

Learning from the Bad Guys

– What Investors learn from Error Announcements over time

Christina E. Banner

Justus-Liebig-Universität Gießen (Germany)

christina.banner@wirtschaft.uni-giessen.de

Licher Straße 62, 35394 Gießen, Germany

Corinna Ewelt-Knauer

Justus-Liebig-Universität Gießen (Germany)

corinna.ewelt-knauer@wirtschaft.uni-giessen.de

Licher Straße 62, 35394 Gießen, Germany

Fabienne Herrmann

Justus-Liebig-Universität Gießen (Germany)

fabienne.herrmann@wirtschaft.uni-giessen.de

Licher Straße 62, 35394 Gießen, Germany

Mohamed Amin Khaled

Justus-Liebig-Universität Gießen (Germany)

mohamed.a.khaled@wirtschaft.uni-giessen.de

Licher Straße 62, 35394 Gießen, Germany

ABSTRACT

This study investigates how investors learn the characteristics of misreporting firms over time from error announcements issued by an enforcement institution. Relying on Fama's theory of efficient capital markets and Lo's theory of adaptive markets, we argue that investors use this information to determine firm-specific error probabilities, which they anticipate in their investment decisions. Our research setting allows us to capture investor's entire learning process over time as an enforcement institution was first implemented in Germany in 2005 and a growing number of error announcements have been issued ever since. Moreover, to the best of our knowledge, we were the first to have access to an estimation model, which is issued by the German enforcement institution (FREP). This model is employed to determine the probability of finding an error during a review, which is based on the FREP's prior experiences regarding characteristics of companies not receiving an error announcement compared to misstating companies. We use this model to proxy investors' estimation about a firm's error probability. By conducting a short-window event study and multivariate regression analysis, we can show that the higher the error probability of a firm, the less surprised is an investor when an actual error announcement is published. This results in a less adverse market reaction of firms with a high error probability. Vice versa, we find a more serious capital market reaction to an error if the FREP announces an error statement for a company with a lower probability of errors. This is due to the fact that information about low financial reporting quality comes unexpectedly and has not been processed by the capital market until then. Moreover, there is a highly significant time-varying effect suggesting that the capital market has learned to recognize infringing firms over time. Our research outlines how enforcement institutions enable investors to anticipate firm-specific error probabilities over time and explains why capital market reactions upon error announcements are weak in some cases. Moreover, in a broader research context, our dataset allows us to prove investor's adaptive learning over time empirically which prior studies have only predicted analytically so far given efficient capital markets.

Keywords: enforcement, accounting quality, market efficiency, adaptive markets, Germany

I. INTRODUCTION

This paper investigates how investors learn from financial reporting-related information over time and how they anticipate this information in their investment decisions. In detail, we focus on how investors learn about characteristics of misreporting firms based on error announcements issued by the German Enforcement Institution FREP (German Financial Reporting Enforcement Panel) and the German securities regulator BaFin (Bundesanstalt für Finanzdienstleistungsaufsicht). Since July 2005, the FREP reviews financial statements of publicly traded companies and issues publicly available error announcements, when errors are found during its review. Prior to the implementation of the FREP, the German enforcement quality was classified as rather weak (Leuz & Wüstemann, 2003) and investors had little information about a firm's financial reporting quality. By building on Fama's theory of efficient capital markets (Fama, 1970) and Lo's theory of adaptive markets (Lo, 2004), we argue that these error announcements allow investors to learn about characteristics of misreporting firms. Consequently, they will be able to determine those firms where it is highly probable that the FREP will find an error during their next inspection (high error probability) compared to firms with a low error probability. More precisely, we reason that if the FREP announces errors for firms with a high error probability, this will no longer constitute a new information for investors resulting in no or only little capital market reaction. In contrast, if investors were assuming a low error probability and the respective firm yet receives an error announcement, this is rather surprising for investors and thus results in a more pronounced negative capital market reaction.

For instance, the firm "loginet3 (formally: PONAXIS AG)" received an error announcement resulting in nearly no abnormal capital market reaction, whereas the capital market abnormally decreased by nearly 18% when the firm "TC Unterhaltungselektronik" received such

an announcement, even though the error severity¹ of the latter was much lower compared to the first one. We attribute these findings to the different error probabilities investors have already anticipated in their investment decisions: Whereas the error probability of “loginet3” was extremely high with over 90%, the error probability of “TC Unterhaltungselektronik” was rather low (<5 %). To determine the error probability of a firm, we are – to the best of our knowledge – the first to have access to the official model of the FREP, which was developed by the FREP to determine the probability of finding an error during a review (Pasch, 2017). This model is based on the FREP’s prior experiences about characteristics of companies that did not get an error announcement compared to companies that have conducted misreporting. In the FREP’s model, the probability of errors builds on 26 factors in the following four main domains: accruals, corporate governance, capital market pressure and blockholding controls. All components of this model originate from publicly available resources also accessible for investors.

This research setting is unique especially with respect to the following two issues: First, we pick up the German particularity that there was no real enforcement system implemented before 2005. Thus, in the starting point of our investigation there is no objective information available to investors about a firm’s financial reporting quality. The ongoing publications of error announcements therefore allow us to cover investor’s entire learning-process about a firm’s financial reporting quality over time. Second, the recently developed model of the FREP for estimating a firm’s error probability enables us to operationalize investors’ heuristic to identify misreporting firms. This enables us to proxy the error probability in our sample and to test (1) whether the error probability significantly effects the capital market reaction, and (2) whether this effect accelerates over time by conducting a short-window event study. In detail, we assess whether the error probability has a significant effect on the abnormal returns and the abnormal volatilities in a multivariate regression model. Moreover, we include interaction terms

¹ We measure error severity by using Principal Components Analysis, including number of errors, the impact on net profit and the impact on OCI.

with a time variable to further investigate the impact of the error probability on the adverse market reaction over time. We conduct additional analysis by evaluating the marginal effect of our time variable on abnormal returns and abnormal volatilities for different error probabilities and furthermore create model predictions for our dependent variables (abnormal returns/abnormal volatilities) by specifying our time and error probability variables at low, average and high values via predictive margins.

Our results support our reasoning: There is a significant negative impact of error probability especially on abnormal returns. The higher the error probability, the less surprised is an investor, when an actual error announcement is published. This results in a less adverse market reaction for firms with a high error probability, and vice versa. Moreover, there is a highly significant time-varying effect of error probability for both abnormal returns and abnormal volatilities suggesting that over time, the capital market has learned to recognize infringing firms. Our additional analysis moreover reveals that a positive (negative) change of abnormal returns (volatilities) from the mean of zero is most profound for firms that possess a higher probability of errors in their financial statements while firms with a very low error probability display no difference to the average abnormal capital market reaction, further supporting our results.

Our results contribute to theory and practice in several ways: With respect to accounting research, we underline the importance of considering investors' ability to learn accounting-related issues over time when focusing on capital market reactions and the 'name and shame' mechanism in an enforcement context. In detail, we can show that the results of prior event studies such as Hitz et al. (2012) do not completely hold when anticipating investors' learning. In a broader context, we contribute to all research streams concentrating on how investors process and anticipate information. There is a lot of research arguing analytically that investors learn from ongoing information over time by referring to Fama's theory of efficient capital markets and Lo's theory of adaptive markets (e.g., Fraser, 2003; Rejeb & Boughrara, 2013;

Banarjee et al., 2018). Our rare research setting allows us to test this analytical reasoning empirically and provide empirical evidence for these theories. Focusing on practice, one could argue that the FREP's 'name and shame' sanctioning mechanism has lost its effectiveness over time, because in newer days investors often do not react negatively to error announcements anymore. However, our results reveal that the contrary is correct: The work of the FREP enables investors over time to learn characteristics of misreporting firms and to develop heuristics for determining firm-specific error probabilities, which investors anticipate in their investment decisions. Thus, the FREP's review allows investors to make more comprehensive investment decisions.

The remainder of this paper is organized as follows. In Section 2, we provide an overview of the German two-tier enforcement system and develop our hypotheses. In Section 3 we outline our methodology including our sample selection and a description of our univariate and multivariate approach to test our hypotheses. Our empirical results and additional analysis are presented and discussed in Section 4. Finally, we provide conclusions in Section 5 and point out limitations of this paper and potential future research

II. BACKGROUND & HYPOTHESES

Background: Enforcement in Germany

Research in financial accounting deduces that a strong enforcement influences accounting quality significantly (e.g., Daske et al., 2008; Landsman et al., 2012). In detail, the stronger a country's enforcement actions, the lower the occurrence of earnings management (Cai et al., 2008; Leuz et al., 2003; Nagar and Petacchi, 2005) and the higher the forecast accuracy (Hope, 2003). Therefore, it is not surprising that announcements of errors in the financial statements of a firm issued by enforcement institutions derive in an adverse stock price reaction (e.g., for the US: Hribar and Jenkins, 2004; Palmrose et al., 2004; Wu, 2002; for Germany: Hitz et al., 2012), an increase in the cost of capital and a loss of financial statement credibility (e.g., Chen et al., 2014; Wilson, 2008) for the respective firm.

Focusing on Germany, in prior years, various studies classified the then prevailing German enforcement quality as rather weak (Hope, 2003; La Porta, 1998; Leuz et al., 2003). As a reaction, in 2005, the German enforcement system has undergone some major reforms reorganizing its former structure resulting in a two-tier system: On the first level, the German Financial Reporting Enforcement Panel (FREP) as a private body reviews the audited financial statements of publicly listed companies. Since this private panel has no given legal power to enforce companies to cooperate with them, the system is complemented by a Federal Financial Supervisory Authority (so called: BaFin). The latter is ultimately responsible for all enforcement matters and supports the system through its given executive power. When an error in the financial statements of a company is found, the error needs to be publicly disclosed in the Federal Gazette as well as in at least two daily financial newspapers, so called error announcements. The error announcements are written in German, structured in a similar style and mostly contain the same scope of detailed information. They include the name of the misstating company, the year of

the erroneous report as well as the relevant information of the financial amount, the consequences and the magnitude of errors made. Furthermore, they cite the standards that were violated and reveal whether the FREP or the BaFin has conducted the review. Thus, instead of additionally imposing monetary injunctive sanctions like the SEC does (Karpoff et al., 2008, p. 595), the German enforcement system solely relies on the ‘name and shame’ mechanism of the market as a sanctioning tool. This sanction mechanism is based on the assumptions that investors calculate the present value of a firm based on the firm’s future cash flows discounted at the expected cost of capital and that a publicly announced error finding constitutes a new negative information to investors. This shows for instance that the firm’s internal control system has weaknesses that need to be addressed resulting in cash outflows. The subsequent loss of market value penalizes the firm.

Prior research shows that financial reports are relevant information for investors in this context (e.g., Healy and Palepu, 2001; Kothari, 2001) and that investors use financial statement information for firm valuation (e.g., Ball and Brown, 1968; Beaver, 1968; Easton and Zmijewski, 1989). Beyond this background, it is not surprising that prior literature has shown that error announcements result in an immediate decrease of a firm’s market value (e.g., Hitz et al., 2012, p. 261). Hitz et al. (2012) were the first to exhibit the effectiveness of the two-tier enforcement mechanism in Germany. Conducting an event study from 2005 to 2009, they examine short- and long-term market reactions upon error announcements and provide evidence for the adverse disclosure being an effective instrument in the German setting for penalizing infringing firms. The negative market reaction is proportional to the adverse effect of the error announcement on the market value of a firm: A more severe error announcement has a larger impact on a firm’s market value compared to a less severe finding. Their study also reveals an interrelationship between the investor reaction and the companies’ willingness to cooperate, the errors referring

to individual financial statements, as well as the firm's liquidity and change of auditors or top management.

In this study, we go a step further and make use of the fact that the German enforcement system was comprehensively revised in 2005. For years prior to 2005 it was nearly impossible for investors to get a clear picture of the financial reporting quality of German publicly listed companies. Thus, at the beginning of 2005 investors' knowledge about a firm's reporting quality was limited. Then, since 2005 investors are being informed about companies with a low financial reporting quality based on the error announcements issued by the FREP. Between 2005 and 2017 the FREP conducted 1,338 audits and issued 250 error announcements, with 2 error announcements in 2005 at a minimum and 31 error announcements in 2010 as a maximum.

<Insert table 1 about here.>

Hence, over time these error announcements allow investors to gather a deeper understanding about characteristics of misreporting firms. Building on Fama's (1970) theory of efficient capital markets and Lo's (2004) theory of adaptive markets we research, whether investors actually learn from these error announcements by developing a heuristic about misreporting firms over time. Therefore, we argue in our hypotheses that error announcements enable investors to learn over time and to determine a company-specific error probability that in turn is anticipated in stock prices. Before we do so, we replicate prior research as a starting point for our argumentation.

Hypotheses H1a and H1b:

In detail, we argue that error announcements help investors to learn about the characteristics of misreporting firms over time, which allows them to calculate a firm specific error probability. This error probability is defined as the probability that the FREP will find an error in

the firm's financial statements in their next review and is anticipated when valuing the firm and therefore reflected in a firm's stock price.

According to Fama (1965; 1970, p. 383) an efficient capital market is characterized by the fact that stock prices "fully reflect" all relevant information available to market participants at any times. Following the information efficiency hypothesis, the current stock price corresponds to investors' expectations based on all available information (Guimaraes et al., 1989, p. 4). Fama (1976) furthermore emphasizes that an efficient capital market is also efficient in processing information. Based on efficient capital markets the theory of adaptive markets underlines that investors learn over time by validating available information before they can process information resulting in adjustments to prior expectations (Lo, 2004). In detail, a substantial environmental change will reduce the utility investors derive from established heuristics and create a necessity to adjust prior expectations. The implementation of the new enforcement mechanism by the FREP in 2005 constitutes such a substantial environmental change as its error announcements offer investors valuable new information about the financial reporting quality of firms.

Prior research has emphasized the importance of financial reporting quality for investors. High accounting quality reduces information asymmetry and risk (e.g., Brown and Hillegast, 2007) and influences investors in making their investment decisions (e.g., IASB, 2008). However, for investors it is difficult to determine which company provides high quality in financial reporting (e.g., van Beest et al., 2009) compared to companies providing rather low quality in financial reporting. Therefore, investors are highly sensitized for characteristics and key figures of firms with high compared to low financial reporting quality (e.g., Beneish, 1999a; Dechow et al., 2011; DeFond and Jiambalvo, 1991; Ernstberger et al., 2012b). In this vein, various studies demonstrate that companies with higher accruals (e.g., Healy, 1985; Jones et al., 2008; Strohmenger, 2014), more capital market pressure (e.g., Dechow et al., 1996, 2011;

Watts and Zimmerman, 1986) lower blockholder shareholdings (e.g., Boehmer and Kelley, 2009; Edmans, 2009; Shleifer and Vishny 1997) and a comparatively poor corporate governance (e.g., Baber et al., 2012; Böcking et al., 2015; Ernstberger et al., 2012b; Witzky, 2016) are more likely to publish erroneous information resulting in low financial reporting quality. These findings of prior research confirm a certain predictability of misstating companies meaning that companies with specific characteristics are more likely to provide low financial reporting quality meanwhile resulting in error announcements compared to companies with different characteristics. Thus, investors learn “error-indications” based on company-specific characteristics by evaluating error announcements of the FREP over time.

Starting in 2005, the FREP issued the first two error announcements followed by 8 to 35 error announcements annually for subsequent years with an average of 20 error announcements per year signaling investors a low financial reporting quality of the respective firms. Moreover, the disclosure of these error announcements allows investors to learn about characteristics of misreporting companies. Hence, every new error announcement contributes to investors’ general knowledge about characteristics of misreporting firms. This is in line with Lo’s idea of an adaptive market (Lo, 2004) in terms of investors who learn from and adapt to changing market variables and new information. Thus, the error announcements of the FREP help investors to fine-tune their heuristics about misreporting firms over time. However, this explorative process cannot be achieved instantaneously as the learning process is dependent on the repeated error announcements issued by the FREP over the years. The more error announcements the FREP publishes the more differentiate are investors’ estimations about misreporting companies helping them to update their assumptions on which firms have a higher probability of misreporting and which have a lower probability of getting an error announcement issued by

the FREP in the future. Thus, the error probability of a firm is not static but instead gets dynamically more accurate over time as a growing number of error announcements get published by the FREP helping investors to determine the error probability for each firm more precisely.

Capital market efficiency requires that first-time or updated error probabilities are immediately anticipated in stock prices. Hence, when investors are actually enabled to gather a first or new impression about a firm's error probability based on prior error announcements issued by the FREP investors anticipate this error probability immediately in their investment decisions resulting in re-adjustments of the market value of the respective firm. For instance, if investors gather knowledge about a high error probability for a specific firm, stock prices decrease immediately for anticipating that the financial statements have a low financial reporting quality. Building on this, when the FREP actually announces an error finding for this respective firm, it is not surprising for investors anymore resulting in no or only little capital market reactions, because the announced low financial reporting quality was already anticipated based on the high error probability investors have assumed in advance. Thus, the capital market reaction to an error announcement depends upon whether and to what degree the information about the low financial reporting quality had already been expected by investors and anticipated in their prior investment decisions based on their learning process about characteristics of misreporting companies. This implies that the capital market reaction to an error announcement is less negative, when investors have already classified the company as one with a high error probability based on prior experiences with misreporting companies. The other way around, we expect a more serious capital market reaction to an error finding, if the FREP announces an error statement for a company with a lower probability of errors, as information about low financial reporting quality comes unexpectedly and has not been processed by the capital market until then. Moreover, we expect that this reaction is even more pronounced over time, because investors can improve their heuristic for determining the error probability for a specific

company the more error announcement are issued by the FREP. This reasoning derives in the following two hypotheses:

- H1a:** The magnitude of adverse market reaction upon error announcements is negatively associated with a firm's probability of errors.
- H1b:** The effect of the error probability on the market reaction upon error announcements is stronger over time.

III. METHODOLOGY

Sample Selection and Data Collection

Our database is compiled of firms that were subject of error announcements from the beginning of the new enforcement system the FREP implemented in July 2005 to the end of December 2017. We started with an initial sample of 250 error announcements even though we lost several error announcements due to the following reasons: We dropped 16 error announcements since they were duplicates or corrected reports of prior error announcements. Further, to avoid biases, 19 error announcements from companies based abroad were eliminated as well as 16 announcements relating only to interim reports. We assume these interim reports have a different relevance for the investor compared to annual reports and are thus not comparable in terms of their market effects. Furthermore, if the firm received more than one error announcement throughout the years, the focus was laid on the first announcement, as this is the moment where the market came to know about the misreporting behavior of the respective firm. Therefore, we further omitted 11 error announcements. To prevent influences from other corporate news, we checked for confounding events in our largest event window [-2; 2] (i.e., two days before and after the announcement) that might have led to a distortion of the market reaction and might have caused biased results (McWilliams and Siegel, 1997, p. 637). Consequently,

another 43 error announcements were excluded. As the study requires a lot of data for the dependent and independent variables, and we aimed at keeping the sample consistent for each analysis step, further 69 observations had to be omitted due to missing data. This adjustment of the data set led to a final sample of 76. Overall, the sample size is comparable to that of previous studies (e.g., Beneish, 1999a; Dechow et al., 1996; Hitz et al., 2012).

Several sources were consulted to compile the financial and non-financial information needed for this study. Daily market data for the event study originates from Datastream. All other variables used for the multivariate regression and the compounding of the error probability were either hand-collected from error announcements, the respective financial reports or obtained also from Datastream.

Market Reaction Tests and univariate analysis

An event study is an effective statistical tool in financial accounting research to evaluate the impact of a particular corporate event on a firm's market value (Brown and Warner, 1985, pp. 13-16; McKinlay, 1997). The market reaction may be used as a metric for the scope of information provided by the enforcement system (Nourayi, 1994) when issuing an error announcement.

We assess the impact of these error announcements upon the capital market by conducting an event study based around the date of the error disclosure in the German Federal Gazette. The date of the event is defined as [0] and is easily observable on each error announcement. The economic consequences are measured using financial market data regarding stock performance and stock volatility. For this we use the respective tools, i.e., (cumulative) abnormal returns and (cumulative) abnormal volatility. We consider a short-term time window, which investigates investor reactions within up to five days ([0], [-1; 1], [-2; 2]) around the date of the

adverse disclosure to avoid that the event of an error announcement is biased from other external influences when the event window is enlarged (Brown and Warner, 1985).

Cumulative abnormal returns (CARs) result from adding up the daily abnormal returns over the particular event window. Daily abnormal returns are defined as the difference of the actual daily stock return of a firm and the return that would have been expected without any special event providing new information to the investors. We estimate the expected daily return applying a stock-specific market model (MacKinlay, 1997), which is commonly used in recent capital market-based research (e.g., Lackmann et al., 2012; Lee, 2015; Lam et al., 2016). Daily stock returns are based on a return index in order to explicitly incorporate dividend payouts. Returns are assessed by regressing daily returns on daily returns of an equally weighted portfolio (Brown and Warner, 1985) of all listed German companies. For the market model we apply an estimation period of 150 trading days prior to the beginning of each event window. We compute the mean cumulative abnormal return for each event window ($[0]$, $[-1; 1]$, $[-2; 2]$) by averaging the CARs across the 76 firms of our sample. Abnormal stock volatility is characterized as the difference between the observed stock volatility at the event window and the respective expectation based on an average value of said stock 150 days before the event window. The cumulative abnormal volatility and the cumulative average abnormal volatility are computed analogous to the cumulative abnormal return and the cumulative average abnormal return.

To test whether our cumulative abnormal returns/our cumulative abnormal stock volatilities are significantly different from zero, we apply the common t-test as well as the non-parametric Corrado Rank test, which has the advantage of being independent of symmetrically distributed abnormal returns (Corrado, 1989). Moreover, we apply the Patell test, which is a parametric test designed to reveal whether the (cumulative) abnormal returns are different from zero at a certain significance level (Patell, 1976). We also utilize the Sign test as it has the advantage of identifying even small levels of abnormal returns.

Multivariate Regression Model

To test our other hypotheses, we run a multivariate regression model as we include (cumulative) abnormal returns and (cumulative) abnormal volatilities as our two dependent variables, because a highly negative abnormal rate of return typically results in a highly positive abnormal volatility. The volatility thus shows whether investors have actually sold their investment in the respective company. These two dependent variables are jointly regressed on our variable of interest ERROR PROBABILITY as our independent predictor. Further, we include several company-specific and economic control variables. In a second step, we extend our regression model by incorporating interaction terms to investigate the time-varying effect of ERROR PROBABILITY on our (cumulative) abnormal returns and our (cumulative) abnormal volatilities, since we argue that investors can anticipate the error probability in their investment decisions over time. TIME reflects the number of days the market was able to learn from the FREP's actions, starting from the day of the first error announcement in 2005 as the base line and counting the days up to the respective announcement. Table 2 provides a concise overview of the definitions for the variables employed. To test our hypothesis H1a, we estimate the following multivariate regression model: (1)

$$CAR_i/CAV_i = \beta_0 + \beta_1 \cdot ERROR\ PROBABILITY_i + contols + \varepsilon_i$$

While we compute following multivariate regression to test our hypothesis H1b:

$$CAR_i/CAV_i = \beta_0 + \beta_1 \cdot ERROR\ PROBABILITY_i + \beta_2 \cdot ERROR\ PROBABILITY_i * TIME + contols + \varepsilon_i \quad (2)$$

Independent Variable

As a potential determinant of market reaction, we identify a company's ERROR PROBABILITY, which can be anticipated by investors and is – under the assumption of market efficiency (Fama, 1970) – already reflected in the stock price. We proxy investor's assumption

regarding a firm's error probability based on the FREP's estimation model. To the best of our knowledge, we are the first who uses the recently published model issued by the FREP (Pasch, 2017). This model bases on the FREP's prior experiences about characteristics of companies that did not get an error announcement compared to companies that have conducted misreporting resulting in an error announcement issued by the FREP. We apply this estimation model, as shown in formula (3), to our sample of misstating firms to determine the error probability of these firms. In detail, the predicted value MISST is obtained by plugging each firm characteristic of the year when the errors were actually made into the model and multiplying them with the respective coefficient.

$$\begin{aligned}
 \text{MISST} = & -3.93 - 0.026 \cdot C_WC_ACC_AVTOAS - 0.232 \cdot C_RECEIV_AVTOAS + 3.284 \cdot INVENT_AVTOAS + 1.179 \cdot \\
 & SOFT_TOAS + 0.351 \cdot MJ_ACC_ABS + 5.842 \cdot C_GOODWN_AVTOAS + 2.313 \cdot DTAXA_TOAS + 0.858 \cdot \\
 & FINN - 1.843 \cdot ISSUE_AVTOAS - 0.069 \cdot FIEX_AVDB + 2.256 \cdot LEV - 0.961 \cdot INST_SH + 0.098 \cdot CORP_SH - \\
 & 4.984 \cdot FAM_SH + 1.462 \cdot SB_SH - 0.767 \cdot SB_IND + 9.777 \cdot SB_COMP_TOAS + 0.091 \cdot SB_VARIABLE_COMP + \\
 & 0.066 \cdot SB_NO_MEETINGS - 0.302 \cdot AC + 0.72 \cdot SGI - 2.007 \cdot ROA + 0.031 \cdot LN_MARTCAP + 0.794 \cdot EB_SH - \\
 & 0.607 \cdot BIG_5 + 0.343 \cdot AUD_CHANGE + \varepsilon
 \end{aligned} \tag{3}$$

Following Dechow et al. (2011, p. 60) from this predicted value, the variable ERROR PROBABILITY is calculated as in formula (4):

$$\text{ERROR PROBABILITY} = \frac{e^{(\text{predicted value})}}{(1+e^{(\text{predicted value})})} \tag{4}$$

In the model of FREP (Pasch, 2017), the probability of errors in audited financial statements is composed of four main factors: *accruals*, *corporate governance*, *capital market pressure* and *blockholdings control*.² These are proxied by various financial and non-financial company characteristics and key figures from the fiscal year of the financial reporting violation.

² For a more detailed explanation of the parameters of the error probability, see Pasch (2017), pp. 16-22.

Changes (C_) in variables refer to the difference from the previous year of the misstatement by subtracting the values of the erroneous year from values of the respective previous year.

The *accruals* policy of a company is proxied by changes in working capital accruals (C_WC_ACC_AVTOAS), receivables (C_RECEIV_AVTOAS), inventories (C_INVENT_AVTOAS) and goodwill (C_GOODWN_AVTOAS), as well as the absolute amount of soft assets (SOFT_TOAS), deferred tax assets (DTAXA_TOAS) and earnings management (MJ_ACC_ABS) all scaled by total assets. Soft assets are considered as the percentage of assets that are neither cash nor “property, plant and equipment”. Furthermore, we calculate earning management using the adjusted modified Jones (1991) model.

The evaluation of *corporate governance* structures are represented by various characteristics of a company’s supervisory board, which have an impact on a company’s susceptibility to errors (e.g., Abbott et al., 2004; Campbell et al., 2014; Dechow et al., 1996; Keune and Johnstone, 2015; Peasnell, 2001; Vafeas, 1999): The percentage of supervisory board shareholdings (SB_SH), the supervisory board compensation (SB_COMP_TOAS) scaled by total assets and the number of supervisory board meetings (SB_NO_MEETINGS) that measure the extent of monitoring activities. These components are supplemented by three dummy variables indicating if the firm states that the supervisory board was independent (SB_IND), if the supervisory board received a performance-based compensation (SB_VARIABLE_COMP), and if an audit committee (AC) was established.

Regarding existing market-related incentives, which lead to a manipulation of financial statements, further four different variables are consulted to measure a firm’s *capital market pressure*. A company's financing needs (FINN) is included as a dummy variable coded 1, if the net cash flow from operating activities minus the three-year average capital expenditures proportioned by current assets was smaller than -0.5. The sum of long-term borrowings and equity issuance is divided by total assets, to measure capital issuance (ISSUE_AVTOS). In cases with

no issuance, we insert zero. Financial expenses (FIEX_AVDB) are compounded by dividing interest expenses on debt by the average debt. Leverage (LEV) is the value of long-term debt per total assets.

To take the influence of *blockholders* and their implied scope and incentive of control into account, the percentages of shares held by the largest institutional (INST_SH), corporate (CORP_SH) or family (FAM_SH) shareholder are applied.

Following various previous studies (e.g., Beneish, 1999a; Dechow et al., 2011; Ernstberger et al., 2012b; Hoehn and Strohmenger, 2013; Peasnell, 2001; Witzky, 2016), the model is supplemented by several *control variables*: A firm's growth is proxied by its sales growth (SGI), which is calculated on the net sales of the error year compared to the previous year. The performance of a firm is measured by its return on assets (ROA). To control for size, the natural logarithm of the company's market capitalization (LN_MARTCAP). is used as a reflection of its market value. Another control is the percentage of a company's shares that are owned by executive board members (EB_SH). Additionally, two dummy variables are applied to control whether a BIG 5 auditor (i.e., BDO, Deloitte, EY, KMPG or PwC) had audited the misstatement (coded 1) and whether there was a change of the audit firm (AUD_CHANGE) in the year prior to the erroneous statement (coded 1).

The original FREP model also includes a variable that measures a firm's willingness to cooperate with the FREP. As this kind of information cannot be accessed prior to the announcement by anyone but the FREP itself, we exclude it from our calculation. This is in line with the objective of this study, namely to analyze the impact of the error probability estimated by an external investor. Thus, all data considered for determining the error probability are taken from a firm's financial statements or other open sources investors can access.

Control Variables

To enhance the explanatory power and to avoid variable bias we control for numerous factors which could influence the market reaction to enforcement actions. First, we control for the magnitude of the errors (ERROR SEVERITY). We measure ERROR SEVERITY by aggregating measure of three variables using Principal Components Analysis (PCA). We measure severity by the error's impact on the annual net profit and on other comprehensive income (OCI), both scaled by total assets of the fiscal year prior to the error announcement. Also, we take the number of errors into account that were displayed in the announcement, to capture their pervasiveness on the balance sheet. BAFIN is a binary variable taking the value of 1, if not the FREP but the BaFin conducted the review. It serves as a proxy for a firm's willingness to cooperate on a voluntary basis. LISTING YEARS represents the number of years a firm had been listed on the stock market at the time of its error finding and refers to a firm's experience with accounting issues. We conjecture that errors of a firm, who is classified as relatively experienced, are more likely to be interpreted as the result of fraudulent actions. Since fraud is more severe than unintended errors, this should evoke higher penalties. Other control variables are SIZE, which we measure as the natural logarithm of market capitalization (in million Euros) and financial LEVERAGE. We also assume that companies with a high concentration of OWNERSHIP react less profound to the adverse disclosure, as company insiders already have access to more information. This is measured by the proportion of closely held shares in the previous year of the error disclosure. We measure stock LIQUIDITY by the proportion of non-zero return trading days in the year of announcement. We capture a day as "non-trading" whenever the stock price did not change from one day to another. We further capture the portion of unexpected firm earnings that could influence market reaction by creating the variable EPS_SURPRISE as a difference between forecasted and realized earnings per share. The forecasted earnings per share are created by an aggregate of different analyst forecasts provided by the I/B/E/S

database. We use the firm's beta (COM_BETA) as a proxy to measure the systemic risk of a firm's equity compared to the overall market to control for different risk profiles and differences in the cost of capital between firms. To make sure that our results are not primarily driven by the market turbulence during the financial crisis in 2007 and 2008 that saw a heightened general stock volatility (Schwert, 2011), we create a dummy variable (FCR_DUMMY) to capture the effects that can be attributed to these two years. Additionally, we include two variables to capture the general economic situation during the error announcements and to control for the effects attributed to the different stages of the business cycle that potentially influences investors' market reaction. BND_1Y is used as a proxy for the risk-free rate measured by the 1-year German government bond yield, while GDP_GROWTH is the annual growth rate of the German gross domestic product measured conventionally by a combination of labor force, capital and factor productivity growth.

IV. EMPIRICAL RESULTS

Univariate Results

Table 3, Panel A presents the descriptive statistics of the independent variables for all observations of the multivariate regression model. On average, the error announcement consists of 3.4 single errors. The average impact of errors on OCI is -3.2% of the total assets of the fiscal year prior to the error announcement, whereas the average impact of errors on the annual net profit is -1.65% compared to the total assets of the fiscal year prior to the error announcement. Furthermore, 22.3% of the investigations were forwarded to the BaFin. The average censured company has been listed for 16.8 years and has a mean leverage of 0.88. The error probability has a mean of 16.3%.

Panel B of Table 3 displays a pair-wise correlations matrix for both Pearson's and Spearman's measures. Notably, ERROR PROBABILITY and ERROR SEVERITY exhibit a moderate negative correlation in the Pearson measure, while just displaying a weak negative correlation according to Spearman. Other than that, our variable of interest shows no moderate or strong correlation with any of the control variables in both measures. For our control variables we find a strong Spearman correlation between SIZE and LIQUIDITY, as well as a strong negative Spearman correlation for LIQUIDITY and our variable that measures the unexpected part of the earnings per share of a firm (EPS SURPRISE). ERROR SEVERITY is furthermore moderate positive correlated with the financial LEVERAGE of a firm. Expectedly, we also find a strong positive correlation in both the Pearson and the Spearman measure between our proxy for the risk-free interest rate (BND 1Y) and our dummy variable that captures the impact of the financial crisis (FCR DUMMY) as the years 2007 and 2008 were characterized by sharply rising government bond yield spreads (Antonakakis and Vergos 2013). Aside from the correlations mentioned, the other connotations are below the threshold of 0.5, so collinearity is not deemed a concern for our data set. Due to the multiplicity and complexity of the composite error probability, some individual variables are also included in the error probability (yet for another year). But as this only contributes to a small proportion of the variable, we do not see any multicollinearity problem here either.

< Insert table 3 about here.>

Market Reaction Findings

Table 4 depicts the results of the market reactions upon error announcements for the three different event windows [0; -1, 1; -2, 2]. Panel A shows the results for the (cumulative) abnormal returns (CAR) and Panel B those for the (cumulative) abnormal volatilities (CAV). Panel C and D present the abnormal returns differentiated between companies with a low and a high error probability.

<Insert table 4 about here.>

First, we examine whether there is an adverse market reaction upon the announcement of an error in the financial statements of a firm. Focusing on Panel A consistent with Hitz et al. (2012), we find weak significant cumulative abnormal returns around the date of the error announcement. CARs are negative with a mean of -0.66% on the event day on the 5% level for the Corrado Rank Test. The three-day window [-1; 1] shows on average cumulative abnormal returns of -1.01% with a 0.05 significance level for the Corrado Rank Test. For the five-day window [-2; 2], we find CARs with an average of -0.56%, which, however, lack any statistical significance. Focusing on the (cumulative) abnormal volatilities (CAV) in Panel B, the CAVs are positive for all three event windows with a mean of 6.73% for the event day hinting at an increasing trading frequency upon error announcements. The positive effect gets substantially stronger in the latter two event windows. The conventional t-test shows that these results are significant at the 5% level for the event day and at the 1% level for the three-day [-1; 1] and five-day [-2; 2] windows. The Patell test also confirms these results as it shows significant results at the 10% and 1% level for the event day and the two wider event windows respectively. In sum, these results confirm that there is indeed an adverse market reaction upon the announcement of an error in the financial statements of a firm. Yet, the results are rather weak. This could be a first indication that the capital market reaction is significantly influenced by investors' assumption about a firm's error probability resulting in a lower surprise and meanwhile a less negative adverse market reaction when investors have assumed a high error probability. The other way around, an error announcement should only provoke adverse investor reaction if it constitutes actual unexpected news to the investors because investors have classified the error probability for the respective firm as rather low. Beyond this background and for a first indication, we cluster our sample in firms with an error probability of lower or equal to 30% and firms with an error probability higher than 30% (see Table 4, Panel C and Panel D). Regarding the

results of each subsample, we observe a more pronounced stock price reaction for entities with a low error probability, because for these firms the capital market has not expected an error announcement and thus needs to integrate this surprising information in the market price. In detail, we find higher negative CARs for firms with a low probability compared to firms with a high probability on average (for the event day: -1.05% (+0.94%) for firms with a low (high) error probability; for the three-day event window -1.28% (-0.91%) for firms with a low (high) error probability; for the five-day event window -0.88% (-0.1%) for firms with a low (high) error probability). Significance of the market reactions again varies within the event windows and the respective test statistics but is overall more robust for firms with a low error probability compared to those with a high error probability

Consistent with our reasoning for deriving our hypotheses H1a and H1b these findings hint at the notion that some error announcements are at some point already anticipated by the investors when they ex ante recognize conspicuous features of a firm. This would imply that gradually the capital market learns to identify characteristics of misreporting firms. This aspect, how investors learn over time and anticipate information in their investment decisions is further investigated in a multivariate context. The results of which is elucidated in the following.

Multivariate Regression Findings

Table 5 displays the results of the multivariate regression analyses for all time windows. We consider two different kinds of regression models to support our reasoning. The first kind of model (Panel A and Panel B) consists of our variable of interest ERROR PROBABILITY as well as all our control variables.³ We refer to the impact of ERROR PROBABILITY on capital market reaction in our hypothesis in H1a. In the second kind of model (Panel C and Panel D), we additionally include two interaction terms to measure the effect of error probability and error

³ Panel A und C show show the abnormal returns for all three event windows whereas Panel B and Panel D shows abnormal volatility for all three event windows.

severity over time (ERROR PROBABILITY x TIME; ERROR SEVERITY x TIME), which enables us to analyze whether investors learn about determinants of misreporting firms over time. This allows us to test our hypothesis H1b. To generally illustrate the importance of integrating time effects, we first show in panel A and panel B the regression models *without* the time effects, what is state of the art in current research (e.g., Hitz et al., 2015). Then, in panel C and panel D, we integrate the time effects. Overall, the time effects mainly contribute to the quality of the models. Whereat R-squared equals 21,13% (16.07%) in the model without time effects presented in Panel A (Panel B), R-squared increases to 31,52% (29.03%) when time effects are considered in Panel C (Panel D) when focusing on the event day. Generally, we consider the results for the event day as the most relevant since the standardized publication mechanism of the FREP allows us to unambiguously determine when the information is available for the market. Given market efficiency, the market reaction to the new information should therefore be largely concentrated on this respective event day, thus, in the following we concentrate our descriptions of the results on the event day.

In our multivariate regression model without time effects (Panel A) we observe a highly significant effect ($p < 0,01$) of SIZE on abnormal returns on the event day and the three-day event window ($p < 0,05$). Furthermore, BAFIN possesses a significant negative effect on the abnormal returns on the event day hinting that investors interpret the involvement of the governmental agency as a lack of willingness on part of the respective company to cooperate with the FREP. Also LEVERAGE is gaining significance in the five-day event window. For our regression model without time effects that examines the determinants for abnormal volatilities (Panel B), SIZE, BAFIN and LEVERAGE lose all significance, instead we find a significant effect of GDP GROWTH on all three event windows, while our variable BND 1Y to control for the risk-free rate, gains significance on the event day. The results in the multivariate regres-

sion model with abnormal returns as the dependent variable and including time effects of ERROR PROBABILITY and ERROR SEVERITY (Panel C) are largely consistent with our findings in Panel A with regards to the control variables as here again SIZE, BAFIN and LEVERAGE are significant in various event horizons. Moreover, OWNERSHIP gains significance on the event day. Contrary to that, in the model depicted in Panel D that examines the determinants on abnormal volatilities and that furthermore includes the time-varying effects of ERROR PROBABILITY and ERROR SEVERITY, GDP GROWTH retains its significant effect only on the five-day event window, while BND 1Y loses its significance at the event day. Regarding the impact of our control variable ERROR SEVERITY on the capital market reaction in a setting *without* time effects, we cannot replicate the findings of Hitz et al. (2012) that error severity has a significant negative effect on abnormal returns (Panel A) and a significant positive effect on abnormal trading volume (Panel B), even though the coefficient signs match our expectations. This might be caused by our larger time frame and investors' learning process over time. Whereas Hitz et al. (2012) focus on a time period between 2005 und 2009, we investigate the years from 2005 to 2017. Moreover, when error severity is regarded in a model with time effects (Panel C and Panel D) we find a significant negative (positive) effect of ERROR SEVERITY on abnormal returns (abnormal volatilities) at the 10% level. In addition, we find a significant interaction effect between ERROR SEVERITY and time in both models. Thus, over time a higher magnitude of an error has a stronger effect on the market reaction leading to more negative abnormal returns and to a more positive abnormal volatility upon an error announcement. The other way around, the market has learned over time which errors are less severe and in these cases reacts less pronounced. This indicates that the ability of market participants to classify the magnitude of an error accurately increases over the years as the availability of more and more error announcements allows the market to contextualize the content of the error findings with respect to economic consequences resulting from the error in the financial statements.

Regarding our hypothesis 1a, our variable of interest ERROR PROBABILITY has a significant negative impact on abnormal returns in both settings with and without time effects (Panel A versus Panel C), which is highly significant on the 5% level respectively on the 10% level. This supports our hypothesis H1a, even though a significant impact of error probability on abnormal volatility cannot be determined. Focusing on the time-varying effect of ERROR PROBABILITY argued in H1b, we find a significant time effect at the 5% level for both abnormal returns and abnormal volatilities, meaning that the positive (negative) effect on the abnormal returns (volatilities) by a higher ERROR PROBABILITY is more profound over time. Thus, the higher a company's error probability the less surprised is an investor throughout the years, when an actual error announcement is published, resulting in a less adverse market reaction for firms with a high error probability. Focusing on volatility, investors' expectation of an error announcement derives in a negative impact on trading volume over time, meaning that investors sell shares less often when they have expected an error announcement for the respective firm. Overall, the results support our hypothesis H1b and suggest that gradually, the capital market has learned to recognize infringing firms. As the market anticipates assumed low accounting quality in share prices, the market reaction is generally weaker when the enforcer reveals error findings.

Additional Analysis

To further illustrate the interaction between an adverse market reaction upon error announcements and the probability of an error over time, we capture the effect on our dependent variables for firms with different error probabilities. We do this by increasing our independent variable TIME (measured by days) by one unit while keeping all our other independent variables at observed values, i.e. the marginal effect. For the prediction of our model for our dependent variables, we specify our TIME and ERROR PROBABILITY variables at low, average and

high values while keeping all our other independent variables at observed values, i.e. the predictive margins of our regression model.

In Table 6 the marginal effects of our time variable on the abnormal returns (Panel A) and abnormal volatilities (Panel B) for firms with different error probabilities are displayed. As postulated by our hypothesis H1b, Table 6 Panel A (Panel B) shows a clear relationship between the positive (negative) marginal effects on abnormal returns (volatilities) over time on the one hand and the error probability of a firm on the other hand. In detail, a positive (negative) change of abnormal returns (volatilities) from the mean of zero is most profound for firms that possess a higher probability of errors in their financial statements. In more detail, for firms with a high error probability of 90% there is the strongest positive (negative) marginal effect on abnormal returns (volatilities) over time with a coefficient of 0,000062 (-0,0004723), which additionally is significantly different from 0 at the 5% level. This means, that the abnormal rate of return for companies with a high error probability is significantly lower than the average abnormal rate of return, meaning that there is a less negative capital market reaction compared to the average market reaction. In contrast, for firms with a low error probability of 1% the change in abnormal returns (volatilities) over time is with a coefficient of -0.00000191 (0.0000161) negative (positive) but not significantly different from zero, thus there is no difference to the average abnormal capital market reaction.

<Insert table 6 about here.>

Table 7 provides further support for our hypothesis H1b, that investors learn from prior error announcements enabling them to anticipate a firm-specific error probability over time in their firm valuation. Doing so, we transform our observation period from the first error announcement, when the FREP started to review firm's financial statements, to the last announcement of our sample into the absolute amount of days (4045 days). Then, for specific error prob-

abilities we compare the respective abnormal returns (volatilities) with the mean-centered abnormal return (volatility) of our entire sample what is shown in Panel A (Panel B): 1%, 10%, 20%... up to 90%.

For a firm with a very high error probability of 90% our model predicts a strongly significant positive (negative) tendency over time compared to the average abnormal returns (volatilities) of 0.0047794 (0.5634094) at day 353 compared to the average capital market reaction, 0.0804222 (-0.0133262) at day 1574 compared to the average capital market reaction and 0.2335042 (-1.180495) at day 4045 compared to the average capital market reaction with levels of significance up to 1%. Focusing on abnormal returns this means that the abnormal returns for firms with a high error probability are less negative compared to the average abnormal return and that this effect gets more pronounced over time. Thus, the longer an investor can learn characteristics of infringing companies, the more restrained is the capital market reaction to an error announcement for firms with a high error probability. In contrast, for firms with a very low error probability (1%) our models do *not* predict a significant difference from the mean-centered abnormal returns (volatilities) with coefficients of 0,0024258 (-0,0010742) at day 353, 0,0000935 (0,0185607) at day 1574 and -0,0046266 (0,0582968) nearing the end of our observation period at day 4045. This is in line with the assumption that the market reaction upon error announcement of firms with low error probability remains the same over the course of time as the market did not anticipate the error and is therefore surprised by the announcements.

<Insert table 7 about here.>

For further illustration, the results are graphically depicted in Figure 1 for the abnormal returns and in Figure 2 for the abnormal volatilities. For a better overview only the slopes of the error probabilities of 1%, 30%, 60% and 90% on the three different dates are presented. The graphics underline our reasoning that a higher probability of an error derives in more positive (less negative) abnormal returns (abnormal volatilities) compared to the average capital market

reaction and that these effects accelerate over time: focusing on abnormal returns the steepest positive (negative) gradient can be observed for firms with the highest error probability (90%) while the slopes get gradually less steep as the probability of an error decreases. These results graphically support our prior findings that indeed the magnitude of the adverse market reaction is not only determined by the probability of an error but also by the time variable. Thus, time is a critical component when analyzing market reactions upon error announcements.

< Insert Figure 1 and Figure 2 about here.>

V. CONCLUSION

This paper shows how investors learn about the characteristics of misreporting firms from error announcements issued by the FREP by assessing a firm-specific error probability, which is defined as the probability that the FREP will find an error in the financial statements of the respective firm. Our results yield strong evidence that investors have already anticipated a low financial reporting quality, as the negative market response to an actual error announcement issued by the FREP is more profound for those companies for which investors have not expected an erroneous annual report. Consistent with this, multivariate regression analysis and marginal effect measurements also reveal a highly significant time-varying effect of error probability for both abnormal returns and abnormal volatilities. This suggests that the ability of investors to anticipate errors in a firm's financial statement increases over time as the FREP publishes a growing number of error findings allowing investors to identify characteristics of misreporting firms. These results confirm our hypotheses as they indicate that the error probability contributes to the explanation of the market reaction and that this contribution increases over time.

Our study adds to the understanding how the 'name and shame' mechanism of an enforcement system works over time. Explicitly, one could argue that this mechanism loses its effectiveness in the course of time as in some cases no abnormal capital market reactions are observable upon error announcements, and thus, that the work of an enforcement institution gradually becomes meaningless to investors. Our study reveals that investors' reactions to error announcements depend on their prior assumption about the error probability of a firm. Moreover, our results provide evidence that investors actively use and rely on the work of enforcement institutions to adjust their own expectations with regard to the evaluation of a firm's financial reporting quality. Indeed, only announcements by enforcement institutions enable investors to keep their estimated error probabilities up to date and to adapt to changing conditions. Thus,

overall announcements by enforcement institutions constitute a value-relevant information for markets as they enable investors to make more comprehensive investment decisions by anticipating erroneous financial reports and identifying firms with low financial reporting quality. In a broader context, we can provide empirical evidence for analytical models on how investors learn over time and may thus anticipate new information in their investment decisions.

Implications for future research relate to limitations of this study. Firstly, we do not consider the potential influence of media coverage of error announcements. While the FREP's disclosure of error findings follows a standardized process that ensures the publication of each error in the Federal Gazette, there is still the possibility that the individual error announcements differ in the public attention they generate. Additionally, we assume that 'peer benchmarking' might be an appropriate measure to investigate the learning and adaptation process of new accounting-related information in more detail. By matching infringing firms with non-infringing firms based on similar characteristics that are included in the FREP's error probability model, we conjecture that upon error announcements of the infringing firms an additional price adjustment for the non-infringing firms will be observable as investors will adapt their expectations regarding a probability of an error for firms that share the relevant characteristics with the infringing firms. Furthermore, even though we have checked extensively for confounding events, previous information leakage cannot be ruled out. Finally, the study was carried out on the German market and as the quality of financial reporting is determined by country-specific parameters such as governance systems, degree of investor protection, litigation environment or the enforcement mechanism in place (Holthausen, 2009; Leuz et al., 2003), the results of this paper may not be transferable to publicly traded companies in other countries. For example, the SEC does not solely rely on the 'name and shame' mechanism but instead imposes additional monetary injunctive sanctions on infringing firms that might explain the stronger adverse market reactions upon error announcements in the US setting. However, the underlying learning

and adaption process of accounting-related information should not be impeded by the additional penalties. The incentive for investors to anticipate errors in the financial statements of firms, and thus to identify firms possessing low accounting quality should indeed not be subject to the design of the specific sanction mechanism. On the contrary, the incentive for all investors should be to improve their decision making.

APPENDIX

Table 1. Examinations completed and error announcements by the FREP

Table 2. Definitions of variables and data source

Table 3. Descriptive statistics and correlations

Table 4. Capital market reactions upon error announcements

Table 5. Determinants of market reaction upon error announcements

Table 6. Marginal effects

Table 7. Predictive Margins

Figure 1. Predictive margins on abnormal returns

Figure 2. Predictive margins on abnormal volatility

Table 1. Examinations completed and error announcements by the FREP

	Calendar year													TOTAL	[Prop.]
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017		
<i>Examinations by the FREP</i>															
Total	7	109	135	138	118	118	110	113	110	104	81	96	99	1338	[100%]
Random Sampling	4	98	118	118	103	106	90	110	98	99	71	87	91	1193	[89.2%]
Indication based	3	10	15	19	14	8	6	2	6	3	6	7	3	102	[7.6%]
At mandatory request of BaFin	0	1	2	1	1	1	0	14	1	6	2	4	5	38	[2.8%]
<i>Error announcements</i>															
Total	2	19	35	37	23	31	27	18	14	10	8	13	13	250	[18.7%]
Proportion	28,6%	17,4%	25,9%	26,8%	19,5%	26,3%	24,5%	15,9%	12,7%	9,6%	9,9%	13,5%	13,1%	18,7%	

Notes: This table displays the number of examinations and error findings as reported in the FREP's annual activity reports (FREP, 2005-2018). Error announcements are disclosed timely delayed and therefore do not regularly correspond with investigations completed in the respective calendar year.

Table 2. Definitions of variables and data source

	Definition	Data Source
<i>Dependent variable</i>		
Cumulative abnormal returns	Calculated with the stock-specific market model (MacKinlay, 1997) using an equally weighted portfolio of all publicly traded German firms, as well as an estimation window of 150 trading days prior to the beginning of the event windows ([0], [-1;1], [-2,2]).	Datastream
Cumulative abnormal volatilities	Abnormal stock volatility is characterized as the difference between the observed stock volatility at the event window and the respective expectation based on an average value of 150 days before the event window.	Datastream
<i>Variable of interest</i>		
ERROR PROBABILITY	Calculated using the estimation model of Pasch (2017, p. 32-35).	Handcollected and Datastream
<i>*Low error probability (LOW_PROB)</i>	Included in the subsample, when the value of ERROR PROBABILITY is below or equal to 30 %.	
<i>*High error probability (HIGH_PROB)</i>	Included in the subsample, when the value of ERROR PROBABILITY is above 30 %.	
<i>Controls</i>		
Components of ERROR SEVERITY	An aggregated measure by Principal Components Analysis, including number of errors, the impact on net profit and the impact on OCI.	Handcollected
Number of errors	The number of single errors within an error announcement.	Handcollected
Impact on net profit	The impact of errors on the annual net profit scaled by total assets of the year prior to the misstatement.	Handcollected
Impact on OCI	The impact of errors on the Other Comprehensive Income (OCI) scaled by total assets of the year prior to the misstatement.	Handcollected
TIME	The number of days between the first published error finding in 2005 and the respective error announcement of a firm.	Handcollected
SIZE	The natural logarithm of market capitalization at the beginning of the year of the error finding.	Datastream
LEVERAGE	Measured as total debt per common equity.	Datastream
LIQUIDITY	The proportion of non-zero return trading days over the calendar year of the error finding.	Datastream

BAFIN	A dummy variable coded 1 if the BaFin has conducted the investigation; 0 otherwise.	Handcollected
LISTING YEARS	The number of years the company has been listed on the stock market at the time of the error announcement.	Handcollected
OWNERSHIP	The proportion of closely held shares at the end of the year prior to the error finding.	Datastream
EPS SURPRISE	The difference between forecasted and realized earnings per share. The forecasted earnings per share are created by an aggregate of different analyst forecasts provided by the I/B/E/S database accessed via Datastream.	Datastream
COM BETA	Measure of the systemic risk of a firm's equity compared to the overall market via regression of the firm's return against the market return.	Datastream
BND 1Y	Used as a proxy for the risk-free rate measured by the 1-year German government bond yield.	Datastream
FCR DUMMY	A dummy variable to capture the effects of the financial crisis of 2007-2008. Coded 1 if the year of the error announcement is 2007 or 2008, and 0 otherwise.	Handcollected
GDP GROWTH	Annual growth rate of the German gross domestic product measured conventionally by a combination of labor force, capital and factor productivity growth.	Datastream

Notes: This table defines variables as used in our regression analyses. Variables marked with an * are not used for the regression but refer to a subsample of the event study.

Table 3. Descriptive statistics and correlations

<i>Panel A: Descriptive statistics</i>	Mean [Prop.]	Standard deviation	Lower Quar- tile	Median	Upper Quartile	Number of observa- tions
ERROR PROBABIL- ITY	0,1626	0,1869	0,0402	0,0971	0,2078	76
Components of ERROR SEVERITY						
Number of errors	3,45	2,89	1,00	2,00	4,00	76
Impact on net profit	-0,016	0,071	-0,008	0,000	0,000	76
Impact on OCI	-0,032	0,130	-0,009	0,000	0,000	76
BAFIN	[0,223]					76
LISTING YEARS	16,78	12,19	10,00	13,00	19,00	76
SIZE	11,972	2,023	10,581	11,804	13,326	76
LEVERAGE	0,882	3,177	0,842	0,579	1,348	76
OWNERSHIP	0,459	0,281	0,246	0,488	0,700	76
LIQUIDITY	0,849	0,154	0,793	0,898	0,962	76
EPS_SURPRISE	0,768	13,602	-0,238	0,000	0,249	76
COM_BETA	0,788	0,564	0,473	0,702	1,090	76
FCR_DUMMY	[0,316]					76
BND_1Y	1,288	1,748	0,001	0,754	2,171	76
GDP_GROWTH	1,594	3,006	0,816	2,454	3,721	76

Note: Table 3 continues on the next page.

Panel B: Correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
ERROR PROBABILITY (1)		-0,12	-0,03	-0,10	-0,36	0,13	-0,14	-0,25	-0,02	0,03	0,06	0,11	0,03
ERROR SEVERITY (2)	-0,41		0,07	-0,11	-0,02	-0,09	0,26	-0,20	0,18	-0,23	-0,01	-0,06	-0,27
BAFIN (3)	-0,12	0,12		0,10	0,25	0,23	-0,02	-0,03	0,10	-0,03	-0,17	-0,19	-0,04
LISTING YEARS (4)	-0,16	0,09	0,04		0,08	-0,05	0,40	-0,01	0,26	-0,33	-0,23	-0,38	0,10
SIZE (5)	-0,28	0,10	0,29	0,13		0,26	0,08	0,58	-0,27	0,27	0,12	0,02	-0,02
LEVERAGE (6)	-0,18	0,43	0,26	-0,02	0,14		0,06	0,17	-0,18	0,22	-0,02	0,00	-0,04
OWNERSHIP (7)	-0,23	0,26	-0,02	0,43	0,08	0,16		-0,31	0,18	-0,29	-0,12	0,00	0,12
LIQUIDITY (8)	-0,06	-0,07	-0,07	-0,23	0,39	0,10	-0,41		-0,53	0,37	-0,19	-0,34	-0,05
EPS SURPRISE (9)	-0,04	0,07	0,01	0,37	-0,12	-0,03	0,25	-0,42		-0,30	0,15	0,12	-0,16
COM BETA (10)	-0,02	-0,05	-0,04	-0,24	0,30	0,10	-0,28	0,43	-0,27		-0,01	0,09	-0,09
FCR DUMMY (11)	0,15	-0,19	-0,17	-0,10	0,12	-0,12	-0,11	-0,18	-0,12	0,04		0,78	-0,03
BND 1Y (12)	0,19	-0,11	-0,21	-0,11	0,01	-0,05	-0,04	-0,24	-0,08	0,05	0,82		0,09
GDP GROWTH (13)	0,04	-0,04	-0,08	0,11	0,03	-0,19	-0,03	-0,10	0,04	-0,16	0,19	0,20	

Notes: Panel A illustrates descriptive statistics and Panel B shows Pearson (below the diagonal) and Spearman correlations (above the diagonal) for all independent variables included in the multivariate regressions. Variables are defined in Table 2 and Section 4.3 of this paper. In Panel B, highlighted correlations show a correlation above 0,5.

Table 4. Capital market reactions upon error announcements

<i>Panel A</i>				<i>Panel B</i>			
	TOTAL (Cumulative) abnormal returns (in %)				TOTAL (Cumulative) abnormal volatilities (in %)		
Event Window	[0]	[-1; 1]	[-2; 2]	Event Window	[0]	[-1; 1]	[-2; 2]
Mean	-0.66	-1.01	-0.56	Mean	6,73**	17,94***	27,83***
(t-statistic)	(-1.5884)	(-1.4234)	(-0.6092)	(t-statistic)	(2,4454)	(3,7665)	(4,3018)
Patell-Z	-1.4529	-1.2235	-0.6605	Patell- Z	1,8833*	2,9432***	3,9455***
Corrado Rank Test	-2.0224**	-1.9854**	-1.475	Corrado Rank Test	1,1760	1,7123*	2,0651**
Sign Test	-1.3176	-1.3477	-0.1875	Sign Test	1,2882	0,6063	-0,6155
Observations	76	76	76	Observations	76	76	76
<i>Panel C</i>				<i>Panel D</i>			
	LOW ERROR PROBABILITY (< 30 %) (Cumulative) abnormal returns (in %)				HIGH ERROR PROBABILITY (> 30 %) (Cumulative) abnormal returns (in %)		
Event Window	[0]	[-1; 1]	[-2; 2]	Event Window	[0]	[-1; 1]	[-2; 2]
Mean	-1.05	-1.28	-0.88	Mean	0,94	-0,91	-0,1
(t-statistic)	-2.239**	-1.5779	-0.8375	(t-statistic)	1.0948	-0.6137	-0.0535
Patell- Z	-1.8035**	-1.6053*	-1.0043	Patell -Z	0.3665	-0.049	0.1823
Corrado Rank Test	-2.383**	-2.5744***	-1.7929*	Corrado Rank Test	0.5805	0.564	0.2386
Sign Test	-2.014**	-1.6479*	-0.369	Sign Test	1.0946	0.0069	0.0618
Observations	61	61	61	Observations	15	15	15

Notes: This table shows descriptive statistics for (cumulative) abnormal returns (CARs) and (cumulative) abnormal volatilities (CAV) upon error announcements of our sample until end of December 2017. Statistics are provided for the event day [0] as well as for the three-day [-1;1] and five-day window [-2;2] surrounding the event day of the error announcement in the Federal Gazette. Panel B reports (cumulative) abnormal returns for two subsamples, clustered in entities with a probability of errors above or below a value of 30%. The calculation of ERROR PROBABILITY is explained in Section X. *, **, and *** indicate two-tailed significance at the 10%, 5%, and 1% level, respectively.

Table 5: Multivariate Regression*Panel A: Abnormal returns*

Variables	(1)		(2)		(3)	
	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
Intercept	-0.0348	(-0.75)	-0.0609	(-1.04)	0.0178	(0.22)
<u>Variable of Interest</u>						
ERROR PROBABILITY	0.0677**	(2.16)	0.00896	(0.22)	0.0516	(0.95)
<u>Control Variables</u>						
ERROR SEVERITY	-0.00357	(-0.53)	-0.0107	(-1.25)	-0.0100	(-0.87)
SIZE	0.00979***	(2.70)	0.0100**	(2.18)	0.00832	(1.32)
LEVERAGE	0.00000114	(0.06)	0.00000795	(0.33)	0.0000934***	(2.80)
LIQUIDITY	-0.0717	(-1.34)	-0.0542	(-0.79)	-0.122	(-1.31)
BAFIN	-0.0342**	(-2.31)	-0.0302	(-1.60)	-0.0370	(-1.44)
LISTING YEARS	-0.000159	(-0.33)	-0.000490	(-0.79)	-0.000538	(-0.63)
OWNERSHIP	-0.000370	(-1.53)	-0.000167	(-0.54)	-0.000382	(-0.91)
EPS SURPRISE	-0.0000472	(-0.11)	-0.0000931	(-0.17)	-0.000304	(-0.40)
COM BETA	-0.00601	(-0.56)	0.00373	(0.27)	0.0149	(0.80)
FCR DUMMY	-0.0176	(-0.87)	0.0128	(0.50)	0.00946	(0.27)
BND 1Y	0.00112	(0.21)	-0.00429	(-0.63)	-0.00630	(-0.68)
GDP GROWTH	-0.00168	(-0.94)	-0.00166	(-0.73)	-0.00278	(-0.90)
R ²	0,2113		0,165		0,202	
F-statistic	1,277987		0,9450135		1,210176	
Number of observations	76		76		76	

Note: Table 5 continues on the next page.

Panel B: Abnormal volatilities

Variables	(1)		(2)		(3)	
	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
Intercept	0.0709	(0.21)	0.0549	(0.05)	0.0302	(0.02)
<u>Variable of Interest</u>						
ERROR PROBABILITY	0.134	(0.57)	0.502	(0.74)	0.817	(0.75)
<u>Control Variables</u>						
ERROR SEVERITY	-0.0272	(-0.54)	-0.0709	(-0.49)	-0.152	(-0.65)
SIZE	-0.0105	(-0.39)	-0.0218	(-0.28)	-0.0195	(-0.15)
LEVERAGE	0.000166	(1.16)	0.000559	(1.34)	0.00104	(1.57)
LIQUIDITY	0.113	(0.28)	0.326	(0.28)	0.325	(0.17)
BAFIN	-0.135	(-1.22)	-0.481	(-1.49)	-0.785	(-1.53)
LISTING YEARS	-0.00204	(-0.56)	-0.00701	(-0.66)	-0.0104	(-0.61)
OWNERSHIP	0.00190	(1.05)	0.00594	(1.12)	0.00887	(1.05)
EPS SURPRISE	0.00242	(0.74)	0.00796	(0.83)	0.0133	(0.87)
COM BETA	-0.0348	(-0.44)	-0.0891	(-0.38)	-0.110	(-0.30)
FCR DUMMY	0.135	(0.89)	0.372	(0.84)	0.616	(0.87)
BND 1Y	-0.0697*	(-1.76)	-0.191	(-1.65)	-0.302	(-1.63)
GDP GROWTH	0.0255*	(1.92)	0.0809**	(2.09)	0.129**	(2.08)
R ²	0,1607		0,1777		0,1768	
F-statistic	0,9132832		1,030936		1,024299	
Number of observations	76		76		76	

Note: Table 5 continues on the next page.

Panel C: Abnormal returns including time effects

Variables	(1)		(2)		(3)	
	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
Intercept	-0.0117	(-0.26)	-0.0550	(-0.92)	0.0544	(0.68)
<u>Variable of Interest</u>						
ERROR PROBABILITY	0.103***	(3.08)	0.0157	(0.35)	0.0799	(1.34)
<u>Interaction effects</u>						
Time x ERROR PROBABILITY	0.0000718**	(2.52)	0.0000171	(0.45)	0.0000631	(1.24)
Time x ERROR SEVERITY	-0.0000246*	(-1.85)	-0.0000247	(-1.38)	-0.0000451*	(-1.89)
<u>Control Variables</u>						
ERROR SEVERITY	-0.0261*	(-2.00)	-0.0323*	(-1.84)	-0.0491**	(-2.10)
TIME	-0.00000263	(-0.26)	0.00000619	(0.45)	-0.00000836	(-0.46)
SIZE	0.0109***	(3.01)	0.0109**	(2.24)	0.00881	(1.35)
LEVERAGE	0.00000662	(0.36)	0.0000119	(0.48)	0.000104***	(3.13)
LIQUIDITY	-0.0807	(-1.55)	-0.0654	(-0.94)	-0.130	(-1.40)
BAFIN	-0.0369**	(-2.60)	-0.0325*	(-1.71)	-0.0403	(-1.59)
LISTING YEARS	-0.000191	(-0.39)	-0.000614	(-0.94)	-0.000525	(-0.60)
OWNERSHIP	-0.000478*	(-2.00)	-0.000209	(-0.65)	-0.000565	(-1.32)
EPS SURPRISE	0.0000116	(0.03)	0.00000140	(0.00)	-0.000195	(-0.26)
COM BETA	-0.0108	(-1.04)	0.00211	(0.15)	0.00874	(0.47)
FCR DUMMY	-0.000835	(-0.09)	-0.000518	(-0.04)	-0.0133	(-0.82)
BND 1Y	-0.0247	(-1.19)	0.00546	(0.20)	0.00558	(0.15)
GDP GROWTH	-0.00105	(-0.54)	-0.00196	(-0.75)	-0.00142	(-0.41)
R ²	0,3152		0,1934		0,265	
F-statistic	1,697502*		0,8840841		1,329501	
Number of observations	76		76		76	

Note: Table 5 continues on the next page.

Panel D: Abnormal volatilities including time effects

Variables	(1)		(2)		(3)	
	[0]		[-1; 1]		[-2; 2]	
	Coef.	t-stat.	Coef.	t-stat.	Coef.	t-stat.
Intercept	-0.0223	(-0.07)	-0.116	(-0.12)	0.0000181	(0.05)
<u>Variable of Interest</u>						
ERROR PROBABILITY	-0.130	(-0.53)	-0.224	(-0.31)	-0.311	(-0.27)
<u>Interaction effects</u>						
Time x ERROR PROBABILITY	-0.000549**	(-2.61)	-0.00150**	(-2.42)	-0.00233**	(-2.32)
Time x ERROR SEVERITY	0.000219**	(2.23)	0.000582**	(2.00)	0.000850*	(1.82)
<u>Control Variables</u>						
ERROR SEVERITY	0.171*	(1.78)	0.460	(1.61)	0.628	(1.37)
TIME	0.0000216	(0.29)	0.00000844	(0.04)	0.0000181	(0.05)
SIZE	-0.0191	(-0.71)	-0.0498	(-0.63)	-0.0622	(-0.49)
LEVERAGE	0.000118	(0.86)	0.000439	(1.08)	0.000867	(1.33)
LIQUIDITY	0.188	(0.49)	0.564	(0.50)	0.679	(0.37)
BAFIN	-0.113	(-1.08)	-0.417	(-1.35)	-0.688	(-1.38)
LISTING YEARS	-0.00177	(-0.49)	-0.00563	(-0.53)	-0.00844	(-0.49)
OWNERSHIP	0.00281	(1.60)	0.00813	(1.56)	0.0122	(1.45)
EPS SURPRISE	0.00187	(0.60)	0.00637	(0.69)	0.0110	(0.74)
COM BETA	0.00398	(0.05)	0.0113	(0.05)	0.0424	(0.12)
FCR DUMMY	-0.0525	(-0.79)	-0.181	(-0.92)	-0.285	(-0.90)
BND 1Y	0.190	(1.24)	0.556	(1.22)	0.895	(1.22)
GDP GROWTH	0.0202	(1.41)	0.0714*	(1.68)	0.114*	(1.67)
R ²	0,2113		0,165		0,202	
F-statistic	1,277987		0,9450135		1,210176	
Number of observations	76		76		76	

*** p<0.01, ** p<0.05, * p<0.1

Table 6: Marginal Effects

<i>Panel A: Marginal effects on abnormal returns</i>				
	(1)	(2)	(3)	(4)
at	Margins	SE	t-statistics	p-value
Error Probability				
1%	-0.00000191	(0.00001026)	-0.19	0.853
10%	0.00000455	(0.00001097)	0.41	0.680
20%	0.00001172	(0.00001235)	0.95	0.346
30%	0.00001890	(0.00001417)	1.33	0.188
40%	0.00002607	(0.00001630)	1.60	0.115
50%	0.00003325*	(0.00001861)	1.79	0.079
60%	0.00004043*	(0.00002106)	1.92	0.060
70%	0.00004760**	(0.00002360)	2.02	0.048
80%	0.00005478**	(0.00002620)	2.09	0.041
90%	0.00006195**	(0.00002885)	2.15	0.036
Observations	76			
<i>Panel B: Marginal effects on abnormal volatilities</i>				
	(1)	(2)	(3)	(4)
at	Margins	SE	t-statistics	p-value
Error Probability				
1%	0.00001608	(0.00007560)	0.21	0.832
10%	-0.00003331	(0.00008083)	-0.41	0.682
20%	-0.00008819	(0.00009099)	-0.97	0.336
30%	-0.00014307	(0.00010443)	-1.37	0.176
40%	-0.00019795	(0.00012006)	-1.65	0.105
50%	-0.00025283*	(0.00013713)	-1.84	0.070
60%	-0.00030771*	(0.00015517)	-1.98	0.052
70%	-0.00036259**	(0.00017387)	-2.09	0.041
80%	-0.00041747**	(0.00019304)	-2.16	0.035
90%	-0.00047235**	(0.00021255)	-2.22	0.030
Observations	76			

*** p<0.01, ** p<0.05, * p<0.1

Table 7: Predictive Margins

Panel A: Predictive margins on abnormal returns

at	(1) Margins	(2) SE	(3) t-statistics	(4) p-value
Day x Error Probability				
353 x 1%	0.00242584	(0.01488076)	0.16	0.871
353 x 10%	0.00266384	(0.01544014)	0.17	0.864
353 x 20%	0.00292829	(0.01691691)	0.17	0.863
353 x 30%	0.00319274	(0.01909000)	0.17	0.868
353 x 40%	0.00345719	(0.02175170)	0.16	0.874
353 x 50%	0.00372164	(0.02474483)	0.15	0.881
353 x 60%	0.00398609	(0.02796317)	0.14	0.887
353 x 70%	0.00425054	(0.03133741)	0.14	0.893
353 x 80%	0.00451499	(0.03482225)	0.13	0.897
353 x 90%	0.00477944	(0.03838760)	0.12	0.901
1574 x 1%	0.00009350	(0.00534753)	0.02	0.986
1574 x 10%	0.00821663	(0.00631239)	1.30	0.198
1574 x 20%	0.01724232**	(0.00843684)	2.04	0.045
1574 x 30%	0.02626801**	(0.01106070)	2.37	0.021
1574 x 40%	0.03529371**	(0.01390405)	2.54	0.014
1574 x 50%	0.04431940**	(0.01685619)	2.63	0.011
1574 x 60%	0.05334510***	(0.01986868)	2.68	0.009
1574 x 70%	0.06237079***	(0.02291774)	2.72	0.009
1574 x 80%	0.07139648***	(0.02599050)	2.75	0.008
1574 x 90%	0.08042217***	(0.02907944)	2.77	0.008
4045 x 1%	-0.00462657	(0.02447233)	-0.19	0.851
4045 x 10%	0.01945408	(0.02712892)	0.72	0.476
4045 x 20%	0.04621035	(0.03205308)	1.44	0.155
4045 x 30%	0.07296662*	(0.03827858)	1.91	0.061
4045 x 40%	0.09972289**	(0.04527170)	2.20	0.032
4045 x 50%	0.12647916**	(0.05272791)	2.40	0.020
4045 x 60%	0.15323543**	(0.06047616)	2.53	0.014
4045 x 70%	0.17999169**	(0.06841730)	2.63	0.011
4045 x 80%	0.20674797***	(0.07649128)	2.70	0.009
4045 x 90%	0.23350423***	(0.08466010)	2.76	0.008

Note: Table 7 continues on the next page.

<i>Panel B: Predictive margins on abnormal volatilities</i>				
at	(1) Margins	(2) SE	(3) t-statistics	(4) p-value
<i>Day x Error Probability</i>				
353 x 1%	-0.00107417	(0.10963920)	-0.01	0.992
353 x 10%	0.05600844	(0.11376058)	0.49	0.624
353 x 20%	0.11943356	(0.12464124)	0.96	0.342
353 x 30%	0.18285869	(0.14065222)	1.30	0.199
353 x 40%	0.24628381	(0.16026319)	1.54	0.130
353 x 50%	0.30970892*	(0.18231613)	1.70	0.095
353 x 60%	0.37313406*	(0.20602837)	1.81	0.075
353 x 70%	0.43655916*	(0.23088924)	1.89	0.064
353 x 80%	0.49998429*	(0.25656506)	1.95	0.056
353 x 90%	0.56340939*	(0.28283397)	1.99	0.051
1574 x 1%	0.01856070	(0.03939976)	0.47	0.639
1574 x 10%	0.01533618	(0.04650874)	0.33	0.743
1574 x 20%	0.01175339	(0.06216132)	0.19	0.851
1574 x 30%	0.00817060	(0.08149352)	0.10	0.920
1574 x 40%	0.00458780	(0.10244293)	0.04	0.964
1574 x 50%	0.00100501	(0.12419384)	0.01	0.994
1574 x 60%	-0.00257779	(0.14638943)	-0.02	0.986
1574 x 70%	-0.00616058	(0.16885441)	-0.04	0.971
1574 x 80%	-0.00974337	(0.19149402)	-0.05	0.960
1574 x 90%	-0.01332617	(0.21425288)	-0.06	0.951
4045 x 1%	0.05829678	(0.18030838)	0.32	0.748
4045 x 10%	-0.06697434	(0.19988176)	-0.34	0.739
4045 x 20%	-0.20616447	(0.23616222)	-0.87	0.386
4045 x 30%	-0.34535461	(0.28203073)	-1.22	0.226
4045 x 40%	-0.48454473	(0.33355500)	-1.45	0.152
4045 x 50%	-0.62373485	(0.38849119)	-1.61	0.114
4045 x 60%	-0.76292501*	(0.44557912)	-1.71	0.092
4045 x 70%	-0.90211509*	(0.50408822)	-1.79	0.079
4045 x 80%	-1.04130525*	(0.56357610)	-1.85	0.070

4045 x 90%	-1.18049533*	(0.62376271)	-1.89	0.063
------------	--------------	--------------	-------	-------

Observations	76			
--------------	----	--	--	--

*** p<0.01, ** p<0.05, * p<0.1

Figure 1:
Predictive margins on abnormal returns

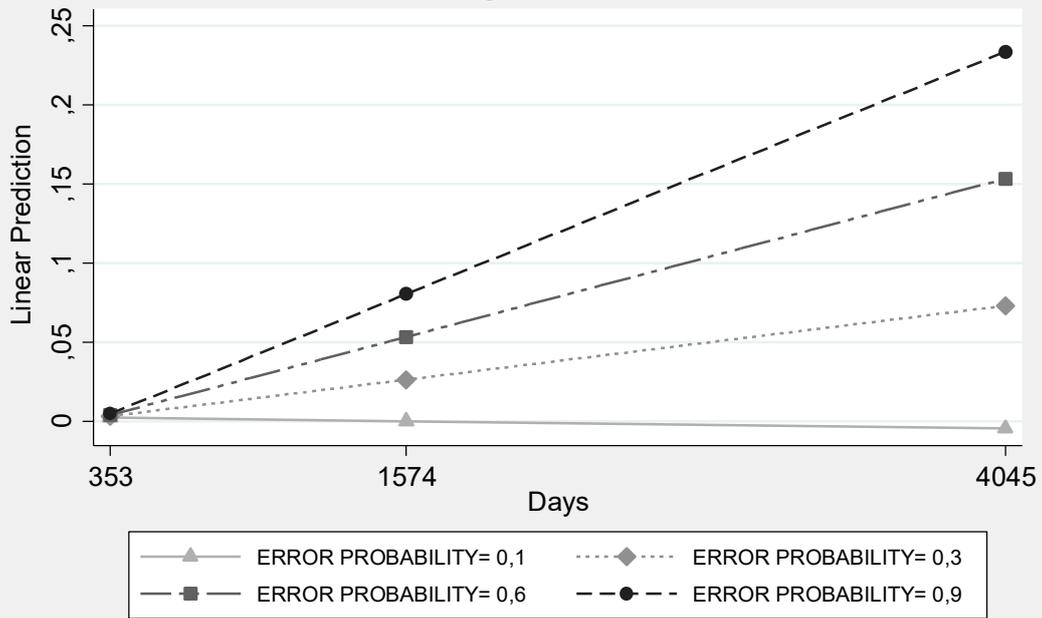
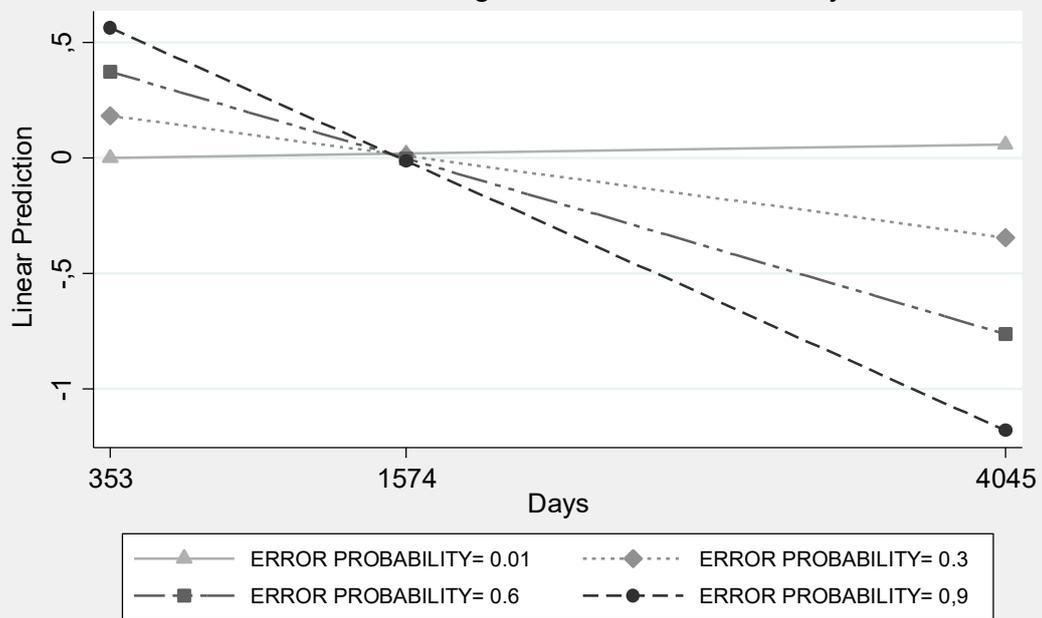


Figure 2:
Predictive margins on abnormal volatility



REFERENCES

- Abbott, L. J., Parker, S., and Peters, G. F. (2004). Audit Committee Characteristics and Restatements. *Auditing: a Journal of Practice & Theory*, 23(1), 69–87.
- Antonakakis, N. and K. Vergos (2013). Sovereign bond yield spillovers in the euro zone during the financial and debt crisis. *Journal of International Financial Markets, Institutions and Money* 26(1), 258–272.
- Baber W.R., Liang L. and Zhu, Z. (2012). Associations between Internal and External Corporate Governance Characteristics: Implications for Investigating Financial Accounting Restatements. *Accounting Horizons*, 26(2), 219–237.
- Ball, R. and Brown, P. (1968). An empirical evaluation of accounting numbers. *Journal of Accounting Research*, 6(2), 159–178.
- Banerjee, S., Davis, J., & Gondhi, N. (2018). When transparency improves, must prices reflect fundamentals better?. *The Review of Financial Studies*, 31(6), 2377-2414.
- Beaver, W. H. (1968). The information content of annual earnings announcements. *Journal of Accounting Research*, 6, 67–92.
- van Beest, F., Braam, G. and Boelens, S. (2009). *Quality of financial reporting: measuring qualitative characteristics*. Working Paper, Radboud University Nijmegen.
- Beneish, M. D. (1999a). Incentives and penalties related to earnings overstatements that violate GAAP. *The Accounting Review*, 74(4), 425–457.
- Böcking, H.-J., Gros, M., and Worret, D. (2015). Enforcement of accounting standards: How effective is the German two-tier system in detecting earnings management?. *Review of Managerial Science*, 9(3), 431–485.
- Boehmer, E., and Kelley, E.K. (2009). Institutional investors and the informational efficiency of prices. *The Review of Financial Studies*, 22(9), 3563–3594.
- Brown, S., and Warner, J. (1985). Using daily stock returns: The case of event studies. *Journal of Financial Economics*, 14(1), 3–31.
- Brown, S., and Hillegeist, S. A. (2007). How disclosure quality affects the level of information asymmetry. *Review of Accounting Studies*, 12(2-3), 443–477.
- Cai, L., Rahman, A., and Courtenay, S. (2008). *The effect of IFRS and its enforcement on earnings management: an international comparison*. Working Paper, Massey University.
- Campbell, J. L., Hansen, J., Simon, C. A., and Smith, J. L. (2014). Audit committee stock options and financial reporting quality after the Sarbanes-Oxley Act of 2002. *Auditing: A Journal of Practice and Theory*, 34(2), 91–120.
- Chen, X., Cheng, Q., and Lo, A. K. (2014). Is the Decline in the Information Content of Earnings Following Restatements Short-Lived?. *Accounting Review*, 89(1), 177–207.
- Corrado, C. J. (1989). A Nonparametric Test for Abnormal Security-Price Performance in Event Studies. *Journal of Financial Economics*, 23, 385–395.
- Daske, H., Hail, L., Leuz, C. and Verdi, R. S. (2008). Mandatory IFRS reporting around the world: early evidence on the economic consequences. *Journal of Accounting Research*, 46(5), 1085–1142.
- Dechow, P. M., Sloan, R. G. and Sweeney, A. P. (1996). Causes and consequences of earnings manip-

- ulation: an analysis of firms subject to enforcement actions by the SEC. *Contemporary Accounting Research*, 13(1), 1–36.
- Dechow, P. M., Ge, W., Larson, C. R., and Sloan, R. G. (2011). Predicting material accounting misstatements. *Contemporary Accounting Research*, 28(1), 17–82.
- DeFond, M. L., and Jiambalvo, J. (1991). Incidence and Circumstances of Accounting Errors. *The Accounting Review*, 66(3), 643–655.
- Easton, P. and Zmijewski, M. (1989). Cross-sectional Variation in the Stock Market Response to Accounting Earnings Announcements. *Journal of Accounting and Economics*, 11(2-3), 117–141.
- Edmans, A. (2009). Blockholder trading, market efficiency, and managerial myopia. *The Journal of Finance*, 64(6), 2481–2513.
- Ernstberger, J., J.-M. Hitz, and M. Stich. (2012b). *Why do firms produce erroneous IFRS financial statements?*. Working paper, Ruhr-University Bochum, Georg-August-University Göttingen, Friedrich-Alexander-University Erlangen-Nürnberg.
- Fama, E. (1965). Random Walks in Stock Market Prices. *Financial Analyst Journal*, 21(5), 55–59.
- Fama, E. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, 25(2), 383–417.
- Fama, E. (1976). *Foundations of finance. Portfolio decisions and securities prices*. New York: Basic Books.
- Fraser, P. (2004). How do US and Japanese investors process information, and how do they form their expectations of the future? Evidence from quantitative survey based data. *Journal of Asset Management*, 5(2), 77-90.
- Guimarães, R. M. C., Kingsman, B. G., and Taylor, S. J. (1989). *A Reappraisal of the Efficiency of Financial Markets. NATO ASI Series, Series F: 54*. Berlin, Heidelberg: Springer.
- Hitz, J.-M., Ernstberger, J., and Stich, M. (2012). Enforcement of Accounting Standards in Europe: Capital Market Based Evidence for the Two-Tier Mechanism in Germany. *European Accounting Review*, 21(2), 253–281.
- Healy, P. M. (1985). The effect of bonus schemes on accounting decisions. *Journal of Accounting and Economics*, 7, 85–107.
- Healy, P. M. and Palepu, K. G. (2001). Information Asymmetry, Corporate Disclosure, and the Capital Markets: A Review of the Empirical Disclosure Literature. *Journal of Accounting and Economics*, 31, 405–440.
- Hoehn, B., and Strohmenger, M. (2013). *The effects of earnings management on enforcement releases and their recognition in audit fees*. Working paper, University of Wuerzburg.
- Holthausen, R. W. (2009). Accounting standards, financial reporting outcomes, and enforcement. *Journal of Accounting Research*, 47 (2), 447–458.
- Hope, O- K. (2003). Disclosure practice, enforcement of accounting standards and analysts' forecast accuracy: an international study. *Journal of Accounting Research*, 41, 235–272.
- Hribar, P. and Jenkins, N. T. (2004). The Effect of Accounting Restatements on Earnings Revisions and the Estimated Cost of Capital. *Review of Accounting Studies*, 9, 337–356.
- IASB (2008). Exposure Draft on an improved Conceptual Framework for Financial Reporting: The Objective of Financial Reporting and Qualitative Characteristics and Constrains of Decision-useful Financial Reporting-Information.

Available at: <http://www.assb.gov.sg/docs/attachments/EDofChapters1and2theJointImprovedConceptualFramework.pdf> (last retrieved: 08/11/2018).

- Jones, K. L., Krishnan, G.V. and Melendrez, K. D. (2008). Do models of discretionary accruals detect actual cases of fraudulent and restated earnings? Empirical Analysis. *Contemporary Accounting Research*, 25(2), 499–531.
- Karpoff, J., Lee, S., and Martin, G. (2008). The cost to firms of cooking the books. *Journal of Financial and Quantitative Analysis*, 43(3), 581–611.
- Keune, M. B., and Johnstone, K.M. (2015). Audit committee incentives and the resolution of detected misstatements. *Auditing: A Journal of Practice and Theory*, 34(4), 109–137.
- Kothari, S. (2001). Capital markets research in accounting. *Journal of Accounting and Economics*, 31(1-3), 105–231.
- La Porta, R., Lopez-de-Silanes, F., Shleifer, A., and Vishny, R. W. (1998). Law and finance. *Journal of Political Economy*, 106(6), 1113–1155.
- Lackmann, Julia, Jürgen Ernstberger, and Michael Stich. "Market reactions to increased reliability of sustainability information." *Journal of business ethics* 107.2 (2012): 111-128.
- Lam, Hugo KS, et al. "Corporate environmental initiatives in the Chinese context: Performance implications and contextual factors." *International Journal of Production Economics* 180 (2016): 48-56.
- Landsman, W. R., Maydew E. L., and Thornock, J.R. (2012). The information content of annual earnings announcements and mandatory adoption of IFRS. *Journal of Accounting and Economics*, 53, 34–54.
- Lee, Su-Yol, Yun-Seon Park, and Robert D. Klassen. "Market responses to firms' voluntary climate change information disclosure and carbon communication." *Corporate Social Responsibility and Environmental Management* 22.1 (2015): 1-12.
- Leuz, C., Nanda, D., and Wysocki, P. (2003). Earnings management and investor protection: an international comparison. *Journal of Financial Economics*, 69, 505–527.
- Leuz, C., & Wüstemann, J. (2003). The role of accounting in the German financial system. CFS Working Paper Series 2003/16
- Lo, A.W. (2004). The adaptive markets hypothesis: Market efficiency from an evolutionary perspective. *The Journal of Portfolio Management*, 30th anniversary issue, 15–29.
- MacKinlay, A. G. (1997). Event Studies in Economics and Finance. *Journal of Economic Literature*, 35, 13–39.
- McWilliams, A., and Siegel, D. (1997). Event Studies in Management Research: Theoretical and Empirical Issues. *Academy of Management Journal*, 40, 626–657.
- Nagar, V., & Petacchi, P. (2005). An economy-level model of earnings management with endogenous enforcement. SSRN.com/abstract=806684.
- Nourayi, M. M. (1994). Stock Price Responses to the SECs Enforcement Actions. *Journal of Accounting and Public Policy*, 13, 333–347.
- Palmrose, Z.-V., Richardson, V. J. and Scholz, S. (2004). Determinants of market reactions to restatement announcements. *Journal of Accounting and Economics*, 37, 59–58.
- Palmrose, Z., and Scholz, S. (2004). The Circumstances and Legal Consequences of Non-GAAP Reporting: Evidence from Restatements. *Contemporary Accounting Research*, 21(1), 139–180.

- Pasch, L. (2017). *What drives misstatements in financial statements? Evidence from Germany*. Doctoral Dissertation, Ruhr-University Bochum.
- Patell, J. (1976). Corporate forecasts of earnings per share and stock price behavior: Empirical tests. *Journal of Accounting Research*, 14(2), 246–276.
- Peasnell, K., Pope, P., and Young, S. (2001). The characteristics of firms subject to adverse rulings by the Financial Reporting Review Panel. *Accounting and Business Research*, 31(4), 291–311.
- Rejeb, A. B., & Boughrara, A. (2013). Financial liberalization and stock markets efficiency: New evidence from emerging economies. *Emerging Markets Review*, 17, 186-208.
- Schwert, G. W. (2011). Stock volatility during the recent financial crisis. *European Financial Management*, 17(5), 789-805.
- Strohmeier, M. (2014). Enforcement releases, Firm Characteristics and Earnings Quality: Insights from Germany's Two-tiered Enforcement System. *Journal of International Financial Management & Accounting*, 21(25:3), 271–302.
- Vafeas, N. (1999). Board meeting frequency and firm performance. *Journal of Financial Economics*, 53(1), 113–142.
- Vishny, R., and Shleifer, A. (1997). A Survey on Corporate Governance. *Journal of Finance*, 52, 737–783.
- Watts, R. W., and Zimmerman, J. L. (1986). *Positive Accounting Theory*, Upper Saddle River, New Jersey: Prentice-Hall.
- Witzky, M. (2016). *Enforcement of Accounting Standards and Changes in Corporate Governance*. Working paper, London School of Economics & Political Science.
- Wu, M. (2002). *Earnings restatements: a capital market perspective*. Working Paper, New York University.
- Wilson, M. W (2008). An Empirical Analysis of the Decline in the Information Content of Earnings Following Restatements. *The Accounting Review*, 83(2), 519–548.