the latter can be done.	• More precision with a smaller sample size and less costs. • Very representative of the population. • Subgroups (strata) can be represented proportionately.	• Strata can be hard to define. • Most complex method.
Cluster Sampling *Use when on a budget, when clusters naturally exist, or when clusters can easily be created.	• Convenient to use when clusters naturally exist in the data. • Inexpensive • Simple technique	• Data can be more complicated to analyze. • Larger sampling errors than other methods. • Least representative of the population compared with the other methods. • Entities within each cluster could be very similar and could lead to skewed results.

Data Quality Software

Below is a list of popular data quality software current available on the market. This list does not encompass all available software.

- BDQS (BDQS)
- Data Quality (Business Objects)
- DataFlux (SAS)
- Data State (IBM)
- Data Quality (Informatica)
- Trillium Software
- Data Quality Tool (SOA)

Glossary

- **Coding Errors** – one of the Data Validity Errors. These are also called mapping or translation errors, where the value of a field falls outside the acceptable values. For example, if the gender field contains the values M, F, U, a value of X would be considered a coding error.
- **Data Accuracy Errors** – second part of the data cleansing process. Data accuracy errors include experience period, other missing values, and relational numeric field errors.
- **Data Cleansing** – process of producing accurate and valid, error-free data.
- **Data Completeness Errors** – part of the data validation process. Data completeness refers to the amount of accurate and available data for use in the experience study analysis.
- **Data Consistency Errors** – part of the data validation process. Data consistency checks for possible errors through fluctuation of business across time.
- **Data Format Errors** – one of the Data Validity Errors. These are errors with the wrong format. Examples include inconsistent date fields (MM-DD-YY versus DD-MM-YY) as well numeric fields showing up as characters ('01', '1 ', ' 1').
- **Data Reasonability Errors** – part of the data validation process. These errors are more easily seen within the results of the experience study. Reasonability and trend of the results should exist. Changes in trends, experience or spikes in lapse rates would signal potential data errors.
- **Data Validation** – process of producing consistent, reasonable, and complete data.
- **Data Validity Errors**– first part of the data cleansing process. Data validity errors include missing values, coding errors, and format errors.
- **Experience Period Errors** – one of the Data Accuracy Errors. This error is specific to data outside of the experience period. Any policy not within the experience period is considered inaccurate. This includes policies issued after the experience period and terminations not within the experience period.
- **Inconsistency Errors** – one of the Data Consistency Errors. Data used for experience studies, when aggregate, should contain minimal fluctuation from study to study. This is especially true for inter/intra-company studies and individual studies of companies with mature blocks of business.
- **Longitudinal Errors** – one of the Data Consistency Errors. These errors occur when there are changes to the inforce status of the policy between time spans of separate study. When these studies are compiled into a larger experience study, longitudinal errors occur.
- **Missing Value Errors** – one of the Data Validity Errors. These are errors within fields where values are blank or zero but should not be.
- **Relationship of Numeric Field Errors** – one of the Data Accuracy Errors. Certain numeric fields in the experience data are relational to each other. Examples would be premium, face amount, and cash value. Premium, or cash value, should never be greater than face amount.
- **Time Horizon Errors** – one of the Data Consistency Errors. The time span of the experience data should depend on the type of experience study and experience study results will be used. The timing of the data as well as the time span of the data must be considered. Results from using older experience data may not be reasonable and using one year's worth of data may not be appropriate.

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