

Titel der Arbeit:
**>>Forecasting Methods in Audit
Analytical Procedures**
–
**Potential improvements in the
Process and the Case for eDSS-
assisted coreRule-Based
Forecasting<<**

Inauguraldissertation
zur Erlangung des akademischen Grades
Doctor rerum politicarum

vorgelegt und angenommen
an der Fakultät für Wirtschaftswissenschaft
der Otto-von-Guericke-Universität Magdeburg

Verfasser: Manuel Bern

Geburtsdatum und -ort: 31. Dezember 1981, Hamburg

Arbeit eingereicht am: 28. Oktober 2018

Gutachter der Dissertation: Frau Prof. Dr. Barbara Schöndube-Pirchegger
Herr Prof. Edward Lusk, PhD

Datum der Disputation: 17. Juni 2019

Table of Contents

| | |
|--|----|
| List of Tables..... | 8 |
| List of Abbreviations..... | 10 |
| 1. Introduction..... | 12 |
| 2. Analytical Procedures..... | 16 |
| 2.1. Introduction..... | 16 |
| 2.2. AP in the Risk-Based Year-End Audit..... | 17 |
| 2.2.1. Preliminary AP..... | 18 |
| 2.2.2. Substantive AP..... | 19 |
| 2.2.3. Concluding Analytical Procedures..... | 22 |
| 2.3. Historical Development..... | 23 |
| 2.4. AP in the context of Error vs. Fraud..... | 26 |
| 2.5. What does Effectiveness of AP mean?..... | 32 |
| 2.6. What does Efficiency of AP mean?..... | 36 |
| 2.7. Section Summary..... | 40 |
| 3. Survey on Analytical Procedures..... | 41 |
| 3.1. Introduction..... | 41 |
| 3.2. Perceived Effectiveness and Efficiency of AP..... | 45 |
| 3.3. Actual Effectiveness and Efficiency of AP..... | 46 |
| 3.4. Determination of Risk Thresholds..... | 49 |
| 3.5. Section Summary..... | 50 |
| 4. Determination of Expected Value..... | 51 |
| 4.1. Introduction..... | 51 |
| 4.2. Selection Criteria for Forecasting Models..... | 53 |
| 4.2.1. How can AP Effectiveness Performance be measured?..... | 53 |
| 4.2.1.1. Auditing Standards and Recommendations..... | 54 |
| 4.2.1.2. General Approach for Measuring Forecasting Precision..... | 56 |
| 4.2.1.3. Effectiveness Measurement Criteria..... | 57 |

| | | |
|-----------|--|-----|
| 4.2.2. | How can AP Efficiency Performance be measured? | 62 |
| 4.2.3. | Selection Criteria for AP | 63 |
| 4.3. | Forecasting Models | 64 |
| 4.3.1. | Introduction..... | 64 |
| 4.3.2. | Assumptions on the AP Forecasting Situation | 66 |
| 4.3.3. | Applicability of Empirical Studies to the AP situation | 68 |
| 4.3.4. | Client’s Planning Figures..... | 70 |
| 4.3.5. | Judgmental Methods..... | 72 |
| 4.3.5.1. | Unstructured Judgmental Forecasts | 73 |
| 4.3.5.2. | Guided Judgmental Forecasts | 75 |
| 4.3.5.3. | Graphically supported Judgmental Forecast..... | 79 |
| 4.3.6. | Naïve Methods | 81 |
| 4.3.6.1. | Naïve 1..... | 82 |
| 4.3.6.2. | Naïve 2..... | 84 |
| 4.3.6.3. | Last Year plus X..... | 85 |
| 4.3.6.4. | Fixed Ratios..... | 87 |
| 4.3.7. | Exponential Smoothing Methods..... | 88 |
| 4.3.7.1. | Single Exponential Smoothing | 89 |
| 4.3.7.2. | Double Exponential Smoothing..... | 91 |
| 4.3.7.3. | Triple Exponential Smoothing | 92 |
| 4.3.7.4. | Quadratic Exponential Smoothing | 94 |
| 4.3.7.5. | Trend-Dampening Exponential Smoothing | 96 |
| 4.3.8. | Autoregressive Methods | 98 |
| 4.3.8.1. | ARIMA..... | 99 |
| 4.3.9. | Other Regression Models | 101 |
| 4.3.9.1. | Linear Regression | 102 |
| 4.3.9.2. | Multivariate Econometric Methods (STAR)..... | 104 |
| 4.3.10. | Combining Forecasts | 107 |
| 4.3.10.1. | Equal Weight Combination..... | 107 |
| 4.3.10.2. | Rule-Based Forecasting | 108 |
| 4.3.10.3. | RBF - Original Model..... | 109 |
| 4.3.10.4. | Reduced Rule-Based Forecasting | 112 |
| 4.3.10.5. | CoreRBF | 114 |
| 4.3.10.6. | CoreRBF electronic Decision Support System | 116 |
| 4.4. | Section Summary..... | 118 |
| 5. | Determination of Risk Thresholds | 119 |

| | | |
|--------|---|-----|
| 5.1. | Introduction..... | 119 |
| 5.2. | Threshold Determination in Practice (Deloitte)..... | 121 |
| 5.3. | Additional Considerations | 123 |
| 5.4. | Section Summary..... | 125 |
| 6. | Rule-Based Forecasting Electronic Decision Support System | 126 |
| 6.1. | Introduction..... | 126 |
| 6.2. | Software and User Interface | 127 |
| 6.3. | Data Input..... | 128 |
| 6.3.1. | Step 1: Data Input and Auto-Completion..... | 128 |
| 6.4. | Causal Forces..... | 129 |
| 6.4.1. | Step 2: Identification of Causal Forces | 129 |
| 6.5. | Data Preparation | 130 |
| 6.5.1. | Step 3: Definition of a Cut-Off Point..... | 130 |
| 6.5.2. | Step 4: Manual Data Adjustment | 130 |
| 6.5.3. | Step 5: Functional Form and Automatic Outlier Elimination | 130 |
| 6.6. | Rule-Based Forecasting | 131 |
| 6.6.1. | Step 6: Model Applications and Feature Identification..... | 131 |
| 6.6.2. | Step 7: Short-Range Model and Long-Range Model | 133 |
| 6.6.3. | Step 8: Period Length, Blending- and Forecasting Horizon | 135 |
| 6.7. | Risk Threshold | 136 |
| 6.7.1. | Step 9: Identification of Risk Threshold..... | 136 |
| 6.8. | Final Forecast..... | 137 |
| 6.8.1. | Step 10: Calculate Final Forecast and Risk Intervals | 137 |
| 6.9. | Section Summary..... | 140 |
| 7. | Validation and Testing | 141 |
| 7.1. | Introduction..... | 141 |
| 7.2. | Functional Validation..... | 142 |

| | | |
|------------------------|------------------------------------|-----|
| 7.3. | Real-Life Testing | 143 |
| 7.3.1. | Testing parameters..... | 143 |
| 7.3.2. | Testing Questionnaire | 144 |
| 7.3.3. | Testing Feedback..... | 146 |
| 7.4. | Section Summary..... | 147 |
| 8. | Conclusion | 148 |
| 9. | Suggested Research..... | 150 |
| 9.1. | eDSS..... | 150 |
| 9.2. | Risk Threshold Determination..... | 151 |
| 9.3. | Rule-Based Forecasting | 152 |
| 9.4. | Questioning the RBF Approach | 154 |
| Appendix..... | | 155 |
| Appendix I | Detailed Survey Results | 155 |
| Appendix II | ClearSight Programming Code | 157 |
| Appendix II a | Introduction..... | 157 |
| Appendix II b | Modules..... | 158 |
| Module: Steps..... | | 158 |
| Sub DummyStart() | | 162 |
| Sub StartProgram() | | 162 |
| Sub CreateChart0() | | 167 |
| Sub Autoc() | | 168 |
| Sub CreateChart1() | | 173 |
| Sub CausFor() | | 173 |
| Sub CutOff() | | 177 |
| Sub CreateChart2() | | 179 |
| Sub ManDatAdj() | | 180 |
| Sub CreateChart3() | | 183 |
| Sub FForm() | | 184 |
| Sub ForeMod() | | 189 |
| Sub SRMLev() | | 203 |
| Sub Blend() | | 214 |
| Sub RskThr() | | 220 |
| Sub Forecast() | | 226 |
| Sub CreateChartFinal() | | 233 |

| | |
|---|-----|
| Module: Function_HoltMSE | 236 |
| Function HoltMSE(LevelArrayStart As Double, TreArrayStart As Double, HoltAlpha As Single, HoltBeta As Single, DatArray() As Double, Datapoints As Integer) | 236 |
| Module: Function_Last..... | 238 |
| Function Last(choice As Long, rng As Range) | 238 |
| Module: Function_LinRegBeta | 240 |
| Function LinRegBeta(X As Range, Y As Range) | 240 |
| Function LinRegAlpha(X As Range, Y As Range) | 241 |
| Function LinRegRSquare(X As Range, Y As Range) | 242 |
| Module: Function_LinRegBeta2 | 245 |
| Function LinRegBeta2(X As Range, Y As Range) | 245 |
| Function LinRegAlpha2(X As Range, Y As Range) | 246 |
| Function LinRegRSquare2(X As Range, Y As Range) | 247 |
| Module: Function_StdDev..... | 250 |
| Function StdDev(X As Range, Start As Range)..... | 250 |
| Module: Function_StdDev2..... | 251 |
| Function StdDev2(X As Range, Start As Range)..... | 251 |
| Module: Function_StErBeta | 252 |
| Function StErBeta(X As Range, Y As Range) | 252 |
| Module: Function_StErBeta2 | 254 |
| Function StErBeta2(X As Range, Y As Range) | 254 |
| Module: Function_TStat005nminus2..... | 256 |
| Function Tstat(Y As Range)..... | 256 |
| Appendix II c Forms | 258 |
| Form: ConHlp1..... | 258 |
| Form: ConHlp2..... | 259 |
| Form: ConHlp3..... | 260 |
| Form: ConHlp3_2..... | 261 |
| Form: ConHlp3_3..... | 262 |
| Form: ConHlp4..... | 263 |
| Form: ConHlp5..... | 264 |
| Form: ConHlp6..... | 265 |
| Form: ConHlp6_2..... | 266 |
| Form: ConHlp6_3..... | 267 |
| Form: ConHlp7..... | 268 |
| Form: ConHlp8..... | 269 |
| Form: ConHlp9..... | 270 |
| Form: ConHlp10..... | 271 |
| Form: ConHlp10_2..... | 272 |
| Form: ConHlp11..... | 273 |
| Step2_UsrFrm1..... | 274 |
| Step3_UsrFrm1..... | 275 |
| Step4_UsrFrm1..... | 276 |
| Step5_UsrFrm1..... | 277 |
| Step6_UsrFrm1..... | 278 |

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

| | |
|--------------------------------------|-----|
| Step7_UsrFrm1..... | 279 |
| Step8_UsrFrm1..... | 280 |
| Step9_UsrFrm1..... | 281 |
| Step9_UsrFrm2..... | 282 |
| Step9_UsrFrm3..... | 283 |
| Step9_UsrFrm4..... | 284 |
| Step9_UsrFrm5..... | 285 |
| Step9_UsrFrm6..... | 286 |
| Appendix III Life Testing Data | 287 |
| List of References | 289 |

List of Tables

| | |
|---|-----|
| Table 1: AP Survey - Operational Roles of Participants..... | 45 |
| Table 2: AP Survey - Determination of Expected Values | 46 |
| Table 3: AP Survey - Scoring of Methods employed by Practitioners | 47 |
| Table 4: AP Survey - Risk Threshold Determination | 49 |
| Table 5: Overview Scoring of Forecasting Methods, please refer to section 4.2 for the rating methodology..... | 65 |
| Table 6: Scoring of Client's Planning Figures..... | 70 |
| Table 7: Scoring of Unstructured Judgmental Forecasts | 73 |
| Table 8: Scoring of Guided Judgmental Forecasts..... | 75 |
| Table 9: Scoring of graphically supported Judgmental Forecasts..... | 79 |
| Table 10: Scoring of Naive 1 | 82 |
| Table 11: Scoring of Naive 2 | 84 |
| Table 12: Scoring of Last Year plus X..... | 85 |
| Table 13: Scoring of Fixed Ratios..... | 87 |
| Table 14: Scoring of Single Exponential Smoothing..... | 89 |
| Table 15: Scoring of Double Exponential Smoothing | 91 |
| Table 16: Scoring of Triple Exponential Smoothing | 92 |
| Table 17: Scoring of Quadratic Exponential Smoothing | 94 |
| Table 18: Scoring of Trend Dampening Exponential Smoothing..... | 96 |
| Table 19: Scoring of ARIMA..... | 99 |
| Table 20: Scoring of Linear Regression..... | 102 |
| Table 21: Scoring of Multivariate Econometric Methods (STAR)..... | 104 |
| Table 22: Scoring Equal Weights Combination..... | 107 |
| Table 23: Scoring of RBF - Original Model | 109 |
| Table 24: Scoring of Reduced Rule-Based Forecasting..... | 112 |

| | |
|--|-----|
| Table 25: Scoring of Core Rule-Based Forecasting..... | 114 |
| Table 26: Scoring of CoreRBF electronic Decision Support System | 116 |
| Table 27: Risk Threshold Determination Matrix | 121 |
| Table 28: eDSS Practical Testing Feedback | 146 |
| Table 29: Conclusion - Top Three AP Forecasting Methods..... | 148 |
| Table 30: Conclusion - Forecasting Methods employed by Practitioners | 148 |
| Table 31: Detailed AP Survey Results | 156 |
| Table 32: Life-Testing Data and Forecasting Results | 288 |

List of Abbreviations

| | |
|----------------------|--|
| ACCA: | Association of Chartered Certified Accountants |
| AICPA: | American Institute of Certified Public Accountants |
| ANN: | Artificial Neural Network |
| AP: | Analytical Procedures |
| AR: | Autoregressive |
| ARIMA: | Autoregressive Integrated Moving Average |
| ARMA: | Autoregressive Moving Average |
| CI: | Confidence Interval |
| CLT: | Cognitive Load Theory |
| coreRBF: | Rule-Based Forecasting as per Adya and Lusk (2013) |
| ccoreRBF: | Complexity-sensitive coreRBF |
| CST: | Complexity Scoring Technique |
| Dampen: | Dampen Trend Exponential Smoothing |
| Deloitte: | Deloitte Wirtschaftsprüfungsgesellschaft mbH |
| DSS: | Decision Support System |
| eDSS: | electronic Decision Support System |
| Excel: | Microsoft Excel 2010 |
| Graphical Forecasts: | Graphically supported Judgmental Forecasts |
| IAASB: | International Auditing and Assurance Standards Board |
| IDW: | German Institute of Certified Public Accountants ("Institut der deutschen Wirtschaftsprüfer") |
| IFAC: | International Federation of Accountants |
| INTOSAI: | International Organization of Supreme Audit Institutions |
| ISA: | International Standard of Accounting |
| IPO: | Initial Public Offer |
| JMP: | SAS Institute JMP v.10 |
| KPI: | Key Performance Indicator |

| | |
|---------|--|
| LRM: | Long-Range Model |
| MA: | Moving Average |
| MAPE: | Mean absolute percentage error |
| MdAPE: | Median absolute percentage error |
| MdRAE: | Median relative absolute error |
| MdsAPE: | Median symmetric absolute percentage error |
| MSE: | Mean Squared Error |
| PCOAB: | Public Company Accounting Oversight Board |
| RBF: | Rule-Based Forecasting |
| RMBS: | Residential Mortgage-Backed Security |
| RMSE: | Root mean squared error |
| RRBF: | Reduced Rule-Based Forecasting |
| RTI: | Risk Threshold Interval |
| sMAPE: | Symmetric mean absolute percentage error |
| SOX: | Sarbanes-Oxley Act |
| SRM: | Short-Range Model |
| STAR: | Statistical Techniques for Analytical Review |
| VBA: | Visual Basics for Applications |

1. Introduction

Analytical Procedures (“AP”) are one of the core concepts of organizational year-end auditing. The idea behind AP is both simple and powerful: Expectations about the organization’s most relevant financial accounts and key performance indicators (“KPIs”) are formed and compared with the organization’s actual figures to be audited. Unexplained material discrepancies warrant additional audit resources while the absence of discrepancies may lead to a re-distribution of resources to other auditing fields.

AP are procedures with multiple applications:

- Identification of high- and low-risk areas during the planning phase of the audit;
- Supplement to- or substitution for test of detail in the substantive phase of the audit and
- Reviewing of (corrected) impressions gained by the auditor during the closing phase of the audit.

Auditing literature and -standards¹ generally agree that AP are among the most important concepts of auditing, especially with respect to identifying management fraud and especially after the massive occurrences of such frauds leading to the Sarbanes-Oxley Act in the US.

At the outset of this thesis, there was an in essence very simple question:

- **Given their importance for year-end auditing, are AP conducted in an optimal way in practice?**

While this question is a simple one, answering it requires several intermediate steps. The thesis will start by exploring AP as a concept (section 2):

- What are analytical procedures?

¹ In the following text, there are several topics in which general statements concerning accounting standards and guidance provided by auditing- or accounting organizations is made.

To put this into context, there are a large number of professional organizations providing guidance on auditing in their specific field of activity. Reviewing guidance provided by a number of organizations has shown that there also exists a high degree of uniformity with respect to concepts as well as detail provided.

In order to capture nuances in guidance and standards, publications of the following organizations were considered:

- German Institute of Certified Public Accountants (“IDW”);
- International Federation of Accountants (“IFAC”);
- International Organization of Supreme Audit Institutions (“INTOSAI”);
- International Auditing and Assurance Standards Board (“IAASB”);
- Public Company Accounting Oversight Board (“PCOAB”);
- American Institute of Certified Public Accountants (“AICPA”) and
- Association of Chartered Certified Accountants (“ACCA”).

- What role do they play in year-end auditing?
- What does the literature say about AP?
- Why are AP crucial for the success of audits and what does effective and efficient AP actually mean?

The discussion will focus on current audit guidance and -literature and also examine underlying concepts.

After this introductory chapter, the first step in actually exploring the complex is undertaken:

- How are AP performed in practice?

To answer this question, the author conducted interviews with auditing partners in Germany and the US as well as surveyed all auditing practitioners at Deloitte Germany. Section 3 presents and discusses the results of this survey.

The survey showed strong preferences for specific forecasting models by audit practitioners, some formal, some informal. But are those methods “good methods”? What does “good methods” actually mean in an AP context?

At its core, AP is a forecasting problem. Effective forecasts are a prerequisite for identifying unusual deviations in the audit field.

- But what does effective forecasting mean?
- How can or should this be measured?
- What kind of forecasting models can practitioners choose from?
- What are their relative strengths and weaknesses?
- How do they perform empirically?
- And what are the relative performance costs of the methods?

In section 4, a broad discussion of forecasting models and methods based on extensive empirical competitions is undertaken. The discussion includes general criteria of forecasting as well as taking into account the specific requirements of public auditing.

Then in section 5, the second important component of AP, besides forecasting, will be discussed:

- What constitutes an unusual deviation from the forecast?

This is a question without clear answer in the literature. Nevertheless, it needs to be dealt with in a practical context. Section 5 will explore the issue and introduce an approach implemented at a Big4 auditing firm.

Comparing practice (reflecting a Big4 auditing firm in one of the major world economies,²) and theory, this thesis will show a significant conceptual discrepancy. In the second part of the thesis, the author proposes steps for closing this gap:

Section 4 comes to the conclusion that a strong candidate forecasting model for AP would be coreRule-Based Forecasting as per Adya & Lusk (2013) (“coreRBF”). For this thesis, the author programmed an eDSS (a forecasting software) using coreRBF as basis, which is introduced in section 6. The system incorporates all requirements of AP in ten easy and structured working steps, significantly reducing application cost/time of coreRBF while at the same time potentially increasing effectiveness by reducing sources of application error.

CoreRBF has not been automated like this before. The resulting software, while focusing on AP, can be applied to other forecasting questions and the program code can be used as basis for further forecasting model development.

Section 7 documents the testing of the new eDSS using a two-step approach: First, parallel forecasts on twelve random time series using the software and a manual application of coreRBF were produced. The results showed that the eDSS was able to replicate the forecasting process of coreRBF.

After this, the software was tested on seven life audit engagements resulting in 64 separate forecasts. Practitioners’ feedback showed good marks in usability as well as perceived increases in AP effectiveness and efficiency.

² This thesis has been created with the support of the auditing- and professional services firm Deloitte & Touche Tohmatsu, particularly its German member firm, Deloitte Wirtschaftsprüfungsgesellschaft mbH (“Deloitte”). The survey discussed within the thesis has been conducted exclusively within Deloitte. Also, when discussing the risk threshold determination process in section 4, Deloitte regulations and standards have been taken as an example.

Deloitte & Touche Tohmatsu is, with approximately 200.000 employees worldwide (Deloitte & Touche LLP, 2013 (a)), one of the ‘Big 4’ auditing firms (Deloitte & Touche Tohmatsu, PriceWaterhouseCoopers, Ernst & Young and KPMG) which dominate the global auditing market (comp. e.g. Reuters, 2013).

This does not, however, mean that the results of the study are only applicable to Deloitte as an organization or to Deloitte audit engagements.

The past has shown that even if substantial procedural differences between the dominating auditing firms exist, these differences tend to disappear over time, as developments are communicated across the industry and personnel switch between audit firms. The following thesis therefore assumes that Deloitte gives a fair representation of the auditing industry in general.

Finally, section 9 gives an outlook / suggestion for further development and research on this issue.

Each section is closed with a short summary for reading convenience.

2. Analytical Procedures

2.1. Introduction

Analytical Procedures are ‘*evaluations of financial information through analysis of plausible relationships among both financial and non-financial data. Analytical procedures also encompass such investigation as is necessary of identified fluctuations or relationships that are inconsistent with other relevant information or that differ from expected values by a significant amount*’ (International Standard of Accounting (“ISA”) 520).

Based on this definition, the following section discusses the following issues:

- What is the role of AP in the overall year-end audit process?
- How has the role of AP developed over time and how is this role seen today?
- Why are AP so important, especially relative to tests of detail?
- What constitutes effective AP?
- What constitutes efficient AP and what is the overall efficiency contribution of AP to the audit?

2.2. AP in the Risk-Based Year-End Audit

AP ...are to be conducted during the audit planning, the conduct of the audit as well as during the audit review before the closing of the audit³.

The year-end auditing process knows three kinds- or stages in which AP are conducted (IDW, PS 312, IFAC, ISA 520):

1. Planning phase (*‘Preliminary Analytical Procedures’*).
2. Substantive / Testing phase (*‘Substantial Analytical Procedures’*).
3. Concluding phase / Review of the audit results (*‘Concluding Analytical Procedures’*) (Deloitte & Touche LLP, 2013 (b); Millichamp & Taylor, 2008).

In each of the three phases, the goals pursued with AP differ. Consequently, data interrogated as well as appropriate methods employed would differ as well.

³ „...sind sowohl bei der Prüfungsplanung, Prüfungsdurchführung, als auch als abschließende prüferische Durchsicht vor Beendigung der Prüfung durchzunehmen“ (IDW, 2017, L739)

2.2.1. Preliminary AP

Before the introduction of SAS No. 56, talking about AP would typically refer to Preliminary AP: Developing a priori expectations of the client's key value drivers (by themselves as well as in relation to peer organizations) in order to identify areas which demanded special audit attention and resources (Kayadelen, 2008, S. 20) in the context of the risk-oriented audit approach:

The demand for an economical audit demands of the auditor to evaluate the risk of the different audit fields, which allows putting special emphasis on areas of increased risk during the allocation of audit resources.⁴

In this development of the audit strategy, Preliminary AP are among the most important factors (Millichamp & Taylor, 2008). In the literature, they are therefore sometimes also referred to as '*attention-directing procedures*' (Ashton & Wright, 1989).

Data interrogated may include financial accounting information on profit-center level such as turnover, procurement cost of key production inputs, KPIs such as asset coverage ratio or non-financial ratios such as turnover per retail-shop-floor or goods produced per production staff. As Preliminary AP refer to the planning phase of the audit, the data interrogated is typically relatively highly aggregated (AICPA, 2012, p. 3).

Preliminary Analytical Procedures are a mandatory component of year-end audit planning (IFAC, ISA 315).

⁴ „Die Forderung nach einer möglichst wirtschaftlichen Prüfung verlangt vom Abschlussprüfer, bei der Allokation von Prüfungsressourcen risikoreiche Bereiche besonders zu berücksichtigen“ (Marten, Quick, & Ruhnke, 2015, p. 287)

2.2.2. Substantive AP

Substantive AP, i.e. AP during the substantive phase of the audit, may be used to supplement or to substitute tests of detail in the audit.

AP play an important role in effectivity but also in economicality of a year-end audit, as they may be used to reduce the number of tests of detail and thus the overall scope of the audit for obtaining a necessary level of assurance.⁵

Or:

If an analytical procedure reveals no unusual fluctuations, the implication is that the possibility of a material misstatement is minimized. In that case, the analytical procedure constitutes substantive evidence in support of the fair statement of the related account balances, and it is possible to perform fewer detailed tests in connection with those accounts. (Arens & Loebbecke, 2000)

The actual effectiveness of AP depends on the forming of precise forecasts and on the correct interpretation of results (see section 2.4). Independent of that, there are three prerequisites that need to be met and which the literature mainly discusses in the context of substantive procedures:

- Relative homogeneity of data

If the total volume of an auditing field is significantly influenced by a small number of very large infrequent transactions, then any forecasts (i.e. expectations) based on this modified data pool will be subject to very large errors. Normalizing, excluding or truncating the data (i.e. standard data preparation procedures for data-based forecasts) may or may not solve this problem:

- If the events are non-repeating, not excluding these “outlier” data points will potentially lead to biased forecasts (depending on the forecasting model);
- If the events are infrequent, but repeating, excluding the outliers will lead to biased forecasts and
- If the events are infrequent, but repeating and the outliers are not excluded, the forecasts will be unbiased but (again depending on the model) likely still be

⁵ „Analytische Prüfungshandlungen spielen für die Effektivität, aber auch für die Wirtschaftlichkeit einer Abschlussprüfung eine bedeutende Rolle, da durch sie die aussagebezogenen Einzelfallprüfungen und damit der Prüfungsumfang insgesamt zur Gewinnung eines hinreichend sicheren Prüfungsurteils reduziert werden können.“ (IDW, 2017, L 738)

subject to large forecasting errors (because the occurrence of the next outlier cannot be accurately predicted).

It follows that if the auditing field is subject to such infrequent but significant events, the assurance gained from AP alone is limited:

[The auditor may not] solely rely on the results of analytical procedures in case of material single transactions or significant risks.⁶

The IDW sees this issue primarily in connection with small- and medium organizations (IDW, 2017, L770). However, the same effect may be found in large organizations, if the audit field in question is either sufficiently dis-aggregated or if the data is subject to sufficiently large events (e.g. large external shocks).

- Availability of data

Not all forecasting methods require the same number of data points. Many time-series based forecasting methods require several cycles of data (e.g. several years if seasonal effects are to be forecasted) or forecasting error will be very large on average.

While this generally means that AP may be less useful for very young organizations or organizations that have changed significantly in recent times, not all forecasting methods require the same data horizon. Forecasting methods emphasizing recent data, such as exponential smoothing models, are less dependent on a large number of data points than e.g. time-series regression models.

As the accuracy of any given forecast is not readily transparent ex-ante, it follows that in case of doubt, the auditor needs to have an understanding of the data requirements of any model employed in order to understand the assurance gained from AP.

- Reliability of data

If effective internal controls exist and if the analytical procedures confirm the preliminary evaluation of low risk of a material misstatement in the year-end closing, then [the auditor] may forego test of detail to the greatest possible extent.⁷

The reverse is of course also true: If the data is unreliable, either because of uncontrolled business processes or because of the intent of the auditee to manipulate the client, then necessarily all forecasts based on this data have to be useless as well. The

⁶ „Allerdings darf der Prüfer sich bei wesentlichen Posten bzw. Signifikanten Risiken nicht ausschließlich auf die Ergebnisse analytischer Prüfungshandlungen stützen“ (Marten, Quick, & Ruhnke, 2015, p. 387, IFAC, ISA 320.21, IDW PS 312.12)

⁷ „Existieren wirksame interne Kontrollen und bestätigen analytische Prüfungen die vorläufige Einschätzung eines niedrigen Risikos einer wesentlichen Falschaussage im Jahresabschluss, so kann auf Einzelfallprüfungen weitestgehend verzichtet werden.“ (Marten, Quick, & Ruhnke, 2015, p. 387)

topic of intentional manipulation (i.e. fraud) will be discussed in more detail in section 2.4.

Examining the reliability of data used in substantive AP is a requirement as per IFAC, ISA 520.05b.

The efficiency gain due to the employment of AP is generally the most significant in auditing fields in which a small amount per transaction makes testing a sufficient share of the field problematic and where other kinds of auditing evidence (such as outside confirmation) are no alternative. Nevertheless, as Trompeter & Wright (2010) found, potential efficiency gains resulting from substantive AP may in practice not be realized as a ‘negative’ in AP is often not followed-up by a reduction of test sample size. This finding was confirmed by Marten, Quick, & Ruhnke (2015, p. 346), who refer to this phenomenon as „*assymetrical application*“.

2.2.3. Concluding Analytical Procedures

AP during the concluding review of the audit (Concluding Analytical Procedures) have the goal of supporting the overall judgement of the audit or of identifying discrepancies previously undiscovered (IDW, 2017, 769L, IDW PS 312, Tz. 23, IFAC ISA 520.6).

In the concluding phase of the audit, previous audit analyses are re-visited taking under consideration additional information that surfaced during the audit process. In this context, AP may be conducted, typically analogously to the preliminary AP and results are compared (Kayadelen, 2008, S. 37).

If this re-visiting of information leads to discrepancies, the corresponding audit fields require additional investigation or a change of the overall risk classification (comp. IFAC ISA 520.A18 or IDW PS 312, Tz. 23).

Concluding AP give the auditor the chance to have a second look at the ‘big picture’. In this context, they may play a major role in uncovering material fraud, e.g. if corrections made during the course of the audit lead to certain KPIs making no sense anymore.

2.3. Historical Development

AP has always been part of organizational audits. At Deloitte, AP as a concept has been the subject of several intra-firm bulletins in the 1930s (Stringer & Stewart, 1996, S. 15). Taking into account that external company audits in the United States only became mandatory mostly as a result of 1929 stock market crash and especially with the Security and Exchange Act of 1934 (Byrnes, et al., 2012), it is clear that AP is one of the basic- or earliest principles / processes of auditing.

Despite AP being a comparatively old auditing concept, formally, it was introduced in the United States only in 1972 by the American Institute of Certified Public Accountants (“AICPA”) under the name ‘analytical review’ (AICPA, 1972). Since then, AP has gradually been receiving more attention. In 1988, AICPA issued SAS No. 53 on “The Auditor’s Responsibility to Detect and Report Errors and Irregularities”, imposing greater responsibility on auditors to detect financial statement fraud. In the same year, SAS No. 56 “Analytical Procedures”, clarified that AP may also be used as substantive test (as opposed to being solely “attention directing”).

Trompeter and Wright found that until the mid-1990’s, research on AP was relatively limited (Trompeter & Wright, 2010, S. 672). Hirst & Koonce (1996) took a survey on the practical implementation of AP into auditing. They interviewed 36 practitioners from different audit firms and levels of experience. They found that in most cases, AP was based on information obtained from the client (financial accounting data, planning- and budgeting documentation) and that decision aids and statistical methods were rarely used. Furthermore, Hirst & Koonce observed that in most cases of dissonance between expectation derived by AP and data provided by the client, corroborating information of the client’s data was only obtained from the client itself, mostly by interview.

Hirst & Koonce drew the conclusion that the reliance on client-generated planning data as well as client interviews for the generation of corroborating evidence weakened the audit against top-management manipulative behavior, i.e. fraud (Hirst & Koonce, 1996, S. 467).

In the beginning of the 2000’s, several high-profile balance sheet fraud cases such as the Enron and WorldCom accounting scandals called into doubt the efficacy of external auditing processes (Palmrose & Scholz (2004), Agrawal & Chadha (2005)) and gave momentum to a tightening in accounting and auditing oversight, most noteworthy the Sarbanes-Oxley Act of 2002 (“SOX”) in the United States and the subsequent formation of the PCOAB.

These highly visible fraud-caused bankruptcy cases focused regulatory attention on processes for the detection of material fraud, meaning foremost an increase in the sophistication of AP. Nelson & Tan (2005) noted that the formation of the PCOAB would likely lead to a general re-evaluation of the auditing approach. Bell, Peecher, & Solomon (2005) observed increased usage of external data sources such as industry databases for AP. Trompeter & Wright (2010) found in an interview-based survey, replicating the Hirst & Koonce (1996) approach, that audit resources allocated to AP had increased to 25% in the mid-2000s from 15% in the mid-1990s.

Furthermore, based on their interviews, they concluded that due to SOX section 404, auditing had become more focused on controls which in return allowed a heavier reliance on AP in the substantive phase (as assurance of data quality had supposedly improved). As one interviewee put it:

“We do a lot more of internal control work so therefore we get more comfortable with the process around each account rather than substantively auditing the account... we do a walkthrough of the controls and then test the controls. Then at year end we only have to do analytics over those accounts. So whereas we used to ignore kind of the controls and assume that there were no effective controls over any counter process [we now test controls and rely on analytics to] audit the accounting year end” (Trompeter & Wright, 2010, S. 679).

Interestingly, most participants in the study stated that they would increase testing resources allocated to auditing fields in which AP had detected anomalies but were reluctant to decrease resources, if no such anomalies were identified. This was justified with the risk of missing errors. It could be argued that this reasoning is flawed as the increase of resources in fields with anomalies automatically leads to a decrease of resources in other fields, given fixed auditing budgets. On the other hand, it is plausible that the auditors in question were arguing from the point of view of liability in front of a court of law. It seems plausible that the active reduction of resources which lead to missing an error would be difficult to argue, not from a logical, but from a psychological point of view.

Trompeter & Wright (2010) furthermore identified ISA 315 (“Identifying and assessing the Risks of material Misstatement through understanding the Entity and its Environment” (IFAC, 2009a)) as well as ISA 330 (“The auditor’s response to assessed risks” (IFAC, 2009b)) as the driving forces behind AP.

Summarizing, in the last 20 years, auditing focus has continually shifted towards the utilization of AP a) for the increase of auditing effectiveness, especially with regards to fraud, and b) for the increase of efficiency, especially with respect to substantive procedures.

At the same time, Trompeter & Wright (2010) found that in most cases auditors did not develop a priori expectations, i.e. did not use formal forecasting methods for AP, a finding that was confirmed during the the more extensive survey conducted for this thesis.

2.4. AP in the context of Error vs. Fraud

Audit literature in general agrees that AP play a key role in identifying first indicators of material misstatements (Millichamp & Taylor (2008), or Arens & Loebbecke (2000)). Wright & Ashton (1989) found that more than 50% of all material mistakes identified by tests of detail could have been identified with AP. Biggs & Wild (1984) came to the conclusion that 41.5% of identified mistakes examined, had originally been flagged by AP. Fraser, Hatherly and Lyn (1997) conducted a survey in which the participant stated that around 44% of all identified mistakes had been found by AP.

The importance of AP becomes even clearer when different kinds of misstatements are discussed.

From a conceptual point of view, three kinds of misstatements can be distinguished:

1. Unintentional unsystematic errors or “sloppiness”;
2. Unintentional systematic errors or “incompetence”;
3. Intentional errors or “fraud”.

Sloppiness refers to cases in which the person entering the posting “just makes a mistake” such as switching the digits in the value of the transaction, entering an incorrect account or accidentally adding a zero. In most cases, it would be expected that unsystematic errors have a negligible effect on a financial statement level.

Practice shows that unsystematic errors may have material impact if they occur at neuralgic points: In October 2011, the German Ministry of Finance announced a correction of the national debt level to 81.1%, 2.6% lower than previously reported. During year-end audit, it had been found that risk provisions of state-owned HRE Bank needed to be \$78.7 billion lower than previously expected. Apparently, in aggregating figures at an organizational level, a sum had been entered... twice (Reuters, 2011). Irregularities of this magnitude should be identified as suspicious during the preliminary Analytical Procedures phase. On the other hand, audit practitioners frequently argue that for unsystematic errors to affect an organization on a material level, substantial postings need to have been corrupted, as in the example above. As has been pointed out in section 2.2.2, substantive testing should include these transactions in any case (as it was in fact in the case above). It follows that for material unsystematic errors, there is more than one way of detection.

Examples of **incompetence** in this context may include incorrect depreciation methods, wrongful classification of assets or non-compliant tax treatments. The point is that the errors are systematic but unintentional, i.e. the individual conducting the error was convinced that he or she was being compliant. As a consequence, it is likely that in the organization in question there are multiple occurrences of the error (often one-sided) and the errors are not hidden. Consequently, material systematic errors (single transaction or aggregation) might be detected either by AP or by substantive testing.

Fraud, i.e. an intentional misstatement, poses a completely different challenge to an external auditor. From an auditor's point of view, fraud falls in two broad categories:

External fraud aims at gaining advantages from third parties. The fraud is perpetrated by the organization itself (or to be more precise: One or more individuals within the organization, most often including upper management). These kinds of frauds often aim at deceiving the public about the state of the organization, be it to inflate stock prices, gain loan-financing, acquire participants for investment schemes or pose as reliable customer to defraud third companies of goods and services. Some of the overall highest impacting criminal transgressions fall into this category, including the Enron meltdown (2001, \$74 billion loss in shareholder value), the WorldCom scandal (2002, \$11 billion overstatement of assets) or Bernie Madoff's Ponzi Scheme (2008, \$64.8 billion of lost investments).

Internal fraud, in contrast, refers to instances of fraud which are conducted from within and against the organization. Generally speaking, internal fraud has smaller impact than external fraud. This is due to the fact that typically, a smaller number of persons is involved (most often this kind of fraud is located in mid-management and below), i.e. the threshold for internal discovery is much lower. Nevertheless, there are scenarios in which internal fraud can reach dimensions which are material to the organization. One of the most prominent examples is former Société Générale investment banker Jérôme Kerviel who falsified bank internal reporting from 2006 until 2008 in order to conceal his unauthorized dealings in index futures, eventually leading to net losses of €4.82 billion for his organization.

Irrespective of its precise nature, fraud poses a special challenge to auditors, as it always involves an element of concealment. Business forensics practice shows that there are virtually as many strategies of concealment as there are fraud scenarios, some sophisticated, some not. However, even the least proficient perpetrator usually expects that 'his' transactions might become part of the testing sample of an external audit. It follows that most fraud-related

transactions are either set-up in a way that they will typically pass inspection or are hidden in obscure accounts which are not expected to be part of the audit.

KPMG found in a 2011 survey that the average fraudster had in excess of ten years of experience with the company he or she defrauded (KPMG, 2011). It can therefore be assumed that the person in question has witnessed more than one year-end audit with the organization and also has some expectations as to the usual focus of the auditors.

At this point, the strength of AP needs to be stressed. Marten, Quick, & Ruhnke, (2015) argue that

...the sole reliance on analytical procedures carries the danger that the client manipulates the data in such a way that the analytical procedures lead nowhere.⁸

It needs to be stressed that this opinion presents only part of the picture: It is self-evident that a client who is engaged in balance sheet fraud will of course try to conceal this fact (possibly by manipulating data). The strength of AP, however, lies in exactly the point that it is a magnitude more difficult to conceal the distortionary aggregated effect, which most material fraud scenarios have on financial accounting, than just to mask the transactions themselves. This is especially the case if AP include the full range of financial-, non-financial- and peer group data, as the difficulty to conceal contradictions grows exponentially with the variety of data which needs to be manipulated in consistency.

There are many historical examples of cases of fraud that were or should have been discovered by AP. For example, Lynn E. Turner, former chief accountant for the SEC, argues that Frierling & Horowitz, the auditing firm hired by Mr. Madoff, should at the very least have detected the Ponzi Scheme by means of AP (Bernhard L. Madoff Securities' trading volume in relation to claimed returns had been implausibly low for years) (Crawford & Dugan, 2009).

Taking the point of view of the auditor, fraud poses a special risk. Palmrose & Scholz (2004) found, examining 492 cases of public company restatements, that cases involving fraud had a higher than average restatement value, more often led to the company going bankrupt and

⁸ „Vielmehr besteht bei einer alleinigen Anwendung von analytischen Prüfungshandlungen die Gefahr, dass der Mandant die angeprüften Datenkonstellationen dergestalt manipuliert, dass analytische Prüfungshandlungen ins Leere gehen.“ (Marten, Quick, & Ruhnke, 2015, p. 387)

also more often leading to litigation including litigation against the auditing firm. It follows that effective AP should be understood as crucial to the auditing process / risk management.

Having pointed out the special significance of AP for discovering fraud, it also needs to be pointed out that the detection of fraud requires special strategies.

Especially in the case of fraud, there is usually no reason to assume that a misstatement is limited to the present period, i.e. that there are discrepancies between past and present. This issue of data reliability can be addressed with a combination of the following three approaches:

- Consideration of fraud-relevant business events;
- AP on non-financial KPIs;
- AP on industry KPIs.

As will be discussed below, all three strategies increase the chance of discovering fraud, while none may be considered an absolute guarantee. Well-balanced AP include all three aspects in order to maximize effectiveness.

Fraud-Relevant Business Events

In the standard work on white-collar criminology “Other People's Money: A Study in the Social Psychology of Embezzlement”, Cressey pointed out that one of the prerequisites of fraud is a financial motive, a “perceived unshareable financial need” (Cressey, 1973, S. 30).

While practice shows that other motives such as revenge or thrill-seeking may act as substitute triggers for financial fraud (comp. the alleged manipulations of Jérôme Kerviel at Société Générale 2007 / 2008), it is still true that the vast majorities of fraud cases center around direct or indirect financial gain.

It follows that the trigger for most cases of balance sheet fraud is a specific financial need. In some cases, it is possible to identify specific business events which may trigger the need of immediate balance-sheet improvement. Unless the organization is able to solve its immediate difficulties, these misstatements will stay in the financial accounting (and often grow with time).

One measure of data sanitation is therefore to perform AP not only for the present period but also for KPIs around the dates of specific events in the past. Examples of material fraud-relevant business events include:

- Mergers, buy-outs and initial public offers (“IPOs”);
- Major treasury events;
- Business crises such as class-action suits, non-approval of pharmaceutical products etc.

Non-Financial KPIs

Non-financial KPIs refer to all performance indicators not- or not completely derived from financial accounting. Examples include turnover per shop-floor or -per operative headcount, percentage machine utilization or storage space per sales.

As Brazel, Jones, & Zimbelman (2009) showed, the difference in non-financial KPIs between organizations involved in material fraud to those which are not, is significantly larger than the difference in financial KPIs. They argue convincingly that it is generally more difficult to falsify non-financial data, which is often also relatively easy to verify. It might be added that it is also more difficult to foresee which non-financial data / KPIs would be required by auditors.

Investigations practice shows that in nearly all cases, non-financial data is a “source of truth” for auditors.

Industry KPIs

Cross-organizational data may also function as a point of safe reference. An analysis of KPIs across organization may generate additional indications of balance sheet fraud. While it is inconceivable that a group of individuals could influence data on an industry level, industry KPIs pose a different set of challenges to auditors:

- At the time of the audit, there will be only limited audited information from peer companies. AP on industry KPIs therefore typically work with a time lag.
- AP on industry KPIs will not pick up on any systematic misstatements which are applied across organizations. The inflated valuation of Residential Mortgage-Backed Securities (“RMBS”) might for example be considered as such a case: The US department of justice stated in a press release on its \$ 16.65bn settlement with Bank of

America that “*Today’s settlement attests to the fact that fraud pervaded every level of the RMBS industry...*” (DoJ, 2014).

Other scandals in the banking world in recent years have followed a similar pattern.

- AP on industry KPIs will typically not identify cases in which individuals try to hide the fact that their organization diverged from average industry performance. In case an organization tries, for example, to secure financing because it has been underperforming in relation to its peers, the manipulated accounts will most likely aim at simulating KPIs average to the industry.

2.5. What does Effectiveness of AP mean?

It has been discussed in detail that **effective** AP can be a major contributing factor to the successful conduct of a year-end audit, be it in the planning-, the substantive- or the concluding phase. It is also clear that ineffective AP may hurt the overall success of the audit.

From this follow two logical next questions: What does **effective** with respect to AP actually mean and what can an auditor do to ensure the effectiveness of his AP?

Based on the ISA definition quoted in the introduction to this section⁹, three ‘tasks’ within AP can be derived: (I) the identification of *plausible relationships* between key figures, which can be translated into finding of appropriate methods for forming expectations, (II) the identification of *fluctuations or relationships that are inconsistent*, meaning cases, in which the actual data significantly deviates from the expectation and (III) to *investigate* the reasons behind any discrepancies (this last step is mentioned here for the sake of completeness. It feeds back into the regular audit process in the sense of interviewing the client and conducting tests of detail and is as such outside the scope of this thesis).

It is clear then, that **effective** forecasts are a prerequisite for overall effective AP (i.e. **step I**). In current auditing literature, this is often something of a blind spot. The IDW, for example, gives the following guidance:

The success of analytical procedures decisively depends on the quality of the prognosis [performed for this purpose].¹⁰

This is certainly a good starting point, but: What does *quality* mean in this context? How is it measured? Are there specific forecasting methods which score better than others with respect to this criterion?

As another example, Marten, Quick, & Ruhnke (2015) advise that the following methods are possible options for AP: Last year’s figures, KPIs, trend analyses, regression and Box-Jenkins exponential smoothing (p. 336 ff). Besides the facts that KPIs are not a forecasting method by themselves, but rather a data pool to forecast on, and that regression may actually be a type of trend analysis, the reader is not provided with any qualitative criteria by which to distinguish

⁹ AP are ‘...evaluations of financial information through analysis of plausible relationships among both financial and non-financial data. Analytical procedures also encompass such investigation as is necessary of identified fluctuations or relationships that are inconsistent with other relevant information or that differ from expected values by a significant amount’ (IFAC ISA 520)

¹⁰ „Der Erfolg der analytischen Prüfungshandlungen hängt entscheidend von der Qualität dieses Prognosewertes ab.“ (IDW, 2017, L 742)

or select these methods (other than Box-Jenkins being both “*precise*” but also “*complex*” (p. 343)).

The AICPA guide on AP (2012) goes a step further: The **effectiveness** of AP is linked to the precision of the forecast, which is defined as

“...a measure of the closeness of the auditor’s expectation to the correct amount...” (p. 5),

which is dependent on “*the type of expectation developed*” (ibid) (i.e. the forecasting method), data employed and type of AP.

It is a conceptual step forward that the connection between the forecasting method and the precision of the forecast, the auditor may expect, is drawn, as it makes clear that not all forecasting methods are created equal.

The guidance, nevertheless, also highlights some of the problematic views widespread in auditing literature: The precision of forecasting models is linked to the complexity of the model (p. 10, comp. e.g. also Kayadelen, 2008), a hypothesis that has been conclusively disproven, as discussed in section 3. The guidance furthermore gives goodness-of-fit of forecasting models on historical data as a measurement of forecasting precision. As discussed in section 4.2.1.2, this is a common misconception.

Last, but not least, “*correct*” is somewhat of an ambiguous word in this context. It is not immediately clear whether “*correct*” refers to the actual outcome as posted by the audit client, or if it refers to the outcome the client would have posted in the absence of misstatements.

The latter should, of course, be the right answer. It relies on a specific assumption, which serves as a good conceptual starting point for **effective** AP:

The conceptual basis of AP is necessarily the assumption that in the absence of misstatements, any given financial account or KPI of the audit client on average follows a predictable development path.

In an idealized forecasting setting, AP forecasts would exactly match this ‘normal’ development path of accounts / KPIs. Deviations from the forecast would be caused by a supposed random error function (unforeseeable fluctuations in the environment). Any

deviations larger than a threshold (say, a 95% confidence interval estimate of the supposed error function) would constitute an improbable anomaly that would need to be investigated.

The assumption that a forecast precisely hits the development path of the account / KPI is of course an idealized one. In order to come close to it, the forecasted numbers need to be an unbiased estimate with preferably minimal variance. In other words: For AP to be effective, forecasts need to be precise.

According to practical forecasting literature, such as Armstrong (2001), there are three key factors in setting up effective forecasts that can be summarized in three broad topics, the first two of which are both discussed in section 3 (the third one, data preparation, is a separate topic outside the scope of this thesis):

1. The choice of a forecasting model which gives optimal results, given the forecasting scenario;
2. A working understanding of the application of the model, its strengths, weaknesses and limitations as well as general knowledge of forecasting methodology and
3. The usage and selection of contributing data and information as well as the exclusion of distorting data (data preparation).

For overall **effective** AP, **step II**, the analysis of the results of the forecast, plays an equally important role. In simple words, it is the question of: “How much deviation from the forecast would be plausible?”

As with the topic of forecasting, the concrete guidance in the auditing literature is comparatively sparse. The AICPA guidance on AP (2012), for example, offers no methodological approach to this topic whatsoever.

The IDW provides some framework that directs the discussion to some degree. In the 2017 edition auditor’s manual (“*WP-Handbuch*”), three important points are made:

- Threshold levels, i.e. the maximum acceptable deviation from the forecast that does trigger an investigation, need to be defined before the actual forecast is produced (L 743);
- “*The acceptable deviation is influenced by the audit materiality...*”

- *...and the desired level of assurance”.*¹¹

Section 5 discusses how these requirements are translated into auditing practice at Deloitte. As will be discussed in more detail below, the guidance or definitions provided by the literature leave several methodological gaps which may decrease the effectivity of AP.

While researching alternative approaches to these gaps is outside the scope of this work, the author has aimed at identifying these gaps in the form of research questions for follow-up.

¹¹ „Die akzeptable Abweichung wird beeinflusst durch die Wesentlichkeitsgrenzen und den gewünschten Grad der Prüfungssicherheit.“ (IDW, 2017, L 749)

2.6. What does Efficiency of AP mean?

Accounting literature frequently states that AP may increase the **efficiency** of audits (comp. e.g. Broesel, Freichel, Toll, & Buchner (2015), Marten, Quick, & Ruhnke, (2015), Guy, Alderman, & Winters, 1996). It is worthwhile to discuss the term “efficiency” in this context, as it has several different meanings that should be discussed separately.

In the context of AP, “efficient” refers to the following dimensions:

1. The degree by which AP lead to an efficient re-distribution of audit resources in the planning phase of the audit;
2. The degree by which AP saves audit resources by being substituted for tests of detail in the substantive phase of the audit and
3. Resources consumed by AP (per outcome), i.e. how complex and costly the methods employed are.

Concerning the first dimension of **efficiency**, Trompeter & Wright (2010) showed in their survey of audit practitioners that most participants were willing to increase audit resources in fields that preliminary AP flagged as “high risk”, but were reluctant to reduce audit resources allocated to fields which showed no anomalies. This finding is confirmed by Marten, Quick, & Ruhnke (2015, p. 347), who complain of an “*assymetric implementation*”, namely that audit resources are increased, but seldom reduced, based on the results of preliminary AP.

The reason why practitioners were often unwilling to accept a reduction in audit resources was not directly addressed in the survey of Trumpeter & Wright (2010), but it may be inferred: It seemed that the auditors were not fully comfortable with AP, the methods involved therein or their statistical implications.

Reducing resource allocation based on AP results requires a high degree of confidence not only in AP but also in one’s understanding of AP. Reducing audit resources in a field that might potentially contain a material misstatement would require the auditor to justify the decision at a later stage, in extreme cases in front of a court of law.

It is therefore clear that a prerequisite for such decisions are effective AP. To be precise: *The perception of the effectivity of AP.*

It follows that only forecasting methods with *empirically proven track records* (and which are in compliance with applicable auditing standards and recommendations made by auditing

associations) may realistically hope to achieve the necessary acceptance of practitioners needed for an efficient re-distribution of audit resources.

In the following discussion, proven track records will therefore play a major role.

For the second type of **efficiency**, the question if and to which degree AP may be substituted for tests of detail in the substantive phase of the audit, it makes sense to review the applicable audit standards.

AICPA (2012, p. 3f) lists the following preconditions:

- Suitability of the audit field for AP;
- Reliability of data;
- Sufficiently precise estimates and
- Ex-ante determined threshold levels.

The first bullet can actually be transformed into a requirement for the model employed: The forecasting model needs to offer robust forecasts and be adaptable to a multitude of forecasting situations. The broader the scope of situation in which a model works and the fewer requirements on the data employed (such as minimum data points, non-cyclicity, no trend changes etc.) the broader the field in which AP may be effectively used. It follows that the more robust the forecasting model is in practice with respect to forecasting circumstances, the higher the potential efficiency gain for the audit. Conversely, methods relying on extensive assumptions on data are probably less useful for audit needs.

The second bullet, data reliability, is in the literature often linked to the issue of the strength of the control environment (e.g. *“When evaluating the reliability of the data, [...] the auditor could test the controls, if any, over the entity’s preparation of information [...]. When such controls are effective, the auditor has greater confidence in the reliability of the information and, therefore, in the results of analytical procedures”*, AICPA, 2012, p.4). The assumption behind this argument is that the lower the degree of trust in the origin of the data, the lower any assurance any calculations based on this data can produce.

The argument is undeniably valid. It could be extended by stressing that even in the case of a very good control environment, data can be unreliable if the errors are intentional and have a collusive background, i.e. fraud. AP are the preferred method for identifying certain kinds of fraudulent behavior. It is nevertheless equally true that other types of fraud can only be identified on a substantial level, as the author can confirm from the perspective of long

personal experience in the field of fraud investigation (comp. e.g. also (Marten, Quick, & Ruhnke, 2015, p. 387). While this argument might seem counter-intuitive in a thesis on AP, the point is that an efficient use of AP should not be understood as a complete replacement of transaction-level testing. However, as this issue applies irrespective of the forecasting method used, it will not be a focus of the methods-review in section 3.

The third- and fourth bullets in the list of requirements have been discussed in the preceding section, as they can be paraphrased as “good forecasts” and “unbiased thresholds” respectively.

Summarizing, the prerequisites of this second dimension of **efficiency** are actually prerequisites of **effective** AP. In order to realize the potential efficiency gain of employing AP, it needs to be assured that AP is effective. In other words, this second dimensions of efficiency is in fact equivalent to the first one.

The third type of **efficiency**, resources consumed by performing AP, is of course always a relevant factor for audit practitioners.

In the survey at Deloitte (see section 3), one of the questions asked the participants for their preferred model or method for performing AP. The results showed a strong preference for simple methods, independent of hierarchical level and work experience of the participant. The comments given by the participants showed a general concern that more sophisticated techniques might not be efficient. Or as one participant put it: *‘If I need two semesters of statistics just to learn how to handle the program, I might as well just audit all of the transactions.’*

The survey did not differentiate between different cost drivers per model. Nevertheless, four main factors can be identified which all will be considered in the discussion of forecasting methods:

1. Training cost for forecasting methods;
2. Licensing cost for proprietary methods;
3. Time cost for performing forecasts and
4. Data cost (e.g. for providing data from proprietary sources).

In the discussion on forecasting methods, these drivers will be estimated (realistic resources consumed are difficult to measure and vary widely by user and forecasting situation) and

summarized as an overall cost score from 1 to 5. Dividing effectiveness by cost gives the actual **cost efficiency** of a forecasting method for the AP setting.

While the first (and by extension second-) dimension of efficiency discussed here is a necessary prerequisite for the acceptance of AP in an audit setting in general, it is this score that gives what is most of the time understood by efficiency. Consequently, it is this dimension that the following discussion will mostly focus on.

2.7. Section Summary

Analytical procedures are one of the core concepts of auditing. They can play an important role in the detection of all three types of misstatements. AP are especially significant for the detection of fraudulent behavior.

AP as a concept is as old as organizational auditing but has gained increased attention in recent years, especially in the context of several major accounting scandals.

AP are part of all three major stages of the year-end audit (planning, testing / substantive phase, conclusion).

In the planning phase, AP may help in efficiently re-distributing audit resources, but also play a major role in identifying risk areas. In the substantive phase, AP can be used to substitute test of detail, thereby drastically reducing resources needed. In the conclusion phase, AP can help to confirm (or reject) the overall impressions gained.

Prerequisites for these positive effects are effective and efficient AP.

The effectiveness of AP relies on two major factors:

- Precision of forecasts and
- Realistic and unbiased risk thresholds around that forecast.

The efficiency of AP is directly dependent on training- plus application cost of the forecasting method employed.

3. Survey on Analytical Procedures

3.1. Introduction

How are AP being performed in practice?

To gain a meaningful data basis, a survey on analytical procedures (with focus on the forecasting process) was sent out to all active audit professionals in the assurance department of Deloitte Germany (on 12/28/2012). As has been pointed out in a footnote to the introduction, the underlying assumption was that the survey population gives a fair representation of the auditing industry in general.

The questionnaire was sent out to 1,903 individuals, using a web-based survey solution. In total, 169 completed questionnaires were returned. Of the 169 participants, 126 made statements concerning their current position with Deloitte, their total work experience and whether they held a certified / chartered accountant title (*‘Wirtschaftsprüfer’*).

Deloitte Germany currently has six hierarchical levels (in increasing order):

- Professional
 - Senior
 - Manager
 - Senior Manager
 - Director
 - Partner
-
- The diagram uses curly braces to group the hierarchical levels into three categories:
- Operational work /client services (Professional, Senior)
 - Operational management / project management (Manager, Senior Manager)
 - Strategic management (Director, Partner)

31 of the participants ranked ‘Professional’, 32 ‘Senior’, 31 ‘Manager’, 29 ‘Senior Manager’, 12 ‘Director’ and 9 ‘Partner’. In the following discussion of the results, these hierarchical levels are grouped by main practical task, i.e. Professional and Senior as “Operational Work”, Manager and Senior Manager as “Operational Management” and Director and Partner as “Strategic Management”.

The average work experience of the participants was 8.13 years, the median was 6.5 years. 55 of the participants held the *Wirtschaftsprüfer* title.

The mean work experience of the participants was interesting because it was far higher than that of the mean employee in the assurance department of Deloitte Germany. Two possible explanations came to mind: The participants might have had more than average working experience because (1) inexperienced employees felt they could not contribute to the discussion or because (2) with increasing insight into audit processes, practitioners felt that contributing to the process of improving AP was a meaningful use of their time, i.e. an improvement may have been useful. Interestingly, the survey showed little indication that practitioners saw any necessity for improvement (see section 3.2).

Favorably, assuming a correlation between experience and understanding of the processes, the ‘skew’ towards experience might have increased the significance of the other findings of the survey.

The survey was conducted in German. In the following, the English translation is given:

Analytical Procedures Questionnaire

We are currently developing a tool for structuring, formalizing and increasing the ‘effectiveness’ of analytical procedures in executing the audit. Please take a few minutes to complete this survey and help us improve our auditing processes. All data is confidential and anonymous at the individual level; the results will only be reported in the aggregate. Thank you, for your assistance in this important project.

Context:

Analytical procedures are:

- *Forming expectations/forecasts/predictions of values for certain accounts and/or performance ratios of the client based upon:*
 - *Historical client data;*
 - *Industry Benchmarks;*
 - *Experience of the auditor;*
 - *Using various models.*
- *The analysis of the deviation of the actual YE-figures as reported by the client from these expectations/forecasts/predictions.*

Given an un-explained deviation larger than a specific pre-determined threshold value or interval, a potential risk is identified requiring an audit-investigation resulting in a 'disposition' memo to be written that will become part of the audit working papers of the audit engagement.

Question 1:

Please rate the following statement:

'Analytical Procedures, as conducted by Deloitte, are effective and efficient audit procedures to contribute to the Substantive Phase of an assurance audit engagement.'

- *Strongly Agree*
- *Agree*
- *Neutral*
- *Disagree*
- *Strongly Disagree*
- *No Opinion*

Question 2:

Please choose the method(s) that you use for forming expectations for analytical procedures (more than one answer is possible):

- *STAR (Multivariate Econometric Model)*
- *Fixed Ratios (e.g. account X = Y% of revenue)*
- *Last year plus X%*
- *Regression Projection*
- *Exponential Smoothing (Holt-Winters)*
- *Client budgetary Figures*
- *Other (free text)*

Question 3:

Analytical procedures identify an audit field as "increased risk", if the actual figure provided by the client deviates from the expectation by more than a pre-defined threshold and no satisfactory explanation is given. Please state the method you are using OR would recommend for calculating that threshold (more than one answer possible).

- *As per Deloitte auditing policy recommendation (smaller of specific percentage of Performance Materiality and Account Volume, percentage depending on risk classification of auditing field)*
- *Other Method (free text)*

Question 4:

Please state your level of audit experience in auditing including any with other firms—i.e., your total overall.

- *Number of years of experience in auditing (number)*
- *Certified/Chartered Public Accountant (yes/no)*
- *Current Position within Deloitte:*
 - *Professional/Client Services*
 - *Senior/Client Services*
 - *Manager*
 - *Senior Manager*
 - *Director*
 - *Partner*

End of Questionnaire

3.2. Perceived Effectiveness and Efficiency of AP

18 participants had no opinion on the effectiveness and efficiency of AP. The answers of the remaining 151 participants were collected in form of a 5-point Likert-score (“Strongly Agree” = 1, “Strongly Disagree” = 5) (Likert, 1932). In the table below, the results are displayed by participant task/experience grouping:

| Task Grouping | Number of Participants | Mean Likert Score | Median Likert Score |
|-----------------------------|------------------------|-------------------|---------------------|
| Operational Work | 63 | 1,62 | 1,5 |
| Operational Management | 60 | 1,38 | 1,5 |
| Strategic Management | 21 | 1,38 | 1,5 |
| (No statement on job level) | 7 | 1,57 | 2 |
| Total | 151 | 1,49 | 1,5 |

Table 1: AP Survey - Operational Roles of Participants

The results displayed a general perception that AP as they were performed at that time, effectively and efficiently contributed to the success of auditing. Though not significantly different, this feeling was even more present among experienced auditors.

These results lead to some rather interesting implications when regarded in conjunction with the answers given as to what methods were employed in AP: As will be discussed below, empirical evidence does not necessarily back up the confidence shown in the strength of the procedures as they were performed in auditing.

As a consequence, there is an indication of a practical gap between perceived audit assurance provided by AP and the actual strength of the processes. And while this gap might not have immediately measurable consequences for auditing work, it clearly shows that not only may processes be improved, but also that awareness for the necessity of changes needs to be raised.

3.3. Actual Effectiveness and Efficiency of AP

In the survey, the participants were given a selection of potential AP forecast methods to choose from as well as the option to fill out a free text field. Multiple answers were possible.

It may be argued that by presenting a limited number of options to choose from explicitly, the survey may be biased towards those methods. The reason for the limitation of selection options was a purely practical one. At Deloitte, there were concerns that a further extension of the questionnaire would increase completion time and thereby costs for the organization. As a compromise, two audit partners at Deloitte were interviewed as to which forecasting methods, they were familiar with or had ever heard about. Selection options were then limited to the methods named, with the proviso that a free text field would allow for further options.

The participants stated that the following methods were used in practice:

| Method | Number of participants selected | % of participants selected |
|---|---------------------------------|----------------------------|
| STAR (multivariate econometric) | 17 | 10,06% |
| Fixed Ratios (e.g. account X = Y% of revenue) | 105 | 62,13% |
| Last year plus X% | 132 | 78,11% |
| Regression Projection | 19 | 11,24% |
| Exponential Smoothing (Holt-Winters) | 8 | 4,73% |
| Client budgetary Figures | 67 | 39,64% |
| Other | 26 | 15,38% |

Table 2: AP Survey - Determination of Expected Values

In case ‘other’ was chosen by the participant, the free text field had to be filled out. In all but one case in which ‘other’ was chosen, the free text described in effect an unstructured judgmental forecast (see section 4.3.1). In the one case, the participant suggested using last year’s number corrected by special items, which might be interpreted as Random Walk. No other statistical model was suggested.

In the following table, answers given in the survey are set into relation with the effectiveness- / efficiency scores (“Other” was distributed according to the method mentioned in the free text field).

For a detailed development of the method of ranking as well as the scores, please refer to section 4. For illustrating the findings of the survey, it is sufficient to point out that methods were ranked by:

- effectiveness from 1-5 (1 = least effective);
- cost from 1-5 (1 = least costly); and

- efficiency as quotient cost / effectiveness (0.2 = least efficient, 5 = most efficient).

| Method | Number of participants selected | % of participants selected | Effectiveness short-term | Effectiveness long-term | Cost | Efficiency short-term | Efficiency long-term |
|--------------------------------------|---------------------------------|----------------------------|--------------------------|-------------------------|-------------|-----------------------|----------------------|
| Last year plus X% | 132 | 78,11% | 3 | 3 | 2 | 1,50 | 1,50 |
| Fixed Ratios | 105 | 62,13% | 2 | 1 | 1 | 2,00 | 1,00 |
| Client budgetary Figures | 67 | 39,64% | 1 | 1 | 1 | 1,00 | 1,00 |
| Unstructured judgmental Forecast | 25 | 14,79% | 2 | 1 | 1 | 2,00 | 1,00 |
| Regression Projection | 19 | 11,24% | 2 | 3 | 1 | 2,00 | 3,00 |
| STAR | 17 | 10,06% | 2 | 3 | 4 | 0,50 | 0,75 |
| Exponential Smoothing (Holt-Winters) | 8 | 4,73% | 4 | 3 | 3 | 1,33 | 1,00 |
| Random Walk | 1 | 0,59% | 2 | 1 | 1 | 2,00 | 1,00 |
| Total / Mean | 374 | - | 2,22 | 1,94 | 1,53 | 1,56 | 1,27 |

Table 3: AP Survey - Scoring of Methods employed by Practitioners

A strong preference for simpler or less costly methods is immediately visible. 349 of the 374 method selections or 93% had a cost rating of 1 or 2. This result was already foreseeable to some degree in advance due to the selection options provided by the auditing partners, i.e. the methods at all employed in practice.

There are two possible conclusions which can be drawn from this finding:

- Total cost of methods employed is a strong factor in method selection. As effectiveness of methods employed is probably not readily transparent to most auditors, cost factor necessarily dominates discussions. As a result, any method that aims at realistically gaining acceptance in the practical auditing world must be relatively cheap overall.
- While being less costly, the methods of choice, with the possible exception of linear regression, were non-statistical forecasting models. It might be inferred that there is not necessarily a high degree of statistical expertise available in all auditing teams. Consequently, employing or introducing methods which rely on substantial statistical expert user knowledge, such as autoregressive methods, run an increased risk of “hidden errors” due to incorrect application.

The second observation is the relatively low effectiveness of methods employed. As will be discussed in section 4.3.6.3, the “Last Year plus X%” method may be regarded as equivalent to a seasonally adjusted random walk assumption and as such produce reasonably effective forecasts.

On the other hand, the numbers show a relatively widespread use of unstructured judgmental forecasts, which empirically have low accuracy. Furthermore, the apparently strong reliance on client-provided forecasts implies high risk of blindness against deliberate misstatements, i.e. fraud. The empirically strongest forecasting method seen in practice, triple- or Holt-Winters exponential smoothing, was at the same time the least used one (with the exception of the single auditor who stated he was using a random walk variant).

The effectiveness-scores assigned to different methods are of ordinal nature only and in some cases just estimates at that. Nevertheless, it can be concluded that with mean short- and long-term effectiveness scores well below those assigned to Naïve 2 (see section 4.3.6.2), there is general room for improvement.

3.4. Determination of Risk Thresholds

As discussed above, auditing literature offers little clear guidance on how to determine risk thresholds for AP. Deloitte suggested, but did not stipulate, a method by which to arrive at risk thresholds: Intervals around the estimate are calculated using a decision tree considering overall risk classification of the engagement and local control effectiveness. The outcome returns percentage values of audit materiality and account value of which the lower one is to constitute the threshold value.

Despite being a secondary objective of this study, a question as to the level of implementation of this method or the usage of viable alternatives was included in the survey. The motivation behind this was a) to create implementation alternatives for the decision support system and b) to identify potential research questions for subsequent studies.

As in the preceding question, participants were able to make multiple selections in the case the Deloitte suggested method was one of several. In case “other” was selected, a free text field needed to be filled.

| Method | Number of participants selected | % of participants selected |
|---|---------------------------------|----------------------------|
| As per Deloitte auditing recommendation | 143 | 84,62% |
| Other | 7 | 4,14% |
| (No selection) | 23 | 13,61% |

Table 4: AP Survey - Risk Threshold Determination

The overwhelming majority recommended / uses the Deloitte approach. All seven participants who chose ‘other’ described methods which could be summarized as “personal judgment”. Three of those seven checked the Deloitte methodology in addition; four solely relied on their own judgment. 23 participants made no statement concerning risk threshold. As the AP process logically requires a risk threshold, even if it just an implicit one, these 23 cases might potentially also be sorted under “personal judgment”.

None of the participants offered a method that was in any way dependent on the method which formed the expected value.

As will be discussed in section 5, forecasting accuracy, or the lack thereof, should contribute to the way in which risk intervals or thresholds for AP are formed. The results of the survey show no evidence that this is the case in practice.

3.5. Section Summary

A survey on analytical procedures methodology was performed at Deloitte Germany. The survey resulted in a meaningful number of replies of above-average professional experience level.

The survey at Deloitte revealed an interesting contradiction: On the one hand, participants displayed a high level of confidence in the process as such. On the other hand, AP forecasting methods employed by practitioners, as stated in the survey, were in many cases empirically of low accuracy compared to other methods.

This clearly indicated that in practice there is indeed room for an improvement of AP methodology, but also shows that there might be limited demand for change due to incorrect perception of process strength.

Cost structures of methods employed furthermore showed a strong preference for simple models.

Finally, risk threshold forming methods employed in practice do not consider relative forecasting accuracy.

4. Determination of Expected Value

4.1. Introduction

“It is important to understand that there is no such thing as the best approach or method [to forecasting] as there is no such thing as the best car or best hi-fi system. Cars or hi-fis differ among themselves and are bought by people who have different needs and budgets. What is important, therefore, is not to look for ‘winners’ or ‘losers’, but rather to understand how various forecasting approaches and methods differ from each other and how information can be provided so that forecasting users can be able to make rational choices for their situation.” (Makridakis, et al., The Accuracy of Extrapolation (Time Series) Methods: Results of a Forecasting Competition, 1982)

As described in section 2.1, the development of expected values for financial accounts or KPIs is the first of three conceptual process steps of AP. As discussed in section 2.5, current auditing literature and –standards do not stipulate (actually -hardly ever recommend) specific forecasting methods. On the other hand, the qualitative factors of effective AP have been identified, one of them being precise forecasts of the expected value of the account or KPI in question.

In the following section, two topics connected to the expected value process are discussed:

- Selection criteria for forecasting models.

In order to conduct a structured discussion on the relative merits of forecasting models, measurement or comparison criteria for forecasting need to be discussed.

- Forecasting models.

The second part of this section discusses a number of forecasting methods and models. All models which have been named in the AP survey are discussed, as well as several models which have not been mentioned but which might positively contribute.

The discussion will start with the least formalized group of forecasting methods (judgmental forecasting techniques) and will then gradually approach more standardized methods up to purely statistical models. At the end of the section, Rule-Based Forecasting, a hybrid approach combining several statistical models as well as judgmental elements is introduced and discussed in detail.

It will become apparent that there is not one strictly preferable model for conducting AP, just as there is not one strictly preferable forecasting model in general. From an effectiveness- as well as an efficiency point of view, the choice of forecasting models needs to be tailored to the situation, or as an auditing partner with Deloitte put it in a preliminary interview to the conduction of the survey:

'If there were ten guys working in the shop and last year, they hired the eleventh guy, I don't need rocket science to estimate labor costs.'

4.2. Selection Criteria for Forecasting Models

4.2.1. How can AP Effectiveness Performance be measured?

Precise forecasts. What does that actually mean?

There are some general misconceptions on the precision of forecasts are directly connected to the quantity of data and the complexity of the model involved, also in auditing literature. Kayadelen for example writes:

‘Basically, the precision of generated expectations increases with the complexity of the model used.’¹²

This, rather intuitive, thesis has been quoted here in the beginning of this section, as empirical forecasting research over the last several decades has actually disproven many of the widespread and intuitive ideas on forecasts: Large-scale forecasting competitions show that there is no inherent link between the complexity of a model and the performance of the forecasts generated by it (Makridakis & Hibon, The M3-Competition: results, conclusions and implications, 2000, S. 455). In fact, the competitions showed that in many cases ‘simple’ models outperformed complex ones on average (ibid).

The same competitions and the research they triggered furthermore showed that even the term “precision” is a non-trivial statement, as the choice of measurement criterion can have significant impact on the rating of methods.

For the following discussion, the term of forecasting “precision” (and consequently “AP effectiveness”) is first examined from the perspective of audit practitioners, as audit practice provides the framework within all further considerations of this thesis have to be seen. Then, “precision” is discussed from a technical, that is statistical, perspective. Here, the judging parameters for model selection are calibrated.

¹² ,Grundsätzlich gilt, dass mit steigender Komplexität der Methode gleichzeitig die Verlässlichkeit des generierten Erwartungswerts zunimmt.‘ Kayadelen on Trend Analyses (Kayadelen, 2008, S. 43)

4.2.1.1. Auditing Standards and Recommendations

When discussing AP forecasting methods, it is of course necessary to first discuss considerations special to year-end auditing. Section 2.6 discussed the reluctance of auditors, as identified by Trompeter & Wright (2010), to reduce resources in audit fields that AP identified as “low-risk areas”. This reluctance could implicitly be traced to a lack of confidence in AP methods, especially a lack of confidence to hold up in front of a peer-review board or even a court of law, if a material error were missed due to reliance on AP.

As has been discussed, auditing standards offer little help in giving a definite answer as to how the AP process could be designed in a way to eliminate this risk.

Nevertheless, when turning this risk into a requirement, an important parameter or prerequisite for finding an effective AP forecasting method can be identified. The question is: “Given the risk of potential later scrutiny by a group of peers or a court of law, what criteria does a model need to fulfill, in order to minimize risk?”

Without digressing too much, the low-risk answer seems to be that AP methods employed would have to have a proven track record with a broad empirical (scientifically defensible) basis.

Three extensive empirical studies on the effectiveness of various forecasting methods by Makridakis et. al. between 1982 and 2000, also known as M-Competitions, provide such an empirical basis and are in the following quoted repeatedly and the outcomes analyzed. A fourth competition was announced for 2010, the results of which have not been published yet.

Following an empirical study by Hibon and Makridakis (1979) the M1 competition tested 24 forecasting methods and variations of methods against 1001 real-life time series, measuring forecasts against actual outcomes (Makridakis et. al., 1982). Conclusions drawn from this study called into question several beliefs firmly held by the majority of scholars.

For example, the study showed the relative in-effectiveness of the Box-Jenkins ARIMA method of forecasting, a method which had received strong attention after its initial publication in 1970 (Box & Jenkins, 1970). Consequently and unsurprisingly, methodological criticisms / calls for improvement were raised, many of which were collected and published by Armstrong and Lusk (1983). In the second M-Competition, the number of series used as basis was drastically reduced to 29, placing the emphasis on a detailed in-depth forecasting process and addressing for example the criticism, the Box-Jenkins method might have

performed poorly because it might have been applied incorrectly (Geurts in Armstrong & Lusk, 1983, p. 10). Results of the first M-Competition were largely confirmed. Finally, the M3-Competition (Makridakis and Hibon, 2000) extended the scope of the test to 3003 time series, included newly developed forecasting techniques and augmented the methodology, for example by providing different benchmark / error measuring criteria.

To the knowledge of the author, the M-Competitions were the most comprehensive studies of their kind to date. It therefore makes sense to use them as a judgment basis for the performance of forecasting models.

4.2.1.2. General Approach for Measuring Forecasting Precision

It is self-explaining that the precision of a forecast cannot be pinpointed in advance. It is potentially less self-explaining that forecasting precision cannot necessarily be approximated with goodness-of-fit indicators such as R^2 either: As Armstrong (2001, p. 457) pointed out, forecasting models can have a perfect R^2 while the values of the forecast are substantially different. Ames and Reiter (1961) found R^2 of usually larger 0.5 („explaining“ half the variation) between their time series and two- to six randomly selected time series. In essence, R^2 gives an indication as to how the explanatory variable(s) explain the data, but not necessarily the future.

It is not to say that there is necessarily no positive correlation between R^2 (or other goodness-of-fit indicators) and forecasting precision. This is certainly the case in presence of strong and stable trends within the data. It is, however, no reliable / robust indication of the forecasting performance of a specific model against a specific time series.

In the end, there can only be an empirical solution of measuring forecasting performance. For this, three factors have to be present:

- Assumptions have to be made as to the general forecasting situation in an AP setting in order to have a ceteris paribus standard for comparative discussion (section 4.3.2);
- The criteria for measuring forecasting effectiveness (in an AP setting) need to be defined (section 4.2.1.3) and
- Empirical studies of the model / forecasting situation defined above have to be reviewed and different solutions need to be discussed by performance measurement (which leads to the M-Competitions described above).

Not included in the M-Competitions were models which did not employ statistical elements such as judgmental- or graphical forecasts. As these models play an active role in AP practice, they will be discussed using different studies as available.

4.2.1.3. Effectiveness Measurement Criteria

The performance of forecasts is assessed using forecasted values and calculating their errors against the actual outcomes of the data series (comp. Armstrong & Collopy, 1992). In order to gain an empirical understanding of the relative performance of forecasting models, different error measures can be applied, the result often depending on the choice of the metric. In the following, a number of performance measures are discussed including all measures which have been considered in the M3-Competition (Makridakis & Hibon, 2000):

- Mean squared error (“MSE”) / Root mean squared error (“RMSE”);
- Mean absolute percentage error (“MAPE”) / Symmetric mean absolute percentage error (“sMAPE”);
- Median absolute percentage error (“MdAPE”) / Median symmetric absolute percentage error (“MdsAPE”);
- Average ranking;
- Percentage better;
- Median relative absolute error (“MdRAE”).

As discussed below, the first four criteria are absolute measures, while the latter three measure accuracy relative to a benchmark. In the section on forecasting methods, average ranking and MdRAE will be primarily discussed, taking both types of criteria into account.

As has been pointed out, not all methods generally employed in AP (based on the survey) were tested in the M-Competitions. As a matter of fact, for methods such as graphical estimation, there are no reliable empirical accuracy studies available which would enable easy comparison. As these methods are nevertheless used in practice, they need to be part of the discussion.

In general, a direct comparison of models which were not part of the M-Competitions with models which were, is difficult, even if the same errors metrics are available. For starters, no other forecasting competitions of comparable scale have been undertaken for these models.

To mitigate this problem, the study will, after the initial discussion, departed from the objective effectiveness criteria and use an effectiveness grading to approximate comparability. The grading was done using five-point-scale (5 = “very effective / accurate”, 3 = “neutral”, 1 = “very ineffective / inaccurate”).

MSE / RMSE

MSE used to be a widespread criterion of forecasting accuracy. Armstrong & Carbone (1982) found that 30 of 70 surveyed academicians and 20 of 75 practitioners used MSE as criterion for measuring accuracy, making MSE the most popular criterion by a margin of roughly 2 to 1 to the next one (mean absolute error).

The result is a bit puzzling as MSE neither allows for the comparison between series, as MSE includes no scaling factor, nor is it easily interpreted when reviewing the forecasting accuracy within a single series. The latter could be mitigated using the easier-to-interpret RMSE. As Armstrong & Lusk (1983, p.5) point out, this would be defeating the main strength of MSE, the sensitivity to large forecasting errors. As Armstrong & Lusk argue, large forecasting errors may have an unproportionate impact on business. As the other criteria, by design, do not include this sensitivity, employing MSE as criterion between series of similar scale does have specific merit.

However, the AP setting is a special situation. AP forecasting aims at accurately predicting a “natural” trend path, thus identifying anomalous deviations if the prediction is off by more than a threshold-value. As will be discussed in section 5, this threshold must be interpreted as a composite of the forecasting error against the actual trend path of the series and the random movement of the series around the trend path.

The crucial point is that AP focuses on a binary decision. Either the threshold is crossed or it is not. For the subsequent re-allocation of audit resources, it should not be important by how much the threshold is crossed (whether this is a realistic assumption for practitioners, is a question beyond the scope of this study).

Given that the threshold value is not defined as excessively large (i.e. only very large deviations would trigger an investigation), there is only limited value in focusing on an accuracy criterion of which the primary merit is that it is sensitive to large forecasting errors.

MAPE / sMAPE

MAPE is defined as $\sum \left| \frac{X-F}{X} \right| * 100$, where X is the actual value and F is the forecast.

The symmetric MAPE is defined as $\sum \frac{|X-F|}{(X+F)/2} * 100$, (Makridakis & Hibon, 2000, p. 461).

According to Armstrong & Collopy (1982), the perhaps most widely used unit-free accuracy criterion for forecast comparisons is MAPE. Connected with MAPE are a number of difficulties, however:

- MAPE is undefined for the actual value equaling zero;
- MAPE may distort accuracy comparisons in case of forecasts erring on the high side, especially if X is small (For non-negative scales, MAPE is bound on the lower side by 100% but there is no boundary on the upper side: X = 10, F = 3: MAPE = 70%, X = 3, F = 10: MAPE = 233%).

The latter difficulty can be circumvented using the sMAPE which treats both errors in the example equally and which runs from 0% to 200%. Connected with the sMAPE, on the other hand, is the problem that for equal X, overstating forecasts are punished less severely:

- E.g.: X = 10, F = 3: sMAPE = 108%, X = 10, F = 17: sMAPE: 52%.

Furthermore, by its non-linear scale, sMAPE is biased in favor of models which produce few large forecasting errors over those which make many smaller ones:

- Model 1:
 - Series 1: X = 10, F = 15, sMAPE = 40%
 - Series 2: X = 10, F = 14, sMAPE = 33%
 - Overall sMAPE = 37%
- Model 2:
 - Series 1: X = 10, F = 19, sMAPE = 62%
 - Series 2: X = 10, F = 10, sMAPE = 0%
 - Overall sMAPE = 31%

MdAPE / MdsAPE

The MdAPE / MdsAPE in essence use the same metric as the MAPE / sMAPE with the difference that the median- instead of the mean value is calculated.

While in general the same critique with respect to bias applies as for the MAPE / sMAPE, the result of employing the median is that the bias resulting from within the series (vs. across time series) is less severe.

As Everette Gardner points out in Armstrong & Lusk (1983, p. 5): *“The error distributions from all methods are badly skewed, which distorts the MAPE. The median APE is less effected.”*

Average Ranking

In the M3-Competition, participating models were ranked by their forecasting performance by series (according to the MdsAPE criterion). The rank was then averaged over the study.

Evaluating the MdsAPE criterion by rank instead of absolute is like to decrease the impact of criterion bias. If the MdsAPE criterion is accepted, the average ranking is therefore probably the least biased way to compare forecasting performance.

Percent Better

Percent better uses a different approach than the metrics described above. Instead of measuring accuracy against the time series, percent better records the percentage of instances that the model in question outperforms a benchmark model against the time series (Makridakis & Hibon, 2000).

From an AP point of view, it is perhaps more interesting to compare forecasting methods using a directly comparative method, as this might be easier to interpret for a non-expert third party (say, in front of a court of law). It could also be argued that from a risk-management perspective, the actual performance of a forecasting method for AP is of secondary interest, as long as it is the best suited model, i.e. at least outperforms the benchmark.

In the M-3 Competition, the benchmark model was the so-called Naïve2. Naïve2 is a random walk forecast (see section 4.3.6), the data adjusted for seasonality.

MdRAE

As in percent better, median relative absolute error uses a benchmark approach. Different than percent better, MdRAE measures error as a multiple of the forecasting error of a benchmark model, where $RAE = \frac{|F-X|}{|F_B-X|}$ and F is the forecast, F_B is the forecast of the benchmark model and X is the actual value. Consequently, RAE of < 1 outperform the benchmark while RAE > 1 perform worse.

The method has originally been proposed by Armstrong & Collopy (1992) and been adopted for the M3-Competition (Makridakis & Hibon, 2000).

The benchmark model used in the M3-Competition for MdRAE is not the same as for percent better (Naïve2). The benchmark method employed here is Dampen Trend Exponential Smoothing (“Dampen”) as per Gardner & McKenzie (1985).

4.2.2. How can AP Efficiency Performance be measured?

As has been discussed in section 2.6, efficiency of AP can in fact be reduced to a simple effectiveness / cost equation. It follows that the cost drivers of AP application are the main component in efficiency measurement:

- Training cost for forecasting methods;
- Licensing cost for proprietary methods;
- Time cost for performing forecasts and
- Data cost (e.g. for providing data from proprietary sources).

Exactly determining these factors per method is challenging. Licensing fees depend on many factors, time costs are subject to learning curves, training costs depend on the professional background of audit personnel etc.

For the following discussion, cost factors will therefore be expressed as an estimated aggregate on a five-point-scale (5 = “very high cost”, 3 = “neutral”, 1 = “very low cost”). From the cost estimate and including the effectiveness-scale, a quotient approximating efficiency is calculated by effectiveness divided by cost, where a value > 1 indicates an efficient model (max value = 5) and a value < 1 an inefficient one (min value = 0.2).

4.2.3. Selection Criteria for AP

After having explored methods for ranking forecasting methods, the next question presents itself to auditing practitioners: How does this help for selecting an AP forecasting model? What is more important: Effectiveness or efficiency?

The answer to this question is: “Both”.

As the survey showed, practitioners had strong preferences for simple / low cost methods. This is absolutely in line with the efficiency-gains aspect of AP. Conversely: A method with low effectiveness in relation to cost has no chance of being accepted in practice. Methods like ARIMA, for example, were long perceived to be a very effective, as discussed below. Nevertheless, they found no application by audit practitioners in the survey.

On the other hand, in order to fulfill the requirement of holding up to a (potentially hostile) peer review, the method needs to be demonstrably effective. Based on this reasoning, methods like linear regression are basically unsuited for AP: Linear regression is very efficient, because it can deliver some information at very little cost. It is questionable, however, if the selection of linear regression could withstand a hostile expert opinion.

It is therefore clear that the selection of an AP method needs to be a compromise of effectiveness and efficiency.

Without bootstrapping criteria in a way to bias selection to specific methods, it is probably safe to recommend a method of short-term effectiveness ≥ 4 and short-term efficiency ≥ 1 , as per the rating system employed here. Note that in the context of year-end auditing, long-term effectiveness (> 5 years) is less of a criterion. It is being discussed in the following mainly for completeness sake.

4.3. Forecasting Models

4.3.1. Introduction

The AP survey, and the preceding interviews leading to it, identified several forecasting methods as being used in practice. In addition to these, several methods might be potential candidates for AP, even though these do not seem to see widespread application as of now. In the following, a structured discussion on these different methods, based on the criteria laid out in the preceding section is conducted. The general criteria of effectiveness and efficiency are examined in the cases of both the availability of short- and long horizons of forecasting data. Five-point-scales are used to evaluate the models for both criteria. While an in-depth discussion of the underlying theories of the methods is beyond the scope of this thesis, the features most significant to the scenario at hand are introduced.

It should be pointed out that the following discussion does not focus on the *general* relative merit of forecasting methods. Instead, the focus is on the *specific* set of circumstances likely faced in an AP setting and laid out in the preceding section. Some methods might find reasonable, even compelling, application in certain situations while not at all applying to AP.

In the following table, a summary of the evaluations of methods is given. Based on the assumptions underlying the discussion and the methods, discussed in the following, coreRBF embedded in an electronic decision support system and in the presence of domain knowledge (basic assumption for AP, see section 4.3.2) is a powerful candidate for AP, as it combines high effectiveness with comparatively low application cost (as is trend-dampening exponential smoothing, with slightly less versatility for long-term forecasts).

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

| Method | Effectiveness Short-Term | Effectiveness Long-Term | Cost | Efficiency Short-Term | Efficiency Long-Term |
|--|-----------------------------|----------------------------|------|--------------------------|-------------------------|
| Client's Planning Figures | * | * | 1 | * | * |
| Judgmental Methods | | | | | |
| Unstructured Judgmental Forecast | 2 | 1 | 1 | 2,00 | 1,00 |
| Guided Judgmental Forecast | 2 | 2 | 2 | 1,00 | 1,00 |
| Graphically supported Judgmental Forecast | 2 | 3 | 1 | 2,00 | 3,00 |
| Naive Methods | | | | | |
| Naive 1 | 2 | 1 | 1 | 2,00 | 1,00 |
| Naive 2 | 3 | 3 | 2 | 1,50 | 1,50 |
| Last year plus X | 3 | 3 | 2 | 1,50 | 1,50 |
| Fixed Ratios | 2 | 1 | 1 | 2,00 | 1,00 |
| Exponential Smoothing Methods | | | | | |
| Single Exponential Smoothing | 2 | 3 | 3 | 0,67 | 1,00 |
| Double Exponential Smoothing | 4 | 3 | 3 | 1,33 | 1,00 |
| Triple Exponential Smoothing | 4 | 3 | 3 | 1,33 | 1,00 |
| Quadratic Exponential Smoothing | 1 | 1 | 3 | 0,33 | 0,33 |
| Trend-Dampening Exponential Smoothing | 5 | 4 | 3 | 1,67 | 1,33 |
| Autoregressive Methods | | | | | |
| ARIMA | 4 | 3 | 5 | 0,80 | 0,60 |
| Other Regression Methods | | | | | |
| Linear Regression | 2 | 3 | 1 | 2,00 | 3,00 |
| Multivariate Econometric Methods (STAR) | 2 | 3 | 4 | 0,50 | 0,75 |
| Combining Forecast | | | | | |
| Equal Weight Combination | 4-5 | 4-5 | 4 | 1,00-1,25 | 1,00-1,25 |
| RBF-Original Model | 5 | 5 | 5 | 1,00 | 1,00 |
| Reduced Rule-Based Forecasting | 5 | 5 | 5 | 1,00 | 1,00 |
| CoreRBF | 5 | 5 | 4 | 1,25 | 1,25 |
| CoreRBF electronic Decision Support System | 5 | 5 | 3 | 1,67 | 1,67 |

Table 5: Overview Scoring of Forecasting Methods, please refer to section 4.2 for the rating methodology

4.3.2. Assumptions on the AP Forecasting Situation

Based on the results of the survey at Deloitte (section 3), both the forecasting techniques employed and the data analyzed by practitioners point at that AP was understood as a time-series forecast problem by the vast majority of participants (as opposed to cross-sectional forecasts).

Consequently, the first assumption for the following discussion is that **time-series models are the most relevant methods** for AP. It could be argued that cross-sectional analyses might contribute valuable analytical insights as well. Then again, important cross-sectional relations may also be investigated using time-series analysis on quotient data / KPIs (dependent variable / independent variable). It follows that from an efficiency point of view, it might make sense to substitute for cross-sectional analyses in any case.

The second assumption is that auditors are equipped with a **sufficient** depth of **domain knowledge**. The term “domain knowledge” refers to underlying- or background information on the data series. In an auditing situation this might include the client’s market situation, factors influencing the economy in general or information on ongoing mergers and acquisitions. Consequently, the acquisition of information that can function as domain knowledge for forecasting purposes can be assumed to be part of every given organizational audit preparation phase.

Domain knowledge is, by its very nature, difficult to quantify. So the question of how much domain knowledge should be assumed to be present in any given audit team, is not easy to answer. On the other hand, forecasting research indicates a strongly diminishing return of domain knowledge / subject matter experience on forecasting accuracy. Armstrong (1980) found in a literature review that most studies show an increase in forecasting accuracy that correlates with a basic level of expertise in the subject matter but no increase of accuracy beyond that level. Armstrong and Green (2004) experimentally showed that the forecasting accuracy of subject matter ‘experts’ was no greater than the accuracy of subject matter ‘novices’ in a complex judgmental forecast setting. For a discussion on the relative merits of forecasting models for AP, it should therefore be sufficient to assume that some domain knowledge is present within the team.

Third, the discussion will make **no assumptions on** the period length of **available data**. It could be argued that the availability of sufficient and reliable data is the Achilles-heel of AP. Especially in small- and or new entities, as well as in auditing fields that see few- but high-

impacting transactions, forecasting based on data available is necessarily a challenge. It follows that exploring methods under the assumption of always sufficient data would probably be a systematic mistake. AP methods should therefore ideally produce reasonable results in a variety of data-availability scenarios.

In fact it was also with this last thought in mind that coreRule-Based Forecasting was tested as an AP candidate. One of the major strengths of the Rule-Based Forecasting methods is its flexibility with respect to data availability, substituting short-term- for long-term-models in case of doubt.

4.3.3. Applicability of Empirical Studies to the AP situation

During the review of the first draft of this thesis, one of the reviewers came up with a critical question: Can the results of the empirical studies that are mostly used as an empirical basis for judging the relative effectiveness of forecasting methods, actually be applied to the situation of analytical procedures forecasts?

This question was not only very interesting in itself, it also highlighted a potential concern that many practitioners would most probably also have, it is therefore discussed here separately and explicitly. It may make sense to split the issue into two separate aspects:

1. Are the data that have been used as basis for the M-Competitions of a sufficiently similar nature to data one would expect in an AP scenario, so that a direct application of the results from the one to the other is justifiable?
2. Is there a sound underlying theory that gives a logical explanation for the success of one particular model over another (especially with respect to the model that is then later translated into a decision support system for AP, coreRBF), so that there is a theoretical basis for arguing the continued success of that model?

Question 1 has a comparatively straightforward answer: All M-Competitions used a wide array of socio-economic data including company revenue- and profit figures. It can be expected that these behave in a way comparable to most AP forecasting situations. The exception to the rule are such audit fields that produce highly fluctuating- (e.g. real estate transactions) or frequently interrupted data. Such data are a challenge for any kind of forecasting model, simply for the fact that one can expect little- or no relevant (trend-) information to be extracted and to base a forecast on. For these kinds of series, a forecasting model needs to be as robust as possible, heavily reliant on domain knowledge and probably emphasizing recent- over older data.

The answer to question 2 is much less straightforward, because to some degree, it is a (probably valid) criticism of forecasting in general. As will be discussed below in greater detail when focusing on the different models, the M-Competitions have somewhat disenchanted the notion that there is an easily explainable theory that would lead to optimal forecasts.

The Box-Jenkins autoregressive forecasting approach (Box & Jenkins, 1970) used to be a very popular forecasting approach. One aspect that which probably contributed strongly to its popularity was its deep and highly complex theoretical foundation. Nevertheless, in the M-

Competitions Box-Jenkins was on average outperformed by Naïve 2. Naïve 2 stands for simply de-seasonalizing the data and then taking the last value as forecast (de-seasonalized Random Walk).

Following the results of the M-Competitions to some degree stands for a preference of Aristotelian empiricism over Platonian logic. The underlying empirical theory of this “wind-canal” approach is undoubtedly valid. Nevertheless, it is also likely that audit practitioners would have an easier time accepting such an approach, if there were a wider body of conceptual work behind it.

It is with this gap in mind that the author recommends further practical tests of the electronic decision support system, in addition to the ones performed, in the conclusion section: On the one hand this of course aims at “shaking out” any previously undiscovered bugs or issues in the software. On the other hand, however, this also aims at increasing the perception of reliability and validity of the approach chosen, in the eyes of audit practitioners, a crucial prerequisite of acceptance, as has been discussed above.

4.3.4. Client's Planning Figures

| Summary | Client's Planning Figures |
|--------------------------|--|
| Effectiveness Short-Term | * |
| Effectiveness Long-Term | * |
| Cost | 1 |
| Efficiency Short-Term | * |
| Efficiency Long-Term | * |
| Remarks | Method by itself not sufficient to fulfill AP requirements |

Table 6: Scoring of Client's Planning Figures

Effectiveness

40% of the surveyed audit practitioners stated that they used forecasting figures produced by their client as basis for their AP forecasting. They were not asked to differentiate between the methods their respective clients used to come up with their forecasts.

From a legal point of view, using the client's own planning numbers for AP purposes should generally be permissible. Several applicable auditing standards explicitly mention the client's planning as an admissible data source for AP (e.g. PCOAB AU329, 2010). Furthermore, year-end auditing usually assumes the information being provided by the client as generally being reliable, unless professional skepticism gives reason to believe otherwise.

This notwithstanding, there are reasons against solely relying on planning figures produced by the client for AP:

- Most companies are conscious about any information provided to the auditor. Irrespective of whether the budgetary figures would be provided to the auditor at the time of planning and resource allocation or at the beginning of the audit, it is safe to assume that the company would be well aware of the information contained in the budget. If there were an unintentional material misstatement (sloppiness or incompetence) that could be identified by comparing the budget to the actual numbers, chances are that the client would have found it by itself.
- In case of an intentional misstatement, i.e. fraud, the client would have to be incredibly foolish for that fraud to show up in a discrepancy to the budget: In case the budget has to be handed in well in advance to the audit, the fraud would be either incorporated in the budget or hidden outside the information provided. In case the planning figures are handed over to the auditor at the beginning of the audit, hiding the fraud is of course even easier, as the figures would be tailored to

the effect of the fraud. It should be stressed that budgetary figures can, by definition, never be a data safe-haven. Backdating manipulated budget figures, for example, is as easy as resetting the CPU-clock of the computer on which the file is created.

The *only* conceivable scenario in which budget figures would potentially contribute to identifying accounting fraud would be if (a) the person or department liaising with auditors is unaware of the intended fraud, (b) the person(s) responsible of the fraud are unaware of the planning budget or it being handed to the auditors and (c) the fraud has not been ongoing since the preceding business year AND distorts the client's balance / P+L, as opposed to a fraud that is aimed at for example hiding losses incurred. Otherwise it would just not show.

Of course, the budget need not necessarily be taken at face value. The information could be incorporated into a judgmental forecast by the auditor. Even then, as the information cannot be regarded as impartial, it might have a distorting impact on forecasts by the auditor due to the anchoring effect discussed in the section on judgmental forecasts.

Efficiency

Costs of relying on the client for forecast are, of course, very low. In light of the general problems connected with using the clients' own planning, it is difficult to talk about efficiency in this context.

There seems to be limited reason to incorporate clients' forecasts into AP. In light of the systemic problems connected herewith it should furthermore be pointed out that there might be an increased legal risk in the case of misstatements, irrespective of the practice having been allowed in the applicable standards in the first place.

4.3.5. Judgmental Methods

AP estimates do not necessarily have to employ statistical models or sets of formal rules. The use of professional judgment for forming expectations has not been excluded by auditing standards. As a matter of fact, there are situations in which the predictive power of statistical forecasting models is limited / potentially inferior to judgmental methods. Armstrong & Green (2014) advise that judgmental methods might be selected especially if little data is available. The same applies if data is only available in an unquantified and unquantifiable state, i.e. non-numeric and cannot be translated into e.g. binary factors.

It could furthermore be argued that a prerequisite of preferring judgmental methods over methods making no forecasting assumption whatsoever (i.e. random walk), should at least be the presence of some level of domain knowledge. As the assumption for the AP is that domain knowledge is present, this is of no consequence.

While judgmental methods do not rely on statistical models, this does not necessarily imply that judgmental forecasting needs- or should be conducted in an un-structured way.

4.3.5.1. Unstructured Judgmental Forecasts

| Summary | Unstructured Judgmental Forecasts |
|--------------------------|-----------------------------------|
| Effectiveness Short-Term | 2 |
| Effectiveness Long-Term | 1 |
| Cost | 1 |
| Efficiency Short-Term | 2 |
| Efficiency Long-Term | 1 |

Table 7: Scoring of Unstructured Judgmental Forecasts

Effectiveness

Daniel Kahnemann (2011) in “Thinking – fast and slow”, his bestselling summary on his thirty years of research on human cognitive mechanisms, gives a superb overview of factors influencing human prediction and decision making. He points out that most decisions are not the end result of logical / rational decision-making processes but instead the outcome of heuristics mimicking such processes.

While, as he points out, heuristics have been- and still are often the preferable way of processing information, the human mind is prone to producing biases when faced with complex information input. Areas, in which the decision heuristics perform especially poorly, include statistics and forecasting (Tversky & Kahnemann, 1982).

Potentially biasing cognitive mechanisms include, but are not limited to:

- Anchoring, i.e. the tendency to orient forecasts on recently heard numbers, even if the numbers are completely irrelevant to the problem;
- The subconscious process of substituting complex statistical problems with simpler ersatz problems;
- The tendency to weight all available information equally – irrespective of the reliability of the source (‘What-you-see-is-all-there-is’) and
- Overconfidence in own forecasts.

The effect of anchoring, for example, was shown in an experimental study by Northcraft & Neale (1987). Participants (professional real-estate agents) were asked to estimate the value of a piece of real estate. In the preparation package for the estimate, a seemingly neutral valuation of the property was included, which either gave a high- or a low estimate of the property’s value. Northcraft and Neale found that by this, participants were influenced in their personal estimate by on average 41%.

Makridakis et. al. (1993) arrive at the same conclusion in the M2-competition:

‘Our empirical findings reinforce those of the psychological literature (see... Kahnemann et.al. (1982)...) which have shown that judgmental biases might negatively influence the subjective forecasts...’ (Makridakis, et al., 1993, S. 17)

It is clear that in an AP setting, where most of the data is potentially provided by the client and is bound to include the client’s own estimates, there is increased risk of forecasting bias, even absent any ill intentions of the client.

It should furthermore be mentioned that judgmental forecasting is bound to be less accurate in the long-run as the impact of any domain knowledge lessens.

Efficiency

Un-structured judgmental forecasts are, of course, very inexpensive. If domain knowledge is assumed to be present due to the conduct of the engagement, cost is basically limited to any data that is to be used as basis for the estimate.

In the survey, 15% of the participants listed (unstructured) judgmental forecasts as a method they employed in AP. The limited effort connected with these kinds of forecasts certainly plays a role in that number.

Nevertheless, the biasing tendencies in unstructured forecasts are well-documented and have been so for a long time (comp. McGregor (1938) or Ogburn (1934)). Consequently, basing AP predictions on professional judgment only and without a structured process not only bears the risk of not identifying misstatements, any ensuing legal case might be difficult to argue.

4.3.5.2. Guided Judgmental Forecasts

| Summary | Guided Judgmental Forecasts |
|--------------------------|-----------------------------|
| Effectiveness Short-Term | 2 |
| Effectiveness Long-Term | 2 |
| Cost | 2 |
| Efficiency Short-Term | 1 |
| Efficiency Long-Term | 1 |

Table 8: Scoring of Guided Judgmental Forecasts

Effectiveness

Stewart (2001) identified four basic factors decreasing judgmental forecasting accuracy, which, in essence, duplicate the findings of Kahnemann & Tversky:

- Subjective information acquisition;
- Subjective information processing;
- Uncertainty about the environment and
- Complex forecasting situations.

It is clear that any structure mitigating these factors should lead to an increase in forecasting accuracy. An audit team aiming at decreasing distortion in judgmental forecasts for AP purposes should establish processes which address these factors. Such processes could, for example, be structured along five principles Steward (2001) suggests in this context (paraphrased):

- Structure information acquisition.

Forecast input should be presented in a standardized way, which requires only a minimum of interpretation on the part of the forecaster. The goal is to make the acquisition of information as effort-less as possible.

While Steward sees the largest benefit of this principle in forecasting fields which heavily rely on graphical pattern interpretation, such as weather-forecasting, in theory this should apply to economic forecasting as well.

Conway, Jako, & Goodman (1995) found in a metastudy on personnel selection interviews a clear connection between structured information provision to the forecaster and judgment (i.e. forecasting) accuracy.

- Limit informational input to key cues.

At first glance it seems counterintuitive that limiting the information available to forecasters should increase forecasting accuracy. As was discussed in the previous section, the human mind tends to assign all available pieces of information the same

importance. Unimportant pieces of information therefore gain an over-proportionate impact.

Furthermore, forecasters might only be capable to effectively process a limited amount of information at any given time. MacGregor (2001) in a research review provides broad evidence that decomposing research questions, i.e. splitting a complex scenario into several simple ones, strongly increases forecasting accuracy. This is especially the case in the presence of a high degree of uncertainty.

- Use automated processes where possible.

A substantial body of research finds that forecasting accuracy can be improved if the forecaster's knowledge is used to calibrate a forecasting model but the information processing itself is performed by a machine in order to eliminate inconsistencies. Judgmental bootstrapping (Goldberg (1970), Camerer, (1981)) for example has been shown to increase the accuracy above that of the underlying judgments (Cooksey, Freebody, & A.J. (1990), Goldberg & Ramanaiah (1977)).

Judgmental bootstrapping might be difficult to apply to an AP setting, where a large body of judgments is not necessarily available to infer rules from (premise of judgmental bootstrapping). However, as Stewart (2001) points out, even simpler processing methods such as linear models can be used to decrease inconsistencies.

This line of thought might give rise to the question if there is scientific reason at all to perform judgmental forecasts or if a machine model is strictly preferable in general.

As Stewart points out, mechanical processing of information might be superior if and only if it has access to the same set of information as the human forecaster. To switch terminology, the machine needs to have access to the forecaster's domain knowledge.

As the complete transportation of environmental information remains a non-trivial challenge, this seems to be an unrealistic assumption in most cases.

Consequently, the integration of human- and automated capabilities might produce more accurate results than either on their own (Blattberg & Hoch (1990), Brown & Murphy (1984), Bosart & Roebber (1996). And this is of course also one of the driving ideas behind Rule-Based Forecasting (see section 4.3.10.2).

- Combine several forecasts.

That combining forecasts may increase accuracy by eliminating unsystematic errors, has long been shown (Stroop, 1932). McNees (1987) showed in an economic forecasting setting that aggregate forecasts tend to be more accurate than individual

ones, if the forecasts are based on independent assumptions or information (comp. also Winkler, 1981).

Ashton & Ashton (1985) came to the result that the major share of accuracy gain can be realized by combining two- to five individual forecasts. It should be pointed out, however, that accuracy gain in combining forecasts can only be realized to the degree that the sources of the forecasts do not share a common bias.

If, for example, an audit team creates individual forecasts for combination in the AP process, but the team works all based on the same biased assumptions or information, then this is obviously a limiting factor.

- Require justification for forecasts.

Finally, inconsistencies in information processing may be reduced by having to subsequently justify the forecast, as Hagafors & Bremer (1983) suggest. Documenting the forecasting process may here force forecasters to apply standardized approaches instead of intuition.

Application of these principles as a whole is likely to significantly increase forecasting accuracy compared with unstructured judgmental forecast (the estimate in the summary table at the beginning of this section reflects this statement).

An audit firm would need to establish a customized and standardized process. Alternatively, a standardized judgmental forecasting model such as the Delphi process could be used, though Delphi might encounter practical challenges with its comparatively high demands on participating forecasting experts (typically five to twenty, comp. Rowe & Wright (2001)).

While the measures described above are likely to increase forecasting accuracy, there is some limited evidence that even structured judgmental forecasts might not measure up to the benchmark of Naïve 2 (see below for discussion on Naïve 2). In the M2-Competition, five forecasters were asked to provide their individual assessments of the time-series (Makridakis, et al., 1982, S. 8). Makridakis et al. deliberately give no additional information as to how the forecasters created their respective opinions other than that there have been formal models as per the discretion of the forecasters involved as well as judgmental adjustments.

None of the five forecasters were able to outperform Naïve 2 in the short- or the long run.

Due to the intransparency of the forecasters' methods and the relatively small size of the M2-Competition, results might be expected to vary. Still, the available data is not encouraging for the (purely) human ability to forecast.

Efficiency

While the principles introduced above likely increase accuracy, they also, without a doubt, strongly increase cost compared to unstructured judgmental forecasts:

- Definition of unified process and training therein (training costs);
- Preparation of information (data costs);
- Application of automated data processing (training- and time cost);
- Cost incurred by performing same forecasts several times in parallel (time costs);
- Justification / documentation effort (time costs).

Anecdotic evidence (especially from the interviews preceding the survey) suggests that the primary reason for employing judgmental forecasts is the ease of use. Other valid reasons for using experts' judgments such as scarcity of data points or the inability to translate certain environmental factors into processable form seem to play smaller roles.

Consequently, it might be argued that other, more accurate forecasting of comparable costs could be found. I.e. it is unlikely that judgmental forecasts would continue to play their role in AP if they were set-up in a way that reflects research results.

| Summary | Graphically supported Judgmental Forecast |
|--------------------------|---|
| Effectiveness Short-Term | 2 |
| Effectiveness Long-Term | 3* |
| Cost | 1 |
| Efficiency Short-Term | 2 |
| Efficiency Long-Term | 3* |
| Remarks | *if linear regression is employed |

4.3.5.3. Graphically supported Judgmental Forecast

Table 9: Scoring of graphically supported Judgmental Forecasts

Effectiveness

A sub-category of guided judgmental forecasts are processes which use a visualization of data in order to support information processing. Forecasters either use the “raw” data points- or the data in conjunction with a calculated trend function, for example linear regression, as basis for their estimate.

Graphically supported judgmental forecasts (“graphical forecasts”) deserve special attention because auditing literature frequently recommends this technique as a possible method for AP (e.g. Marten, Quick, & Ruhnke, 2006, p. 792). On the other hand, practitioners in the survey did not name this method.

As has been discussed in the preceding section, this corresponds with Stewart’s (2001) principle of outsourcing part of the information processing to a machine. Harvey (2001) also recommends using reviewing data as basis for a judgmental forecast in a graphical rather than a tabular form and furthermore recommends calculating a trend line (= linear regression).

As will be discussed in section 4.3.9.1, linear regression has reasonably strong long-term prediction power. Together with mediating inconsistencies, using this support may be expected to increase long-term accuracy.

Efficiency

One reason to discuss graphical forecasts separately is that compared with the preceding method, costs are comparatively low. Displaying data points in a graph and calculating a trend line is very straight-forward. At the same time a major share of the accuracy gain is likely to be realized.

Consequently, graphical forecasts may be expected to yield the highest efficiency in the judgmental methods group.

4.3.6. Naïve Methods

Naïve methods refer to the “no-assumptions”- or random-walk approach in which the forecast for the next period is simply the value of the last data-point.

Naïve forecasting is a logical benchmark for other forecasting methods, as for a symmetrical and proportionate error metric, performance equal to the random walk means that the model performs no better than random for a sufficiently large testing basis. Worse average performance indicates a bias, either in the model or in the error metric.

Despite its straightforwardness, there are several variants of naïve forecasting which merit separate discussion.

4.3.6.1. Naïve 1

| Summary | Naïve 1 |
|--------------------------|---------|
| Effectiveness Short-Term | 2 |
| Effectiveness Long-Term | 1 |
| Cost | 1 |
| Efficiency Short-Term | 2 |
| Efficiency Long-Term | 1 |

Table 10: Scoring of Naïve 1

Effectiveness

Naïve 1 refers to the standard random walk without any adjustments in the forecasting data, i.e. $X_t = \hat{X}_{t+1}$. Naïve 1 was entered as a separate candidate in the M1- and M2-Competitions (Makridakis, et al., 1982, Makridakis, et al., 1993). In the M3-Competition, Naïve 1 was not entered as a separate method any longer (Makridakis & Hibon, 2000).

The primary merit of Naïve 1 for the forecasting competitions was as a performance benchmark for other forecasting methods. Given an un-skewed error-metric, a model contributing value to the forecasting process should outperform Naïve 1 more than 50% of the time. A striking result of the M1-Competition was that not all models did outperform Naïve 1 (Quadratic Exponential Smoothing, Brown Exponential Smoothing for Median APE and Average MAPE (Makridakis, et al., 1982, pp. 115)).

It was furthermore interesting that both the absolute- (Median APE) and relative (average ranking) performance of Naïve 1 grew worse with increasing forecasting horizon (Makridakis, et al., 1982, pp. 117). This finding was consistent with theory. Naïve 1 is believed to perform comparably well:

- In situations of high randomness, i.e. time-series in which trend is not a dominant factor and in which models with strong trend components are likely to over-estimate trend.
- In situations in which trend may not have on average become dominant, i.e. in the short run.

Translating into an AP setting, auditors might find Naïve 1 a useful forecasting assumption in cases of high uncertainty, such as the financial crisis of 2008 or if forecasts are performed for the very immediate future. Nevertheless, it is probably doubtful whether in an environment such as the financial crisis of 2008 an AP forecast alone would trigger additional auditing, as the corresponding risk threshold would need to be extremely wide.

Efficiency

It is self-evident that carrying over last-period's number has to be the least costly forecasting method.

4.3.6.2. Naïve 2

| Summary | Naïve 2 |
|--------------------------|---------|
| Effectiveness Short-Term | 3 |
| Effectiveness Long-Term | 3 |
| Cost | 2 |
| Efficiency Short-Term | 1,5 |
| Efficiency Long-Term | 1,5 |

Table 11: Scoring of Naïve 2

Effectiveness

The M-Competitions distinguished a variant of Random Walk, Random Walk performed on de-seasonalized data, the so-called Naïve 2. Data here was de-seasonalized (where applicable) using ratio-to-moving average decomposition. Other methods of de-seasonalization (seasonal indices obtained by the Census II method as well as one-year-ahead forecasts of the same) produced non-significantly different results (Makridakis, et al., 1984, p. 153).

The underlying assumption was that it was known to the forecaster if a seasonality factors exists, an assumption on domain knowledge that seems reasonable also to apply to the AP context.

Naïve 2 performed well in all three M-Competitions, forming one the pillars of the statement concluded from all three competitions that there is no inherent connection between the complexity of a forecasting method and its performance. In the M1-Competition, Naïve 2 was performing seventh-best by overall Median APE criterion (Makridakis, et al., 1982, p. 118). In M2, Naïve 2 was tenth-best of eighteen by overall MAPE (Makridakis, et al., 1993, p. 9). In the M3-Competition, nearly all methods were able to outperform Naïve 2 on average by the sMAPE criterion (Makridakis & Hibon, 2000, p. 457). As with Naïve 1, Naïve 2 performed best in the short run in relative terms.

The M-Competitions in general proved that simple domain-knowledge driven seasonal decomposition with no further assumption produces relatively effective forecasts, which provides justification for its inclusion in Rule-Based Forecasting, as discussed below.

Efficiency

Clearly, seasonal decomposition adds additional time- and training-cost to producing forecasts, compared to Naïve 1. Nevertheless, the effort to be invested, if applicable, is comparatively limited, while the efficiency gain due to seasonal decomposition cannot be denied.

4.3.6.3. Last Year plus X

| Summary | Last Year plus X |
|--------------------------|------------------|
| Effectiveness Short-Term | 3 |
| Effectiveness Long-Term | 3 |
| Cost | 2 |
| Efficiency Short-Term | 1,5 |
| Efficiency Long-Term | 1,5 |

Table 12: Scoring of Last Year plus X

Effectiveness

The notion that Random Walk forecasts, i.e. effectively making no forecast at all, could produce relatively effective forecasts, evoked skepticism from the practitioners consulted during this study. It was also widely believed that using such a “method” might be difficult to defend, should the need arise.

The irony in those statements was that the survey on AP showed that as a matter of fact, a variant of the Random Walk was by far the most widespread forecasting method used in practice. Over 78% of all participants stated that they used a method that was christened ‘Last Year plus X’.

Last Year plus X simply assumes that all values to be determined in the AP phase equal the client’s last year’s figures plus a fixed percentage, the percentage being the same for all time-series to be forecasted for the client (with the obvious exception of KPIs). Following points stand out:

- There was no systematic way of estimating the percentage increase or decrease. Consequently, depicting Last Year plus X as a method which includes a trend component is somewhat misleading.
- After conducting the survey, the author had several informal talks with participants in which the concrete application of this method came up. A resulting insight was that usually, this method is to be understood as “*triggering additional auditing if last year’s number increases by more than X %*”. Considering this statement reveals three issued:
 - The wording in the survey was potentially too ambiguous with respect to this point.
 - It may be the case that the plus X % should not be interpreted as a forecast as such. Instead, it may be concluded that there is just no clear distinction between the forming of the forecast and the forming of the AP risk threshold!

- If this interpretation is believed, it follows that “Last Year plus X” is in fact a Random Walk forecast in all but name.

It followed that Last Year plus X should be regarded the same way as the Naïve methods, ideally Naïve 2, as discussed above.

Efficiency

See above.

4.3.6.4. Fixed Ratios

| Summary | Fixed Ratios |
|--------------------------|--------------|
| Effectiveness Short-Term | 2 |
| Effectiveness Long-Term | 1 |
| Cost | 1 |
| Efficiency Short-Term | 2 |
| Efficiency Long-Term | 1 |

Table 13: Scoring of Fixed Ratios

Effectiveness

One of the methods brought up by the practitioners during the preparation interviews was the use of fixed financial- or non-financial ratios or KPIs. In the survey, this forecasting method was chosen 105 times (62% of participants).

Conceptually, fixed ratios are a “naïve” stationary regression heuristic. As such, the effectiveness of fixed ratios largely depends on two factors:

- The actual explanatory power of the independent variable in the ratio and
- The stability of the relation between the variables (implicitly assumed as stationary).

Consequently, the effectiveness of the method is crucially dependent on the professional judgment / experience of the auditor. Furthermore, fixed ratios as a forecasting method can in many cases be expected to very vulnerable to disruptive events or external shocks such as the financial crisis of 2008. By this latter rationale, especially the long-term effectiveness of the method is not likely to be very high.

Summarizing, depending on the auditor in question, fixed ratios may occasionally produce good results for AP in the short term. As a broadly applied method (which the survey indicated that it was) fixed ratios lacks reliability and robustness. This method has not been evaluated during one of the M-Competitions.

Efficiency

The calculations behind fixed ratio numbers are trivial. This low cost in application is most likely the factor which contributed to the method’s popularity in the survey.

4.3.7. Exponential Smoothing Methods

Exponential smoothing was first developed by Robert G. Brown in (1956) as a forecasting method for production and inventory planning. Subsequent developments included an expansion of the original model by Charles C. Holt in (1957), introduction of a trend component in 1960 by Holt et. al., leading to the Holt-Winters method of (double) exponential smoothing and the expansion of the model by Peter Winters in 1960 by a seasonal factor (triple exponential smoothing).

The original drawback of exponential smoothing methods was the difficulty of identifying optimal smoothing parameters, a non-trivial optimization problem. Consequently, and similar to autoregressive models, exponential smoothing became more widespread with the introduction of powerful electronic computing.

Variants of exponential smoothing have been tested in all M-Competitions and interestingly both the best- and worst performing methods come from this family.

In the following, exponential smoothing variants which were tested in M-Competitions and which also represent the widespread “families” of smoothing models are discussed.

4.3.7.1. Single Exponential Smoothing

| Summary | Single Exponential Smoothing |
|--------------------------|------------------------------|
| Effectiveness Short-Term | 2 |
| Effectiveness Long-Term | 3 |
| Cost | 3 |
| Efficiency Short-Term | 0,67 |
| Efficiency Long-Term | 1 |

Table 14: Scoring of Single Exponential Smoothing

Effectiveness

“Single-“or “simple” exponential smoothing is given by:

$$\hat{X}_{t+1} = \alpha X_t + (1 - \alpha)\hat{X}_t$$

where \hat{X} is the estimate for period t, X is the value of the data point and α is the smoothing factor. This method is a variant of the exponential smoothing developed by Brown (1956). What differentiates it from the original method introduced by Brown and further developed by Holt (1957) is that no trend component is assumed / built into the model.

Single exponential smoothing was tested in all three M-Competitions. In all cases, single exponential smoothing performed in the middle of the field: Single exponential smoothing outperformed Naïve 1 in M1 and M2. It failed to outperform Naïve 2 in the M1-Competition (Makridakis, et al., 1982, p. 120) but did beat Naïve 2 in M3 by the sMAPE criterion (Makridakis & Hibon, 2000, p. 463).

The competitions also showed that the addition of trend and / or seasonal components to smoothing models does contribute to general forecasting accuracy: Other participating smoothing models such as Holt (double exponential models), Winter (triple-) or Dampen (Trend-damped-) consistently outperformed single exponential smoothing.

It might be argued that due to the absence of a trend component, a lag of the forecasted values behind the actual series is a logical consequence. Consequently, performance was worst on average for the first forecasting periods, a fact that all but disqualifies single exponential smoothing for AP.

Efficiency

Brown originally called his method “*not statistically efficient, but [...] economically efficient, when the cost of computation is considered*” (Brown R. G., 1956, S. 1).

This may be true for the calculation of the model as such, which today of course can be done with any spreadsheet software. It is not necessarily true for identifying an optimal smoothing parameter α (minimizing MSE). α should be approximated with an optimization algorithm, something that is generally available in statistical software packages but not necessarily in an audit team. Consequently, and also considering training, costs were estimated as comparatively high.

This issue is present for all smoothing models as well as the Rule-Based Forecasting variant used for the electronic decision support system discussed below, where it was also identified as a field of future improvement (see section 9).

4.3.7.2. Double Exponential Smoothing

| Summary | Double Exponential Smoothing |
|--------------------------|------------------------------|
| Effectiveness Short-Term | 4 |
| Effectiveness Long-Term | 3 |
| Cost | 3 |
| Efficiency Short-Term | 1,33 |
| Efficiency Long-Term | 1 |

Table 15: Scoring of Double Exponential Smoothing

Effectiveness:

Double exponential smoothing contains of a smoothed value- as well as a smoothed trend component. In the method introduced by Holt (1956), the model is calculated by:

$$S_t = \alpha X_t + (1 - \alpha)(S_{t-1} + T_{t-1})$$

$$T_t = \beta(S_t - S_{t-1}) + (1 - \beta)T_{t-1}$$

$$\hat{X}_{t+1} = S_t + T_t$$

where α and β are chosen as to minimize MSE against the data series.

The Holt model was tested in all three M-Competitions. It performed reasonably well, consistently outperforming Naïve 1 and -2 by sMAPE.

As has been stated above, double exponential smoothing clearly outperformed single exponential smoothing. As will be discussed in the following section, the picture becomes less clear when introducing triple exponential smoothing.

Double exponential smoothing performed best in the short- to medium run. Of the 24 models tested in M3, only five outperformed the Holt model in the first forecasting period by sMAPE, underscoring that also relatively simple models may perform effectively. The number rose to 13 for periods 1-4 and to 14 for periods 1-18.

Efficiency

Computation costs of the model are not a significant issue any longer. The challenge of identifying optimal smoothing parameters is in essence identical with single exponential smoothing, i.e. a statistical software package is realistically required if the method is to be employed in AP. Consequently, costs may be assumed to be essentially equal. Combining with increased effectiveness, double exponential smoothing must be considered more efficient than single exponential smoothing.

4.3.7.3. Triple Exponential Smoothing

| Summary | Triple Exponential Smoothing |
|--------------------------|------------------------------|
| Effectiveness Short-Term | 4 |
| Effectiveness Long-Term | 3 |
| Cost | 3 |
| Efficiency Short-Term | 1,33 |
| Efficiency Long-Term | 1 |

Table 16: Scoring of Triple Exponential Smoothing

Effectiveness

Triple- or Holt-Winters exponential smoothing is special insofar as that the model is only conditionally different from double- or Holt exponential smoothing. In triple exponential smoothing, a seasonal parameter is introduced which is applied if and only if seasonal patterns are present in the data. The decision whether seasonal patterns are present may either be automated, if an autocorrelation of data points with a time difference equal the seasons significantly different from zero is present, or decided by judgment (strong domain knowledge).

The model is described by:

$$S_t = \alpha \frac{X_t}{I_{t-L}} + (1 - \alpha)(S_{t-1} + T_{t-1})$$

$$T_t = \gamma(S_t - S_{t-1}) + (1 - \gamma)T_{t-1}$$

$$I_t = \beta \frac{X_t}{S_t} + (1 - \beta)I_{t-L}$$

$$\hat{X}_{t+1} = (S_t + T_t)I_{t-L+1}$$

where L is the length of seasonality and α , β and γ are chosen as to minimize MSE.

As with double exponential smoothing, triple exponential smoothing consistently outperformed the Naïve 1 and -2 benchmarks as well as single exponential smoothing. The evidence regarding performance relative to double exponential smoothing on the other hand is inconclusive based on the M-Competitions:

In M1, Holt-Winters on average outperformed all other single forecasting models (Makridakis, et al., 1982, p. 122). It was only outperformed by the two methods of combining forecasts from different models. Not surprisingly, it performed exactly equal to the Holt model for yearly time series by MAPE (Makridakis, et al., 1982, p. 135), i.e. time series

without seasonality, while clearly outperforming Holt for quarterly data (ibid), i.e. time series potentially including a seasonal factor.

This finding was not supported by the M3 competition (M2 is not discussed here due to its comparatively small data set). While Holt-Winters and Holt again performed identically by sMAPE for yearly data, there was also no significant difference for quarterly and monthly data: Holt-Winters narrowly outperformed Holt for quarterly data-sets. For monthly data-sets, on the other, hand Holt outperformed Holt-Winters by a small margin!

The reason for this seeming contradiction is not clear. Theoretical reasons include the difference in performance measurement criteria (MAPE vs. sMAPE), a difference in the application of either model or potentially even an error. While it therefore remains unclear whether triple exponential smoothing produces an advantage over double exponential smoothing, it seems to be evident that at least no significant loss in accuracy occurs. For evaluation within the context of this thesis, the effectiveness is therefore set as equal.

Efficiency

Costs are assumed to be equal to those of single exponential smoothing and for the same reasons as stated above. This leads to the situation that from an AP perspective employing either model is equally attractive.

4.3.7.4. Quadratic Exponential Smoothing

| Summary | Quadratic Exponential Smoothing |
|--------------------------|---------------------------------|
| Effectiveness Short-Term | 1 |
| Effectiveness Long-Term | 1 |
| Cost | 3 |
| Efficiency Short-Term | 0,33 |
| Efficiency Long-Term | 0,33 |

Table 17: Scoring of Quadratic Exponential Smoothing

Effectiveness

Quadratic exponential smoothing was tested in the first M-Competition and may be regarded as a general representative of higher-order smoothing models. Brown's one parameter quadratic exponential smoothing as used by Makridakis et.al. (1982, p. 144) is defined as follows:

$$S'_t = \alpha X_t + (1 - \alpha)S'_{t-1}$$

$$S''_t = \alpha S'_t + (1 - \alpha)S''_{t-1}$$

$$S'''_t = \alpha S''_t + (1 - \alpha)S'''_{t-1}$$

where

$$a_t = 3S'_t - 3S''_t + 3S'''_t$$

$$b_t = \alpha(2(1 - \alpha)^2)^{-1}((6 - 5\alpha)S'_t - (10 - 8\alpha)S''_t + (4 - 3\alpha)S'''_t)$$

$$c_t = \alpha(1 - \alpha)^{-2}(S'_t - 2S''_t + S'''_t)$$

and

$$\hat{X}_{t+k} = a_{t+k} + b_{t+k}(k) + 1/2c_{t+k}(k)^2$$

where α is chosen as to minimize MSE.

The method described here in essence assumes a second-order trend in the time-series. In M1, quadratic exponential smoothing performed second worst in overall average MAPE, the obvious lesson being that there is little evidence of widespread higher-order trends in the socio-economic type of data used as basis for the competition. Consequently, this kind of model was not tested in the following competitions.

There seems to be no good reason to employ it in AP.

Efficiency

Costs are assumed to be equal to those of single exponential smoothing and for the same reasons as stated above.

4.3.7.5. Trend-Dampening Exponential Smoothing

| Summary | Trend Dampening Exponential Smoothing |
|--------------------------|---------------------------------------|
| Effectiveness Short-Term | 5 |
| Effectiveness Long-Term | 4 |
| Cost | 3 |
| Efficiency Short-Term | 1,67 |
| Efficiency Long-Term | 1,33 |

Table 18: Scoring of Trend Dampening Exponential Smoothing

Effectiveness

Trend-dampening exponential smoothing or „Dampen”, as the method was christened in Gardner & McKenzie (1985), is a method directly developed by Gardner and McKenzie as a response to the results of the first M-Competition (Gardner & McKenzie, 1985, p. 1237). Makridakis et. al. had demonstrated that in the long run, accuracy of all conventional forecasting methods suffered badly, as trends frequently proved unstable in reality and estimated trends consequently overshot.

Gardner and McKenzie took the classical Holt double-exponential smoothing model (Holt, 1960) as basis and added a variable and accumulating trend dampening component:

$$S_t = \alpha X_t + (1 - \alpha)(S_{t-1} + \phi T_{t-1})$$

$$T_t = \beta(S_t - S_{t-1}) + (1 - \beta)\phi T_{t-1}$$

$$\hat{X}_m = S_t + \sum_{i=1}^m \phi^i T_t$$

where α , β and ϕ are chosen to minimize MSE against the data series and ϕ is the dampening factor. If $\phi = 1$, the model is equivalent to the Holt model, for $0 > \phi > 1$, the trend is dampened, for $\phi = 0$, there is no trend component.

The idea to dampen the trend component in forecasting models has not been invented by Gardner and McKenzie. Parzen (1979, 1982) and Lewandowski (1982) had both developed models with dampened trend components which had both already been tested in M1 and performed very well.

Gardner and McKenzie, however, believed that indiscriminately dampening trend components was probably too conservative an approach. Consequently, the model introduced by them dampens the trend if and only if the trend detected is identified as “erratic”. In their study, based on the M1-Competition, only for 20% of data series using annual data, the trend

component was dampened, while for quarterly- and monthly data the number was much higher. As a result, Dampen performed nearly equal to the standard Holt model by Mean APE for yearly data but far outperformed for quarterly- and monthly series. Pronounced advantages could be seen on average from the sixth forecasting period onwards (Gardner & McKenzie, 1985, p. 1242).

Dampen was tested in the M3-Competition, where it performed among the top models by sMAPE (Makridakis & Hibon, 2000, p. 457). Among those methods, the difference in sMAPE was small enough on average to speak of near-parity.

Efficiency

The second major contribution of Gardner and McKenzie was to incorporate the trend dampening idea into a relatively uncomplicated forecasting model. While the other top methods in M3 were expert systems or otherwise time/cost intensive, Dampening is only as resource-consuming as any other smoothing model.

This lead Makridakis and Hibon to conclude: “...*beyond the slightest doubt, that elaborate theoretical constructs or more sophisticated methods do not necessarily improve post-sample forecasting accuracy, over simple methods, although they can better fit a statistical model to the available data*” (Makridakis & Hibon, 2000, p. 459).

4.3.8. Autoregressive Methods

The general autoregressive moving average model (“ARMA”) was formulated by Peter Wittle in 1951. In 1971, George E. P. Box and Gwylim M. Jenkins published a methodology for choosing and estimating the model components.

The ‘Box-Jenkins’ method and its variants gained a broad following, especially among statisticians, possibly due to the large theoretical body underlying the method. In the following, the variant “ARIMA” is discussed in more detail.

One of the reasons for the continuing popularity of the Box-Jenkins approach might be the belief that the model ‘gets everything out of the data there is’. Its continued popularity has the effect that the Box-Jenkins method is one of the few forecasting methods the author found mentioned by name in the auditing literature. Kayadelen, for example, named Box-Jenkins as one of the appropriate statistical methods for Analytical Procedures (comp. Kayadelen, 2008, p. 27).

4.3.8.1. ARIMA

| Summary | ARIMA |
|--------------------------|-------|
| Effectiveness Short-Term | 4 |
| Effectiveness Long-Term | 3 |
| Cost | 5 |
| Efficiency Short-Term | 0,80 |
| Efficiency Long-Term | 0,60 |

Table 19: Scoring of ARIMA

Effectiveness

Autoregressive integrated moving average or ARIMA (n,m) consists of two separate components: A moving average (“MA”) term of accumulated “static” or random movement of the preceding m static terms: and an autoregressive (“AR”) signal term which contains of its own static and the moving average of the preceding n signal terms.

ARIMA variants were tested in all three competitions: In M1, the Box-Jenkins approach to ARIMA performed seventh of twenty-four by average MAPE and 18 periods forecasting horizon but was outperformed by much less sophisticated methods such as Naïve 2 (Makridakis, et al., 1982, S. 115). Makridakis et. al. suggest that this might be rooted in that ‘...statistically sophisticated methods extrapolate too much trend which can cause overestimation’ (Makridakis, et al., 1982, S. 127).

As mentioned above, one of the criticisms of M1 was that Box-Jenkins might not have performed to its full potential because it might have been applied incorrectly (Geurts in Armstrong & Lusk, 1983, p. 10). This is a valid concern, as ARIMA forecasting process requires considerable prior experience and the method described by Box and Jenkins leaves considerable leeway for individual decisions.

From an AP point of view, this poses the question of whether a method with an apparently high risk of user errors may be expected to perform well in a context, such as AP, in which the majority of users are not full-time forecasting specialists. In any case, in M2, the Box-Jenkins forecasts were produced directly by Spyros Makridakis and the results of M1 was confirmed: Box-Jenkins was again outperformed by Naïve 2 (here: Median APE, Makridakis, et al. (1993, p.19)).

In M3, the originally (semi-)manual Box-Jenkins forecasting process was replaced by seven different automatic ARIMA programs. Former results were again confirmed insofar as that all methods performed in the middle of the field by sMAPE (Makridakis & Hibon, 2000, p. 463).

In summary, the conclusion seems to stand that ARIMA models seem to offer little real advantage over less sophisticated models. In addition, a setting of non-fulltime forecast applicators, like AP, might add additional risks, albeit mitigatable by automation.

Efficiency

At the time of the first M-Competition, applying the *'Box-Jenkins Methodology required the most time [of all methods employed in the M1 competition] (on the average more than one hour per series)'* (Makridakis, et al., 1982, S. 113). For this reason, in the original M-Competition, Box-Jenkins was only tested against a subset of 111 of the overall 1001 time series.

In the 35 years since then, computing technology has made tremendous leaps. Already in the M3-Competition, many of the sub-tasks of conducting an ARIMA forecast were automatically executed by a statistical software package.

From the perspective of an auditing firm, this of course means that proprietary forecasting software would need to be acquired. Furthermore, it could be argued that even if pattern recognition and subsequent model design decisions are automated, auditors / users would need to have a basic understanding of the underlying model. This then again leads to the complicated underlying statistical workings of Box-Jenkins, who himself designed his main work, "Time Series Analysis: Forecasting and Control" (1970) as a one- to two semester course for graduate students.

It can be concluded that a broad and reliable introduction of the Box-Jenkins methodology into an audit environment would incur major costs including time costs, training costs and licensing fees.

4.3.9. Other Regression Models

The term ‘regression models’ encompasses a large group of prediction models including single- and multiple linear regression, non- and semi-parametric regression (strictly speaking, autoregressive models, which have been discussed in the previous section, also belong to this group). Many of these methods are of limited interest for the socio-economic set of parameters found in AP (e.g. because of the use of functions of higher order, as has been discussed in the section on quadratic exponential smoothing, 4.3.7.4). Two variants are nevertheless relevant for AP and evaluated:

- Linear regression is perhaps the simplest statistical forecasting model and retains a large following among audit practitioners and
- A multivariate econometric method called “STAR” is of special interest to this study, as STAR has been the standard AP forecasting method at Deloitte until 2009.

4.3.9.1. Linear Regression

| Summary | Linear Regression | |
|--------------------------|-------------------|---|
| Effectiveness Short-Term | | 2 |
| Effectiveness Long-Term | | 3 |
| Cost | | 1 |
| Efficiency Short-Term | | 2 |
| Efficiency Long-Term | | 3 |

Table 20: Scoring of Linear Regression

Effectiveness

Linear Regression is the fitting of a trend line against one independent variable, in this context the time period, by ordinary least squares, a method developed by German mathematician Carl Friedrich Gauss (1823). The trend component is stationary, derived from all data points equally.

In theory this means that linear regression is a good method for identifying underlying long-term trends. In practice, there are serious restrictions to the usefulness of linear regression as a forecasting method:

In M1, linear regression performed worst of all 21 methods with respect to the MAPE criterion (Makridakis, et al., 1982, p. 115). Linear regression was not tested in the subsequent competitions. Interestingly, when applied to yearly time series, Linear Regression performed second best by the same criterion, only being outperformed by the composite model ‘Combining A’ (Makridakis, et al., 1982, p. 128).

Interpreting the empirical results, as well as the characteristics deductible from the model composition, following observations can be made:

- Linear regression performs reasonably well in the long run if, and only if, a strong trend is underlying the data.
- Linear regression performs badly on un-de-seasonalized data in the presence of seasonality.
- Linear regression performs badly in the presence of strong uncertainty / white noise, as trend is obscured.
- Linear regression performs badly in the short run, as no increased weight is put on recent observations.
- Linear regression performs badly in the presence of changing trends, as the model contains no mechanisms to correct for this.

Summarizing, one should keep in mind that linear regression was not developed for forecasting socio-economic figures at all, but for predicting the movement of celestial bodies, a situation in which all the strengths and none of the weaknesses of the model come to bear. Applying to the situation at hand, there is limited use for the method in an AP context as a stand-alone model.

Efficiency

In contrast to the findings above, the AP survey found that linear regression was the most widely used statistical forecasting model, despite its limitations. This is most likely due to the low costs connected with the usage of the model. Linear regression is generally taught in basic statistic courses, which means there is a widespread familiarity with the method in the audit world. Furthermore, linear regression is included as a pre-programmed formula in the MS-Excel spreadsheet package, which means that ordinarily, no additional software needs to be acquired.

Summarizing, the application of linear regression is probably even less expensive than the de-seasonalization required for Naïve 2.

4.3.9.2. Multivariate Econometric Methods (STAR)

| Summary | Multivariate Econometric Methods (STAR) |
|--------------------------|---|
| Effectiveness Short-Term | 2 |
| Effectiveness Long-Term | 3 |
| Cost | 4 |
| Efficiency Short-Term | 0,50 |
| Efficiency Long-Term | 0,75 |

Table 21: Scoring of Multivariate Econometric Methods (STAR)

Effectiveness

Up to this point, the forecasting methods discussed all had in common that time-period was the only explanatory variable employed (excluding the implicit use of other variables summarized under the term “domain knowledge”).

If explanatory variables other than ‘time’ are used, one often speaks of ‘causal’ or ‘econometric’ methods. One reason why causal methods became popular in AP was because they enable auditors to combine forecasting and the determination of meaningful relations between accounting figures and economic drivers into one process, without having to take the additional step of forming KPIs. Unit cost, for example, might be modelled against the industry average per period or revenue might be modelled against macroeconomic drivers such as GDP-growth, household income or unemployment rate.

Deloitte used a decision support system based on econometrics named ‘Statistical Techniques for Analytical Review’ (“STAR”) from the early 1970s until 2009 (Stringer & Stewart, 1996, p. V) as global standard for AP.

Econometric methods were not part of the M-Competitions, the experience Deloitte gained with STAR highlights the characteristics of the method, however.

The multivariate linear regression method used in STAR shares many characteristics with the linear regression method described above, most importantly:

- Best performance in the presence of strong relationships between explanatory- and to-be-estimated variable.
- Vulnerability in the presence of strong uncertainty / white noise, as trend is obscured.
- Vulnerability to changes in the relation between explanatory- and to-be-estimated variable. The impact is the larger, the more ‘old data’ is available and the more recent the change in relations is.

A misunderstanding widespread in econometrics is to equate strong relationships with goodness-of-fit or explanatory power of independent variables, which may lead to over-fitting and which was also present in the STAR instructions (Stringer & Stewart, 1996, pp. 162). The second and third bullet, however, were the ultimate reasons why STAR as a forecasting method was abandoned at Deloitte in 2009: The turbulences resulting from the financial crisis in 2008 made it evident that regression models of the kind underlying STAR were not robust enough to provide forecasts for auditing. As the survey at Deloitte showed, STAR nevertheless still has a certain following.

Efficiency

There are several factors influencing the cost side of applying econometrics to AP.

- First of all, compared to other methods, econometrics potentially involves considerable data costs as the method requires one or more explanatory variables, for which data has to be acquired on a single AP forecast basis (economic data, peer group performance etc.).
- Meaningful econometrics requires both training and experience, lack of which may lead to inferior results.

Anecdotal evidence derived from consultations with former STAR users for example revealed that there was considerable confusion about the difference of causally dependent- and correlated variables. While the latter might exhibit considerable “explanatory power”, the usefulness as an explanatory forecasting variable is not at all guaranteed.

- The method itself is comparatively time intensive. STAR is a decision support system that eases econometric forecasting considerably and has features for the direct AP application as well. Still, the usage requires proficiency with the specific software, which translates to initial training cost. Furthermore, the econometric process of composing, testing (correlation, multicollinearity, autocorrelation etc.) and recalibrating the model is in itself time-consuming and needs to be repeated for every series to be forecasted.

Summarizing, the sophistication of the econometric method may present near-prohibitive costs for proper application, especially for smaller auditing clients.

In practice, cost saving may potentially be achieved by defining standard sets of explanatory variables (in contrast to bespoke forecasting models). This may, however, adversely affect forecasting accuracy.

4.3.10. Combining Forecasts

4.3.10.1. Equal Weight Combination

| Summary | Equal Weight Combinations |
|--------------------------|---------------------------|
| Effectiveness Short-Term | 4-5 |
| Effectiveness Long-Term | 4-5 |
| Cost | 4 |
| Efficiency Short-Term | 1-1,25 |
| Efficiency Long-Term | 1-1,25 |

Table 22: Scoring Equal Weights Combination

Effectiveness

One of the key findings of the M-Competitions was that no forecasting method performs universally well in all forecasting situations.

Another key finding was that combining individual forecast can mitigate individual methods' weaknesses and produce overall superior forecasts. In M1, an equal-weight combination of six forecasting methods performed better than any single one of those methods (or any other method) by MdAPE. This success was, in principle, confirmed in the following competitions.

It is self-evident that there is a prerequisite for combination forecasts to work effectively: The methods chosen have to be individually powerful as well as balance each other. The characteristics of each component model needs to be understood so that ideally each weakness is counteracted by another method. In the M3-Competition, a model combining Single-, Double- and Dampen exponential smoothing was tested. These methods share basic characteristics and of the three, Dampen performed generally most accurately. Consequently, forecasting accuracy did not benefit from mitigating effects and the method performed in essence equally to Dampen.

In an AP setting, it would potentially be difficult to propose combination forecasting without stipulating component models as well. In an effective process, a computer program automatically combining a number of fix / predetermined methods would need to be provided.

Efficiency

The cost side of combination forecasts is necessarily a function of the costs of its components. In the rating above, it was assumed that at least one exponential smoothing model, potentially requiring statistical software support, is included. The combination process itself is straightforward in the case of equal-weights combination.

4.3.10.2. Rule-Based Forecasting

Equal-weight combination of different forecasting methods achieved remarkable success in the M-Competitions. The logical conclusion was that if the mitigating effects of other forecasting methods against individual methods' weaknesses lead to an overall improvement in accuracy, theoretically, accuracy could be improved even further if weights were calibrated in order to specifically address these strengths and weaknesses. These would need to be calibrated by general forecasting scenario (incorporating domain knowledge) as well as over time, as '*the accuracy of the various methods depends on the length of the forecasting horizon*' (Makridakis & Hibon, 2000, p. 452).

Based on these principles, Rule-Based Forecasting ("RBF") was originally developed in 1992 by Scott Armstrong and Fred Collopy. Since then, and especially as a reaction to the M2-competition, the RBF model has been reviewed and modified several times. In the following, the original model with its key features is introduced, followed by a review of the later developments and a discussion of the variant included in the electronic decision support system.

4.3.10.3. RBF - Original Model

| Summary | RBF - Original Model |
|--------------------------|----------------------|
| Effectiveness Short-Term | 5 |
| Effectiveness Long-Term | 5 |
| Cost | 5 |
| Efficiency Short-Term | 1 |
| Efficiency Long-Term | 1 |

Table 23: Scoring of RBF - Original Model

Effectiveness

In its original version, RBF combines four forecasting models: Random Walk, Linear Regression, Brown’s exponential smoothing and Holt-Winters exponential smoothing.

These models are combined into a short- and a long model, both consisting of a level- and a trend component. Short- and long model are then blended into a final forecast, where the weight is gradually shifted from Short- to Long model over time / forecasting horizon.

All four methods are presented in both Short- and Long model, but with different weights. Furthermore, within each model, level and trend component are individual combinations of all four underlying methods.

These individual weights, the modus by which the blend of the models is formed as well as a trend-dampening mechanism and data preparation steps are described in a set of 99 rules (Armstrong & Collopy,1992 (b)).

The majority of rules consist of logical if...then statements, others require judgmental decisions by the forecaster.

The integration of the forecaster’s judgment or domain knowledge into statistical forecasting is one of the core concepts of RBF. Armstrong and Collopy trace the idea back to Makridakis’ and Hibon’s precursor study to the M-Competition (Makridakis & Hibon, 1979) as well as to the commentaries and suggestions which came as a result of the first M-Competition (Armstrong & Lusk, 1983).

The challenge of adding judgmental elements to a forecasting model is to include the domain knowledge without opening up the forecast to personal bias. As Makridakis et al. (1993) put it:

‘...no judgmental revisions ought to be made to the quantitative forecasts without making sure before hand about the need and value of such revisions.’

(Makridakis, et al., 1993, S. 17f)

As Stewart (2001) found, it is the *subjective* acquisition and processing of information that hurts forecasting accuracy. This agrees with current cognitive research (e.g. Kahnemann, 2011, p. 146ff) that in general the human mind has very limited capabilities to unguidedly evaluate statistical mechanics.

The approach to guided and, ideally, objective processing of domain knowledge used in RBF was suggested by Armstrong and Lusk (1983, p. 37): Personal judgment might support weighing the individual models in a combined forecasting method.

In the rule-set, this mainly takes two forms: Features and Causal Forces:

- The term ‘Features’ describes a number of mostly clearly identifiable anomalies in the data, such as conflicting long-term and short-term trends, insignificant trends, level discontinuities in the data, outliers etc. (comp. Armstrong & Collopy, 1992, p.17). Some of these features, such as the significance of the trend, can be identified statistically.
- Causal forces refers to the general underlying (economic) conditions of the series, such as a growing economy which might be supporting revenues, largely independent of the situation of the individual company.

It is clear that there are ususally multiple factors influencing any given economic entity. Armstrong and Collopy clarify: *‘We use the term ‘causal forces’ to represent the cumulative directional effects of the factors that influence the trends in a time series.’*

(Armstrong & Collopy, 1993, p. 104) An in-depth description of the causal forces as well as the reasoning behind many of the rules was published in Armstrong & Collopy (1993).

Both factors, Features and Causal Forces, trigger shifts in method weights in Short- and Long model.

Armstrong and Collopy tested causal forces by forecasting with RBF with- and without causal forces rules on 104 annual demographic and economic time series. They found that the causal forces rules improved forecast accuracy most significantly when the forces were clearly specified and when the causal forces were expected to be strong. Furthermore, they found causal forces effective in cases when the trend contradicted the causal forces (as additional weight is given to Random Walk).

With respect to forecasting accuracy in general, Collopy and Armstrong tested RBF on 90 yearly time-series from the M1-Competition (Armstrong & Collopy, 1992 (b)). Collopy and Armstrong believed that the impact of the judgmental re-calibration of models by the application of causal forces would be strongest in the long run and consequently, they found that RBF outperformed equal-weight combination as in the M1-Competition by 13% MdAPE overall and 42% MdAPE for six-years ahead forecasts.

Efficiency

The limited empirical evidence provided by Collopy and Armstrong shows that RBF can be very effective under the right circumstances. At the same time, the reasons why the original version of RBF was not tested in the subsequent M-Competitions also shows the limitations of the model: It is comparatively complex and (time-)costly to apply.

In an AP setting, producing a single RBF forecast as per the original rule set would take even an auditor experienced with the model several hours. Despite its apparent effectiveness, it is therefore clear that this original version of RBF is not suited for audit application.

4.3.10.4. Reduced Rule-Based Forecasting

| Summary | Reduced Rule-Based Forecasting |
|--------------------------|--------------------------------|
| Effectiveness Short-Term | 5 |
| Effectiveness Long-Term | 5 |
| Cost | 5 |
| Efficiency Short-Term | 1 |
| Efficiency Long-Term | 1 |

Table 24: Scoring of Reduced Rule-Based Forecasting

Effectiveness

In its first major revision, Adya, Armstrong, Collopy and Kennedy drastically cut the complexity of RBF by removing Brown exponential smoothing from the underlying models-pool. This led to a reduction of the number of rules to 64. This elimination was possible because the “role” of Brown’s model could largely be fulfilled by Holt exponential smoothing as well. Adya, Armstrong, Collopy and Kennedy (2000, S. 479) found that a removal of Brown’s model led only to a small decrease of forecasting accuracy in the validation sample. In the following, the set of 64 rules will be referred to as ‘Reduced Rule-Based Forecasting’ (“RRBF”).

RRBF was then tested in the M3-Competition. This test was limited by the fact that for M3, no background information regarding the time-series was available. The detection of data “features”, as described above was partly automated as per Adya et.al. (2001), the decision as to the nature of underlying causal forces could, of course, not be automated. Consequently, a larger portion of the rule set did not find application and without the integration of domain knowledge, one of the core principles / strengths of RBF did not come to bear. As discussed in Adya et. al. (2000) this was expected to lead to a loss in overall performance.

Despite these limitations, RBF performed among the top methods by sMAPE, outperforming ARARMA and being outperformed by Dampen as well as by three expert systems (Makridakis & Hibon, 2000, p. 463).

Furthermore, the original RBF was developed for- and tested on yearly time-series (Armstrong & Collopy, 1992 (b), p. 9) leading to optimal performance in long-term series. Comparing RBF with Dampen, (Makridakis & Hibon, 2000, p. 463), it is consequently evident that the largest gap in performance is in the short run.

Finally, as Adya et. al. (2000) as well as Armstrong & Collopy (1992 (b)) pointed out, there is no reason to assume that the distribution of weights to the individual models, were optimal. In Adya et.al. (2000), rules were partly adjusted or corrected using the ‘wind canal’ approach,

meaning the parameters were adjusted by using the relatively better option in small-scale ex-ante sample testing.

It is clear from the M3 competition that RBF is one of the best-performing forecasting methods and that in addition the model contained potential for additional accuracy increase, driven by the causal forces rules, as evidenced by Collopy and Armstrong (1992 (b)).

Efficiency

From a cost perspective, RRBF was an improvement compared to RBF. Still, within the context of AP, even with this simplification, cost would be near-prohibitive.

The difficulties in applying RBF or RRBF in a practical setting were underlined by Adya, Lusk, & Balhadjali (2009). They demonstrated that the application of RRBF by forecasters not intimately familiar with the model was problematic with respect to cognitive load.

Cognitive Load Theory (“CLT”) suggest that the human mind has a limited amount of working memory. In practice, the processing of complex systems or intellectual constructs without loss of relevant information requires building of the proper conceptual foundation first (Sweller, 2003).

In the study by Adya, Lusk, & Balhadjali (2009), the control group, consisting of students with no prior experience with RBF, produced significantly less precise forecasts using RBF than a group of students which had been instructed in RBF using decomposition teaching techniques. This is especial significant because the rule-set, available to both groups, is structured in discrete IF...THEN commands which can be processed step-by-step, i.e. could even be expected to be “cognitive-load friendly”. Furthermore, the necessary statistical software was provided and no time limit was imposed.

The group which had received prior instruction in return did not perform significantly different than forecasts which had been prepared by the authors using the partly automated RRBF system introduced in Adya et. al. (2001).

These results clearly show that tasking forecasters unfamiliar with RBF, to apply the system, would lead to less-than-optimal results. Consequently, the employment of RBF or RRBF in an AP setting would generate significant costs in excess of the pure forecasting time costs. Auditors would require extensive training.

4.3.10.5. CoreRBF

| Summary | Core Rule-Based Forecasting |
|--------------------------|-----------------------------|
| Effectiveness Short-Term | 5 |
| Effectiveness Long-Term | 5 |
| Cost | 4 |
| Efficiency Short-Term | 1,2 |
| Efficiency Long-Term | 1,2 |

Table 25: Scoring of Core Rule-Based Forecasting

Effectiveness

Adya, Lusk, & Balhadjali (2009) demonstrated that for an RBF-variant to be effective and efficient in practice, a “streamlining” of the rule set was clearly desirable, compared to RRBF.

Adya and Lusk (2013) took the next logical step by reducing the rule-set to what they considered the very core. This “coreRBF” consists of the six time-series features as per Adya et. al. (2001) and 12 essential and modified rules from the original rule-set.

In a study using university students as test subjects, Adya and Lusk (2013) benchmarked forecasting performance using coreRBF, against:

- Forecasts made by untrained students using whatever forecasting method they saw fit.
- RRBF used by the same group.
- RBF and RRBF, both performed by the authors of the study.

While all other methods outperformed the untrained students, there was no statistically significant difference between coreRBF, RRBF and the RRBF expert system. RBF applied by the authors slightly outperformed all other methods, which is consistent with the findings of Adya, Armstrong, Collopy, & Kennedy (2000).

Different than in the 2009 study, the main hypothesis (coreRBF vs RRBF) was tested by students who had already received RBF training. As a result, a cognitive “overload” effect caused by RRBF was not observed, as the subjects were “tainted” (or maybe “cured”) in this respect.

All things being equal, and there was no significant difference in accuracy, this then nevertheless gives strong indication that for an untrained forecaster, compared with RRBF, coreRBF would not only be least costly but also more effective.

Efficiency

Compared with the preceding RBF variants, coreRBF cost in an AP setting are less, but not low. Auditors would still need to calculate three different underlying models, one of which requires statistical software, calculate weights and perform a relatively complex blending procedure.

For the purpose of discussion, coreRBF is therefore still ranked among the more costly methods.

4.3.10.6. CoreRBF electronic Decision Support System

| Summary | coreRBF eDSS |
|--------------------------|--------------|
| Effectiveness Short-Term | 5 |
| Effectiveness Long-Term | 5 |
| Cost | 3 |
| Efficiency Short-Term | 1,7 |
| Efficiency Long-Term | 1,7 |

Table 26: Scoring of CoreRBF electronic Decision Support System

Effectiveness

For this thesis, an electronic decision support system (“eDSS”) was programmed employing coreRBF. The system is referred to as an “eDSS” as opposed to a “DSS” in order to distinguish it from the original “manual” RBF, which was also referred to as a DSS in the respective publications.

As the programming code was an exact replication of the coreRBF rule set, forecasts were expected to be at least as accurate as manually prepared coreRBF-, and by extension RRBF-, forecasts.

Automating the majority of forecasting steps furthermore reduced the risk of computational errors / cognitive overload, so a small increase in accuracy might have been possible. As discussed below, the validity of the eDSS was tested on a small sample vs. forecasts performed using manual coreRBF. Any difference in accuracy was non-significant in the sample.

Efficiency

In the eDSS, the number of tasks the user has to perform has been reduced to the minimum required to incorporate the input required from the human component of the forecast, namely the domain knowledge.

These non-automated tasks include:

- Identification of causal forces;
- Manual identification of outliers (non-mandatory, the eDSS also features an automatic routine);
- Identification of irrelevant early data;
- Choice of functional form of the series;
- Feature identification:
 - Presence of level discontinuities and

- Stability of recent trend.
- Identification of period length (yearly, quarterly, monthly...) and
- Desired forecasting horizon.

As the testing in practice showed, forecasting time cost was effectively cut to around 20 minutes for first-time users and less than ten minutes for a repeat user. This assumes that the auditor in question already had a clear understanding of the client / the area in focus and did not need to gather additional data such as background information.

While these results were rather promising, the CoreRBF eDSS was nevertheless “only” rated as a cost = 3 model as the current version required input from SAS Institute JMP v.10 (“JMP”), which, under most circumstances, would pose additional costs to the auditing firm. At Deloitte, application of JMP was covered by a company-wide contract with the SAS Institute.

4.4. Section Summary

There are several candidate-models to be employed in AP forecasts. The discussion of forecasting methods showed that some methods, such as a strong reliance on planning figures provided by auditing clients, are not suited for AP. Furthermore, other methods often employed in practice, such as taking last year's number and modifying it with a fixed percentage or performing unguided judgmental forecasts, are basically valid methods for AP, but do not provide strong results.

Rule-Based Forecasting is a powerful principle, relying on the combination of different models as well as the systematic inclusion of domain knowledge. The original model was prohibitively complex in its application. Subsequent reductions in the rule set have reduced complexity while keeping accuracy nearly constant.

Through near-complete automation of the processes, the coreRBF eDSS developed for this thesis has reached an effectiveness / efficiency level that can be considered one of the strongest candidates for analytical procedures.

5. Determination of Risk Thresholds

5.1. Introduction

In the preceding section, the first important component of effective AP has been discussed, the determination of realistic expected values. The second important question, as has been discussed in section 2.5, is the setting of a corridor of acceptable deviations from this expected value, the “risk threshold”.

As has been pointed out in section 2.5, neither auditing standards nor auditing literature give guidance as to how risk thresholds should be formed besides the very general:

- AP risk thresholds should be developed a priori.
- There is no conceptual difference in the forming of risk thresholds for Preliminary- Substantial- and Concluding Analytical Procedures.
- The determining factor influencing the acceptability of deviations is the materiality level of the audit. For example: *“This consideration is influenced primarily by materiality...”* (IAASB, 2002, S. 1892f) or *“...difference... that is acceptable without investigation. This determination is influenced by materiality...”* (INTOSAI, 2009).

This lack of guidance seems surprising only at first glance. It is rooted in the fact that determining risk thresholds is very much a non-trivial task. As has been pointed out before, AP risk thresholds determine a corridor of acceptable deviation of audited figures around the expected value. In order to methodologically soundly determine this corridor, the auditor would require two pieces of information:

1. The “normal” fluctuation of audited figures around an idealized trend path, given the nature of the audited organization (plus any special circumstances) and
2. The precision of the forecasting estimate of this idealized trend path.

Unfortunately, the second piece of information cannot logically be obtained: If the true precision of the forecast were known, one would not need a forecast (because one would have the true value).

Also, as the M-Competitions demonstrate, there is still much to understand on the general precision of forecasting models, which would be the step before. It is nevertheless evident that a threshold interval does need to be developed for AP, otherwise the procedure would be moot.

Coming to a definite answer to the issue is beyond the scope of this thesis. Instead, in the following, the approach employed by Deloitte Germany is introduced. As this approach has the advantage of being practical and considering the current audit guidance, it has been included in the electronic decision support system which has been developed as part of this thesis.

Nevertheless, this section also aims at highlighting some conceptual gaps in the approach, which should be considered as fields of further research.

5.2. Threshold Determination in Practice (Deloitte)

The Deloitte model considers three factors in addition to audit materiality: Overall engagement risk, reliability of controls and required extent of substantial tests. The model is summarized in the following table which was taken from the Deloitte auditing manual (2015):

| Threshold, not to exceed the LOWER of the following | Risk (not significant) | | | Significant Risk ⁽¹⁾ |
|---|------------------------|--------------------------|-------------------------|---------------------------------|
| | Relying on Controls | | Not relying on Controls | Relying on Controls |
| | Low Extent of Testing | Normal Extent of Testing | | |
| Percentage of disaggregated recorded amount, or | 25% | 20% | 15% | 15% |
| Percentage of Performance Materiality | 90% | 90% | 45% | 45% |

Table 27: Risk Threshold Determination Matrix

The table is to be understood in the following way: A significant deviation from the forecast has been identified, if:

- The absolute value of the deviation is larger than the lower absolute value of two terms:
 - X% of the disaggregated amount of the audit field (e.g. all amounts credited to vendor(s) XYZ) and
 - Y% of the performance materiality of the audit.

The risk threshold is thus biased towards the lower end, as the risk threshold can never be higher than Y% of the audit performance materiality, even if the audit field has a very high turnover.

- The second dimension of the table is the risk classification of the audit field (significant or not significant). The risk classification relies on the judgment of the auditor.
 - If the risk is classified as “significant”:

- AP are only applicable if the control environment of the audit field is classified as “reliable”. In this case, the threshold is set at $X=15$ and $Y=45$, the lowest possible value;
- In case the control environment is deemed “non-reliable”, AP may not be substituted for tests of detail in the substantive phase of the audit. In the preliminary phase of the audit, such an audit field would be identified as focus in any case, making AP unnecessary. The table does therefore not show this outcome;
- If the risk is classified as “not significant”:
 - “Non-reliable” controls lead to the $X=15$, $Y=45$, the lowest possible value;
 - “Reliable” controls are again subdivided by the amount of testing to be substituted for in the substantive phase:
 - Low testing intensity leads to $X=25$ and $Y=90$ and
 - Normal testing intensity leads to $X=20$ and $Y=90$ (i.e. in case normal testing intensity is being substituted for, AP is more sensitive to deviations).

The risk threshold represents the acceptable deviation from the forecast *for one year* (as opposed to one period, which could be weeks, months or quarters).

It should be mentioned that Deloitte recommends- but does not stipulate this approach.

The survey showed that this approach represents the current best-practice of practitioners (see section 3.4). It therefore made sense to implement it into the electronic decision support system as default option (differing thresholds may be entered manually).

It is nevertheless clear that the approach has several conceptual weaknesses, as discussed below.

5.3. Additional Considerations

KPIs / Non-account-based AP

Audit materiality and account volume refer to AP which are performed on financial accounts or aggregated audit sectors. They do not refer to KPIs such as debt ratios or revenue per productive factor. Especially with respect to the detection of fraudulent behavior, financial and non-financial KPIs are of considerable importance but cannot be reflected by the approach above.

Forecasting assumptions

The approach above basically deals with the question of forecasting accuracy by ignoring it.

The underlying assumption of AP is that the forecast produced represents the “real” trend path of the account or KPI, plus a stationary error term of mean zero. If the deviation is larger than a specific threshold, there is only a small statistical chance that the deviation is a product of the function producing the error term. Thus, the deviation is potentially not produced by the function creating the trend path, i.e. a potential misstatement which requires investigation.

If the risk threshold is calculated based on audit materiality and / or account volume alone, several strong assumptions have to hold:

- Audit materiality is clearly near-independent of any particular object of AP investigation. Conceptually, it serves as a maximum risk limitation. The actual decisive factor therefore has to be the disaggregated account volume. If the factual risk threshold is proportionally dependent on account volume, the implicit assumption would need to be that forecasting error is directly proportionate to account volume as well OR;
- In the determination of risk thresholds, forecasting accuracy does not contribute. For this to be true, forecasting accuracy has to be, if not perfect, then at least constant for any given AP. It follows that:
 - Forecasting accuracy in general has to be independent of forecasting data, i.e. extent, reliability, continuity.
 - Forecasting accuracy has to be independent of general uncertainty of the economic situation, e.g. independent of whether the economy follows a stable trend or is within a major crisis.

- Forecasting accuracy has to be independent of the method employed in producing it. All forecasting models are created equal.

It is self-evident that these assumptions usually do not hold. It follows then that if risk thresholds are formed based on account volume only, there is an increased chance of both type 1- and type 2 errors, decreasing effectiveness of AP.

To put it the other way around, basing the risk threshold on the professional judgment of the auditor, given the presence of reasonable levels of domain knowledge, is probably not a bad idea.

5.4. Section Summary

Risk thresholds determination is the second conceptual step after the forming of the AP expected value. It is of equal importance as it determines the interpretation of forecast vs. actual outcome.

Based on auditing standards, guidance published by professional bodies, guidance provided by a Big 4 auditing firm as well as a survey among practitioners, AP risk thresholds are generally based on audit materiality and disaggregated account volume.

This approach ignores KPIs and is furthermore based on a set of assumptions on the forecasting process which do not hold in practice. It follows that a revision of the risk threshold forming process could lead to a general increase in AP effectiveness.

6. Rule-Based Forecasting Electronic Decision Support System

6.1. Introduction

It was argued in section 4.2.3 that any candidate model for analytical procedures should be a good compromise of forecasting effectiveness, according to certain error criteria, as well as cost efficiency. It was furthermore pointed out that strongly automated Rule-Based Forecasting would potentially be a good fit for those requirements.

In section 3, a survey conducted among audit practitioners at Deloitte showed that there is actual room for improvement of methods employed while emphasizing the cost/efficiency requirements, i.e. using any given model needs to be easy and fast.

The eDSS (working title “ClearSight”) was programmed using coreRBF by Adya and Lusk (2013) as discussed in section 4.3.10.6.

In the following section, a detailed non-technical description of the program is provided. Each decision the user needs to take is described and information on the underlying functionalities is given. For the program code, please refer to Appendix II.

6.2. Software and User Interface

The eDSS was developed using Visual Basics for Applications (“VBA”) using Microsoft Excel 2010 (“Excel”) and JMP.

The eDSS is an Excel-based macro program. To ensure robust applicability, minimum system requirements and prerequisites were crucial. This was both a result of the survey conducted at Deloitte, out of which the strong preference of simple solutions crystalized, and of preliminary interviews conducted with Deloitte auditing partners. It was later on confirmed by the feedback of the auditor test group who, as a whole, appreciated that the eDSS did not require additional software installation. Excel was therefore the logical choice of platform, as it was, to the knowledge of the author, installed on every Deloitte computer.

On opening of the Excel file, a button which, when pressed, starts the eDSS. After activating the button, the initial setting appears and a welcoming message introduces the user to the program. In total, the program guides the user through ten working steps which are necessary to correctly calibrate the eDSS for the analytical procedures forecast. Each step features one or more help screens and chart visualizations for further guidance.

The results of- or decisions made in each step are documented directly in the Excel file. For example, the eDSS asks the user whether it should eliminate data points the user feels are outliers. After the user activates a button that indicates that this step has been completed, the data is left unchanged but the corrected data is carried over to the next column, indicating any outliers which have been replaced. As a result, the complete forecasting process with every decision made is readily available for later review and full replicability.

In addition to Excel, the eDSS features an interface to JMP which is invisible to the user. The JMP interface became necessary in order to calibrate the Holt exponential smoothing model included in Rule-Based Forecasting, as will be discussed in more detail below. At the time of the development of the eDSS, Deloitte held a company license for SAS Jmp, allowing for general access to the program on a virtual machine.

6.3. Data Input

6.3.1. Step 1: Data Input and Auto-Completion

With activation of the ClearSight macro, a dialogue asks the user to enter or paste the data which are to be used as basis of the forecast.

The data has to be sorted by time-period (first period on top), data completeness, on the other hand, is not required by the program. In case the data inserted shows one- or more gaps of maximum one period width, the program automatically fills the gap with the mean of the preceding- and succeeding data-point.

This ‘filler’ routine was introduced so that in cases in which a data point for a specific period is not available (e.g. because of missing records, corrupt data etc.), the eDSS can nevertheless process earlier data. ‘Filler’ data points are highlighted by the program in bold letters.

6.4. Causal Forces

6.4.1. Step 2: Identification of Causal Forces

In the next step and before the technical part of the forecast starts, the user is asked on his or her estimate on the underlying causal forces of the time series. As per Collopy and Armstrong (1993, pp. 3), the user can choose between the following options:

- Growing;
- Decaying;
- Supporting;
- Opposing and
- Regressing

Furthermore, in case the user is unsure as to the nature of the causal forces, the option “Unknown” may be chosen.

The user can select a short tutorial as to the meaning of causal forces which also includes chart illustrations of data series which might correspond to different causal forces.

6.5. Data Preparation

6.5.1. Step 3: Definition of a Cut-Off Point

In step 3, the user may choose to eliminate a part of the data. This may be relevant if the user wants to enter all data points for documenting purposes, but feels that an earlier part of the data would not contribute to the accuracy of the forecast.

Reasons for eliminating data might be if factors influencing the time series have drastically changed at some point, suggesting that behavior of the time series might have changed significantly, such as cases are financial- or political crises major shifts in the business model of the organization (standard data preparation procedure).

6.5.2. Step 4: Manual Data Adjustment

The eDSS has two mechanisms for dealing with data outliers: A manual- and an automatic one. In step 4, the user is asked to identify any data points that he or she feels are outliers. The definition given by the program is ‘extreme value caused by a non-repeating event’.

If the user identifies one or more outliers, the program replaces that data-point by the mean of its predecessor and successor and highlights that point in bold font.

6.5.3. Step 5: Functional Form and Automatic Outlier Elimination

In step 5, the user is asked to make a judgment call regarding the nature of the growth of the time series (additive or multiplicative, see Collopy and Armstrong, 1992, p. 19). In view of the complexity of that topic, the user is provided with several examples in the help-screen featured in step 5. In case of doubt, the user is advised to choose the multiplicative form. If the additive form is chosen, the data remains untransformed. In the multiplicative case, the natural logarithm of the data points is used for the further calculations.

After the choice of functional form, and as the final data-preparation (sub-) step, the program performs an outlier identification- and elimination on the data. As per Adya et. al. (2001), a Linear Regression is performed on the data. The 95% Confidence Interval (“CI”) of the regression is calculated. Every data point outside the CI is replaced by the CI-border and highlighted in bold.

6.6. Rule-Based Forecasting

The ‘Rule-Based Forecasting’ section performs two tasks: The computation of the input models for the final forecast and the identification of several characteristics of the data series. This application of the rule-set is performed in part automatically by the program and in part requires user input.

The rules applied by the eDSS are taken from Collopy and Armstrong (1992) in the version used by Adya and Lusk (2013) (rule text is mostly the same, but weights have been adjusted and one of the original forecasting models has been eliminated, see section 4.3.10.5). For ease of reading, the applicable rules are quoted (Collopy and Armstrong (1992) / Adya and Lusk (2013)) in the following.

6.6.1. Step 6: Model Applications and Feature Identification

Before the identification of features, the eDSS computes the input models for the forecast. As discussed in section 4.3.10.4, these models are:

- Linear Regression;
- Holt Exponential Smoothing and
- Random Walk

The determination of Random Walk and Linear Regression are straightforward and are conducted within Excel.

Holt exponential smoothing, on the other hand, involves a non-trivial optimization problem. Originally, the trend and level smoothing factors (α and β , see section 4.3.7.2) as well as starting values for level and trend were to be determined using a grid-based optimization algorithm programmed into the VBA macro. As there is no publicly available standard search algorithm for the Holt model, outcomes of the algorithm were compared with model components as determined by JMP.

The result of this benchmarking process showed significant deviations in model parameter outcomes. As the algorithm implemented in JMP is proprietary and has not been published, there was no possibility of direct comparison. It was then decided that since the Holt model by itself was not subject of this thesis, to implement the solution with the stronger track record, i.e. the JMP results, and recommend its usage to the user.

In the software, following procedure was implemented:

- The software informs the user that in order to receive optimal forecasts, JMP has to be installed on the computer (this was the case in all validation tests).
- In step 6, the user can choose between using JMP or the essentially unverified built-in Holt-optimization algorithm.
 - If JMP is chosen, the software executes a script that searches for optimal parameters by opening an invisible instance of JMP and using the search algorithm of the software (this approach was used for all further testing).
 - If the built-in solution is chosen, the program runs a grid search for optimal alpha- and beta criteria by MSE criterion of fitting the model against the time-series data. The grid search divides the 0 to 1 x 0 to 1 plane of the alpha and beta parameters into 11 x 11 combinations ($1 * 10^{-1}$ intervals) and compares for minimum MSE. Around that combination, a new grid with interval width $1 * 10^{-(x+1)}$ is created and the procedure is repeated. The program uses 15 iterations of this search.
 - In both cases, the initial level is set at $L_0 = (y_1 + y_2 + y_3 + y_4)/4$ and the initial trend at $T_0 = (y_4 - y_1)/4$. The literature suggests numerous different ways of choosing initial level and trend.

In a small test study on 10 time-series, this parameter choice for initial trend and level performed the closest to the one produced by JMP, using α and β calculated by JMP in both cases (in eight out of ten times, this method actually produced a better fit than JMP. JMP does not disclose the way it chooses its initial level and trend settings).

The results of the three models, i.e. the three respective level- and trend estimates at $t=n$, where n is the number of periods in the time series, are documented in the excel sheet.

Following the models computation, the eDSS automatically identifies and logs the *features* of the time series as per rules 6 to 10 from Collopy and Armstrong (1992) / Adya et. al. (2001):

6. *Recent Trend Down*. IF the trend component from Holt's is down, THEN set the direction of the recent trend to down.
7. *Basic Trend Down*. IF the trend component from the regression is down, THEN set the direction of the basic trend to down.
8. *Significant Basic Trend*. IF the t-statistic for the regression's trend is greater than 2, THEN set the significant basic trend to true.

9. *Recent Run not Long*. IF there has been a movement in the same direction for at least the last six observations, THEN set the ‘recent run not long’ to false.

10. *near a Previous Extreme*. IF the last observation is greater than 90% of the highest, or less than 110% of the lowest historical observation for the trend adjusted series, AND it is not immediately preceded by the previous extreme observation, THEN set near a previous extreme to true.

6.6.2. Step 7: Short-Range Model and Long-Range Model

As discussed in section 4.3.10.3, RBF / coreRBF computes two models, the Short-Range Model (“SRM”) and the Long-Range Model (“LRM”), which are blended with shifting weights with increasing time horizon.

In step 7, the eDSS determines the weights that each of the three underlying forecasting models is assigned for SRM- and LRM level and trend. The user is asked to make two judgment calls on the data:

- To state whether the time series contains any level discontinuities, i.e. ‘steps’ in the data. A real-life example could be seen in company revenue after a significant merger.
- To estimate whether the recent trend in the data is stable, i.e. if whatever direction the data is moving in at the moment, is likely to continue unchanged in the future.

Based on these two decisions and the feature the eDSS identified in the step before, the program applies the following rules (the numbering of the rules references on Collopy and Armstrong, 1992):

Short Model Level

Rule 29: Level Discontinuities (Short Model Level). IF there is a level discontinuity, i.e., sort of a step change, in the series, THEN add 0.10 to the weight on the Random Walk and subtract it from the weight of the Holt model.

Rule 32: Changing Recent Trends (Short Model Level). IF there is an unstable recent trend, THEN add 0.45 to the weight on Random Walk model and subtract 0.15 from the Linear Regression weight and subtract 0.30 from the Holt Model weight.

Short Model Trend

Rule 40: Causal Forces Unknown (Short Model Trend). IF the causal forces are unknown, THEN add 0.05 to the weight on the Random Walk and subtract it from that of the Linear Regression trend estimate.

Rule 41: Dissonance (Short Model Trend). IF the direction of the recent trend and the direction of the basic trend are not the same, OR if the trends agree with one another but differ from the causal forces, THEN add 0.15 to the weight on the Random Walk and subtract 0.05 from the Linear Regression and 0.10 from the Holt Model weight.

Rule 42: Inconsistent Trends (Short Model Trend). IF the direction of the basic trend and the direction of the recent trend are not the same, AND the basic trend is not changing, THEN add 0.20 to the weight on the Linear Regression trend and subtract it from Holt Model trend weight.

Long Model Level

Rule 67: Level Discontinuities (Long Model Level). IF there is a level discontinuity, THEN add 0.10 to the weight on the Random Walk and subtract it from the level weight of the Holt model.

Rule 71: Changing Recent Trends (Long Model Level). IF there is an unstable recent trend, THEN add 0.63 to the level weight of the Random Walk and subtract 0.21 from the Linear Regression level weight and subtract 0.42 from the Holt model level weight.

Long Model Trend

Rule 76: Causal Forces Unknown (Long Model Trend). IF the causal forces are unknown, THEN add 0.10 to the weight on the Random Walk model's trend and subtract it from that on the Linear Regression trend estimate.

Rule 77: Dissonance (Long model Trend). IF the direction of the recent trend and the direction of the basic trend are not the same, OR if the trends agree with one another but differ from the casual forces, THEN add 0.15 to the trend weight on the Random Walk and subtract 0.05 from the Linear Regression and 0.10 from the Holt Model weight.

Rule 78: Inconsistent Trends (Long model Trend). IF the direction of the basic trend and the direction of the recent trend are not the same AND the basic trend is not changing, THEN add 0.10 to the weight of the Linear Regression trend and subtract it from the Holt model.

Rule 86: Inconsistent Trends (Long model Trend). IF the directions of the recent and basic trends are not the same, THEN subtract 0.10 from the weight on Linear Regression and add 0.033 to the weight on the Holt model and 0.067 to the weight on the Random Walk model.

Rule 87: Changing Basic Trend (Long model Trend). IF there is a changing basic trend, THEN add 0.24 to the Random Walk trend weight and 0.06 to the Holt model's trend weight and subtract 0.30 from the Linear Regression's trend weight.

6.6.3. Step 8: Period Length, Blending- and Forecasting Horizon

The last step in the RBF section of the program asks the user for the following information:

- Period length of the data (annual, semi-annual, monthly...)
- Desired forecasting horizon (default 1 year)

Collopy and Armstrong make the assumption (1992) that for the long-range trend to become dominant over the short-range trend, it would take on average six years:

96. Blend Period. IF data are annual, THEN the blend period is 6. {It is assumed that a six-year period is long enough for the causal forces to have had a significant impact for most series.}

In order to correctly apply its blending routine of SRM and LRM, the eDSS therefore identifies, how many forecasting periods equal five years for the time series in question. The forecasting horizon on the other hand defines for how many periods ahead the user would like a forecast. As the intended usage of the eDSS is analytical procedures for the yearly audit, the most likely forecasting horizon is one year.

6.7. Risk Threshold

6.7.1. Step 9: Identification of Risk Threshold

Up to this point, the eDSS performs a generic forecasting process which is not particular to audit analytical procedures and if the user chooses the option to not use the risk threshold function, it stays that way.

In order to be of use for audit however, the forecast to be generated needs to be enriched with a threshold interval which indicates the actual deviation from the forecast that prompts additional audit action. As has been discussed in section 5, there is no generally stipulated way of determining risk thresholds. Consequently, the user is given three options:

- Calculate the risk threshold as per Deloitte recommendation;
- Manually set the risk threshold and
- Proceed without a risk threshold.

Criticism on the way risk thresholds are currently being calculated set aside the Deloitte approach does reflect current recommendations and is set as the default option. Choosing this setting leads to a dialogue which guides the user through the decision tree discussed in section 5.2 and prompts the input of audit materiality and account volume.

In the final result, the risk threshold, if one has been defined, is displayed as an interval around the forecast (graphically and in numbers).

6.8. Final Forecast

6.8.1. Step 10: Calculate Final Forecast and Risk Intervals

For the final forecast, the eDSS needs to calculate the SRM, the LRM and the blending factors.

SRM and LRM again each are a blend of the three underlying models, Linear Regression, Holt Exponential Smoothing and Random Walk. The underlying models themselves as well as the combination-weights for level and trend have been calculated in steps six and seven so the eDSS now performs a simple combination.

In the blending process, the eDSS produces a composite forecast for each forecasting period based on the SRM and the LRM. The blending is performed as per Collopy and Armstrong (1992):

97. *Standard Blend.* IF the trends from the short-range and long-range models are in the same direction OR if the causal forces are unknown, THEN

$$L_h = 1 - \left(\left(\frac{100}{B} \right)^x \left(\frac{1 + B - h}{100} \right) \right)$$

where L_h is the percentage of the long-range model used in forecasting horizon h , and B is the blend period, the number of periods over the forecast horizon until the long-range model equals 100%. {This rule blends the two models gradually from 100% short-range model in horizon 1 to 100% long-range model in horizon B . B can exceed the forecast horizon.}

98. *Quick Blend.* IF the short-range model direction conflicts with the long-range model direction AND the causal force direction is the same as the long-range model, THEN set the share of the long-range model to

$$L_h = \frac{\sum_{x=1}^h (x)}{\sum_{y=1}^B (y)}$$

where h is the horizon and B is the blend period. {When the causal forces agree with the long-range model direction and disagree with the short-range model, this moves the forecast more quickly to the long-range model.}

99. *Slow Blend*. IF the short-range model direction conflicts with the long-range model direction AND the causal force direction is the same as the short-range model, THEN set the share of the long-range model to

$$L_h = \sum_{x=1}^h (1 + B - x) / \sum_{y=1}^B (y)$$

where h is the horizon and B is the blend period. {This is the converse of rule 98.}

The result of the blending process is the final forecast.

Around the forecast, the eDSS then builds the risk threshold interval.

As discussed in section 5.3:

- The risk threshold should be seen as the acceptable deviation from the forecast for *one year*.
- Within that year, the acceptable deviation increases by proportion (e.g. for monthly forecasting periods, in January, the actual data may deviate by $1/12 * \text{risk threshold}$ from the forecast, in February by $2/12$ etc.).

The risk threshold interval can then be calculated as:

$$RTI = f_t \mp \rho t * RT, \rho \in (1, 1/2, 1/4, 1/12, 1/52)$$

where RTI is the risk threshold interval, f_t is the forecast at forecasting period t , ρ is the period factor (for annual-, semi-annual-, quarter-, month- or week periods) and RT is the risk threshold.

The results are presented as five columns of numbers, representing the forecast, the lower- and upper boundaries of the RTI (area of increased risk) and the lower- and upper boundaries

of 2x the RTI (area of strongly increased risk). The eDSS can also display the results in form of an Excel graph.

6.9. Section Summary

ClearSight is an electronic decision support system programmed in Excel and based on coreRBF. It is constructed to meet the particular demands of auditors for the conduction of audit analytical procedures.

Forecasting for AP requires the user to follow the program through ten calibrating steps which include data preparation and incorporate the auditor's domain knowledge into the forecasting process.

The program was designed to pose minimum possible requirements both to available soft- and hardware and to the auditor's prior knowledge of forecasting. Producing a single forecast typically uses less than ten minutes of user time, thus in theory meeting the efficiency gain postulated in section 4.3.10.6.

7. Validation and Testing

7.1. Introduction

Up to this point in the thesis, the requirements for effective and efficient AP have been developed and different forecasting methodologies have been discussed and those most suited for AP have been identified. Following this discussion, it has been shown that the methods employed by practitioners do not necessarily meet the requirements.

Finally, an eDSS for the proposed method for AP, coreRBF, has been developed and programmed in Excel: ClearSight.

As it was the agenda of this thesis to develop a solution of direct applicability, the eDSS needed to be tested for practice. This test had two stages: In the first, the functionality of the eDSS itself, i.e. whether the eDSS was able to produce forecasts according to coreRBF, needed to be validated.

In the second stage, the efficiency proposition behind a partly automated coreRBF eDSS needed to be proven. For this, the eDSS was provided to audit practitioners and tested on seven separate year-end audits.

7.2. Functional Validation

This stage of testing aimed at validating that the eDSS functioned identical to a manual forecast produced under ideal conditions, i.e. validating that no error in the programming of the eDSS biased the results.

Twelve time-series chosen at random from the M-Competition were sent to an expert on forecasting research with the instructions to apply coreRBF using SAS JMP. No domain information was given and all series were annual.

Forecasts using the eDSS were produced on the basis of the same twelve time-series by the author. The results produced during the two testing runs were virtually identical. Small differences were tracked to different decisions made by the two testing persons as well as rounding errors.

Conceptually, this proved that no major error in the coding of the eDSS was present. A more robust testing of the code was conducted in the “real-life testing” phase following.

7.3. Real-Life Testing

7.3.1. Testing parameters

ClearSight was distributed to seven audit practitioners working on seven separate year-end audit engagements. Furthermore, the practitioners were provided with access to the necessary SAS JMP software package.

The practitioners were not given training for the use of ClearSight as one of the testing parameters was the ease-of-use for users not familiar with the software. In addition to ClearSight, the testing group was provided with a simple Excel model performing moving average de-seasonalization of data (and the reverse operation for forecasts produced based on this data). The testing group was instructed to use this spreadsheet if and only if they felt the data to be used in the forecast had strong seasonal cycles.

The practitioners were asked to perform AP using ClearSight on at least ten data sets, if possible, within the context of the audit, alongside their regular method of AP expectation forming. In total, 64 forecasts were produced by the practitioners.

The user experiences were recorded in a questionnaire (see the following section) and any errors occurring during the process were to be reported back directly.

The client data including the ClearSight forecasts were provided to the author afterwards. All data had been anonymized in order to protect client confidentiality (see Appendix III).

7.3.2. Testing Questionnaire

The questionnaire was provided in German. In the following, the English translation is given:

Thank you for volunteering for the beta test of the forecasting decision support system ClearSight for audit analytical procedures. We would like you to provide us with some feedback on your experience of working with ClearSight by rating the following statements on a scale from 1 (strongly disagree) to 5 (strongly agree). All data is confidential and anonymous at the individual level; the results will only be reported in the aggregate.

Statement 1: Working with ClearSight is easy and intuitive.

| | | | | |
|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 |
| | | | | |

Statement 2: In my opinion, ClearSight produced effective forecasts for analytical procedures.

| | | | | |
|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 |
| | | | | |

Statement 3: In my opinion, ClearSight produced more effective forecasts than the usual way I form expectations for analytical procedures.

| | | | | |
|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 |
| | | | | |

Statement 4: Producing a forecast with ClearSight took less than ten minutes time, given I had the data at hand and a good understanding of the subject matter of the forecast.

| | | | | |
|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 |
| | | | | |

Statement 5: Producing a forecast with ClearSight took less time than the usual way I form expectations for analytical procedures.

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

| | | | | |
|----------|----------|----------|----------|----------|
| <i>1</i> | <i>2</i> | <i>3</i> | <i>4</i> | <i>5</i> |
| | | | | |

Thank you for time. Please feel free to provide us with any additional feedback or recommendations in the box below.

7.3.3. Testing Feedback

The seven testing auditors provided the following feedback:

Table 28: eDSS Practical Testing Feedback

| Rating | 1 | 2 | 3 | 4 | 5 | Mean Rating |
|--------------------------------------|---|---|---|---|---|-------------|
| Statement 1 (Usability) | | 1 | | 3 | 3 | 4,1 |
| Statement 2 (Effectiveness) | | | | 2 | 5 | 4,7 |
| Statement 3 (Relative Effectiveness) | | | 2 | 3 | 2 | 4,0 |
| Statement 4 (Time Cost) | | 1 | | 2 | 4 | 4,3 |
| Statement 5 (Relative Time Cost) | 1 | 2 | 2 | 3 | | 2,9 |

Furthermore, following feedback was given in text format:

- The de-seasonalization should be included in order to streamline the process / increase efficiency (four times mentioned).
- Usability could be designed in a more robust way by locking the Excel fields / transferring the program into a format working with user forms, such as MS Access.
- The eDSS should be re-designed to function without JMP, as a limited number of parallel licenses might lead to capacity issues if the eDSS were to be used on a broader scale.
- One participant had initial difficulties in understanding the user interface of the eDSS but stated that he eventually overcame these using the help-functions of the program.

7.4. Section Summary

The validation showed virtually no discrepancy between forecasts produced manually by an expert forecaster and by the eDSS. This in combination with the feedback obtained by the life-testing evidenced that the eDSS was functional with respect to producing valid coreRBF forecasts.

The life-testing of ClearSight furthermore evidenced several important points which were prerequisites for the eDSS being an AP solution with a realistic practical outlook:

- Usability was rated with an average of 4.1 of 5. The test group consisted of audit professionals, who were unfamiliar with the software. From this, it can be concluded that the eDSS performed on a stable level and that it is easy enough to handle as to not create excessive training / introductory costs.
- The perception of effectiveness and relative effectiveness (questions two and three) are not objectively relevant in judging the actual effectiveness of the eDSS (this was done in the validation phase).

The perception of effectiveness is crucial, however, in evaluating whether the eDSS could gain the necessary acceptance to be employed in practice on a relevant scale. Both the ratings of absolute and relative perception of effectiveness on average scored 4.0 or higher.

- The questions on time costs touched on the potentially most important issue for the testing, as the main value proposition of the eDSS with respect to “normal” coreRBF was a strong increase in efficiency.

All but one of the participants agreed with the statement that they needed less than ten minutes on average to produce AP forecasts.

On the other hand, the average statement concerning relative time costs compared to the methods previously used, was neutral (2.9). This is not surprising as the general survey showed that most auditors preferred methods associated with low time costs.

8. Conclusion

This study aimed to explore two different but connected theses:

- I. **Even though AP are crucial to year-end auditing, the way they are performed by audit professionals is generally not very effective.**

and

- II. **The effectiveness of AP could be increased using an electronic Decision Support System (“eDSS”) based on coreRule-Based Forecasting.**

As has been discussed above, the selection of forecasting models suited for the AP context is crucial to answering the first question. Candidates for AP forecasting should fulfill both effectiveness and efficiency criteria. Weighting both criteria, as well as short- and long term forecasting horizon, equally, of the discussed models, the following top three emerge (taking only the CoreRBF eDSS into account from the RBF family):

| Method | Effectiveness Short-Term | Effectiveness Long-Term | Cost | Efficiency Short-Term | Efficiency Long-Term | Equal Weights Score |
|--|--------------------------|-------------------------|------|-----------------------|----------------------|---------------------|
| CoreRBF electronic Decision Support System | 5 | 5 | 3 | 1,67 | 1,67 | 3,33 |
| Equal Weight Combination | 4-5 | 4-5 | 4 | 1,00-1,25 | 1,00-1,25 | 2,00-3,13 |
| Trend-Dampening Exponential Smoothing | 5 | 4 | 3 | 1,67 | 1,33 | 3,00 |

Table 29: Conclusion - Top Three AP Forecasting Methods

In contrast to the models suggested here, a survey of practitioners showed preferences for models which are empirically less suited for the task:

| Method | Number of participants selected | % of participants selected | Effectiveness short-term | Effectiveness long-term | Cost | Efficiency short-term | Efficiency long-term | Equally weighted Score |
|--------------------------------------|---------------------------------|----------------------------|--------------------------|-------------------------|-------------|-----------------------|----------------------|------------------------|
| Last year plus X% | 132 | 78,11% | 3 | 3 | 2 | 1,50 | 1,50 | 2,25 |
| Fixed Ratios | 105 | 62,13% | 2 | 1 | 1 | 2,00 | 1,00 | 1,50 |
| Client budgetary Figures | 67 | 39,64% | 1 | 1 | 1 | 1,00 | 1,00 | 1,00 |
| Unstructured judgmental Forecast | 25 | 14,79% | 2 | 1 | 1 | 2,00 | 1,00 | 1,50 |
| Regression Projection | 19 | 11,24% | 2 | 3 | 1 | 2,00 | 3,00 | 2,50 |
| STAR | 17 | 10,06% | 2 | 3 | 4 | 0,50 | 0,75 | 1,56 |
| Exponential Smoothing (Holt-Winters) | 8 | 4,73% | 4 | 3 | 3 | 1,33 | 1,00 | 2,33 |
| Random Walk | 1 | 0,59% | 2 | 1 | 1 | 2,00 | 1,00 | 1,50 |
| Total / Mean | 374 | - | 2,22 | 1,94 | 1,53 | 1,56 | 1,27 | 1,75 |

Table 30: Conclusion - Forecasting Methods employed by Practitioners

This contradiction clearly illuminates that audit processes could benefit from a paradigm change with respect to AP.

As for the second thesis, the CoreRBF eDSS developed for this study has been shown to not only be a theoretically valid method for AP forecasting. The tests undertaken (conceptual validation against manual application of the model, as well as audit field tests by practitioners) show that the eDSS has the chance to deliver practical value.

It is not, however, the claim of this study to have found an optimal solution to RBF forecasting or the application of forecasting methods to AP. As is discussed below, both topics offer diverse avenues for research and optimization. The contribution of the coreRBF eDSS is an improvement to widespread processes but also, and maybe even more important, a platform which allows for further development and improvement. For this reason, the source code, which in itself doubtlessly offers a lot of potential for optimization, is included in the Appendix to this work.

Any modifications to the RBF methodology will be much easier to implement and test on a systematic scale, using an eDSS platform as easy-to-modify basis.

Consequently, in the following, possible areas for such work are pointed out.

9. Suggested Research

Systematically speaking, three sectors of research and optimization are apparent, based on this thesis:

- Technical (non-theoretical) improvements to the eDSS;
- Research on AP methodology (Risk Threshold) and
- Research on RBF.

9.1. eDSS

- Broader testing

The feedback provided by practitioners was generally positive. Nevertheless, in order to have a more robust basis for practical discussions, such as the implementation of ClearSight or a system like it to regular business processes, more extensive practical test should be conducted, potentially directly by an auditing firm.

- Inclusion of Holt parameter optimization

One of the prerequisites for the usage of the eDSS was a working instance of SAS JMP on the system, something which cannot be expected to generally be the case. Practitioners looking into implementing the eDSS might want to consider finding an alternative solution for the calculation of Holt Exponential Smoothing parameters. Possible ways could be the implementation of an interface to an open-source statistical software package or the development of a respective optimization algorithm.

- Inclusion of de-seasonalization feature

In the testing described above, de-seasonalization was performed using a small separate Excel program. As this poses an additional work step, including this feature on the eDSS level would be a logical add-on.

9.2. Risk Threshold Determination

As has been pointed out in section 5, at this point there seems to be a conceptual gap in the way deviations from AP forecasts are being discussed: While controls as well as desired level of assurance are taken into account, deviations / errors based on (lack of) forecasting accuracy seem to be a blind spot to professional auditing organizations. Here, a conceptual framework should be established.

In practice, forecasting accuracy is not readily available ex-ante. As a starting point for discussion, the author would suggest a simple multiplicative model which modifies overall risk threshold by a factor based on estimated (in-) accuracy of the forecast. This inaccuracy or uncertainty could be estimated based on judgment / domain knowledge of the practitioner but possibly assisted by a fixed set of criteria (guided judgment).

9.3. Rule-Based Forecasting

In their original 1992 paper on RBF, Collopy and Armstrong pointed out that they understood their model as well as their rule set as a starting point that was in no way set in stone.

As subsequent publications, as discussed above, have shown, there has been steady development in RBF processes. The author would like to suggest several additional optimization steps. All following suggestions have in common that they should be tested against or optimized on a significant body of actual time-series, such as the 10.001 data sets Spyros Makridakis has gathered for the, not yet published, M4-Competition.

The processes should then be conducted using powerful optimization algorithms, such as variants of the artificial neural network (“ANN”) model. ANN has not been discussed as a pure forecasting tool, as the set-up and training prerequisites are generally too extensive for the models to be of practical use for a non-mass-data forecast situation such as most AP. For the general calibration or optimization of RBF parameters on the other hand, the advent of machine learning opens up several exciting possibilities:

- **Model composition variations**
RBF originally included four single forecasting models: Naïve 1, Brown Exponential Smoothing, Holt Exponential Smoothing and Linear Regression. Brown’s model has been excluded in the RBF variant introduced by Adya, Armstrong, Collopy, & Kennedy (2000) and it is by no means certain that the current composition of the models has to remain constant.
One way forward could be the replacement of a single model with a “champion” of that class of characteristics of models, such as the replacement of the Holt model with Dampen exponential smoothing, while keeping the rules constant and testing the relative performance of both variations.
- **A different and more systematic approach would be to question the basic set-up of RBF.** For this, a competition of a broad range of different model combinations and against a large data set and utilizing ANN would have to be held. The single models would obviously need to be completely automatized in order to keep total effort within acceptable limits. For the implementation of the overall winners of the competition, a new rule set would need to be developed or the existing one adapted.
- **Automatized feature identification**
Beyond what has already been automatized at this point, efficiency could be gained by reducing manual steps in the forecasting process to a minimum. Features such as

discontinuities could be automatically identified by training an ANN algorithm based on a broad dataset. For this, the data set would need to be reviewed manually for the characteristics. The results would be used as training input for the ANN and the resulting criteria would be implemented in the eDSS.

- **Optimized rules**

It has yet to be proven that the changes in model weights triggered by the rule set are at an optimal level. Collopy and Armstrong developed the original weights assigned by each Rule-Based on their personal forecasting expertise.

Based on a largely automatized forecasting software and using a large data set for which causal forces have been assigned / identified on a per case basis, a general weight setting optimization, probably using an ANN instance, could be undertaken.

9.4. Questioning the RBF Approach

Monica Adya and Edward Lusk in “Development and validation of a rule-based time series complexity scoring technique to support design of adaptive forecasting DSS” (2016) found evidence that in general, forecasting accuracy is adversely affected by time-series complexity. This was based on a complexity scoring technique (“CST”) using 12 rules on 14 time-series features. CST was validated on 336 structured judgmental forecasts by 14 participants, where the corresponding time-series were classified as either simple or complex.

This finding potentially has strong implications for the RBF approach: The logical question which results from this finding is whether the accuracy of all forecasting methods is affected equally, which could be tested using an automated forecasting approach on a sufficiently large set of time-series, pre-scored for complexity.

If the loss accuracy turns out to be model-sensitive, and there is no reason to assume otherwise, the RBF optimization process would logically need to be expanded by another dimension: Complexity-sensitive coreRBF (“ccoreRBF”) would need to integrate CST into the rule set and add a set of model-weighting parameters based on CST score.

Consequently, the optimization research sketched under 9.3, including model selection, would need to be extended by CST weight optimization.

In any case, this potential paradigm shift highlights one apparent truth: There is no guarantee that all dimensions relevant to optimal forecasting accuracy have yet been identified.

For forecasting researchers as well as practitioners, this has certain implications: Each such dimension increases the underlying rule- / model- optimization problem by one magnitude (which emphasizes the need for as near to fully-automated forecasting as possible DSSs, in order to enable large-scale testing / optimization runs).

At the same time, added complexity, especially if not fully automated, poses the paradoxical danger of reducing forecasting accuracy by increasing the risk of user errors as well as for falling into the “trap of over-fitting”.

While this does not immediately lead to a solution the author can think of, it seems at least clear that this field of research, also in the digitalized future, will continue to offer numerous unanswered questions and opportunities for fruitful investigation.

Appendix

Appendix I Detailed Survey Results

| # | Question 1 | Question 2 | | | | | | | Question 3 | | Question 4: | | Current Position |
|----|---|------------|--------------|-------------------|-----------------------|-----------------------|-------------------------|--------|---------------------------------|--------------|---|---|------------------|
| | 1 = strongly agree; 5 = strongly disagree; 0 = no opinion | STAR | Fixed Ratios | Last year plus X% | Regression Projection | Exponential Smoothing | Client's Budget Figures | Other* | As per Deloitte auditing policy | Other Method | Number of years of experience in Auditing | Certified / Chartered Public Accountant | |
| 1 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 9 | 1 | Senior Manager |
| 2 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 4 | 0 | Manager |
| 3 | 2 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 12 | 1 | Senior Manager |
| 4 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 4 | 0 | Senior |
| 5 | 2 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 5 | 0 | Senior |
| 6 | 4 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 5 | 0 | Manager |
| 7 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 20 | 1 | Director |
| 8 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 6 | 0 | Professional |
| 9 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 4 | 0 | Senior |
| 10 | 2 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 11 | 1 | Manager |
| 11 | 2 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 16 | 1 | Director |
| 12 | 2 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 4 | 0 | Senior |
| 13 | 1 | 0 | 0 | 1 | 1 | 1 | 0 | 1 | 0 | 0 | - | 0 | - |
| 14 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 10 | 1 | Senior Manager |
| 15 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | Professional |
| 16 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 13 | 1 | Senior Manager |
| 17 | 2 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 7 | 0 | Manager |
| 18 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | Professional |
| 19 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | - | 0 | - |
| 20 | 2 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | Professional |
| 21 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 2 | 0 | Senior |
| 22 | 2 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 30 | 1 | Partner |
| 23 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 25 | 1 | Director |
| 24 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 11 | 0 | Manager |
| 25 | 5 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 10 | 1 | Senior Manager |
| 26 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 20 | 1 | Director |
| 27 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 4 | 0 | Manager |
| 28 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 5 | 0 | Senior |
| 29 | 2 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 2 | 0 | Professional |
| 30 | 2 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 5 | 0 | Senior |
| 31 | 2 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 12 | 0 | Manager |
| 32 | 2 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | Professional |
| 33 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 4 | 0 | Senior |
| 34 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 5 | 0 | Senior |
| 35 | 2 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 16 | 1 | Senior Manager |
| 36 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 4 | 0 | Senior |
| 37 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 2 | 0 | Professional |
| 38 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | - | 0 | - |
| 39 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | - | 0 | - |
| 40 | 2 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | Professional |
| 41 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 2 | 0 | Professional |
| 42 | 2 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 6 | 1 | Manager |
| 43 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 15 | 1 | Partner |
| 44 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | - | 0 | - |
| 45 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | - | 0 | Senior |
| 46 | 2 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 15 | 1 | Senior Manager |
| 47 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 7 | 1 | Manager |
| 48 | 2 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 1 | 0 | 4 | 0 | Senior |
| 49 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | - | 0 | - |
| 50 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 20 | 1 | Partner |
| 51 | 2 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 0 | Professional |
| 52 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | Professional |
| 53 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | - |
| 54 | 4 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 4 | 0 | Senior |
| 55 | 4 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 4 | 0 | Senior |
| 56 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | Professional |
| 57 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 5 | 0 | Manager |
| 58 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 10 | 0 | Manager |
| 59 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | - | 0 | - |
| 60 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | - | 0 | - |
| 61 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 10 | 0 | Senior Manager |
| 62 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | Professional |
| 63 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | - | 0 | - |
| 64 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 8 | 1 | Senior Manager |
| 65 | 2 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 6 | 1 | Senior Manager |
| 66 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 5 | 0 | Manager |
| 67 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 11 | 1 | Senior Manager |
| 68 | 2 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 4 | 0 | Senior |
| 69 | 2 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 15 | 0 | Senior Manager |
| 70 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | - | 0 | - |
| 71 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 | Manager |
| 72 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 4 | 0 | Senior |
| 73 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 15 | 1 | Partner |
| 74 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 18 | 1 | Senior Manager |
| 75 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 2 | 0 | Senior |
| 76 | 3 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | Professional |
| 77 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 25 | 0 | Senior Manager |
| 78 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 7 | 1 | Manager |
| 79 | 2 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 2 | 0 | Professional |
| 80 | 2 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 4 | 0 | Senior |
| 81 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 | 13 | 0 | Manager |
| 82 | 5 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 3 | 0 | Professional |
| 83 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 5 | 0 | Senior |
| 84 | 2 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 8 | 1 | Senior Manager |
| 85 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 4 | 0 | Senior |
| 86 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 8 | 0 | Manager |
| 87 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 10 | 1 | Senior Manager |
| 88 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | - | 0 | - |
| 89 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 7 | 1 | Senior Manager |
| 90 | 2 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 4 | 0 | Senior |
| 91 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 3 | 0 | Manager |
| 92 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 10 | 1 | Senior Manager |
| 93 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 7 | 1 | Manager |

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

| # | Question 1 | Question 2 | | | | | | | Question 3 | | Question 4: | | Current Position | |
|-----|---|------------|--------------|-------------------|-----------------------|-----------------------|-------------------------|--------|---------------------------------|--------------|---|---|------------------|----------------|
| | 1 = strongly agree; 5 = strongly disagree; 0 = no opinion | STAR | Fixed Ratios | Last year plus X% | Regression Projection | Exponential Smoothing | Client's Budget Figures | Other* | As per Deloitte auditing policy | Other Method | Number of years of experience in Auditing | Certified / Chartered Public Accountant | | |
| 94 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 2 | 0 | Professional | |
| 95 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | Professional | |
| 96 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 7 | 1 | Manager | |
| 97 | 2 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 5 | 0 | Manager | |
| 98 | 1 | 1 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 2 | 0 | Senior | |
| 99 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 2 | 0 | Senior | |
| 100 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 13 | 1 | Director | |
| 101 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 7 | 1 | Manager | |
| 102 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 20 | 1 | Partner | |
| 103 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | - | 0 | - | |
| 104 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | - | 0 | - | |
| 105 | 4 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | Judgmental Forecast | 1 | 0 | 3 | 0 | Professional |
| 106 | 2 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 2 | 0 | Professional | |
| 107 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | - | 0 | - | |
| 108 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | - | 0 | - | |
| 109 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 5 | 0 | Manager | |
| 110 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | - | 0 | - | |
| 111 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | - | 0 | - | |
| 112 | 2 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 22 | 0 | Manager | |
| 113 | 2 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | - | 0 | Manager | |
| 114 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 1 | Judgmental Forecast | 1 | 0 | 6 | 0 | Senior |
| 115 | 3 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 23 | 1 | Director | |
| 116 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 20 | 1 | Partner | |
| 117 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | - | 0 | - | |
| 118 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | Random Walk | 0 | 0 | - | 0 | - |
| 119 | 2 | 0 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | Professional | |
| 120 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 6 | 0 | Senior | |
| 121 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 35 | 1 | Partner | |
| 122 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 16 | 1 | Director | |
| 123 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 3 | 0 | Senior | |
| 124 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 8 | 0 | Manager | |
| 125 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | Judgmental Forecast | 1 | 0 | 6 | 1 | Manager |
| 126 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 13 | 1 | Senior Manager | |
| 127 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | Professional | |
| 128 | 2 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | Professional | |
| 129 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 13 | 1 | Senior Manager | |
| 130 | 3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | - | 0 | - | |
| 131 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 20 | 1 | Partner | |
| 132 | 2 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | Judgmental Forecast | 1 | 0 | 19 | 1 | Partner |
| 133 | 1 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 15 | 1 | Senior Manager | |
| 134 | 2 | 0 | 1 | 1 | 1 | 0 | 0 | 0 | 1 | 0 | 2 | 0 | Professional | |
| 135 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | Professional | |
| 136 | 2 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 14 | 1 | Director | |
| 137 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 25 | 0 | Manager | |
| 138 | 2 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | Professional | |
| 139 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | Judgmental Forecast | 1 | 0 | 1 | 0 | Professional |
| 140 | 2 | 1 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | Professional | |
| 141 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | Professional | |
| 142 | 3 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | Professional | |
| 143 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | - | 0 | - | |
| 144 | 2 | 1 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 2 | 0 | Senior | |
| 145 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 14 | 1 | Senior Manager | |
| 146 | 2 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 12 | 1 | Senior Manager | |
| 147 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 10 | 1 | Manager | |
| 148 | 2 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 4 | 0 | Senior | |
| 149 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 8 | 1 | Senior Manager | |
| 150 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 11 | 1 | Senior Manager | |
| 151 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 3 | 0 | Senior | |
| 152 | 2 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 17 | 1 | Director | |
| 153 | 2 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 5 | 0 | Manager | |
| 154 | 2 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 12 | 0 | Senior Manager | |
| 155 | 2 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 3 | 0 | Senior | |
| 156 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | Judgmental Forecast | 1 | 0 | - | 0 | - |
| 157 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | Judgmental Forecast | 1 | 0 | 18 | 1 | Director |
| 158 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 0 | 20 | 1 | Director | |
| 159 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 5 | 0 | Senior | |
| 160 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 1 | Judgmental Forecast | 1 | 0 | 9 | 1 | Senior Manager |
| 161 | 2 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 14 | 1 | Director | |
| 162 | 3 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | - | 0 | - | |
| 163 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | Professional | |
| 164 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 10 | 1 | Senior Manager | |
| 165 | 1 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 15 | 1 | Senior Manager | |
| 166 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 1 | Judgmental Forecast | 0 | 0 | - | 0 | - |
| 167 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 7 | 0 | Manager | |
| 168 | 1 | 0 | 1 | 1 | 0 | 0 | 1 | 0 | 1 | 0 | 10 | 0 | Senior | |
| 169 | 1 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 | 0 | 6 | 0 | Manager | |

| Mean (excluding "0") | Sum / Percentage | | | | | | | | Sum / Percentage | | Mean (excluding "-") | Sum |
|----------------------|------------------|--------|--------|--------|-------|--------|--------|--|------------------|-------|----------------------|-----|
| 1,49 | 17 | 105 | 132 | 19 | 8 | 67 | 26 | | 143 | 7 | 8,13 | 55 |
| | 10,06% | 62,13% | 78,11% | 11,24% | 4,73% | 39,64% | 15,38% | | 84,62% | 4,14% | | |

* Information Summarized

Table 31: Detailed AP Survey Results

Appendix II ClearSight Programming Code

Appendix II a Introduction

The following is an exact copy of the programming code employed in ClearSight (V1.0) for review purposes. This appendix is structured equivalently to the coding. This means that each headline signals a new module or form in the programming code.

The programming code is the intellectual property of the author. Please contact Manuel Bern under manuel.bern@hotmail.de before sharing, publishing or distributing the programming code.

Appendix II b Modules

“Modules” in VBA contain the majority of executable code. Sub-programs are identified by either the command “sub” or “function”. For convenience sake, the beginnings of these sub-programs have been highlighted in the programming text in bold.

The main forecasting process of the eDSS starts with the sub “Sub DummyStart”, which activates the correct fields in the Excel sheet and initializes the further program steps.

The following code does not include calculations performed by SAS JMP.

Module: Steps

Option Explicit

```
' Colors
' Bordercolor
Dim ThClr1 As Long
' Labelcolor 1
Dim ThClr2 As Long
' Labelcolor 2
Dim ThClr3 As Long

' Var Step 1: Autocompletion
Dim RowStep1 As Long
Dim StepRange As Range
Dim lastrowstep1 As Long

' Var Step2: Causal Forces
Public CancStep As Boolean
Public StateCausalForce As String

' Var Step 3: CutOff
Public CutOffPoint As Variant

' Var Step 4: ManDatAdjier Elimination
Public ManDatAdjIdent As Variant
Public AddManDatAdj As Boolean
Dim ManDatAdjTxt As String
Dim LoopCount As Long

' Var Step 5: Functional Form
Public FFormM As Boolean
Dim FFormTxt As String

Dim T005 As Double
Dim Alpha As Double
Dim Beta As Double
Dim RgDef1 As String
Dim RgDef2 As String
Dim RgDef3 As String
Dim RgDef4 As String
Dim term1 As Double
Dim term2 As Double
Dim term3 As Double
Dim term4 As Double
Dim term5 As Double
```

```
Dim Residuals() As Double
Dim LinReg95CI As Double

' Var Step 6: Forecasting Models
Public HoldOpti As String

Dim CurLvl As Double

Dim HoltArray(1 To 20, 1 To 20) As Double
Dim LevArrayStart As Double
Dim TreArrayStart As Double
Dim AlphaElements As Integer
Dim BetaElements As Integer
Dim TrendLoop As Integer
Dim ALoopCount As Integer
Dim BLoopCount As Integer
Dim MSEMIn As Double
Dim MinIndexA As Integer
Dim MinIndexB As Integer
Dim GridLoop As Integer
Dim lastrow As Integer
Dim Datapoints As Integer
Dim Counter As Integer
Dim DatArray() As Double
Dim LevArray() As Double
Dim TreArray() As Double
Dim ForeArray() As Double
Dim HoltAlpha As Double
Dim HoltBeta As Double
Dim HoltAlphaState As Integer
Dim HoltBetaState As Integer

Dim JMPApp As New JMP.Application
Dim DataInput As JMP.DataTable
Dim ParaTable As JMP.DataTable

Dim DataCol As Object
Dim TimeSeries As Object
Dim SmoothDummy As Long
Dim Hand As Long

Dim SM_LR_Lvl As Double
Dim SM_LR_TrD As Double
Dim SM_HM_Lvl As Double
Dim SM_HM_TrD As Double
Dim SM_RW_Lvl As Double
Dim SM_RW_TrD As Double

Dim LM_LR_Lvl As Double
Dim LM_LR_TrD As Double
Dim LM_HM_Lvl As Double
Dim LM_HM_TrD As Double
Dim LM_RW_Lvl As Double
Dim LM_RW_TrD As Double

Dim TStatBeta As Double

Dim RRArray() As Double
Dim RRCount As Integer
```

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

Dim FillRR As Integer
Dim RecentRun As String

Dim PrevExtreme As String
Dim RgDefPE As String
Dim LstDtPE As Double
Dim SecLstDtPE As Double

' Var Step 7: Short Range Level and Trend, Long Range Level and Trend
Public LevelDiscont As Boolean
Public RecTreUnst As Boolean

Dim Step7String As String
Dim NearExtreme30 As Boolean

Dim CausFor40 As String

Dim Diss41 As Boolean

Dim dataodd33 As Boolean
Dim data33_1 As Single
Dim data33_2 As Single
Dim RgDef33_1_1 As String
Dim RgDef33_1_2 As String
Dim RgDef33_1_3 As String
Dim RgDef33_1_4 As String
Dim RgDef33_2_1 As String
Dim RgDef33_2_2 As String
Dim RgDef33_2_3 As String
Dim RgDef33_2_4 As String
Dim Trend33_1 As Double
Dim Trend33_2 As Double
Dim Trendchange33 As Boolean
Dim InconTrend42 As Boolean

Dim Incoher43 As Boolean

Dim Unusual48Str As String
Dim Unusual48 As Boolean

Dim InconTrd86 As Boolean

' Var Step 8: Period, Blending, Dampening, Forecasting Horizon
Public Period As String
Public ForeCastHorizon As Integer

Dim PeriodPA As Integer
Dim ForecastPer As Integer
Dim BlendPeriod As Integer
Dim BlendMethod As String

' Var Step9: Risk Threshold calculation
Public Method As String
Public MisstRisk As String
Public ControlEffect As String
Public Testing As String
Public PerfMat As Variant
Public RisThrProf As Variant

Dim Step9String As String

Dim PerRecAm As Double
Dim PerPerMat As Double
Dim RecAmount As Double
Dim Threshold As Variant
Dim TrePerfMat As Double
Dim TreRecAmount As Double

Dim RowsForecast As Integer

' Var Step10: Forecast

Dim LinRegLevel As Double
Dim LinRegTrend As Double
Dim HoltLevel As Double
Dim HoltTrend As Double
Dim RandomWalkLevel As Double
Dim RandomWalkTrend As Double

Dim LongModelLevel As Double
Dim LongModelTrend As Double
Dim ShortModelLevel As Double
Dim ShortModelTrend As Double
Dim LastDif As Double
Dim State3435 As String
Dim TrAdjSerStdDev As Double

Dim FCount As Integer
Dim SRMForecasts() As Double
Dim LRMForecasts() As Double
Dim BlendFactors() As Double
Dim SumBlendPeriods As Double
Dim SumForecast98() As Double
Dim SumForecast99() As Double
Dim FinalForecasts() As Double
Dim LowBounds() As Double
Dim UppBounds() As Double
Dim LowBoundsHR() As Double
Dim UppBoundsHR() As Double
Dim FFormStr As String
Dim FFormMul As Boolean

Sub LoadConHlp1()
 ConHlp1.Show
End Sub

Sub LoadConHlp2()
 ConHlp2.Show
End Sub

Sub LoadConHlp3()
 ConHlp3.Show
End Sub

Sub LoadConHlp3_2()
 ConHlp3_2.Show
End Sub

Sub LoadConHlp3_3()
 ConHlp3_3.Show
End Sub

```
Sub LoadConHlp4()  
  ConHlp4.Show  
End Sub
```

```
Sub LoadConHlp5()  
  ConHlp5.Show  
End Sub
```

```
Sub LoadConHlp6()  
  ConHlp6.Show  
End Sub
```

```
Sub LoadConHlp6_2()  
  ConHlp6_2.Show  
End Sub
```

```
Sub LoadConHlp6_3()  
  ConHlp6_3.Show  
End Sub
```

```
Sub LoadConHlp7()  
  ConHlp7.Show  
End Sub
```

```
Sub LoadConHlp8()  
  ConHlp8.Show  
End Sub
```

```
Sub LoadConHlp9()  
  ConHlp9.Show  
End Sub
```

```
Sub LoadConHlp10()  
  ConHlp10.Show  
End Sub
```

```
Sub LoadConHlp10_2()  
  ConHlp10_2.Show  
End Sub
```

```
Sub LoadConHlp11()  
  ConHlp11.Show  
End Sub
```

Sub DummyStart()

```
Columns("A:A").Delete Shift:=xlToLeft
```

```
StartProgram
```

```
End Sub
```

Sub StartProgram()

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

' Format Makro

' Sets formatting in preparation of STEP 1

' Disables screen updates and instant calculation
' in order to improve performance and eliminate
' annoying 'screen flickering'

With Application

 .ScreenUpdating = False

 .Calculation = xlCalculationManual

 .EnableEvents = False

End With

' Defines / names columns by their function
' for information on each step, refer to there

' Legend: Data Label

Names.Add Name:="Legend", RefersToR1C1:="=R1C1"

Names.Add Name:="CLLegend", RefersToR1C1:="=C1"

' Data: Original Data

Names.Add Name:="Data", RefersToR1C1:="=R1C2"

Names.Add Name:="CLData", RefersToR1C1:="=C2"

' Step1: Autocompletion

Names.Add Name:="Autoc", RefersToR1C1:="=R1C3"

Names.Add Name:="CLAutoc", RefersToR1C1:="=C3"

' Step2: Causal Forces

Names.Add Name:="CausFor", RefersToR1C1:="=R1C4"

Names.Add Name:="CLCausFor", RefersToR1C1:="=C4"

' Step3: Cut-Off Point

Names.Add Name:="CutOff", RefersToR1C1:="=R1C5"

Names.Add Name:="CLCutOff", RefersToR1C1:="=C5"

' Step4: ManDatAdjier Elimination

Names.Add Name:="ManDatAdj", RefersToR1C1:="=R1C6"

Names.Add Name:="CLManDatAdj", RefersToR1C1:="=C6"

' Step5: Functional Form

Names.Add Name:="FForm", RefersToR1C1:="=R1C7"

Names.Add Name:="CLFForm", RefersToR1C1:="=C7"

Names.Add Name:="OutEl", RefersToR1C1:="=R1C8"

Names.Add Name:="CLOutEl", RefersToR1C1:="=C8"

' Step6: Forecasting Models

Names.Add Name:="ForeMod_1", RefersToR1C1:="=R1C9"

Names.Add Name:="CLForeMod_1", RefersToR1C1:="=C9"

Names.Add Name:="ForeMod_2", RefersToR1C1:="=R1C10"

Names.Add Name:="CLForeMod_2", RefersToR1C1:="=C10"

Names.Add Name:="ForeMod_3", RefersToR1C1:="=R1C11"

Names.Add Name:="CLForeMod_3", RefersToR1C1:="=C11"

Names.Add Name:="ForeMod_4", RefersToR1C1:="=R1C12"

Names.Add Name:="CLForeMod_4", RefersToR1C1:="=C12"

' Step7: SRM Level, SRM Trend, LRM Level, LRM Trend

Names.Add Name:="SRMLEv", RefersToR1C1:="=R1C13"

Names.Add Name:="CLSRMLEv", RefersToR1C1:="=C13"

Names.Add Name:="LRMLEv", RefersToR1C1:="=R1C14"

Names.Add Name:="CLLRMLEv", RefersToR1C1:="=C14"

' Step8: Period length of data, blending, trend dampening and length of
' forecasting horizon

Names.Add Name:="Blend", RefersToR1C1:="=R1C15"

Names.Add Name:="CLBlend", RefersToR1C1:="=C15"

' Step9: Risk Level Threshold

Names.Add Name:="RskThr", RefersToR1C1:="=R1C16"

Names.Add Name:="CLRskThr", RefersToR1C1:="=C16"

Step 10: Forecasting

```
Names.Add Name:="Forecast_1", RefersToR1C1:="=R1C17"  
Names.Add Name:="CLForecast_1", RefersToR1C1:="=C17"  
Names.Add Name:="Forecast_2", RefersToR1C1:="=R1C18"  
Names.Add Name:="CLForecast_2", RefersToR1C1:="=C18"  
Names.Add Name:="Forecast_3", RefersToR1C1:="=R1C19"  
Names.Add Name:="CLForecast_3", RefersToR1C1:="=C19"  
Names.Add Name:="Forecast_4", RefersToR1C1:="=R1C20"  
Names.Add Name:="CLForecast_4", RefersToR1C1:="=C20"  
Names.Add Name:="Forecast_5", RefersToR1C1:="=R1C21"  
Names.Add Name:="CLForecast_5", RefersToR1C1:="=C21"  
Names.Add Name:="Forecast_6", RefersToR1C1:="=R1C22"  
Names.Add Name:="CLForecast_6", RefersToR1C1:="=C22"  
Names.Add Name:="Forecast_7", RefersToR1C1:="=R1C23"  
Names.Add Name:="CLForecast_7", RefersToR1C1:="=C23"  
Names.Add Name:="Forecast_8", RefersToR1C1:="=R1C24"  
Names.Add Name:="CLForecast_8", RefersToR1C1:="=C24"  
Names.Add Name:="Forecast_9", RefersToR1C1:="=R1C25"  
Names.Add Name:="CLForecast_9", RefersToR1C1:="=C25"
```

Formatting of table

Further formatting is performed at beginning of
each program step as necessary

```
ActiveWindow.SplitColumn = 1  
ActiveWindow.FreezePanels = True
```

```
Range("CLLegend").NumberFormat = "0"  
Range("CLLegend").HorizontalAlignment = xlRight  
Range("CLData").NumberFormat = "0.00"  
Range("CLData").HorizontalAlignment = xlRight
```

```
Rows("1:6").Font.Bold = True  
Rows("1:1").RowHeight = 30  
Rows("2:4").RowHeight = 25.5  
Rows("1:1").VerticalAlignment = xlBottom  
Rows("2:6").VerticalAlignment = xlTop  
Rows("5:5").RowHeight = 76.5  
Rows("6:6").RowHeight = 30  
Rows("5:6").WrapText = True
```

```
Range("CLLegend").ColumnWidth = 17  
Range("CLLegend").Font.Bold = True  
Range("CLData", "CLAutoc").ColumnWidth = 18.71  
Range("CLCausFor", "CLForecast_8").ColumnWidth = 17
```

```
Range("Data") = "Data Entry"  
Range("Legend").Offset(1, 0) = "Execute Procedure"  
Range("Legend").Offset(2, 0) = "Contextual Help"  
Range("Legend").Offset(3, 0) = "Create Chart"  
Range("Legend").Offset(4, 0) = "Decision Variable"  
Range("Legend").Offset(5, 0) = "Data Point Period"  
Range("Legend").Offset(6, 0).Value = 1  
Range("Data").Offset(5, 0) = "Data"
```

Formatting of borders

Modify these in order to change border colors

These colors are defined on a program step basis,

i.e. to modify all borders, use search and replace

ThClr1 = 5
ThClr2 = 1
ThClr3 = 4

' Before any data is entered, format is performed for
' 20 rows. This is for beauty reasons only. Format is adjusted
' once data is entered.

```
With Range(Range("Legend"), Range("Autoc").Offset(20, 0)).Borders(xlEdgeLeft)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlMedium
```

End With

```
With Range(Range("Legend"), Range("Autoc").Offset(20, 0)).Borders(xlEdgeTop)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlMedium
```

End With

```
With Range(Range("Legend"), Range("Autoc").Offset(20, 0)).Borders(xlEdgeBottom)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlThin
```

End With

```
With Range(Range("Legend"), Range("Autoc").Offset(20, 0)).Borders(xlEdgeRight)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlMedium
```

End With

```
With Range(Range("Legend"), Range("Autoc").Offset(20, 0)).Borders(xlInsideVertical)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlThin
```

End With

```
With Range(Range("Legend"), Range("Autoc").Offset(20, 0)).Borders(xlInsideHorizontal)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlThin
```

End With

```
With Range("Data").Interior
    .Pattern = xlSolid
    .PatternColorIndex = xlAutomatic
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .PatternTintAndShade = 0
```

End With

```
With Range("Data").Font
    .ThemeColor = ThClr2
    .TintAndShade = 0
```

End With

```
With Range("Data").Interior
    .Pattern = xlPatternLinearGradient
    .Gradient.Degree = 45
```

```
.Gradient.ColorStops.Clear  
End With  
With Range("Data").Interior.Gradient.ColorStops.Add(0)  
    .ThemeColor = 1  
    .TintAndShade = 0  
End With  
With Range("Data").Interior.Gradient.ColorStops.Add(1)  
    .ThemeColor = ThClr3  
    .TintAndShade = 0  
End With
```

- ' Inserts Buttons and Userforms in preparation of Step 1: Autocompletion
- ' Creates Step 1: Autocompletion Button and assigns Step 1: Autocompletion Sub

```
ActiveSheet.Shapes.AddShape(msoShapeRectangle, Range("Autoc").Offset(1, 0).Left, Range("Autoc").Offset(1, 0).Top,  
53.25, 18).Select
```

```
Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37  
Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "Step 1"  
With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 6).Font  
    .NameComplexScript = "+mn-cs"  
    .NameFarEast = "+mn-ea"  
    .Fill.Visible = msoTrue  
    .Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1  
    .Fill.ForeColor.TintAndShade = 0  
    .Fill.Transparency = 0  
    .Fill.Solid  
    .Size = 12  
    .Name = "+mn-lt"  
End With
```

- ```
Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter
Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle
Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue
```
- ' Here, the Step 1: Autocompletion sub is assigned
- ```
Selection.OnAction = "Steps.Autoc"
```

```
Selection.ShapeRange.IncrementLeft 24.75  
Selection.ShapeRange.IncrementTop 3
```

- ' Creates Step 1: Autocompletion Contextual Help Button

```
ActiveSheet.Shapes.AddShape(msoShapeOval, Range("Autoc").Offset(2, 0).Left, Range("Autoc").Offset(2, 0).Top, 20.25,  
20.25).Select
```

```
Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37  
Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "?"  
With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 1).Font  
    .NameComplexScript = "+mn-cs"  
    .NameFarEast = "+mn-ea"  
    .Fill.Visible = msoTrue  
    .Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1  
    .Fill.ForeColor.TintAndShade = 0  
    .Fill.Transparency = 0  
    .Fill.Solid  
    .Size = 12  
    .Name = "+mn-lt"  
End With
```

```
Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter  
Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle  
Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue
```

```
Selection.OnAction = "LoadConHlp2"
```

```
Selection.ShapeRange.IncrementLeft 41.25
```

```
Selection.ShapeRange.IncrementTop 3
```

```
' Creates Step 1: Autocompletion Chart Button and Connects Step 1: Autocompletion CreateChart0 Sub
```

```
ActiveSheet.Shapes.AddShape(msoShapeRectangle, Range("Data").Offset(3, 0).Left, Range("Data").Offset(3, 0).Top,  
53.25, 18).Select
```

```
Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37
```

```
Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "Chart"
```

```
With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 5).Font
```

```
.NameComplexScript = "+mn-cs"
```

```
.NameFarEast = "+mn-ea"
```

```
.Fill.Visible = msoTrue
```

```
.Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1
```

```
.Fill.ForeColor.TintAndShade = 0
```

```
.Fill.Transparency = 0
```

```
.Fill.Solid
```

```
.Size = 12
```

```
.Name = "+mn-lt"
```

```
End With
```

```
Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter
```

```
Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle
```

```
Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue
```

```
Selection.OnAction = "CreateChart0"
```

```
Selection.ShapeRange.IncrementLeft 24.75
```

```
Selection.ShapeRange.IncrementTop 3
```

```
Range("Data").Offset(6, 0).Select
```

```
' Re-activation of screen update and instant calculation
```

```
With Application
```

```
.ScreenUpdating = True
```

```
.Calculation = xlCalculationAutomatic
```

```
.EnableEvents = True
```

```
End With
```

```
' Loads introductory message
```

```
LoadConHlp1
```

```
End Sub
```

Sub CreateChart0()

```
' Disables screen updates and instant calculation
```

```
' in order to improve performance and eliminate
```

```
' annoying 'screen flickering'
```

```
With Application
```

```
.ScreenUpdating = False
```

```
.Calculation = xlCalculationManual
```

```
.EnableEvents = False
```

End With

' Creates chart on original data

```
ActiveSheet.Shapes.AddChart(xlLineMarkers, 100, 100, 300, 200).Select
ActiveChart.SetSourceData Source:=Range(Range("Data").Offset(5, 0), Range("Data").Offset(5, 0).End(xlDown))
ActiveChart.Legend.Position = xlBottom
With ActiveChart.SeriesCollection(1).Format.Line
    .Weight = 1
    .Visible = msoTrue
    .ForeColor.ObjectThemeColor = msoThemeColorDark1
End With
```

' Transfers chart to second worksheet

```
ActiveChart.Parent.Cut
Sheets(2).Activate
Range("b2").Select
ActiveSheet.Paste
```

With Application

```
.ScreenUpdating = True
.Calculation = xlCalculationAutomatic
.EnableEvents = True
```

End With

End Sub

Sub Autoc()

' Step 1: Autocomplete

' Sub checks whether data has been entered and fills any gaps
' with mean of predecessor and successor

With Application

```
.ScreenUpdating = False
.Calculation = xlCalculationManual
.EnableEvents = False
```

End With

' Selects the column of the original data

```
Set StepRange = Range("CLData")
```

' Determines the last row number of the last filled cell in

' the data column using the custom 'Last' function

```
lastrowstep1 = Last(1, StepRange)
```

' Labels the autocomplete column

```
Range("Autoc").Offset(5, 0) = "Autocompleted Data"
```

' Re-Labels the row count in column 1

' and thereby defines bottom end of data (for formatting)

```
For RowStep1 = 7 To lastrowstep1 - 1
```

```
    Range("Data").Offset(RowStep1, -1) = "(R[-1]C[0]+1)"
```

```
Next RowStep1
```

' Autocompletes data to column autoc

```
For RowStep1 = 6 To lastrowstep1 - 1
```

```
    Select Case Range("Data").Offset(RowStep1, 0)
```


**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

```
Case Is <> ""
Range("Data").Offset(RowStep1, 1) = Range("b1").Offset(RowStep1, 0)
Case Is = ""
Range("Data").Offset(RowStep1, 1) = "(R[-1]C[-1]+R[1]C[-1])/2"
Range("Data").Offset(RowStep1, 1).Font.Bold = True
End Select
Next RowStep1
```

```
' Re-does format on columns Legend:Autoc (changed number
' of rows
```

```
ThClr1 = 5
ThClr2 = 1
ThClr3 = 4
```

```
Range("Legend").Offset(6, 0).Select
Range(Selection, Selection.End(xlDown)).Select
Range(Selection, Selection.Offset(0, 2)).Select
With Selection.Borders(xlEdgeLeft)
.LineStyle = xlContinuous
.ThemeColor = ThClr1
.TintAndShade = 0
.Weight = xlMedium
```

```
End With
```

```
With Selection.Borders(xlEdgeTop)
.LineStyle = xlContinuous
.ThemeColor = ThClr1
.TintAndShade = 0
.Weight = xlThin
```

```
End With
```

```
With Selection.Borders(xlEdgeBottom)
.LineStyle = xlContinuous
.ThemeColor = ThClr1
.TintAndShade = 0
.Weight = xlMedium
```

```
End With
```

```
With Selection.Borders(xlEdgeRight)
.LineStyle = xlContinuous
.ThemeColor = ThClr1
.TintAndShade = 0
.Weight = xlMedium
```

```
End With
```

```
With Selection.Borders(xlInsideVertical)
.LineStyle = xlContinuous
.ThemeColor = ThClr1
.TintAndShade = 0
.Weight = xlThin
```

```
End With
```

```
With Selection.Borders(xlInsideHorizontal)
.LineStyle = xlContinuous
.ThemeColor = ThClr1
.TintAndShade = 0
.Weight = xlThin
```

```
End With
```

```
' Formats column CausFor
```

```
Range("CausFor") = "Causal Forces"
Range("CausFor").HorizontalAlignment = xlRight
```

```
With Range("CausFor").Borders(xlEdgeLeft)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlMedium
End With
With Range("CausFor").Borders(xlEdgeTop)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlMedium
End With
With Range("CausFor").Borders(xlEdgeBottom)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlThin
End With
With Range("CausFor").Borders(xlEdgeRight)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlMedium
End With

With Range("CausFor").Interior
    .Pattern = xlSolid
    .PatternColorIndex = xlAutomatic
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .PatternTintAndShade = 0
End With
With Range("CausFor").Font
    .ThemeColor = ThClr2
    .TintAndShade = 0
End With
With Range("CausFor").Interior
    .Pattern = xlPatternLinearGradient
    .Gradient.Degree = 45
    .Gradient.ColorStops.Clear
End With
With Range("CausFor").Interior.Gradient.ColorStops.Add(0)
    .ThemeColor = 1
    .TintAndShade = 0
End With
With Range("CausFor").Interior.Gradient.ColorStops.Add(1)
    .ThemeColor = ThClr3
    .TintAndShade = 0
End With

Range("CausFor").Offset(1, 0).Select
Range(Selection, Selection.Offset(lastrowstep1 - 2, 0)).Select
With Selection.Borders(xlEdgeLeft)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlMedium
End With
With Selection.Borders(xlEdgeTop)
    .LineStyle = xlContinuous
```

```
.ThemeColor = ThClr1
.TintAndShade = 0
.Weight = xlThin
End With
With Selection.Borders(xlEdgeBottom)
.LineStyle = xlContinuous
.ThemeColor = ThClr1
.TintAndShade = 0
.Weight = xlMedium
End With
With Selection.Borders(xlEdgeRight)
.LineStyle = xlContinuous
.ThemeColor = ThClr1
.TintAndShade = 0
.Weight = xlMedium
End With
With Selection.Borders(xlInsideVertical)
.LineStyle = xlContinuous
.ThemeColor = ThClr1
.TintAndShade = 0
.Weight = xlThin
End With
With Selection.Borders(xlInsideHorizontal)
.LineStyle = xlContinuous
.ThemeColor = ThClr1
.TintAndShade = 0
.Weight = xlThin
End With
```

' Creates Step2: Causal Forces Button and Connects Step2: Causal Forces Sub

```
ActiveSheet.Shapes.AddShape(msoShapeRectangle, Range("CausFor").Offset(1, 0).Left, Range("CausFor").Offset(1,
0).Top, 53.25, 18).Select
Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37
Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "Step 2"
With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 6).Font
.NameComplexScript = "+mn-cs"
.NameFarEast = "+mn-ea"
.Fill.Visible = msoTrue
.Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1
.Fill.ForeColor.TintAndShade = 0
.Fill.Transparency = 0
.Fill.Solid
.Size = 12
.Name = "+mn-lt"
End With
Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter
Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle
Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue
Selection.OnAction = "Steps.CausFor"

Selection.ShapeRange.IncrementLeft 21
Selection.ShapeRange.IncrementTop 3
```

' Creates Step2: Causal Forces Contextual Help

```
ActiveSheet.Shapes.AddShape(msoShapeOval, Range("CausFor").Offset(2, 0).Left, Range("CausFor").Offset(2, 0).Top,
20.25, 20.25).Select
Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37
Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "?"
```

```
With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 1).Font
.NameComplexScript = "+mn-cs"
.NameFarEast = "+mn-ea"
.Fill.Visible = msoTrue
.Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1
.Fill.ForeColor.TintAndShade = 0
.Fill.Transparency = 0
.Fill.Solid
.Size = 12
.Name = "+mn-lt"
End With
```

```
Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter
Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle
Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue
Selection.OnAction = "LoadConHlp3"
```

```
Selection.ShapeRange.IncrementLeft 38.5
Selection.ShapeRange.IncrementTop 3
```

' Creates create chart on autocompleted data button and assigns CreateChart1 Sub

```
ActiveSheet.Shapes.AddShape(msoShapeRectangle, Range("Autoc").Offset(3, 0).Left, Range("Autoc").Offset(3, 0).Top,
53.25, 18).Select
```

```
Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37
Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "Chart"
With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 5).Font
.NameComplexScript = "+mn-cs"
.NameFarEast = "+mn-ea"
.Fill.Visible = msoTrue
.Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1
.Fill.ForeColor.TintAndShade = 0
.Fill.Transparency = 0
.Fill.Solid
.Size = 12
.Name = "+mn-lt"
End With
```

```
Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter
Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle
Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue
Selection.OnAction = "CreateChart1"
```

```
Selection.ShapeRange.IncrementLeft 21
Selection.ShapeRange.IncrementTop 3
```

```
Range("Legend").Select
```

' Re-activation of screen update and instant calculation

With Application

```
.ScreenUpdating = True
.Calculation = xlCalculationAutomatic
.EnableEvents = True
```

End With

End Sub

Sub CreateChart1()

' Creates chart on autocompleted data

With Application

```
.ScreenUpdating = False  
.Calculation = xlCalculationManual  
.EnableEvents = False
```

End With

```
ActiveSheet.Shapes.AddChart(xlLineMarkers, 100, 100, 300, 200).Select  
ActiveChart.SetSourceData Source:=Range(Range("Autoc").Offset(5, 0), Range("Autoc").Offset(5, 0).End(xlDown))  
ActiveChart.Legend.Position = xlBottom  
With ActiveChart.SeriesCollection(1).Format.Line  
.Weight = 1  
.Visible = msoTrue  
.ForeColor.ObjectThemeColor = msoThemeColorDark1  
End With
```

```
ActiveChart.Parent.Cut  
Sheets(2).Activate  
Range("b16").Select  
ActiveSheet.Paste
```

' Re-activation of screen update and instant calculation

With Application

```
.ScreenUpdating = True  
.Calculation = xlCalculationAutomatic  
.EnableEvents = True
```

End With

End Sub

Sub CausFor()

' Step 2: Causal Forces

' Sub lets user chose nature of causal forces

' dominating the time series (refer to Armstrong and Collopy, 1992)

' Disables screen updates and instant calculation
' in order to improve performance and eliminate
' annoying 'screen flickering'

With Application

```
.ScreenUpdating = False  
.Calculation = xlCalculationManual  
.EnableEvents = False
```

End With

' Determines last data row for formatting

```
Set StepRange = Range("CLAutoc")  
lastrowstep1 = Last(1, StepRange)
```

```
CancStep = True
```

```
' Lets user enter causal forces

Step2_UsrFrm1.Show

' Sub is exited if selection of causal force has been cancelled
If CancStep = True _
    Then Exit Sub
' Labels the causal forces column
Range("CausFor").Offset(5, 0) = "Causal Forces"

' State of causal forces is displayed
Range("CausFor").Offset(6, 0) = StateCausalForce
Range("CausFor").Offset(6, 0).Font.Bold = True

' Formats columns CutOff:FForm for Data Preparation

ThClr1 = 5
ThClr2 = 1
ThClr3 = 4

Range("CutOff") = "Data Preparation"
Range("CutOff").HorizontalAlignment = xlRight

With Range("CutOff", "OutEl").Borders(xlEdgeLeft)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlMedium
End With
With Range("CutOff", "OutEl").Borders(xlEdgeTop)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlMedium
End With
With Range("CutOff", "OutEl").Borders(xlEdgeBottom)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlThin
End With
With Range("CutOff", "OutEl").Borders(xlEdgeRight)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlMedium
End With

With Range("CutOff").Interior
    .Pattern = xlSolid
    .PatternColorIndex = xlAutomatic
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .PatternTintAndShade = 0
End With
With Range("CutOff").Font
    .ThemeColor = ThClr2
    .TintAndShade = 0
End With
```

```
With Range("CutOff").Interior
    .Pattern = xlPatternLinearGradient
    .Gradient.Degree = 45
    .Gradient.ColorStops.Clear
End With
With Range("CutOff").Interior.Gradient.ColorStops.Add(0)
    .ThemeColor = 1
    .TintAndShade = 0
End With
With Range("CutOff").Interior.Gradient.ColorStops.Add(1)
    .ThemeColor = ThClr3
    .TintAndShade = 0
End With
```

```
Range("CutOff").Offset(1, 0).Select
Range(Selection, Selection.Offset(lastrowstep1 - 2, 3)).Select
With Selection.Borders(xlEdgeLeft)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlMedium
End With
With Selection.Borders(xlEdgeTop)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlThin
End With
With Selection.Borders(xlEdgeBottom)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlMedium
End With
With Selection.Borders(xlEdgeRight)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlMedium
End With
With Selection.Borders(xlInsideVertical)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlThin
End With
With Selection.Borders(xlInsideHorizontal)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlThin
End With
```

' Creates Step3: Cut-Off Point Button and Connects Step3: Cut-Off Point Sub

```
ActiveSheet.Shapes.AddShape(msoShapeRectangle, Range("CutOff").Offset(1, 0).Left, Range("CutOff").Offset(1, 0).Top,
53.25, 18).Select
    Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37
    Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "Step 3"
    With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 6).Font
```

```
.NameComplexScript = "+mn-cs"  
.NameFarEast = "+mn-ea"  
.Fill.Visible = msoTrue  
.Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1  
.Fill.ForeColor.TintAndShade = 0  
.Fill.Transparency = 0  
.Fill.Solid  
.Size = 12  
.Name = "+mn-lt"  
End With  
Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter  
Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle  
Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue  
Selection.OnAction = "Steps.CutOff"
```

```
Selection.ShapeRange.IncrementLeft 21  
Selection.ShapeRange.IncrementTop 3
```

' Creates Step3: Cut-Off Point Contextual Help

```
ActiveSheet.Shapes.AddShape(msoShapeOval, Range("CutOff").Offset(2, 0).Left, Range("CutOff").Offset(2, 0).Top,  
20.25, 20.25).Select
```

```
Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37  
Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "?"  
With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 1).Font  
.NameComplexScript = "+mn-cs"  
.NameFarEast = "+mn-ea"  
.Fill.Visible = msoTrue  
.Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1  
.Fill.ForeColor.TintAndShade = 0  
.Fill.Transparency = 0  
.Fill.Solid  
.Size = 12  
.Name = "+mn-lt"  
End With  
Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter  
Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle  
Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue  
Selection.OnAction = "LoadConHlp4"
```

```
Selection.ShapeRange.IncrementLeft 38.5  
Selection.ShapeRange.IncrementTop 3
```

```
Range("CutOff").Select
```

' Re-activation of screen update and instant calculation

With Application

```
.ScreenUpdating = True  
.Calculation = xlCalculationAutomatic  
.EnableEvents = True
```

End With

End Sub

Sub CutOff()

' Step3: Cut-Off Point / elimination of irrelevant data
' Sub allows user to define a cut-off point. All data up to- and
' including this point are ignored

' Disables screen updates and instant calculation
' in order to improve performance and eliminate
' annoying 'screen flickering'

With Application

```
.ScreenUpdating = False  
.Calculation = xlCalculationManual  
.EnableEvents = False
```

End With

' Labels the cut-off column
Range("CutOff").Offset(5, 0) = "Trimmed Data"

CancStep = True

' Determines last data row for formatting
Set StepRange = Range("CLAutoc")
lastrowstep1 = Last(1, StepRange)

' Performs cutting-off of the data

Step3_UsrFrm1.Show

' Sub is exited if selection of cut-off point has been cancelled
If CancStep = True _
Then Exit Sub

' If cut-off point has been left blank or set to zero (for whatever reasons)
' data is transferred from previous step. If cut-off point >0, those first date
' points are taken out

```
Select Case CutOffPoint  
Case Is = ""  
For RowStep1 = 6 To lastrowstep1 - 1  
Range("CutOff").Offset(RowStep1, 0) = Range("Autoc").Offset(RowStep1, 0)  
Next RowStep1  
Range("CutOff").Offset(4, 0) = "Cut-off Point: N/A"  
Case Is = 0  
For RowStep1 = 6 To lastrowstep1 - 1  
Range("CutOff").Offset(RowStep1, 0) = Range("Autoc").Offset(RowStep1, 0)  
Next RowStep1  
Range("CutOff").Offset(4, 0) = "Cut-off Point: N/A"  
Case Is > 0  
For RowStep1 = 6 To lastrowstep1 - 1  
Range("CutOff").Offset(RowStep1, 0) = Range("Autoc").Offset(RowStep1 + CutOffPoint, 0)  
Next RowStep1  
Range("CutOff").Offset(4, 0) = "Cut-off Point: " & CutOffPoint  
End Select
```

' Creates Step4: Manual Data Adjustment Button and Connects Step4: Manual Data Adjustment Sub

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

```
ActiveSheet.Shapes.AddShape(msoShapeRectangle, Range("ManDatAdj").Offset(1, 0).Left,
Range("ManDatAdj").Offset(1, 0).Top, 53.25, 18).Select
    Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37
    Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "Step 4"
    With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 6).Font
        .NameComplexScript = "+mn-cs"
        .NameFarEast = "+mn-ea"
        .Fill.Visible = msoTrue
        .Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1
        .Fill.ForeColor.TintAndShade = 0
        .Fill.Transparency = 0
        .Fill.Solid
        .Size = 12
        .Name = "+mn-lt"
    End With
    Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter
    Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle
    Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue
    Selection.OnAction = "Steps.ManDatAdj"

    Selection.ShapeRange.IncrementLeft 21
    Selection.ShapeRange.IncrementTop 3
```

' Creates Step4: Manual Data Adjustment Contextual Help

```
ActiveSheet.Shapes.AddShape(msoShapeOval, Range("ManDatAdj").Offset(2, 0).Left, Range("ManDatAdj").Offset(2,
0).Top, 20.25, 20.25).Select
    Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37
    Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "?"
    With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 1).Font
        .NameComplexScript = "+mn-cs"
        .NameFarEast = "+mn-ea"
        .Fill.Visible = msoTrue
        .Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1
        .Fill.ForeColor.TintAndShade = 0
        .Fill.Transparency = 0
        .Fill.Solid
        .Size = 12
        .Name = "+mn-lt"
    End With
    Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter
    Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle
    Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue
    Selection.OnAction = "LoadConHlp5"

    Selection.ShapeRange.IncrementLeft 38.5
    Selection.ShapeRange.IncrementTop 3
```

' Creates create chart on trimmed data button and assigns CreateChart2 Sub

```
ActiveSheet.Shapes.AddShape(msoShapeRectangle, Range("CutOff").Offset(3, 0).Left, Range("CutOff").Offset(3, 0).Top,
53.25, 18).Select
    Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37
    Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "Chart"
    With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 5).Font
        .NameComplexScript = "+mn-cs"
        .NameFarEast = "+mn-ea"
        .Fill.Visible = msoTrue
        .Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1
```

```
.Fill.ForeColor.TintAndShade = 0
.Fill.Transparency = 0
.Fill.Solid
.Size = 12
.Name = "+mn-lt"
End With
Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter
Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle
Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue
Selection.OnAction = "CreateChart2"

Selection.ShapeRange.IncrementLeft 21
Selection.ShapeRange.IncrementTop 3
```

```
Range("CutOff").Select
```

```
With Application
```

```
.ScreenUpdating = True
.Calculation = xlCalculationAutomatic
.EnableEvents = True
```

```
End With
```

```
End Sub
```

Sub CreateChart2()

```
' Creates chart on trimmed data
```

```
' Disables screen updates and instant calculation
' in order to improve performance and eliminate
' annoying 'screen flickering'
```

```
With Application
```

```
.ScreenUpdating = False
.Calculation = xlCalculationManual
.EnableEvents = False
```

```
End With
```

```
ActiveSheet.Shapes.AddChart(xlLineMarkers, 100, 100, 300, 200).Select
ActiveChart.SetSourceData Source:=Range(Range("CutOff").Offset(5, 0), Range("CutOff").Offset(5, 0).End(xlDown))
ActiveChart.Legend.Position = xlBottom
With ActiveChart.SeriesCollection(1).Format.Line
.Weight = 1
.Visible = msoTrue
.ForeColor.ObjectThemeColor = msoThemeColorDark1
End With
```

```
ActiveChart.Parent.Cut
Sheets(2).Activate
Range("b31").Select
ActiveSheet.Paste
```

```
' Re-activation of screen update and instant calculation
```

```
With Application
```

```
.ScreenUpdating = True
.Calculation = xlCalculationAutomatic
```

```
.EnableEvents = True  
End With  
  
End Sub
```

Sub ManDatAdj()

```
' Step 4: Manual Data Adjustments  
' Sub allows user to identify one or more outliers data points. Outliers are  
' replaced by mean of predecessor and successor OR the second data point, if the  
' outlier is data point #1 OR eliminates the data point if the outlier is the last  
' data point (in that case, the last observation is flagged as 'unusual' and the forecasting  
' horizon is automatically expanded by one)  
  
' Disables screen updates and instant calculation  
' in order to improve performance and eliminate  
' annoying 'screen flickering'  
  
With Application  
.ScreenUpdating = False  
.Calculation = xlCalculationManual  
.EnableEvents = False  
End With  
  
Range("ManDatAdj").Offset(5, 0) = "Manual Outlier Correction"  
  
CancStep = True  
AddManDatAdj = False  
Set StepRange = Range("clCutOff")  
lastrowstep1 = Last(1, StepRange)  
ManDatAdjTxt = "Corrected Data: "  
LoopCount = 0  
  
' Manual Data Adjustments:  
' Functions in two steps: The form is called, data is transferred from the preceding  
' column and the outlier correction takes place. Depending on whether the user has chosen  
' the 'Add additional outlier option (=> AddManDatAdj = True), the sub enters a loop until  
' (=> AddManDatAdj = False)  
  
Step4_UsrFrm1.Show  
  
If CancStep = True _  
Then Exit Sub  
  
' Transfers data from the preceding column  
  
For RowStep1 = 6 To lastrowstep1 - 1  
Range("ManDatAdj").Offset(RowStep1, 0) = Range("CutOff").Offset(RowStep1, 0)  
Next RowStep1  
  
' In case an outlier has been entered, the data point is replaced as per the description  
' at the beginning of the sub. Also, any replaced data points are fonted 'bold' and the #  
' of the data point is reported in the column header  
  
Select Case ManDatAdjIdent
```

```

Case Is < 1
  ManDatAdjTxt = ManDatAdjTxt & "N/A"
Case Is = 1
  Range("ManDatAdj").Offset(5, 0).Offset(ManDatAdjIdent, 0) = Range("CutOff").Offset(7, 0)
  Range("ManDatAdj").Offset(5, 0).Offset(ManDatAdjIdent, 0).Font.Bold = True
  If LoopCount > 1 Then ManDatAdjTxt = ManDatAdjTxt & ", "
  ManDatAdjTxt = ManDatAdjTxt & ManDatAdjIdent
Case 2 To (lastrowstep1 - 7)
  Range("ManDatAdj").Offset(5, 0).Offset(ManDatAdjIdent, 0) = "(R[-1]C[-1]+R[1]C[-1])/2"
  Range("ManDatAdj").Offset(5, 0).Offset(ManDatAdjIdent, 0).Font.Bold = True
  If LoopCount > 1 Then ManDatAdjTxt = ManDatAdjTxt & ", "
  ManDatAdjTxt = ManDatAdjTxt & ManDatAdjIdent
Case Is = lastrowstep1 - 6
  Range("ManDatAdj").Offset(5, 0).Offset(ManDatAdjIdent, 0) = ""
  If LoopCount > 1 Then ManDatAdjTxt = ManDatAdjTxt & ", "
  ManDatAdjTxt = ManDatAdjTxt & ManDatAdjIdent & ", Last observation unusual = True"
Case Is > lastrowstep1 - 6
  MsgBox "Please enter a valid Data Point"
  AddManDatAdj = True
End Select

```

Range("ManDatAdj").Offset(4, 0) = ManDatAdjTxt

' After the first outlier, the sub checks the state of 'AddManDatAdj', if AddManDatAdj = True
' the adjustment is repeated until AddManDatAdj = False (this state is also reached if the data entry
' is cancelled). The reporting of outliers replaced ('bold' fonting, data point # in the heading)
' is updated

Select Case AddManDatAdj

Case Is = True

Do

Step4_UsrFrm1.Show

Select Case CancStep

Case Is = True

Case Is = False

Select Case ManDatAdjIdent

Case Is < 1

ManDatAdjTxt = ManDatAdjTxt & "N/A"

Case Is = 1

Range("ManDatAdj").Offset(5, 0).Offset(ManDatAdjIdent, 0) = Range("CutOff").Offset(7, 0)

Range("ManDatAdj").Offset(5, 0).Offset(ManDatAdjIdent, 0).Font.Bold = True

If LoopCount > 1 Then ManDatAdjTxt = ManDatAdjTxt & ", "

ManDatAdjTxt = ManDatAdjTxt & ManDatAdjIdent

Case 2 To (lastrowstep1 - 7)

Range("ManDatAdj").Offset(5, 0).Offset(ManDatAdjIdent, 0) = "(R[-1]C[-1]+R[1]C[-1])/2"

Range("ManDatAdj").Offset(5, 0).Offset(ManDatAdjIdent, 0).Font.Bold = True

If LoopCount > 1 Then ManDatAdjTxt = ManDatAdjTxt & ", "

ManDatAdjTxt = ManDatAdjTxt & ManDatAdjIdent

Case Is = lastrowstep1 - 6

Range("ManDatAdj").Offset(5, 0).Offset(ManDatAdjIdent, 0) = ""

If LoopCount > 1 Then ManDatAdjTxt = ManDatAdjTxt & ", "

ManDatAdjTxt = ManDatAdjTxt & ManDatAdjIdent & ", Last observation unusual = True"

Case Is > lastrowstep1 - 6

MsgBox "Please enter a valid Data Point"

AddManDatAdj = True

End Select

End Select

Loop Until AddManDatAdj = False

Case Is = False

End Select

' Creates Step5: Functional Form Button and Connects Step5: Functional Form Sub

```
ActiveSheet.Shapes.AddShape(msoShapeRectangle, Range("FForm").Offset(1, 0).Left, Range("FForm").Offset(1, 0).Top, 53.25, 18).Select
```

```
Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37
Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "Step 5"
With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 6).Font
.NameComplexScript = "+mn-cs"
.NameFarEast = "+mn-ea"
.Fill.Visible = msoTrue
.Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1
.Fill.ForeColor.TintAndShade = 0
.Fill.Transparency = 0
.Fill.Solid
.Size = 12
.Name = "+mn-lt"
End With
Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter
Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle
Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue
Selection.OnAction = "Steps.FForm"
```

```
Selection.ShapeRange.IncrementLeft 21
```

```
Selection.ShapeRange.IncrementTop 3
```

' Creates Step 5: Functional Form Contextual Help

```
ActiveSheet.Shapes.AddShape(msoShapeOval, Range("FForm").Offset(2, 0).Left, Range("FForm").Offset(2, 0).Top, 20.25, 20.25).Select
```

```
Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37
Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "?"
With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 1).Font
.NameComplexScript = "+mn-cs"
.NameFarEast = "+mn-ea"
.Fill.Visible = msoTrue
.Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1
.Fill.ForeColor.TintAndShade = 0
.Fill.Transparency = 0
.Fill.Solid
.Size = 12
.Name = "+mn-lt"
End With
Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter
Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle
Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue
Selection.OnAction = "LoadConHlp6"
```

```
Selection.ShapeRange.IncrementLeft 38.5
```

```
Selection.ShapeRange.IncrementTop 3
```

' Creates create chart on adjusted data button and assigns CreateChart3 Sub

```
ActiveSheet.Shapes.AddShape(msoShapeRectangle, Range("ManDatAdj").Offset(3, 0).Left, Range("ManDatAdj").Offset(3, 0).Top, 53.25, 18).Select
```

```
Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37
Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "Chart"
With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 5).Font
.NameComplexScript = "+mn-cs"
```

```
.NameFarEast = "+mn-ea"  
.Fill.Visible = msoTrue  
.Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1  
.Fill.ForeColor.TintAndShade = 0  
.Fill.Transparency = 0  
.Fill.Solid  
.Size = 12  
.Name = "+mn-lt"  
End With  
Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter  
Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle  
Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue  
Selection.OnAction = "CreateChart3"
```

```
Selection.ShapeRange.IncrementLeft 21  
Selection.ShapeRange.IncrementTop 3
```

```
Range("d1").Select
```

```
' Re-activation of screen update and instant calculation
```

```
With Application
```

```
.ScreenUpdating = True  
.Calculation = xlCalculationAutomatic  
.EnableEvents = True
```

```
End With
```

```
End Sub
```

Sub CreateChart3()

```
' Creates chart on data post Manual Data Adjustment / Outlier Correction
```

```
' Disables screen updates and instant calculation  
' in order to improve performance and eliminate  
' annoying 'screen flickering'
```

```
With Application
```

```
.ScreenUpdating = False  
.Calculation = xlCalculationManual  
.EnableEvents = False
```

```
End With
```

```
ActiveSheet.Shapes.AddChart(xlLineMarkers, 100, 100, 300, 200).Select  
ActiveChart.SetSourceData Source:=Range(Range("ManDatAdj").Offset(5, 0), Range("ManDatAdj").Offset(5,  
0).End(xlDown))
```

```
ActiveChart.Legend.Position = xlBottom  
With ActiveChart.SeriesCollection(1).Format.Line  
.Weight = 1  
.Visible = msoTrue  
.ForeColor.ObjectThemeColor = msoThemeColorDark1  
End With
```

```
ActiveChart.Parent.Cut  
Sheets(2).Activate  
Range("b46").Select  
ActiveSheet.Paste
```

```
With Application
    .ScreenUpdating = True
    .Calculation = xlCalculationAutomatic
    .EnableEvents = True
End With

End Sub
```

Sub FForm()

```
' Step 5: Choice of functional form & automatic outlier correction
' Sub allows user to identify functional form of data. If additive
' form is chosen, data remains as is. If multiplicative
' form is chosen, LogN is performed on data
' Afterwards, the data are checked for outliers as per Adya et. al. (2001)

' Disables screen updates and instant calculation
' in order to improve performance and eliminate
' annoying 'screen flickering'

With Application
    .ScreenUpdating = False
    .Calculation = xlCalculationManual
    .EnableEvents = False
End With

    ThClr1 = 5
    ThClr2 = 1
    ThClr3 = 4

    Range("FForm").Offset(5, 0) = "Functional Form"
    Range("OutEl").Offset(5, 0) = "Automatic Outlier Elimination"

    CancStep = True
    Set StepRange = Range("CLManDatAdj")
    lastrowstep1 = Last(1, StepRange)
    FFormTxt = "Functional form: "
    FFormM = False

' User chooses the functional form. If 'multiplicative' (FFormM = True)
' is chosen, a LogN transformation on the data is performed. Otherwise
' the data from the preceding step is just written into this step's column.
' The choice of functional form is documented in the column heading

    Step5_UsrFrm1.Show

    If CancStep = True _
        Then Exit Sub

    Select Case FFormM
        Case Is = False
            For RowStep1 = 6 To lastrowstep1 - 1
                Range("FForm").Offset(RowStep1, 0) = Range("ManDatAdj").Offset(RowStep1, 0)
                Next RowStep1
                FFormTxt = FFormTxt & "Additive"
            Case Is = True
```


**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

```

For RowStep1 = 6 To lastrowstep1 - 1
Range("FForm").Offset(RowStep1, 0) = "=LN(RC[-1])"
Next RowStep1
FFormTxt = FFormTxt & "Multiplicative"
End Select

```

```
Range("FForm").Offset(4, 0) = FFormTxt
```

- ' Performs automatic outlier correction: A linear regression is performed on the data.
- ' For the regression line, i.e. for every point estimate separately, a 95% Confidence Interval is calculated.
- ' Any data point outside the interval is replaced by the corresponding interval border.

- ' First, a linear regression is performed
- ' on the data.

- ' Definition of explanatory variables (time)
- RgDef1 = Range("legend").Offset(6, 0).Address
- RgDef2 = Range("legend").Offset(6, 0).End(xlDown).Address
- ' Definition of corresponding variable (data)
- RgDef3 = Range("FForm").Offset(6, 0).Address
- RgDef4 = Range("FForm").Offset(6, 0).End(xlDown).Address
- ' Calculation of Alpha (intercept) and Beta (slope) parameters (see corresponding functions)
- Beta = LinRegBeta(Range(RgDef1, RgDef2), Range(RgDef3, RgDef4))
- Alpha = LinRegAlpha(Range(RgDef1, RgDef2), Range(RgDef3, RgDef4))

- ' The 95% Confidence Interval (CI) for the Linear Regression can be calculated by
- ' $(a, b) = \text{ESTIMATE} \pm t((1-\text{CI})/2, n-2) * s * (1 + 1/n + (x - xAV)^2 / Sxx)^{0.5}$
- ' where: (a, b) are the borders of the interval
- ' ESTIMATE is the point estimate (slope, intercept) for the data point
- ' $t((1-\text{CI})/2, n-2)$ is the t-statistic corresponding to half the desired alpha level ($1-\text{CI} = 0.05$)
- ' and $n-2$ degrees of freedom, where n is the number of data points
- ' $s = ((\text{SUM } r_i^2) / n-2)^{0.5}$
- ' where: r_i is the residual at data point i , meaning the data point minus the corresponding Linear
- ' Regression point estimate, i.e. 's' is approximately the average absolute value of the residuals ($n-2$ instead of n)
- ' $Sxx = \text{SUM}(x^2) - (\text{SUM}x)^2 / n$
- ' where x is the explanatory variable, i.e. the time period
- ' xAV is the average value of explanatory variables

- ' calculates $t((1-\text{CI})/2, n-2)$ for $\text{CI} = 95\%$, i.e. $\alpha = 0.05$ and varying degrees of freedom
- ' (calculating is too strong a word. The corresponding function lists the t-table for $\alpha = 0.05$)
- T005 = Tstat(Range(RgDef3, RgDef4))

- ' Counter = n
- Counter = Range(RgDef3, RgDef4).Count

- ' term1 = $\text{SUM } r_i^2$, i.e. the sum of the squared residuals
- For LoopCount = 1 To Counter
- term1 = term1 + (Range("FForm").Offset(5 + LoopCount, 0) - (Alpha + (Beta * LoopCount))) ^ 2
- Next LoopCount

- ' term2 = s , i.e. approximately the average absolute value of the residuals
- term2 = (term1 / (Counter - 2)) ^ 0.5

- ' term3 = $\text{SUM}(x^2)$, i.e. sum of explanatory variables (time periods) squared
- For LoopCount = 1 To Counter
- term3 = term3 + (LoopCount ^ 2)
- Next LoopCount

- ' term4 = $\text{SUM}x$, i.e. sum of explanatory variables (time periods)

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

```
For LoopCount = 1 To Counter
    term4 = term4 + LoopCount
Next LoopCount
```

```
' term5 = Sxx = SUM(x^2) - (SUMx)^2 / n
term5 = term3 - ((term4 ^ 2) / Counter)
```

```
' In the following, the data point (Range("FForm").Offset(5 + LoopCount, 0)) is compared to the upper and lower
' boundary of the CI. If it is either larger than the upper- or smaller than the lower boundary, it is replaced by
' that boundary. Otherwise, it is carried over. Replaced values are marked in bold font.
```

```
For LoopCount = 1 To Counter
    Select Case Range("FForm").Offset(5 + LoopCount, 0)
        ' ESTIMATE = (Alpha + (Beta * LoopCount))
        ' t((1-CI)/2, n-2) = T005
        ' s = term2
        ' (x - xAV)^2 = (LoopCount - (term4 / Counter)) ^ 2
        ' Sxx = term5
        Case Is > (Alpha + (Beta * LoopCount)) + T005 * term2 * ((1 + (1 / Counter) + ((LoopCount - (term4 / Counter)) ^ 2) / term5) ^ 0.5)
            Range("OutEI").Offset(5 + LoopCount, 0) = (Alpha + (Beta * LoopCount)) + T005 * term2 * ((1 + (1 / Counter) + ((LoopCount - (term4 / Counter)) ^ 2) / term5) ^ 0.5)
            Range("OutEI").Offset(5 + LoopCount, 0).Font.Bold = True
        Case Is < (Alpha + (Beta * LoopCount)) - T005 * term2 * ((1 + (1 / Counter) + ((LoopCount - (term4 / Counter)) ^ 2) / term5) ^ 0.5)
            Range("OutEI").Offset(5 + LoopCount, 0) = (Alpha + (Beta * LoopCount)) - T005 * term2 * ((1 + (1 / Counter) + ((LoopCount - (term4 / Counter)) ^ 2) / term5) ^ 0.5)
            Range("OutEI").Offset(5 + LoopCount, 0).Font.Bold = True
        Case Else
            Range("OutEI").Offset(5 + LoopCount, 0) = Range("FForm").Offset(5 + LoopCount, 0)
    End Select
Next LoopCount
```

```
' Formats columns CLForeMod_1:CLBlend
```

```
Range("ForeMod_1").HorizontalAlignment = xlRight
Range("ForeMod_1").WrapText = True
Range("ForeMod_1") = "Rule-based Forecasting"
```

```
With Range("ForeMod_1", "Blend").Borders(xlEdgeLeft)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlMedium
End With
```

```
With Range("ForeMod_1", "Blend").Borders(xlEdgeTop)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlMedium
End With
```

```
With Range("ForeMod_1", "Blend").Borders(xlEdgeBottom)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlThin
End With
```

```
With Range("ForeMod_1", "Blend").Borders(xlEdgeRight)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
End With
```

```
.TintAndShade = 0
.Weight = xlMedium
End With

With Range("ForeMod_1").Interior
.Pattern = xlSolid
.PatternColorIndex = xlAutomatic
.ThemeColor = ThClr1
.TintAndShade = 0
.PatternTintAndShade = 0
End With
With Range("ForeMod_1").Font
.ThemeColor = ThClr2
.TintAndShade = 0
End With
With Range("ForeMod_1").Interior
.Pattern = xlPatternLinearGradient
.Gradient.Degree = 45
.Gradient.ColorStops.Clear
End With
With Range("ForeMod_1").Interior.Gradient.ColorStops.Add(0)
.ThemeColor = 1
.TintAndShade = 0
End With
With Range("ForeMod_1").Interior.Gradient.ColorStops.Add(1)
.ThemeColor = ThClr3
.TintAndShade = 0
End With

Range(Range("ForeMod_1").Offset(1, 0), Range("Blend").Offset(31, 0)).Select
With Selection.Borders(xlEdgeLeft)
.LineStyle = xlContinuous
.ThemeColor = ThClr1
.TintAndShade = 0
.Weight = xlMedium
End With
With Selection.Borders(xlEdgeTop)
.LineStyle = xlContinuous
.ThemeColor = ThClr1
.TintAndShade = 0
.Weight = xlThin
End With
With Selection.Borders(xlEdgeBottom)
.LineStyle = xlContinuous
.ThemeColor = ThClr1
.TintAndShade = 0
.Weight = xlMedium
End With
With Selection.Borders(xlEdgeRight)
.LineStyle = xlContinuous
.ThemeColor = ThClr1
.TintAndShade = 0
.Weight = xlMedium
End With
With Selection.Borders(xlInsideVertical)
.LineStyle = xlContinuous
.ThemeColor = ThClr1
.TintAndShade = 0
.Weight = xlThin
```

```
End With
With Selection.Borders(xlInsideHorizontal)
    .LineStyle = xlContinuous
    .ThemeColor = ThClr1
    .TintAndShade = 0
    .Weight = xlThin
End With
```

' Creates Step 6: Calculation of Forecasting Models Button and assigns Step 6: Calculation of Forecasting Models Sub

```
ActiveSheet.Shapes.AddShape(msoShapeRectangle, Range("ForeMod_1").Offset(1, 0).Left,
Range("ForeMod_1").Offset(1, 0).Top, 53.25, 18).Select
    Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37
    Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "Step 6"
    With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 6).Font
        .NameComplexScript = "+mn-cs"
        .NameFarEast = "+mn-ea"
        .Fill.Visible = msoTrue
        .Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1
        .Fill.ForeColor.TintAndShade = 0
        .Fill.Transparency = 0
        .Fill.Solid
        .Size = 12
        .Name = "+mn-lt"
    End With
    Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter
    Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle
    Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue
    Selection.OnAction = "Steps.ForeMod"

    Selection.ShapeRange.IncrementLeft 21
    Selection.ShapeRange.IncrementTop 3
```

' Creates Step 6: Calculation of Forecasting Models Contextual Help

```
ActiveSheet.Shapes.AddShape(msoShapeOval, Range("ForeMod_1").Offset(2, 0).Left, Range("ForeMod_1").Offset(2,
0).Top, 20.25, 20.25).Select
    Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37
    Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "?"
    With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 1).Font
        .NameComplexScript = "+mn-cs"
        .NameFarEast = "+mn-ea"
        .Fill.Visible = msoTrue
        .Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1
        .Fill.ForeColor.TintAndShade = 0
        .Fill.Transparency = 0
        .Fill.Solid
        .Size = 12
        .Name = "+mn-lt"
    End With
    Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter
    Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle
    Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue
    Selection.OnAction = "LoadConHlp7"

    Selection.ShapeRange.IncrementLeft 38.5
    Selection.ShapeRange.IncrementTop 3
```

```
Range("Foremod_1").Select
```

```
' Re-activation of screen update and instant calculation
```

```
With Application
```

```
  .ScreenUpdating = True
```

```
  .Calculation = xlCalculationAutomatic
```

```
  .EnableEvents = True
```

```
End With
```

```
End Sub
```

Sub ForeMod()

```
' Step 6: Calculation of Forecasting Models
```

```
' Sub executes procedures for calculating forecasting models,
```

```
' executes rules 1 to 10 and
```

```
' displays results in column CLForemod_1:CLForemod_4
```

```
' Disables screen updates and instant calculation
```

```
' in order to improve performance and eliminate
```

```
' annoying 'screen flickering'
```

```
With Application
```

```
  .ScreenUpdating = False
```

```
  .Calculation = xlCalculationManual
```

```
  .EnableEvents = False
```

```
End With
```

```
' THE BUILT-IN HOLT OPTIMIZATION HAS BEEN DISABLED. THE SAS JMP OPTIMIZATION PROCESS  
COULD NOT BE
```

```
' RE-PRODUCED
```

```
" Lets user choose form of Holt Optimization
```

```
,
```

```
  Step6_UsrFrm1.Show
```

```
,
```

```
  If CancStep = True _
```

```
  Then Exit Sub
```

```
' Inserts labels for forecasting models
```

```
Range("ForeMod_1").Offset(5, 0) = "Forecasting Models"
```

```
Range("ForeMod_1").Offset(6, 0) = "Linear Regression"
```

```
Range("ForeMod_1").Offset(6, 0).Font.Bold = True
```

```
Range("ForeMod_1").Offset(7, 0) = "Intercept:"
```

```
Range("ForeMod_1").Offset(8, 0) = "Level:"
```

```
Range("ForeMod_1").Offset(9, 0) = "Trend:"
```

```
Range("ForeMod_1").Offset(11, 0) = "Holt Model"
```

```
Range("ForeMod_1").Offset(11, 0).Font.Bold = True
```

```
Range("ForeMod_1").Offset(12, 0) = "Holt Alpha:"
```

```
Range("ForeMod_1").Offset(13, 0) = "Holt Beta:"
```

```
Range("ForeMod_1").Offset(14, 0) = "Level:"
```

```
Range("ForeMod_1").Offset(15, 0) = "Trend:"
```

```
Range("ForeMod_1").Offset(17, 0) = "Random Walk"
```

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

Range("ForeMod_1").Offset(17, 0).Font.Bold = True
 Range("ForeMod_1").Offset(18, 0) = "Level:"
 Range("ForeMod_1").Offset(19, 0) = "Trend:"

Range("ForeMod_1").Offset(23, 0) = "Short Range Model"
 Range(Range("ForeMod_1").Offset(23, 0), Range("foremod_3").Offset(23, 0)).Font.Bold = True
 Range("ForeMod_2").Offset(23, 0) = "Level"
 Range("ForeMod_3").Offset(23, 0) = "Trend"

Range("ForeMod_1").Offset(24, 0) = "Linear Regression"
 Range("ForeMod_1").Offset(25, 0) = "Holt Model"
 Range("ForeMod_1").Offset(26, 0) = "Random Walk"

Range("ForeMod_1").Offset(28, 0) = "Long Range Model"
 Range(Range("ForeMod_1").Offset(28, 0), Range("foremod_3").Offset(28, 0)).Font.Bold = True
 Range("ForeMod_2").Offset(28, 0) = "Level"
 Range("ForeMod_3").Offset(28, 0) = "Trend"

Range("ForeMod_1").Offset(29, 0) = "Linear Regression"
 Range("ForeMod_1").Offset(30, 0) = "Holt Model"
 Range("ForeMod_1").Offset(31, 0) = "Random Walk"

' Sets default values for Long- and Short Model
 ' NOTE: ALL RULES ARE APPLIED AS PER ED LUSK'S GUIDANCE
 ' IN 'USING REDUCED RULE-BASED FORECASTING' In the following,
 ' the wording from the guidance paper is pasted where applicable

'The Model Categories Starting Weights

| | Random Walk | Linear Regression | Holt |
|--------------------|-------------|-------------------|------|
| 'Short Model Level | 0,40 | 0,20 | 0,40 |
| 'Short Model Trend | 0,40 | 0,20 | 0,40 |
| 'Long Model Level | 0,33 | 0,33 | 0,34 |
| 'Long Model Trend | 0,00 | 0,60 | 0,40 |

SM_LR_Lvl = 0.2
 SM_HM_Lvl = 0.4
 SM_RW_Lvl = 0.4

SM_LR_Trđ = 0.2
 SM_HM_Trđ = 0.4
 SM_RW_Trđ = 0.4

LM_LR_Lvl = 0.33
 LM_HM_Lvl = 0.34
 LM_RW_Lvl = 0.33

LM_LR_Trđ = 0.6
 LM_HM_Trđ = 0.4
 LM_RW_Trđ = 0

Range("ForeMod_2").Offset(24, 0) = SM_LR_Lvl
 Range("ForeMod_3").Offset(24, 0) = SM_LR_Trđ
 Range("ForeMod_2").Offset(25, 0) = SM_HM_Lvl
 Range("ForeMod_3").Offset(25, 0) = SM_HM_Trđ
 Range("ForeMod_2").Offset(26, 0) = SM_RW_Lvl
 Range("ForeMod_3").Offset(26, 0) = SM_RW_Trđ
 Range(Range("ForeMod_2").Offset(24, 0), Range("ForeMod_3").Offset(26, 0)).NumberFormat = "0.000"

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

```
Range("ForeMod_2").Offset(29, 0) = LM_LR_Lvl
Range("ForeMod_3").Offset(29, 0) = LM_LR_Trld
Range("ForeMod_2").Offset(30, 0) = LM_HM_Lvl
Range("ForeMod_3").Offset(30, 0) = LM_HM_Trld
Range("ForeMod_2").Offset(31, 0) = LM_RW_Lvl
Range("ForeMod_3").Offset(31, 0) = LM_RW_Trld
Range(Range("ForeMod_2").Offset(29, 0), Range("ForeMod_3").Offset(31, 0)).NumberFormat = "0.000"
```

' A Linear Regression (Beta = slope, Alpha = intercept) is performed on the data using the Linear Regression function and using the time period as explanatory variable to determine the Linear Regression parameters for the final forecast

```
RgDef1 = Range("legend").Offset(6, 0).Address
RgDef2 = Range("legend").Offset(6, 0).End(xlDown).Address
RgDef3 = Range("OutEL").Offset(6, 0).Address
RgDef4 = Range("OutEL").Offset(6, 0).End(xlDown).Address
```

```
Beta = LinRegBeta2(Range(RgDef1, RgDef2), Range(RgDef3, RgDef4))
Alpha = LinRegAlpha2(Range(RgDef1, RgDef2), Range(RgDef3, RgDef4))
```

' Current Level (CurLvl) is the point estimate of the linear regression for the last time period for which there is actual data
CurLvl = Alpha + (Beta * Range(RgDef3, RgDef4).Count)

```
Range("foremod_2").Offset(7, 0) = Alpha
Range("foremod_2").Offset(8, 0) = CurLvl
Range("foremod_2").Offset(9, 0) = Beta
```

' A Holt-Winters exponential smoothing (Holt Model) is performed on the data using SAS JMP 10 to determine the Holt parameters for the final forecast.

```
'Get Data
Set StepRange = Range("CLOutEL")
lastrow = Last(1, StepRange)
Datapoints = lastrow - 6
ReDim DatArray(1 To Datapoints) As Double

For Counter = 1 To Datapoints
    DatArray(Counter) = Range("OutEL").Offset(Counter + 5, 0)
Next Counter
```

' Set initial Level and Trend
' The initial level and trend settings for the Holt Model cannot be extracted from JMP (not displayed).
' The closest approximation was experimentally found to be
' Level = (DataPoint1+...+Datapoint4)/4 and
' Trend = (Datapoint4-Datapoint1)/3
' In the small-sample experiment used for determining an initial Level- and Trend setting method, the method described above on average produced a smaller fitting APE of the model against the data than the function given out by JMP,
' the method is provisionally accepted for the tool. In case less than 4 data points are available, the method is modified accordingly:

```
Select Case Datapoints
Case Is < 4
    For Counter = 1 To Datapoints
        LevArrayStart = LevArrayStart + DatArray(Counter)
    Next Counter
    LevArrayStart = LevArrayStart / Datapoints
    TreArrayStart = (DatArray(Datapoints) - DatArray(1)) / (Datapoints - 1)
```

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

```

Case Is >= 4
  For Counter = 1 To 4
    LevArrayStart = LevArrayStart + DatArray(Counter)
  Next Counter
  LevArrayStart = LevArrayStart / 4
  TreArrayStart = (DatArray(4) - DatArray(1)) / 3
End Select

```

```

' The following 'select case' construction originally distinguished between using the built-in- and the
' JMP Holt optimization model. In order to ensure scientific comparability, it was decided that the Holt
' optimization needed to be an exact reproduction of the algorithm employed in JMP. Therefore:
' THE BUILT-IN HOLT OPTIMIZATION HAS BEEN DISABLED. THE SAS JMP OPTIMIZATION PROCESS
COULD NOT BE
' RE-PRODUCED

```

```
HoldOpti = "JMP"
```

```

Select Case HoldOpti
  Case Is = "Built-In"

```

```

' ' Step 6a)
' ' Holt MSE search
' ' Performs a grid search for min Holt Alpha and Beta:
' ' In Loop one, Alpha and Beta ranges (0 to 1, 0 to 1) are separated in 11 x 11 steps, MinMSE is identified
' ' In Loop 2 to 25, MinMSE Alpha and Beta from preceeding loop is taken and in case Alpha (Beta) is <> 0 or 1
' ' => MinMSE on Alpha - 1 / ( 10 ^ (Loops - 1)) and from there + 1 / ( 10 ^ (Loops))
' ' => e.g. Loop 1 gives Alpha = 0.5, then Loop 2 tests Alpha = 0.41 to 0.59 in 0.01 steps
' ' In case of Alpha (Beta) being 0 or 1, the intervals are shortened, number of steps is reduced from 19 to 10
'
' ' Calculates MinMSEs for Alphas and Betas
'   ' Loop 1
'     ' Initial screening phase
'     ' Divides the original Holt Alpha and Beta possibilities in 121 combinations (0.1 steps)
'
'     AlphaElements = 11
'     BetaElements = 11
'
'     ' Determines minimum MSE for this initial screening
'
'     For ALoopCount = 1 To AlphaElements
'       For BLoopCount = 1 To BetaElements
'         HoltArray(ALoopCount, BLoopCount) = HoltMSE(LevArrayStart, TreArrayStart, (ALoopCount - 1) /
10, (BLoopCount - 1) / 10, DatArray(), Datapoints)
'       Next BLoopCount
'     Next ALoopCount
'
'     ' Searches for minimum MSE among initial screening results
'
'     MSEMIn = HoltArray(1, 1)
'     MinIndexA = 1
'     MinIndexB = 1
'
'     For ALoopCount = 1 To AlphaElements
'       For BLoopCount = 1 To BetaElements
'         If MSEMIn > HoltArray(ALoopCount, BLoopCount) _
'           Then MSEMIn = HoltArray(ALoopCount, BLoopCount) _
'             : MinIndexA = ALoopCount - 1 _
'             : MinIndexB = BLoopCount - 1
'       Next BLoopCount
'     Next ALoopCount

```


**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

```

' Captures Holt Alpha and Beta results from initial screening

HoltAlpha = MinIndexA / 10
HoltBeta = MinIndexB / 10
GridLoop = 1

' Loop 2 to x
GridLoop = 2

' Determines the number of iterations, the grid search goes through
For GridLoop = 2 To 15

' Determines the state of Holt Alpha and Beta. Why? Because if = 0 or 1
' the search must only be allowed to go into one direction to keep the constraints (0 to 1)
' on the parameters
  Select Case HoltAlpha
    Case Is = 0
      HoltAlphaState = 1
    Case Is = 1
      HoltAlphaState = 3
    Case Else
      HoltAlphaState = 2
  End Select

  Select Case HoltBeta
    Case Is = 0
      HoltBetaState = 1
    Case Is = 1
      HoltBetaState = 3
    Case Else
      HoltBetaState = 2
  End Select

' Grid search process. The main difference to the screening process above is that
' a 'select case' construction is installed in front of the search in order to restrain
' the search if necessary (see above) and that the width of the steps searched is controlled by
' the ((ALoopCount - 1) / (10 ^ GridLoop)) construction in the MSE search

  Select Case HoltAlphaState
    ' This means: Holt Alpha = 0
    Case Is = 1
      Select Case HoltBetaState
        ' This means: Holt Beta = 0
        Case Is = 1
          ' Here, the number of elements = search steps is reduced from 19 to 10
          ' respectively for reason of parameter constraints (see above)
          AlphaElements = 10
          BetaElements = 10

          For ALoopCount = 1 To AlphaElements
            For BLoopCount = 1 To BetaElements
              HoltArray(ALoopCount, BLoopCount) = HoltMSE(LevArrayStart, TreArrayStart,
(HoltAlpha + ((ALoopCount - 1) / (10 ^ GridLoop))), (HoltBeta + ((BLoopCount - 1) / (10 ^ GridLoop))), DatArray(),
Datapoints)

              Next BLoopCount
            Next ALoopCount

          MSEMin = HoltArray(1, 1)
          MinIndexA = 0

```

```

'
    MinIndexB = 0
'
'
    For ALoopCount = 1 To AlphaElements
'
        For BLoopCount = 1 To BetaElements
'
            If MSEMin > HoltArray(ALoopCount, BLoopCount) _
'
                Then MSEMin = HoltArray(ALoopCount, BLoopCount) _
'
                    : MinIndexA = ALoopCount - 1 _
'
                    : MinIndexB = BLoopCount - 1
'
            Next BLoopCount
'
        Next ALoopCount
'
'
' captures the new (!) Holt Alpha and Beta
'
    HoltAlpha = (HoltAlpha + (MinIndexA / (10 ^ GridLoop)))
'
    HoltBeta = (HoltBeta + (MinIndexB / (10 ^ GridLoop)))
'
Case Is = 2
'
' This means, Beta >0 and <1
'
    AlphaElements = 10
'
    BetaElements = 19
'
'
' Difference to case above: the beta search does not start at the old Holt Beta
' (as would be the case if it were 0), but at old Hold Beta -(!) 9 interval steps
'
    For ALoopCount = 1 To AlphaElements
'
        For BLoopCount = 1 To BetaElements
'
            HoltArray(ALoopCount, BLoopCount) = HoltMSE(LevArrayStart, TreArrayStart,
(HoltAlpha + ((ALoopCount - 1) / (10 ^ GridLoop))), (HoltBeta - (1 / (10 ^ (GridLoop - 1))) + (BLoopCount / (10 ^
GridLoop))), DatArray(), Datapoints)
'
            Next BLoopCount
'
        Next ALoopCount
'
'
    MSEMin = HoltArray(1, 1)
'
    MinIndexA = 0
'
    MinIndexB = 1
'
'
    For ALoopCount = 1 To AlphaElements
'
        For BLoopCount = 1 To BetaElements
'
            If MSEMin > HoltArray(ALoopCount, BLoopCount) _
'
                Then MSEMin = HoltArray(ALoopCount, BLoopCount) _
'
                    : MinIndexA = ALoopCount - 1 _
'
                    : MinIndexB = BLoopCount
'
            Next BLoopCount
'
        Next ALoopCount
'
'
    HoltAlpha = (HoltAlpha + (MinIndexA / (10 ^ GridLoop)))
'
    HoltBeta = (HoltBeta - (1 / (10 ^ (GridLoop - 1))) + (MinIndexB / (10 ^ GridLoop)))
'
Case Is = 3
'
    AlphaElements = 10
'
    BetaElements = 10
'
'
    For ALoopCount = 1 To AlphaElements
'
        For BLoopCount = 1 To BetaElements
'
            HoltArray(ALoopCount, BLoopCount) = HoltMSE(LevArrayStart, TreArrayStart,
(HoltAlpha + ((ALoopCount - 1) / (10 ^ GridLoop))), (HoltBeta - (1 / (10 ^ (GridLoop - 1))) + (BLoopCount / (10 ^
GridLoop))), DatArray(), Datapoints)
'
            Next BLoopCount
'
        Next ALoopCount
'
'
    MSEMin = HoltArray(1, 1)
'
    MinIndexA = 0
'
    MinIndexB = 1
'
'

```

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

```

'
'           For ALoopCount = 1 To AlphaElements
'             For BLoopCount = 1 To BetaElements
'               If MSEMin > HoltArray(ALoopCount, BLoopCount) _
'                 Then MSEMin = HoltArray(ALoopCount, BLoopCount) _
'                   : MinIndexA = ALoopCount - 1 _
'                   : MinIndexB = BLoopCount
'               Next BLoopCount
'             Next ALoopCount
'
'           HoltAlpha = (HoltAlpha + (MinIndexA / (10 ^ GridLoop)))
'           HoltBeta = (HoltBeta - (1 / (10 ^ (GridLoop - 1))) + (MinIndexB / (10 ^ GridLoop)))
'         End Select
'       Case Is = 2
'       Select Case HoltBetaState
'         Case Is = 1
'           AlphaElements = 19
'           BetaElements = 10
'
'           For ALoopCount = 1 To AlphaElements
'             For BLoopCount = 1 To BetaElements
'               HoltArray(ALoopCount, BLoopCount) = HoltMSE(LevArrayStart, TreArrayStart,
' (HoltAlpha - (1 / (10 ^ (GridLoop - 1))) + (ALoopCount / (10 ^ GridLoop))), (HoltBeta + ((BLoopCount - 1) / (10 ^
' GridLoop))), DatArray(), Datapoints)
'             Next BLoopCount
'           Next ALoopCount
'
'           MSEMin = HoltArray(1, 1)
'           MinIndexA = 1
'           MinIndexB = 0
'
'           For ALoopCount = 1 To AlphaElements
'             For BLoopCount = 1 To BetaElements
'               If MSEMin > HoltArray(ALoopCount, BLoopCount) _
'                 Then MSEMin = HoltArray(ALoopCount, BLoopCount) _
'                   : MinIndexA = ALoopCount _
'                   : MinIndexB = BLoopCount - 1
'             Next BLoopCount
'           Next ALoopCount
'
'           HoltAlpha = (HoltAlpha - (1 / (10 ^ (GridLoop - 1))) + (MinIndexA / (10 ^ GridLoop)))
'           HoltBeta = (HoltBeta + (MinIndexB / (10 ^ GridLoop)))
'         Case Is = 2
'           AlphaElements = 19
'           BetaElements = 19
'
'           For ALoopCount = 1 To AlphaElements
'             For BLoopCount = 1 To BetaElements
'               HoltArray(ALoopCount, BLoopCount) = HoltMSE(LevArrayStart, TreArrayStart,
' (HoltAlpha - (1 / (10 ^ (GridLoop - 1))) + (ALoopCount / (10 ^ GridLoop))), (HoltBeta - (1 / (10 ^ (GridLoop - 1))) +
' (BLoopCount / (10 ^ GridLoop))), DatArray(), Datapoints)
'             Next BLoopCount
'           Next ALoopCount
'
'           MSEMin = HoltArray(1, 1)
'           MinIndexA = 1
'           MinIndexB = 1
'
'           For ALoopCount = 1 To AlphaElements
'             For BLoopCount = 1 To BetaElements
'               If MSEMin > HoltArray(ALoopCount, BLoopCount) _

```

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

```

'
'           Then MSEMin = HoltArray(ALoopCount, BLoopCount) _
'           : MinIndexA = ALoopCount _
'           : MinIndexB = BLoopCount
'       Next BLoopCount
'   Next ALoopCount
'
'
'           HoltAlpha = (HoltAlpha - (1 / (10 ^ (GridLoop - 1))) + (MinIndexA / (10 ^ GridLoop)))
'           HoltBeta = (HoltBeta - (1 / (10 ^ (GridLoop - 1))) + (MinIndexB / (10 ^ GridLoop)))
'   Case Is = 3
'       AlphaElements = 19
'       BetaElements = 10
'
'       For ALoopCount = 1 To AlphaElements
'           For BLoopCount = 1 To BetaElements
'               HoltArray(ALoopCount, BLoopCount) = HoltMSE(LevArrayStart, TreArrayStart,
(HoltAlpha - (1 / (10 ^ (GridLoop - 1))) + (ALoopCount / (10 ^ GridLoop))), (HoltBeta - (1 / (10 ^ (GridLoop - 1))) +
(BLoopCount / (10 ^ GridLoop))), DatArray(), Datapoints)
'               Next BLoopCount
'           Next ALoopCount
'
'       MSEMin = HoltArray(1, 1)
'       MinIndexA = 1
'       MinIndexB = 1
'
'       For ALoopCount = 1 To AlphaElements
'           For BLoopCount = 1 To BetaElements
'               If MSEMin > HoltArray(ALoopCount, BLoopCount) _
'                   Then MSEMin = HoltArray(ALoopCount, BLoopCount) _
'                   : MinIndexA = ALoopCount _
'                   : MinIndexB = BLoopCount
'               Next BLoopCount
'           Next ALoopCount
'
'       HoltAlpha = (HoltAlpha - (1 / (10 ^ (GridLoop - 1))) + (MinIndexA / (10 ^ GridLoop)))
'       HoltBeta = (HoltBeta - (1 / (10 ^ (GridLoop - 1))) + (MinIndexB / (10 ^ GridLoop)))
'   End Select
'   Case Is = 3
'       Select Case HoltBetaState
'           Case Is = 1
'               AlphaElements = 10
'               BetaElements = 10
'
'               For ALoopCount = 1 To AlphaElements
'                   For BLoopCount = 1 To BetaElements
'                       HoltArray(ALoopCount, BLoopCount) = HoltMSE(LevArrayStart, TreArrayStart,
(HoltAlpha - (1 / (10 ^ (GridLoop - 1))) + (ALoopCount / (10 ^ GridLoop))), (HoltBeta + ((BLoopCount - 1) / (10 ^
GridLoop))), DatArray(), Datapoints)
'                       Next BLoopCount
'                   Next ALoopCount
'
'               MSEMin = HoltArray(1, 1)
'               MinIndexA = 1
'               MinIndexB = 0
'
'               For ALoopCount = 1 To AlphaElements
'                   For BLoopCount = 1 To BetaElements
'                       If MSEMin > HoltArray(ALoopCount, BLoopCount) _
'                           Then MSEMin = HoltArray(ALoopCount, BLoopCount) _
'                           : MinIndexA = ALoopCount _
'                           : MinIndexB = BLoopCount - 1

```

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

```

'
'           Next BLoopCount
'           Next ALoopCount
'
'
'           HoltAlpha = (HoltAlpha - (1 / (10 ^ (GridLoop - 1))) + (MinIndexA / (10 ^ GridLoop)))
'           HoltBeta = (HoltBeta + (MinIndexB / (10 ^ GridLoop)))
'
'           Case Is = 2
'           AlphaElements = 10
'           BetaElements = 19
'
'           For ALoopCount = 1 To AlphaElements
'               For BLoopCount = 1 To BetaElements
'                   HoltArray(ALoopCount, BLoopCount) = HoltMSE(LevArrayStart, TreArrayStart,
(HoltAlpha - (1 / (10 ^ (GridLoop - 1))) + (ALoopCount / (10 ^ GridLoop))), (HoltBeta - (1 / (10 ^ (GridLoop - 1))) +
(BLoopCount / (10 ^ GridLoop))), DatArray(), Datapoints)
'                   Next BLoopCount
'               Next ALoopCount
'
'           MSEMin = HoltArray(1, 1)
'           MinIndexA = 1
'           MinIndexB = 1
'
'           For ALoopCount = 1 To AlphaElements
'               For BLoopCount = 1 To BetaElements
'                   If MSEMin > HoltArray(ALoopCount, BLoopCount) _
'                       Then MSEMin = HoltArray(ALoopCount, BLoopCount) _
'                           : MinIndexA = ALoopCount _
'                           : MinIndexB = BLoopCount
'                   Next BLoopCount
'               Next ALoopCount
'
'           HoltAlpha = (HoltAlpha - (1 / (10 ^ (GridLoop - 1))) + (MinIndexA / (10 ^ GridLoop)))
'           HoltBeta = (HoltBeta - (1 / (10 ^ (GridLoop - 1))) + (MinIndexB / (10 ^ GridLoop)))
'
'           Case Is = 3
'           AlphaElements = 10
'           BetaElements = 10
'
'           For ALoopCount = 1 To AlphaElements
'               For BLoopCount = 1 To BetaElements
'                   HoltArray(ALoopCount, BLoopCount) = HoltMSE(LevArrayStart, TreArrayStart,
(HoltAlpha - (1 / (10 ^ (GridLoop - 1))) + (ALoopCount / (10 ^ GridLoop))), (HoltBeta - (1 / (10 ^ (GridLoop - 1))) +
(BLoopCount / (10 ^ GridLoop))), DatArray(), Datapoints)
'                   Next BLoopCount
'               Next ALoopCount
'
'           MSEMin = HoltArray(1, 1)
'           MinIndexA = 1
'           MinIndexB = 1
'
'           For ALoopCount = 1 To AlphaElements
'               For BLoopCount = 1 To BetaElements
'                   If MSEMin > HoltArray(ALoopCount, BLoopCount) _
'                       Then MSEMin = HoltArray(ALoopCount, BLoopCount) _
'                           : MinIndexA = ALoopCount _
'                           : MinIndexB = BLoopCount
'                   Next BLoopCount
'               Next ALoopCount
'
'           HoltAlpha = (HoltAlpha - (1 / (10 ^ (GridLoop - 1))) + (MinIndexA / (10 ^ GridLoop)))
'           HoltBeta = (HoltBeta - (1 / (10 ^ (GridLoop - 1))) + (MinIndexB / (10 ^ GridLoop)))
'
'           End Select

```

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

```
'      End Select
'      Next GridLoop
Case Is = "JMP"

' Step 6b)
' Import of Holt parameters from SAS JMP
' This was scripted with SAS JMP v.10. Downward compatibility has not been tested.

' Creates a JMP data object and sets JMP to invisible
Set JMPApp = CreateObject("JMP.Application")
JMPApp.Visible = False

' Creates a JMP table with one data column
Set DataInput = JMPApp.NewDataTable("temptable")
Set DataCol = DataInput.NewColumn("JmpCol1", dtTypeNumeric, 0, 8)
DataInput.Activate

' Creates rows in the JMP table by the number of Datapoints
DataInput.AddRows Datapoints, 0

' Populates JMP chart from the DatArray variable
For Counter = 1 To Datapoints
    DataCol.SetCellVal Counter, DatArray(Counter)
Next Counter

' Opens Time Series set of JMP analyses for the data column
DataInput.Activate
Set TimeSeries = DataInput.Document.CreateTimeSeries
TimeSeries.LaunchAddYSeries ("JMPCol1")
TimeSeries.LaunchAddNumAutoCorrLags (4)

' Runs Holt exponential Smoothing (Linear, zero to one => (2,0)) on the column
TimeSeries.Launch
SmoothDummy = TimeSeries.SmoothingModel(2, 0)

' Extracts Holt Alpha and Hol Beta into Table
Hand = TimeSeries.GetGraphicItemByType("tablebox", 8)
Set ParaTable = TimeSeries.TableBoxMakeDataTable(Hand)

' Gets values for Holt Alpha and Beta
HoltAlpha = ParaTable.GetColumnByIndex(2).GetCellVal(1)
HoltBeta = ParaTable.GetColumnByIndex(2).GetCellVal(2)

' Closes JMP
JMPApp.CloseAllWindows
End Select

' Calculate Level and Trend and display results
' The following displays the Holt model forecasts in the excel sheet

Range("foremod_1").Offset(33, 0) = "Period"
Range("foremod_2").Offset(33, 0) = "Holt Level"
Range("foremod_3").Offset(33, 0) = "Holt Trend"
Range("foremod_4").Offset(33, 0) = "Holt Forecast"
Range(Range("foremod_1").Offset(33, 0), Range("foremod_4").Offset(33, 0)).Font.Bold = True
```

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

```
Range(Range("foremod_1").Offset(33, 0), Range("foremod_4").Offset(33, 0).Offset(Datapoints + 1, 0)).Font.color = RGB(210, 210, 210)
```

```
ReDim LevArray(1 To Datapoints) As Double  
ReDim TreArray(1 To Datapoints) As Double  
ReDim ForeArray(1 To Datapoints) As Double
```

```
' period 1  
' Here, the Level- and Trend initial levels as determined above are called
```

```
' Period Labelling  
Range("foremod_1").Offset(34, 0) = "1"
```

```
' Initial Level  
LevArray(1) = LevArrayStart  
Range("foremod_2").Offset(34, 0) = LevArray(1)
```

```
' Initial Trend  
TreArray(1) = TreArrayStart  
Range("foremod_3").Offset(34, 0) = TreArray(1)
```

```
' Forecast (non-existent for period 1)  
Range("foremod_4").Offset(34, 0) = ""
```

```
' periods > 1  
' Here, the model is executed with the parameters determined above
```

```
' Period Labelling  
For Counter = 2 To Datapoints + 1  
    Range("foremod_1").Offset(33, 0).Offset(Counter, 0) = Counter  
Next Counter
```

```
' Level and Trend calculations  
For Counter = 2 To Datapoints  
    LevArray(Counter) = HoltAlpha * DatArray(Counter) + (1 - HoltAlpha) * (LevArray(Counter - 1) +  
TreArray(Counter - 1))  
    Range("foremod_2").Offset(33, 0).Offset(Counter, 0) = LevArray(Counter)  
    TreArray(Counter) = HoltBeta * (LevArray(Counter) - LevArray(Counter - 1)) + (1 - HoltBeta) * TreArray(Counter -  
1)  
    Range("foremod_3").Offset(33, 0).Offset(Counter, 0) = TreArray(Counter)  
Next Counter
```

```
' Forecasts  
' forecast(1) is for time period t = 2
```

```
For Counter = 1 To Datapoints  
    ForeArray(Counter) = LevArray(Counter) + TreArray(Counter)  
    Range("foremod_4").Offset(34, 0).Offset(Counter, 0) = ForeArray(Counter)  
Next Counter
```

```
' Displays Holt parameters as calculated above  
' Holt Alpha and Beta  
Range("foremod_2").Offset(12, 0) = HoltAlpha  
Range("foremod_2").Offset(13, 0) = HoltBeta  
' Current Holt Level and Trend  
Range("foremod_2").Offset(14, 0) = LevArray(Datapoints)  
Range("foremod_2").Offset(15, 0) = TreArray(Datapoints)
```

' Last but not least, Random Walk is 'calculated'. The level equals the last data point, the trend is = 0

```
Range("foremod_2").Offset(18, 0) = Range("OutEI").Offset(6, 0).End(xlDown)
Range("foremod_2").Offset(19, 0) = 0
```

' Feature Identificaton: Rules 6, 7, 8, 9, 10

' The data preparation / feature identification rules (rules 1-10 in Armstrong & Collopy 1992) are the only ones
' that are NOT taken out of the guidance provided by Ed Lusk. The reason is that these rules have never been revised
' and are therefore still taken from the original paper. Rules 1-5 have been incorporated in the data preparaion steps
' above.

'6. Recent Trend Down. IF the trend component from Holt's is down, THEN set the direction of the recent trend to
'down.

'7. Basic Trend Down. IF the trend component from the regression is down, THEN set the direction of the basic
'trend to down.

'8. Significant Basic Trend. IF the t-statistic for the regression's trend is greater than 2, THEN set the significant
'basic trend to true.

'9. Recent Run not Long. IF there has been a movement in the same direction for at least the last six observations,
'THEN set the 'recent run not long' to false.

'10. Near a Previous Extreme. IF the last observation is greater than 90% of the highest, or less than 110% of the
'lowest historical observation for the trend adjusted series, AND it is not immediately preceded by the previous
'extreme observation, THEN set near a previous extreme to true.

' Rule 6 Recent Trend Down

```
Range("foremod_4").Offset(6, 0) = "Recent Trend:"
Range("foremod_4").Offset(6, 0).Font.Bold = True
```

' Check sign of current trend component of the Holt model

```
Select Case Range("foremod_2").Offset(15, 0)
  Case Is < 0
    Range("foremod_4").Offset(7, 0) = "Down"
  Case Is = 0
    Range("foremod_4").Offset(7, 0) = "Neutral"
  Case Is > 0
    Range("foremod_4").Offset(7, 0) = "Up"
End Select
```

' Rule 7 Basic Trend Down

```
Range("foremod_4").Offset(9, 0) = "Basic Trend:"
Range("foremod_4").Offset(9, 0).Font.Bold = True
```

' Check sign of slope estimate of the Linear Regression

```
Select Case Range("foremod_2").Offset(9, 0)
  Case Is < 0
    Range("foremod_4").Offset(10, 0) = "Down"
  Case Is = 0
    Range("foremod_4").Offset(10, 0) = "Neutral"
  Case Is > 0
    Range("foremod_4").Offset(10, 0) = "Up"
End Select
```

' Rule 8 Significant Basic Trend

```
Range("foremod_4").Offset(12, 0) = "Basic Trend:"
Range("foremod_4").Offset(12, 0).Font.Bold = True
```

' Significance here stands for significant difference from zero.

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

' The general t-statistic for any given parameter estimate is
' $t = (\text{BETAest} - \text{BETAzero}) / \text{s.e.BETA}$
' where: BETAest is the parameter (here: Beta)
' BETAzero is the value from which the significant difference is tested (here: 0)
' s.e.BETA is the standard error of beta

TStatBeta = Beta / StErBeta2(Range(RgDef1, RgDef2), Range(RgDef3, RgDef4))

Select Case TStatBeta

Case Is <= 2

Range("foremod_4").Offset(13, 0) = "Not Significant"

Case Is > 2

Range("foremod_4").Offset(13, 0) = "Significant"

End Select

' Rule 9 Recent Run not Long

' The original rule had a double negative ('if run at least 6 long, then recent run not long = false')

' For the sake of clarity, the double negative has not been included in the code

RecentRun = "False"

Range("foremod_4").Offset(15, 0) = "Recent Run Long:"

Range("foremod_4").Offset(15, 0).Font.Bold = True

RgDef3 = Range("OutE1").Offset(6, 0).Address

RgDef4 = Range("OutE1").Offset(6, 0).End(xlDown).Address

RRCount = Range(RgDef3, RgDef4).Count

Select Case RRCount

' If less than 6 observations, recent run cannot be long

Case Is < 6

RecentRun = "False"

Case Is >= 6

ReDim RRArray(1 To RRCount)

For FillRR = 1 To RRCount

RRArray(FillRR) = Range("OutE1").Offset(5, 0).Offset(FillRR, 0)

Next FillRR

' If second-to-last data point smaller than last data point, then the four data

' points before that need to be consecutively smaller

If RRArray(RRCount) > RRArray(RRCount - 1) _

And RRArray(RRCount - 1) > RRArray(RRCount - 2) _

And RRArray(RRCount - 2) > RRArray(RRCount - 3) _

And RRArray(RRCount - 3) > RRArray(RRCount - 4) _

And RRArray(RRCount - 4) > RRArray(RRCount - 5) _

Then RecentRun = "True"

' Vice versa for condition above

If RRArray(RRCount) < RRArray(RRCount - 1) _

And RRArray(RRCount - 1) < RRArray(RRCount - 2) _

And RRArray(RRCount - 2) < RRArray(RRCount - 3) _

And RRArray(RRCount - 3) < RRArray(RRCount - 4) _

And RRArray(RRCount - 4) < RRArray(RRCount - 5) _

Then RecentRun = "True"

End Select

Range("foremod_4").Offset(16, 0).NumberFormat = "@"

Range("foremod_4").Offset(16, 0) = RecentRun

- ' Rule 10 Near previous Extreme
- ' In the Reduced Rule Set, this rule has no practical implications any more

```
PrevExtreme = "False"
```

```
Range("CLForeMod_4").ColumnWidth = 18.14  
Range("foremod_4").Offset(18, 0) = "Near Prev. Extreme:"  
Range("foremod_4").Offset(18, 0).Font.Bold = True
```

```
RgDef3 = Range("OutEI").Offset(6, 0).Address  
RgDefPE = Range("OutEI").Offset(6, 0).End(xlDown).Offset(-1, 0).Address  
LstDtPE = Range("OutEI").Offset(6, 0).End(xlDown)  
SecLstDtPE = Range("OutEI").Offset(6, 0).End(xlDown).Offset(-1, 0)
```

```
If LstDtPE > 0.9 * WorksheetFunction.Max(Range(RgDef3, RgDefPE)) _  
    And SecLstDtPE <> WorksheetFunction.Max(Range(RgDef3, RgDefPE)) _  
Then PrevExtreme = "True"
```

```
If LstDtPE < 1.1 * WorksheetFunction.Min(Range(RgDef3, RgDefPE)) _  
    And SecLstDtPE <> WorksheetFunction.Min(Range(RgDef3, RgDefPE)) _  
Then PrevExtreme = "True"
```

```
Range("foremod_4").Offset(19, 0).NumberFormat = "@"  
Range("foremod_4").Offset(19, 0) = PrevExtreme
```

- ' Creates Step 7: Short Range Level, Short Range Trend, Long Range Level Button and Assigns SRMLev Sub

```
Sheets(1).Activate
```

```
ActiveSheet.Shapes.AddShape(msoShapeRectangle, Range("SRMLev").Offset(1, 0).Left, Range("SRMLev").Offset(1,  
0).Top, 53.25, 18).Select
```

```
Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37  
Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "Step 7"  
With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 6).Font  
.NameComplexScript = "+mn-cs"  
.NameFarEast = "+mn-ea"  
.Fill.Visible = msoTrue  
.Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1  
.Fill.ForeColor.TintAndShade = 0  
.Fill.Transparency = 0  
.Fill.Solid  
.Size = 12  
.Name = "+mn-lt"  
End With  
Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter  
Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle  
Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue  
Selection.OnAction = "Steps.SRMLev"
```

```
Selection.ShapeRange.IncrementLeft 21  
Selection.ShapeRange.IncrementTop 3
```

- ' Creates Step 7: Short Range Level, Short Range Trend, Long Range Level Contextual Help

```
ActiveSheet.Shapes.AddShape(msoShapeOval, Range("SRMLev").Offset(2, 0).Left, Range("SRMLev").Offset(2, 0).Top,  
20.25, 20.25).Select
```

```
Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37  
Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "?"  
With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 1).Font
```

```
.NameComplexScript = "+mn-cs"  
.NameFarEast = "+mn-ea"  
.Fill.Visible = msoTrue  
.Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1  
.Fill.ForeColor.TintAndShade = 0  
.Fill.Transparency = 0  
.Fill.Solid  
.Size = 12  
.Name = "+mn-lt"  
End With  
Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter  
Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle  
Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue  
Selection.OnAction = "LoadConHlp8"  
  
Selection.ShapeRange.IncrementLeft 38.5  
Selection.ShapeRange.IncrementTop 3
```

```
Range("ForeMod_1").Select
```

```
' Re-activation of screen update and instant calculation
```

```
With Application
```

```
.ScreenUpdating = True  
.Calculation = xlCalculationAutomatic  
.EnableEvents = True
```

```
End With
```

```
End Sub
```

Sub SRMLev()

```
' Step 7: Short Range Level, Short Range Trend, Long Range Level, Long Range Trend
```

```
' Sub executes procedures for Rules 29, 32, 40, 41,  
' 42, 67, 71, 76, 77, 78, 86, 87
```

```
' The above mentioned rules compose the remaining Reduced Rules excluding forecast blending.  
' The rule text from Ed Lusk's guidance is inserted above the rules.
```

```
' Disables screen updates and instant calculation  
' in order to improve performance and eliminate  
' annoying 'screen flickering'
```

```
With Application
```

```
.ScreenUpdating = False  
.Calculation = xlCalculationManual  
.EnableEvents = False
```

```
End With
```

```
CancStep = True  
LevelDiscont = False  
RecTreUnst = False
```

```
Range("SRMLev").Offset(5, 0) = "SRM: Level"
```

```
' The user form for this step lets the user identify level discontinuities and  
' instabilities in the recent trend
```

Step7_UsrFrm1.Show

If CancStep = True _
Then Exit Sub

Select Case LevelDiscont
Case Is = True
Step7String = "Lev. Discont.: Present; "
Case Is = False
Step7String = "Lev. Discont.: Not Present; "
End Select

Select Case RecTreUnst
Case Is = True
Step7String = Step7String & "Recent Trend: Unstable"
Case Is = False
Step7String = Step7String & "Recent Trend: Stable"
End Select

Range("SRMLev").Offset(4, 0) = Step7String

' SHORT RANGE LEVEL

'Rule 29: Level Discontinuities (Short Model Level)

'IF there is a level discontinuity, i.e., sort of a step change, in the series,

'THEN add 0,10 to the weight on the Random Walk and subtract it from the weight of the Holt Model.

'Rule 32: Changing Recent Trends (Short Model Level)

'IF there is an unstable recent Trend, THEN add 0,45 to the weight on Random Walk model and subtract

'0,15 from the Linear Regression Weigh and subtract 0,30 from the Holt Model Weight.

' Gets the current weights of the Short Range Level from the Excel sheet

SM_LR_Lvl = Range("ForeMod_2").Offset(24, 0)

SM_HM_Lvl = Range("ForeMod_2").Offset(25, 0)

SM_RW_Lvl = Range("ForeMod_2").Offset(26, 0)

' Rule 29 Level Discontinuities

Range("SRMLev").Offset(6, 0) = "Level"

Range("SRMLev").Offset(6, 0).Font.Bold = True

Range("SRMLev").Offset(7, 0) = "Discontinuities:"

Range("SRMLev").Offset(7, 0).Font.Bold = True

Range("SRMLev").Offset(8, 0).NumberFormat = "@"

Select Case LevelDiscont

Case Is = True

SM_HM_Lvl = SM_HM_Lvl - 0.1

SM_RW_Lvl = SM_RW_Lvl + 0.1

Range("SRMLev").Offset(8, 0) = "True"

Case Is = False

Range("SRMLev").Offset(8, 0) = "False"

End Select

' Rule 32 Unstable Recent Trend

Range("SRMLev").Offset(10, 0) = "Recent Trend:"

Range("SRMLev").Offset(10, 0).Font.Bold = True

Select Case RecTreUnst

Case Is = True

SM_LR_Lvl = SM_LR_Lvl - 0.15

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

```
SM_HM_Lvl = SM_HM_Lvl - 0.3
SM_RW_Lvl = SM_RW_Lvl + 0.45
Range("SRMLev").Offset(11, 0) = "Unstable"
Case Is = False
Range("SRMLev").Offset(11, 0) = "Stable"
End Select
```

' Re-insert weights of Short Range Level to the Excel sheet

```
Range("ForeMod_2").Offset(24, 0) = SM_LR_Lvl
Range("ForeMod_2").Offset(25, 0) = SM_HM_Lvl
Range("ForeMod_2").Offset(26, 0) = SM_RW_Lvl
```

' Changing basic trend

' Originally, the changing basic trend feature was first checked for in rule 33,
' a rule that is no longer incorporated in the reduced ruleset. The feature is still
' needed in several other rules, so here the identification of this feature is performed

' performs linear regression on first and second half of data
' and checks whether basic trend is changing, signs of trends differ

```
Set StepRange = Range("CLOutEL")
lastrow = Last(1, StepRange)
Datapoints = lastrow - 6
```

Select Case Datapoints

```
Case Is < 4
    Trendchange33 = False
Case Is >= 4
    dataodd33 = WorksheetFunction.Odd(Datapoints)
```

Select Case dataodd33

```
Case Is = False
    data33_1 = Datapoints / 2
    data33_2 = Datapoints / 2
Case Is = True
    data33_1 = (Datapoints / 2) - 0.5
    data33_2 = (Datapoints / 2) + 0.5
```

End Select

```
RgDef33_1_1 = Range("legend").Offset(6, 0).Address
RgDef33_1_2 = Range("legend").Offset(data33_1 + 5, 0).Address
RgDef33_1_3 = Range("OutEL").Offset(6, 0).Address
RgDef33_1_4 = Range("OutEL").Offset(data33_1 + 5, 0).Address
```

```
RgDef33_2_1 = Range("legend").Offset(data33_1 + 6, 0).Address
RgDef33_2_2 = Range("legend").Offset(data33_1 + data33_2 + 5, 0).Address
RgDef33_2_3 = Range("OutEL").Offset(data33_1 + 6, 0).Address
RgDef33_2_4 = Range("OutEL").Offset(data33_1 + data33_2 + 5, 0).Address
```

```
Trend33_1 = LinRegBeta(Range(RgDef33_1_1, RgDef33_1_2), Range(RgDef33_1_3, RgDef33_1_4))
Trend33_2 = LinRegBeta(Range(RgDef33_2_1, RgDef33_2_2), Range(RgDef33_2_3, RgDef33_2_4))
```

Select Case Trend33_1

```
Case Is > 0
    Select Case Trend33_2
        Case Is > 0
            Trendchange33 = False
        Case Is = 0
            Trendchange33 = True
```

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

```

        Case Is < 0
            Trendchange33 = True
        End Select
    Case Is = 0
        Select Case Trend33_2
            Case Is > 0
                Trendchange33 = True
            Case Is = 0
                Trendchange33 = False
            Case Is < 0
                Trendchange33 = True
        End Select
    Case Is < 0
        Select Case Trend33_2
            Case Is > 0
                Trendchange33 = True
            Case Is = 0
                Trendchange33 = True
            Case Is < 0
                Trendchange33 = False
        End Select
    End Select
End Select

' Range("SRMLev").Offset(25, 0) = "Changing Basic"
' Range("SRMLev").Offset(25, 0).Font.Bold = True
' Range("SRMLev").Offset(26, 0) = "Trend:"
' Range("SRMLev").Offset(26, 0).Font.Bold = True
'
' Select Case Trendchange33
'     Case Is = True
'         Range("SRMLev").Offset(27, 0) = "True"
'     Case Is = False
'         Range("SRMLev").Offset(27, 0) = "False"
' End Select

' SHORT RANGE TREND
'Rule 40: Causal Forces Unknown (Short Model Trend)
'IF the causal forces are unknown, THEN add 0,05 to the weight on the Random Walk
'and subtract it from that on the Linear regression trend estimate.
'Rule 41: Dissonance (Short Model Trend)
'IF the direction of the recent trend and the direction of the basic trend are not the same,
'OR if the trends agree with one another but differ from the causal forces,
'THEN add 0,15 to the weight on the Random Walk and subtract 0,05 from the Linear regression and 0,10 from the Holt
Model Weight.
'Rule 42: Inconsistent Trends (Short Model Trend)
'IF the direction of the basic trend and the direction of the recent trend are not the same,
'AND the basic trend is not changing, THEN add 0,20 to the weight on the Linear regression trend and subtract it from
Holt Model trend weight.

' Gets the current weights of the Short Range Trend from the Excel sheet
SM_LR_Trnd = Range("ForeMod_3").Offset(24, 0)
SM_HM_Trnd = Range("ForeMod_3").Offset(25, 0)
SM_RW_Trnd = Range("ForeMod_3").Offset(26, 0)

Range("SRMLev").Offset(13, 0) = "SRM: Trend"
Range("SRMLev").Offset(13, 0).Font.Bold = True

' Rule 40 Causal Forces Unknown

```

CausFor40 = "False"

Select Case Range("causfor").Offset(6, 0)

Case Is = "Unknown"

SM_LR_Trld = SM_LR_Trld - 0.05

SM_RW_Trld = SM_RW_Trld + 0.05

CausFor40 = "True"

End Select

Range("SRMLev").Offset(15, 0) = "Causal Forces"

Range("SRMLev").Offset(15, 0).Font.Bold = True

Range("SRMLev").Offset(16, 0) = "Unknown:"

Range("SRMLev").Offset(16, 0).Font.Bold = True

Range("SRMLev").Offset(17, 0).NumberFormat = "@"

Range("SRMLev").Offset(17, 0) = CausFor40

' Rule 41 Dissonance

Diss41 = False

Select Case Range("foremod_2").Offset(9, 0)

Case Is > 0

Select Case Range("foremod_2").Offset(15, 0)

Case Is > 0

Select Case Range("causfor").Offset(6, 0)

Case Is = "Growing"

Diss41 = False

Case Is = "Decaying"

Diss41 = True

Case Is = "Supporting"

Diss41 = False

Case Is = "Opposing"

Diss41 = True

Case Is = "Regressing"

Diss41 = False

Case Is = "Unknown"

Diss41 = False

End Select

Case Is = 0

Diss41 = True

Case Is < 0

Diss41 = True

End Select

Case Is = 0

Select Case Range("foremod_2").Offset(15, 0)

Case Is > 0

Diss41 = True

Case Is = 0

Select Case Range("causfor").Offset(6, 0)

Case Is = "Growing"

Diss41 = True

Case Is = "Decaying"

Diss41 = True

Case Is = "Supporting"

Diss41 = False

Case Is = "Opposing"

Diss41 = True

Case Is = "Regressing"

Diss41 = False

```
Case Is = "Unknown"
  Diss41 = False
End Select
Case Is < 0
  Diss41 = True
End Select
Case Is < 0
  Select Case Range("foremod_2").Offset(15, 0)
  Case Is > 0
    Diss41 = True
  Case Is = 0
    Diss41 = True
  Case Is < 0
    Select Case Range("causfor").Offset(6, 0)
    Case Is = "Growing"
      Diss41 = True
    Case Is = "Decaying"
      Diss41 = False
    Case Is = "Supporting"
      Diss41 = False
    Case Is = "Opposing"
      Diss41 = True
    Case Is = "Regressing"
      Diss41 = False
    Case Is = "Unknown"
      Diss41 = False
    End Select
  End Select
End Select

Range("SRMLev").Offset(19, 0) = "Dissonance:"
Range("SRMLev").Offset(19, 0).Font.Bold = True
Range("SRMLev").Offset(20, 0).NumberFormat = "@"

Select Case Diss41
Case Is = True
  SM_LR_Trđ = SM_LR_Trđ - 0.05
  SM_HM_Trđ = SM_HM_Trđ - 0.1
  SM_RW_Trđ = SM_RW_Trđ + 0.15
  Range("SRMLev").Offset(20, 0) = "True"
Case Is = False
  Range("SRMLev").Offset(20, 0) = "False"
End Select
```

' Rule 42 Inconsistent Trends

' compares basic and recent trend

```
Select Case Range("foremod_2").Offset(9, 0)
Case Is > 0
  Select Case Range("foremod_2").Offset(15, 0)
  Case Is > 0
    InconTrend42 = False
  Case Is = 0
    Select Case Trendchange33
    Case Is = True
      InconTrend42 = True
    Case Is = False
      InconTrend42 = False
    End Select
End Select
```



```
Case Is < 0
  Select Case Trendchange33
    Case Is = True
      InconTrend42 = True
    Case Is = False
      InconTrend42 = False
  End Select
End Select
Case Is = 0
Select Case Range("foremod_2").Offset(15, 0)
  Case Is > 0
    Select Case Trendchange33
      Case Is = True
        InconTrend42 = True
      Case Is = False
        InconTrend42 = False
    End Select
  Case Is = 0
    InconTrend42 = False
  Case Is < 0
    Select Case Trendchange33
      Case Is = True
        InconTrend42 = True
      Case Is = False
        InconTrend42 = False
    End Select
End Select
Case Is < 0
Select Case Range("foremod_2").Offset(15, 0)
  Case Is > 0
    Select Case Trendchange33
      Case Is = True
        InconTrend42 = True
      Case Is = False
        InconTrend42 = False
    End Select
  Case Is = 0
    Select Case Trendchange33
      Case Is = True
        InconTrend42 = True
      Case Is = False
        InconTrend42 = False
    End Select
  Case Is < 0
    InconTrend42 = False
End Select
End Select
Range("SRMLev").Offset(22, 0) = "Incons. Trends:"
Range("SRMLev").Offset(22, 0).Font.Bold = True
Range("SRMLev").Offset(23, 0).NumberFormat = "@"

Select Case InconTrend42
  Case Is = True
    SM_LR_Trđ = SM_LR_Trđ + 0.2
    SM_HM_Trđ = SM_HM_Trđ - 0.2
    Range("SRMLev").Offset(23, 0) = "True"
  Case Is = False
    Range("SRMLev").Offset(23, 0) = "False"
End Select
```

' Update Weights on Short Range Trend

```
Range("ForeMod_3").Offset(24, 0) = SM_LR_Trđ  
Range("ForeMod_3").Offset(25, 0) = SM_HM_Trđ  
Range("ForeMod_3").Offset(26, 0) = SM_RW_Trđ
```

' LONG RANGE LEVEL

```
'Rule 67: Level Discontinuities (Long Model Level)  
'IF there is a level discontinuity, THEN add 0,10 to the weight on the Random Walk  
'and subtract it from the level weight of the Holt Model.  
'Rule 71: Changing Recent Trends (Long Model Level)  
'IF there is an unstable recent trend, THEN add 0,63 to the level weight of the Random Walk  
'and subtract 0,21 from the Linear regression Level Weigh and subtract 0,42 from the Holt Model Level Weight.
```

```
LM_LR_Lvl = Range("ForeMod_2").Offset(29, 0)  
LM_HM_Lvl = Range("ForeMod_2").Offset(30, 0)  
LM_RW_Lvl = Range("ForeMod_2").Offset(31, 0)
```

```
Range("LRMLev").Offset(5, 0) = "LRM: Level"
```

' Rule 67 Level Discontinuities

```
Range("LRMLev").Offset(6, 0) = "Level"  
Range("LRMLev").Offset(6, 0).Font.Bold = True  
Range("LRMLev").Offset(7, 0) = "Discontinuities:"  
Range("LRMLev").Offset(7, 0).Font.Bold = True  
  
Range("LRMLev").Offset(8, 0).NumberFormat = "@"
```

Select Case LevelDiscont

```
Case Is = True  
    LM_HM_Lvl = LM_HM_Lvl - 0.1  
    LM_RW_Lvl = LM_RW_Lvl + 0.1  
    Range("LRMLev").Offset(8, 0) = "True"  
Case Is = False  
    Range("LRMLev").Offset(8, 0) = "False"  
End Select
```

' Rule 71 Unstable Recent Trend

```
Range("LRMLev").Offset(10, 0) = "Recent Trend:"  
Range("LRMLev").Offset(10, 0).Font.Bold = True
```

Select Case RecTreUnst

```
Case Is = True  
    LM_LR_Lvl = LM_LR_Lvl - 0.21  
    LM_HM_Lvl = LM_HM_Lvl - 0.42  
    LM_RW_Lvl = LM_RW_Lvl + 0.63  
    Range("LRMLev").Offset(11, 0) = "Unstable"  
Case Is = False  
    Range("LRMLev").Offset(11, 0) = "Stable"  
End Select
```

' Update Weights on Long Range Level

```
Range("ForeMod_2").Offset(29, 0) = LM_LR_Lvl  
Range("ForeMod_2").Offset(30, 0) = LM_HM_Lvl  
Range("ForeMod_2").Offset(31, 0) = LM_RW_Lvl
```

' LONG RANGE TREND

'Rule 76: Causal Forces Unknown (Long Model Trend)

'IF the causal forces are unknown, THEN add 0,10 to the weight on the Random Walk Model's Trend
'and subtract it from that on the Linear regression trend estimate.

'Rule 77: Dissonance (Long model Trend)

'IF the direction of the recent trend and the direction of the basic trend are not the same,

'OR if the trends agree with one another but differ from the casual forces, THEN add 0,15 to the
'trend weight on the Random Walk and subtract 0,05 from the Linear Regression and 0,10 from the Holt Model Weight.

'Rule 78: Inconsistent Trends (Long model Trend)

'IF the direction of the basic trend and the direction of the recent trend are not the same

'AND the Basic trend is not changing, THEN add 0,10 to the weight of the Linear regression trend and subtract it from the
Holt Model.

'Rule 86: Inconsistent Trends (Long model Trend)

'IF the directions of the recent and basic trends are not the same, THEN subtract 0,10 from

'the weight on Linear regression and add 0.033 to the Weight on the Holt model and 0.067 to the weight on the Random
Walk Model.

'Rule 87: Changing Basic Trend (Long model Trend)

'IF there is a changing basic trend, THEN add 0,24 to the Random Walk Trend weight and 0,06

'to the Holt Model's Trend weight and subtract 0,30 from the Linear regression's Trend weight.

LM_LR_Trnd = Range("ForeMod_3").Offset(29, 0)

LM_HM_Trnd = Range("ForeMod_3").Offset(30, 0)

LM_RW_Trnd = Range("ForeMod_3").Offset(31, 0)

Range("LRMLev").Offset(13, 0) = "LRM: Trend"

Range("LRMLev").Offset(13, 0).Font.Bold = True

' Rule 76 Causal Forces Unknown

CausFor40 = "False"

Select Case Range("causfor").Offset(6, 0)

Case Is = "Unknown"

LM_LR_Trnd = LM_LR_Trnd - 0.1

LM_RW_Trnd = LM_RW_Trnd + 0.1

CausFor40 = "True"

End Select

Range("LRMLev").Offset(15, 0) = "Causal Forces"

Range("LRMLev").Offset(15, 0).Font.Bold = True

Range("LRMLev").Offset(16, 0) = "Unknown:"

Range("LRMLev").Offset(16, 0).Font.Bold = True

Range("LRMLev").Offset(17, 0).NumberFormat = "@"

Range("LRMLev").Offset(17, 0) = CausFor40

' Rule 77 Dissonance

Range("LRMLev").Offset(19, 0) = "Dissonance:"

Range("LRMLev").Offset(19, 0).Font.Bold = True

Range("LRMLev").Offset(20, 0).NumberFormat = "@"

Select Case Diss41

Case Is = True

LM_LR_Trnd = LM_LR_Trnd - 0.05

LM_HM_Trnd = LM_HM_Trnd - 0.1

LM_RW_Trnd = LM_RW_Trnd + 0.15

Range("LRMLev").Offset(20, 0) = "True"

Case Is = False

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

```
Range("LRMLEv").Offset(20, 0) = "False"  
End Select
```

' Rule 78 Inconsistent Trends

```
Range("LRMLEv").Offset(22, 0) = "Incons. Trends:"  
Range("LRMLEv").Offset(22, 0).Font.Bold = True  
Range("LRMLEv").Offset(23, 0).NumberFormat = "@"
```

Select Case InconTrend42

```
Case Is = True  
    LM_LR_Trnd = LM_LR_Trnd + 0.1  
    LM_HM_Trnd = LM_HM_Trnd - 0.1  
    Range("LRMLEv").Offset(23, 0) = "True"  
Case Is = False  
    Range("LRMLEv").Offset(23, 0) = "False"  
End Select
```

' Rule 86 Direction of basic and recent trend not the same

```
Range("LRMLEv").Offset(25, 0) = "Trends Differ:"  
Range("LRMLEv").Offset(25, 0).Font.Bold = True  
Range("LRMLEv").Offset(26, 0).NumberFormat = "@"
```

Select Case Range("foremod_2").Offset(9, 0)

```
Case Is > 0  
    Select Case Range("foremod_2").Offset(15, 0)  
        Case Is > 0  
            InconTrd86 = False  
        Case Is = 0  
            InconTrd86 = True  
        Case Is < 0  
            InconTrd86 = True  
    End Select
```

```
Case Is = 0  
    Select Case Range("foremod_2").Offset(15, 0)  
        Case Is > 0  
            InconTrd86 = True  
        Case Is = 0  
            InconTrd86 = False  
        Case Is < 0  
            InconTrd86 = True  
    End Select
```

```
Case Is < 0  
    Select Case Range("foremod_2").Offset(15, 0)  
        Case Is > 0  
            InconTrd86 = True  
        Case Is = 0  
            InconTrd86 = True  
        Case Is < 0  
            InconTrd86 = False  
    End Select
```

End Select

Select Case InconTrd86

```
Case Is = True  
    LM_LR_Trnd = LM_LR_Trnd - 0.1  
    LM_HM_Trnd = LM_HM_Trnd + 0.033  
    LM_RW_Trnd = LM_RW_Trnd + 0.067  
    Range("LRMLEv").Offset(26, 0) = "True"
```

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

```
Case Is = False
  Range("LRMLev").Offset(26, 0) = "False"
End Select

' Rule 87 Changing Basic Trend

Range("LRMLev").Offset(28, 0) = "Basic Trend:"
Range("LRMLev").Offset(28, 0).Font.Bold = True

Select Case Trendchange33
  Case Is = True
    LM_LR_Trld = LM_LR_Trld - 0.3
    LM_HM_Trld = LM_HM_Trld + 0.06
    LM_RW_Trld = LM_RW_Trld + 0.24
    Range("LRMLev").Offset(29, 0) = "Changing"
  Case Is = False
    Range("LRMLev").Offset(29, 0) = "Not Changing"
End Select

' Update Weights on Long Range Trend

Range("ForeMod_3").Offset(29, 0) = LM_LR_Trld
Range("ForeMod_3").Offset(30, 0) = LM_HM_Trld
Range("ForeMod_3").Offset(31, 0) = LM_RW_Trld

' Creates Step 8: Period length of data, blending and length of
' forecasting horizon Button and assigns Step 8: Period length of data, blending and length of
' forecasting horizon Sub

Sheets(1).Activate

ActiveSheet.Shapes.AddShape(msoShapeRectangle, Range("Blend").Offset(1, 0).Left, Range("Blend").Offset(1, 0).Top,
53.25, 18).Select
  Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37
  Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "Step 8"
  With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 6).Font
    .NameComplexScript = "+mn-cs"
    .NameFarEast = "+mn-ea"
    .Fill.Visible = msoTrue
    .Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1
    .Fill.ForeColor.TintAndShade = 0
    .Fill.Transparency = 0
    .Fill.Solid
    .Size = 12
    .Name = "+mn-lt"
  End With
  Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter
  Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle
  Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue
  Selection.OnAction = "Steps.Blend"

  Selection.ShapeRange.IncrementLeft 21
  Selection.ShapeRange.IncrementTop 3

' Creates Step 8: Period length of data, blending and length of
' forecasting horizon Contextual Help

ActiveSheet.Shapes.AddShape(msoShapeOval, Range("Blend").Offset(2, 0).Left, Range("Blend").Offset(2, 0).Top, 20.25,
20.25).Select
```

```
Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37
Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "?"
  With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 1).Font
    .NameComplexScript = "+mn-cs"
    .NameFarEast = "+mn-ea"
    .Fill.Visible = msoTrue
    .Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1
    .Fill.ForeColor.TintAndShade = 0
    .Fill.Transparency = 0
    .Fill.Solid
    .Size = 12
    .Name = "+mn-lt"
  End With
Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter
Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle
Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue
Selection.OnAction = "LoadConHlp9"

Selection.ShapeRange.IncrementLeft 38.5
Selection.ShapeRange.IncrementTop 3
```

```
Range("ForeMod_1").Select
```

```
' Re-activation of screen update and instant calculation
```

```
With Application
```

```
.ScreenUpdating = True
.Calculation = xlCalculationAutomatic
.EnableEvents = True
```

```
End With
```

```
End Sub
```

Sub Blend()

```
' Step 8: Period length of data, blending and length of
' forecasting horizon
```

```
' Disables screen updates and instant calculation
' in order to improve performance and eliminate
' annoying 'screen flickering'
```

```
With Application
```

```
.ScreenUpdating = False
.Calculation = xlCalculationManual
.EnableEvents = False
```

```
End With
```

```
ThClr1 = 5
ThClr2 = 1
ThClr3 = 4
```

```
CancStep = True
```

```
' In the user form, the user is asked whether the data is annual, semi-annual
' quarterly, monthly or weekly.
Step8_UsrFrm1.Show
```

If CancStep = True _
Then Exit Sub

Range("blend").Offset(5, 0) = "Blending & Forecast. Horizon"

Range("blend").Offset(6, 0) = "Period Length:"

Range("Blend").Offset(6, 0).Font.Bold = True

Range("blend").Offset(7, 0) = Period

' Defines the number of periods/data points per year

Select Case Period

Case Is = "Annual"

PeriodPA = 1

Case Is = "Semi-Annual"

PeriodPA = 2

Case Is = "Quarterly"

PeriodPA = 4

Case Is = "Monthly"

PeriodPA = 12

Case Is = "Weekly"

PeriodPA = 52

End Select

' BLENDING

' The blending governs the composition of the final forecast (short- and long model)

' There are two factors: The blend period governs how long it takes to come from

' 100% short model to 100% long model.

' The blending method governs the shares of each model for the transition period

' (the transitions is not necessarily linear).

' The rules have not been modified over the years, i.e. they are taken from the 1992 Armstrong and Collopy paper.

' Rule 96 Blend Period

' 96. Blend Period. IF data are annual, THEN the blend period is 6. {It, is assumed that a six-year period is long enough for the causal forces to have had a significant impact for most series. }

' => Blend Period equals six years * number of periods p.a.

BlendPeriod = PeriodPA * 6

Range("Blend").Offset(9, 0) = "Blend Periods:"

Range("Blend").Offset(9, 0).Font.Bold = True

Range("Blend").Offset(10, 0).HorizontalAlignment = xlLeft

Range("Blend").Offset(10, 0) = BlendPeriod

' Rule 97, 98, 99 Choice of Blending Method

'97. Standard Blend. IF the trends from the short-range and long-range models are in the same direction. OR if the 'causal forces are unknown, THEN $L_h = 1 - \{(100/B) \times [(1 + B - h) / 100]\}$, where L_h is the percentage of the 'long-range model used in forecasting horizon h , and B is the blend period, the number of periods over the forecast 'horizon until the long-range model equals 100%. {This rule blends the two models gradually from 100% short-range 'model in horizon 1 to 100% long-range model in horizon B . B can exceed the forecast horizon. }

'98. Quick Blend. IF the short-range model direction conflicts with the long-range model direction AND the 'causal force direction is the same as the long-range model, THEN set the share of the long-range model to ' $L_h = \text{SUM}(x=1 \text{ to } h) / \text{SUM}(y=1 \text{ to } B)$ where h is the horizon and B is the number of periods over the forecast horizon 'until the long model reaches 100%. {When the causal forces agree with the longrange 'model direction and disagree with the short-range model, this moves the forecast more quickly to the 'long-range model. }

'99. Slow Blend. IF the short-range model direction conflicts with the long-range model direction AND the causal

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

'force direction is the same as the short-range model, THEN set the share of the long-range model to
'Lh = SUM (x=1 to h) of (1+B-x) / SUM (y=1 to B) where h is the horizon and B is the blend period. { This is the converse
of rule 98. }

```
Range("Blend").Offset(12, 0) = "Blending Method:"  
Range("Blend").Offset(12, 0).Font.Bold = True
```

```
Select Case Range("foremod_2").Offset(9, 0)  
  Case Is > 0  
    Select Case Range("foremod_2").Offset(15, 0)  
      Case Is > 0  
        BlendMethod = "Standard Blend"  
      Case Is = 0  
        Select Case Range("causfor").Offset(6, 0)  
          Case Is = "Growing"  
            BlendMethod = "Quick Blend"  
          Case Is = "Decaying"  
            BlendMethod = "Standard Blend"  
          Case Is = "Supporting"  
            BlendMethod = "Quick Blend"  
          Case Is = "Opposing"  
            BlendMethod = "Slow Blend"  
          Case Is = "Regressing"  
            BlendMethod = "Standard Blend"  
          Case Is = "Unknown"  
            BlendMethod = "Standard Blend"  
        End Select  
      Case Is < 0  
        Select Case Range("causfor").Offset(6, 0)  
          Case Is = "Growing"  
            BlendMethod = "Quick Blend"  
          Case Is = "Decaying"  
            BlendMethod = "Slow Blend"  
          Case Is = "Supporting"  
            BlendMethod = "Quick Blend"  
          Case Is = "Opposing"  
            BlendMethod = "Slow Blend"  
          Case Is = "Regressing"  
            BlendMethod = "Standard Blend"  
          Case Is = "Unknown"  
            BlendMethod = "Standard Blend"  
        End Select  
    End Select  
  Case Is = 0  
    Select Case Range("foremod_2").Offset(15, 0)  
      Case Is > 0  
        Select Case Range("causfor").Offset(6, 0)  
          Case Is = "Growing"  
            BlendMethod = "Slow Blend"  
          Case Is = "Decaying"  
            BlendMethod = "Standard Blend"  
          Case Is = "Supporting"  
            BlendMethod = "Quick Blend"  
          Case Is = "Opposing"  
            BlendMethod = "Slow Blend"  
          Case Is = "Regressing"  
            BlendMethod = "Standard Blend"  
          Case Is = "Unknown"  
            BlendMethod = "Standard Blend"  
        End Select  
    End Select
```



```
Case Is = 0
  BlendMethod = "Standard Blend"
Case Is < 0
  Select Case Range("causfor").Offset(6, 0)
    Case Is = "Growing"
      BlendMethod = "Standard Blend"
    Case Is = "Decaying"
      BlendMethod = "Slow Blend"
    Case Is = "Supporting"
      BlendMethod = "Quick Blend"
    Case Is = "Opposing"
      BlendMethod = "Slow Blend"
    Case Is = "Regressing"
      BlendMethod = "Standard Blend"
    Case Is = "Unknown"
      BlendMethod = "Standard Blend"
  End Select
End Select
Case Is < 0
  Select Case Range("foremod_2").Offset(15, 0)
    Case Is > 0
      Select Case Range("causfor").Offset(6, 0)
        Case Is = "Growing"
          BlendMethod = "Slow Blend"
        Case Is = "Decaying"
          BlendMethod = "Quick Blend"
        Case Is = "Supporting"
          BlendMethod = "Quick Blend"
        Case Is = "Opposing"
          BlendMethod = "Slow Blend"
        Case Is = "Regressing"
          BlendMethod = "Standard Blend"
        Case Is = "Unknown"
          BlendMethod = "Standard Blend"
      End Select
    Case Is = 0
      Select Case Range("causfor").Offset(6, 0)
        Case Is = "Growing"
          BlendMethod = "Standard Blend"
        Case Is = "Decaying"
          BlendMethod = "Quick Blend"
        Case Is = "Supporting"
          BlendMethod = "Quick Blend"
        Case Is = "Opposing"
          BlendMethod = "Slow Blend"
        Case Is = "Regressing"
          BlendMethod = "Standard Blend"
        Case Is = "Unknown"
          BlendMethod = "Standard Blend"
      End Select
    Case Is < 0
      BlendMethod = "Standard Blend"
  End Select
End Select

Range("Blend").Offset(13, 0) = BlendMethod

' Display of Forecasting Horizon

Range("Blend").Offset(15, 0) = "Forecast. Horizon:"
```

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

```
Range("Blend").Offset(15, 0).Font.Bold = True  
Range("Blend").Offset(16, 0) = ForeCastHorizon & " year(s)"
```

```
Range("Blend").Offset(18, 0) = "Forecast. Periods:"  
Range("Blend").Offset(18, 0).Font.Bold = True
```

```
ForecastPer = ForeCastHorizon * PeriodPA
```

```
Unusual48Str = Range("ManDatAdj").Offset(4, 0)  
If InStr(1, Unusual48Str, "Last observation unusual = True", vbTextCompare) _  
Then ForecastPer = ForecastPer + 1
```

```
Range("Blend").Offset(19, 0).HorizontalAlignment = xlLeft  
Range("Blend").Offset(19, 0) = ForecastPer
```

' Formats column CLRskThr

```
Range("RskThr").HorizontalAlignment = xlRight  
Range("RskThr").WrapText = True  
Range("RskThr") = "Risk Threshold"
```

```
With Range("RskThr").Borders(xlEdgeLeft)  
.LineStyle = xlContinuous  
.ThemeColor = ThClr1  
.TintAndShade = 0  
.Weight = xlMedium
```

End With

```
With Range("RskThr").Borders(xlEdgeTop)  
.LineStyle = xlContinuous  
.ThemeColor = ThClr1  
.TintAndShade = 0  
.Weight = xlMedium
```

End With

```
With Range("RskThr").Borders(xlEdgeBottom)  
.LineStyle = xlContinuous  
.ThemeColor = ThClr1  
.TintAndShade = 0  
.Weight = xlThin
```

End With

```
With Range("RskThr").Borders(xlEdgeRight)  
.LineStyle = xlContinuous  
.ThemeColor = ThClr1  
.TintAndShade = 0  
.Weight = xlMedium
```

End With

```
With Range("RskThr").Interior  
.Pattern = xlSolid  
.PatternColorIndex = xlAutomatic  
.ThemeColor = ThClr1  
.TintAndShade = 0  
.PatternTintAndShade = 0
```

End With

```
With Range("RskThr").Font  
.ThemeColor = ThClr2  
.TintAndShade = 0
```

End With

```
With Range("RskThr").Interior  
.Pattern = xlPatternLinearGradient  
.Gradient.Degree = 45
```

```
.Gradient.ColorStops.Clear  
End With  
With Range("RskThr").Interior.Gradient.ColorStops.Add(0)  
    .ThemeColor = 1  
    .TintAndShade = 0  
End With  
With Range("RskThr").Interior.Gradient.ColorStops.Add(1)  
    .ThemeColor = ThClr3  
    .TintAndShade = 0  
End With
```

```
Range(Range("RskThr").Offset(1, 0), Range("RskThr").Offset(31, 0)).Select  
With Selection.Borders(xlEdgeLeft)  
    .LineStyle = xlContinuous  
    .ThemeColor = ThClr1  
    .TintAndShade = 0  
    .Weight = xlMedium  
End With  
With Selection.Borders(xlEdgeTop)  
    .LineStyle = xlContinuous  
    .ThemeColor = ThClr1  
    .TintAndShade = 0  
    .Weight = xlThin  
End With  
With Selection.Borders(xlEdgeBottom)  
    .LineStyle = xlContinuous  
    .ThemeColor = ThClr1  
    .TintAndShade = 0  
    .Weight = xlMedium  
End With  
With Selection.Borders(xlEdgeRight)  
    .LineStyle = xlContinuous  
    .ThemeColor = ThClr1  
    .TintAndShade = 0  
    .Weight = xlMedium  
End With  
With Selection.Borders(xlInsideVertical)  
    .LineStyle = xlContinuous  
    .ThemeColor = ThClr1  
    .TintAndShade = 0  
    .Weight = xlThin  
End With  
With Selection.Borders(xlInsideHorizontal)  
    .LineStyle = xlContinuous  
    .ThemeColor = ThClr1  
    .TintAndShade = 0  
    .Weight = xlThin  
End With
```

' Creates Step 9: Risk Threshold Button and assigns Step 9: Risk Threshold Sub

```
Sheets(1).Activate
```

```
ActiveSheet.Shapes.AddShape(msoShapeRectangle, Range("RskThr").Offset(1, 0).Left, Range("RskThr").Offset(1,  
0).Top, 53.25, 18).Select  
Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37  
Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "Step 9"  
With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 6).Font  
    .NameComplexScript = "+mn-cs"
```

```
.NameFarEast = "+mn-ea"  
.Fill.Visible = msoTrue  
.Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1  
.Fill.ForeColor.TintAndShade = 0  
.Fill.Transparency = 0  
.Fill.Solid  
.Size = 12  
.Name = "+mn-lt"  
End With  
Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter  
Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle  
Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue  
Selection.OnAction = "Steps.RskThr"
```

```
Selection.ShapeRange.IncrementLeft 21  
Selection.ShapeRange.IncrementTop 3
```

' Creates RskThr Contextual Help

```
ActiveSheet.Shapes.AddShape(msoShapeOval, Range("RskThr").Offset(2, 0).Left, Range("RskThr").Offset(2, 0).Top,  
20.25, 20.25).Select
```

```
Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37  
Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "?"  
With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 1).Font  
.NameComplexScript = "+mn-cs"  
.NameFarEast = "+mn-ea"  
.Fill.Visible = msoTrue  
.Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1  
.Fill.ForeColor.TintAndShade = 0  
.Fill.Transparency = 0  
.Fill.Solid  
.Size = 12  
.Name = "+mn-lt"  
End With  
Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter  
Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle  
Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue  
Selection.OnAction = "LoadConHlp10"
```

```
Selection.ShapeRange.IncrementLeft 38.5  
Selection.ShapeRange.IncrementTop 3
```

```
Range("RskThr").Select
```

' Re-activation of screen update and instant calculation

```
With Application  
.ScreenUpdating = True  
.Calculation = xlCalculationAutomatic  
.EnableEvents = True  
End With
```

End Sub

Sub RskThr()

' Step 9: Specifies the Method by which the Risk Threshold of the analytical procedures

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

' forecast is calculated

' Disables screen updates and instant calculation
' in order to improve performance and eliminate
' annoying 'screen flickering'

With Application

.ScreenUpdating = False
.Calculation = xlCalculationManual
.EnableEvents = False

End With

ThClr1 = 5
ThClr2 = 1
ThClr3 = 4

CancStep = True

' In this form, the user can choose between three types of risk threshold determination
' (the risk threshold is the maximum deviation from the forecast, the actual data is
' allowed to have without triggering an 'increased risk' state)
' The three options are
' - no threshold (if the user does not want the threshold level to be determined at this point)
' - professional judgment (user sets threshold him-/herself)
' - AAM 5210 (user follows the Deloitte guidance, meaning the threshold is determined according to
' a decision tree. this does not apply to performance ratios)

Step9_UsrFrm1.Show

If CancStep = True _
 Then Exit Sub

Range("RskThr").Offset(5, 0) = "Risk Threshold"

Range("RskThr").Offset(6, 0) = "Threshold Method:"
Range("RskThr").Offset(6, 0).Font.Bold = True
Range("RskThr").Offset(7, 0) = Method

Select Case Method

 Case Is = "No Threshold"
 Case Is = "AAM 5210"

' The following us an excerpt from the Deloitte auditing guidance AAM 5210

' Theshold level

' Risk: not significant
' relying on controls
' low extent of testing
' lower of: 25% PDGA or 90% PPM
' normal extent of testing
' lower of: 20% PDGA or 90% PPM
' not relying on controls
' lower of: 15% PDGA or 45% PPM
' significant risk
' lower of: 15% PDGA or 45% PPM

' where PDGA is percentage of disaggregated recorded amount
' and PPM is percentage of performance materiality

Range("RskThr").Offset(9, 0) = "Risk of Material"
Range("RskThr").Offset(9, 0).Font.Bold = True
Range("RskThr").Offset(10, 0) = "Misstatement:"

```

Range("RskThr").Offset(10, 0).Font.Bold = True
Range("RskThr").Offset(11, 0) = MisstRisk
Select Case MisstRisk
  Case Is = "Not Significant"
    Range("RskThr").Offset(13, 0) = "Effectiveness of"
    Range("RskThr").Offset(13, 0).Font.Bold = True
    Range("RskThr").Offset(14, 0) = "Controls:"
    Range("RskThr").Offset(14, 0).Font.Bold = True
    Range("RskThr").Offset(15, 0) = ControlEffect
  Select Case ControlEffect
    Case Is = "Reliable"
      Range("RskThr").Offset(17, 0) = "Extend of"
      Range("RskThr").Offset(17, 0).Font.Bold = True
      Range("RskThr").Offset(18, 0) = "Testing necessary:"
      Range("RskThr").Offset(18, 0).Font.Bold = True
      Range("RskThr").Offset(19, 0) = Testing
      Range("RskThr").Offset(21, 0) = "Performance"
      Range("RskThr").Offset(21, 0).Font.Bold = True
      Range("RskThr").Offset(22, 0) = "Materiality:"
      Range("RskThr").Offset(22, 0).Font.Bold = True
      Range("RskThr").Offset(23, 0) = PerfMat
      Select Case Testing
        Case Is = "Normal"
          PerRecAm = 0.2
          PerPerMat = 0.9
        Case Is = "Low"
          PerRecAm = 0.25
          PerPerMat = 0.9
      End Select
    Case Is = "Not Reliable"
      Range("RskThr").Offset(17, 0) = "Performance"
      Range("RskThr").Offset(17, 0).Font.Bold = True
      Range("RskThr").Offset(18, 0) = "Materiality:"
      Range("RskThr").Offset(18, 0).Font.Bold = True
      Range("RskThr").Offset(19, 0) = PerfMat
      PerRecAm = 0.15
      PerPerMat = 0.45
    End Select
  Case Is = "Significant"
    Range("RskThr").Offset(13, 0) = "Performance"
    Range("RskThr").Offset(13, 0).Font.Bold = True
    Range("RskThr").Offset(14, 0) = "Materiality:"
    Range("RskThr").Offset(14, 0).Font.Bold = True
    Range("RskThr").Offset(15, 0) = PerfMat
    PerRecAm = 0.15
    PerPerMat = 0.45
  End Select
  Case Is = "Professional Judg."
End Select

' The recorded amount is set to the value of the last observation
' the performance materiality has been entered in the user form
RecAmount = Range("ManDatAdj").Offset(5, 0).End(xlDown)
TrePerfMat = PerfMat * PerPerMat
TreRecAmount = RecAmount * PerRecAm

Select Case Method
  Case Is = "No Threshold"
    Threshold = "N/A"
  Case Is = "AAM 5210"

```

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

```
' Determined the smaller of PDGA and PPM
  Select Case TrePerfMat
    Case Is > TreRecAmount
      Threshold = TreRecAmount
    Case Is = TreRecAmount
      Threshold = TreRecAmount
    Case Is < TreRecAmount
      Threshold = TrePerfMat
  End Select
' The professional judgment threshold is entered in the user form if applicable
  Case Is = "Professional Judg."
    Threshold = RisThrProf
  End Select

Range("RskThr").Offset(25, 0) = "Risk Threshold:"
Range("RskThr").Offset(25, 0).Font.Bold = True
Range("RskThr").Offset(26, 0) = Threshold

' Formats column Forecast_1:forecast_8

Datapoints = Range(Range("ManDatAdj").Offset(6, 0), Range("ManDatAdj").Offset(6, 0).End(xlDown)).Count

Select Case Range("blend").Offset(19, 0) + Datapoints
  Case Is > 13
    RowsForecast = 5 + Range("blend").Offset(19, 0) + Datapoints
  Case Is <= 13
    RowsForecast = 5 + 13
End Select

Range("Forecast_1").HorizontalAlignment = xlRight
Range("Forecast_1").WrapText = True
Range("Forecast_1") = "AP Forecast"

With Range("Forecast_1").Borders(xlEdgeLeft)
  .LineStyle = xlContinuous
  .ThemeColor = ThClr1
  .TintAndShade = 0
  .Weight = xlMedium
End With
With Range("Forecast_1").Borders(xlEdgeTop)
  .LineStyle = xlContinuous
  .ThemeColor = ThClr1
  .TintAndShade = 0
  .Weight = xlMedium
End With
With Range("Forecast_1").Borders(xlEdgeBottom)
  .LineStyle = xlContinuous
  .ThemeColor = ThClr1
  .TintAndShade = 0
  .Weight = xlThin
End With
With Range("Forecast_1").Borders(xlEdgeRight)
  .LineStyle = xlContinuous
  .ThemeColor = ThClr1
  .TintAndShade = 0
  .Weight = xlMedium
End With

With Range("Forecast_1").Interior
  .Pattern = xlSolid
```

```
.PatternColorIndex = xlAutomatic
.ThemeColor = ThClr1
.TintAndShade = 0
.PatternTintAndShade = 0
End With
With Range("Forecast_1").Font
.ThemeColor = ThClr2
.TintAndShade = 0
End With
With Range("Forecast_1").Interior
.Pattern = xlPatternLinearGradient
.Gradient.Degree = 45
.Gradient.ColorStops.Clear
End With
With Range("Forecast_1").Interior.Gradient.ColorStops.Add(0)
.ThemeColor = 1
.TintAndShade = 0
End With
With Range("Forecast_1").Interior.Gradient.ColorStops.Add(1)
.ThemeColor = ThClr3
.TintAndShade = 0
End With

Range(Range("Forecast_1").Offset(1, 0), Range("forecast_8").Offset(RowsForecast, 0)).Select
With Selection.Borders(xlEdgeLeft)
.LineStyle = xlContinuous
.ThemeColor = ThClr1
.TintAndShade = 0
.Weight = xlMedium
End With
With Selection.Borders(xlEdgeTop)
.LineStyle = xlContinuous
.ThemeColor = ThClr1
.TintAndShade = 0
.Weight = xlThin
End With
With Selection.Borders(xlEdgeBottom)
.LineStyle = xlContinuous
.ThemeColor = ThClr1
.TintAndShade = 0
.Weight = xlMedium
End With
With Selection.Borders(xlEdgeRight)
.LineStyle = xlContinuous
.ThemeColor = ThClr1
.TintAndShade = 0
.Weight = xlMedium
End With
With Selection.Borders(xlInsideVertical)
.LineStyle = xlContinuous
.ThemeColor = ThClr1
.TintAndShade = 0
.Weight = xlThin
End With
With Selection.Borders(xlInsideHorizontal)
.LineStyle = xlContinuous
.ThemeColor = ThClr1
.TintAndShade = 0
.Weight = xlThin
```


End With

' Creates Step 10: Forecast button and assigns Step 10: Forecast Sub

Sheets(1).Activate

ActiveSheet.Shapes.AddShape(msoShapeRectangle, Range("Forecast_1").Offset(1, 0).Left, Range("Forecast_1").Offset(1, 0).Top, 53.25, 18).Select

```
Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37
Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "Step 10"
With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 7).Font
.NameComplexScript = "+mn-cs"
.NameFarEast = "+mn-ea"
.Fill.Visible = msoTrue
.Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1
.Fill.ForeColor.TintAndShade = 0
.Fill.Transparency = 0
.Fill.Solid
.Size = 12
.Name = "+mn-lt"
```

End With

```
Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter
Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle
Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue
Selection.OnAction = "Steps.Forecast"
```

Selection.ShapeRange.IncrementLeft 21

Selection.ShapeRange.IncrementTop 3

' Creates Step 10: Forecast Contextual Help

ActiveSheet.Shapes.AddShape(msoShapeOval, Range("Forecast_1").Offset(2, 0).Left, Range("Forecast_1").Offset(2, 0).Top, 20.25, 20.25).Select

```
Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37
Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "?"
With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 1).Font
.NameComplexScript = "+mn-cs"
.NameFarEast = "+mn-ea"
.Fill.Visible = msoTrue
.Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1
.Fill.ForeColor.TintAndShade = 0
.Fill.Transparency = 0
.Fill.Solid
.Size = 12
.Name = "+mn-lt"
```

End With

```
Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter
Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle
Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue
Selection.OnAction = "LoadConHlp11"
```

Selection.ShapeRange.IncrementLeft 38.5

Selection.ShapeRange.IncrementTop 3

Range("forecast_1").Select

' Re-activation of screen update and instant calculation

With Application

.ScreenUpdating = True

```
.Calculation = xlCalculationAutomatic
.EnableEvents = True
End With

End Sub
```

Sub Forecast()

```
' Step 10: Forecast calculates:
' - The Short Model Level and Trend
' - The Long Model Level and Trend
' - The Blending Factors
' - The Blended Forecasts
' - The Risk Threshold around the Forecast
```

```
' Disables screen updates and instant calculation
' in order to improve performance and eliminate
' annoying 'screen flickering'
```

With Application

```
.ScreenUpdating = False
.Calculation = xlCalculationManual
.EnableEvents = False
End With
```

```
Range("Forecast_1").Offset(5, 0) = "SRM & LRM Parameters"
Range("Forecast_2").Offset(5, 0) = "Data / Forecast Period"
Range("Forecast_3").Offset(5, 0) = "Data (Step 4)"
Range("forecast_4").Offset(5, 0) = "Lower Bound Thr. High Risk"
Range("forecast_4").Offset(5, 0).Interior.color = RGB(255, 229, 229)
Range("forecast_5").Offset(5, 0) = "Lower Bound Threshold"
Range("forecast_5").Offset(5, 0).Interior.color = RGB(255, 255, 193)
Range("forecast_6").Offset(5, 0) = "Forecast"
Range("forecast_7").Offset(5, 0) = "Upper Bound Threshold"
Range("forecast_7").Offset(5, 0).Interior.color = RGB(255, 255, 193)
Range("forecast_8").Offset(5, 0) = "Upper Bound Thr. High Risk"
Range("forecast_8").Offset(5, 0).Interior.color = RGB(255, 229, 229)
' Collects Level and Trend for LinReg, Holt and RW
```

```
LinRegLevel = Range("foremod_2").Offset(8, 0)
LinRegTrend = Range("foremod_2").Offset(9, 0)
HoltLevel = Range("foremod_2").Offset(14, 0)
HoltTrend = Range("foremod_2").Offset(15, 0)
RandomWalkLevel = Range("foremod_2").Offset(18, 0)
RandomWalkTrend = Range("foremod_2").Offset(19, 0)
```

```
' Collects the weights of Short and Long Model Level and Trends
```

```
SM_LR_Lvl = Range("ForeMod_2").Offset(24, 0)
SM_HM_Lvl = Range("ForeMod_2").Offset(25, 0)
SM_RW_Lvl = Range("ForeMod_2").Offset(26, 0)
```

```
SM_LR_Trnd = Range("ForeMod_3").Offset(24, 0)
SM_HM_Trnd = Range("ForeMod_3").Offset(25, 0)
SM_RW_Trnd = Range("ForeMod_3").Offset(26, 0)
```

```
LM_LR_Lvl = Range("ForeMod_2").Offset(29, 0)
LM_HM_Lvl = Range("ForeMod_2").Offset(30, 0)
LM_RW_Lvl = Range("ForeMod_2").Offset(31, 0)
```

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

LM_LR_Trnd = Range("ForeMod_3").Offset(29, 0)
LM_HM_Trnd = Range("ForeMod_3").Offset(30, 0)
LM_RW_Trnd = Range("ForeMod_3").Offset(31, 0)

' Calculates Short Model Level
' THE CALCULATION OF THE SHORT MODEL LEVEL AND TREND ARE BASED ON A VERY
' CRUCIAL ASSUMPTION: THAT NO ACTUAL HOLT MODEL FORECASTING IS PERFORMED BUT THAT
' THE CUURRENT LEVEL AND TREND (HOLT MODEL COMPONENTS) ARE TAKEN AS CONSTANTS AT THE
' LAST DATA POINT. TBD WITH ED!!!!
ShortModelLevel = LinRegLevel * SM_LR_Lvl + HoltLevel * SM_HM_Lvl + RandomWalkLevel * SM_RW_Lvl

Range("Forecast_1").Offset(6, 0) = "SRM Level:"
Range("Forecast_1").Offset(6, 0).Font.Bold = True
Range("Forecast_1").Offset(7, 0) = ShortModelLevel

' Calculates Short Model Trend
ShortModelTrend = LinRegTrend * SM_LR_Trnd + HoltTrend * SM_HM_Trnd + RandomWalkTrend * SM_RW_Trnd

Range("Forecast_1").Offset(8, 0) = "SRM Trend:"
Range("Forecast_1").Offset(8, 0).Font.Bold = True
Range("Forecast_1").Offset(9, 0) = ShortModelTrend

' Calculates Long Model Level
LongModelLevel = LinRegLevel * LM_LR_Lvl + HoltLevel * LM_HM_Lvl + RandomWalkLevel * LM_RW_Lvl

Range("Forecast_1").Offset(11, 0) = "LRM Level:"
Range("Forecast_1").Offset(11, 0).Font.Bold = True
Range("Forecast_1").Offset(12, 0) = LongModelLevel

' Calculates Long Model Trend
LongModelTrend = LinRegTrend * LM_LR_Trnd + HoltTrend * LM_HM_Trnd + RandomWalkTrend * LM_RW_Trnd

Range("Forecast_1").Offset(13, 0) = "LRM Trend:"
Range("Forecast_1").Offset(13, 0).Font.Bold = True
Range("Forecast_1").Offset(14, 0) = LongModelTrend

' Enters Forecasting Period Numbers

ForecastPer = Range("blend").Offset(19, 0)
Datapoints = Range(Range("ManDatAdj").Offset(6, 0), Range("ManDatAdj").Offset(6, 0).End(xlDown)).Count

' Labels data points periods

For FCount = 1 To Datapoints
Range("Forecast_2").Offset(5 + FCount, 0) = FCount
Next FCount

' Labels forecasting periods

For FCount = 1 To ForecastPer
Range("Forecast_2").Offset(5 + Datapoints + FCount, 0) = Datapoints + FCount
Next FCount

Range(Range("Forecast_2").Offset(5 + Datapoints + 1, 0), Range("Forecast_2").Offset(5 + Datapoints + ForecastPer, 0)).Font.Bold = True

' Carries over Data

' This data is taken from the step BEFORE ANY FUNCTIONAL FORM DECISION AND BEFORE ANY AUTOMATIC
' OUTLIER ELIMINATION. THIS IS FOR ILLUSTRATIONAL PURPOSES ONLY. THERE ARE NO ACTUAL
CALCULATIONS

' MADE ON BASIS OF THIS DATA.

For FCount = 1 To Datapoints

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

```
Range("Forecast_3").Offset(5 + FCount, 0) = Range("ManDatAdj").Offset(5 + FCount, 0)
Next FCount
```

```
' Short Range Model Forecast
ReDim SRMForecasts(1 To ForecastPer)
```

```
SRMForecasts(1) = ShortModelLevel + ShortModelTrend
```

```
For FCount = 2 To ForecastPer
```

```
SRMForecasts(FCount) = SRMForecasts(FCount - 1) + ShortModelTrend
Next FCount
```

```
' Long Range Model Forecasts
ReDim LRMForecasts(1 To ForecastPer)
```

```
LRMForecasts(1) = LongModelLevel + LongModelTrend
```

```
For FCount = 2 To ForecastPer
```

```
LRMForecasts(FCount) = LRMForecasts(FCount - 1) + LongModelTrend
Next FCount
```

```
' Calculates Blending Factors
```

```
' Based on the Armstrong and Collopy 1992 paper, it is assumed that the blending period is 6 YEARS
```

```
' i.e. 6 years * periods per year
```

```
' Rule 97, 98, 99 Choice of Blending Method
```

```
'97. Standard Blend. IF the trends from the short-range and long-range models are in the same direction. OR if the
'causal forces are unknown, THEN  $L_h = 1 - \{(100/B) \times [(1 + B - h) / 100]\}$ , where  $L_h$  is the percentage of the
'long-range model used in forecasting horizon  $h$ , and  $B$  is the blend period, the number of periods over the forecast
'horizon until the long-range model equals 100%. {This rule blends the two models gradually from 100% short-range
'model in horizon 1 to 100% long-range model in horizon  $B$ .  $B$  can exceed the forecast horizon.}
```

```
'98. Quick Blend. IF the short-range model direction conflicts with the long-range model direction AND the
'causal force direction is the same as the long-range model, THEN set the share of the long-range model to
' $L_h = \text{SUM}(x=1 \text{ to } h) / \text{SUM}(y=1 \text{ to } B)$  where  $h$  is the horizon and  $B$  is the number of periods over the forecast horizon
'until the long model reaches 100%. {When the causal forces agree with the longrange
'model direction and disagree with the short-range model, this moves the forecast more quickly to the
'long-range model.}
```

```
'99. Slow Blend. IF the short-range model direction conflicts with the long-range model direction AND the causal
'force direction is the same as the short-range model, THEN set the share of the long-range model to
' $L_h = \text{SUM}(x=1 \text{ to } h) \text{ of } (1+B-x) / \text{SUM}(y=1 \text{ to } B)$  where  $h$  is the horizon and  $B$  is the blend period. {This is the converse
of rule 98.}
```

```
' The applicable blending period has been identified in step 8. Here, the actual blending factors are calculated
```

```
BlendPeriod = Range("blend").Offset(10, 0)
ReDim BlendFactors(1 To BlendPeriod)
```

```
Select Case Range("blend").Offset(13, 0)
```

```
Case Is = "Standard Blend"
```

```
' Rule 97 Standard Blend
```

```
Select Case BlendPeriod
```

```
Case Is > ForecastPer
```

```
For FCount = 1 To ForecastPer
```

```
BlendFactors(FCount) = 1 - (1 + BlendPeriod - FCount) / BlendPeriod
```

```
Next FCount
```

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

```
Case Is = ForecastPer
  For FCount = 1 To ForecastPer
    BlendFactors(FCount) = 1 - (1 + BlendPeriod - FCount) / BlendPeriod
  Next FCount
```

```
Case Is < ForecastPer
  ReDim BlendFactors(1 To ForecastPer)

  For FCount = 1 To BlendPeriod
    BlendFactors(FCount) = 1 - (1 + BlendPeriod - FCount) / BlendPeriod
  Next FCount
```

```
  For FCount = BlendPeriod + 1 To ForecastPer
    BlendFactors(FCount) = 1
  Next FCount
```

End Select

```
Case Is = "Quick Blend"
' Rule 98 Quick Blend
ReDim SumForecast98(1 To ForecastPer)
```

```
  For FCount = 1 To BlendPeriod
    SumBlendPeriods = SumBlendPeriods + FCount
  Next FCount
```

```
  SumForecast98(1) = 1
  For FCount = 2 To ForecastPer
    SumForecast98(FCount) = SumForecast98(FCount - 1) + FCount
  Next FCount
```

Select Case BlendPeriod

```
Case Is > ForecastPer
  For FCount = 1 To ForecastPer
    BlendFactors(FCount) = SumForecast98(FCount) / SumBlendPeriods
  Next FCount
```

```
Case Is = ForecastPer
  For FCount = 1 To ForecastPer
    BlendFactors(FCount) = SumForecast98(FCount) / SumBlendPeriods
  Next FCount
```

Case Is < ForecastPer

```
  For FCount = 1 To BlendPeriod
    BlendFactors(FCount) = SumForecast98(FCount) / SumBlendPeriods
  Next FCount
```

```
  For FCount = BlendPeriod + 1 To ForecastPer
    BlendFactors(FCount) = 1
  Next FCount
```

End Select

```
Case Is = "Slow Blend"
' Rule 99 Slow Blend
ReDim SumForecast99(1 To ForecastPer)
```

```
  For FCount = 1 To BlendPeriod
    SumBlendPeriods = SumBlendPeriods + FCount
  Next FCount
```

```
SumForecast99(1) = BlendPeriod
For FCount = 2 To ForecastPer
    SumForecast99(FCount) = SumForecast99(FCount - 1) + (1 + BlendPeriod - FCount)
Next FCount
```

```
Select Case BlendPeriod
Case Is > ForecastPer
```

```
    For FCount = 1 To ForecastPer
        BlendFactors(FCount) = SumForecast98(FCount) / SumBlendPeriods
    Next FCount
```

```
Case Is = ForecastPer
```

```
    For FCount = 1 To ForecastPer
        BlendFactors(FCount) = SumForecast98(FCount) / SumBlendPeriods
    Next FCount
```

```
Case Is < ForecastPer
```

```
    For FCount = 1 To BlendPeriod
        BlendFactors(FCount) = SumForecast98(FCount) / SumBlendPeriods
    Next FCount
```

```
    For FCount = BlendPeriod + 1 To ForecastPer
        BlendFactors(FCount) = 1
    Next FCount
```

```
End Select
```

```
End Select
```

- ' Calculates Final Forecasts
- ' The SRM Forecasts are multiplied with 1-Blendfactor for the period
- ' The Forecasts are multiplied with Blendfactor for the period

```
ReDim FinalForecasts(1 To ForecastPer)
```

```
    For FCount = 1 To ForecastPer
        FinalForecasts(FCount) = (1 - BlendFactors(FCount)) * SRMForecasts(FCount) + BlendFactors(FCount) *
LRMForecasts(FCount)
    Next FCount
```

- ' In case 'multiplicative functional form' was chosen,
- ' the results are transformed into the old data format by applying the Excel exponential function
- ' else, nothing happens.

```
' Reads out the functional form
FFormStr = Range("fform").Offset(4, 0)
If InStr(1, FFormStr, "Functional form: Multiplicative", vbTextCompare) Then FFormMul = True
```

```
Select Case FFormMul
Case Is = False
Case Is = True
    For FCount = 1 To ForecastPer
        FinalForecasts(FCount) = Exp(FinalForecasts(FCount))
    Next FCount
End Select
```

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

```
' The final forecasts are displayed after the data
  For FCount = 1 To ForecastPer
    Range("forecast_6").Offset(FCount + Datapoints + 5, 0) = FinalForecasts(FCount)
  Next FCount

' Calculates Boundaries

ReDim LowBounds(1 To ForecastPer)
ReDim UppBounds(1 To ForecastPer)
ReDim LowBoundsHR(1 To ForecastPer)
ReDim UppBoundsHR(1 To ForecastPer)

' Reads out the value of the threshold
Threshold = Range("RskThr").Offset(26, 0)

Select Case Threshold
' In case no threshold has been defined, these fields remain empty
Case Is = "N/A"
  For FCount = 1 To ForecastPer
    Range("forecast_4").Offset(FCount + Datapoints + 5, 0) = ""
    Range("forecast_5").Offset(FCount + Datapoints + 5, 0) = ""
    Range("forecast_7").Offset(FCount + Datapoints + 5, 0) = ""
    Range("forecast_8").Offset(FCount + Datapoints + 5, 0) = ""
  Next FCount
' Else, the boundaries of the risk-zones are calculated by adding/substracting 1x the risk threshold PER YEAR
' to the forecast for 'elevated risk' and 2x for strongly elevated risk
Case Is <> "N/A"
  Select Case Period
  Case Is = "Annual"
    For FCount = 1 To ForecastPer
      LowBounds(FCount) = FinalForecasts(FCount) - (FCount * Threshold)
      UppBounds(FCount) = FinalForecasts(FCount) + (FCount * Threshold)
      LowBoundsHR(FCount) = FinalForecasts(FCount) - (FCount * 2 * Threshold)
      UppBoundsHR(FCount) = FinalForecasts(FCount) + (FCount * 2 * Threshold)

      Range("forecast_4").Offset(FCount + Datapoints + 5, 0) = LowBoundsHR(FCount)
      Range("forecast_5").Offset(FCount + Datapoints + 5, 0) = LowBounds(FCount)
      Range("forecast_7").Offset(FCount + Datapoints + 5, 0) = UppBounds(FCount)
      Range("forecast_8").Offset(FCount + Datapoints + 5, 0) = UppBoundsHR(FCount)
    Next FCount
  Case Is = "Semi-Annual"
    For FCount = 1 To ForecastPer
      LowBounds(FCount) = FinalForecasts(FCount) - (FCount * Threshold / 2)
      UppBounds(FCount) = FinalForecasts(FCount) + (FCount * Threshold / 2)
      LowBoundsHR(FCount) = FinalForecasts(FCount) - (FCount * 2 * Threshold / 2)
      UppBoundsHR(FCount) = FinalForecasts(FCount) + (FCount * 2 * Threshold / 2)

      Range("forecast_4").Offset(FCount + Datapoints + 5, 0) = LowBoundsHR(FCount)
      Range("forecast_5").Offset(FCount + Datapoints + 5, 0) = LowBounds(FCount)
      Range("forecast_7").Offset(FCount + Datapoints + 5, 0) = UppBounds(FCount)
      Range("forecast_8").Offset(FCount + Datapoints + 5, 0) = UppBoundsHR(FCount)
    Next FCount
  Case Is = "Quarterly"
    For FCount = 1 To ForecastPer
      LowBounds(FCount) = FinalForecasts(FCount) - (FCount * Threshold / 4)
      UppBounds(FCount) = FinalForecasts(FCount) + (FCount * Threshold / 4)
      LowBoundsHR(FCount) = FinalForecasts(FCount) - (FCount * 2 * Threshold / 4)
      UppBoundsHR(FCount) = FinalForecasts(FCount) + (FCount * 2 * Threshold / 4)

      Range("forecast_4").Offset(FCount + Datapoints + 5, 0) = LowBoundsHR(FCount)
```

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

```
Range("forecast_5").Offset(FCount + Datapoints + 5, 0) = LowBounds(FCount)
Range("forecast_7").Offset(FCount + Datapoints + 5, 0) = UppBounds(FCount)
Range("forecast_8").Offset(FCount + Datapoints + 5, 0) = UppBoundsHR(FCount)
Next FCount
Case Is = "Monthly"
For FCount = 1 To ForecastPer
  LowBounds(FCount) = FinalForecasts(FCount) - (FCount * Threshold / 12)
  UppBounds(FCount) = FinalForecasts(FCount) + (FCount * Threshold / 12)
  LowBoundsHR(FCount) = FinalForecasts(FCount) - (FCount * 2 * Threshold / 12)
  UppBoundsHR(FCount) = FinalForecasts(FCount) + (FCount * 2 * Threshold / 12)

  Range("forecast_4").Offset(FCount + Datapoints + 5, 0) = LowBoundsHR(FCount)
  Range("forecast_5").Offset(FCount + Datapoints + 5, 0) = LowBounds(FCount)
  Range("forecast_7").Offset(FCount + Datapoints + 5, 0) = UppBounds(FCount)
  Range("forecast_8").Offset(FCount + Datapoints + 5, 0) = UppBoundsHR(FCount)
Next FCount
Case Is = "Weekly"
For FCount = 1 To ForecastPer
  LowBounds(FCount) = FinalForecasts(FCount) - (FCount * Threshold / 52)
  UppBounds(FCount) = FinalForecasts(FCount) + (FCount * Threshold / 52)
  LowBoundsHR(FCount) = FinalForecasts(FCount) - (FCount * 2 * Threshold / 52)
  UppBoundsHR(FCount) = FinalForecasts(FCount) + (FCount * 2 * Threshold / 52)

  Range("forecast_4").Offset(FCount + Datapoints + 5, 0) = LowBoundsHR(FCount)
  Range("forecast_5").Offset(FCount + Datapoints + 5, 0) = LowBounds(FCount)
  Range("forecast_7").Offset(FCount + Datapoints + 5, 0) = UppBounds(FCount)
  Range("forecast_8").Offset(FCount + Datapoints + 5, 0) = UppBoundsHR(FCount)
Next FCount
End Select
End Select
```

' Creates Create Chart Button and Connects CreateChartFinal Sub

```
ActiveSheet.Shapes.AddShape(msoShapeRectangle, Range("Forecast_1").Offset(3, 0).Left,
Range("ManDatAdj").Offset(3, 0).Top, 53.25, 18).Select
  Selection.ShapeRange.ShapeStyle = msoShapeStylePreset37
  Selection.ShapeRange(1).TextFrame2.TextRange.Characters.Text = "Chart"
  With Selection.ShapeRange(1).TextFrame2.TextRange.Characters(1, 5).Font
    .NameComplexScript = "+mn-cs"
    .NameFarEast = "+mn-ea"
    .Fill.Visible = msoTrue
    .Fill.ForeColor.ObjectThemeColor = msoThemeColorLight1
    .Fill.ForeColor.TintAndShade = 0
    .Fill.Transparency = 0
    .Fill.Solid
    .Size = 12
    .Name = "+mn-lt"
  End With
  Selection.ShapeRange.TextFrame2.TextRange.ParagraphFormat.Alignment = msoAlignCenter
  Selection.ShapeRange.TextFrame2.VerticalAnchor = msoAnchorMiddle
  Selection.ShapeRange.TextFrame2.TextRange.Font.Bold = msoTrue
  Selection.OnAction = "CreateChartFinal"
```

```
Selection.ShapeRange.IncrementLeft 21
Selection.ShapeRange.IncrementTop 3
```

```
Range("Forecast_1").Select
```

' Re-activation of screen update and instant calculation


```
With Application
    .ScreenUpdating = True
    .Calculation = xlCalculationAutomatic
    .EnableEvents = True
End With

End Sub
```

Sub CreateChartFinal()

```
' Creates chart on final data

'   Disables screen updates and instant calculation
'   in order to improve performance and eliminate
'   annoying 'screen flickering'

With Application
    .ScreenUpdating = False
    .Calculation = xlCalculationManual
    .EnableEvents = False
End With

ForecastPer = Range("blend").Offset(19, 0)
Datapoints = Range(Range("ManDatAdj").Offset(6, 0), Range("ManDatAdj").Offset(6, 0).End(xlDown)).Count

ActiveSheet.Shapes.AddChart(xlLineMarkers, 100, 100, 600, 400).Select
ActiveChart.SetSourceData Source:=Range(Range("forecast_3").Offset(6, 0), Range("forecast_8").Offset(5 + ForecastPer
+ Datapoints, 0))
With ActiveChart.SeriesCollection(1).Format.Line
    .Weight = 1
    .Visible = msoTrue
    .ForeColor.ObjectThemeColor = msoThemeColorDark1
End With

ActiveChart.Legend.Delete

ActiveChart.SetElement (msoElementChartTitleAboveChart)
ActiveChart.ChartTitle.Text = "Analytical Procedures Forecast"
Selection.Format.TextFrame2.TextRange.Characters.Text = _
    "Analytical Procedures Forecast"
With Selection.Format.TextFrame2.TextRange.Characters(1, 30).ParagraphFormat
    .TextDirection = msoTextDirectionLeftToRight
    .Alignment = msoAlignCenter
End With
With Selection.Format.TextFrame2.TextRange.Characters(1, 30).Font
    .BaselineOffset = 0
    .Bold = msoTrue
    .NameComplexScript = "+mn-cs"
    .NameFarEast = "+mn-ea"
    .Fill.Visible = msoTrue
    .Fill.ForeColor.RGB = RGB(0, 0, 0)
    .Fill.Transparency = 0
    .Fill.Solid
    .Size = 18
    .Italic = msoFalse
    .Kerning = 12
    .Name = "+mn-lt"
```

```
.UnderlineStyle = msoNoUnderline
.Strike = msoNoStrike
End With
,
' ActiveChart.SeriesCollection(6).MarkerStyle = -4142
' ActiveChart.SeriesCollection(5).MarkerStyle = -4142
' ActiveChart.SeriesCollection(4).MarkerStyle = -4142
' ActiveChart.SeriesCollection(3).MarkerStyle = -4142
' ActiveChart.SeriesCollection(2).MarkerStyle = -4142

ActiveChart.SeriesCollection(6).Select
  With Selection.Format.Line
    .Weight = 1
    .Visible = msoTrue
    .ForeColor.RGB = RGB(255, 229, 229)
    .ForeColor.TintAndShade = 0
    .ForeColor.Brightness = -0.25
    .Transparency = 0
  End With

ActiveChart.SeriesCollection(2).Select
  With Selection.Format.Line
    .Weight = 1
    .Visible = msoTrue
    .ForeColor.RGB = RGB(255, 229, 229)
    .ForeColor.TintAndShade = 0
    .ForeColor.Brightness = -0.25
    .Transparency = 0
  End With

ActiveChart.SeriesCollection(5).Select
  With Selection.Format.Line
    .Weight = 1
    .Visible = msoTrue
    .ForeColor.RGB = RGB(255, 224, 93)
    .ForeColor.TintAndShade = 0
    .ForeColor.Brightness = 0.400000006
    .Transparency = 0
  End With

ActiveChart.SeriesCollection(3).Select
  With Selection.Format.Line
    .Weight = 1
    .Visible = msoTrue
    .ForeColor.RGB = RGB(255, 224, 93)
    .ForeColor.TintAndShade = 0
    .ForeColor.Brightness = 0.400000006
    .Transparency = 0
  End With

ActiveChart.SeriesCollection(4).Select
  With Selection.Format.Line
    .Weight = 1
    .Visible = msoTrue
    .ForeColor.ObjectThemeColor = msoThemeColorDark1
    .ForeColor.TintAndShade = 0
    .ForeColor.Brightness = 0.400000006
    .Transparency = 0
  End With
```

```
ActiveChart.Parent.Cut  
Range("forecast_9").Offset(1, 0).Select  
ActiveSheet.Paste
```

```
' Re-activation of screen update and instant calculation
```

```
With Application  
  .ScreenUpdating = True  
  .Calculation = xlCalculationAutomatic  
  .EnableEvents = True  
End With  
  
End Sub
```

Module: Function_HoltMSE

Option Explicit

Function HoltMSE(LevelArrayStart As Double, TreArrayStart As Double, HoltAlpha As Single, HoltBeta As Single, DatArray() As Double, Datapoints As Integer)

```
Dim StepRange As Range
Dim lastrow As Integer
Dim Counter As Integer
Dim LevArray() As Double
Dim TreArray() As Double
Dim ForeArray() As Double
Dim SQEArray() As Double
Dim SumMSE As Double

' Calculate Level and Trend

ReDim LevArray(1 To Datapoints) As Double
ReDim TreArray(1 To Datapoints) As Double

LevArray(1) = LevelArrayStart
TreArray(1) = TreArrayStart

For Counter = 2 To Datapoints
    LevArray(Counter) = HoltAlpha * DatArray(Counter) + (1 - HoltAlpha) * (LevArray(Counter - 1) + TreArray(Counter - 1))
    TreArray(Counter) = HoltBeta * (LevArray(Counter) - LevArray(Counter - 1)) + (1 - HoltBeta) * TreArray(Counter - 1)
Next Counter

' Calculate Forecast
ReDim ForeArray(1 To Datapoints - 1) As Double

' forecast(1) is for t = 2

For Counter = 1 To Datapoints - 1
    ForeArray(Counter) = LevArray(Counter) + TreArray(Counter)
Next Counter

' Calculate SQE
ReDim SQEArray(1 To Datapoints - 1) As Double

' SQEarray(1) is for t = 2

For Counter = 1 To Datapoints - 1
    SQEArray(Counter) = (ForeArray(Counter) - DatArray(Counter + 1)) ^ 2
Next Counter

' Calculate MSE

For Counter = 1 To Datapoints - 1
    SumMSE = SumMSE + SQEArray(Counter)
```

Next Counter

HoltMSE = SumMSE / (Datapoints - 1)

End Function

Module: Function_Last

Option Explicit

Function Last(choice As Long, rng As Range)

```
' 1 = last row
' 2 = last column
' 3 = last cell
Dim lrw As Long
Dim lcol As Long

Select Case choice

Case 1:
    On Error Resume Next
    Last = rng.Find(What:="*", _
        After:=rng.Cells(1), _
        Lookat:=xlPart, _
        LookIn:=xlFormulas, _
        SearchOrder:=xlByRows, _
        SearchDirection:=xlPrevious, _
        MatchCase:=False).Row
    On Error GoTo 0

Case 2:
    On Error Resume Next
    Last = rng.Find(What:="*", _
        After:=rng.Cells(1), _
        Lookat:=xlPart, _
        LookIn:=xlFormulas, _
        SearchOrder:=xlByColumns, _
        SearchDirection:=xlPrevious, _
        MatchCase:=False).Column
    On Error GoTo 0

Case 3:
    On Error Resume Next
    lrw = rng.Find(What:="*", _
        After:=rng.Cells(1), _
        Lookat:=xlPart, _
        LookIn:=xlFormulas, _
        SearchOrder:=xlByRows, _
        SearchDirection:=xlPrevious, _
        MatchCase:=False).Row
    On Error GoTo 0

    On Error Resume Next
    lcol = rng.Find(What:="*", _
        After:=rng.Cells(1), _
        Lookat:=xlPart, _
        LookIn:=xlFormulas, _
        SearchOrder:=xlByColumns, _
        SearchDirection:=xlPrevious, _
        MatchCase:=False).Column
    On Error GoTo 0
```

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

```
On Error Resume Next
Last = rng.Parent.Cells(lrw, lcol).Address(False, False)
If Err.Number > 0 Then
    Last = rng.Cells(1).Address(False, False)
    Err.Clear
End If
On Error GoTo 0

End Select
End Function
```

Module: Function_LinRegBeta

Option Explicit

Function LinRegBeta(X As Range, Y As Range)

'IMPORTANT: THE ARRAY IS FIXED IN THE SECOND WORKSTEP

```
Dim XArray() As Double
Dim YArray() As Double
Dim Count As Integer
Dim FillX As Integer
Dim FillY As Integer
Dim SumX As Double
Dim SumY As Double
Dim MeanX As Double
Dim MeanY As Double
Dim VarX As Double
Dim VarY As Double
Dim SumVarX As Double
Dim SumVarY As Double
Dim CovXY As Double
Dim SumCovXY As Double
Dim Beta As Double
Dim Alpha As Double

' Identifies the arrays of X and Y
Count = Y.Count

ReDim XArray(1 To Count)
ReDim YArray(1 To Count)

' Fills the arrays of X and Y

For FillX = 1 To Count
    XArray(FillX) = Worksheets(1).Range("Legend").Offset(5, 0).Offset(FillX, 0)
Next FillX

For FillY = 1 To Count
    YArray(FillY) = Worksheets(1).Range("FForm").Offset(5, 0).Offset(FillY, 0)
Next FillY

' Calculates Mean of X and Y

For FillX = 1 To Count
    SumX = SumX + XArray(FillX)
Next FillX

For FillY = 1 To Count
    SumY = SumY + YArray(FillY)
Next FillY

MeanX = SumX / Count
MeanY = SumY / Count

' Calculates Variance of X and Y
```



```
For FillX = 1 To Count
    SumVarX = SumVarX + ((XArray(FillX) - MeanX) ^ 2)
Next FillX
```

```
For FillY = 1 To Count
    SumVarY = SumVarY + ((YArray(FillY) - MeanY) ^ 2)
Next FillY
```

```
VarX = SumVarX / Count
VarY = SumVarY / Count
```

' Calculates Covariance of X and Y

```
For FillX = 1 To Count
    SumCovXY = SumCovXY + ((XArray(FillX) - MeanX) * (YArray(FillX) - MeanY))
Next FillX
```

```
CovXY = SumCovXY / Count
```

' Calculates model alpha and beta

```
Beta = CovXY / VarX
Alpha = MeanY - (Beta * MeanX)
LinRegBeta = Beta
```

End Function

Function LinRegAlpha(X As Range, Y As Range)

IMPORTANT: THE ARRAY IS FIXED IN THE SECOND WORKSTEP

```
Dim XArray() As Double
Dim YArray() As Double
Dim Count As Integer
Dim FillX As Integer
Dim FillY As Integer
Dim SumX As Double
Dim SumY As Double
Dim MeanX As Double
Dim MeanY As Double
Dim VarX As Double
Dim VarY As Double
Dim SumVarX As Double
Dim SumVarY As Double
Dim CovXY As Double
Dim SumCovXY As Double
Dim Beta As Double
Dim Alpha As Double
```

```
' Identifies the array of X and Y
Count = Y.Count
```

```
ReDim XArray(1 To Count)
ReDim YArray(1 To Count)
```

```
' Fills the arrays of X and Y
```

```
For FillX = 1 To Count
  XArray(FillX) = Worksheets(1).Range("Legend").Offset(5, 0).Offset(FillX, 0)
Next FillX
```

```
For FillY = 1 To Count
  YArray(FillY) = Worksheets(1).Range("FForm").Offset(5, 0).Offset(FillY, 0)
Next FillY
```

' Calculates Mean of X and Y

```
For FillX = 1 To Count
  SumX = SumX + XArray(FillX)
Next FillX
```

```
For FillY = 1 To Count
  SumY = SumY + YArray(FillY)
Next FillY
```

```
MeanX = SumX / Count
MeanY = SumY / Count
```

' Calculates Variance of X and Y

```
For FillX = 1 To Count
  SumVarX = SumVarX + ((XArray(FillX) - MeanX) ^ 2)
Next FillX
```

```
For FillY = 1 To Count
  SumVarY = SumVarY + ((YArray(FillY) - MeanY) ^ 2)
Next FillY
```

```
VarX = SumVarX / Count
VarY = SumVarY / Count
```

' Calculates Covariance of X and Y

```
For FillX = 1 To Count
  SumCovXY = SumCovXY + ((XArray(FillX) - MeanX) * (YArray(FillX) - MeanY))
Next FillX
```

```
CovXY = SumCovXY / Count
```

' Calculates model alpha and beta

```
Beta = CovXY / VarX
Alpha = MeanY - (Beta * MeanX)
LinRegAlpha = Alpha
```

End Function

Function LinRegRSquare(X As Range, Y As Range)

IMPORTANT: THE ARRAY IS FIXED IN THE SECOND WORKSTEP

```
Dim XArray() As Double
Dim YArray() As Double
```

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

Dim Count As Integer
Dim FillX As Integer
Dim FillY As Integer
Dim SumX As Double
Dim SumY As Double
Dim MeanX As Double
Dim MeanY As Double
Dim VarX As Double
Dim VarY As Double
Dim SumVarX As Double
Dim SumVarY As Double
Dim CovXY As Double
Dim SumCovXY As Double
Dim CorrXY As Double

' Identifies the arrays of X and Y
Count = Y.Count

ReDim XArray(1 To Count)
ReDim YArray(1 To Count)

' Fills the arrays of X and Y

For FillX = 1 To Count
XArray(FillX) = Worksheets(1).Range("Legend").Offset(5, 0).Offset(FillX, 0)
Next FillX

For FillY = 1 To Count
YArray(FillY) = Worksheets(1).Range("FForm").Offset(5, 0).Offset(FillY, 0)
Next FillY

' Calculates Mean of X and Y

For FillX = 1 To Count
SumX = SumX + XArray(FillX)
Next FillX

For FillY = 1 To Count
SumY = SumY + YArray(FillY)
Next FillY

MeanX = SumX / Count
MeanY = SumY / Count

' Calculates Variance of X and Y

For FillX = 1 To Count
SumVarX = SumVarX + ((XArray(FillX) - MeanX) ^ 2)
Next FillX

For FillY = 1 To Count
SumVarY = SumVarY + ((YArray(FillY) - MeanY) ^ 2)
Next FillY

VarX = SumVarX / Count
VarY = SumVarY / Count

' Calculates Covariance of X and Y

For FillX = 1 To Count

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

SumCovXY = SumCovXY + ((XArray(FillX) - MeanX) * (YArray(FillX) - MeanY))
Next FillX

CovXY = SumCovXY / Count

' Calculates Correlation Coefficient

LinRegRSquare = CovXY ^ 2 / ((VarX ^ 2) * (VarY ^ 2))

End Function

Module: Function_LinRegBeta2

Option Explicit

Function LinRegBeta2(X As Range, Y As Range)

'IMPORTANT: THE ARRAY IS FIXED IN THE SECOND WORKSTEP

Dim XArray() As Double

Dim YArray() As Double

Dim Count As Integer

Dim FillX As Integer

Dim FillY As Integer

Dim SumX As Double

Dim SumY As Double

Dim MeanX As Double

Dim MeanY As Double

Dim VarX As Double

Dim VarY As Double

Dim SumVarX As Double

Dim SumVarY As Double

Dim CovXY As Double

Dim SumCovXY As Double

Dim Beta As Double

Dim Alpha As Double

' Identifies the arrays of X and Y

Count = Y.Count

ReDim XArray(1 To Count)

ReDim YArray(1 To Count)

' Fills the arrays of X and Y

For FillX = 1 To Count

 XArray(FillX) = Worksheets(1).Range("Legend").Offset(5, 0).Offset(FillX, 0)

Next FillX

For FillY = 1 To Count

 YArray(FillY) = Worksheets(1).Range("OutEl").Offset(5, 0).Offset(FillY, 0)

Next FillY

' Calculates Mean of X and Y

For FillX = 1 To Count

 SumX = SumX + XArray(FillX)

Next FillX

For FillY = 1 To Count

 SumY = SumY + YArray(FillY)

Next FillY

MeanX = SumX / Count

MeanY = SumY / Count

' Calculates Variance of X and Y

```
For FillX = 1 To Count
    SumVarX = SumVarX + ((XArray(FillX) - MeanX) ^ 2)
Next FillX
```

```
For FillY = 1 To Count
    SumVarY = SumVarY + ((YArray(FillY) - MeanY) ^ 2)
Next FillY
```

```
VarX = SumVarX / Count
VarY = SumVarY / Count
```

' Calculates Covariance of X and Y

```
For FillX = 1 To Count
    SumCovXY = SumCovXY + ((XArray(FillX) - MeanX) * (YArray(FillX) - MeanY))
Next FillX
```

```
CovXY = SumCovXY / Count
```

' Calculates model alpha and beta

```
Beta = CovXY / VarX
Alpha = MeanY - (Beta * MeanX)
LinRegBeta2 = Beta
```

End Function

Function LinRegAlpha2(X As Range, Y As Range)

IMPORTANT: THE ARRAY IS FIXED IN THE SECOND WORKSTEP

```
Dim XArray() As Double
Dim YArray() As Double
Dim Count As Integer
Dim FillX As Integer
Dim FillY As Integer
Dim SumX As Double
Dim SumY As Double
Dim MeanX As Double
Dim MeanY As Double
Dim VarX As Double
Dim VarY As Double
Dim SumVarX As Double
Dim SumVarY As Double
Dim CovXY As Double
Dim SumCovXY As Double
Dim Beta As Double
Dim Alpha As Double
```

```
' Identifies the array of X and Y
Count = Y.Count
```

```
ReDim XArray(1 To Count)
ReDim YArray(1 To Count)
```

```
' Fills the arrays of X and Y

For FillX = 1 To Count
  XArray(FillX) = Worksheets(1).Range("Legend").Offset(5, 0).Offset(FillX, 0)
Next FillX

For FillY = 1 To Count
  YArray(FillY) = Worksheets(1).Range("OutEl").Offset(5, 0).Offset(FillY, 0)
Next FillY

' Calculates Mean of X and Y

For FillX = 1 To Count
  SumX = SumX + XArray(FillX)
Next FillX

For FillY = 1 To Count
  SumY = SumY + YArray(FillY)
Next FillY

MeanX = SumX / Count
MeanY = SumY / Count

' Calculates Variance of X and Y

For FillX = 1 To Count
  SumVarX = SumVarX + ((XArray(FillX) - MeanX) ^ 2)
Next FillX

For FillY = 1 To Count
  SumVarY = SumVarY + ((YArray(FillY) - MeanY) ^ 2)
Next FillY

VarX = SumVarX / Count
VarY = SumVarY / Count

' Calculates Covariance of X and Y

For FillX = 1 To Count
  SumCovXY = SumCovXY + ((XArray(FillX) - MeanX) * (YArray(FillX) - MeanY))
Next FillX

CovXY = SumCovXY / Count

' Calculates model alpha and beta

Beta = CovXY / VarX
Alpha = MeanY - (Beta * MeanX)
LinRegAlpha2 = Alpha

End Function
```

Function LinRegRSquare2(X As Range, Y As Range)

IMPORTANT: THE ARRAY IS FIXED IN THE SECOND WORKSTEP

Dim XArray() As Double

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

```
Dim YArray() As Double
Dim Count As Integer
Dim FillX As Integer
Dim FillY As Integer
Dim SumX As Double
Dim SumY As Double
Dim MeanX As Double
Dim MeanY As Double
Dim VarX As Double
Dim VarY As Double
Dim SumVarX As Double
Dim SumVarY As Double
Dim CovXY As Double
Dim SumCovXY As Double
Dim CorrXY As Double

' Identifies the arrays of X and Y
Count = Y.Count

ReDim XArray(1 To Count)
ReDim YArray(1 To Count)

' Fills the arrays of X and Y

For FillX = 1 To Count
    XArray(FillX) = Worksheets(1).Range("Legend").Offset(5, 0).Offset(FillX, 0)
Next FillX

For FillY = 1 To Count
    YArray(FillY) = Worksheets(1).Range("OutEl").Offset(5, 0).Offset(FillY, 0)
Next FillY

' Calculates Mean of X and Y

For FillX = 1 To Count
    SumX = SumX + XArray(FillX)
Next FillX

For FillY = 1 To Count
    SumY = SumY + YArray(FillY)
Next FillY

MeanX = SumX / Count
MeanY = SumY / Count

' Calculates Variance of X and Y

For FillX = 1 To Count
    SumVarX = SumVarX + ((XArray(FillX) - MeanX) ^ 2)
Next FillX

For FillY = 1 To Count
    SumVarY = SumVarY + ((YArray(FillY) - MeanY) ^ 2)
Next FillY

VarX = SumVarX / Count
VarY = SumVarY / Count

' Calculates Covariance of X and Y
```


**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

For FillX = 1 To Count

SumCovXY = SumCovXY + ((XArray(FillX) - MeanX) * (YArray(FillX) - MeanY))

Next FillX

CovXY = SumCovXY / Count

' Calculates Correlation Coefficient

LinRegRSquare2 = CovXY ^ 2 / ((VarX ^ 2) * (VarY ^ 2))

End Function

Module: Function_StdDev

Option Explicit

Function StdDev(X As Range, Start As Range)

```
Dim XArray() As Double
Dim Count As Integer
Dim FillX As Integer
Dim SumX As Double
Dim MeanX As Double
Dim SumVarX As Double
Dim VarX As Double

' Identifies the array of X
Count = X.Count

ReDim XArray(1 To Count)

' Fills the array of X

For FillX = 1 To Count
    XArray(FillX) = Start.Offset(FillX, 0)
Next FillX

' Calculates Mean of X

For FillX = 1 To Count
    SumX = SumX + XArray(FillX)
Next FillX

MeanX = SumX / Count

' Calculates Variance of X

For FillX = 1 To Count
    SumVarX = SumVarX + ((XArray(FillX) - MeanX) ^ 2)
Next FillX

VarX = SumVarX / Count

' Calculates StdDev of X

StdDev = VarX ^ 0.5

End Function
```

Module: Function_StdDev2

Option Explicit

Function StdDev2(X As Range, Start As Range)

```
Dim XArray() As Double
Dim Count As Integer
Dim FillX As Integer
Dim SumX As Double
Dim MeanX As Double
Dim SumVarX As Double
Dim VarX As Double

' Identifies the array of X
Count = X.Count

ReDim XArray(1 To Count)

' Fills the array of X

For FillX = 1 To Count
    XArray(FillX) = Start.Offset(FillX, 0)
Next FillX

' Calculates Mean of X

For FillX = 1 To Count
    SumX = SumX + XArray(FillX)
Next FillX

MeanX = SumX / Count

' Calculates Variance of X

For FillX = 1 To Count
    SumVarX = SumVarX + ((XArray(FillX) - MeanX) ^ 2)
Next FillX

VarX = SumVarX / Count

' Calculates StdDev of X

StdDev = VarX ^ 0.5

End Function
```

Module: Function_StErBeta

Option Explicit

Function StErBeta(X As Range, Y As Range)

IMPORTANT: THE ARRAY IS FIXED IN THE SECOND WORKSTEP

```
Dim XArray() As Double
Dim YArray() As Double
Dim Count As Integer
Dim FillX As Integer
Dim FillY As Integer
Dim SumX As Double
Dim SumY As Double
Dim MeanX As Double
Dim MeanY As Double
Dim VarY As Double
Dim SumVarX As Double
Dim SumVarY As Double
Dim VarBeta As Double

' Identifies the array of X and Y
Count = Y.Count

ReDim XArray(1 To Count)
ReDim YArray(1 To Count)

' Fills the arrays of X and Y

For FillX = 1 To Count
    XArray(FillX) = Worksheets(1).Range("Legend").Offset(5, 0).Offset(FillX, 0)
Next FillX

For FillY = 1 To Count
    YArray(FillY) = Worksheets(1).Range("FForm").Offset(5, 0).Offset(FillY, 0)
Next FillY

' Calculates Mean of X and Y

For FillX = 1 To Count
    SumX = SumX + XArray(FillX)
Next FillX

For FillY = 1 To Count
    SumY = SumY + YArray(FillY)
Next FillY

MeanX = SumX / Count
MeanY = SumY / Count

' Calculates Variance of X and Y

For FillX = 1 To Count
    SumVarX = SumVarX + ((XArray(FillX) - MeanX) ^ 2)
Next FillX
```

```
For FillY = 1 To Count
    SumVarY = SumVarY + ((YArray(FillY) - MeanY) ^ 2)
Next FillY
```

```
VarY = SumVarY / Count
```

```
' Calculates variance and standard error of Beta
```

```
VarBeta = VarY / SumVarX
StErBeta = VarBeta ^ 0.5
```

```
End Function
```

Module: Function_StErBeta2

Option Explicit

Function StErBeta2(X As Range, Y As Range)

'IMPORTANT: THE ARRAY IS FIXED IN THE SECOND WORKSTEP

```
Dim XArray() As Double
Dim YArray() As Double
Dim Count As Integer
Dim FillX As Integer
Dim FillY As Integer
Dim SumX As Double
Dim SumY As Double
Dim MeanX As Double
Dim MeanY As Double
Dim VarY As Double
Dim SumVarX As Double
Dim SumVarY As Double
Dim VarBeta As Double

' Identifies the array of X and Y
Count = Y.Count

ReDim XArray(1 To Count)
ReDim YArray(1 To Count)

' Fills the arrays of X and Y

For FillX = 1 To Count
    XArray(FillX) = Worksheets(1).Range("Legend").Offset(5, 0).Offset(FillX, 0)
Next FillX

For FillY = 1 To Count
    YArray(FillY) = Worksheets(1).Range("OutEl").Offset(5, 0).Offset(FillY, 0)
Next FillY

' Calculates Mean of X and Y

For FillX = 1 To Count
    SumX = SumX + XArray(FillX)
Next FillX

For FillY = 1 To Count
    SumY = SumY + YArray(FillY)
Next FillY

MeanX = SumX / Count
MeanY = SumY / Count

' Calculates Variance of X and Y

For FillX = 1 To Count
    SumVarX = SumVarX + ((XArray(FillX) - MeanX) ^ 2)
Next FillX
```

```
For FillY = 1 To Count
    SumVarY = SumVarY + ((YArray(FillY) - MeanY) ^ 2)
Next FillY
```

```
VarY = SumVarY / Count
```

```
' Calculates variance and standard error of Beta
```

```
VarBeta = VarY / SumVarX
StErBeta2 = VarBeta ^ 0.5
```

```
End Function
```

Module: Function_TStat005nminus2

Option Explicit

Function Tstat(Y As Range)

Dim Count As Integer

' Counts the sample size
Count = Y.Count

' Calculates T0.05, n-2

Select Case Count - 2

Case Is = 1
Tstat = 63.657
Case Is = 2
Tstat = 9.925
Case Is = 3
Tstat = 5.841
Case Is = 4
Tstat = 4.604
Case Is = 5
Tstat = 4.032
Case Is = 6
Tstat = 3.707
Case Is = 7
Tstat = 3.5
Case Is = 8
Tstat = 3.355
Case Is = 9
Tstat = 3.25
Case Is = 10
Tstat = 3.169
Case Is = 11
Tstat = 3.106
Case Is = 12
Tstat = 3.054
Case Is = 13
Tstat = 3.012
Case Is = 14
Tstat = 2.977
Case Is = 15
Tstat = 2.947
Case Is = 16
Tstat = 2.921
Case Is = 17
Tstat = 2.898
Case Is = 18
Tstat = 2.878
Case Is = 19
Tstat = 2.861
Case Is = 20
Tstat = 2.845
Case Is = 21

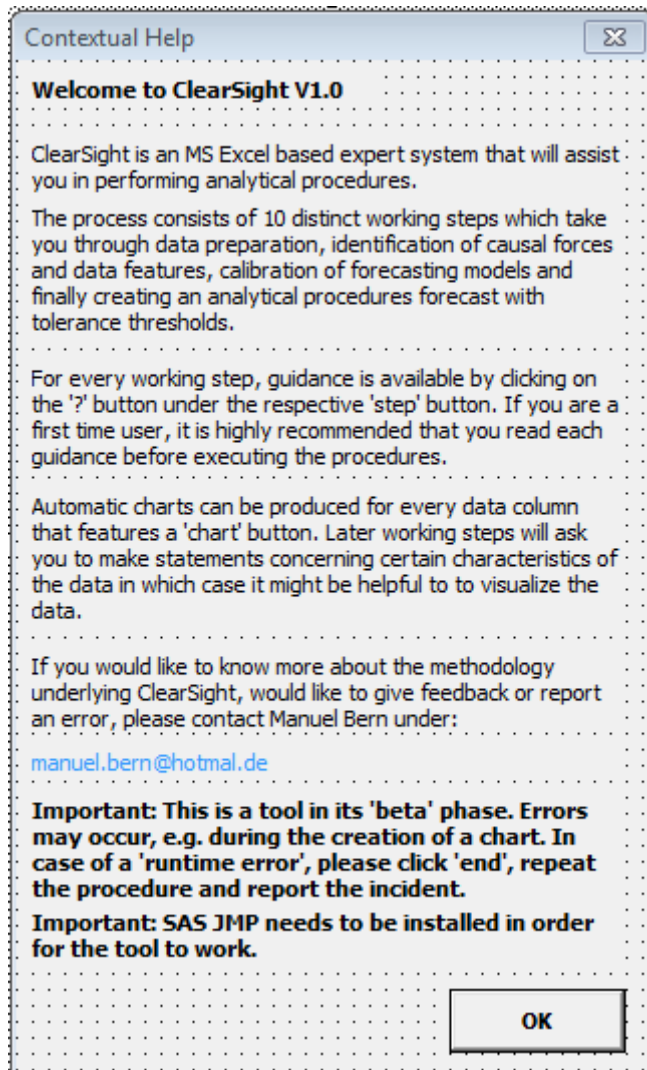

```
Tstat = 2.831
Case Is = 22
  Tstat = 2.819
Case Is = 23
  Tstat = 2.807
Case Is = 24
  Tstat = 2.797
Case Is = 25
  Tstat = 2.787
Case Is = 26
  Tstat = 2.779
Case Is = 27
  Tstat = 2.771
Case Is = 28
  Tstat = 2.763
Case Is = 29
  Tstat = 2.756
Case Is > 29
  Tstat = 2.575
End Select
```

End Function

Appendix II c Forms

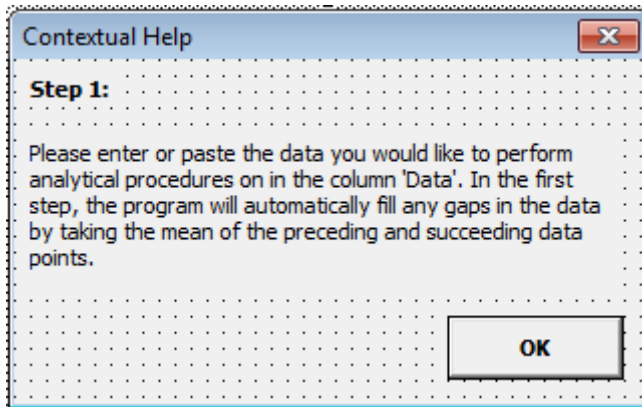
“Forms” refer to interactive user elements, i.e. the user is shown a text field and may then either select an option, enter data into a text field or activate a button. In the following, the forms are shown as graphic displays and the programming code of any active fields follows in the order from top left to bottom right.

Form: ConHlp1



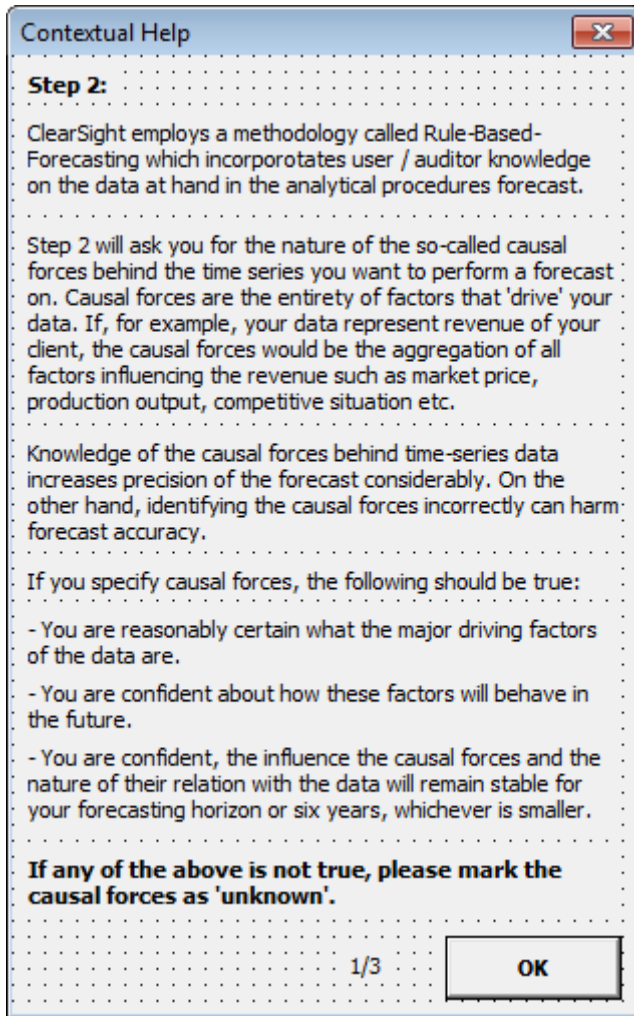
```
Private Sub CommandButton1_Click()  
    Unload ConHlp1  
End Sub
```

Form: ConHlp2



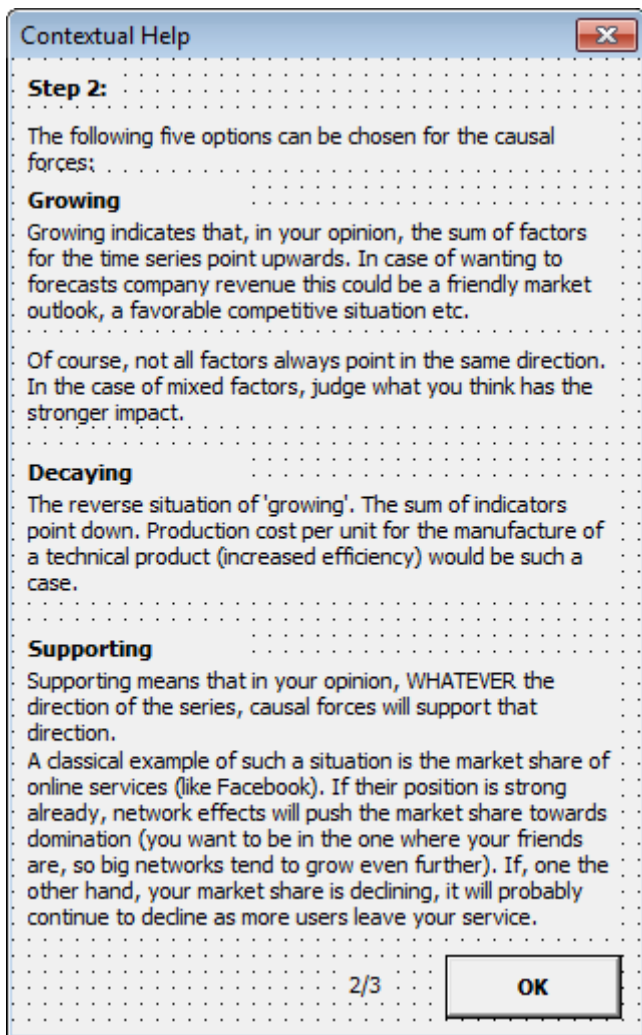
```
Private Sub CommandButton1_Click()  
    Unload ConHlp2  
End Sub
```

Form: ConHlp3



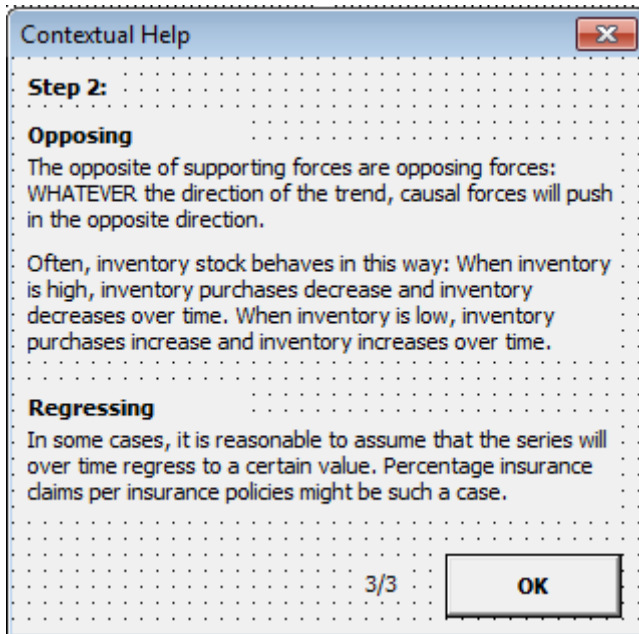
```
Private Sub CommandButton1_Click()  
    Unload ConHlp3  
    Steps.LoadConHlp3_2  
End Sub
```

Form: ConHlp3_2



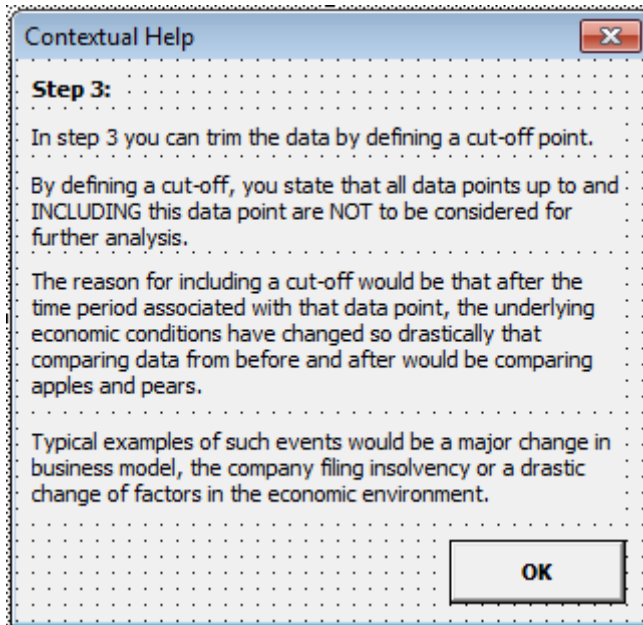
```
Private Sub CommandButton1_Click()  
    Unload ConHlp3_2  
    Steps.LoadConHlp3_3  
End Sub
```

Form: ConHlp3_3



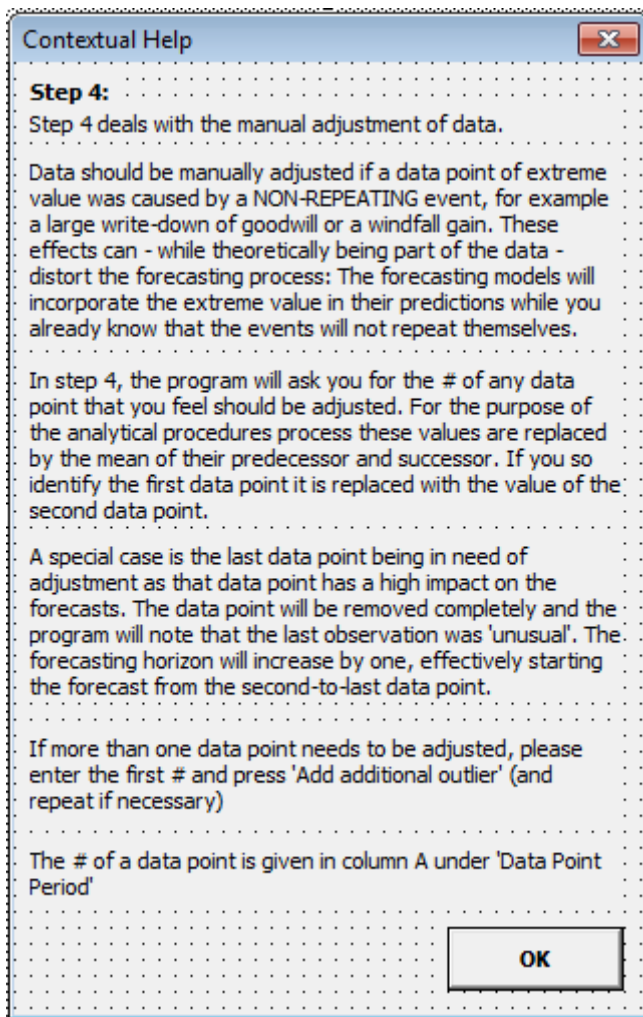
```
Private Sub CommandButton1_Click()  
    Unload ConHlp3_3  
End Sub
```

Form: ConHlp4



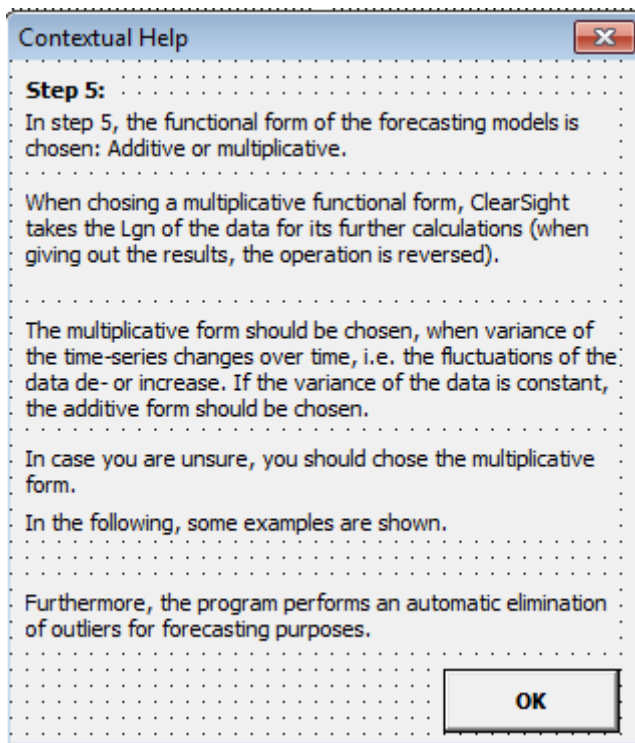
```
Private Sub CommandButton1_Click()  
    Unload ConHlp4  
End Sub
```

Form: ConHlp5



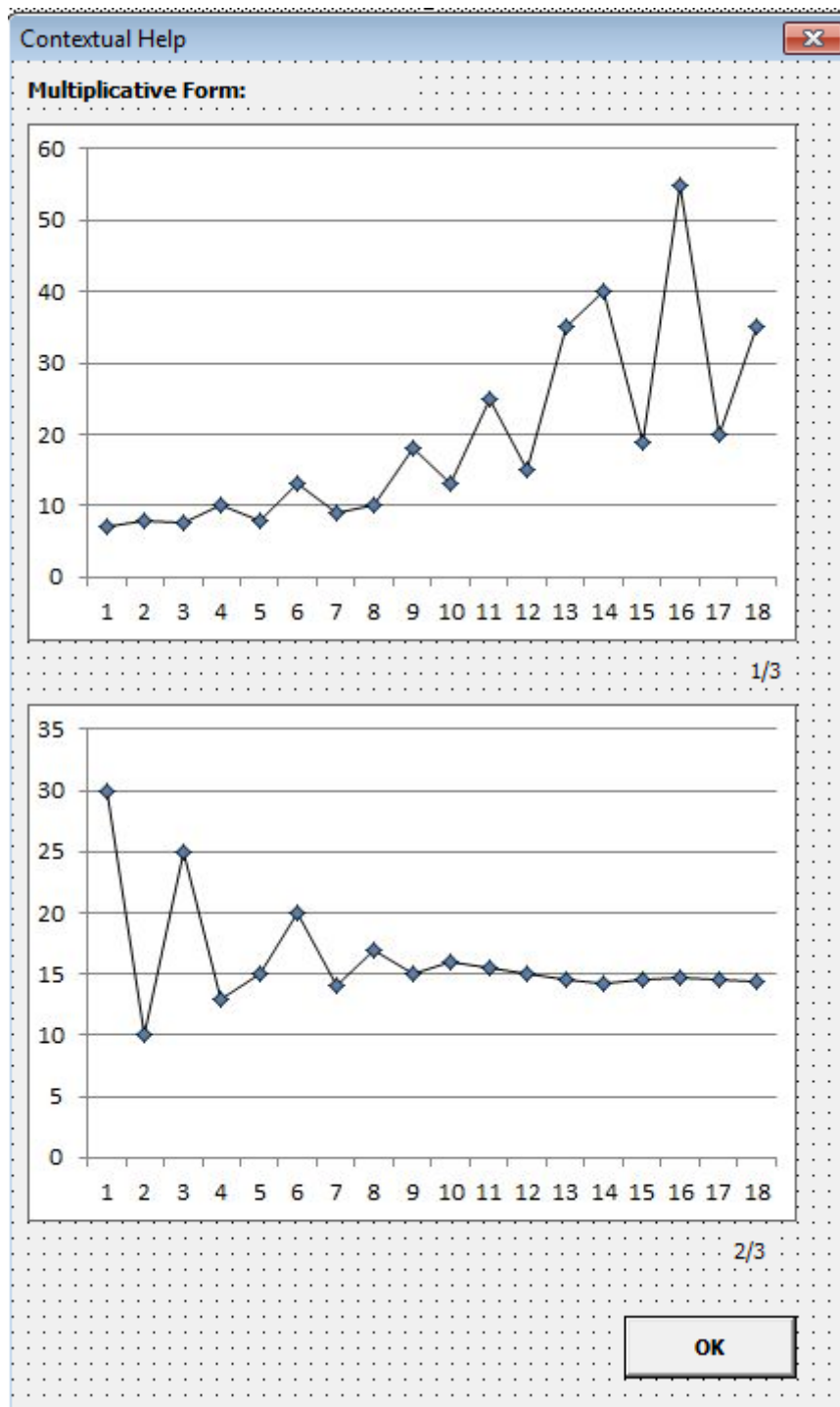
```
Private Sub CommandButton1_Click()  
    Unload ConHlp5  
End Sub
```


Form: ConHlp6



```
Private Sub CommandButton1_Click()  
    Unload ConHlp6  
    Steps.LoadConHlp6_2  
End Sub
```

Form: ConHlp6_2

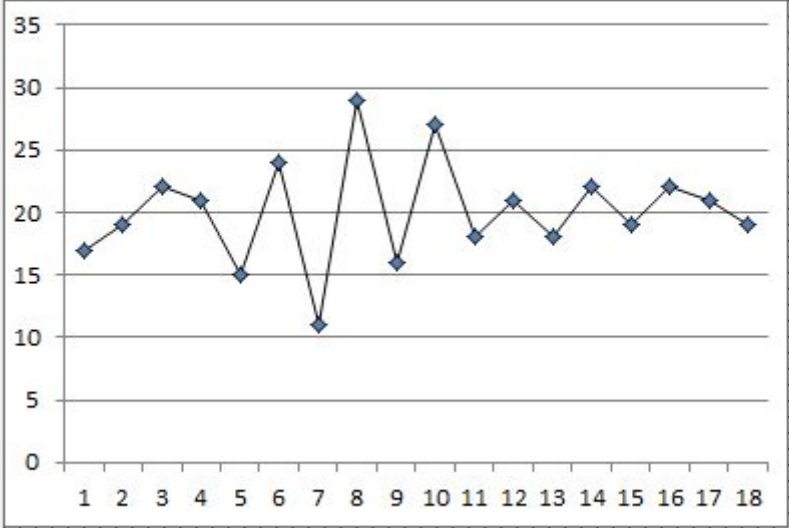


```
Private Sub CommandButton1_Click()  
    Unload ConHlp6_2  
    Steps.LoadConHlp6_3  
End Sub
```

Form: ConHlp6_3

Contextual Help ✕

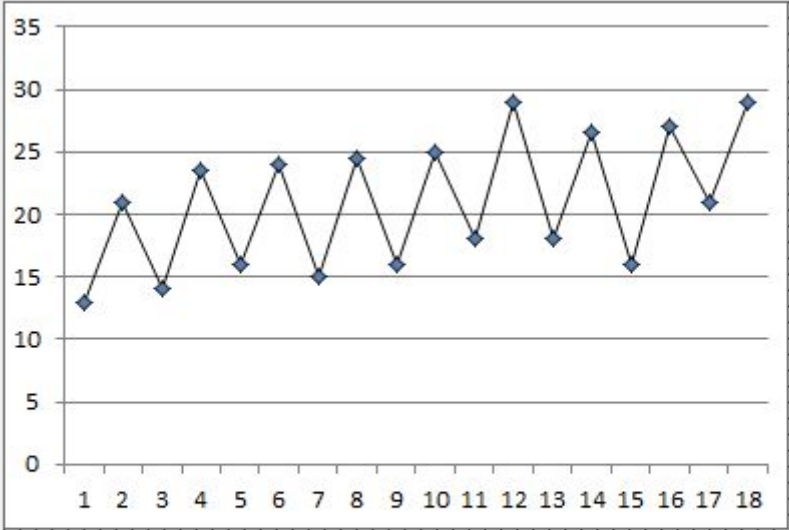
Multiplicative Form:



| Period | Value |
|--------|-------|
| 1 | 17 |
| 2 | 19 |
| 3 | 22 |
| 4 | 21 |
| 5 | 15 |
| 6 | 24 |
| 7 | 11 |
| 8 | 29 |
| 9 | 16 |
| 10 | 27 |
| 11 | 18 |
| 12 | 21 |
| 13 | 18 |
| 14 | 22 |
| 15 | 19 |
| 16 | 22 |
| 17 | 21 |
| 18 | 19 |

3/3

Additive Form:



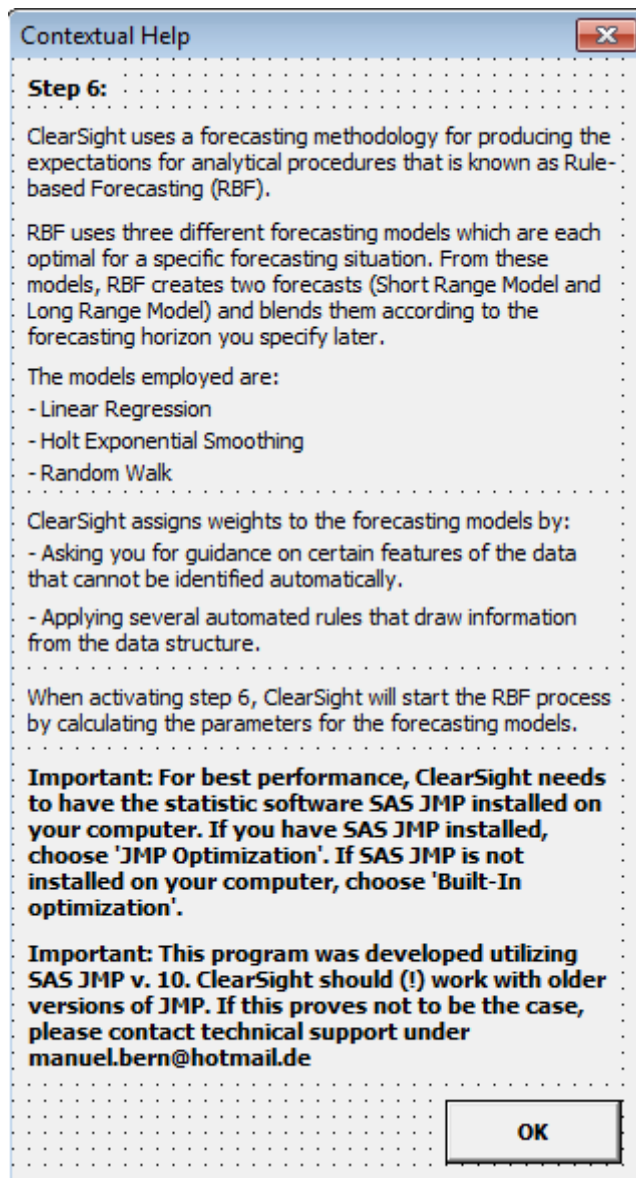
| Period | Value |
|--------|-------|
| 1 | 13 |
| 2 | 21 |
| 3 | 14 |
| 4 | 23 |
| 5 | 16 |
| 6 | 24 |
| 7 | 15 |
| 8 | 24 |
| 9 | 16 |
| 10 | 25 |
| 11 | 18 |
| 12 | 29 |
| 13 | 18 |
| 14 | 26 |
| 15 | 16 |
| 16 | 27 |
| 17 | 21 |
| 18 | 29 |

1/1

OK

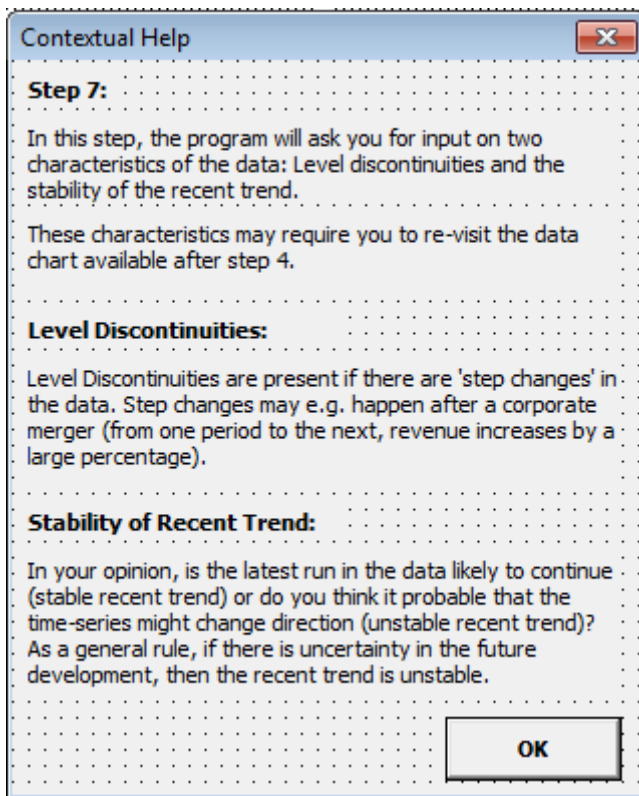
```
Private Sub CommandButton1_Click()  
    Unload ConHlp6_3  
End Sub
```

Form: ConHlp7



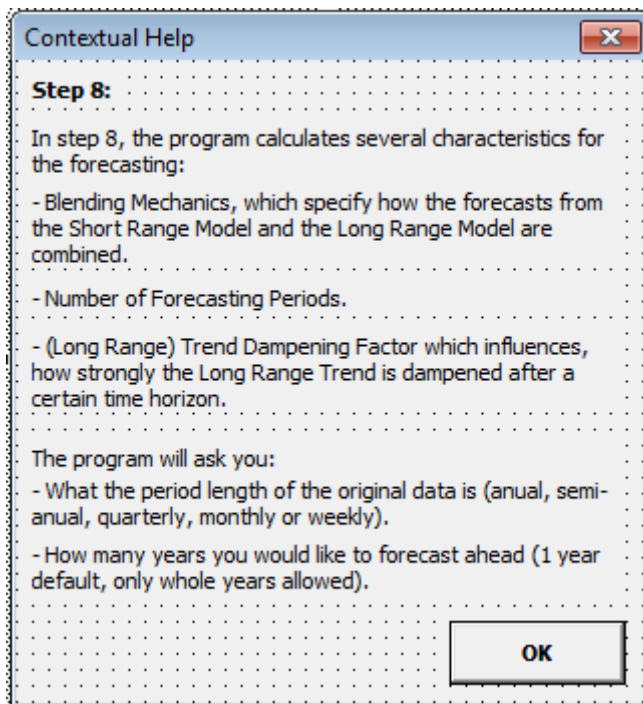
```
Private Sub CommandButton1_Click()  
    Unload ConHlp7  
End Sub
```

Form: ConHlp8



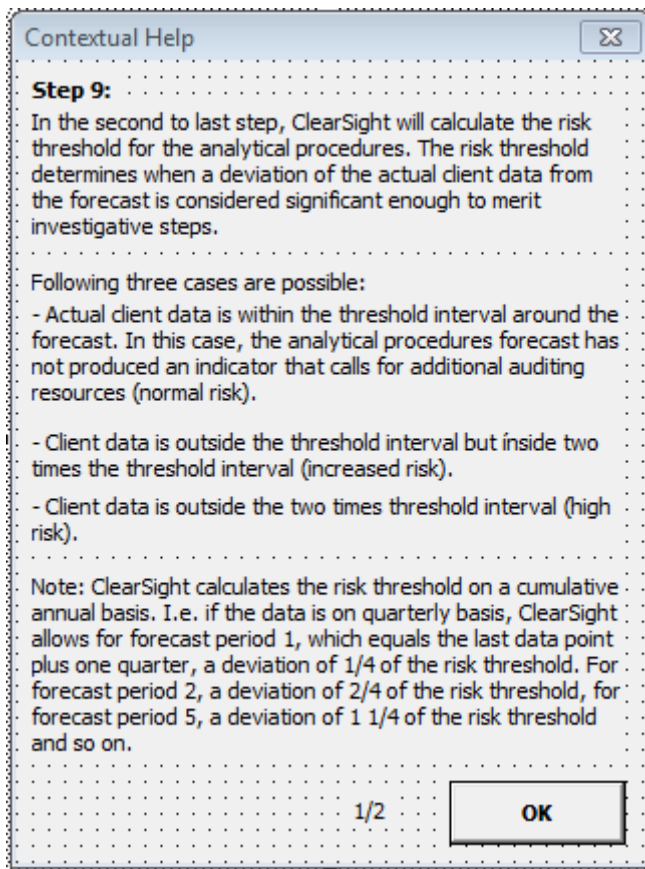
```
Private Sub CommandButton1_Click()  
    Unload ConHlp8  
End Sub
```

Form: ConHlp9



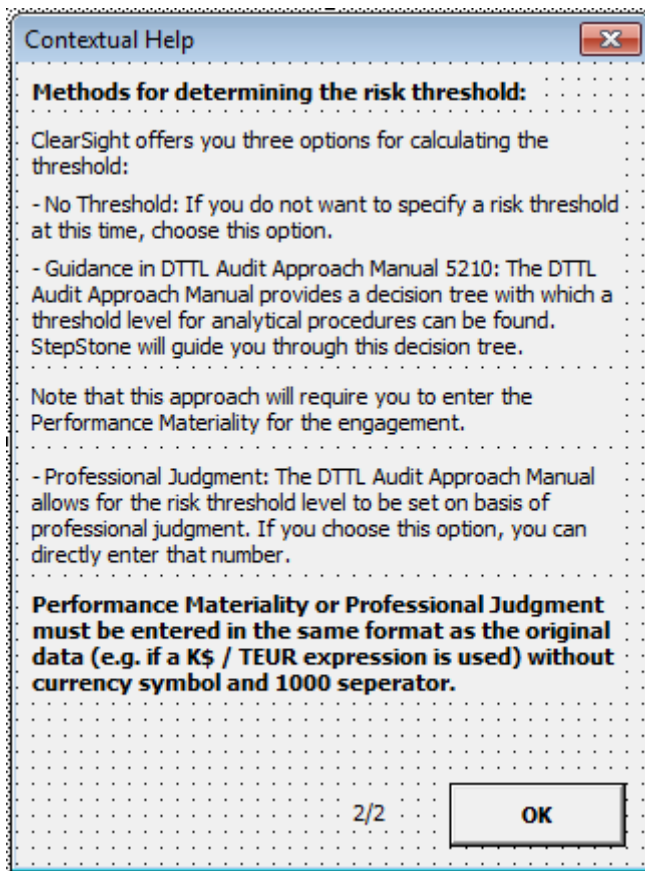
```
Private Sub CommandButton1_Click()  
    Unload ConHlp9  
End Sub
```

Form: ConHlp10



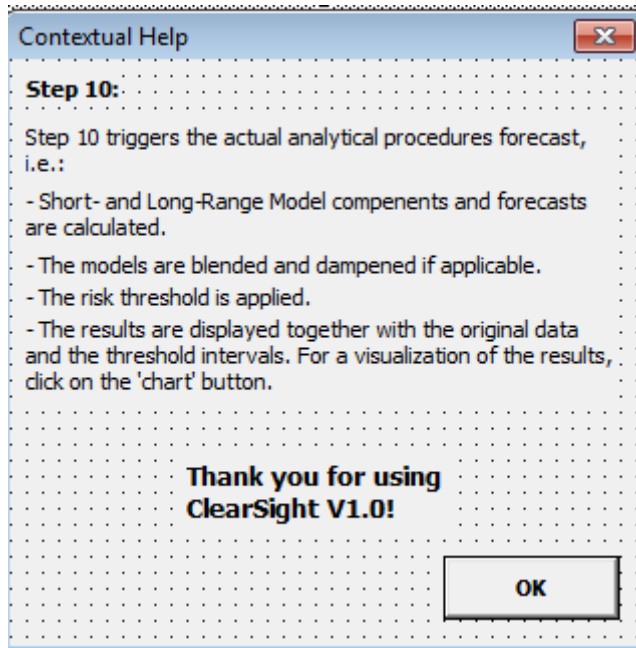
```
Private Sub CommandButton1_Click()  
    Unload ConHlp10  
    Steps.LoadConHlp10_2  
End Sub
```

Form: ConHlp10_2



```
Private Sub CommandButton1_Click()  
    Unload ConHlp10_2  
End Sub
```


Form: ConHlp11



```
Private Sub CommandButton1_Click()  
    Unload ConHlp11  
End Sub
```

Step2_UsrFrm1

Specify Causal Forces

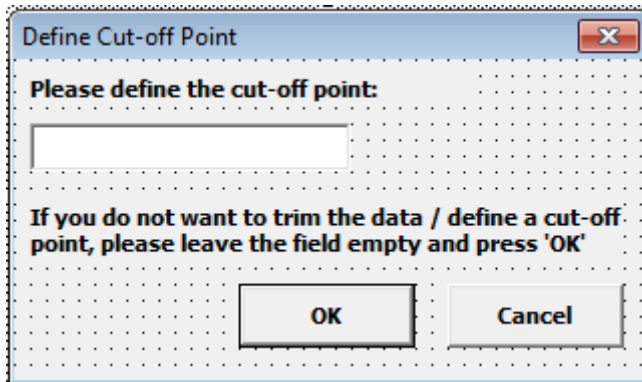
Please specify the nature of causal forces:

- Growing
- Decaying
- Supporting
- Opposing
- Regressing
- Unknown

OK Cancel

```
Private Sub CommandButton1_Click()  
    If OptionButton1 = True Then StateCausalForce = "Growing"  
    If OptionButton2 = True Then StateCausalForce = "Decaying"  
    If OptionButton3 = True Then StateCausalForce = "Supporting"  
    If OptionButton4 = True Then StateCausalForce = "Opposing"  
    If OptionButton5 = True Then StateCausalForce = "Regressing"  
    If OptionButton6 = True Then StateCausalForce = "Unknown"  
  
    CancStep = False  
  
    Unload Step2_UsrFrm1  
End Sub  
  
Private Sub CommandButton2_Click()  
    Unload Step2_UsrFrm1  
End Sub
```

Step3_UsrFrm1



```
Private Sub Step3_TextBox1_Change()  
    CutOffPoint = Step3_TextBox1.Value  
End Sub
```

```
Private Sub CommandButton1_Click()
```

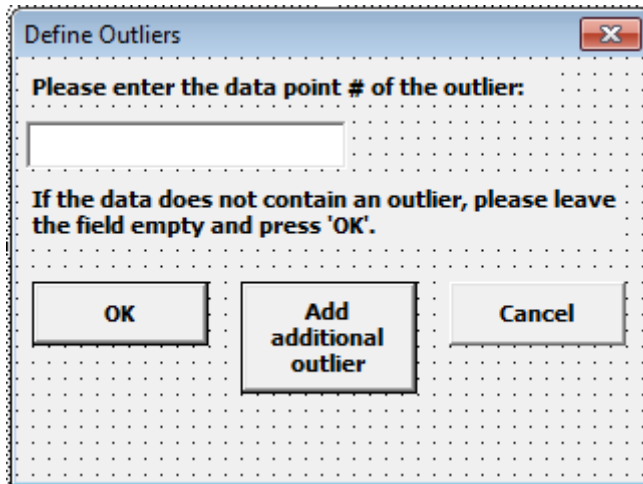
```
    CancStep = False
```

```
    Unload Step3_UsrFrm1  
End Sub
```

```
Private Sub CommandButton2_Click()
```

```
    Unload Step3_UsrFrm1  
End Sub
```

Step4_UsrFrm1



Define Outliers

Please enter the data point # of the outlier:

If the data does not contain an outlier, please leave the field empty and press 'OK'.

OK Add additional outlier Cancel

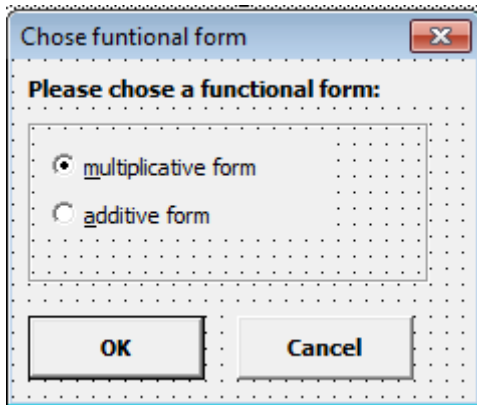
```
Private Sub Step4_TextBox1_Change()  
    ManDatAdjIdent = Step4_TextBox1.Value  
End Sub
```

```
Private Sub CommandButton1_Click()  
    AddManDatAdj = False  
  
    CancStep = False  
  
    Unload Step4_UsrFrm1  
End Sub
```

```
Private Sub CommandButton2_Click()  
    Unload Step4_UsrFrm1  
End Sub
```

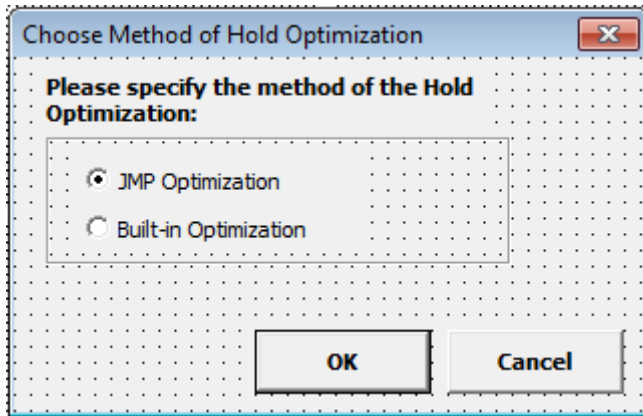
```
Private Sub CommandButton3_Click()  
    AddManDatAdj = True  
    CancStep = False  
    Unload Step4_UsrFrm1  
End Sub
```

Step5_UsrFrm1



```
Private Sub CommandButton1_Click()  
    If Step5_OptionButton1 = True Then FFormM = True  
  
    CancStep = False  
  
    Unload Step5_UsrFrm1  
End Sub  
  
Private Sub CommandButton2_Click()  
    Unload Step5_UsrFrm1  
End Sub
```

Step6_UsrFrm1



```
Private Sub CommandButton1_Click()  
    If OptionButton1 = True Then HoldOpti = "JMP"  
    If OptionButton2 = True Then HoldOpti = "Built-In"  
    CancStep = False
```

```
    Unload Step6_UsrFrm1  
End Sub
```

```
Private Sub CommandButton2_Click()  
    Unload Step6_UsrFrm1  
End Sub
```

Step7_UsrFrm1

Data Characteristics

Does the data have level discontinuities?

Level Discontinuities present

NO Level Discontinuities present

Is the recent trend in the data stable?

Recent Trend stable

Recent Trend unstable

OK Cancel

```
Private Sub CommandButton1_Click()  
    If OptionButton1 = True Then LevelDiscont = True  
    If OptionButton4 = True Then RecTreUnst = True  
  
    CancStep = False  
  
    Unload Step7_UsrFrm1  
End Sub
```

```
Private Sub CommandButton2_Click()  
  
    Unload Step7_UsrFrm1  
End Sub
```

Step8_UsrFrm1

Period Length, Blending and Forecast Horizon

Please specify the period length of the data:

Annual
 Semi-Annual
 Quarterly
 Monthly
 Weekly

Please choose the forecasting horizon:

1 years

OK Cancel

```
Private Sub UserForm_Activate()  
    FCHorizon_Text = 1  
End Sub
```

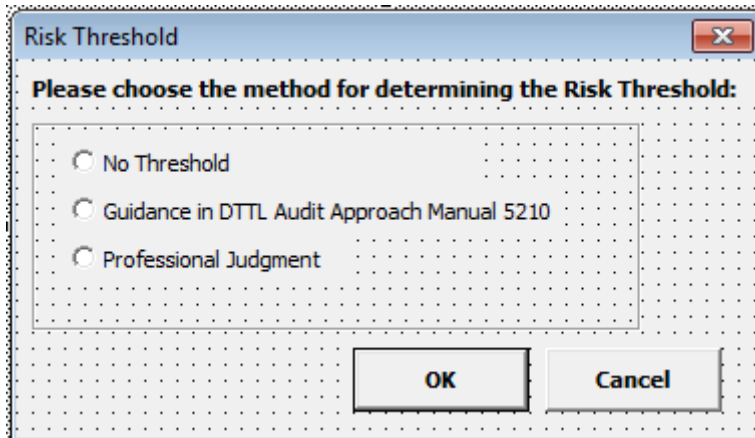
```
Private Sub CommandButton1_Click()  
    If OptionButton1 = True Then Period = "Annual"  
    If OptionButton2 = True Then Period = "Semi-Annual"  
    If OptionButton3 = True Then Period = "Quarterly"  
    If OptionButton4 = True Then Period = "Monthly"  
    If OptionButton5 = True Then Period = "Weekly"  
    ForeCastHorizon = FCHorizon_Text
```

```
    CancStep = False
```

```
    Unload Step8_UsrFrm1  
End Sub
```

```
Private Sub CommandButton2_Click()  
    Unload Step8_UsrFrm1  
End Sub
```


Step9_UsrFrm1



```
Private Sub CommandButton1_Click()  
    If OptionButton1 = True Then Method = "No Threshold"  
    If OptionButton2 = True Then Method = "AAM 5210"  
    If OptionButton3 = True Then Method = "Professional Judg."
```

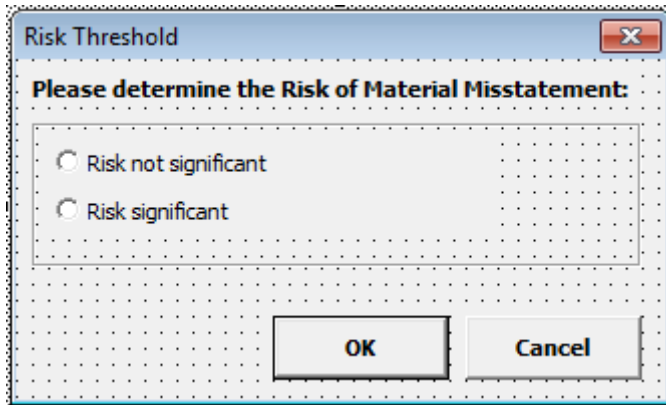
```
    Select Case Method  
        Case Is = "No Threshold"  
            Unload Step9_UsrFrm1  
        Case Is = "AAM 5210"  
            Unload Step9_UsrFrm1  
            Step9_UsrFrm2.Show  
        Case Is = "Professional Judg."  
            Unload Step9_UsrFrm1  
            Step9_UsrFrm6.Show  
    End Select
```

```
    CancStep = False
```

```
End Sub
```

```
Private Sub CommandButton2_Click()  
    Unload Step9_UsrFrm1  
End Sub
```

Step9_UsrFrm2



```
Private Sub CommandButton1_Click()
```

```
    If OptionButton1 = True Then MisstRisk = "Not Significant"
```

```
    If OptionButton2 = True Then MisstRisk = "Significant"
```

```
    Select Case MisstRisk
```

```
        Case Is = "Not Significant"
```

```
            Unload Step9_UsrFrm2
```

```
            Step9_UsrFrm3.Show
```

```
        Case Is = "Significant"
```

```
            Unload Step9_UsrFrm2
```

```
            Step9_UsrFrm5.Show
```

```
    End Select
```

```
End Sub
```

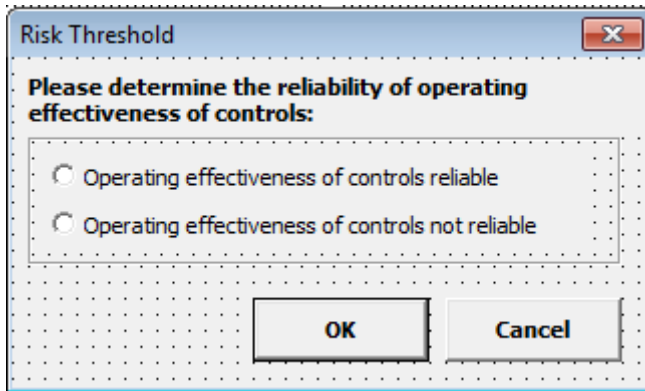
```
Private Sub CommandButton2_Click()
```

```
    CancStep = True
```

```
    Unload Step9_UsrFrm2
```

```
End Sub
```

Step9_UsrFrm3



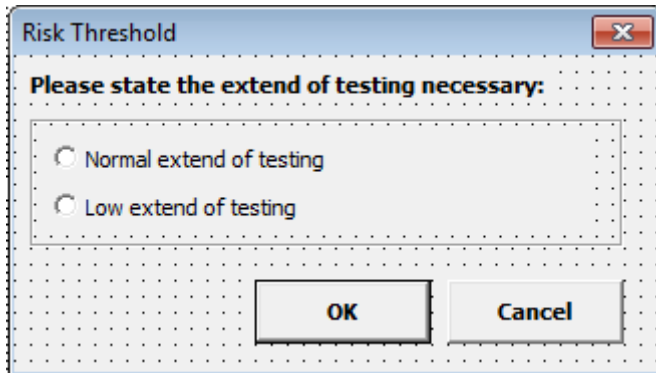
```
Private Sub CommandButton1_Click()  
    If OptionButton1 = True Then ControlEffect = "Reliable"  
    If OptionButton2 = True Then ControlEffect = "Not Reliable"
```

```
    Select Case ControlEffect  
        Case Is = "Reliable"  
            Unload Step9_UsrFrm3  
            Step9_UsrFrm4.Show  
        Case Is = "Not Reliable"  
            Unload Step9_UsrFrm3  
            Step9_UsrFrm5.Show  
    End Select
```

```
End Sub
```

```
Private Sub CommandButton2_Click()  
    CancStep = True  
    Unload Step9_UsrFrm3  
End Sub
```

Step9_UsrFrm4



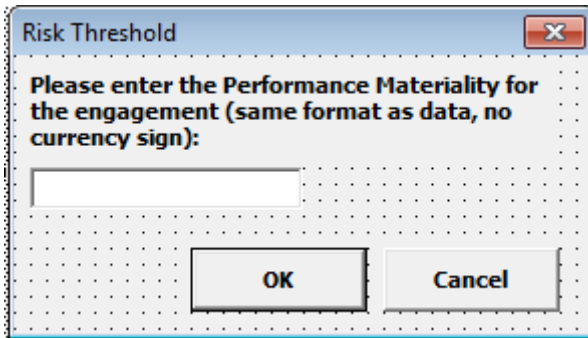
```
Private Sub CommandButton1_Click()  
    If OptionButton1 = True Then Testing = "Normal"  
    If OptionButton2 = True Then Testing = "Low"
```

```
    Unload Step9_UsrFrm4  
    Step9_UsrFrm5.Show
```

```
End Sub
```

```
Private Sub CommandButton2_Click()  
    CancStep = True  
    Unload Step9_UsrFrm4  
End Sub
```

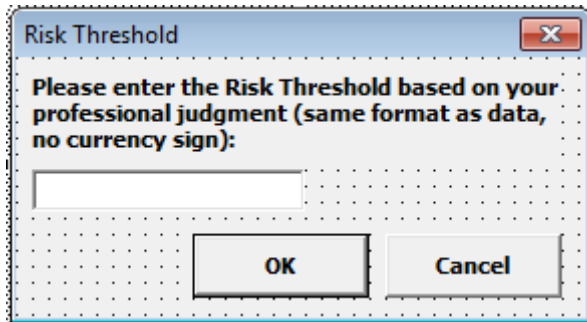
Step9_UsrFrm5



```
Private Sub CommandButton1_Click()  
    If PerfMat_Text = "" Then _  
        MsgBox "Please enter a number.": _  
        Exit Sub  
  
    PerfMat = PerfMat_Text  
  
    Unload Step9_UsrFrm5  
  
End Sub
```

```
Private Sub CommandButton2_Click()  
    CancStep = True  
    Unload Step9_UsrFrm5  
End Sub
```

Step9_UsrFrm6



```
Private Sub CommandButton1_Click()  
    If RisThrProf_Text = "" Then _  
        MsgBox "Please enter a number.": _  
        Exit Sub  
  
    RisThrProf = RisThrProf_Text  
  
    Unload Step9_UsrFrm6  
  
End Sub  
  
Private Sub CommandButton2_Click()  
    CancStep = True  
    Unload Step9_UsrFrm6  
End Sub
```

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

Appendix III Life Testing Data

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | |
|-----------------|------|---|---|---|---------|---------|---------|---------|---------|---------|---------|---------|---------|----------|---------|---------|----------|---------|---------|---------|---------|---------|---------|---------|----------------------------|---------|---------|---------|---------|
| | Data | | | | | | | | | | | | | | | | | | | | | | | | Audited Periods / Forecast | | | | |
| Audit 01 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Series 0101 | | | | | 3.730 | 5.413 | 5.124 | 7.612 | 9.561 | 9.127 | 8.692 | 11.047 | 12.219 | 9.553 | 7.259 | 9.200 | 11.403 | 9.152 | 11.829 | 20.425 | 11.795 | 9.330 | 23.983 | 21.072 | 54.012 | 8.969 | 19.933 | 39.144 | |
| Forecast 0101 | | | | | | | | | | | | | | | | | | | | | | | | | | 28.831 | 24.003 | 26.399 | 39.419 |
| Series 0102 | | | | | 162.604 | 178.588 | 167.394 | 148.415 | 152.932 | 159.080 | 165.228 | 167.352 | 157.237 | 155.452 | 166.544 | 163.963 | 151.607 | 159.704 | 176.130 | 158.119 | 146.122 | 161.741 | 186.303 | 181.070 | 183.046 | 202.344 | 217.991 | 203.926 | |
| Forecast 0102 | | | | | | | | | | | | | | | | | | | | | | | | | | 176.430 | 174.868 | 173.312 | 171.760 |
| Series 0103 | | | | | 36.779 | 33.415 | 34.826 | 39.096 | 33.640 | 35.411 | 37.182 | 43.341 | 41.023 | 45.192 | 39.237 | 36.976 | 41.355 | 42.329 | 43.965 | 47.388 | 44.953 | 45.439 | 49.480 | 79.894 | 61.322 | 67.729 | 69.307 | 76.146 | |
| Forecast 0103 | | | | | | | | | | | | | | | | | | | | | | | | | | 73.163 | 77.893 | 81.501 | 91.260 |
| Series 0104 | | | | | 75.229 | 79.646 | 89.434 | 82.567 | 77.081 | 80.652 | 84.223 | 79.708 | 81.159 | 73.912 | 82.128 | 76.897 | 70.361 | 81.826 | 86.901 | 79.829 | 72.002 | 91.899 | 101.396 | 81.763 | 93.005 | 104.651 | 123.987 | 96.872 | |
| Forecast 0104 | | | | | | | | | | | | | | | | | | | | | | | | | | 88.496 | 89.596 | 90.724 | 91.881 |
| Series 0105 | | | | | 75.593 | 63.519 | 69.719 | 67.077 | 65.307 | 75.750 | 86.192 | 69.220 | 74.905 | 84.333 | 111.451 | 75.786 | 85.207 | 92.881 | 93.193 | 132.986 | 94.530 | 100.577 | 128.765 | 97.167 | 143.046 | 121.685 | 151.489 | 162.987 | |
| Forecast 0105 | | | | | | | | | | | | | | | | | | | | | | | | | | 86.872 | 86.882 | 86.935 | 87.031 |
| Series 0106 | | | | | -11.456 | -17.160 | -12.259 | -13.063 | -12.860 | -13.383 | -13.906 | -10.802 | -12.607 | -6.748 | -13.359 | -16.382 | -9.685 | -12.504 | -10.241 | -4.090 | -10.106 | -10.082 | -10.027 | -12.004 | 88.875 | -9.895 | -3.729 | -9.628 | -13.322 |
| Forecast 0106 | | | | | | | | | | | | | | | | | | | | | | | | | | -13.169 | -13.197 | -13.220 | -13.238 |
| Series 0107 | | | | | 6.392 | 19.308 | 29.184 | 15.838 | 22.425 | 26.322 | 30.219 | 18.501 | 17.880 | 25.954 | 28.445 | 6.918 | 15.430 | 25.051 | 38.618 | 15.303 | 18.836 | 28.327 | 44.738 | 18.120 | 20.911 | 33.124 | 55.116 | 19.023 | |
| Forecast 0107 | | | | | | | | | | | | | | | | | | | | | | | | | | 24.275 | 34.655 | 46.385 | 20.332 |
| Series 0108 | | | | | 41.267 | 24.625 | 23.827 | 108.581 | 41.392 | 43.323 | 45.253 | 31.374 | 32.701 | 56.206 | 117.014 | 67.280 | 37.585 | 36.014 | 46.386 | 48.555 | 31.022 | 41.135 | 46.008 | 53.087 | 50.373 | 80.976 | 70.649 | 65.588 | |
| Forecast 0108 | | | | | | | | | | | | | | | | | | | | | | | | | | 51.214 | 50.174 | 49.157 | 48.165 |
| Series 0109 | | | | | -43.270 | -54.722 | 19.536 | -19.913 | 69.248 | -64.726 | -45.669 | -30.127 | -73.919 | -133.875 | -69.163 | 65.678 | -139.377 | 26.863 | -53.061 | -53.137 | -7.692 | -6.854 | -8.545 | -8.106 | -6.412 | -65.987 | -36.370 | -11.807 | |
| Forecast 0109 | | | | | | | | | | | | | | | | | | | | | | | | | | 5.529 | 14.678 | 23.954 | 33.358 |
| Audit 02 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Series 0201 | | | | | 387 | 446 | 457 | 526 | 472 | 515 | 524 | 605 | 533 | 562 | 557 | 619 | 514 | 564 | 560 | 652 | 576 | 602 | 615 | 706 | 620 | 680 | 665 | 789 | |
| Forecast 0201 | | | | | | | | | | | | | | | | | | | | | | | | | | 613 | 653 | 656 | 746 |
| Series 0202 | | | | | 81.7 | 91.1 | 88.6 | 100.8 | 92.8 | 101.5 | 95.1 | 106.3 | 89.9 | 109.1 | 104.0 | 112.2 | 101.2 | 103.4 | 111.1 | 117.2 | 113.4 | 117.4 | 74.6 | 170.6 | 121.2 | 128.1 | 125.1 | 142.6 | |
| Forecast 0202 | | | | | | | | | | | | | | | | | | | | | | | | | | 154.0 | 158.9 | 164.1 | 169.5 |
| Series 0203 | | | | | 10.3 | 10.9 | 15.3 | 16.9 | 11.8 | 14.4 | 15.2 | 17.9 | 13.6 | 15.7 | 15.0 | 19.4 | 15.0 | 16.2 | 16.8 | 17.2 | 17.2 | 15.6 | 16.3 | 20.9 | 18.2 | 17.4 | 19.2 | 22.2 | |
| Forecast 0203 | | | | | | | | | | | | | | | | | | | | | | | | | | 16.3 | 17.6 | 18.7 | 21.1 |
| Series 0204 | | | | | -0.5 | -0.9 | -0.2 | -0.2 | 0.5 | 0.4 | 1.0 | 0.6 | -4.8 | -4.9 | -5.3 | -5.7 | -5.1 | -7.2 | -4.9 | -4.8 | -4.0 | -3.8 | -4.4 | -5.4 | -2.9 | -3.9 | -5.7 | -2.3 | |
| Forecast 0204 | | | | | | | | | | | | | | | | | | | | | | | | | | -5.6 | -5.9 | -6.1 | -6.4 |
| Series 0205 | | | | | 196.2 | 203.6 | 212.0 | 198.0 | 241.0 | 256.6 | 288.7 | 248.0 | 288.7 | 288.0 | 293.6 | 254.3 | 299.2 | 304.0 | 313.6 | 271.4 | 309.9 | 327.5 | 338.4 | 299.3 | 335.1 | 345.0 | 347.6 | 316.7 | |
| Forecast 0205 | | | | | | | | | | | | | | | | | | | | | | | | | | 348.9 | 357.4 | 372.0 | 324.2 |
| Series 0206 | | | | | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 403.4 | 300.1 | 218.0 | 171.4 | 200.6 | 147.4 | 161.2 | 216.9 | 300.8 | 235.6 | 192.8 | 242.0 | 210.5 | |
| Forecast 0206 | | | | | | | | | | | | | | | | | | | | | | | | | | 325.4 | 362.3 | 403.4 | 449.1 |
| Series 0207 | | | | | 0.4 | 11.3 | 46.4 | 54.8 | 0.1 | -2.1 | -3.0 | 69.7 | -0.3 | -4.8 | 74.3 | 58.8 | 7.8 | -16.5 | 36.9 | 39.3 | -10.9 | -4.3 | 77.4 | 48.0 | -14.4 | -3.6 | 76.6 | 85.6 | |
| Forecast 0207 | | | | | | | | | | | | | | | | | | | | | | | | | | -1.2 | -6.4 | 30.3 | 54.1 |
| Series 0208 | | | | | -55.5 | -1.6 | 4.0 | -22.2 | -49.6 | -20.5 | -7.6 | -4.2 | -31.3 | -16.6 | -25.3 | -36.1 | -35.0 | -15.0 | -2.8 | -120.5 | 27.9 | -29.0 | -19.8 | -13.7 | -50.7 | -16.8 | -25.6 | -91.7 | |
| Forecast 0208 | | | | | | | | | | | | | | | | | | | | | | | | | | -8.8 | -4.1 | 0.6 | 5.3 |
| Audit 03 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Series 0301 | | | | | 498 | 469 | 423 | 477 | 572 | 502 | 509 | 551 | 582 | 670 | 561 | 479 | 626 | 548 | 457 | 407 | 507 | 461 | 451 | 465 | 608 | 501 | 471 | 511 | |
| Forecast 0301 | | | | | | | | | | | | | | | | | | | | | | | | | | 467 | 472 | 477 | 482 |
| Series 0302 | | | | | 616 | 275 | 305 | 532 | 683 | 282 | 307 | 439 | 459 | 288 | 319 | 420 | 615 | 285 | 321 | 531 | 641 | 374 | 335 | 429 | 727 | 287 | 382 | 529 | |
| Forecast 0302 | | | | | | | | | | | | | | | | | | | | | | | | | | 542 | 283 | 295 | 452 |
| Series 0303 | | | | | 151 | 119 | 79 | 127 | 202 | 184 | 171 | 181 | 208 | 240 | 158 | 165 | 209 | 182 | 107 | 54 | 134 | 159 | 111 | 84 | 183 | 144 | 93 | 127 | |
| Forecast 0303 | | | | | | | | | | | | | | | | | | | | | | | | | | 128 | 134 | 91 | 93 |
| Series 0304 | | | | | 108 | 22 | 32 | 77 | 139 | 11 | 13 | 48 | 45 | 12 | 5 | 0 | 73 | 14 | 9 | 22 | 89 | 2 | 50 | 32 | 142 | 43 | 71 | 11 | |
| Forecast 0304 | | | | | | | | | | | | | | | | | | | | | | | | | | 93 | 14 | 16 | 44 |
| Series 0305 | | | | | 321 | 163 | 89 | 253 | 350 | 202 | 161 | -80 | 265 | 212 | 136 | -6 | 277 | 138 | 74 | 268 | 379 | 137 | 107 | 95 | 309 | 131 | 110 | 120 | |
| Forecast 0305 | | | | | | | | | | | | | | | | | | | | | | | | | | 329 | 180 | 121 | 77 |
| Series 0306 | | | | | 27 | 32 | 43 | 86 | 29 | 48 | 94 | 121 | 41 | 78 | 103 | 244 | 111 | 191 | 186 | 254 | 165 | 272 | 295 | 422 | 200 | 356 | 350 | 374 | |
| Forecast 0306 | | | | | | | | | | | | | | | | | | | | | | | | | | 139 | 221 | 263 | 434 |
| Series 0307 | | | | | 2.380 | 2.598 | 2.477 | 2.652 | 2.809 | 2.627 | 2.815 | 3.085 | 3.202 | 3.181 | 3.315 | 3.394 | 3.647 | 3.418 | 3.433 | 3.397 | 3.483 | 3.575 | 3.855 | 3.975 | 4.425 | 4.314 | 4.135 | 4.296 | |
| Forecast 0307 | | | | | | | | | | | | | | | | | | | | | | | | | | 4.044 | 4.126 | 4.213 | 4.305 |
| Series 0308 | | | | | 1.049 | 862 | 789 | 733 | 727 | 769 | 675 | 611 | 630 | 813 | 750 | 827 | 619 | 791 | 902 | 1.037 | 832 | 1.098 | 1.305 | 1.626 | 1.653 | 2.019 | 2.224 | 2.400 | |
| Forecast 0308 | | | | | | | | | | | | | | | | | | | | | | | | | | 1.511 | 1.631 | 1.762 | 1.905 |
| Series 0309 | | | | | 0.8 | 1.1 | 1.2 | 0.8 | 0.4 | 0.8 | 0.7 | 0.5 | 0.5 | 0.7 | 0.7 | 0.8 | 0.5 | 0.9 | 0.9 | 1.1 | 1.0 | 1.3 | 1.5 | 1.8 | 1.7 | 2.0 | 2.1 | 2.3 | |
| Forecast 0309 | | | | | | | | | | | | | | | | | | | | | | | | | | 1.2 | 2.0 | 2.1 | 2.0 |
| Series 0310 | | | | | 14.069 | 14.021 | 14.197 | 14.186 | 14.173 | 14.279 | 14.433 | 14.338 | 14.323 | 14.325 | 14.352 | 14.362 | 14.300 | 14.255 | 14.473 | 14.421 | 14.330 | 14.248 | 14.334 | 14.295 | 14.248 | 14.201 | 14.378 | 14.383 | |
| Forecast 0310 | | | | | | | | | | | | | | | | | | | | | | | | | | 14.299 | 14.296 | 14.294 | 14.292 |
| Audit 04 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Series 0401 | | | | | 683 | 615 | 784 | 623 | 773 | 674 | 842 | 721 | 821 | 753 | 892 | 805 | 782 | 692 | 813 | 698 | 726 | | | | | | | | |

**Forecasting Methods in Audit Analytical Procedures –
Potential improvements in the Process and the Case for eDSS-assisted core Rule-Based Forecasting**

| Period | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 | 21 | 22 | 23 | 24 | 25 | 26 | 27 | 28 | |
|-----------------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|-----------|----------------------------|-----------|-----------|-----------|---------|
| | Data | | | | | | | | | | | | | | | | | | | | | | | | Audited Periods / Forecast | | | | |
| Series 0405 | | | | | -84 | 39 | 0 | 62 | -153 | 102 | -81 | 149 | -200 | 53 | -26 | 165 | -154 | 41 | 17 | 124 | -132 | 60 | -42 | 178 | 67 | 365 | 220 | 450 | |
| Forecast 405 | | | | | | | | | | | | | | | | | | | | | | | | | 155 | 398 | 302 | 462 | |
| Series 0406 | | | | | -14 | -100 | -18 | -21 | -49 | -22 | -14 | -25 | -101 | -21 | -19 | -25 | -26 | -19 | -15 | -20 | -15 | -20 | -36 | 143 | -18 | -9 | -18 | -25 | |
| Forecast 406 | | | | | | | | | | | | | | | | | | | | | | | | | -38 | -36 | -35 | -34 | |
| Series 0407 | | | | | 379 | 321 | 417 | 308 | 417 | 353 | 431 | 339 | 415 | 371 | 442 | 368 | 373 | 330 | 378 | 291 | 321 | 278 | 374 | 311 | 378 | 359 | 408 | 361 | |
| Forecast 407 | | | | | | | | | | | | | | | | | | | | | | | | | 366 | 328 | 414 | 334 | |
| Series 0408 | | | | | 227 | 209 | 264 | 242 | 242 | 224 | 295 | 275 | 268 | 256 | 311 | 317 | 256 | 227 | 297 | 284 | 246 | 241 | 323 | 293 | 280 | 263 | 347 | 355 | |
| Forecast 408 | | | | | | | | | | | | | | | | | | | | | | | | | 263 | 242 | 306 | 290 | |
| Series 0409 | | | | | 78 | 86 | 103 | 74 | 114 | 97 | 16 | 107 | 139 | 753 | 139 | -507 | 152 | 136 | 138 | 123 | 159 | 134 | 147 | 147 | 163 | 151 | 159 | 163 | |
| Forecast 409 | | | | | | | | | | | | | | | | | | | | | | | | | 145 | 144 | 144 | 143 | |
| Audit 05 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Series 0501 | 23.589 | 23.237 | 22.980 | 22.158 | 21.295 | 20.755 | 20.444 | 19.265 | 19.981 | 19.967 | 20.559 | 20.361 | 21.158 | 23.140 | 22.413 | 23.399 | 24.873 | 23.170 | 24.400 | 20.806 | 23.488 | 22.060 | 23.932 | 20.540 | 21.925 | 21.394 | 21.711 | 37.110 | |
| Forecast 501 | | | | | | | | | | | | | | | | | | | | | | | | | 20.654 | 20.543 | 20.432 | 20.322 | |
| Series 0502 | -5.477 | 3.191 | 4.600 | -81.965 | 8.374 | 3.231 | -23.148 | 11.749 | 9.866 | 8.947 | 8.771 | -136 | 10.229 | 11.483 | 10.814 | 7.385 | 15.001 | 14.026 | -4.938 | 14.856 | 4.017 | 2.543 | 12.315 | 18.078 | -10.532 | 25.592 | 9.014 | -135.453 | |
| Forecast 502 | | | | | | | | | | | | | | | | | | | | | | | | | 18.908 | 20.581 | 22.269 | 23.971 | |
| Series 0503 | 1.797.050 | 1.758.445 | 1.721.330 | 1.425.440 | 1.429.341 | 1.356.984 | 1.359.039 | 1.348.400 | 1.408.924 | 1.425.116 | 1.528.589 | 1.528.589 | 1.529.007 | 1.628.710 | 1.629.905 | 1.622.988 | 1.599.890 | 1.597.569 | 1.635.928 | 1.632.362 | 1.630.679 | 1.639.747 | 1.593.362 | 1.645.840 | 1.650.664 | 1.614.851 | 1.607.681 | 3.260.467 | |
| Forecast 503 | | | | | | | | | | | | | | | | | | | | | | | | | 1.641.566 | 1.634.749 | 1.628.070 | 1.621.570 | |
| Series 0504 | 38,9 | 38,2 | 39,1 | 40,3 | 44,1 | 42,5 | 47,4 | 49,8 | 55,8 | 53,2 | 48,7 | 48,7 | 52,9 | 48,8 | 49,5 | 50,0 | 51,5 | 50,9 | 49,6 | 50,9 | 51,2 | 48,8 | 49,3 | 50,2 | 55,5 | 54,3 | 54,2 | 49,4 | |
| Forecast 504 | | | | | | | | | | | | | | | | | | | | | | | | | 50,7 | 51,1 | 51,5 | 51,9 | |
| Series 0505 | | | | 867.000 | 821.000 | 820.000 | 794.000 | 778.000 | 807.000 | 814.000 | 864.000 | 862.000 | 860.000 | 930.000 | 927.000 | 929.000 | 919.000 | 903.000 | 912.000 | 894.000 | 890.700 | 881.300 | 884.500 | 875.100 | 873.300 | 873.000 | 878.800 | 1.724.100 | |
| Forecast 505 | | | | | | | | | | | | | | | | | | | | | | | | | 873.204 | 869.256 | 865.159 | 860.917 | |
| Series 0506 | | | | 5,7 | 6,5 | 7,7 | 7,3 | 7,6 | 7,5 | 7,7 | 8,5 | 8,6 | 10,7 | 11,5 | 11,2 | 11,4 | 11,6 | 11,0 | 10,1 | 9,1 | 9,5 | 10,6 | 9,9 | 12,6 | 12,7 | 12,4 | 11,7 | 11,8 | |
| Forecast 506 | | | | | | | | | | | | | | | | | | | | | | | | | 12,9 | 13,3 | 13,8 | 14,2 | |
| Series 0507 | | | | 9,6 | 9,2 | 9,2 | 8,7 | 8,4 | 8,2 | 8,2 | 7,7 | 7,7 | 7,9 | 7,4 | 7,2 | 7,1 | 6,7 | 6,9 | 6,6 | 6,8 | 6,6 | 6,7 | 6,8 | 6,8 | 6,8 | 6,8 | 6,8 | 6,8 | 6,8 |
| Forecast 507 | | | | | | | | | | | | | | | | | | | | | | | | | 6,8 | 6,8 | 6,8 | 6,8 | |
| Series 0508 | | | | 9,93 | 9,80 | 9,86 | 9,94 | 10,00 | 10,00 | 10,13 | 10,38 | 10,60 | 10,58 | 10,68 | 10,66 | 10,70 | 10,75 | 10,76 | 10,93 | 10,90 | 10,95 | 10,80 | 10,70 | 10,90 | 10,90 | 10,90 | 10,90 | 11,50 | |
| Forecast 508 | | | | | | | | | | | | | | | | | | | | | | | | | 10,95 | 10,97 | 10,99 | 11,01 | |
| Series 0509 | 4.932 | 9.857 | 7.170 | 11.212 | 9.206 | 4.158 | 3.185 | 12.725 | 8.042 | 3.943 | 16.757 | 9.715 | 18.553 | 4.483 | 11.881 | 45.977 | 21.246 | 4.894 | 11.631 | 45.518 | 7.988 | 16.214 | 12.988 | 15.699 | 7.532 | 8.394 | 9.791 | 19.914 | |
| Forecast 509 | | | | | | | | | | | | | | | | | | | | | | | | | 14.686 | 14.322 | 13.976 | 13.646 | |
| Audit 06 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Series 0601 | | | | | | | | | | 256 | 268 | 272 | 257 | 271 | 280 | 286 | 270 | 278 | 294 | 302 | 283 | 306 | 307 | 318 | 295 | 317 | 327 | 342 | 313 |
| Forecast 601 | | | | | | | | | | | | | | | | | | | | | | | | | 310 | 317 | 323 | 302 | |
| Series 0602 | | | | | | | | | | 1.588 | 1.753 | 1.746 | 1.653 | 1.704 | 1.764 | 1.795 | 1.807 | 1.704 | 1.828 | 1.943 | 1.845 | 1.855 | 1.870 | 1.906 | 1.959 | 1.871 | 1.930 | 1.977 | 2.034 |
| Forecast 602 | | | | | | | | | | | | | | | | | | | | | | | | | 1.969 | 1.984 | 2.001 | 2.017 | |
| Series 0603 | | | | | | | | | | -33 | 18 | 91 | 57 | 56 | 72 | 28 | 141 | -77 | 59 | 45 | -3 | 70 | 50 | 82 | -46 | 39 | 57 | 54 | 11 |
| Forecast 603 | | | | | | | | | | | | | | | | | | | | | | | | | 20 | 25 | 31 | 36 | |
| Series 0604 | | | | | | | | | | -7 | -9 | -8 | -14 | -6 | -7 | -6 | -13 | -4 | -10 | -8 | -25 | -8 | -8 | -9 | -15 | -11 | -13 | -9 | -20 |
| Forecast 604 | | | | | | | | | | | | | | | | | | | | | | | | | -27 | -27 | -28 | -29 | |
| Series 0605 | | | | | | | | | | 13.715 | 13.655 | 14.297 | 14.871 | 14.801 | 14.787 | 15.486 | 15.494 | 15.470 | 15.427 | 16.176 | 16.158 | 16.024 | 16.030 | 16.741 | 16.732 | 16.671 | 16.566 | 17.318 | 17.287 |
| Forecast 605 | | | | | | | | | | | | | | | | | | | | | | | | | 16.831 | 16.960 | 17.097 | 17.243 | |
| Series 0606 | | | | | | | | | | 10.047 | 10.462 | 10.280 | 10.537 | 10.001 | 9.648 | 9.789 | 10.240 | 9.675 | 9.522 | 10.229 | 9.705 | 9.551 | 9.606 | 9.567 | 9.361 | 9.762 | 9.307 | 9.301 | 11.442 |
| Forecast 606 | | | | | | | | | | | | | | | | | | | | | | | | | 9.289 | 9.198 | 9.106 | 9.013 | |
| Series 0607 | | | | | | | | | | 105.456 | 103.016 | 101.317 | 96.908 | 109.293 | 108.281 | 105.716 | 98.199 | 111.206 | 111.462 | 109.560 | 108.848 | 123.402 | 122.702 | 124.385 | 122.605 | 141.876 | 140.133 | 134.980 | 133.108 |
| Forecast 607 | | | | | | | | | | | | | | | | | | | | | | | | | 137.332 | 136.692 | 135.110 | 130.136 | |
| Series 0608 | | | | | | | | | | 58.747 | 53.401 | 55.120 | 54.189 | 60.537 | 57.387 | 50.667 | 19.037 | 19.413 | 19.425 | 17.062 | 18.370 | 19.548 | 22.500 | 21.829 | 20.961 | 22.124 | 22.860 | 21.954 | 22.747 |
| Forecast 608 | | | | | | | | | | | | | | | | | | | | | | | | | 20.791 | 20.612 | 20.440 | 20.277 | |
| Series 0609 | | | | | | | | | | 92.307 | 100.096 | 80.803 | 123.872 | 171.482 | 234.045 | 149.431 | 277.995 | 195.887 | 244.087 | 165.573 | 136.488 | 197.653 | 238.996 | 188.739 | 127.337 | 154.335 | 197.328 | 105.304 | 95.649 |
| Forecast 609 | | | | | | | | | | | | | | | | | | | | | | | | | 139.201 | 145.835 | 152.962 | 160.623 | |
| Audit 07 | | | | | | | | | | | | | | | | | | | | | | | | | | | | | |
| Series 0701 | | | | | 225.579 | 382.810 | 337.393 | 358.892 | 232.986 | 301.858 | 218.759 | 292.857 | 170.493 | 169.587 | 128.820 | 137.494 | 112.202 | 88.967 | 144.455 | 110.197 | 99.420 | 128.675 | 180.823 | 164.464 | 149.083 | 170.888 | 211.819 | 231.675 | |
| Forecast 701 | | | | | | | | | | | | | | | | | | | | | | | | | 172.743 | 183.051 | 194.064 | 205.835 | |
| Series 0702 | | | | | -173.374 | -217.975 | -220.607 | -222.825 | -201.251 | -206.488 | -250.675 | -166.988 | -125.791 | -163.356 | -119.842 | -128.373 | -51.169 | -64.099 | -78.925 | -78.473 | -77.108 | -89.871 | -120.113 | -126.846 | -129.691 | -123.606 | -129.474 | -136.372 | |
| Forecast 702 | | | | | | | | | | | | | | | | | | | | | | | | | -130.795 | -136.198 | -141.893 | -147.880 | |
| Series 0703 | | | | | -27.438 | -31.034 | -30.778 | -37.032 | -34.986 | -35.056 | -34.391 | -33.791 | -36.158 | -35.468 | -28.881 | -28.871 | -30.279 | -27.767 | -27.588 | -26.732 | -30.287 | -37.107 | -34.695 | -36.192 | -41.082 | -39.471 | -40.066 | -37.370 | |
| Forecast 703 | | | | | | | | | | | | | | | | | | | | | | | | | -36.956 | -37.910 | -38.873 | -39.845 | |
| Series 0704 | | | | | 25.873 | 57.865 | 49.836 | 59.177 | 26.288 | 41.337 | 19.233 | -321.911 | 31.503 | -170.393 | -45.782 | -430.745 | -32.323 | -26.706 | -35.951 | -93.685 | 127.412 | -46.484 | -4.183 | -14.370 | -8.029 | -4.162 | -6.077 | 14.117 | |
| Forecast 704 | | | | | | | | | | | | | | | | | | | | | | | | | -13.900 | -11.382 | -8.956 | -6.623 | |
| Series 0705 | | | | | 5.278 | 29.532 | 18.054 | 34.448 | 12.477 | 9.9 | | | | | | | | | | | | | | | | | | | |

List of References

- Adya, M., & Lusk, E. J. (2013). Rule Based Forecasting [RBF] - Improving Efficacy of Judgmental Forecasts Using Simplified Expert Rules. *International Research Journal of Applied Finance*, 1006-1024.
- Adya, M., & Lusk, E. J. (01 2016). Development and validation of a rule-based time series complexity scoring technique to support design of adaptive forecasting DSS. *Decision Support Systems*. Elsevier.
- Adya, M., Armstrong, J. S., Collopy, F., & Kennedy, M. (2000). An application of rule-based forecasting to a situation lacking domain knowledge. *International Journal of Forecasting*, 477-484.
- Adya, M., Armstrong, J. S., & Collopy, F. (1994). Principles for Examining Predictive Validity: The Case of Information Systems Spending Forecasts. *Information Systems Research*, S. 170-179.
- Adya, M., Armstrong, J. S., Collopy, F., & Kennedy, M. (2001). Automatic Identification of Time Series Features for Rule-Based Forecasting. *International Journal of Forecasting*, 143-157.
- Adya, M., Lusk, E. J., & Balhadjali, M. (2009). Decomposition as a Complex-Skill Acquisition Strategy in Management Education: A Case Study in Business Forecasting. *Decision Sciences Journal of Innovative Education*, 9-37.
- Agrawal, A., & Chadha, S. (2005). Corporate Governance and Accounting Scandals. *Journal of Law and Economics*, 371-406.
- AICPA. (1972). Statement on Auditing Procedures No. 54.
- AICPA. (2012). *Analytical Procedures Audit Guide*. New York: Wiley.
- Allen, R. D., Beasley, M. S., & Branson, B. C. (1997). *Improving the Accuracy and Precision of Analytical Procedures Using Multilocation Data*. Abgerufen am 30. 01 2017 von [ssrn.com](https://ssrn.com/abstract=53200):
<https://ssrn.com/abstract=53200>

- Ames, E., & Reiter, S. (1961). Distributions of correlation coefficients in economic time series. *Journal of the American Statistical Association*, S. 637-656.
- Arens, A. A., & Loebbecke, J. K. (2000). *Auditing - An Integrated Approach* (8. Ausg.). Upper Saddle River: Prentice-Hall.
- Arkes, H. R. (2001). Overconfidence in Judgmental Forecasting. In J. S. Armstrong, *Principles of Forecasting* (S. 495-516). Boston: Kluwer Academic Publishers.
- Armstrong, J. S. (1970). An Application of Econometric Models to International Marketing. *Journal of Marketing Research*, S. 190-198.
- Armstrong, J. S. (August 1970). How to avoid exploratory research. *Journal of Advertising Research*, S. 27-30.
- Armstrong, J. S. (1978). Econometric Forecasting and the Science Court. *Journal of Business*, S. 595-600.
- Armstrong, J. S. (1978). Forecasting with Econometric Methods: Folklore versus Fact. *Journal of Business*, S. 549-564.
- Armstrong, J. S. (1979). The Natural Learning Project. *Journal of Experiential Learning and Simulation*, S. 5-12.
- Armstrong, J. S. (1980). The Seer-Sucker Theory: The Value of Experts in Forecasting. *Technology Review*, Technology Review.
- Armstrong, J. S. (Nov.-Dec. 1984). Forecasting by Extrapolation: Conclusions from 25 Years of Research. *Interfaces*, S. 52-66.
- Armstrong, J. S. (1991). Prediction of Consumer Behavior by Experts and Novices. *Journal of Consumer Research*, S. 251-256.

- Armstrong, J. S. (1999). Forecasting for Environmental Decision Making. *Tools to Aid Environmental Decision Making*, S. 192-225.
- Armstrong, J. S. (1999). Introduction to paper and commentaries on the Delphi technique. *International Journal of Forecasting*, S. 351–352.
- Armstrong, J. S. (2001). *Principles of Forecasting*. Boston: Kluwer Academic Publishers.
- Armstrong, J. S. (2001). Should We Redesign Forecasting Competitions? *International Journal of Forecasting*, S. 542-545.
- Armstrong, J. S. (2004). Damped Seasonality Factors: Introduction. *International Journal of Forecasting*, S. 523-527.
- Armstrong, J. S. (June 2005). The Forecasting Canon: Nine Generalizations to Improve Forecast Accuracy. *Foresight*, S. 29-35.
- Armstrong, J. S. (2006). Findings from evidence-based forecasting: methods for reducing forecast error. *International Journal of Forecasting*.
- Armstrong, J. S. (2006). *Statistical Significance Tests are Unnecessary Even When Properly Done and Properly Interpreted: Reply to Commentaries*. Abgerufen am 30. 01 2017 von ssrn.com:
<http://ssrn.com/abstract=988481>
- Armstrong, J. S. (2007). Significance Tests Harm Progress in Forecasting. *International Journal of Forecasting*, S. 321-327.
- Armstrong, J. S., & Brodie, R. J. (11 1994). Effects of Portfolio Planning Methods on Decision Making: Experimental Results. *International Journal of Research in Marketing*, S. 73-84.
- Armstrong, J. S., & Carbone, R. (1982). Evaluation of Extrapolative Forecasting Methods: Resulty of a Survey of Academicians and Practicioners. *Journal of Forecasting*, S. 215-217.

- Armstrong, J. S., & Collopy, F. (10 1992 (b)). Rule-Based Forecasting: Development and Validation of an Expert Systems Approach to Combining Time series Extrapolations. *Management Science*, S. 1394-1414.
- Armstrong, J. S., & Collopy, F. (1992). A Commentary on Error Measures. *International Journal of Forecasting*, S. 99-111.
- Armstrong, J. S., & Collopy, F. (1992). Error Measures For Generalizing About Forecasting Methods Empirical Comparisons. *International Journal of Forecasting*(8), 69-80.
- Armstrong, J. S., & Collopy, F. (1992). Expert Opinions About Extrapolation And The Mystery Of The Overlooked Discontinuities. *International Journal of Forecasting*, S. 575-582.
- Armstrong, J. S., & Collopy, F. (1993). Causal Forces: Structuring Knowledge for Time-series Extrapolation. *Journal of Forecasting*, 103-115.
- Armstrong, J. S., & Collopy, F. (1998). Integration of Statistical Methods and Judgment for Time Series Forecasting: Principles from Empirical Research. *Forecasting with Judgment*, S. 269-293.
- Armstrong, J. S., & Green, K. C. (2004). *Structured Analogies for Forecasting*. Abgerufen am 30. 01 2017 von kestengreen.com: http://www.kestengreen.com/structured_analogy_90.pdf
- Armstrong, J. S., & Green, K. C. (2004). *Value of expertise for forecasting decisions in conflicts*. Abgerufen am 30. 01 2017 von researchgate.com: https://www.researchgate.net/publication/5179894_Value_of_Expertise_For_Forecasting_Decisions_in_Conflicts
- Armstrong, J. S., & Green, K. C. (2007). Global Warming: Forecasts by Scientists Versus Scientific Forecasts. *Energy & Environment*, S. 997-1021.
- Armstrong, J. S., & Green, K. C. (13. 12 2014). *Forecastingprinciples.com*. Abgerufen am 17. 3 2016 von <http://www.forecastingprinciples.com/index.php/selection-tree>

- Armstrong, J. S., & Grohmann, M. C. (1972). A Comparative Study of Methods for Long-Range Market Forecasting. *Management Science*, S. 211-221.
- Armstrong, J. S., & Hubbard, R. (2005). *Why We Don't Really Know What "Statistical Significance" Means: A Major Educational Failure*. Abgerufen am 30. 01 2017 von ssrn.com:
<http://ssrn.com/abstract=988461>
- Armstrong, J. S., & Lusk, E. J. (1983). Commentary on the Makridakis Time Series Competition (M-Competition). *Journal of Forecasting*(2), 259-311.
- Armstrong, J. S., & Lusk, E. J. (1987). Return Postage in Mail Surveys: A Meta Analysis. *Public Opinion Quarterly*, S. 233-248.
- Armstrong, J. S., & MacGregor, D. G. (1994). Judgmental Decomposition: When Does It Work? *International Journal of Forecasting*, 495-506.
- Armstrong, J. S., & Reibstein, D. J. (1985). Evidence on the Value of Strategic Planning in Marketing: How Much Planning Should a Marketing Planner Plan? In D. Gardner, & H. Thomas, *Strategic Marketing and Management* (S. 73-87). John Wiley & Sons, Ltd.
- Armstrong, J. S., & Shapiro, A. C. (1974). Analyzing Quantitative Models. *Journal of Marketing*, S. 61-66.
- Armstrong, J. S., & Soelberg, P. (1968). On the Interpretation of Factor Analysis. *Psychological Bulletin*, S. 361-364.
- Armstrong, J. S., & Yokum, J. T. (1995). Beyond Accuracy: Comparison of Criteria Used to Select Forecasting Methods. *International Journal of Forecasting*, 591-597.
- Armstrong, J. S., Brodie, R. J., & McIntyre, S. H. (1987). Forecasting Methods for Marketing: Review of Empirical Research. *International Journal of Forecasting*, S. 355-376.

- Armstrong, J. S., Collopy, F., & Yokum, J. T. (2004). *Decomposition by Causal Forces: A Procedure for Forecasting Complex Time Series*. Abgerufen am 30. 01 2017 von upenn.edu:
http://repository.upenn.edu/cgi/viewcontent.cgi?article=1058&context=marketing_papers
- Armstrong, J. S., Denniston, W. B., & Gordon, M. M. (1975). The Use of the Decomposition Principle in Making Judgments. *Organizational Behavior and Human Performance*, S. 257-263.
- Armstrong, J., & Brodie, R. J. (1999). Forecasting for Marketing. In M. K. Hussey, *Quantitative Methods in Marketing* (S. 92-119). London: International Thompson Business Press.
- Armstrong, J., & Collopy, F. (2001). Identification of Asymmetric Prediction Intervals through Causal Forces. *Journal of Forecasting*, S. 273-283.
- Armstrong, J., & Yokum, T. (2001). Potential Diffusion of Expert Systems in Forecasting. *Technological Forecasting and Social Change*, S. 93-103.
- Armstrong, J., Morwitz, V., & Kumar, V. (2000). *Sales Forecasts for Existing Consumer Products and Services: Do Purchase Intentions Contribute to Accuracy?* Abgerufen am 30. 01 2017 von Forecasters.org: <http://forecasters.org/pdfs/ijf/Sales%20Forecasts-Armstrong-Morwitz-Kumar.pdf>
- Ashton, A., & Ashton, R. (1985). Aggregating subjective forecasts: Some empirical results. *Management Science*, S. 1499-1508.
- Ashton, R. H., & Wright, A. (1989). Identifying Audit Adjustments with Attention-Directing Procedures. *The Accounting Review*, 710-728.
- Baker, M. J. (1999). Sales Forecasting. In M. J. Baker, *The IEBM Encyclopedia of Marketing*. International Thompson Business Press.
- Balhadjali, M., Lusk, E. J., & Matzner, D. (2004). *A test of a minimalist rule*. Abgerufen am 30. 01 2017 von forecastingprinciples.com: <http://www.forecastingprinciples.com/files/RBF2004.pdf>
- Bell, T., Peecher, M., & Solomon, I. (2005). *The 21st century public company audit*. New York: KPMG.

Bhattacharjee, S., Brandon, D., & Moreno, K. K. (2005). *The Effectiveness of Alternative Training*

Techniques on Analytical Procedures Performance. Abgerufen am 30. 01 2017 von ssrn.com:

https://papers.ssrn.com/sol3/papers.cfm?abstract_id=739785

Biggs, S. F., & Wild, J. J. (1984). A Note on the Practice of Analytical Review. *Auditing: A Journal of Practice and Theory*, 68-79.

Blattberg, R. C., & Hoch, S. J. (1990). Database models and managerial intuition: 50% model, 50% manager. *Management Science*, 887-899.

Board, P. C. (2010). AU Section 329.

Bosart, L. F., & Roebber, P. J. (1996). The contributions of education and experience to forecasting skills. *Weather and Forecasting*, 21-40.

Box, G. E., & Jenkins, G. M. (1970). *Time Series Analysis: Forecasting and Control*. San Francisco: Holden-Day.

Brazel, J. F., Jones, K. L., & Prawitt, D. F. (2011). *Improving Fraud Detection: Evaluating Auditors' Reactions to Abnormal Inconsistencies between Financial and Nonfinancial Measures*. Abgerufen am 30. 01 2017 von ssrn.com: <http://ssrn.com/abstract=1534778>

Brazel, J. F., Jones, K. L., & Zimbelman, M. F. (July 2009). Using Nonfinancial Measures to Assess Fraud Risk. *Journal of Accounting Research*.

Brazel, J., Jones, K., & Zimbelman, M. (2009). Using Nonfinancial Measures to Assess Fraud Risk. *Journal of Accounting Research*.

Brewster, B. E. (2010). How a Systems Perspective Improves Knowledge Acquisition and Performance in Analytical Procedures. *The Accounting Review*.

Broesel, G., Freichel, C., Toll, M., & Buchner, R. (2015). *Wirtschaftliches Prüfungswesen*. München: Franz Vahlen.

- Brown, B. G., & Murphy, A. H. (1984). A comparative evaluation of objective and subjective weather forecasts in the United States. *Journal of Forecasting*, 369-393.
- Brown, R. G. (1956). *Exponential Smoothing for Predicting Demand*. Cambridge, MA: Arthur D. Little.
- Bunn, D., & Wright, G. (1991). Interaction of judgmental and statistical Forecasting Methods: Issues and Analysis. *Management Science*, 501-518.
- Burkom, H. S., Murphy, S. P., & Shmueli, G. (2006). *Automated Time Series Forecasting for Biosurveillance*. Abgerufen am 30. 01 2017 von [ssrn.com: http://ssrn.com/abstract=923635](http://ssrn.com/abstract=923635)
- Byrnes, P. E., Al-Awadhi, A., Gullvist, B., Brown-Libur, H., Teeter, R., Warren, J. D., & Vasarhelyi, M. (11 2012). *aicpa.org*. Abgerufen am 05. 11 2014 von http://www.aicpa.org/InterestAreas/FRC/AssuranceAdvisoryServices/DownloadableDocuments/Whitpaper_Evolution-of-Auditing.pdf
- Camerer, C. (1981). General conditions for the success of bootstrapping models. *Organizational Behavior and Human Performance*, 411-422.
- Chen, Q., Kelly, K., & Salterio, S. E. (2010). *Does Auditing Deter Potentially Fraudulent Earnings Management? An Experimental Investigation*. Abgerufen am 30. 01 2017 von [ssrn.com: http://ssrn.com/abstract=1529807](http://ssrn.com/abstract=1529807)
- Clemen, R. T. (1989). Combining forecasts: A review and annotated bibliography. *International Journal of Forecasting*, S. 559-583.
- Conway, J. M., Jako, R. A., & Goodman, D. F. (1995). A meta-analysis of interrater and internal consistency reliability of selection interviews. *Journal of applied Psychology*, S. 565-579.
- Cooksey, R. W., Freebody, P., & Bennett, A. J. (1990). The ecology of spelling: A lens model analysis of spelling errors and student judgments of spelling difficulty. *Reading Psychology: An international Quarterly*, 293-322.

Crawford, D., & Dugan, J. (18. 02 2009). *Wall Street Journal*. Abgerufen am 05. 11 2014 von

<http://online.wsj.com/articles/SB123491638561904323>

Cressey, D. R. (1973). *Other People's Money: A Study in the Social Psychology of Embezzlement*. New Jersey: Patterson-Smith.

Croux, C., Fried, R., & Gelper, S. (2008). *Robust forecasting with exponential and Holt-Winters Smoothing*.

Abgerufen am 30. 01 2017 von kuleuven.be: [https://feb.kuleuven.be/public/ndbae06/PDF-](https://feb.kuleuven.be/public/ndbae06/PDF-FILES/Robust_Holt_Winters.pdf)

[FILES/Robust_Holt_Winters.pdf](https://feb.kuleuven.be/public/ndbae06/PDF-FILES/Robust_Holt_Winters.pdf)

D., K., & Tversky, A. (1992). Advances in Prospect Theory: Cumulative Representation of Uncertainty.

Journal of Risk and Uncertainty, S. 297-323.

de Gooijer, J. G., & Hyndmann, R. J. (2005). 25 Years of IIF Time Series Forecasting: A Selective Review.

Tinbergen Institute Discussion Paper, S. TI 2005-068/4.

Deloitte & Touche LLP. (2013 (a)). Abgerufen am 18. 04 2013 von

http://www.deloitte.com/view/de_DE/de/uber-uns/index.htm

Deloitte & Touche LLP. (2013 (b)). *Deloitte Auditing Manual*.

DoJ. (21. 08 2014). www.justice.gov. Abgerufen am 29. 02 2016 von [https://www.justice.gov/opa/pr/bank-](https://www.justice.gov/opa/pr/bank-america-pay-1665-billion-historic-justice-department-settlement-financial-fraud-leading)

[america-pay-1665-billion-historic-justice-department-settlement-financial-fraud-leading](https://www.justice.gov/opa/pr/bank-america-pay-1665-billion-historic-justice-department-settlement-financial-fraud-leading)

Edmundson, R. H. (1990). Decomposition: A strategy for judgmental forecasting. *Journal of Forecasting*, S.

305-314.

Elliott, G. R., & Stock, J. H. (1992). Efficient Tests for an Autoregressive Unit Root. *Nber Technical*

Working Papers, S. Technical Working Paper No. 130.

Elliott, G., & Müller, U. K. (2003). *Optimally Testing General Breaking Processes in Linear Time Series*

Models. Abgerufen am 30. 01 2017 von ssrn.com:

https://papers.ssrn.com/sol3/papers.cfm?abstract_id=410927

- Elliott, G., & Timmermann, A. (2002). *Optimal Forecast Combinations Under General Loss Functions and Forecast Error Distributions*. Abgerufen am 30. 01 2017 von ssrn.com:
https://papers.ssrn.com/sol3/papers.cfm?abstract_id=318723
- Feroz, E. H., Kim, S., & Raab, R. L. (2003). *Analytical Procedures: A Data Envelopment Analysis Approach*. Abgerufen am 30. 01 2017 von ssrn.com: <http://ssrn.com/abstract=1179302>
- Fildes, R., & Makridakis, S. (1995). The Impact of Empirical Accuracy Studies on Time Series Analysis and Forecasting. *International Statistical Review*, S. 289-308.
- Fraser, I. A., Hatherly, D. J., & Lin, K. Z. (1997). An Empirical Investigation of the Use of Analytical Review by External Auditors. *The British Accounting Review*, 35-47.
- Gardner, E. S., & McKenzie, E. (10 1985). Forecasting Trend in Time Series. *Management Science*, S. 1237-1246.
- Gardner, E. S., & McKenzie, E. (1. 10 1985). Forecasting Trends in Time Series. *Management Science*, S. 1237-1246.
- Gauss, C. F. (1821-23). *Theoria combinationis observationum erroribus minimis obnoxiae*. Göttingen.
- Goldberg, L. R. (1970). Man vs. Model of Man: A rationale, plus some evidence, for a method of improving on clinical inferences. *Psychological Bulletin*, 422-432.
- Goldberg, L. R., & Ramanaiah, N. V. (1977). Stylistic Components of Human Judgment: The Generality of Individual Differences. *Applies Psychological Measurement*, 23-39.
- Goodwin, P. (2005). How to Integrate Management Judgment with Statistical Forecasts. *Foresight*, S. 8-12.
- Guy, D. M., Alderman, C. W., & Winters, A. J. (1996). *Auditing* (4. Ausg.). Orlando: The Dryden Press.
- Hagafors, R., & Bremer, B. (1983). Does having to justify one's judgments change the nature of the judgment process? *Organizational Behavior and Human Performance*, S. 223-232.

- Harvey, N. (2001). Improving Judgment in Forecasting. In J. Armstrong, *Principles of Forecasting* (S. 59-80). New York: Springer Science+Media.
- Hertwig, R., & Hertog, S. M. (2009). The Wisdom of Many in One Mind - Improving Individual Judgments With Dialectical Bootstrapping. *Psychological Science*, S. 231-237.
- Hibon, M., & Makridakis, S. (1979). Accuracy of Forecasting: An empirical Investigation (with discussion). *Journal of the Royal Statistical Society*, 97-145.
- Hibon, M., & Makridakis, S. (1997). *ARMA Models and the Box Jenkins Methodology*. Abgerufen am 30. 01 2017 von researchgate.net:
<https://www.researchgate.net/file.PostFileLoader.html?id=555be79e614325fdb8b4567&assetKey=AS%3A273780117573632%401442285674744>
- Hirst, D. E., & Koonce, L. (07 1996). Audit Analytical Procedures: A Field Investigation. *Contemporary Accounting Research*, S. 457-486.
- Hogarth, R. M., & Karelaia, N. (2006). *On heuristic and linear models of judgment: Mapping the demand for knowledge*. Abgerufen am 30. 01 2017 von ssrn.com: <http://ssrn.com/abstract=1002514>
- Holt, C. C. (1957). Forecasting Trends and Seasonal by Exponentially Weighted Averages. *Office of Naval Research Memorandum*.
- Holt, C. C., Muth, J. F., Simon, H. A., Bonini, C. P., & Winters, P. R. (1960). *Planning Production, Inventories, and Work Force*. Englewood Cliffs: Prentice Hall.
- Hyndmann, K., Kraiselbund, S., & Watson, N. (2010). *Coordination in Supply Chains When Demand Forecasts Are Not Common Knowledge: Theory and Experiment*. Abgerufen am 30. 01 2017 von researchgate.net:
https://www.researchgate.net/publication/267552008_Coordination_in_Supply_Chains_When_Demand_Forecasts_Are_Not_Common_Knowledge_Theory_and_Experiment

IAASB. (2002). AU Section 329 Analytical Procedures.

IDW, I. d. (2017). *WP Handbuch*. Düsseldorf: IDW Verlag.

IDW, I. d. (kein Datum). PS 312.

IFAC. (2009). ISA 315: Identifying and assessing the Risks of material Misstatements through understanding the Entity and its Environment.

IFAC. (2009). ISA 330: The auditor's response to assessed risks.

IFAC. (kein Datum). ISA 520.

International Federation of Accountants (IFAC). (2010). ISA 315: Identifying and assessing the Risk of material Misstatement through understanding the Entity and its Environment.

INTOSAI. (2009). ISSAI 1520.

Kahnemann, D. (2011). *Thinking, Fast and Slow*. London: Penguin Books Ltd.

Kahnemann, D., & Tversky, A. (1974). Judgment under Uncertainty: Heuristics and Biases. *Science*, S. 1124-1131.

Kahnemann, D., & Tversky, A. (1979). Prospect Theory: An Analysis of Decision under Risk. *Econometrica*, S. 263-292.

Kayadelen, E. (2008). Zur Durchführung von analytischen Prüfungshandlungen im Rahmen der Jahresabschlussprüfung. Darmstadt: Technische Universität Darmstadt.

Knapp, C. A., & Knapp, M. C. (2001). The effects of experience and explicit fraud risk assessment in detecting fraud with analytical procedures. *Accounting, Organizations and Society*, S. 25-37.

KPMG. (2011). *www.kpmg.com*. Abgerufen am 07. 12 2015 von

<http://www.kpmg.com/US/en/IssuesAndInsights/ArticlesPublications/Pages/typical-fraudster.aspx>

- Lewandowski, R. (1982). Sales Forecasting by FORSYS. *Journal of Forecasting*, S. 205-214.
- Likert, R. (1932). A Technique for the Measurement of Attitudes. *Archives of Psychology*, 55.
- MacGregor, D. G. (2001). Decomposition for Judgmental Forecasting and Estimation. In J. Armstrong, *Principles of Forecasting* (S. 107-123). New York: Springer Science+Media.
- Makridakis, S. (1983). The Combination of Forecasts. *Journal of the Royal Statistical Society*, S. 150-157.
- Makridakis, S., & Hibon, M. (1979). Accuracy of Forecasting: An empirical Investigation. *Journal of Royal Statistics Society Series*, S. 97-145.
- Makridakis, S., & Hibon, M. (2000). The M3-Competition: results, conclusions and implications. *International Journal of Forecasting*, 451-476.
- Makridakis, S., Andersen, A., Carbone, R., Fildes, R., Hibon, M., Lewandowski, R., . . . Winkler, R. (1982). The Accuracy of Extrapolation (Time Series) Methods: Results of a Forecasting Competition. *Journal of Forecasting*(1), 111-153.
- Makridakis, S., Andersen, A., Carbone, R., Fildes, R., Hibon, M., Lewandowski, R., . . . Winkler, R. (1984). *The Forecasting Accuracy of Major Time Series Methods*. John Wiley & Sons.
- Makridakis, S., Chatfield, C., Hibon, M., Lawrence, M., Mills, T., Ord, K., & Simmons, L. (1993). The M2-Competition: A real-time judgmentally based forecasting study. *International Journal of Forecasting*, 5-22.
- Marten, K.-U., Quick, R., & Ruhnke, K. (2006). *Lexikon der Wirtschaftsprüfung*. Stuttgart: Schäffer-Poeschel Verlag für Wirtschaft.
- Marten, K.-U., Quick, R., & Ruhnke, K. (2015). *Wirtschaftsprüfung - Grundlage des betriebswirtschaftlichen Prüfungswesens nach nationalen und internationalen Normen*. Stuttgart: Schäffer Poeschel.

- McGregor, D. (1938). The major determinants in the prediction of social events. *Journal of Abnormal and Social Psychology*, S. 179-204.
- McNees, S. K. (1987). Consensus forecasts: Tyranny of the majority? *New England Economic Review*, S. 15-21.
- Millichamp, A., & Taylor, J. (2008). *Auditing* (9. Ausg.). London: South-Western CENGAGE Learning.
- Musgrave, J. C., Shiskin, J., & Young, A. H. (1967). The X-11 Variant of the Census Method Seasonal Adjustment Program. *Bureau of the Census Technical Paper Series*, S. Technical Paper No. 15.
- Nelson, M., & Tan, H. (2005). Judgment and decision making research: A task, person, and interpersonal interaction perspective. *Auditing: A Journal of Practice and Theory*, 41-71.
- Newbold, P. (1983). The competition to end all competitions. *Journal of Forecasting*, 276-279.
- Northcraft, G. B., & Neale, M. A. (1987). Experts, Amateurs and Real Estate: An Anchoring-and-Adjustment Perspective on Property Price Decisions. *Organizational Behavior and Human Decision Processes*, 84-97.
- Ogburn. (1934). Studies in prediction and the distortion of reality. *Social Forces*, S. 224-229.
- Palmrose, Z. V., & Scholz, S. (1 2004). The Circumstances and Legal Consequences of Non-GAAP Reporting: Evidence from Restatements. *Contemporary Audit Research*, S. 139-180.
- Parzen, E. (12 1979). Time Series and Whitening Filter Estimation. *TIMS Studies in the Management Sciences*, S. 149-165.
- Parzen, E. (1982). ARARMA Models for Time Series Analysis and Forecasting. *Journal of Forecasting*, S. 67-82.

- Prawitt, D. F., & Stuart, I. (2004). *The Influence of Audit Structure on Auditors' Performance in High and Low Complexity Task Settings*. Abgerufen am 30. 01 2017 von [ssrn.com](http://papers.ssrn.com):
https://papers.ssrn.com/sol3/papers.cfm?abstract_id=569871
- Reuters. (31. 10 2011). *reuters.com*. Abgerufen am 03. 11 2014 von
<http://www.reuters.com/article/2011/10/31/us-germany-blunder-idUSTRE79U5MW20111031>
- Reuters. (30. 01 2013). Abgerufen am 18. 04 2013 von <http://www.reuters.com/article/2013/01/30/us-accounting-idUSBRE90T15W20130130>
- Rowe, G., & Wright, G. (2001). Expert Opinions in Forecasting: The Role of the Delphi Technique. In J. Armstrong, *Forecasting Principles* (S. 125-144). New York: Springer Science+Media.
- S., A. J., & Fildes, R. (1995). On the Selection of Error Measures for Comparisons Among Forecasting Methods. *Journal of Forecasting*, S. 67-71.
- Stewart, T. R. (2001). Improving Reliability in Judgmental Forecasts. In J. S. Armstrong, *Principles of Forecasting* (S. 81-101). Boston: Kluwer Academic Publishers.
- Stringer, K. W., & Stewart, T. R. (1996). *Statistical Techniques for Analytical Review in Auditing* (2. Ausg.). New York: John Wiley & Sons / Deloitte & Touche LLP.
- Stroop, J. R. (1932). Is the judgment of the group better than that of the average member of the group? *Journal of Experimental Psychology*, S. 550-560.
- Sweller, J. (2003). Evolution of human cognitive architecture. *The psychology of learning and motivation: Advances in research and theory*, 215-266.
- Trompeter, G., & Wright, A. (2010). The World has Changed - Have Analytical Procedure Practices. *Contemporary Accounting Research*, 669-700.

- Tversky, A., & Kahnemann, D. (1982). Availability: A Heuristic for judging Frequency and Probability. In D. Kahnemann, P. Slovic, & A. Tversky, *Judgment under Uncertainty: Heuristics and Biases*. Cambridge: Cambridge University Press.
- Whittle, P. (1951). *Hypothesis Testing in Time Series Analysis*. New York: Hafner Publishing Company.
- Winkler, R. L. (1981). Combining probability distributions from dependent information sources. *Management Science*, S. 479-488.
- Winters, P. R. (1960). Forecasting Sales by Exponentially Weighted Moving Averages. *Management Science*, 324-342.
- Woolf, E. (1997). *Auditing Today* (6. Ausg.). Harlow, UK: Prentice Hall.
- Wright, A., & Ashton, R. H. (1989). Identifying Audit Adjustments with Attention-Directing Procedures. *The Accounting Review*, 710-728.
- Wright, A., & Wright, S. (1997). *The Effect of Industry Experience on Hypothesis Generation and Audit Planning Decisions*. Abgerufen am 30. 01 2017 von [ssrn.com](http://papers.ssrn.com/paper.taf?abstract_id=42913):
http://papers.ssrn.com/paper.taf?abstract_id=42913