2009

The Impact of Data Quality on Value Based Management of Financial Institutions

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Becker, Jörg; Poeppelbuss, Jens; Gloerfeld, Fabian; and Bruhns, Peter, "The Impact of Data Quality on Value Based Management of Financial Institutions" (2009). *AMCIS 2009 Proceedings*. 490.  
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The Impact of Data Quality on Value Based Management of Financial Institutions

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ABSTRACT

Data quality plays a crucial role for financial institutions. Some would even say that data quality is one of the principal reasons for the current financial crisis. Anyway, sufficient data quality is needed to make well-informed business decisions. The dependence on good data quality is especially high if value based management is applied, since then the control of an institution only depends on a few selected key indicators. Bad data quality will lead to inaccurate indicators. To achieve a higher level of data quality, financial institutions need to invest in data quality projects. Although they are generally willing to do this, data quality projects need to be justified through business cases. In this research-in-progress paper, we present the results of a survey in which we asked German financial institutions to give their perspective on the influence of data quality on value based management. The findings of this study provide the basis for our future research as we finally aim at developing a business case model that financial institutions can apply to prepare business cases for data quality projects.

Keywords  
Data quality, financial institutions, value based management, business case model.

INTRODUCTION

In nearly every information system (IS) there are problems with ‘dirty data’ (Marsh, 2005). According to a study from The Data Warehouse Institute (TDWI) there is a net loss of 611 billion US dollars (USD) per year in the United States alone due to poor data quality (Eckerson, 2002). 53% of enterprises name bad data quality as a cause for problems, losses, and additional costs (Russom, 2006). Gartner estimates the total loss to be 20% of business volume. In fact, these losses are so damaging that, if it were possible to effectively curtail these losses, an economic boom could be generated (Meiser, 2008). To say that data quality is one of the principal reasons for the current financial crisis, like Focardi (2008), is perhaps overstated, but certainly higher standards in analysis requirements are absolutely essential. Companies that do not have their data under control risk exponential losses at such a critical juncture (Focardi, 2008). Data quality should never be underestimated; according to Montandon (2006) “data quality is not everything, but without data quality everything is nothing”.

For financial institutions, data quality plays a unique role. In the banking and insurance sector, the number of M&A transaction increases followed by post merger integration endeavors related IS and data (Seibel, 2007; Storn, 2008). Furthermore, the financial industry must work on numerous projects because of regulation requirements like Basel II (Hartmann-Wendels, 2003). Both aspects lead to the circumstance that data, which have been considered to be mutually exclusive until then, have to be integrated replying to these advanced requirements. Nevertheless, the financial industry wastes 40-50% of its IT budget because of ‘dirty data’ (Pütter, 2007). Intricate and expensive business intelligence solutions are useless if the contained data is of a poor quality (Pütter, 2007).

Poor quality in data exerts a profound negative influence on managerial decisions. Poor data quality bears the danger of making unfavorable decisions that may have serious consequences for the business. This danger is even greater if value based management (VBM) is pursued – which is done by a large portion of companies (Enthofer, 2006; Horváth & Partners, 2006) – since the control of a company only depends on a few selected key indicators. And bad data quality leads to inaccurate indicators.
Therefore, the main research question of this paper is if financial institutions estimate that data quality impacts value based management. We present the results of a survey which we conducted to address this question. We asked German financial institutions to give their perspective on the influence of data quality on their business. Furthermore we investigated the current state of calculating costs and benefits of data quality activities.

The paper is structured as follows. In the next section we introduce related work on data quality. We then give details on how we conducted the survey. Next, we present its results. Finally, we conclude with a brief discussion of implications of our study for our future research agenda.

BACKGROUND

Framework of Data Quality

In business literature, scholars adduce a seemingly endless array of definitions for quality of data. For instance, Olson (2003) defines data quality as follows: “Data has quality if it satisfies the requirements of its intended use. It lacks quality to the extent that it does not satisfy the requirements”. A similar definition is given by the Gesellschaft für Informatik e. V. who define data quality – also called information quality – as the ability of the data to satisfy the requirements of the processing applications. Data of poor quality contains mistakes, duplications, missing values, inconsistencies and similar (Naumann, 2007).

In this paper we define data quality as the excellence of a data stock evaluated by means of fixed criteria. The criteria and data quality requirements are always drawn from the data’s intended use. A data stock which is satisfactory for one task may be unsatisfactory for other tasks. The quality of a data stock is satisfactory if it fulfils all of the requirements of its users.

There are many who say “you can only manage what you can measure” (Wheatley and Kellner-Rogers, 1999). The same is true with data quality. To manage and improve the data quality of a company there should be well-defined metrics in place to measure the quality of data. Literature proposes many different perspectives on data quality. In order to derive a comprehensive idea of data quality, we developed a framework of data quality (FDQ). The FDQ provided the basic structure for our empirical study and our further research.

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Table 1: Data Quality Dimensions in Literature
Through a review of sources meaningful for the literature on data quality, we were able to identify 17 different dimensions for data quality (see Table 1). The dimensions mentioned most frequently are completeness, accuracy, timeliness and consistency which we decided to include in our framework.

Completeness means that all needed values of the real world object have to be stored. A missing last name or address would be a violation to this dimension. Timeliness means that the data has to be up to date. Accuracy refers to the correctness of data. It is the degree of how the object in the database fits to the real world object. For instance, a customer’s name in the real world is John Doe. A violation of accuracy would occur if the value for the first name in the information system was “John” and the value for the last name was “Johnson”, because the last name does not fit to the real world object. Consistency means, that the data is in a reasonable logical structure. A mistake would be a five year old child with the marital status “married” or the case of zip codes not in the allowed range.

However, data quality does not only refer to values in the database fields. There are three different views on data quality. The first view is data structure quality, i.e. the IS must be capable to store the entire data required, e.g. all fields to be filled with concrete values must be defined. The second view is data content quality which mainly refers to the field values. The third view is data presentation quality meaning that the data has to be presented in a user-adequate way. The aforementioned data quality dimensions are relevant to all views (English, 1999; Gaulke, 2004). The matrix of dimensions and views spans our Framework of Data Quality (FDQ; see Figure 1).

For instance, data structures would not be complete, if the whole field “last name” was missing. It would be inaccurate, if the field (not the value) “last name” had another name than expected. A problem in timeliness would occur when a needed field was not considered early enough leading to the loss of data that had not been stored until then. Shortcomings in the dimension consistency refer to logical problems with the data structure like problems with the primary keys in a database. The target for every company should be to achieve a high level of quality in every view and in every data quality dimension.

### Determination of Data Quality

Many companies perceive data quality as a non-tangible value. It is common that employees and managers mistrust data, but they can rarely make precise statements about the type and frequency of errors. Expensive projects to improve data quality without analyzing the real problems are not unusual (Hildebrand, Mielke, Gebauer and Hinrichs, 2008). Data quality must be made measurable to control success or failure of data quality projects. The best definition of data quality dimensions is useless, as long as there are no metrics to measure them. In his study, Russom (2006) shows how companies typically measure the quality of data (see Figure 2). Obviously, most companies determine their level of data quality by the level of user complaints; i.e. ex post, only giving the symptoms of the actual problem.
Impact of Data Quality on Value Based Management at Financial Institutions

Financial institutions commonly use value based management (VBM). For instance, 70% of insurers apply this management paradigm according to a study by Horváth & Partners (2005). In essence, VBM means that the company is mainly controlled by decisions based on a few key indicators like Economic Value Added (EVA) or Return on Investment (ROI) (Enthofer, 2006). If these key indicators are imprecise, incorrect management decisions may result, which in turn can lead to high losses. The key indicators are based on the company’s data. Thus, successful application of VBM requires data quality to be good (Reindl and Parthe, 2003).

We give the following simple hypothetical example to illustrate how insufficient data quality can influence key indicators like ROI. Table 2 provides the values used for computing the ROI before the data quality project. In this example, there are problems in nearly every data quality dimension. For example, completeness is weak and there are 10% of the sales figures and 15% of the cost values missing. Further values needed to calculate the ROI are: capital assets 3,000,000 USD, circulating assets 500,000 USD, and imputed interests 350,000 USD. The resulting ROI based on these values is 35.71% (see Figure 3).

After the data quality project, the data quality problems have been resolved. As a result, sales and cost figures have become more precise. The other values remain unchanged. Now, the ROI is only 27.14% with a difference of 8.57% compared to the old ROI. This simple example shows how incorrect data can negatively influence key indicators for decision making. Figure 3 summarizes how the ROI was calculated at both times (Grob, 2008).

The example illustrates the impact of data quality on value based management. If data quality is poor the accuracy of the calculated key indicators is bad, too. As a result, decisions made on inaccurate key indicators may also be wrong. A wrong decision could lead to great losses for the business. Concerning the different views, especially the data content quality influences the accuracy of key indicators.

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**Table 2: Values Prior to the Data Quality Project**

<table>
<thead>
<tr>
<th>DQ-Dimensions</th>
<th>Completeness</th>
<th>Consistency</th>
<th>Accuracy</th>
<th>Timeliness</th>
<th>Values for Calculation</th>
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<td>Data for ROI</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Sales (Volume)</td>
<td>90%</td>
<td>98%</td>
<td>87%</td>
<td>98%</td>
<td>2,000,000 USD</td>
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<tr>
<td>Costs</td>
<td>85%</td>
<td>97%</td>
<td>90%</td>
<td>96%</td>
<td>1,200,000 USD</td>
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**Table 3: Values after Performing the Data Quality Project**

<table>
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<th>DQ-Dimensions</th>
<th>Completeness</th>
<th>Consistency</th>
<th>Accuracy</th>
<th>Timeliness</th>
<th>Values for Calculation</th>
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<tbody>
<tr>
<td>Data for ROI</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sales (volume)</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>2,100,000 USD</td>
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<tr>
<td>Cost</td>
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<td>100%</td>
<td>100%</td>
<td>100%</td>
<td>1,500,000 USD</td>
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The example illustrates the impact of data quality on value based management. If data quality is poor the accuracy of the calculated key indicators is bad, too. As a result, decisions made on inaccurate key indicators may also be wrong. A wrong decision could lead to great losses for the business. Concerning the different views, especially the data content quality influences the accuracy of key indicators.
Values in **bold** are those who have changed after the data quality project.

**Figure 3: ROI Calculations before and after the Data Quality Project**

**RESEARCH METHOD**

The objectives of our survey were to show how financial institutions define data quality, what the impact of data quality on their business is, and how they determine the benefits of (good) data quality. The questionnaire of the survey presented in this paper totaled 29 questions and was separated into three parts.

The first part was general questions about the company and value based management. Key indicators that companies prefer for value based management were questioned. Business volume was asked to be able to separate small and big companies.

The second part dealt with data quality in particular. We analyzed whether the questioned financial institutions agree with our perception of data quality which we defined by our Framework of Data Quality (FDQ). We asked, in which areas the participants see damages due to bad data quality and how they determine these damages.

The third and last part was on the economic analysis of data quality projects. We asked the financial institutions for their assumptions about which benefits can be achieved in which areas through improvements to data quality. Furthermore, their willingness to invest in order to improve data quality was inquired.

The survey was set online from 10\textsuperscript{th} December 2008 to 30\textsuperscript{th} January 2009. The link to the online questionnaire was sent to 62 different financial institutions. We received 35 returns with at least 80\% of questions answered. Only taking these returns into account, the return rate was 57\%. Most of the respondents were public banks (see Figure 4).
RESULTS

Overview

In this section, we give an overview of the results we gained from our survey. The responses confirmed that VBM is widely applied by financial institutions. Most of the respondents also agreed that the dimensions of data quality which we proposed in our FDQ are relevant. The questioned financial institutions are aware about the importance of good data quality for their business. Nevertheless, these financial institutions face substantial damages due to insufficient data quality. Only 11% claimed that they do not have data quality problems. They particularly emphasized that the significance of key indicators – which are crucial for VBM – is diminished because of data quality issues. 80% of the respondents said that management decisions are influenced negatively.

Concerning business cases for data quality projects, more than 60% of the respondents said that a detailed cost-benefits-analysis would increase the enforceability of data quality projects in their company. Our study provides hints on benefits that can be achieved through data quality projects. On the one hand, those benefits can be achieved by selectively addressing and resolving the data-quality-related causes for losses or damages which were mentioned in our study. On the other hand, potential benefits that were explicitly named can be realized; e.g. cost reductions (97%) and increased productivity (94%). In particular, 94% said that improved data quality leads to improved management information.

Company Details and Application of Value Based Management

The responses to the first part of our questionnaire confirmed our previous discussion since VBM is used by 88% of the respondents. Most companies use the key indicator Return on Investment (ROI) for their management decisions. Another large share applies the Economic Value Added (EVA) and the Value at Risk (VaR; see Figure 5). Although we did not provide VaR as a predefined choice, it was given remarkably often in the ‘Other’ field. Concerning the importance of data quality for financial institutions, 91% answered that data quality has an impact or even a big impact on business success. Only 3% said that there is no connection between data quality and business success.
Problems Related to Data Quality Issues

The second part of the questionnaire referred to data quality in particular. We asked the companies for their comprehension of relevant data quality dimensions. The four dimensions which constitute our FDQ were almost always confirmed by the participants of the survey. The four dimensions accuracy, completeness, timeliness and consistency were ticked by 77% at minimum (see Figure 6). Only 11% made statements for other dimensions. This fact underlines that the data quality dimensions gained from the literature are also very popular in practice.

Next, we asked in which dimensions data quality problems exist. Only 11% of the attendants stated to have no data quality problems. All other companies have issues with at least one data quality dimension. Most problems relate to accuracy followed by completeness (see Figure 7).

Subsequently, we asked for quantifying the yearly losses resulting from bad data quality. It was observed that, measured on business volume, small companies (business volume lower than 10 billion Euros) have fewer losses because of data quality issues than large companies (business volume of 10 billion Euros and more; see Figure 8).
However, the amounts of specified losses may be doubtful because many companies have no central responsibility for data quality issues. Only 14% of the respondents have a particular department dedicated to data quality issues. This leads to our assumption that most companies probably do not even know how high the losses due to ‘dirty data’ really are. Just 30% of the respondents’ companies have assigned responsibilities related to data quality, but none of these have assigned responsibilities at the management level.

Another key finding is that companies who have institutionalized responsibilities on a higher organizational level have less cost due to data quality problems. 67% of those have losses less than 100,000 Euros, the rest (33%) estimate their loss between 500,000 and 1,000,000 Euros. Big companies (business volume of 10 billion Euros or more) tend to have even higher losses due to bad data quality if they do not have institutionalized responsibilities for data quality issues. 40% of these big companies without institutionalized responsibilities said that they have losses between 1 and 5 million Euros, 20% have losses between 5 and 10 million Euros, and 20% have more than 10 million Euros in losses. Only 20% have losses less than 100,000 Euros.

To determine the origin of such immense losses, we asked the participants for their view on the effects related to bad data quality (see Figure 9; all values in %). Remarkably, the various respondents agreed on points which are directly or indirectly linked to VBM. Most respondents said that bad data quality leads to lower significance of key indicators. Another point of wide acceptance was that insufficient data quality has bad influence on management decisions which in turn may lead to large losses. Projects that lead to better data quality have the potential to reduce these losses and thereby provide the opportunity to achieve durable savings.

Furthermore, over 39% of the companies who argued to have a good data quality still have losses between 100,000 Euros and 500,000 Euros, 4% of that group have losses between 1 and 5 million Euros and another 4% have losses between 5 and 10 million Euros. This points out that nearly every second financial institution that estimates its data quality as good has a meaningful potential to improve.

Generally, the evaluation of the own data quality is surprisingly positive. More than 88% of participants think that their data quality is “excellent” or “very good”. In another study, which not only surveyed financial institutes, 40% of participants said that their data quality is only “satisfactory” and even 7% called it “insufficient” (Martin and Seufert, 2008). This may lead to the interpretation that financial institutions tend to overestimate their data quality.
Cost Benefit Analysis of Data Quality Projects

The third part of the questionnaire was on the profitability analysis of data quality projects. In accordance with our expectations, most participants agreed that a detailed representation of costs and benefits would increase the enforceability of data quality projects in their company (see Figure 10). However, at least 37% indicated that this would be far from a deciding factor.

Would a detailed cost benefits analysis increase the enforceability of data quality projects in your company?

![Figure 10: Agreement with the Influence of Cost Benefits Analyses on Data Quality Projects](image)
The aforementioned results have shown that there are many different types of damages caused by bad data quality and that a detailed cost benefit analysis may help to increase the enforceability of data quality projects. However, to prepare adequate cost benefits analyses the specification of benefits of improved data quality is necessary. We provided the participants with a list of possible benefits. Nearly every given point was confirmed to be a benefit by the attendants. Combining the possible answers “completely agree” and “mostly agree”, 97% of the participants think that improved data quality leads to cost reduction. 94% are convinced that there is benefit through raised productivity. Lower risks for the company are confirmed with 92%. Different views exist about the improvement of reactions to external shocks like the current financial crisis. Here, only 49% of the companies think that data quality would help (see Figure 11; all values in %).

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</table>

**Figure 11: Benefits of Good Data Quality (all values in %)**

We finally asked how much companies really invest in data quality projects. As depicted in Figure 12, the participants said that management is willing to invest in data quality projects. However, the actual volume of investments can be regarded as quite low. 45% of the companies whose management does have a high propensity to invest in data quality projects do not provide an explicit budget for such projects or invest less than 150,000 Euros per year. This shows a gap between the subjective feeling for investments by the management and the objective invested capital. To improve the management’s propensity to invest business cases with a detailed costs and benefits analysis could help.
CONCLUSIONS AND IMPLICATIONS FOR FUTURE RESEARCH

Although we have only conducted a small survey with 35 returns, which we mainly received from public banks, the results provide an understanding about the consequences of lacking data quality on financial institutions and their VBM in particular. Our study shows that many financial institutions have problems with their data quality. In the course of the current financial crisis, they should ask themselves if their data quality is good enough or if it could be improved to realize reductions in risk and cost as well as other benefits. Although it is widely recognized that good data quality is important, it seems that comparatively little money is spent on data quality improvement projects.

Financial institutions that apply VBM heavily rely on a high level of data quality. To achieve higher levels of data quality they need to invest in data quality projects. Probably, one of the main challenges is to prepare adequate business cases for such projects since their benefits are often perceived as intangible and hardly to be expressed in monetary values. Obviously, benefits from data quality projects are difficult to estimate, measure, and monetize. Nevertheless, the persons in charge for preparing business cases of data quality projects need to convey the designated benefits and their monetary value to the decision-makers in a comprehensible manner. In the case that the benefits are justified and made transparent by a business case, the decision in favor or a data quality project will be facilitated.

Financial institutions seemingly do not have the proper means to justify purposeful data quality projects. Therefore, we argue that there is a need for innovative instruments that allow for justifying these projects through adequate business cases. The financial benefits resulting from improved data quality need to be made measurable and controllable in a reasonable manner. Hence, we think that consecutive research needs to answer the following research question: How must an artifact be designed that better supports the preparation of adequate business cases for data quality projects at financial institutions?

Addressing this question, the objective of our future research will be to develop a business case model that serves financial institutions as a blueprint for preparing adequate business cases for data quality projects. For the development of this artifact we expect design science to be an adequate research paradigm (Hevner, March, Park and Ram, 2004; Peffers, Tuunanen, Rothenburger and Chatterjee, 2007).
The development of the business case model will be informed by existing knowledge on data quality that we have presented in the previous sections. We will also examine existing business case models (Brugger, 2005; Loshin, 2006; Schmidt, 2002a; Schmidt, 2002b) to receive helpful advice on the design of our business case model.

We will apply the FDQ as a basic structure for our model (see Figure 13) since we hypothesize that the major potential benefits can be referred to improvements to the four dimensions completeness, accuracy, timeliness, and consistency. Admittedly, this hypothesis needs to be validated empirically in future research. Finally, to achieve a useful business case model, these dimensions need to be operationalized to metrics that are applicable in practice.

**Figure 13: Extending the FDQ Framework to a Business Case Model**

**ACKNOWLEDGMENTS**

We thank all respondents for participating in our study and Scott E. Todd for proofreading the article.
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