The short-term effect of a Natural Disaster on Audit Quality

Erasmus University Rotterdam
Erasmus School of Economics
Accounting, Auditing and Control
Author: F. (Felix) van der Kaaden, 377502
Supervisor: Dr. J. (Jeayoon) Yu
Co-Reader: Prof. Dr. J.P.M. (Jeroen) Suijs

Abstract

This study examines the effect of hurricane Katrina on the allowance of Discretionary Accruals by auditors. By inserting a Difference-in-Difference research design into the study, the effect of the hurricane is measured for auditors located in a specific affected area, while controlling for auditors located in an unaffected area. For the treatment, hurricane Katrina is used. The results suggest that auditors behave more pessimistic and allow a more conservative use of discretionary accruals. The overall use of discretionary accruals does not change significantly, which implies that the audit quality does not change. The results are robust after Propensity Score Matching is applied. Furthermore, the study implies that the result is influenced by extreme positive values of discretionary accruals.

Keywords: Audit Quality, Hurricane Katrina, Natural Experiment, Auditor Conservatism

Preface

Writing this thesis is one of the last steps before completing my MSc Accounting and Auditing at the ESE. At first I was dreading to begin writing, since it is a big task to complete. Luckily, I was able to do an internship at PwC, which made it a lot easier to set my mind to actually writing a manuscript. When looking back, I did not accomplish that much in the first months, since the pressure was not that high and I still had to complete some lectures. When the deadline and sub-deadlines came closer I started to invest more time in this thesis. One thing I that stands out when writing my literature review is that it is very easy to be trapped by the confirmation bias. I am very pleased with the end result and the lessons I learned writing this thesis.

Before discussing my findings I would like to thank some people. At first I would like to thank Jeayoon Yu for helping me accomplish my thesis with constructive feedback and useful information so I was able to lift the quality of my work. I would like to thank PwC for the opportunity to write my thesis at their office. In particular I would like to thank Lisa van der Wereld, who was my PwC coach, for all the help and feedback. Lastly I would like to thank all PwC thesis colleagues who helped me when I was stuck and gave me motivation to proceed the process.

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1. Introduction

In the past years, losses resulting from a natural disaster were increasing significantly. These losses where eight times smaller sixty years ago and are nowadays estimated on 35 billion dollars on a yearly basis (EM-DAT, 2009). This significant increase is mainly due to two reasons. Firstly, the social and economic impact of a natural disaster has increased, as disasters are becoming more disastrous (UNDP, 2008). Secondly, due to climate change and global warming, scientists have predicted that there will be an increase in the frequency of natural disasters, including tropical storms and floods (IPCC, 2001). This increase will have a big impact on several topics including life conditions and personal preferences. This means that not only direct losses occurring from a natural disaster, but also the aftermath and indirect losses have a big impact on the society.

This paper focuses on the short-term impact of a natural disaster in the lives of auditors on the quality of and audit report. Moreover this study provides an insight in the occurrence of a hurricane and the change in quality of an audit report. The study will provide an answer to the following research question:

RQ: *Does the occurrence of a natural disaster affect the quality of an audit report on the short-term?*

The Code of Ethics for Professional Accountants states that an accountant should act in an objective way, which includes not allowing any bias, conflict of interest or undue influence of others to override professional or business judgement (IFAC, 2006). In theory, the quality of and audit report should be the same for all reports. Nonetheless, prior literature shows differences in quality. These differences are mainly due to two factors. Firstly, an existing base of literature consists of firm and office level characteristics that have an impact on audit quality. The main topics in this base are auditor size (e.g. DeAngelo, 1981; Francis and Yu, 2009; Davidson and Neu, 1993), firm rotation (e.g. Jackson et al., 2008; Daniels and Booker, 2011) and auditor conservatism (e.g. Watts, 2003a, Lee et al., 2006). Secondly, a growing body of literature covers individual auditor characteristics and the impact of auditors' personal traits and experience on the quality of an audit report. These studies include for instance the impact of gender (e.g. Burke et al., 2017; Sundgren and Svanström, 2014) and auditor tenure (e.g. Ghosh and Moon, 2005; Chen et al., 2008).

The main variable of interest in this paper is accounting conservatism. Literature states that natural disasters have an impact on risk perception, making an affected person more conservative (e.g. Reynaud and Aubert, 2014; Eckel et al., 2009). This has in turn an effect on audit quality as it is stated as one of the variables influencing audit quality above. The study hypothesizes that an affected auditor is likely to allow a more conservative way of earnings management and use of Discretionary Accruals (*DA*). The more conservative use of *DA* subsequently has a positive effect on the absolute use of *DA* and therefore the audit quality. These effects are tested using Hurricane Katrina as the natural disaster, since it was one of the most disastrous events in this century and affected a large area at once (Beven et al., 2008).

Two samples are used to test the effect of the hurricane. The data is gathered through the use of the Compustat and AuditAnalytics databases over the years 2004 and 2005. The Compustat database provides the necessary information to calculate the different numerical variables, while AuditAnalytics gives the location of the audit office needed to assign the different groups. The first sample consists of all observations that are assigned to a specific group. The second sample consists of the observations that are matched to each other using Propensity Score Matching (PSM).

To test the hypothesis, a Difference-in-Difference design is used, by comparing the audit quality of affected audit firms with the audit quality of unaffected firms. Likewise, the audited companies need to be located outside the affected area, so that the effect can be assigned to the auditor. When hurricane Katrina has indeed an impact on audit quality a change in quality will be seen after the hurricane. To make sure that the two groups match and to boost the robustness of the results, PSM is used to match observations of the control group to observations of the treatment group. PSM has the benefit of assessing a score to an observation by using multiple confounding variables, without needing a massive sample. This score is then used to match the different observations to each other.

The results of this paper suggest a couple of things. Firstly, the full sample test with and without control variables, suggests that there is a negative tendency in *DA* for firms that received the treatment. This result is also backed up by the same test using the PSM sample. Therefore it is assumed that the results of these tests are robust. Secondly, by performing the same tests with the absolute value of *DA*, no significant change is found. This also is robust after testing the same effect using the PSM sample. This implies that there is no change in audit quality after Katrina, when controlling for an untreated group, but auditors only behave more conservative.

This paper contributes to the existing literature in a couple of ways. Firstly, zero research is conducted on the effect of a natural disaster on audit quality and auditor conservatism. It is interesting to conduct this research, because the chance on a natural disaster is growing as stated earlier. Therefore, it can be helpful to know what can be expected regarding the audit quality after the occasion of a hurricane or any other (natural) disaster. These insights can be used by standard-setters, audit firms and other bodies that are interested in audit reports.

Secondly, this paper is related to a growing interest in audit office level measures and characteristics. Many research has been conducted on audit quality in a general way, where this paper focusses on a more specific area and the offices inside this area, rather than on the differences between audit firms. Moreover, the research contains a non-economic variable which influences audit quality. These kind of variables are used in a limited amount of papers, but still can have a significant effect.

The reminder of this paper is organized as follows. In Section 2, related literature is summarized and a hypothesis, to answer the research question, is developed. Section 3 introduces the empirical part, including data and research design, which are used in the study. Section 4 presents the results following the study. Section 5 concludes this paper and tries to answer the research question.

2. Related literature

In this paragraph, prior literature is discussed in order to create a theory and gain understanding in the way a natural disaster will affect audit quality. At the end of the paragraph, hypotheses will be formulated which are tested later in this paper.

2.1. Natural Disaster

A (natural) disaster is often referred to as a “low-probability, high-consequence event”. In other words, the chance of a disaster occurring is very low, but when it happens, the aftermath will be huge for multiple variables, including the economy, wealth and personal preferences and characteristics (Gigerenzer, 2004). Thus, communities are not only directly affected by a decrease in income and a destruction of assets, but also indirectly by a higher degree of for instance risk aversity. Victims of natural disasters are more likely to be worried and fearful, which in turn leads to more risk-averse choices (van den Berg et al., 2009).

Two theories give an understanding to the effect of a natural disaster, in which the aftermath comes with a period of uncertainty (Berkes, 2007). The *Expected Utility Theory* (EUT), or gaming theory, states that the possible outcome of the situation in uncertainty is the chance of the possible outcome times the utility of the outcome. Theoretically, a person will always choose the option with the best utility. This theory does not include the variable of risk perception and therefore Kahneman and Tversky (1979) developed the *Prospect Theory* (PT), focusing on the values assigned to gains and losses with respect to a reference point and decision weights, rather than focusing solely on the outcome of the situation. PT includes the so called *framing effect*, in which people react to a situation differently, depending on how the situation is presented. It is proven that in a situation which includes a positive outcome, people will react risk-averse and in a situation with a negative outcome, the reaction tends to be more risk seeking. This will result in more pessimistic and conservative outcomes of the situation.

This theory is backed up by most prior literature about the effect of a (natural) disaster on risk perception, particularly on the short term. Bourveau and Law (2016) investigated the effect of hurricane Katrina on forecast analysts. They found that analysts tend to give a more pessimistic and conservative forecast. Their results are very robust due to the use of the difference-in-difference research design. They furthermore concluded that the effect was only on the short term and was terminated one year after the hurricane. The same effect on risk perception is found by Sacco et al. (2003), who reported that after the 9/11 terrorist attacks, people tended to make more conservative and less risky decisions. They also found out that the effect only had a short term impact on conservatism and lasted for six months. After these six months, there was a tendency towards less conservative decisions.

Some papers dive into the effect of the availability heuristic. This heuristic states that a person will use anything that is available in their memory, in assessing risks. When the environment is threatening, the perceived risk of this person will be higher, due to traumatic memories, which are raised first (Keller et al, 2006). Bernile et al. (2017) compared CEO's who witnessed the extreme downside of a natural disaster to CEO's who experienced a disaster without extreme negative consequences. They found that a CEO who experienced the negative downside is more likely to behave conservative. This effect also is the case in the study of Cassar et al. (2017), who found that people who experienced the tsunami in Asia in 2004 are more risk averse and conservative. They believe that this experience "can make people more aware of the potential adverse events that can occur". Another study which included floods is Cameron and Shah (2015). They also conclude that people affected by natural disaster exhibit greater risk aversion. Moreover, they conclude that people who are more vulnerable to risk are even more risk averse.

On the other hand, some literature states that persons affected by a disaster tend to be less conservative. Li et al. (2011) studied the effect of snowstorms in China on risk perception. They found that Chinese individuals are more risk averse when exposed to a possible loss and less risk averse when exposed to a possible gain. This is the opposite of what is expected following *PT*. Also Eckel et al. (2009) find more risk-seeking behavior. They used hurricane Katrina as treatment, which is very relevant for this paper. They state that the data shows an increase in risk-loving behavior. On the other hand, they also conclude that a heightened level of solidarity within the society, results in a social-risk aversion, which implies a more conservative outcome over the society as a whole. Furthermore, Reynaud and Aubert (2014) investigated the experience of a flood in villages and found that these villagers are more risk averse, only in the loss domain. Thus, these paper give examples in which a less conservative approach is enhanced.

2.2. Hurricane Katrina

The natural disaster of interest in this paper is hurricane Katrina. This specific natural disaster is picked for several reasons. First of all, Katrina is one of the biggest natural disasters in the history of the United States and is the biggest hazardous event in this century. The hurricane cost life to around 1,500 persons and the damage was estimated to be more than one-hundred billion dollars (Beven et al., 2008). Secondly, the second biggest event in this century was the tornado season in 2011 (NOAA, 2018). However, a tornado has an impact on a small group of people, while a hurricane has an impact on a big region at once. Therefore it is easier to test the effect of the disaster by using the hurricane. Lastly, hurricane Katrina emerged in late August 2005 (Beven et al., 2008). This means that audits of the fiscal year 2004 already had been done, but the year-end audit on the next fiscal year, 2005, had not yet been started. In this way, it is easier to assign values to the dummy variable which reflects the timestamp of the observation. Therefore less observations will be left out of the sample.

The state which is hit the hardest is Louisiana and more specific the city of New Orleans. Because of the number of observations in this region on its own, is most likely to result in insignificant results, the region of interest contains four states: Louisiana, Mississippi, Alabama and Florida. These states were hit the hardest and were under some sort of evacuation order during the hurricane (Beven et al., 2008). Because of the evacuation order, the hurricane affected all these states as a whole and not just parts. On the other hand, it needs to be verified that the auditor offices do not change location after the hurricane, but stay located on the same address. Furthermore, Ai et al. (2006) investigated the effect of the 9/11 attack and Oklahoma City bombing on the chance of developing Posttraumatic Stress Disorder (PTSD). The study concludes that these traumatic events have a significant influence in the development of PTSD and the effect is even there when knowing someone who died as a result of the disaster. This also strengthens the motivation to pick those four states as treatment group, since it is likely that inhabitants of the states know someone who is a victim or are a victim them self.

The literature discussed above can be merged in a logical way. A natural disaster has a significant effect on the risk perception of an affected person. This person tends to behave in a more conservative way. Taking into account *PT* of Kahneman and Tversky (1979), conservative persons tend to be risk-averse concerning positive outcomes and risk-seeking concerning negative outcomes. Conservatism experienced by auditors thus results in the use of more income decreasing *DA* (Bannister and Wiest, 2001). This effect is even greater when the experience is life threatening (Holman and Silver, 1998). Prior literature on conservatism is summarized in the following hypothesis:

> ***H1:*** *Auditors affected by hurricane Katrina are likely to allow a more conservative use of earnings management via the use of income decreasing Discretionary Accruals.*

2.3. Auditor Conservatism and Audit Quality

To understand how a natural disaster affects audit quality, an understanding of the concept audit quality needs to be acquired. DeFond and Zhang (2014) define audit quality as “the height of assurance that the financial statements faithfully reflect the firm's underlying economics, conditioned on its financial reporting system and innate characteristics”. In other words, the financial statements must reflect the true and fair value of the company. The higher the audit quality, the higher the assurance that the financial statements indeed reflect the true and fair value of the company.

Earnings management is a variable that influences the financial statements in a way that they do not reflect the true performance of a company. Earnings management can be seen as the judgement of a manager to select certain reporting methods to alter the financial statements in order to potentially increase the value of the company (Healy and Wahlen, 1999). The use of discretionary accruals is the most widely used way to manage earnings in a company, since those accruals are hard to detect and give a manager some sort of discretion (Dechow et al., 1995). There are two parties that can lower the amount of discretionary accruals used in the financial statements and therefore decrease the amount of earnings that are managed by a company. Firstly, managers can logically influence the amount of earnings that are managed. Secondly, auditors can constrain earnings management. They use certain techniques and measures that detect earnings management (DeFond and Zhang, 2014). The interest of this paper lies on influence on earnings management of the second party, auditors.

Since auditors need to adapt certain standards and rules, it would be logical to argue that the quality of audit reports is the same for all auditors. Prior literature states otherwise and finds differences in quality among individual auditors (Gul et al., 2013). Chen et al. (2010) find that auditors decrease audit quality for their economic important clients during a weak legal and regulatory environment, while there is a conservative way of auditing when the legal and regulatory environment is strong. This relation is only found when analysing individual auditors. There is no evidence for the relations when looking at office or firm level, which implies that individual auditors compensate audit quality among their clients. As stated before, Burke et al. (2017) also found that there are differences in audit quality when looking at certain auditor characteristics like age and gender. This implies that auditors are able to alter the quality of the audit report, which in turn does not reflect a true and fair view of the company.

By selecting more conservative auditing choices, auditors are able to improve the audit quality (Fafatas, 2010). Conservatism can be split up in two types. Firstly, unconditional conservatism is the kind of conservatism that is always there. It has a constant influence on accounting numbers and audits and is thus hard to measure. Secondly, conditional conservatism depends on (economic) events. An event that can trigger conditional conservatism is a natural disaster and is therefore interesting for this research. This kind of conservatism has a more variable influence and fluctuates more. This makes it also easier to measure conditional conservatism (Ruch and Taylor, 2015).

There is an existing base of literature on the relation between conservatism, earnings management and audit quality. A traditional definition of conservatism is: “Anticipate no profit, but anticipate all losses” (Watts, 2003a). Prior literature states that companies with conservative auditors will show less unexpected accruals on the earnings component. This will reduce the use of earnings management and will increase audit quality (Lee et al., 2006). Big N firms are often used as a proxy for audit quality, since bigger companies have more resources and therefore perform higher quality audits. Furthermore, Big N firms, which are associated with higher audit quality, have a reputation to protect and thus are likely to behave more conservative (DeAngelo, 1981). Becker et al. (1998) show that companies audited by Big N auditors show less discretionary accruals, which also is a proxy for audit quality. Basu et al. (2001) compared the amount of conservatism used in financial reporting between Big N and non-Big N firms. They found that Big N firms behave more conservative. Also Francis and Krishnan (1999) found that companies who behaved less conservative where more likely to be issued a qualified opinion by their auditor, which also is a widely used proxy for audit quality. They argue that auditors who are more likely to face litigation behave in a more conservative way, since they risk their reputation. This conclusion is also backed up by Clarkson et al. (2003), who argue that firms with a bigger reputation and capital at stake behave more conservative, since the punishment for those firms will be significantly higher than for smaller firms.

As stated before, prior literature has found a relation between auditor conservatism and the quality of an audit report. It can be concluded that a heightened level of conservatism comes with a higher degree of audit quality. When looking at the use of *DA*, prior literature states that the absolute value of *DA* should decline to improve the quality of an audit report. Taking this into account, results in the second hypothesis:

> ***H2:*** *Auditors affected by hurricane Katrina are less likely to allow the use of Discretionary Accruals.*

3. Research Methods

3.1. Sample and Data

Data necessary to conduct the empirical analyses is obtained from two databases. Firstly, to have an understanding of the companies and to measure the amount of discretionary accruals, Compustat database is used. Second, to find the auditor and the location of the audit offices, AuditAnalyitics database is consulted. Likewise, the two databases are merged into one database using a company specific key and the fiscal year. A couple of steps need to be taken before the data is usable for the analyses. Firstly, it is needed to make sure that all observations have sufficient data, needed to calculate Jones accruals and values of control variables or confounders. Second, all financial companies are dropped from the sample, because those companies are structured very differently compared to other companies. Third, firms with auditor rotation during the observed years are dropped from the sample. Fourth, observations with their auditor located outside the affected area and auditee located inside the affected area are dropped from the sample. Those observations will measure the effect of Katrina on the risk perception of the companies' managers and are therefore of no use. Fifth, firms with any other than observations for the years 2004 and 2005 or companies that switch from assigned group are dropped from the sample. Only two years are necessary since the effect of the hurricane lasts for only one year, as stated earlier. Lastly, the sample is winsorized, to make sure that the results are not driven by outliers. The final sample consists of 6,636 year observations, with observations for two years per company likewise. This sample will be called "full sample" hereafter.

For the PSM sample, treatment and control observations are matches to each other based on propensity score and certain confounders, which is explained later in this paper. All observations in the control group that are not matched to a treatment observations are dropped from the sample, which results in a final PSM sample of 350 observations, with observations for two years per company likewise. The full sampling procedure can be found in table 2.

3.2. Research Design

3.2.1. Difference-in-Difference Design

As stated before, hurricane Katrina will be used to find evidence for a difference in audit quality when auditors are exposed to a natural disaster. To test for the effect of this event, a Difference-in-Difference (DiD hereafter) design will be used. This is possible since a hurricane sets the scene of a natural experiment. This design can measure the difference of audit quality in a treatment group between the year before and the year(s) after a certain event and control for the effect of the same event on an untreated group. The assignment of the observations to the specific groups are beyond the control of the researcher, but are (quasi-)randomly assigned. This enables researchers to find a causal relation, since the treatment is the only variable which is different between the two groups. For the treatment group, audit firms will be used, which are located inside the affected area. For the control group, the audit firms logically need to be located outside the affected area. The auditee, the company which is audited, also needs to be located outside the affected area for both groups, to make sure that this company is not affected by the hurricane. Using this design, there can be concluded that the measured effect is due to the behavior of the auditor, since the location of the auditor is the only variable that is different between the two groups and thus receives treatment in the treatment group.

The characteristics of the treatment group and control group need to be identical except for the treatment variable, which will capture the effect of the hurricane on the auditor's behavior. Since this study uses a natural experimental design, the two groups are not randomly assigned and thus might raise endogeneity concerns. Therefore, a test is needed to make sure that the treatment and control group are statistically the same. To do so, a matched-pair research design can be implemented. This design matches an observation from the treatment group with an observation from the control group, which has the exact similar characteristics. In this way, the difference in outcome of the test can, in the absence of any hidden bias, be attributed to the difference in the treatment (Armstrong et al., 2010).

A drawback for a matched-pair research design is that a treatment observation will be matched to a control observation, by using covariate matching. This type of matching restricts the amount of variables used in the matching process, because it exactly matches the observations based on the control variables. Therefore, the sample size needs to grow exponentially when another control variables is added to the matching process (e.g. Blackford, 2009; Armstrong et al., 2010). Since *DA* is a variable that can be influenced by many other variables, it is essential to match the observations based on as many variables as possible, without making the matching process not achievable. One way to perform the matching process, is by using propensity score matching.

The Propensity Score Matching (PSM hereafter), first introduced by Rosenbaum and Rubin. (1983) uses one single score, the propensity score (*P-Score*, herafter) to match two observations from the two different groups to each other, which makes it very easy to find statistical similar pairs. The score reflects the chance of an observation receiving the treatment, based on a selection of variables, called confounders. These confounders would normally be used to control for omitted variables and to reduce endogeneity concerns. To find matches between the two groups, a couple of steps need to be taken, which will be explained hereafter.

The first step in PSM is to identify the confounding variables and insert those in the regression equation used to calculate the propensity score. The confounders of this study are based on the review paper of DeFond and Zhang (2014), which states the most widely used control variables when using *DA* as a dependent variable. Using these variables as

$$Pr(Treatment) = \alpha_k + \beta_1 Size + \beta_2 Leverage + \beta_3 Loss + \beta_4 Sales\ Growth + \beta_5 OCF + \beta_6 Big\ N + \beta_7 MTB + \beta_8 TA + \varepsilon_i \quad (1)$$

confounders, gives the following equation:

Size reflects the size of the company and is computed by taking the natural logarithm of total assets (e.g. Becker et al., 1998; Klein, 2002). The variable *Leverage* indicates the debt to asset ratio and is calculated as the long term debt divided by total assets of the company (Krishnan et al., 2011; Michas, 2011). *Loss* is a dummy variable which indicated if a company experienced a loss, value 1, or profit, value 0 (e.g. Prawitt et al., 2009; Michas, 2011). Following Gul et al. (2009), *Sales Growth* will be computed as current sales minus laggard sales, divided by laggard sales. *OCF* is the variable which reflects the Operating Cash Flow and is computed as total value of OCF divided by laggard total assets (e.g. Becker et al., 1998; Klein, 2002). *Big N* is a dummy variable which takes the value of 1 if the company is audited by a Big N auditor and 0 otherwise (e.g. Menon and Williams, 2004; Lennox and Li, 2011). The Market-To-Book variable (*MTB*) will be computed following Prawitt et al. (2009) as share price at year end multiplied by number of outstanding shares, divides by book value of shares outstanding. *TA* reflects the total amount of accruals in a company. Accruals are the difference between net income before extraordinary items and cash flows from operations, deflated by lagged total assets (e.g. Becker et al., 1998; Klein, 2002).

By using this regression, the propensity score per observation can be computed. The following step is to match an observation from the treatment group to an observation from the control group. This will be done by using the Nearest-Neighbor (NN) principle, which matches the propensity score of a treatment observation to the closest propensity score of an observation from the control group. Prior research states that using the nearest neighbor matching technique, ensures that all treated observations are matched to at least one untreated observation. Because this kind of matching results in a higher amount of matched pairs, the precision of estimates tends to be greater (Austin, 2014). The optimal number of matched control observations is one or two according to Austin (2010). Because the sample size of this study is very low, two matches may result in more significant estimations. Hereafter, it is needed that the propensity score and confounders are matched among the two different groups. This will be tested after matching the different observations and likewise compiling two new groups. When matching succeeds, the variances and means between the two groups should be insignificant different per confounder and *P-Score*. This will be tested by using a variance T-test. When the confounders and *P-Score* match and all non-matched observations are deleted from the sample, the DiD-regression can be run.

3.2.2. Audit Quality

The variable audit quality will be the dependent variable of this study. As stated earlier, there are different ways to measure audit quality. Since it is hard to measure this variable, a proxy for audit quality will be used. The proxy used in this research is the cross-sectional Jones model, which measures discretionary accruals, *DA* hereafter (Jones, 1991). As stated before, the use of *DA* has a negative impact on audit quality, since it can be concluded that a company uses earnings management to alter their financial results (Francis and Yu, 2009). The model consists of a couple of steps to estimate *DA*.

Firstly by running the following regression for every two-digit SIC-year grouping, the coefficients (k_n) can be calculated. This is done, because accounting regulations regarding accruals can be different per industry.

$$\frac{TA_{it}}{Assets_{i,t-1}} = k_1 \frac{1}{Assets_{i,t-1}} + k_2 \frac{\Delta REV_{it}}{Assets_{i,t-1}} + k_3 \frac{PPE_{it}}{Assets_{i,t-1}} + \varepsilon_{it} \quad (2)$$

Next, the calculated coefficients can be inserted into the following regression, to estimate the amount of normal accruals, or Non-Discretionary Accruals (*NDA_{it}*) per observation.

$$NDA_{it} = k_1 \frac{1}{Assets_{i,t-1}} + k_2 \frac{(\Delta REV_{it} - \Delta AR_{it})}{Assets_{i,t-1}} + k_3 \frac{PPE_{it}}{Assets_{i,t-1}} + \varepsilon_{it} \qquad (3)$$

Lastly, the estimated variables can be used to compute the value of Discretionary Accruals (*DA_{it}*). This variable will be used in the tests for hypotheses 1. To do so, the amount of total accruals is subtracted by the amount of non-discretionary accruals, defined as $DA_{it} = (TA_{it} / Assets_{i,t-1}) - NDA_{it}$. For hypothesis 2, the absolute value of *DA* is needed. Therefore the variable *Absolute DA* is generated. The definitions of the variables used to calculate *DA* can be found in table 1.

3.2.3. Empirical Model

To test for the DiD-design, a regression analysis will be used. The following OLS-model is estimated:

$$(Absolute)\ DA_{ijt} = \beta_0 + \beta_1 Treated_i + \beta_2 Post\text{-}Disaster_t + \beta_3 Treated_i \times Post\text{-}Disaster_t + Control\ Variables + \varepsilon_{ijt} \qquad (4)$$

Treated is an indicator for the location of the office of an audit firm. It will take the value of 1 if the auditor's office is located in the affected area and thus receives the treatment and 0 otherwise. *Post-Disaster* takes the value of 1 if the year of interest is after the hurricane and 0 if it relates to the year before the hurricane. The coefficient of interest in this model is β_3 which is the coefficient on *Treated x Post-Disaster*. It catches the DiD result and thus answers the research question. For both hypothesis to be true, the coefficient should be negative.

One last remark for this model has to do with the control variables. Normally, a regression analysis includes several control variables to mitigate the risk on correlated omitted variables and to boost the explanatory power of the test. For both hypotheses, firstly a univariate regression will be presented. Next, control variables will be included in the regression. The last regression follows from the propensity score matching method. The propensity-score matching method uses the most common control variables, the confounders, to match the groups. The groups should be statistically the same based on the matching principle. Therefore inserting the confounding variables with similar statistics as control variables should give no significant relation. Since these statistics should be only statistically similar, the confounders will be inserted as control variables, as they are still able to influence the results.

3.3. Summary Statistics

Table 3 presents the summary statistics of the full sample. Panel A lists statistics for the dependent variable and the control variables. The first thing that stands out in this panel is the high standard deviation for *DA* (4.226) and *Absolute DA* (3.810), while both are measured as a percentage of assets. Therefore it would be logical that the value is much smaller. Even though the sample is winsorized, this value still implies that big values of *(Absolute) DA* have an impact on the outcome of *(Absolute) DA*. Furthermore, it can be seen that the median of *Loss* and *Big N* are zero and one, respectively. This is due to the fact that both variables are dummy variables which take the value of zero and one. Concerning *Loss* and *Big N*, it can be concluded that almost one-third of the companies experience a loss (0.321) and more than three-quarter of the companies are audited by a Big N auditor (0.765). Concerning *TA*, it can be seen that all statistics show a negative number, which implies that the observed companies already show a conservative use of total accruals.

In Panel B of table 3, the means of the dependent variable and control variables are distributed for each group and timeframe. Looking at the total sample, it can be seen that for *DA* the mean of the control group is lower than for the treatment group (0.037 and 0.245, respectively). When looking at before and after Katrina, it can be seen that the treatment group drops very hard from 1.152 to -0.663, while the control group only drops from 0.058 to 0.017. This already suggests that there is a difference between those two groups. In contrast to the difference for *DA*, *Absolute DA* shows a similar drop for both groups. This already suggests no big differences between the two groups concerning the absolute use of *DA* and therefore differences in audit quality. Furthermore, it can be seen that more companies in the control group are audited by a Big N company than companies in the treatment group (0.768 and 0.557, respectively). This statistic does not differ before and after Katrina, because companies must be audited by the same auditor before and after Katrina, as stated before. Lastly, the total observations per group can be derived from this panel. The treatment group only consists of 122 observations over 61 companies, while the control group consists of 6,514 observations over 3,257 companies.

4. Results

4.1. Auditor Conservatism

4.1.1. Full Sample

Table 5 shows the outcome of the regression analyses. The first two columns present the results using regression (4), with and without control variables, for the full sample. The first column uses the regression in the simple form, without any control variables. The variable *Treatment* gives a positive value which is significant at a 5% level. It thus indicates that the use of *DA* will be more conservative for the treatment group, compared to the use of *DA* for the untreated group. For the variable *Post-Disaster* there is no significant relationship, which indicates that for the full sample, the use of *DA* is not different between the two time periods. The coefficient of interest, *Treatment x Post-Disaster*, is negative (-1.774) at a significance level of 5%. This value captures the DiD result and implies that auditors which received the treatment become more conservative in their auditing after Katrina, compared to auditors which are not affected by hurricane Katrina, when controlled for the untreated group.

The second column in table 5 includes the confounding variables which are used in PSM as control variables in the regression. There is no noteworthy change in the coefficient of interest, which is still significant at a 5% level and negative (-1.561). All control variables act in the way that is expected based on prior literature. The only control variable that stands out is *Big N*, which is widely used as a proxy for audit quality. Therefore, it is expected that a *Big N* firm is more conservative with the use of *DA*. Although this variable is not significant, it suggests a positive relation, which is the opposite of what would be expected. Based on the results of these two analyses, it is expected that Katrina has a negative effect on *DA*.

4.1.2. PSM Sample

As stated before, a DiD-design requires the control group and treatment group to be identical, except for the treatment. In the descriptive statistics (table 3) can be seen that the means between the groups are not identical. Therefore it is hard to make any statements about a causal relationship. To make sure that the two groups are indeed similar, PSM is used. Observations of the control group are matched to observations of the treatment group, using the *P-Score*. This score is based on several confounders, which in this paper are the control variables stated earlier.

When looking at table 4, the correlation between variables can be seen. Two things are important in this table. First, *MTB* and *TA* show no significant correlation with *DA* and therefore could be left out as confounders, since their influence in the value of *DA* is limited. This study will use *MTB* and *TA* as confounders, since already few confounders are used and those variables are widely used as control variables in prior literature. Second, all values are below one and above minus one, which implies that there is no autocorrelation present.

Using the *P-Score*, which flows from regression (1), the observations are matched based on the NN principle. NN matches an observation from the treatment group to the two observations with the *P-Score* that is nearest to the *P-Score* of the treatment observation. Hereafter it is necessary to test if the means of the confounders and *P-Score* are statistically similar. This is done using a PSM variance test, which is presented in table 6. The column of interest is the last column, which indicates if the mean of the variable differs between the treatment and control group. For all variables, the difference is insignificant, which suggests that for the confounders and *P-Score* the means are balanced across the two groups. Therefore, these variables will likely not influence the estimates of the average treatment effect.

Afterwards, regression (4) is run using the PSM sample and the result is presented in the third column of table 5. The variable of interest, *Treatment x Post-Disaster*, is negative and significant on a 5% level. The only difference when looking at the full sample, is that the variable is less negative when using the PSM sample (-0.424, compared to -1.774 and -1.561). The only other variables that are significant, are *Leverage, OCF and MTB*. Only *OCF* shows a different direction compared to the results of the full sample regression. Prior literature shows that *OCF* usually has a negative impact, but the PSM sample shows a positive impact on 10% significance level. This difference in direction may be due to the small sample size.

4.2. Audit Quality

4.2.1. Full Sample

The same steps as for the first hypothesis are taken for the second hypothesis. In the first column of table 6, regression (4) can be found in the simple form, with *Absolute DA* as dependent variable. All variables are significant, except *Post-Disaster*, which is significant at a 1% level (-0.993). This implies that the absolute use of *DA* declines after Katrina for all observations. The variable of interest is positive, but insignificant. This means that there is no significant change in the absolute use of *DA* in the treatment group after Katrina when compared to the control group.

The second column in table 6 represents the results of the same regression, but this time the control variables are included. *Treatment* stands out, as it changes direction compared to the first column. Even though the result is not significant, it suggests that the absolute use of *DA* is lower for the treatment group than for the control group. The results also suggest that Big N firms are more likely to allow the use of *DA* as the variable *Big N* is positive and significant at a 10% level (0.241). As stated earlier, this effect is unexpected.

4.2.2. PSM Sample

The last column provides the results of regression (4) when using the PSM sample. The matching process is based on the confounding variables and is not based on the dependent variable, so no new *P-scores* have to be estimated. Therefore, the same PSM sample is used as before. What stands out, is that all coefficients of the DiD-design are insignificant. This can be due to the low sample size, or simply because there is no significant difference. Furthermore, nothing noteworthy arises from this regression.

4.3. Additional Analyses

As stated before, the variance of *DA* is high (4.226) and it is argued that, although the sample is Winsorized, this variable is influenced by outliers. It is important to test if the outliers have an influence on the outcome of the estimated coefficients. Therefore, a robustness test is implemented. All variables used in regression (4) are converted into dummy variables equal to 1 if the value of the variable is equal or higher than the median and 0 otherwise. In this way, it can be seen if the results are driven by few observations with extreme values (Nikolaev, 2010). The test will be done using the PSM sample. The results of this test can be found in the last column of table 5.

For this test, the variables of interest still is negative (-2.659) and significant at a 5% level. It is even more negative compared to the other results. Furthermore, the rest of the results remain very similar to the other tests. This may imply that positive outliers of *DA* have a big influence on the results. Overall, the paper finds evidence that there is a negative tendency in the use of *DA* for auditors affected by Katrina.

5. Conclusions

This study examines the effect of hurricane Katrina on the quality of an audit report. The study uses a regression analysis with a Difference-in-Difference design to capture the effect of the treatment, when controlling for an unaffected group. The regression captures a negative effect of the treatment on the use of *DA*. This implies that the first hypothesis is true. To make this assumption more robust, Propensity Score Matching is applied. The observations in the control group are matched to observations in the treatment group, based on a *P-Score* following certain confounders. The analysis following from this matching process also supports the first hypothesis. Another robustness test is applied in response to the high standard deviation of *DA*. This test is designed to capture the effect of outliers. The results suggest that positive outliers of *DA* have an impact on the results of this study.

The second hypothesis is tested using the same design, but with the absolute value of *DA* as the dependent variable. The results of all tests suggest no significant differences, which implies that the second hypothesis is false. The tests suggest that for the full sample, the absolute use of *DA* declines after Katrina. This implies that the U.S. as a whole may be affected by the aftermath of the hurricane or that some other variable causes this decline. Further research on this topic is needed to make any statements. Therefore, combining the results of the two hypotheses, it can be argued that the overall quality of reported *DA* does not change due to Katrina, but the use of *DA* only becomes more conservative. Furthermore, the answer on the research question is negative, since there is no change in the absolute use of *DA* and therefore no change in the quality of the audit report.

This study has some limitations that the reader of this paper should take in consideration. Firstly, there is no causal relation proven even though a DiD-design is used. Due to the use of a limited amount of confounders, endogeneity concerns still may arise. Using more confounders to assess the *P-Score* may result in an infeasible analysis due to the relative small sample size. Secondly, to boost the sample size, the four regions which were hit the hardest are used as treatment group. There still is a difference in impact size between those regions, since Katrina hit New Orleans, Louisiana the hardest and Florida had the least victims and damage (Beven et al., 2008). This difference in impact, may result in differences in the observed effect in this study between the four states and specifically New Orleans. Lastly, the paper measures the effect on office level rather that personal level. Due to the possible treat of compensating quality for different clients on a personal level following Chen et al. (2010) and the possible evacuation of individual auditors, the results may be biased.

6. References

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7. Appendix

7.1. Variable Definitions

Table 1
Variable Definitions

Variable		Definition
<u>*Dependent Variables*</u>		
DA	=	Discretionary accruals, measured as total accruals divided by laggard assets, minus NA
Absolute DA	=	The absolute value of *DA*
<u>*Independent Variables*</u>		
Size	=	The size of the company, measured as the natural logarithm of laggard assets
Leverage	=	The leverage of the company, measured as long-term debt divided by total assets
Loss	=	Dummy variable equal to 1 if company reported a loss and 0 otherwise
Sales Growth	=	The sales growth of the company, measures as sales minus laggard sales, divided by laggard sales
OCF	=	The operating cash flow, measured as total value of operating cash flow divided by laggard assets
Big N	=	Dummy variable equal to 1 if auditor is a BIG N company and 0 otherwise
MTB	=	The market-to-book ratio, measured as market value, divided by total assets minus total liabilities
TA	=	The total accruals, measured as net income before extraordinary items minus cash flows from operations, divided by lagged assets
<u>*Variables used to calculate DA*</u>		
Assets	=	Total assets
ΔREV	=	The change in revenue measured as revenue minus laggard revenue
PPE	=	The gross value of property, plant and equipment of the company
NDA	=	Non-Discretionary Accruals, measured through equation (3)
ΔAR	=	The change in accounts receivable, measured as accounts receivable minus laggard accounts receivable
<u>*Other variable(s)*</u>		
P-Score	=	The propensity score which flows from regression (1). The higher the score, the higher the change for an observation to receive the treatment

7.2. Sample Selection

TABLE 2

Sampling Procedure

			N
Initial sample resulting from Merged Database			41,729
Less:	Observations with missing values for assets and two-digit SIC-code	4.927	
	Observations with missing values for estimating Jones Accruals	13,488	
	Two-Digit SIC-codes with less than ten observations per year	173	
	Financial firms (Two-Digit SIC-code 60-69)	1,201	
	Firms with less than 3 year observations	2,615	
	Firms which rotated from auditor	4,019	
	Observations with missing values for confounders	4,452	
	Observations with auditor located outside and company located inside affected area	606	
	Observations other than the years 2004 and 2005	3,278	
	Observations that switch from treatment or control group	30	
	Firms with less than two year observations	304	
Full Sample			6,636
Less:	Observations from control group that are not matched	6,286	
PSM Sample			350

7.3. Descriptive Statistics

TABLE 3
Descriptive Statistics

Panel A: Summary Statistics

	N	25th	Mean	Median	75th	Std. Dev.
DA	6636	-0.229	0.041	0.010	0.310	4.226
Absolute DA	6636	0.068	1.829	0.273	1.346	3.810
Size	6636	3.986	5.626	5.862	7.503	2.638
Leverage	6636	0.001	0.191	0.124	0.280	0.244
Loss	6636	0.000	0.321	0.000	1.000	0.467
Sales Growth	6636	0.016	0.236	0.112	0.258	0.721
OCF	6636	0.000	-0.010	0.076	0.143	0.424
Big N	6636	1.000	0.765	1.000	1.000	0.424
MTB	6636	0.897	2.552	1.916	3.384	5.988
TA	6636	-0.107	-0.132	-0.053	-0.015	0.484

Panel B: Means Distribution

	Total Sample		Before Katrina		After Katrina	
	Treatment	Control	Treatment	Control	Treatment	Control
DA	0.245	0.037	1.152	0.058	-0.663	0.017
Absolute DA	2.111	1.823	2.538	2.320	1.683	1.327
Size	4.401	5.649	4.300	5.588	4.502	5.711
Leverage	0.212	0.191	0.219	0.193	0.206	0.189
Loss	0.434	0.319	0.426	0.319	0.443	0.320
Sales Growth	0.367	0.233	0.412	0.262	0.322	0.204
OCF	-0.223	-0.006	-0.280	-0.008	-0.166	-0.004
Big N	0.557	0.768	0.557	0.768	0.557	0.769
MTB	2.038	2.562	3.037	2.620	1.040	2.504
TA	-0.305	-0.129	-0.297	-0.132	-0.314	-0.126
Observations	122	6514	61	3257	61	3257

This table reports the descriptive statistics based on the full sample. Panel A reports the summary statistics of the main variables in this study. Panel B reports the variable means per group and timeframe. See Table 1 for variable definitions.

7.4. Correlation Matrix

TABLE 4
Correlation Matrix

	DA	*Absolute DA*	*Size*	*Leverage*	*Loss*	*Sales Growth*	*OCF*	*Big N*	*MTB*	*TA*
DA	1									
Absolute DA	0.084***	1								
Size	-0.052***	-0.281***	1							
Leverage	0.032*	-0.019	0.124***	1						
Loss	0.095***	0.205***	-0.427***	0.097***	1					
Sales Growth	-0.058***	0.096***	-0.184***	-0.021	0.068***	1				
OCF	-0.123***	-0.270***	0.476***	-0.087***	-0.443***	-0.206***	1			
Big N	-0.031*	-0.178***	0.678***	0.057***	-0.290***	-0.129***	0.343***	1		
MTB	0.004	0.025*	-0.032**	-0.131***	-0.020	0.087***	0.075***	0.011	1	
TA	0.0182	-0.259***	0.340***	-0.082***	-0.281***	-0.193***	0.509***	0.261***	0.058***	1

*, **, *** Significant at 10 percent, 5 percent, and 1 percent, respectively;
This table reports the correlation between the variables used in this study. See Table 1 for variable definitions.

7.5. Regression analyses

TABLE 5
Regression Analyses

Dependent Variable: *DA*	Before PSM		After PSM	
	No Control Variables	With Control Variables	With Control Variables	Robustness Test
Constant	0.058	0.015	1.451*	-1.288
	(0.074)	(0.173)	(0.789)	(1.133)
Treatment	1.095**	0.795	0.547	1.769**
	(0.546)	(0.539)	(0.660)	(0.790)
Post-Disaster	-0.041	-0.063	-2.143*	0.701
	(0.105)	(0.103)	(1.120)	(0.663)
Treatment x Post-Disaster	-1.774**	-1.561**	-0.424**	-2.659**
	(0.772)	(0.760)	(0.178)	(1.115)
Size		-0.009	-0.539	-0.862
		(0.030)	(0.956)	(0.869)
Leverage		0.371*	1.483**	-0.414
		(0.217)	(0.678)	(0.593)
Loss		0.485***	-0.193	1.644**
		(0.128)	(0.289)	(0.823)
Sales Growth		-0.455***	-0.354	-1.521***
		(0.074)	(0.567)	(0.554)
OCF		-1.669***	1.556*	0.001
		(0.158)	(0.909)	(0.722)
Big N		0.074	0.0612	0.742
		(0.164)	(0.0423)	(0.865)
MTB		0.014	1.166***	0.769
		(0.009)	(0.420)	(0.574)
TA		0.910***	0.285	1.321**
		(0.125)	(0.922)	(0.610)
Observations	6,636	6,636	350	350
R-squared	0.001	0.034	0.075	0.073

*, **, *** Significant at 10 percent, 5 percent, and 1 percent, respectively;
This table presents the outcome of the regression analyses in this study. The regression equation used in this table is equation (4): $DA_{ijt} = \beta_0 + \beta_1 Treated_i + \beta_2 Post\text{-}Disaster_t + \beta_3 Treated_i \times Post\text{-}Disaster_t + Control\ Variables + \varepsilon_{ijt}$. The first two columns report the regression analysis based on the full sample, where the first column is the univariate analysis and the second column includes the control variables. The last two columns reports the analyses based on the PSM sample. These analyses do include control variables, since the confounders are not exactly similar and therefore may influence the result. The variable of interest in this table is *Treatment x Post-*Disaster, since it captures the DiD-result. See Table 1 for variable definitions.

TABLE 6
Regression Analyses

Dependent Variable: *Absolute DA*	Before PSM No Control Variables	Before PSM With Control Variables	After PSM With Control Variables
Constant	2.320***	3.209***	4.211***
	(0.0662)	(0.147)	(0.761)
Treatment	0.218	-0.539	-0.326
	(0.488)	(0.459)	(0.652)
Post-Disaster	-0.993***	-0.949***	-0.896
	(0.0936)	(0.0879)	(0.545)
Treatment x Post-Disaster	0.138	0.262	0.158
	(0.690)	(0.648)	(0.925)
Size		-0.246***	-0.390***
		(0.0252)	(0.147)
Leverage		-0.347*	-1.762**
		(0.185)	(0.790)
Loss		0.466***	0.114
		(0.109)	(0.560)
Sales Growth		0.0393	0.0290
		(0.0627)	(0.239)
OCF		-0.936***	-1.013**
		(0.135)	(0.468)
Big N		0.241*	0.379
		(0.140)	(0.751)
MTB		0.0201***	-0.0212
		(0.00740)	(0.0349)
TA		-1.111***	-0.752**
		(0.106)	(0.347)
Observations	6,636	6,636	350
R-squared	0.017	0.137	0.220

*, **, *** Significant at 10 percent, 5 percent, and 1 percent, respectively;
This table presents the outcome of the regression analyses in this study. The regression equation used in this table is equation (4): $Absolute\ DA_{ijt} = \beta_0 + \beta_1 Treated_i + \beta_2 Post\text{-}Disaster_t + \beta_3 Treated_i \times Post\text{-}Disaster_t + Control\ Variables + \varepsilon_{ijt}$. The first two columns report the regression analysis based on the full sample, where the first column is the univariate analysis and the second column includes the control variables. The lasts three columns reports the analysis based on the PSM sample. These analyses do include control variables, since the confounders are not exactly similar and therefore may influence the result. The variable of interest in this table is *Treatment x Post*-Disaster, since it captures the DiD-result. See Table 1 for variable definitions.

7.6. Propensity Score Matching

TABLE 7
Propensity Score Matching Variance Test

	Mean			T-test		V(T) / V(C)
	Treated	Control	% Bias	t	p > | t |	
P-Score	.0265	.0265	0.1	0.01	0.996	1.01
Size	4.300	4.338	-1.3	-0.07	0.944	1.17
Leverage	.219	.228	-3.2	-0.18	0.858	0.90
Loss	.426	.426	0.0	0.00	1.000	.
Sales Growth	.412	.364	4.3	0.24	0.809	1.06
OCF	-.280	-.254	-3.1	-0.17	0.866	1.03
Big N	.557	.557	0.0	0.00	1.000	.
MTB	3.037	1.986	14.6	0.79	0.428	1.16
TA	-.297	-.338	4.7	0.26	0.793	0.62

*, **, *** Significant at 10 percent, 5 percent, and 1 percent, respectively;
This table reports the PSM variance test. The column of interest is the last column, where can be seen if the P-Score and confounding variables are statistically similar between the two groups. See Table 1 for variable definitions.