Corporate Financial Transparency and Credit Ratings*

Steven Vanhaverbeke, Benjamin Balsmeier,
Thorsten Doherr

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Abstract
As corporate financial transparency increases, credit rating agencies are supposed to improve their risk assessments. Theory predicts such an information quality effect but also an adverse reputational concerns effect because credit analysts may become increasingly concerned about alleged rating failures. We empirically examine these predictions using a large scale quasi-natural experiment in Germany, where firms were required to publicly disclose annual financial statements. Consistent with the reputational concerns hypothesis, we find an average increase in credit rating downgrades. Further, we show that downgrades are entirely driven by changes in the discretionary assessment of the credit analysts rather than changes in firm fundamentals, rating accuracy declines due to increases in erroneous default warnings, positive private information is less likely to positively influence ratings, and downgrades are more pronounced the higher the initial risk of firm default. We conclude that increased corporate financial transparency unintendedly contributes to credit rating conservatism.

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Contact information:
Steven Vanhaverbeke: Rotterdam School of Management, Department of Accounting and Control, Rotterdam, Netherlands, email: vanhaverbeke@rsm.nl

Benjamin Balsmeier: University of Luxembourg (and ETH Zurich), Faculty of Law, Economics and Finance, Campus Limpertsberg, 162A, avenue de la Faïencerie, 1511 Luxembourg, email: benjamin.balsmeier@uni.lu

Thorsten Doherr: Centre for European Economic Research (ZEW), Department of Industrial Economics and International Management, Mannheim, Germany, email: doherr@zew.de

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I. Introduction

Over the last decades, policymakers have enacted several changes to disclosure and reporting regulations that have increased corporate financial transparency. Forcing firms to provide standardized financial statements to the public is a key element of these regulatory ambitions. If properly enforced, it becomes harder to hide and manipulate financially relevant information, which should improve the quality of risk assessments (Seligman, 1983; Rock, 2002; Cheng, Liao and Zhang, 2013). This paper challenges this conventional wisdom by demonstrating that increased corporate financial transparency can have unintended and adverse effects on corporate credit ratings.

Theory suggests that public information disclosure can have adverse effects if it crowds out the effective usage of private information (e.g. Morris and Shin, 2002; Angeletos and Pavan, 2007; James and Lawler, 2011). The driving force behind this crowding out effect is that informed professionals care about their reputation with uninformed decision makers (e.g., Morris, 2001; Prat, 2005; Ottaviani and Sørensen, 2006). In the case of credit rating agencies (CRAs), credit analysts are reluctant to use their private information, because rating failures based on private information are more likely to be attributed to misclassifications, than rating failures based on public information (Mariano, 2012).[1] In simpler terms, analysts would rather be wrong, but with a public justification for their choices. This risk of being (wrongly) accused of a rating failure leads analysts to issue credit ratings that confirm credit ratings predicted from publically available financial statements even if they are in possession of contradictory private information. The mechanism is very similar to herding in financial markets where security analysts have incentives to follow the mainstream opinion even if they are privately better informed (Scharfstein and Stein, 1990;

[1] Note that this holds irrespective of whether credit ratings have an influence on the performance of the rated firm.

Trueman 1994).[2] It implies that credit rating accuracy declines in response to increased corporate financial transparency.

Furthermore, if credit analysts are penalized more heavily for overly optimistic ratings than for overly pessimistic ratings (Bolton, Freixas, and Shapiro, 2012; Xia, 2014, Dimitrov et al., 2015), this implies that credit ratings are influenced asymmetrically towards overly conservative ratings. The reasoning is twofold. First, the costs of rating failures for clients are much greater in case of missed defaults as compared to any other rating failure (Bolton, Freixas, and Shapiro, 2012; Xia, 2014). Second, and related to the previous point, the likelihood that a credit rating failure is detected by a client is highest if a firm actually defaults. Intuitively, it is unlikely that a client complains about a speculative grade assigned to a firm that remains solvent, while an optimistic grade assigned to a firm that subsequently defaults may expose the CRA to criticism. Given the greater reputational risk in case of missed defaults, it is especially private information that positively deviates from public information, which is less likely to be used to determine a firm's credit rating (see Brown, Wei, and Wermers, 2014, for a similar argument). Increased financial transparency may thus bias credit ratings towards overly conservative assessments.

Based on these arguments we make five empirically testable predictions about the impact of public financial statement disclosures. We expect (1) credit analysts to issue, on average, worse credit ratings, (2) downgrades to be driven by the discretionary personal assessment of the credit analysts and not by changes in firm fundamentals, (3) credit rating accuracy to decrease due to increases in erroneous default warnings, (4) positive private information to be less likely to positively influence credit ratings, and (5) downgrades to be more pronounced the higher the initial risk of default.

[2] Prior empirical examinations of earnings forecasts support reputational concern-motivated herding theories (e.g. Hong, Kubik, and Solomon, 2000; Clement and Tse, 2005).

Most advocates of increased corporate financial transparency, however, argue that public financial statement disclosure has a positive effect on corporate risk assessments (Seligman, 1983; Rock, 2002). As disclosure regulations typically impose severe penalties on firms that provide incorrect information, firms will disclose not only more information but also more trustworthy information. Financial disclosure regulation should thus improve credit rating analysts' ability to determine a firm's true creditworthiness. In the absence of reputational concerns this should translate into more accurate risk assessments. Therefore, the information quality hypothesis directly contradicts hypotheses (1) to (5). Instead it (6) implies a null hypothesis of no effect on the average credit rating, or across the credit rating distribution[3], and (7) predicts an improvement in credit rating accuracy.

To empirically examine these hypotheses we exploit the introduction of a mandatory disclosure regime in Germany. Since 1987, Germany has required all private limited liability firms to publicly disclose financial statements. However, due to a lack of enforcement, only approximately 5% of private firms had complied with these requirements before 2006 (Bundesanzeiger, 2011; Bernard, 2016). In 2007, a change in the enforcement regime led more than one million firms to disclose their financial statements to the public.

Our empirical setup focuses on those private firms that were obliged to disclose financial statements from 2007 onwards. Private firms that were neither before nor after the reform required to disclose financial statements serve as the main control group. We perform various robustness

[3] The information quality hypothesis would also predict changes in corporate credit ratings, however, on average, we would expect no effect. When a CRA constructs its rating, it is able to estimate the average amount of concealment in the market based on past credit rating failures and success. If disclosure regulation reduces the average concealment in the market, it would lead to rating upgrades for some firms, downgrades for others, which cancel each other out on average. Nonetheless, we test and rule out the learning effect in section IV.F.

and sensitivity checks, including an alternative control group, that all reveal qualitatively the same result.

The main data source is the Mannheim Enterprise Panel (MEP), which includes credit rating data from Creditreform, the largest CRA in Germany. Creditreform's business model is the same as the one of Credit Safe, Dun and Bradstreet, Equifax, or Experian in other parts of the world. It has a stable market share of about 70%. Creditreform creates and sells credit ratings for the entire universe of German firms regardless of whether a firm discloses information to the public or not. Clients are banks and other firms that want to determine the amount of (trade) credit they should provide.

To assess a firm's creditworthiness, credit analysts use public sources of information (e.g., information from trade registers and courts) as well as private sources. Non-public information (e.g., privately disclosed financial statements or management reports) is obtained by directly contacting every firm. Additional information on firms' payment behavior comes from banks and suppliers. Our database contains all issued credit ratings as well as some of the non-public data, including the discretionary personal assessments of the credit analysts. The latter enables us to isolate changes in the subjective opinion of the credit analysts from changes in firm fundamentals.

Based on a panel of approximately 237,000 private firms observed over the period 2004 to 2010, we find that firms receive, on average, more conservative ratings (a one-notch rating downgrade on the S&P rating scale for approximately one out of every four firms) in response to disclosing their financial statements to the public. Consistent with the reputational concerns hypothesis, these changes in credit ratings are entirely driven by changes in the discretionary assessments of the credit analysts and not by changes in fundamentals or the business environment. We further show that rating accuracy declines due to erroneous default warnings and that positive information that the CRA privately possesses about the firm (i.e. information about a firm's payment behavior) is less likely to positively influence the rating decision. Finally, firms in the lower part of the credit rating distribution (i.e., speculative grades) drive the average effect and receive a considerably worse rating after public disclosure, while firms with high creditworthiness (i.e., investment grades) remain largely unaffected. All these results line up with the idea that credit rating quality weakens because credit analysts become more concerned about alleged rating failures when corporate financial transparency increases. They are inconsistent with the commonly held believe that improvements in corporate financial transparency improve credit rating quality.

We also examine whether alternative mechanisms such as changes in coordination costs (Hertzberg, Liberti, and Paravisini, 2011), the banking system (Breuer, Hombach, and Müller, 2017), or competition (Bernard, 2016; Breuer, 2018) drive the credit rating downgrades that we observe. None of these explanations find empirical support.[4] Finally, we show that our results are neither influenced by strategic changes of legal forms nor by changes in the underlying rating model of the CRA.

The examination contributes to three literatures. First, we provide new insights to the ongoing discussion about the costs and benefits of financial statement disclosure regulation (see Leuz and Wysocki, 2016, for an overview). Prior papers show that disclosure regulation reduces problems of adverse selection and moral hazard (e.g., Bushee and Leuz 2005; Greenstone et al., 2006), but entail non-trivial costs, especially for smaller firms (e.g., Verrecchia, 1983; Bushee and Leuz, 2005; Illiev, 2010). Our study extends this literature by investigating how mandatory financial statement disclosures influence corporate credit ratings and may trigger reputational concerns of informed experts.

[4] Note that these mechanisms are not consistent with a decrease in rating accuracy. In addition, the change in credit ratings is entirely driven by the change in the personal opinion of the credit analysts, while these alternative channels would predict real changes in firm fundamentals (e.g. payment behavior).

Second, our results inform the growing theoretical as well as empirical credit rating literature (see Jeon and Lovo, 2013, for an overview). Several theoretical papers have studied biases in credit ratings, highlighting reputational concerns as a key driving force (e.g., Mariano, 2012, and Bouvard and Levy, 2017). While these studies do not explicitly show that reputational concerns are triggered by increased corporate financial tranperency, it is often some type of asymmetry between private and public information that leads to biases in credit ratings.

The early empirical credit rating literature demonstrated that ratings are informative about firms' operating performance and credit risk (Ederington and Goh, 1998, and Kao and Wu, 1990). Others have shown that investors react to credit rating changes, particularly to downgrades (Holthausen and Leftwich, 1986, Hand, Holthausen, and Leftwich, 1992, and Dichev and Piotroski, 2001). That credit ratings may nonetheless be biased has repeatedly been discussed since the adoption of the issuer-pays credit rating model in 1974 (see e.g. Jiang, Stanford and Xie, 2012).[5] Our paper shows that a rating agency that worries about reputation might not provide the most accurate ratings -- even in the absence of conflicts of interest related to the issuer-pay model.

Other empirical studies report that CRAs have provided more conservative ratings over time and the market only partially eliminates the impact of conservatism on debt provision (e.g. Baghai, Servaes, and Tamayo, 2014). Regulatory scrunity and investor criticism following the collapse of WorldCom (Alp, 2013), as well as increased competition from an investor-paid credit rating agency (Xia, 2014), seem to have contributed to rating conservatism, but the mechanisms that drive the long-term trend are still not well understood. Our study contributes to this line of research by providing evidence of a new mechanism that contributes to the provision of conservative ratings.

[5] A number of papers find support for these claims (e.g., Skreta and Veldkamp, 2009; Griffin and Tang, 2011; Bolton, Freixas, and Shapiro, 2012; Xia and Strobl, 2012; He, Qian, and Strahan, 2012; Opp, Opp, and Harris, 2013).

Studies that are conceptually close to ours have examined changes in credit ratings in response to regulatory changes in the U.S. Jorion, Liu, and Shi (2005) found that the information content of both credit rating downgrades and upgrades was greater following the passage of the Regulation Fair Disclosure Act (Reg FD) in 2000. Their findings support the notion that credit ratings are a valuable source of information because they incorporate non-public information. Cheng and Neamtiu (2009) show that following the passage of the Sarbanes-Oxley Act in 2002, CRAs issued more timely downgrades, increased rating accuracy, and reduced rating volatility. It remains unclear though, whether these findings can be attributed to increased regulatory pressure to improve risk assessments or to improvements in accounting quality. Supporting the idea of particularly strong reputational concerns, CRAs issued more rating downgrades and gave more erroneous warnings in response to the Dodd-Frank Act (Dimitrov, Palia, and Tang, 2015).

Finally, our study speaks to the broader debate on how to improve the information environment and resolve market frictions through public information disclosure (e.g. Angeletos and Pavan, 2007; Kurlat and Veldkamp, 2015; Goldstein and Leitner, 2018; Goldstein and Yang, 2018). The conventional wisdom that public information disclosure unambiguously improves economic efficiency has been repeatedly challenged by this literature, albeit not empirically. One of the main arguments brought forward is that public information may crowd out different types of private information (e.g., Gao and Liang, 2013; Edmans, Heinle, and Huang, 2016; Banerjee, Davis, and Gondhi, 2018). Our research supports this argumentation and highlights the relevance of reputational concerns. It establishes a link between information disclosure and credit ratings that has so far been neglected in the theoretical as well as empirical literature.

II. Institutional Background

To empirically examine the impact of increased corporate financial transparency on credit ratings, we draw on a quasi-natural experiment that originates from EU directive 2003/58/EC. This directive required all EU member states to set up an electronic register of limited liability firms by January 1, 2007. The purpose of these national registers was to make all annual financial statements electronically available to the public. Before 2007, the EU had already required private firms to disclose annual financial statements to the public. However, the ensuing regulations were not enforced in Germany. Before 2007, only approximately 5% of German firms that were obliged to publish annual financial statements actually disclosed their financial statements to the public (Ballwieser and Hager, 1991; Bundesanzeiger, 2011; Theile and Nitsche, 2006).[6]

When Germany began to enforce its financial disclosure law in order to comply with EU law, it led to a massive increase in available financial statements via a web-based platform.[7] The platform is similar to the SEC's EDGAR website in the US. Enforcement has been strict since then. If a firm does not file its financial statements within one year after the end of the fiscal year, the Federal Office of Justice (FOJ) launches an administrative procedure that results in a fine between €2,500 and €25,000. Firms are subject to fines every six weeks until their financial statement is available in the electronic register. Paying the fine does not replace the requirement to disclose, and fines can be imposed on the company as well as on its legal representatives. In addition to the newly introduced financial penalties, criminal penalties of up to five years' imprisonment can be imposed on owners of insolvent firms that consistently fail to disclose financial statements. In less

[6] For example, Ballwieser and Hager (1991) gathered financial statements for a sample of firms at 21 local courts in 1987. Only 11.9% of firms filed their financial statements. Others found publication rates of between 10.0% and 16.2% for the fiscal years 1996 to 2004 (Theile and Nitsche, 2006). Furthermore, it was common practice for firms to register in judicial districts far away from their creditors, preferably on commercial registers that were known for lax registration practices (Sandrock and du Plessis, 2012).

[7] Prior to the electronic platform, courts were responsible for making the financial statements of private firms available upon request. However, they have been repeatedly described as antiquated due to their limited scope for obtaining access (Sandrock and du Plessis, 2012).

severe cases, violations can be sanctioned with imprisonment of up to two years. Thus, it hardly ever pays off to evade disclosure of financial statements. This robust change in enforcement practice proved to be very effective. Publication rates increased from approximately 5% to well over 90% two years after the law change (Bundesanzeiger, 2011).

As of today, all 1.1 million financial statements are readily accessible through the website 'www.bundesanzeiger.de'. More than 35 million annual accounts are retrieved from the website on a yearly basis. 80% of the requests refer to the annual accounts of private firms that qualify as small- and medium-sized enterprises (SME). A user survey from 2011 revealed that firms use the platform as the principal source of gathering financial information on their clients and potential business partners (Bundesanzeiger, 2011). Of key interest are figures such as EBIT, balance sheet information, liabilities, and solvency ratios.

III. Data and Identification Strategy

III.A. Data Source – The Mannheim Enterprise Panel (MEP)

Our empirical analysis builds on the Mannheim Enterprise Panel (MEP) hosted by the Centre for European Economic Research (ZEW). It contains credit ratings for almost the entire German economy. The ratings originally stem from Creditreform, the largest credit rating agency in Germany (Creditreform, 2007, 2010).[8] As in most other countries of the world, the credit rating business in Germany is dominated by very few companies that create credit reports for private firms (European Commission, 2012).

Creditreform has regularly screened the official German company register since the late 19th century, ensuring full coverage of the corporate landscape. Comparisons with the company

[8] The market share of Creditreform has stably remained around 70% over recent decades (Creditreform, 2007, 2010).

register of the Federal Statistical Office of Germany confirm that the MEP data is fully representative of the country's corporate landscape.[9]

The core business of Creditreform is selling reports on private firms' creditworthiness. They have an "investor-pays" business model, similar as Credit Safe, Dun and Bradstreet, Equifax, and Experian that operate in other parts of the world.[10] Customers of Creditreform are mainly firms that want to determine the amount of trade credit they offer to their clients and suppliers. In addition, the vast majority of banks use credit ratings for lending decisions (Frame, 2001; Berger and Frame 2006). Banks either use the credit ratings to either automatically approve or reject loan application of private firms, use them to determine the loan conditions, or use them to supplement their own creditworthiness assessments.

The main product of Creditreform is the credit rating, which reflects a firm's ability to pay off its debt and the likelihood of default. Credit ratings range from 100 (best credit score) to 500 (worst credit score). They are based on public sources of information (trade registers, courts, etc.) as well as private sources. Non-public information (e.g., privately disclosed financial statements or management reports) is obtained by interviewing managers. All this information is enriched with data on a firm's payment behavior form suppliers and banks.

If a company refuses to provide certain information, it remains in the database. Similar to other credit rating agencies, a refusal to disclose additional information is taken into account when credit ratings are generated.

[9] For more detailed information about data collection, processing and availability of the MEP data, see Bersch et al. (2014).

[10] The 3 largest credit rating agency in the US that construct credit ratings for *private firms* are Dun and Bradstreet (D&B), Experian, and Equifax. They had a combined revenue of over 10 billion dollars in 2017. In contrast, the revenues of Moody's, S&P and Fitch was 12 billion dollars in 2017. According to a survey done in late 2012 by DG Internal Market (European Commission, 2013), these credit rating agencies indicate that they face only limited competition from the big three international rating agencies (Moody's, Fitch, S&P), as they operate in different market segments under different modalities. The big three CRAs serve large multinationals, while the others serve SME's and large private companies.

III.B. Identification Strategy

To identify the causal impact of financial information disclosure on credit ratings, we compare firms that were affected by the requirement to disclose financial statements with firms that were not affected but follow a similar trend in credit ratings over time. In our main specification, we compare all limited liability firms using the legal form '*GmbH*' and '*GmbH Co. KG*'[11] with unlimited liability firms with the legal form '*OHG'* and '*KG'*. The latter group of firms was required neither before nor after the regulatory change to make financial statements publicly available.[12] Using firms with the legal form '*OHG'* and '*KG'* as a control group has the advantage that they operate in the same industries and regions as their limited liability counterparts. They also show similar distributions of size, age, and productivity.[13] Firms in both groups regularly collaborate with various suppliers and banks, giving them similar incentives to provide information to business partners and CRAs.[14] In addition, owners of limited liability firms often need to provide personal collateral to obtain loans, increasing the comparability of both groups of firms (Ang, Lin and Tyler, 1995; Cerqueiro and Penas, 2016).

Under the assumption that the treated and control group are comparable in terms of reaction to macroeconomic influences and market-wide shocks that are concurrent but unrelated to the regulatory change, we can identify the causal impact of mandatory financial statement disclosure

[11] *GmbH* is comparable to the legal form *LLC* in the United States and *Ltd.* in the United Kingdom. *GmbH Co.KG.* is comparable to the *GP* in the United States and the United Kingdom, but where the general partner in the partnership is a firm with the legal form *GmbH* (i.e. the 'unlimited liability partner' is a 'limited liability firm').

[12] *OHG* is comparable to the legal form *GP* in the United States and the United Kingdom. OHG firms are partnerships where all partners have unlimited liability. *KG* is comparable to the legal form *LP* in the United States and the United Kingdom. *KG* are partnerships where at least one partner has unlimited liability and one partner has limited liability (where the 'unlimited liability partner' cannot be a 'limited liability company').

[13] Other firms with unlimited liability such as one-man companies are mainly dominated by micro firms. These firms may have fewer stakeholders interested in their creditworthiness.

[14] For both groups, we find a similar share of firms that disclosed financial statement through private channels to the CRA before the law change (approximately 25% of firms).

on credit ratings using a Difference-in-Differences (DiD) model. We examine the plausibility of the parallel trends assumption in more detail in Section IV.B.

III.C. Sample Construction

In our baseline empirical set up we focus on credit ratings three years before and three years after the law change in 2007, resulting in a panel dataset that covers the period 2004 to 2010. We keep only treated firms (GmbH and GmbH Co. KG) and control firms (OHG and KG) as outlined above.[15] To minimize potentially confounding selection effects, we further restrict the sample to firms that did not change their legal form over time[16] or voluntarily provided financial information to the public before the law change.[17] In addition, we remove financial sector firms from the sample and keep only firm-year observations that have non-missing information on our variables of interest. To maximize comparability, we exclude the largest 1% of firms from our analyses.[18] Lastly, we only keep firms that we observe for at least two years since we include firm-fixed effects in our analyses.

[15] We exclude listed firms (AG), professions, one-man companies with unlimited liability, and other unlimited liability firms that have special legal forms and are thus less comparable to our treated firms in terms of size, age and productivity.

[16] We find a statistically significant increase in switches around the law change from the treated group to the control group, and a significant decrease in switches from the control group to the treated group. This indicates that the disclosure regulation does indeed incur non-trivial costs for some firms. However, these cases represent less than 0.2% of all firms in the database. They do not alter the results if they remain in the sample. The economic implications of the observed switching behavior are further discussed in section IV.F.

[17] Keeping these firms in the sample (5% of firms that voluntarily disclosed to the public) has a negligible impact on the results as shown in the Appendix Table A.3.

[18] Specifically, we remove firms with more than 5000 employees and sales of more than €130,000,000. Non-treated firms that surpass these thresholds are required to disclose financial information to the public following the classification instituted by German Corporate Law. Given that this group of non-treated firms represent only a very small fraction of the population, we were unable to use this group as a separate control group. Results are nonetheless robust to keeping those large firms in the sample.

The final sample comprises 808,942 firm-year observations on 230,515 firms that were affected by the law change ('treated' firms) and 6,637 firms that were not affected. The composition of the final sample is comparable to the landscape of German firms in terms of size and industry classification (Bersch et al., 2014).

IV. Results

IV.A Descriptive Statistics

Table I presents descriptive statistics for affected and non-affected firms. The average treated firm is 19 years old, which is about half the age of the average untreated firm. The size of the firms in both sub-samples is comparable, with around 19 vs. 20 employees on average, and a median of 6 for both groups. Nor does labor productivity, measured by total sales per employee, differ meaningfully for the median firm. However, due to some extreme values for a selective set of firms, the average differs significantly. To mitigate concerns of potential outliers having an unwarranted strong influence, we take the log of our three main control variables.[19] Regarding the credit ratings, treated firms score 20 points higher than untreated firms, i.e., the treated firms have a worse credit rating on average.

Table I: Descriptive Statistics

Variable	Treated Firms					Non-Treated Firms				
	Obs.: 785,588					Obs.: 23,354				
	Mean	Median	Std Dev	Min	Max	Mean	Median	Std Dev	Min	Max
Credit Rating	270.724	267	57.432	108	500	253.447	244	66.674	100	500
Age	19.467	13	26.066	1	1,010	37.110	21	46.695	1	999
Log Age	2.594	2.639	0.914	.693	6.919	3.048	3.091	1.159	0.693	6.908
Employees$_{(t-1)}$	19.257	6	60.689	1	4,900	19.941	6	83.964	1	4,000
Log Employees$_{(t-1)}$	2.121	1.946	1.153	.693	8.497	2.141	1.946	1.095	0.693	8.294
Productivity $_{(t-1)}$ x 1000	1105	150	4900	0.000	129,100	341	146	1584	0.000	44,482
Log Productivity$_{(t-1)}$	12.152	11.9184	1.311	.0082	18.676	11.985	11.892	0.956	.039	17.611

Notes: This table presents the descriptive statistics of the subsamples of treated and non-treated firms. Treated firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. The credit rating index range from 100 (good rating) to 500 (bad rating). Variable definitions are provided in section IV.A.

[19] As a robustness test, we also eliminate extreme values by dropping values above either the 90th, 95th or 99th percentile for each continuous variable, and find statistically the same results (untabulated).

IV.B Impact of Disclosure Regulation on Credit Ratings

To identify the causal effect of mandatory financial statement disclosure on credit ratings, we rely on a DiD estimation strategy. Thus, it is of crucial importance that both groups of firms are comparable in terms of how credit analysts determines credit ratings when no difference in disclosure regulation exists. In addition, both groups should be affected in the same way by various kinds of institutional changes, macroeconomic changes and market-wide shocks that are concurrent but unrelated to the regulatory change.

Figure I: Standardized Average Credit Rating of German Firms over Time

This figure shows the standardized average credit ratings over time for the Treated and Non-Treated firms. *Treated* firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. The credit rating index ranges from 100 (good rating) to 500 (bad rating). A higher (lower) value indicates that the credit rating gets worse (better).

Figure I indicates that it is plausible that these assumptions are met. The standardized average credit ratings of our treated and control group firms evolve in parallel up to 2007 when the change in disclosure regulation occurs and the first financial statements become publicly available.[20] In Figure A.1 in the Appendix, we extend the pre-treatment period by five additional years, showing that the common trend is indeed stable over time. After the law change, trends diverge and the average credit rating of the treated firms becomes worse. The graph indicates that credit rating agencies become more conservative when additional financial information becomes publicly available, which is consistent with the reputational concerns hypothesis.

To examine the impact of financial statement disclosure on credit ratings systematically, we run DiD regressions. We adopt a firm fixed-effects OLS regression model following Jiang, Stanford, and Xie (2012), Baghai, Servaes, and Tamayo (2013), and Xia (2014).[21] Our baseline specification is:

$$\begin{aligned} Credit\ Rating_{i,t} = {} & \beta \cdot Treated_i \times Post_t + \beta_2 \cdot Treated_i + \gamma' X_{i,t-1} + \delta_t \\ & + Ind_i + Region_i + \varepsilon_{i,t} \end{aligned} \tag{1}$$

where $Credit\ Rating_{i,t}$, is the credit rating of firm i in year t, $Treated_i$ is a dummy indicating whether the firm has the legal form 'GmbH' or 'GmbH Co. KG', and zero if the firm has a legal form 'OHG' or 'KG', $Post_t$ is a dummy that equals one from 2007 onwards, when the treated firms are required to disclose financial statements to the public. The vector $X_{i,t-1}$ includes controls for firm age, size$_{(t-1)}$, productivity$_{(t-1)}$, and payment behavior reported by suppliers[22], which

[20] In Figure II and Appendix Table A.4, we further show that there is no statistically significant difference over time prior to the change in the law.
[21] Results are robust to estimating ordered logit models as in Dimitrov et al. (2015), see Appendix Table A.2 column f.
[22] To control for a firms' payment behavior, we include 29 dummy variables where each dummy variable indicates a specific payment behavior category reported by their suppliers and banks. These categories range from a good payment behavior category (e.g. paying on time using cash discount utilization) to a bad one (e.g. severe late payments, or bankruptcy procedure are initiated).

may affect credit ratings independent of the requirement to disclose financial information.[23] Finally, we add controls for macroeconomic differences across years (δ_t), and unobserved time invariant heterogeneity across 68 industries (ind_i) and 16 regions ($region_i$).

Alternatively, we estimate the same model as (1) but with firm fixed-effects (f_i) that control for unobserved time invariant heterogeneity across firms:

$$Credit\ Ratings_{i,t} = \beta \cdot Treated_i \cdot Post_t + \gamma' X_{i,t-1} + \delta_t + f_i + \varepsilon_{i,t} \tag{2}$$

Under the assumption that affected and non-affected firms followed similar trends absent the disclosure regulation, β_1 captures the causal impact of financial statement disclosure on credit ratings. To further increase confidence in the identification, we re-estimate (1) and (2) based on a matched sample of affected firms that are comparable to the control group firms with regard to all our control variables, including industry and regional differences. This exercise addresses concerns that affected firms might be clustered in regions or industries where disclosure regulation had particularly pronounced effects. While we include parametric controls in (1) and (2), differences in terms of industry and regional allocation are hard to effectively control for if treated firms far outnumber firms in the control sample, as is the case in our sample. Hence, to further enhance comparability, we employ nearest-neighbor matching, where we only consider treated firms that are most comparable to a given control group firm. Specifically, we consider, in the case of each untreated firm, only the closest treated firm in terms of size, age and productivity within the same industry and same region, all measured before the law change. In addition, we exactly match treated

[23] In robustness analyses, we include additional controls for performance and leverage. Since we use financial statement information to create these variables, these analyses only include observations from firms that disclose financial statements in both the pre and post period to the credit rating agency. Our results are unaltered when we use this setup.

firms to untreated firms that had the same payment behavior classification, as well as a similar disclosing strategy to the credit rating agency.[24] Results and details of the matching procedure are presented in the Appendix, Table A.1. Then, we re-estimate specification (2) based on the balanced sample.

Finally, we add controls for any remaining unobserved differences in credit-rating trends across industries as well as potential changes in how the control variables affect credit ratings over time coincident with the change in disclosure regulation. Therefore, we add to specification (2), the interaction terms of *Post* and all controls, plus industry-specific linear trends[25], resulting in:

$$Credit\ Ratings_{i,t} = \beta\ Treated_i \cdot Post_t + \gamma' X_{i,t-1} + \gamma' X_{i,t-1} \cdot Post_t + Ind_i \cdot t + \delta_t + f_i + \varepsilon_{i,t} \qquad (3)$$

We estimate (3) based on the full and balanced sample. Table II displays the results.

The results using the unmatched sample (columns a to c) suggest that credit ratings increase on average between 4 and 6 rating points when firms are required to disclose financial statements to the public.[26] To better assess the economic impact of our results, we transform the Credit Rating

[24] We force firms to be in the same industry and region. We also exactly match on a firms' payment behavior reported by suppliers and banks, which is a variable that contains 29 distinct categories. Lastly, we force firms to have a similar reporting strategy to the CRA in the pretreatment period, by exactly matching on a dummy variable which indicates if a given firm has disclosed GAAP financial statement to the credit rating agency through private channels. Since our pool of treated firms is much larger than the pool of untreated firms, we turn the typical matching procedure around. Hence, for each untreated firm, we pick the closest candidate out of the pool of treated firm in the same industry-region-payment behavior-disclosure group (without replacement). See Appendix, Table A.1 for more details. As a robustness test, we also use a one-on-one coarsened exact matching approach, as well as a more conventional propensity score matching where we follow a matching protocol using replacement to find an untreated firm for each treated firm. However, the latter approach leads to several untreated firms that are used more than once as a control firms. Our results are robust using these different matching techniques.

[25] As a robustness check (Appendix, Table A.12), we include year-industry-region fixed effects, as well as firm-specific time trends. Our results remain unaltered.

[26] In further analyses below we show that the effect is several times as high for firms at the lower end of the rating distribution.

Index of Creditreform to the commonly known S&P index that ranges from AAA to D (Creditreform, 2017b). Following prior literature, we assign a numerical value to each of the 22 possible rating on a notch basis (see e.g. Xia, 2014).[27] Using this setup, we find a one notch decrease for one out of four firms (see Appendix, Table A.2). The estimated size of the transparency effect is thus comparable with the competition effect identified by Xia (2014), who finds a one-notch rating downgrade in S&P ratings for approximately one out of two firms in response to new competition from an investor-paid credit rating agency. Similarly, if we follow the approach of Dimitrov et al. (2015) and estimate an ordered logit model to calculate proportional odds ratios between ratings, we find that firms have a 1.30 times greater chance to receive a non-investment grade in response to publishing their financial statements (Appendix, Table A.2). To put things in perspective, the transparency effect is thus about 10% larger than the impact of the passage of the Dodd-Frank act in the U.S., which increased the odds that a corporate bond is rated a non-investment grade by 1.19 times (Dimitrov et al., 2015). Further analyses in the robustness test section suggest that the identified rating reduction relates to a 6.47% reduction in trade credit volume for the affected firms. This effect is economically sizable considering that trade credit is one of the most important sources of external finance for private firms (Deutsche Bundesbank, 2012).

Regarding the control variables, they all demonstrate the anticipated effects. Older, larger and more productive firms have better credit ratings. Estimating the same specifications using the matched sample (Table II, column d) confirms the baseline result, which continues to hold after adding trend controls (Table II, column e).

[27] We follow Xia (2014) and assign a numerical value to each rating as follows: AAA=1, AA+=2, AA=3, AA−=4, A+=5, A=6, A−=7, BBB+=8, BBB=9, BBB−=10, BB+=11, BB=12, BB−=13, B+=14, B=15, B−=16, CCC+=17, CCC=18, CCC−=19, CC=20, C=21, and D=22.

Table II: The Impact of Financial Statement Disclosure on Credit Ratings

	(a)	(b)	(c)	(d)	(e)
Dependent Variable: Credit Rating					
Treated x Post	6.269***	3.599***	4.899***	5.827***	5.765***
	(0.707)	(0.668)	(0.659)	(0.827)	(0.817)
Treated	14.705***				
	(0.562)				
Log Age	-6.224***	-5.815***	-4.973***	-9.688***	-8.679***
	(0.270)	(1.162)	(0.977)	(1.906)	(1.945)
Log Employees$_{(t-1)}$	-9.724***	-3.949***	-2.740***	-3.675***	-2.875***
	(0.194)	(0.202)	(0.160)	(0.581)	(0.582)
Log Productivity$_{(t-1)}$	-2.059***	-1.063***	-0.681***	-1.253***	-0.992**
	(0.149)	(0.117)	(0.110)	(0.378)	(0.421)
Firm fixed effects	No	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Implied	Implied	Implied	Implied
Region fixed effects	Yes	Implied	Implied	Implied	Implied
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Payment Behavior fixed effects	Yes	Yes	Yes	Yes	Yes
Industry Time Trends	No	No	Yes	No	Yes
Controls x Post	No	No	Yes	No	Yes
R^2	0.628	0.847	0.850	0.879	0.881
N	808,942	808,942	808,942	42,608	42,608

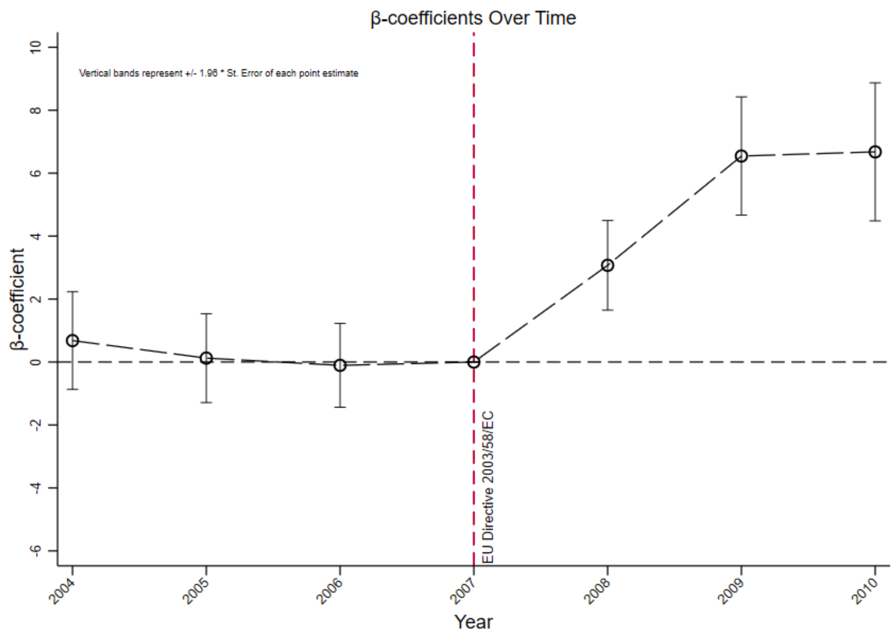
Notes: This table presents OLS regressions of firms' credit ratings. *Treated* firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. *Post* is a dummy variable equal to 1 for all firms for the years after 2007, i.e. the period when financial statements of treated firms became publicly available. The credit rating index ranges from 100 (good rating) to 500 (bad rating). A positive (negative) coefficient indicates that the credit rating gets worse (better). In columns (a) - (c) we use the full sample, and in columns (d) and (e) we use the matched sample (see Appendix Table A.1 for more details on the matching procedure). Heteroscedasticity-robust standard errors are clustered at the credit rating office level and are presented in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively. Variable definitions are provided in section IV.A.

To examine how the effects evolve over time, we re-estimate equation three but add coefficients β_t separately for each year before and after the regulatory change, leading to the following specification:

$$Credit\ Ratings_{i,t} = \sum_{t=2004}^{2010} \beta_t \cdot Treated_i \cdot\ Year_t + \gamma' X_{i,t-1} + \gamma' X_{i,t-1} \cdot\ Post_t + Ind_i \cdot\ t + \delta_t + f_i + \ \varepsilon_{i,t} \qquad (4)$$

Figure II illustrates how the effect evolves over time. Insignificant differences between the treated and non-treated firms before 2007 support the common trend assumption. After the regulatory change, disclosing firms receive a significantly worse credit rating. The effect increases over the two years following disclosures and seems to stabilize thereafter. Table A.4 in the Appendix shows the corresponding results.

Figure II: Coefficients over Time



This figure plots the estimated impact of disclosure regulation on credit rating in each year of the sample period using OLS regressions. The shallow circles represent the series of coefficients $\beta_t$from interacting a set of dummy variables representing each year in the sample with the Treated dummy in the following model specification: $Credit\ Ratings_{i,t} = \sum_{t=2004}^{2010} \beta_t \cdot Treated_i \cdot Year_t + \gamma' X_{i,t-1} + \gamma' X_{i,t-1} \cdot Post_t + Ind_i \cdot t + \delta_t + f_i + \varepsilon_{i,t}$ and the vertical bands represent 95% confidence intervals for the point estimates in each year. *Treated* firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. The credit rating index ranges from 100 (good rating) to 500 (bad rating). A higher (lower) coefficient indicates that the credit rating gets worse (better).

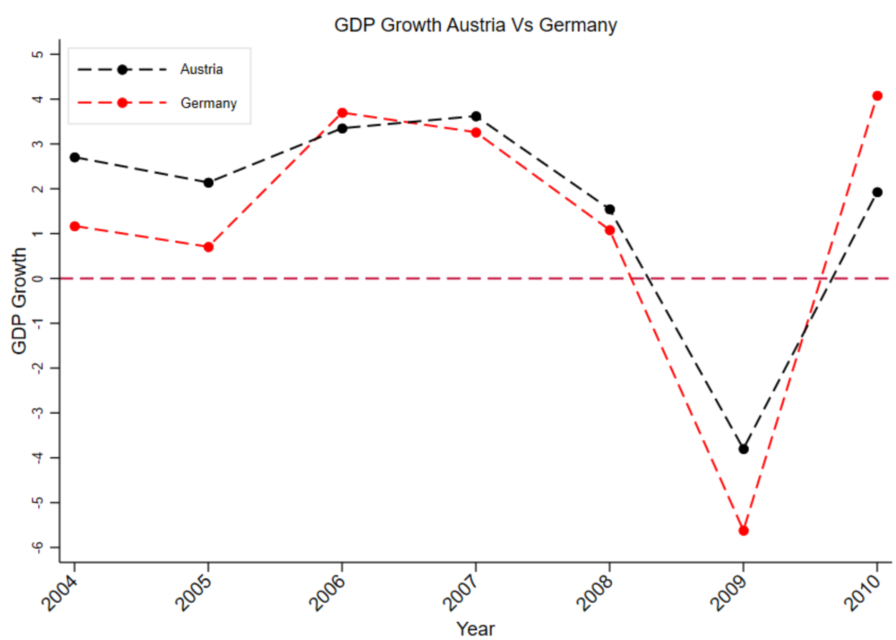
Alternative Control Groups and Placebo Test

To further validate the common trend assumption, we examine the credit ratings of similar firms situated in the neighboring country Austria.[28] Like Germany, Austria is a long-term member

[28] Creditreform is also the market leader in Austria (Creditreform, 2007) and used the same methodology to construct ratings for Austrian firms as for German firms (Creditreform, 2017a). The MEP database includes exactly the same information for Austrian firms as for German Firms.

of the EU, which implies free movement of capital, labor and goods. It has the same currency, same language and overall a very similar institutional environment. There are no legal differences between the two countries concerning strategic default or liquidation of collateral assets. Together with Germany, Austria forms a common market as evidenced by the parallel trend in GDP growth (Figure III) and stock price movements (Appendix, Figure A.2). However, opposite to Germany, Austria has effectively enforced public financial statement disclosure already since 1996 (Eierle, 2008).[29] Hence, Austrian firms can serve as an alternative control group.

Figure III: GDP Growth over Time



This figure shows the GDP Growth rate (Annual %) of Austria and Germany. Data is retrieved from the World Bank.[30]

[29] According to a study on filing practices, only 12% of SMEs in Austria did not deliver their financial statements to the commercial register in 2002 (Eierle 2008), compared to more than 90% of non-compliance in Germany in that time period (Bundesanzeiger, 2011). Austria established an effective enforcement mechanism in 1996. From that point onwards, the Austrian commercial register actively monitors compliance, and imposes fines of up to 3600 euro if an enterprise does not comply with the legal filing requirements.

[30] Data retrieved from the World Bank Website: https://data.worldbank.org/.

Figure IV: Placebo Test Austria Case - Standardized Average Credit Rating of Austrian Firms over Time

This figure shows the standardized average credit ratings over time for Austrian Firms. *Comparable Treated Austrian* firms are Austrian firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements from 1996 onwards (Eierle, 2008). Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. The credit rating index ranges from 100 (good rating) to 500 (bad rating). A higher (lower) value indicates that the credit rating gets worse (better).

To validate our previous results, we take 3 different approaches, which we summarize in Table 3. First, we compare the credit ratings of Austrian firms that operate under comparable legal forms as in the German case, i.e., Austrian firms with the legal form GmbH and GmbH Co. KG (i.e. limited liability firms) that were required to disclose financial information already before the German law change, against Austrian firms with the legal form KG and OHG (i.e. unlimited liability firms) that were never required to disclose financial statements.

Indeed, Figure IV and Table 3 show that Austrian firms with the same legal forms as their German counterparts exhibit no significant change in credit ratings around 2007, despite a very similar institutional environment and common market. The graphical impression is confirmed when we re-estimate equation three based on the Austrian firms sample only (Table III, column a). This exercise increases confidence in the estimation strategy because it suggests that without the change in disclosure of financial information, one would not have observed an increase in credit rating downgrades in Germany.

Given the common movement of GDP growth and stock prices (Appendix Figure A.2), this placebo test should also mitigate concerns that the financial crisis affecting Germany in 2009 is the reason why we observe differences in credit ratings between our treated and non-treated firms.[31] To further back this point we also looked into the preceding recession in 2003. The idea is that if the recession would indeed drive the difference in credit ratings, we would expect to see a similar effect in the aftermath of 2003 as well. Figure A.1 in the Appendix, however, demonstrates that the common trend between both groups firms remained unaffected after the preceding recession, which is also confirmed by formal tests.

Nonetheless, a concern might still be that unlimited liability firms are differently affected by the financial crisis than limited liability firms, which might confound the estimation of the effect of increased financial transparency. To address this concern we estimate a triple DiD model, where we compare the German setting (German limited liability firms vs German unlimited liability firms) against the Austrian setting (Austrian limited liability firms vs Austrian unlimited liability

[31] In appendix Figure A.2 we present the stock prices of the German DAX index and the Austrian ATX index. The two indexes move similar over time further indicating that companies in Germany and Austria were similarly affected by the crisis. Moreover, if the economic crisis was indeed the reason for the deviation in credit ratings between treated and non-treated firms in Germany, the effects would not be observed as early as 2008.

firms). Such a design explicitly controls for confounding trends that may exist between unlimited and limited liability firms over time. Specifically, we estimate the following equation:

$$Credit\ Ratings_{i,t} = \beta_1 \cdot Germany_i \cdot Treated_i \cdot Post_t + \beta_2 \cdot Treated_i \cdot Post_t + \beta_3 \cdot Germany_i \cdot Post_t + \gamma' X_{i,t-1} + \delta_t + f_i + \varepsilon_{i,t} \quad (4)$$

If our reasoning is true, we would expect to find a positive β_1 coefficient on the triple interaction term $Germany_i \cdot Treated_i \cdot Post_t$, while controlling for difference over time between limited and unlimited liability that are captured by the variable $Treated_i \cdot Post_t$. The results are presented in Table III, column (b), and confirm our previous findings.

As an alternative test, we examine the difference between German limited liability firms and Austrian limited liability firms only. In this setting, we are thus comparing limited liability firms from Germany that only started to disclose form 2007 onwards, with comparable limited liability firms from Austria that always disclosed information during the time period of interest. Again, our initial findings remain unchanged as shown in Table III, column c.[32] Using different specifications and control groups, we thus find consistent evidence that credit ratings become on average worse in response to the increased corporate financial transparency.

[32] The Appendix, Tables A.5a to A.5c present estimations of the placebo group test, triple DiD and limited liability only firms based on balanced samples and with further controls.

Table III: Summary Table of Alternative Control Groups

	(a) Placebo Diff-in-Diff	(b) Diff-in-Diff-in-Diff	(c) Diff-in-Diff
	Treated = Austria limited liability firms	*Treated* = German and Austria limited liability firms	*Treated* = German limited liability firms
	Untreated = Austria unlimited liability firms	*Untreated* = German and Austria unlimited liability firms	*Untreated* = Austria limited liability firms
Dependent Variable: Credit Rating			
Treated x Post x Germany		4.222***	
		(1.003)	
Treated x Post	-0.397	-0.490	3.351***
	(0.451)	(0.739)	(0.166)
Germany x Post		-0.871	
		(1.468)	
Log Age	-3.826***	-5.112***	-5.008***
	(0.358)	(0.820)	(0.254)
Log Employees$_{(t-1)}$	-2.384***	-3.687***	-3.713***
	(0.190)	(0.199)	(0.109)
Log Productivity$_{(t-1)}$	-0.393***	-0.980***	-0.979***
	(0.115)	(0.124)	(0.056)
Firm fixed effects	Yes	Yes	Yes
Industry fixed effects	Implied	Implied	Implied
Region fixed effects	Implied	Implied	Implied
Year fixed effects	Yes	Yes	Yes
Payment Behavior fixed effects	Yes	Yes	Yes
R^2	0.914	0.858	0.855
N	194,812	1,003,754	967,134

Notes: This table presents OLS regressions of firms' credit ratings. In column (a) *Treated* firms are Austrian firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements before and after 2007. Non-treated firms in column (a) are Austrian firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. In column (b) *Treated* firms are German or Austria firms with the legal forms GmbH or GmbH Co. KG, and non-treated firms are German and Austrian firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. *Germany* is a dummy variable equal to 1 for all firms within Germany, and 0 for firms that operate in Austria. In column (c) *Treated* firms are *German* firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand, and non-treated firms are *Austrian* firms with the legal forms GmbH or GmbH Co. KG that were required before and after 2007 to disclose financial statements. *Post* is a dummy variable equal to 1 for all firms for the years after 2007, i.e. the period when financial statements of treated firms became publicly available. The credit rating index ranges from 100 (good rating) to 500 (bad rating). A positive (negative) coefficient indicates that the credit rating gets worse (better). In columns (a) - (c) we use the full sample, and in columns (d) and (e) we use the matched sample (see Appendix Table A.1 for more details on the matching procedure). Heteroscedasticity-robust standard errors are clustered at the credit rating office level and are presented in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively. Variable definitions are provided in section IV.A. The Appendix, Tables A.5a to A.5c present estimations of the placebo group test, triple DiD and limited liability only firms based on balanced samples and with further controls.

Change in Assessment of the Credit Analysts or Change in Fundamentals?

The previous results show that credit ratings decline after firms are required to disclose financial information to the public. This result is consistent with the idea that increased public information crowds out (positive) private information of credit analysts. However, an alternative explanation for the change in credit ratings is that disclosure regulation has negative real economic consequences for firms, which in turn lead to a real change in firms' creditworthiness.[33] In that case we may wrongly assign the estimated change in credit ratings to reputational concerns of the credit analysts.

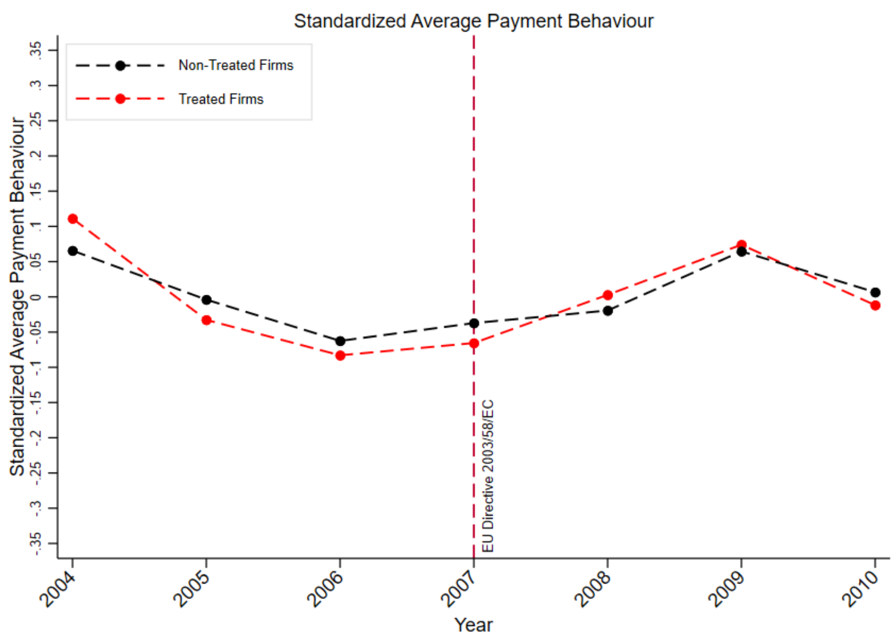
An implication of this alternative explanation is that the observed change in credit ratings is grounded in observable changes in a firm's payment behavior, while the reputational concerns hypothesis would predict the opposite, namely that changes in credit ratings are driven solely by changes in the discretionary opinion of the credit analyst (i.e. unrelated to changes in firm fundamentals). We test these predictions by running our baseline model again but exchange the dependent variable separately first with a measure of firms' payment behavior, and second with the credit analysts' discretionary assessment of firms' creditworthiness.

The payment behavior variable is based on the information that the CRA receives from suppliers and banks. It indicates how well a given firm pays back its credit to banks and suppliers. Next to firms' payment behavior, we employ the discretionary assessment of a firm's creditworthiness by the credit analysts, which is internally assigned to each firm. The personal judgment of the analysts is supposed to be based on all private and public information that is

[33] We pursued various alternative channels that could drive the change in credit ratings that we observe. For example, potential negative consequences of disclosure regulation are (1) changes in coordination costs between banks, (2) changes in lending technologies used by banks, (3) or changes in competition between firms (see e.g. Hertzberg et al., 2011, Breuer, et al., 2017, and Breuer, 2018). In the robustness section, we discuss and examine the consequences of these changes in more detail.

available to the analysts. It has a strong impact of 25% on the final credit rating that the firm receives (Creditreform, 2017a).[34] Such a large influence of the credit expert opinion on the final rating is also consistent with prior studies that find that credit analysts account for 27 to 30% of the within variation in credit ratings (Fracassi, Petry, and Tate, 2016). If reputational concerns drive the credit rating downgrades, we expect that they are determined by a more conservative opinion of the credit analysts, while the payment behavior remains stable. We summarize the results in Table IV.[35]

Figure V: Changes in Payment Behavior over Time



This figure shows the standardized average payment behavior over time for the Treated and Non-Treated firms. *Treated* firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. The payment behavior variable range from 1 (best payment behavior category) to 29 (worst category). A higher (lower) value indicates that the payment behavior gets worse (better).

[34] There are 6 main opinions that are provided, ranging from a positive recommendation (equal to the value 10) to a negative one (equal to the value 60).

[35] Table IV includes the models where we examine the effect on the full sample using firm-fixed effects. Alternative specifications are presented in the online Appendix Table A.6a, A.6b, and A.6c.

Figure V illustrates that the payment behavior remains stable over time and does not deviate between treated and untreated firms after financial statements became publicly available. Table IV column (a), confirms this result, the coefficient of interest is statistically insignificant and close to zero. Using an alternative measure of payment behavior, namely an indicator equal to 1 for payment delays by more than three months, 0 otherwise, reveals the same result (see Appendix, Figure A.3).

Figure VI: Changes in Credit Analysts' Opinion over Time

This figure shows the standardized average credit analysts' opinion over time for the Treated and Non-Treated firms. *Treated* firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. The analysts' opinion consist out of 6 main categories range from 10 (best credit opinion category) to 60 (the worst category). A higher (lower) value indicates that the analysts' opinion gets worse (better).

In contrast, Figure VI and Table IV, column (b), show that the personal assessment of the credit analyst declines rather sharply in response to increased corporate financial transparency. In other words, credit analysts provide a more conservative opinion. Furthermore, our baseline results presented above (Table II) become insignificant once we control for the credit analyst's opinion

(Table IV, column c). The identified change in credit ratings is thus completely driven by the personal assessments of the credit analysts, and not by changes in firm fundamentals. All these results favor the reputational concerns hypothesis.

Table IV: Change in Credit Ratings Driven by the Discretionary Opinion of the Credit Analyst

	(a)	(b)	(c)
Dependent Variable:	Payment Behavior	Credit Analyst Opinion	Credit Rating – Controlling for Credit Analyst Opinion
Treated x Post	0.100	1.365***	-0.076
	(0.176)	(0.160)	(0.441)
Log Age	-0.132	0.196	-9.872***
	(0.378)	(0.221)	(0.492)
Log $Employees_{(t-1)}$	-0.085*	-0.179***	-2.990***
	(0.047)	(0.039)	(0.130)
Log $Productivity_{(t-1)}$	-0.246***	-0.103***	-0.763***
	(0.037)	(0.024)	(0.073)
Additional Control: Credit Analyst Opinion Fixed Effects	No	No	Yes
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Payment Behavior fixed effects	No	Yes	Yes
R^2	0.601	0.690	0.900
N	808,942	808,942	808,942

Notes: This table presents OLS regressions of firms' payment behavior (column a), Credit analyst's opinion (column b) and credit ratings (column c). *Treated* firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. *Post* is a dummy variable equal to 1 for all firms for the years after 2007, i.e. the period when financial statements of treated firms became publicly available. The payment behavior variable range from 1 (best payment behavior category) to 29 (worst category). The analyst opinion consist out of 6 main categories range from 10 (best credit opinion category) to 60 (the worst category). The credit rating index range from 100 (good rating) to 500 (bad rating). A positive (negative) coefficient indicates that the credit rating, payment behavior or credit analyst's opinion gets worse (better). When using an ordered probit model instead of OLS, we find similar results. Heteroscedasticity-robust standard errors are clustered at the credit rating office level and are presented in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively. Variable definitions are provided in section IV.A.

IV.C. Accuracy of Credit Ratings

One could still argue that credit analysts foresee some real changes in firm fundamentals that are not (yet) reflected in firms' payment behavior. The observed rating downgrades might then still be justified because they would stand for correctly updated believes about the true creditworthiness; consistent with the information quality hypothesis.

This explanation, however, has implications with regard to credit rating accuracy that differ from predictions based on the reputational concerns hypotheses. If the former were true, we would expect credit rating accuracy to improve,[36] while if the reputational concerns hypothesis were true, we would expect credit rating accuracy to decline. Furthermore, we would expect that the decline in accuracy stems from overly conservative opinions of the credit analysts.

To empirically test these opposing predictions we follow the recent empirical literature on the accuracy of credit ratings (Cheng and Neamtiu, 2009, Dimitrov et al., 2015). We examine how the likelihoods of Type I and Type II errors change after financial statements become publicly available. We define Type I errors to occur when a firm defaults but receives a low risk rating (credit rating < 301) in the year beforehand, and we define Type II errors to occur when a firm receives a high risk rating (credit rating >= 301) but does not default in the next year.[37] Similar like Cheng and Neamtiu (2009) and Dimitrov et al. (2015), we examine if firms default in the next year. If credit analysts were to become better at predicting defaults due to financial statement disclosure, we expect both errors to decline, whereas only Type II errors should increase if the reputational concerns hypotheses holds.

[36] Alternatively, one could also argue that credit analysts correctly infer that there are negative consequences of disclosure regulation which have a negative impact on firms' creditworthiness (but which for some reason are not (yet) reflected in payment behavior). If this is the case, one would expect that the accuracy stayed constant over the time period.

[37] Creditreform classifies their ratings in 6 main risk classes (Creditreform, 2017b): (1) Companies with very good to good credit ratings (default rate up to 0.3%) (2) Companies with good to satisfactory credit ratings (default rate between 0.3% to 0.7%) (3) Companies with satisfactory but still good credit ratings (default rate between 0.7% to 1.5%) (4) Companies with above-average risk (default rate between 1.5 to 3%) (5) High risk companies (default rate between 3 to 8%) (6) Very high risk companies (default rate above 8%). We follow their categorization and classify low risk ratings as firms in rank 1 to 4 (credit rating < 301), and high risk firms as firms in rank 5 and 6 (credit rating >= 301). We find similar results if we include firms in rank 5 into the low category, or firms in rank 4 into the high category.

The results in Table V support the reputational concerns hypotheses. Financial statement disclosure has no significant effect on Type I errors, while type-two errors are 44% more likely to occur for treated firms after the law change (absolute marginal change of 7%).[38] Firms are thus more likely to receive a speculative grade.

Since credit analysts are more likely to provide worse opinions, we also expect to find the strongest increase in Type II errors when credit analysts provide a negative opinion. Our results on the triple interaction term "treated x post x credit analyst opinion" in column (b) confirm this prediction.

[38] Probit models reveal qualitatively similar results as do models with alternative cut off values, see Appendix Table A.7.

Table V: Accuracy Model - Type I and Type II Errors

	(a)	(b)	(c)	(d)
Dependent Variable:	*Type II Errors*	*Type II Errors*	*Type I Errors*	*Type I Errors*
Treated x Post x Credit Opinion		0.003***		-0.000
		(0.001)		(0.000)
Treated x Post	0.069***	-0.022	-0.001	0.000
	(0.007)	(0.019)	(0.001)	(0.007)
Credit Opinion x Treated		0.005***		0.000
		(0.001)		(0.000)
Credit Opinion x Post		-0.000		-0.000
		(0.001)		(0.000)
Credit Opinion		0.009***		0.000
		(0.001)		(0.000)
Log Age	0.010	0.002	0.014***	0.014***
	(0.009)	(0.007)	(0.001)	(0.001)
Log Employees$_{(t-1)}$	-0.023***	-0.020***	0.002***	0.002***
	(0.002)	(0.002)	(0.000)	(0.000)
Log Productivity$_{(t-1)}$	-0.005***	-0.003***	0.000	0.000
	(0.001)	(0.001)	(0.000)	(0.000)
Firm-fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Payment Behavior fixed effects	Yes	Yes	Yes	Yes
R^2	0.666	0.697	0.441	0.441
N	808,942	808,942	808,942	808,942

Notes: This table presents linear probability models of the likelihood of a type one or type two error. We define type-one errors as firms that default, but received a low risk rating (credit rating < 301) in the year that they default, and we define type-two errors as firms that received a high risk rating (credit rating >= 301) but did not default in that year. Low risk and high risk ratings are defined according to the Creditreform conversion table (Creditreform 2017). We use all firm-year observations of firms that either default or do not default during our sample period. *Treated* firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. *Post* is dummy variable equal to 1 for all firms for the years after 2007, i.e. the period when financial statements of treated firms became publicly available. Results are similar if we use a probit model instead of linear probability model (see Table A.7 in the online Appendix). Heteroscedasticity-robust standard errors are clustered at the firm level. Robust standard errors appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively. Variable definitions are provided in section IV.A

Following the literature on credit accuracy testing (e.g. Cheng and Neamtiu, 2009; Dierkes et al., 2013), we alternatively calculate ROC curves for the treated and non-treated group, and test if the ROC areas are significantly different from each other before and after the increase in financial transparency.[39] Results are presented in Table VI.

Table VI: Accuracy Model - Predictive Power of Credit Ratings on Default

Panel A: ROC Curves of *Treated firms* in pre- and post-period					
Years	Observations	ROC Area	Std. Err.	-Asymptotic Normal- [95% Conf. Interval]	
2004-2006	347,525	0.7849	0.0040	0.777	0.793
2008-2010	328,791	0.7398	0.0029	0.734	0.745
Ho: area(2004-2006) = area(2008-2010)	Chi2(1)=	82.90			Prob>chi2 = 0.000
Panel B: ROC Curves of *Non-Treated Firms* in pre- and post-period					
Years	Observations	ROC Area	Std. Err.	-Asymptotic Normal- [95% Conf. Interval]	
2004-2006	11,984	0.8948	0.0125	0.870	0.919
2008-2010	7,870	0.8704	0.0103	0.850	0.891
Ho: area(2004-2006) = area(2008-2010)	Chi2(1)=	2.29			Prob>chi2 = 0.131

Notes: We split the sample in treated and non-treated firms, and compare the predictive power of the Credit Rating on default in the pre- or post-period for each group. For the two groups, we estimate a logit model where we regress default on the credit rating, and calculate the ROC curve. Next, we test if the area below the ROC curve is statistical different between the pre and post-period for both the treated and non-treated group. *Treated* firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. Variable definitions are provided in section IV.A.

Consistent with the increase in type-two errors, the area under the ROC curve significantly decreases by 5.75% for the treated firms after they made their financial statements publically available (0.7849 to 0.7398). The ROC areas of the non-treated firms, however, do not change in

[39] Specifically, we split the sample between the treated and non-treated firms and compare the predictive power of credit analyst opinion on default in the pre- or post-period for each group. For the treated and non-treated group, we estimate separate logit models where we regress default on the credit rating and calculate the ROC curve. Next, we test if the area below the ROC curve is statistical different between the pre and post-period for both the treated and non-treated group.

a statistically significant way, and the descriptive decrease is not even half as large. Further note that the availability of firm financials improves the accuracy of credit ratings, after controlling for the subjective assessments of analysts (unreported). Overall, our accuracy tests suggest that the predictive power of the credit rating decreases in response to financial statement disclosures, which contradicts the ‘information quality hypothesis’ or ‘real consequences hypothesis’ and supports the ‘reputational concerns hypothesis’.

IV.D. Cross-sectional Evidence

Investment Grades vs. Speculative Grades

The results of the baseline regressions show that credit analysts provide more conservative ratings that are less accurate when firms have to publicly disclose financial information. In the following sections, we provide futher support for the reputational concerns channel by looking at cross sections where we would expect stronger reputational effects.

Prior literature suggests that overrating is more costly than underrating (i.e. not being able to predict a default; see e.g. Bolton, Freixas, and Shapiro, 2012). This is because overly optimistic ratings of eventually defaulting firms are easier to ascertain and more costly to clients than overly pessimistic ratings (Xia, 2014).

Given this asymmetry documented in prior literature, reputational concerns should especially increase for firms with speculative grades (i.e. firms that are more likely to default). The intuition is that clients will hardly complain about firms that receive a speculative rating but remain solvent, while any rating of a firm that defaults will be prone to alleged overrating. Since the group of firms with speculative grades are by definition more likely to default, credit analysts should be most concerned about this group of firms. Technically, this is driven by a non-linear relation between initial default risk and the increase in reputational costs of rating failures; and the effect is reinforced if the credit rating has a direct influence on the performance of the rated firm (Mariano, 2012). Under this assumption, bad ratings tend to be self-fulfilling. They will more likely turn out being correct regardless of whether the firm is actually good or not, whereas good ratings only turn out being correct if the firm is indeed a good one. Hence, the more likely the analyst will be blamed for rating failures the higher the incentive to issue a conservative rating.

In addition, reputational costs particularly increase when firms release a negative signal through their public financial statement. In such cases, when an analyst made a rating failure, clients may believe that the analyst does not properly take into account negative information, or that the private information that the CRA possesses is of no additional value. Anticipating such criticism, credit analysts are more likely to follow the public signal if firms disclose negative news. Since firms with speculative grades are more likely to disclose negative news in public financial statements, and are more likely to default, we would expect more conservative reactions the higher the ex-ante likelihood of default.

To test this conjecture empirically, we estimate quantile regressions. Table VII presents the results. With regard to the top 10% percentile (Table VII, column a) and 25% quartile (Table VII, column b), we find an insignificant positive effect of financial statement disclosure on credit ratings. Put differently, firms with an investment grade, do not receive a significantly worse rating after providing financial information to the public compared to firms that do not disclose financial information to the public.

The median results are slightly larger than the average results obtained from OLS regressions. For firms in the lowest quartile of the credit rating distribution (Table VII, column d and e), we find significantly larger downgrades of credit ratings. In the lowest 10% percentile of the credit rating distribution (Table VII, column e), firms' creditworthiness declines by almost 15 points, corresponding to a relative decline of approximately 6%. Appendix, Table A.8 shows that this is equal to an increase of one notch on the S&P index for every two firms.

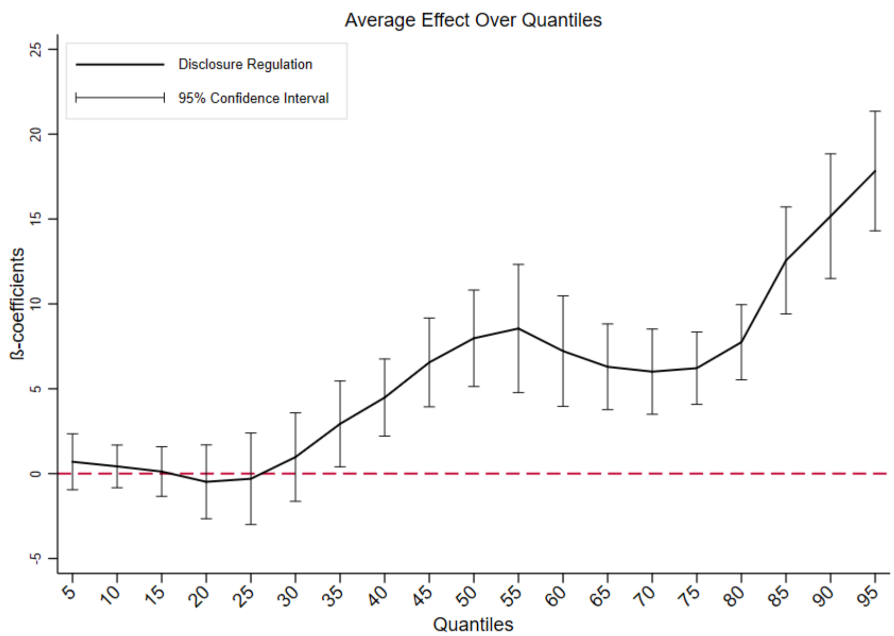
Table VII: Quantile Regressions - The Impact of Financial Statement Disclosure on Credit Ratings across the Credit Rating Distribution

Quantiles:	(a) 10%	(b) 25%	(c) 50%	(d) 75%	(e) 90%
Credit Rating Value at the Quantile:	*CR: 192*	*CR: 220*	*CR: 255*	*CR: 286*	*CR: 326*
Dependent Variable: Credit Rating					
Treated x Post	0.424	-0.305	7.973***	6.212***	15.168***
	(0.642)	(1.376)	(1.450)	(1.089)	(1.872)
Log Age	-10.024***	-12.243***	-7.910***	-8.353***	-6.723***
	(1.356)	(1.935)	(2.645)	(2.298)	(2.026)
Log Employees$_{(t-1)}$	-3.211***	-3.902***	-3.845***	-1.864*	-1.433
	(0.636)	(0.709)	(0.770)	(1.119)	(0.989)
Log Productivity$_{(t-1)}$	-2.665***	-1.520***	-0.890**	0.262	0.243
	(0.443)	(0.427)	(0.424)	(0.650)	(0.392)
Pseudo Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Ind. fixed effects	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes
Payment Behavior fixed effects	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2	0.619	0.663	0.674	0.678	0.652
N	42,608	42,608	42,608	42,608	42,608

Notes: This table presents quantile regressions of firms' credit ratings. We estimate quantile regressions with pseudo firm-fixed effects using the Mundlak-Chamberlain device as proposed by Wooldridge (2010). Time-invariant variables are included in the model, but not reported. *Treated* firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. *Post* is dummy variable equal to 1 for all firms for the years after 2007, i.e. the period when financial statements of treated firms became publicly available. The credit rating index range from 100 (good rating) to 500 (bad rating). A positive (negative) coefficient indicates that the credit rating gets worse (better). We use Parente-Santos Silva clustered-standard errors as proposed by Wooldridge (2010), which are presented in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively. Variable definitions are provided in section IV.A.

Figure VII illustrates the varying effect sizes graphically. It shows a zero-effect for firms with the best ratings (i.e., investment grades), and an almost monotonic increase for firms up to the worst ratings (i.e., speculative grades). The revealed heterogeneity is consistent with the reputational concerns hypothesis. The higher the risk of an alleged rating failure the more pronounced the credit rating downgrade.

Figure VII: Coefficients of Impact of Disclosure Regulation on Credit Rating for each Quantile Regressions



This figure plots the estimated impact of disclosure regulation on credit rating for each percentile of the credit rating distribution using quantile regressions. We extend equation (1) to a quantile regression, and include pseudo firm-fixed effects using the Mundlak-Chamberlain device as proposed by Wooldridge (2010). The solid black line shows the β coefficients of the 5^{th} to 95^{th} quantile regression. The vertical bands represent 95% confidence intervals for each ventile. The credit rating index ranges from 100 (good rating) to 500 (bad rating). A higher (lower) coefficient indicates that the credit rating gets worse (better).

Public information vs Private information

Another implication of the reputational concerns mechanism is that credit analysts become particularly afraid of using positive private information about a firm's creditworthiness. To test this prediction, we draw on information on the payment behavior of firms, which the CRA privately collects and that are not publicly available. Based on this information we construct a dummy variable that indicates particularly well payment behavior, i.e. all firms that pay on time, against firms where the payment behavior variable indicates target overshoots. Using this dummy, we assess a potential weakening in the mediating effect of positive private information by extending our model with these variables plus the interaction term of post, treated and the positive private information variable. This results in the following specification:

$$\begin{aligned} Credit\ Ratings_{i,t} \\ &= \beta_1\ Private\ Information_{i,t} + \beta_2\ Treated_i \cdot\ Post_t \cdot Private\ Information_{i,t} \\ &+ \beta_3\ Treated_i \cdot\ Post_t + \beta_4\ Post_t \cdot Private\ Information_i\ + \gamma' X_{i,t} + \gamma' X_{i,t} \cdot\ Post_t \\ &+ Ind_i \cdot\ t + \ \delta_t\ + f_i + \ \varepsilon_{i,t} \end{aligned} \tag{5}$$

If our informal reasoning is true, we would expect to find β_1 being negative and β_2 being positive while $\beta_2 < (-1) \cdot \beta_1$, i.e. the more positive the private information, the more positive the credit rating but the relation weakens once firms make financial statements publicly available.

Table VIII, columns a and b, confirms this conjecture. On average, positive private information leads to a better rating but this effect is mitigated once firms make their financial statements publicly available. Splitting the sample into firms with investment grades (column c) and those with speculative grades (column d) further reveals that the effect is mainly driven by the latter group of firms. These results are again consistent with the previously presented results and confirm another implication of the reputational concerns hypothesis. Analysts put less weight on private information and more weight on publicly available information after the reform, consistent with the predictions of herding models and more recent theories predicting that public information may crowd out private information (e.g. Morris and Shin, 2002; Angeletos and Pavan, 2007; James and Lawler, 2011; Goldstein and Yang, 2017, 2018)

Table VIII: The Impact of Financial Statement Disclosure on Credit Ratings: Positive Private Information is Less Likely to Influence The Credit Rating

	(a)	(b)	(c)	(d)
	All Firms	All Firms	Firms with investment grades	Firms with speculative grades
Dependent Variable: Credit Rating				
Treated x Post x Private Information		13.705***	4.628	12.901***
		(4.329)	(6.397)	(4.440)
Private Information	-78.388***	-77.851***	-7.524***	-68.794***
	(1.366)	(3.891)	(2.445)	(3.832)
Post x Private Information		-20.804***	-9.277	-14.147***
		(4.234)	(6.187)	(4.179)
Treated x Private Information		3.480	5.659**	-1.238
		(3.256)	(2.787)	(3.374)
Treated x Post	3.151***	-9.073**	-6.339	-6.350
	(0.785)	(4.262)	(6.530)	(4.394)
Log Age	-8.207***	-8.338***	-14.137***	-1.992*
	(1.503)	(1.508)	(0.838)	(1.090)
Log Employees$_{(t-1)}$	-4.326***	-4.276***	-2.689***	-1.754***
	(0.217)	(0.218)	(0.186)	(0.248)
Log Productivity$_{(t-1)}$	-1.504***	-1.491***	-0.938***	-0.305***
	(0.130)	(0.130)	(0.105)	(0.116)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Implied	Implied	Implied	Implied
Region fixed effects	Implied	Implied	Implied	Implied
R^2	0.800	0.800	0.797	0.777
N	808,942	808,942	399,651	409,291

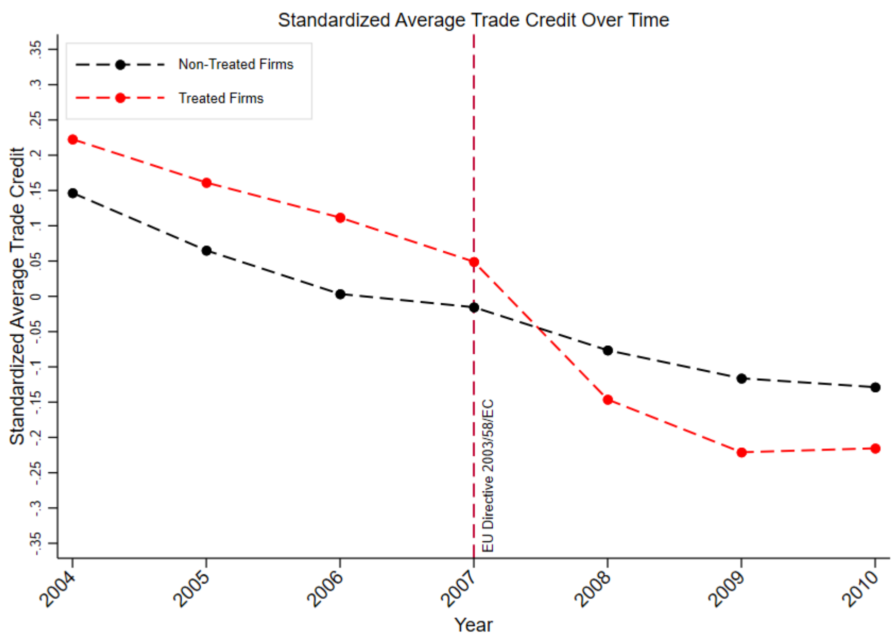
Notes: This table presents OLS regressions of firms' credit ratings. 'Private information' is a dummy variable constructed out of the categorical variable 'payment behavior', and is equal to 1 when there are no payment problems reported, 0 when there is at least one payment delay reported of at least 30 days. *Treated* firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. *Post* is dummy variable equal to 1 for all firms for the years after 2007, i.e. the period when financial statements of treated firms became publicly available. The credit rating index range from 100 (good rating) to 500 (bad rating). A positive (negative) coefficient indicates that the credit rating gets worse (better). Heteroscedasticity-robust standard errors are clustered at the credit office level and appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively. Variable definitions are provided in section IV.A.

IV.E. Economic relevance

To get a better feeling of the economic relevance of the estimated changes in firms' credit ratings, we examine firms' ability to attract trade credit, which is one of the most important sources of external finance for private firms (Deutsche Bundesbank, 2012).

In particular, we draw on the amount of trade credit the analysts recommend to provide to a given firm. Since suppliers buy credit reports to determine the amount of trade credit they provide, the amount that the credit analysts recommend should be highly correlated with the amount of trade credit suppliers actually provide.[40] Figure VIII illustrates how the volume of trade credit changes over time for treated and untreated firms.

Figure VIII: Trade Credit over Time



This figure shows the standardized average recommended amount of trade credit over time for the Treated and Non-Treated firms. *Treated* firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements.

We observe a decline in recommended trade credit volume for treated firms, commensurate with the drop in credit ratings. On average, firms appear to receive 6.47% less trade credit once

[40] When we examined the correlation between the recommended amount of trade credit, and the amount of trade that is disclosed in the financial statements (in the post period for the treated firms) we find a strong correlation of 0.62.

they disclose financial statements to the public.[41] Noteworthy, we examine the impact on the *recommended amount* of trade credit. If suppliers and banks take into account that credit ratings on average became worse because of reputational concerns and not because of changes in fundamentals, we would expect the effect on the actual amount of credit to be mitigated (Baghai et al., 2014).

IV.F. Alternative Explanations

Banking Channel

We also examine several alternative mechanisms that could potentially explain the increase in credit rating downgrades (but not all other results). Two prior studies have shown that disclosure regulation can influence a firm's ability to attract debt (Hertzberg et al., 2011; Breuer et al., 2017). Hertzberg et al. (2011) show that firms with multiple bank relationships receive less credit when firm specific negative information that is privately available to certain lenders becomes publicly available. Involved banks will reduce credit to these firms in anticipation of other lenders' reactions to negative news. Public information thus exacerbates lender coordination and increases the incidence of financial distress.

Similarly, Breuer et al. (2017) show that the availability of public financial statements allows banks to shift from relationship approaches to transactional approaches. This leads to an ex-ante differentiation of firms based on their risk profiles. It improves access to finance for low-risk

[41] According to the Bundesbank the total amount of trade credit provided in Germany is €345.2 billion, averaged over 2001 to 2009. It is the second most important external financing instrument used by non-financial corporations after intergroup loans (€399.4 billion). Measured in terms of the balance sheet total, trade credit reached a ratio of 15.8%, and long and short-term borrowing from banks is one percentage point lower.

firms, while it cuts options for high-risk firms. Some of our results could thus be driven by changes in bank behavior.[42]

To examine if these alternative explanations translate to changes in credit ratings, we run two additional tests. In the first test, we use the same setup as in Hertzeberg et al. (2011), i.e. we compare the effects for firms that rely on a single relationship lender with firms that rely on multiple relationship lenders.[43] If our results would be explained by a change in coordination costs, we expect to find no effect on credit ratings for firms with a single relationship lender.

To check if our results are explained by a shift in banking from relationship to transactional approaches, we examine if differences exist between young and old firms. Especially for young firms, disclosure regulation could make it easier for firms to commit to transparency and hence to obtain funding (see e.g. Leuz and Wysocki, 2008, 2016). In addition, young firms did not have time to build up any long-term relationships with banks yet and it is thus harder for these firms to make a credible disclosure commitment. If disclosure regulation increases the credibility of financial statement disclosures, and at the same time leads banks to shift towards transactional lending techniques (Breuer et al., 2017), we would expect that mainly young firms would benefit. While older firms that are more likely to have a long-term relationship with a lender may potentially lose relationship-specific benefits due to loss of private information by the bank.[44]

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[42] These changes could in principal be rightfully anticipated by credit analysts and in turn bias the estimated change in credit ratings we observe. Note, however, that if this mechanism would be the driving channel, we should observe actual changes in payment behavior and no increase in type-two errors, which we actually do find.

[43] The database of the credit rating agencies contains the six closest bank relationship of a firm.

[44] Alternatively, we split our sample into high-risk, normal and low-risk firms. Directly following the approach of Breuer et al. (2017), we classify firms as “high-risk” if their standard deviation of return on assets is in the top tercile of the risk distribution and “low-risk” if their standard deviation of return on assets is in the bottom tercile. If this channel would drive our results, we would expect to find a positive effect for high-risk firms, and a negative effect for low-risk firms. Similar as in Table A.9, we do not find evidence that there is a different impact on credit ratings for high vs low risk firms.

The results are presented in the Appendix Table A.9. When we compare single vs. relationship lenders, we observe small and insignificant differences between coefficients, suggesting that the coordination of banks does not drive our previous estimates. Second, when we compare young vs. old firms we again find an insignificant difference between both subsamples. Hence, neither the coordination cost nor the bank channel find empirical support. Such an insignificant effect of these channels on credit ratings could be explained by the fact that CRAs emphasize mainly fundamental credit risk and put relatively little weight in their credit analysis process on a company's credit risk in the short term (see e.g. Frost, 2007).

Competition Channel

Bernard (2016) and Breuer (2018) show that disclosure regulation fosters competition among firms, which may have negative consequences on profitability and may thus lead to worse credit ratings. To assess if our results are driven by changes in competition, we split our sample in subsamples where industry-specific competition is fiercer. Specifically, we calculate the Herfindahl index and split on the median. Alternatively, we calculate the (weighted) number of firms that disclosed in the pre-treatment period within each industry-district classification.[45] We split the sample in two equal subsamples using this variable. We thus compare firms that were already operating in a transparent environment against companies in an opaque environment. Table A.10 in the Appendix summarizes the results. In all subsamples, we find a statistically similar

[45] We also used alternative approaches proposed by Breuer (2018) and split the sample using the total number of firms in the pretreatment period. In addition, we also calculate the (weighted) difference in number of firms across the pre and post treatment period within each industry-district classification to examine the impact of induced competition due to disclosure. We split the sample in three equal subsamples using this variable: One section includes firms that operate in an industry-region where there is a net-exit (average of 12% reduction in firms), the second group of firms are firms operating in relatively stable industry (between -2% decrease and 2% increase of firms), and one group where there is a net-entry of firms (average of 19%). Using these measures, we find similar results as presented in Appendix Table A.10.

increase in credit ratings. Changes in competition do not seem to lead to changes in credit ratings, mitigating concerns that our previous results are driven by product market competition or predation risk.[46]

Switching Legal Forms

Prior research has shown that firms delist from public stock exchanges to avoid requirements to publish detailed financial information (Bushee and Leuz, 2005). Hence, a potential concern could be that private firms circumvent publishing financial statements by changing their legal form. If this were to apply specifically to firms with a low (high) creditworthiness, our results could well be biased upwards (downwards). Table A.11 in the Appendix shows, however, that switches are rather low in absolute numbers and there is no clear trend in switches from treated group to control group, and vice versa, over time.

Change in the credit rating model?

One last alternative explanation is that the CRA made a forecastable error, and once the CRA receives more information, it realized it made a mistake, which leads to an increase in rating downgrades. Standard information economics shows that (absent forecastable errors) an increase in quality and quantity of information would *not* lead to an *average* worse rating for firms. It could lead to an improvement in the accuracy of ratings, which we tested and rejected above, but one would not expect a change in the *average* ratings for firms. This is because the CRA should

[46] Prior research showed that an increase in competition among credit rating agencies also leads to more conservative ratings (e.g. Xia, 2014) and financial statement disclosures could potentially attract new CRAs to enter the market. After intensive searches, though, we did not find any new player that entered the German credit rating market though. Creditreform reports to have a stable market share of 70%, and continued to strengthen its position as a leader in the German business information business over the sampling period (Creditreform 2007/2010).

rationally infer the quality of the information that are disclosed to them based on observed failures and successes. Over time, it can thus rationally infer what the quality of the information is that is disclosed and can take into account the average concealment in their ratings. Moreover, if an improvement in quality of information would drive our results, it would also imply that the credit rating agency would not rationally infer that the non-disclosing firms would have acted in a similar way. In other words, they did not only made a forecastable error on the treated firms in the pre-treatment period, but would also not have realized that the non-treated group of firms act in a similar way in the post period. Otherwise, we would have observed an equal increase in ratings for these firms.[47]

To examine if the CRA made such a forecastable error, and in turn changes his credit rating model, we examine how the credit ratings of firms change over time when keeping the emulated version of their credit rating model constant.

$$\begin{aligned} Credit\ Rating_{i,t} &= \beta_1 \cdot Treated_i + \beta_2 \cdot\ Payment\ Behaviour_{it} + \beta_3 \cdot\ Sales_{it} + \beta_3 \\ &\cdot\ Employees_{it} + \beta_3 \cdot\ Age_{it} \\ &+ +\gamma' Financial\ Statement\ Variables\ _{it} \\ &+ \gamma' Dummies\ for\ missing\ Financial\ Statement\ Variables_{it}\ + f_i \\ &+\ \varepsilon_{i,t} \end{aligned} \tag{6}$$

[47] In addition, such a result would also be inconsistent with the result that the increase in credit ratings is completely driven by the credit analysts' personal assessment. If real changes occurred, we would still have observed an effect on credit ratings while controlling for the credit analysts opinion.

Specifically, we emulate the credit rating model based on all information that is available to the CRA in the pre-treatment period. We include in the model all basic information, such as sales, employees, age, industry, as well as all accounting variables available in the financial statements and dummy variables for when this information is missing.[48]

As a first step, we use solely data from the pre-treatment period, and regress the credit ratings that firms receive on all financial information available. Using the coefficients we get from this model, we can predict the credit ratings that firms would receive in the post period, while holding the credit rating model constant. We then re-estimate our base line model but now use the *predicted* credit ratings to see if we observe similar changes across time between our treated and non-treated group. If the CRA did not take into account the average concealment in the market, the *estimated* credit ratings should get worse. This would occur because now on *average* less positive financial statement information will be loaded into the model in the post period, which would lead to lower credit ratings. While if the coefficients of our financial statement variables already take into account that firms may provide fraudulent information, we would not expect any increase.

Results are presented in Table IX, Column a. When we hold the credit rating model constant and estimate how the predicted credit ratings change over time for our treated and control group, we find an insignificant coefficient that is close to zero. In other words, the increase in downgrades observed in our main analyses is not driven by a mechanical effect due to an increase in available information, or an increase in quality of the accounting information.

[48] For roughly 25% of both the treated and non-treated firms we observe financial statement information in the pretreatment period. These firms disclosed financial statement information through private channels to the CRA. The observations where we do not observe accounting information, we impute these variables by -9. To control for these missing variables, we include a dummy variable for each financial statement variable that is missing, which is equal to 1 if the information is missing, 0 otherwise. We used various specification to test this model, such as including polynomials, log transformations, and scaling variables by sales or employees, which lead to similar results.
When we estimate this model, the accounting variables load as expected. For example, having more equity, assets and/or receivables improves your credit rating, while having more overall debt and trade credit payables leads to worse credit ratings. Missing information also have a strong significant impact on the credit rating.

Table IX: Reconstructing Credit Rating Model

	Estimated Credit Rating based on financial statement information	Estimated Credit Rating based on financial statement information and the credit analyst opinion
Dependent variable: Estimated Credit Rating		
Treated x Post	0.300	2.673***
	(0.357)	(0.562)
Log Age	-0.076	2.676***
	(0.758)	(0.986)
Log $\text{Employees}_{(t-1)}$	-0.194**	-0.495***
	(0.096)	(0.128)
Log $\text{Productivity}_{(t-1)}$	-0.526***	-0.804***
	(0.075)	(0.083)
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
Industry fixed effects	Implied	Implied
Region fixed effects	Implied	Implied
R^2	0.945	0.875
N	808,942	808,942

Notes: This table presents OLS regressions of firms' estimated credit ratings. As a first step, we use data from the pre-treatment period, and regress the credit ratings that firms receive on all financial information available (untabulated). Using the coefficients we get from this model, we can predict the credit ratings that firms would receive in the post period, while holding the credit rating model constant. We then re-estimate our base line model but now use the *predicted* credit ratings to see if we observe similar changes across time between our treated and non-treated group. Results in column (a) is when we regress in the first step credit ratings on all financial information, except the credit analyst's opinion. In Column (b) we included the analyst's opinion as an explanatory variable to estimate the credit ratings. Treated firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. *Post* is dummy variable equal to 1 for all firms for the years after 2007, i.e. the period when financial statements of treated firms became publicly available. The estimated credit rating index range from 100 (good rating) to 500 (bad rating). A positive (negative) coefficient indicates that the credit rating gets worse (better). Heteroscedasticity-robust standard errors are clustered at the credit office level. Robust standard errors appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively. Variable definitions are provided in section IV.A.

Note that in the previous model we did not include the credit analyst's opinion as an explanatory variable to estimate the predicted credit ratings. In column b of Table IX, we take the same approach as in column a, but now include the credit analyst's opinion as an additional explanatory variable in equation (6) to estimate the predicted credit ratings. Hence, we again hold the credit market model constant over time, but now include the analyst's opinion as an additional variable to explain the credit ratings. Using the model that incorporates credit analyst's opinion, we would expect to find an increase in the predicted credit ratings. In other words, we expect that in the post time period, credit analysts will provide on average worse opinions, which leads to worse credit ratings, while keeping the rating model constant. Column b of Table IX shows consistent evidence with our prior results. The predicted credit ratings increase for our treated firms after the law change. Overall, these results suggest that when we hold the credit rating model constant, the increase in credit rating downgrades we observe is induced by worse credit analysts' opinions, and not by changes in the credit rating model, or changes in the information content that becomes available to the CRA.

Sensitivity Checks

Finally, we ran various sensitivity checks. Bertrand, Duflo, and Mullainathan (2004) show that auto-correlation in DiD setups can artificially decrease standard errors. In our main analyses, we take this into account by clustering at a higher order, the credit rating office level. As an additional test, we change the time frame into a two time-period structure, which reveals the same results in qualitative terms. Next, we control for firm-specific time trends instead of industry-specific time trends and include year-industry-region fixed effects instead of year-fixed effects. Including these additional controls do not alter results (see Appendix, Table A.12). Next, we examine how robust our results are to different sample compositions. Therefore, we exclude medium-sized firms, reintroduce the largest firms, including firms that voluntarily disclose to the public while controlling for voluntary disclosure, and use different matching algorithms such as Coarsened Exact Matching instead of Propensity Score Matching. All our results are robust to these alterative sample compositions and model specifications.

IV.G. Discussion

There is a strong tendency in public debates to favor calls for increasing corporate (financial) transparency. Claims are fueled by declining costs of information production and dissemination, and the assumption that more transparency has unambiguously positive effects on the information environment. More information should improve risk assessments, help to avoid financial crises, and spur investments.

At the same time, theoretical work points out that more public information can have adverse effects on the information environment and investment decisions (Goldstein and Yang, 2017, 2018). Until now there was little evidence, however, that would support those arguments in a broad and real world setup.

When interpreting the results, it is important to keep in mind that we examined the impact of a mandatory financial statement disclosure regulation on credit ratings. Whether disclosure regulation is overall beneficial or costly for private firms is still not clear (see e.g. Goldstein and Yang, 2017, 2018, and Minnis and Shroff, 2017, for a discussion). Far more evidence is needed to understand the full economic consequences of mandatory disclosure.

Another important aspect to be noted is that, due to our private firm setting, we could not examine a potential change in the impact of credit ratings on investment decisions or whether credit ratings' predictability of stock prices weakens. In principal, it could well be that the market anticipated the observed change in credit rating quality, and automatically corrected for the lower quality. Prior evidence suggests, however, that the market only partly undoes the impact of conservatism on debt prices (Baghai et al., 2012).

In our setting, we focus on changes in how an "investor-pays" CRA assess private firms' creditworthiness. Given the scope of our paper, we are unable to test if similar effects exists for "issuer-pays" CRAs, such as Moody's, S&P and Fitch. However, there are reasons to believe that the reputational concern mechanism may also play a role for "issuer-pays" CRAs. For example, An, Cordell and Nichols (2019) shows suggestive evidence of herding behavior between Moody's, S&P and Fitch in the CMBS market. They find evidence that these CRAs tend to adjust their rating if another CRA had changed its rating on the same bond in the previous period. They are thus more likely to follow the public consensus and ignore their private information, which should reduce the accuracy of their ratings. In contrast, Badoer and Demiroglu, (2018) and Neilson, Ryan, Wang and Xie, (2019) show evidence that an increase in transparency may discipline "issuer-pays" CRAs, and thereby reduce their ability to cater to the demands of the issuer - an inherent problem to the issuer-pays model (see e.g. Jiang, Stanford, and Xie, 2012; Griffin Nickerson, and Tang, 2013; Xia, 2013; Piccolo and Shapiro, 2017). In our setting such a discipline mechanism is absent because investors instead of issuers pay for the credit rating. More evidence is thus needed to examine which mechanism dominates in an "issuer-pays" setting.

Finally, the observed decline in credit rating quality could theoretically be corrected by intensified competition among credit rating agencies. Similar to many other countries, the German market for credit ratings of private firms is highly concentrated with one dominant player and only a few much smaller players. Competition is best characterized as a quasi-monopoly or oligopoly. In such a setting, credit rating agencies will be less worried about declining rating accuracy. Furthermore, typical customers are not investors in financial markets who keep track of every little detail that determines their return on investment, rather, they are managers of private firms who want to determine how much trade credit to provide to their customers. These firms are typically more worried about losing their trade credit to a defaulting firm than about the optimal amount of trade credit provided to a solvent client. These circumstances facilitate the reputational concerns mechanism which in turn leads to more conservative ratings.

Lastly, we want to highlight that regulators should carefully consider all channels through which disclosure regulation impacts the economic environment. Though our study shows that disclosure regulation can have unintended negative consequences on the accuracy of credit ratings, it may have positive consequences with regard to other unexamined variables.

V. Summary and Conclusion

This study demonstrated how increased corporate financial transparency influences credit ratings. Theory predicts a positive information quality effect but also an adverse reputational concerns effect, because credit analysts become increasingly concerned about alleged rating failures. Evidence favors the latter mechanism. Consistent with the reputational concerns hypothesis, the empirical examination first demonstrated that disclosing firms receive on average a worse credit rating. We then showed that the observed rating downgrades do not correspond to equivalent declines in creditworthiness. Indeed, rating accuracy declined because erroneous default warnings increased and positive private information was less likely to positively influence ratings. Further, rating downgrades were entirely driven by worsened discretionary assessments of credit rating analysts rather than changes in firm fundamentals. Quantile regressions revealed that the average effect is largely driven by firms with speculative grades; firms received stronger rating downgrades the higher their initial risk of default. All these results support the reputational concerns mechanism. We showed that the results cannot be explained by alternative mechanisms, including changes in coordination costs, the banking system, strategic choices of legal forms, or changes in the rating model. The conclusion is that regulatory ambitions towards increased corporate financial transparency unintendedly contributed to credit rating conservatism.

Our examination informs the debate on how to improve the information environment, enable more accurate risk assessments, and resolve market frictions. The conventional wisdom is that increased corporate transparency unambiguously improves the information environment and levels the playing field. This wisdom and the increasing ease of digitalization, which minimizes the costs of information production and dissemination, fuel regulatory ambitions towards ever more transparency. We show, however, that increased transparency may unintendedly inhibit more accurate risk assessments. It is thus important to carefully consider not only the benefits of corporate financial transparency but also its costs.

References

Ang, James S., James Wuh Lin, and Floyd Tyler. "Evidence on the lack of separation between business and personal risks among small businesses." *Journal of Small Business Finance, no. 4*, no. 2/3 (1995): 197-210.

Angeletos, George-Marios, and Alessandro Pavan. "Efficient use of information and social value of information." *Econometrica* 75, no. 4 (2007), 1103-1142.

Alp, Aysun. "Structural shifts in credit rating standards." *The Journal of Finance* 68, no. 6 (2013): 2435-2470.

Baghai, Ramin P., Henri Servaes, and Ane Tamayo. "Have rating agencies become more conservative? Implications for capital structure and debt pricing." *The Journal of Finance* 69, no. 5 (2014): 1961-2005.

Ballwieser, Wolfgang, and Ralf Hager, *Das Bilanzierungsverhalten mittelgroßer Kapitalgesellschaften.* In: Chmielewicz, Klaus; Forster, Karl-Heinz. Unternehmensverfassung und Rechnungslegung in der EG. Düsseldorf (1991).

Banerjee, Snehal, Jesse Davis, and Naveen Gondhi. "When transparency improves, must prices reflect fundamentals better?" *The Review of Financial Studies* 31, no. 6 (2018): 2377-2414.

Berger, Allen N., and W. Scott Frame. "Small business credit scoring and credit availability." *Journal of Small Business Management* 45, no. 1 (2007): 5-22.

Berger, Allen N., and Gregory F. Udell. "A more complete conceptual framework for SME finance." *Journal of Banking & Finance* 30, no. 11 (2006): 2945-2966.

Bernard, Darren. "Is the risk of product market predation a cost of disclosure?" *Journal of Accounting and Economics* 62, no. 2-3 (2016): 305-325.

Bersch, Johannes, Sandra Gottschalk, Bettina Müller, and Michaela Niefert, "The Mannheim Enterprise Panel (MEP) and firm statistics for Germany," ZEW-Centre for European Economic Research Discussion Paper 14-104, (2014).

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan. "How much should we trust differences-in-differences estimates?" *The Quarterly Journal of Economics* 119, no. 1 (2004): 249-275.

Bolton, Patrick, Xavier Freixas, and Joel Shapiro. "The credit ratings game." *The Journal of Finance* 67, no. 1 (2012): 85-111.

Breuer, Matthias, Katharina Hombach, and Maximilian A. Müller. "How does financial reporting regulation affect firms' banking." *Review of Financial Studies* 31, no. 4 (2017):1265-1297.

Breuer, Matthias. "How does financial-reporting regulation affect market-wide resource allocation? " University of Chicago Working Paper (2018).

Brown, Nerissa C., Wei, Kelsey D., and Russ Wermers. Analyst Recommendations, Mutual Fund Herding, and Overreaction in Stock Prices. Mangement Science 60, no. 1 (2014):1-20.

Bouvard, Matthieu, and Raphael Levy. "Two-sided reputation in certification markets." *Management Science*, *Forthcoming* (2017).

Bushee, Brian J., and Christian Leuz. "Economic consequences of SEC disclosure regulation: evidence from the OTC bulletin board." *Journal of Accounting and Economics* 39, no. 2 (2005): 233-264.

Bundesanzeiger, *Report on the German Company Register*, 2011, Retrieved from http://www.ecrforum.org/wp-content/uploads/2013/2011%20Germany/Presentations/heinig-german-company-register.pdf.

Cerqueiro, Geraldo, and María Fabiana Penas. "How Does Personal Bankruptcy Law Affect Startups?." *The Review of Financial Studies* 30, no. 7 (2016): 2523-2554.

Cheng, Mei, and Monica Neamtiu. "An empirical analysis of changes in credit rating properties: Timeliness, accuracy and volatility." *Journal of Accounting and Economics* 47, no. 1-2 (2009): 108-130.

Cheng, Lin, Scott Liao, and Haiwen Zhang. "The commitment effect versus information effect of disclosure—Evidence from smaller reporting companies." *The Accounting Review* 88, no. 4 (2013): 1239-1263.

Clement, Michael B., and Senyo Y. Tse. "Financial analyst characteristics and herding behavior in forecasting." *The Journal of Finance* 60, no. 1 (2005): 307-341.

Correia, Sergio. "Singletons, cluster-robust standard errors and fixed effects: A bad mix." Duke University Working Paper (2015).

Creditreform, *Annual Report*, 2007, Retrieved from https://www.creditreform.de/fileadmin/user_upload/crefo/download_de/news_termine/jahresbericht_presse/Jahresbericht_2007-08_englisch.pdf

———, *Annual Report*, 2010, Retrieved from https://www.creditreform.com/fileadmin/user_upload/CR-International/Jahresbericht/Creditreform_Jahresbericht_2009-10_englisch.pdf

———, *Bonitaet-index*, 2017a, Retrieved from http://www.dresdencreditreform.de/auskunft/boni/index.html

———, *Creditreform Rating Map*, 2017b, Retrieved from https://www.creditreform.de/microsites/creditreform-ratingmap-deutschland.html

Deutsche Bundelsbank. "The importance of trade credit for corporate financing in Germany – evidence from financial statements statistics." (2012) Retreived from: https://www.bundesbank.de/Redaktion/EN/Downloads/Publications/Monthly_Report_Articles/2012/2012_10_trade.pdf?__blob=publicationFile

Dichev, Ilia D., and Joseph D. Piotroski. "The long-run stock returns following bond ratings changes." *The Journal of Finance* 56, no. 1 (2001): 173-203.

Dimitrov, Valentin, Darius Palia, and Leo Tang. "Impact of the Dodd-Frank act on credit ratings." *Journal of Financial Economics* 115, no. 3 (2015): 505-520.

Eierle, B., "Filing Practice of Small and Medium-sized Companies Empirical Findings from Austria." *International Small Business Journal, 26* (2008), 491-528

Ederington, Louis H., and Jeremy C. Goh. "Bond rating agencies and stock analysts: who knows what when?" *Journal of Financial and Quantitative Analysis* 33, no. 4 (1998): 569-585.

Edmans, Alex, Mirko S. Heinle, and Chong Huang. "The real costs of financial efficiency when some information is soft." *Review of Finance* 20, no. 6 (2016): 2151-2182.

Easterbrook, Frank H., and Daniel R. Fischel. "Mandatory disclosure and the protection of investors." *Virginia Law Review* (1984): 669-715.

European Commision, Commission Staff Working Document - European Financial Stability and Integration Report (2012), retrieved from https://ec.europa.eu/info/system/files/efsir-2012-25042013_en.pdf

Fracassi, Cesare, Stefan Petry, and Geoffrey Tate. "Does rating analyst subjectivity affect corporate debt pricing?." *Journal of Financial Economics* 120, no. 3 (2016): 514-538.

Frame, W. Scott, Aruna Srinivasan, and Lynn Woosley. "The effect of credit scoring on small-business lending." *Journal of money, credit and banking* (2001): 813-825.

Frost, Carol Ann. "Credit rating agencies in capital markets: A review of research evidence on selected criticisms of the agencies." *Journal of Accounting, Auditing & Finance* 22, no. 3 (2007): 469-492.

Gao, Pingyang, and Pierre Jinghong Lian. "Informational feedback, adverse selection, and optimal disclosure policy." *Journal of Accounting Research* 51, no. 5 (2013): 1133-1158.

Goldstein, Itay, and Yaron Leitner. "Stress test and information disclosure." *Journal of Economic Theory* 177, (2018): 34-69.

Goldstein, Itay, and Liyan Yang. "Information disclosure in finacial markets." *Annual Review of Financial Economics 9*, (2017): 101-125.

Goldstein, Itay, and Liyan Yang. "Good disclosure, bad disclosure." *Forthcoming: Journal of Financial Economics* (2018).

Greenstone, Michael, Paul Oyer, and Annette Vissing-Jorgensen. "Mandated disclosure, stock returns, and the 1964 Securities Acts amendments." *The Quarterly Journal of Economics* 121, no. 2 (2006): 399-460.

Griffin, John M., and Dragon Yongjun Tang. "Did credit rating agencies make unbiased assumptions on CDOs?" *American Economic Review* 101, no. 3 (2011): 125-30.

Hand, John RM, Robert W. Holthausen, and Richard W. Leftwich. "The effect of bond rating agency announcements on bond and stock prices." *The Journal of Finance* 47, no. 2 (1992): 733-752.

He, Jie Jack, Jun Qj Qian, and Philip E. Strahan. "Are all ratings created equal? The impact of issuer size on the pricing of mortgage-backed securities." *The Journal of Finance* 67, no. 6 (2012): 2097-2137.

Hertzberg, Andrew, Jose Liberti, and Daniel Paravisini. "Public information and coordination: evidence from a credit registry expansion." *The Journal of Finance* 66, no. 2 (2011): 379-412.

Holthausen, Robert W., and Richard W. Leftwich. "The effect of bond rating changes on common stock prices." *Journal of Financial Economics* 17, no. 1 (1986): 57-89.

Hong, Harrison, Jeffrey D. Kubik, and Amit Solomon. "Security analysts' career concerns and herding of earnings forecasts." *The Rand Journal of Economics* (2000): 121-144.

Iliev, Peter. "The effect of SOX Section 404: Costs, earnings quality, and stock prices." *The Journal of Finance* 65, no. 3 (2010): 1163-1196.

James, Jonathan G., and Phillip Lawler. "Optimal policy intervention and the social value of public information." *The American Economic Review* 101, no. 4 (2011): 1561-1574.

Jiang, John Xuefeng, Mary Harris Stanford, and Yuan Xie. "Does it matter who pays for bond ratings? Historical evidence." *Journal of Financial Economics* 105, no. 3 (2012): 607-621.

Jeon, Doh-Shin, and Stefano Lovo. "Credit rating industry: A helicopter tour of stylized facts and recent theories." *International Journal of Industrial Organization* 31, no. 5 (2013): 643-651.

Jorion, Philippe, Zhu Liu, and Charles Shi. "Informational effects of regulation FD: evidence from rating agencies." *Journal of Financial Economics* 76, no. 2 (2005): 309-330.

Kao, Chihwa, and Chunchi Wu. "Two-step estimation of linear models with ordinal unobserved variables: The case of corporate bonds." *Journal of Business & Economic Statistics* 8, no. 3 (1990): 317-325.

Kurlat, Pablo, and Laura Veldkamp. "Should we regulate financial information?" *Journal of Economic Theory* 158 (2015): 697-720.

Leuz, Christian, and Peter D. Wysocki. "Economic consequences of financial reporting and disclosure regulation: A review and suggestions for future research." University of Chicago Working Paper (2008).

Leuz, Christian, and Peter D. Wysocki. "The economics of disclosure and financial reporting regulation: Evidence and suggestions for future research." *Journal of Accounting Research* 54, no. 2 (2016): 525-622.

Mahoney, Paul G. "Mandatory disclosure as a solution to agency problems." *The University of Chicago Law Review* 62, no. 3 (1995): 1047-1112.

Mariano, Beatriz. "Market power and reputational concerns in the ratings industry." *Journal of Banking & Finance* 36, no. 6 (2012): 1616-1626.

Minnis, Michael, and Nemit Shroff. "Why regulate private firm disclosure and auditing?." *Accounting and Business Research* 47, no. 5 (2017): 473-502.

Morris, Stephen. "Political correctness." *Journal of Political Economy* 109, no. 2 (2001): 231-265.

Ottaviani, Marco, and Peter Norman Sørensen. "Reputational cheap talk." *The Rand Journal of Economics* 37, no. 1 (2006): 155-175.

Opp, Christian C., Marcus M. Opp, and Milton Harris. "Rating agencies in the face of regulation." *Journal of Financial Economics* 108, no. 1 (2013): 46-61.

Rock, Edward. "Securities regulation as lobster trap: A credible commitment theory of mandatory disclosure." *Cardozo Law Review.* 23 (2001): 675-704.

Sandrock, O., and du Plessis, J. J. "The impact of European developments on German codetermination and German corporate law." *German Corporate Governance in International and European Context,* (2012) 197-273: Springer.

Scharfstein, David S., and Jeremy C. Stein. "Herd behavior and investment." *The American Economic Review* (1990): 465-479.

Seligman, Joel. "The historical need for a mandatory corporate disclosure system." *Journal of Corporation Law* 9 (1983): 1-61.

Skreta, Vasiliki, and Laura Veldkamp. "Ratings shopping and asset complexity: A theory of ratings inflation." *Journal of Monetary Economics* 56, no. 5 (2009): 678-695.

Theile, C., and Nitsche, J., "Praxis der Jahresabschlusspublizität bei der GmbH," *Die Wirtschaftsprüfung* 59, (2006), 1141–1151.

Trueman, Brett. "Analyst forecasts and herding behavior." *The Review of Financial Studies* 7, no. 1 (1994): 97-124.

Verrecchia, Robert E. "Discretionary disclosure." *Journal of Accounting and Economics* 5 (1983): 179-194.

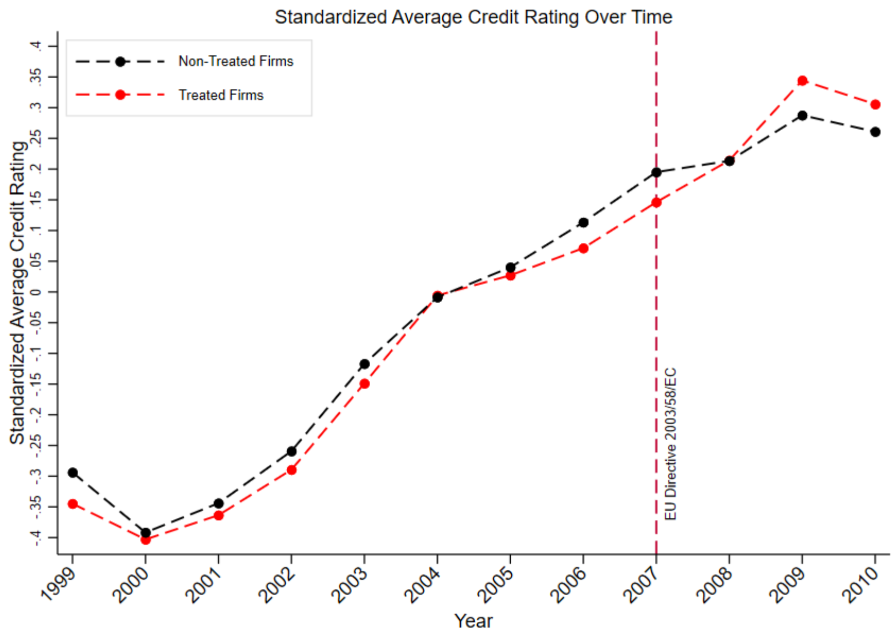
Wooldridge, Jeffrey M. "Econometric analysis of cross section and panel data." MIT press, 2010.

Xia, Han. "Can investor-paid credit rating agencies improve the information quality of issuer-paid rating agencies?." *Journal of Financial Economics* 111, no. 2 (2014): 450-468.

Xia, Han, and Günter Strobl. "The issuer-pays rating model and ratings inflation: Evidence from corporate credit ratings." Working Paper (2012).

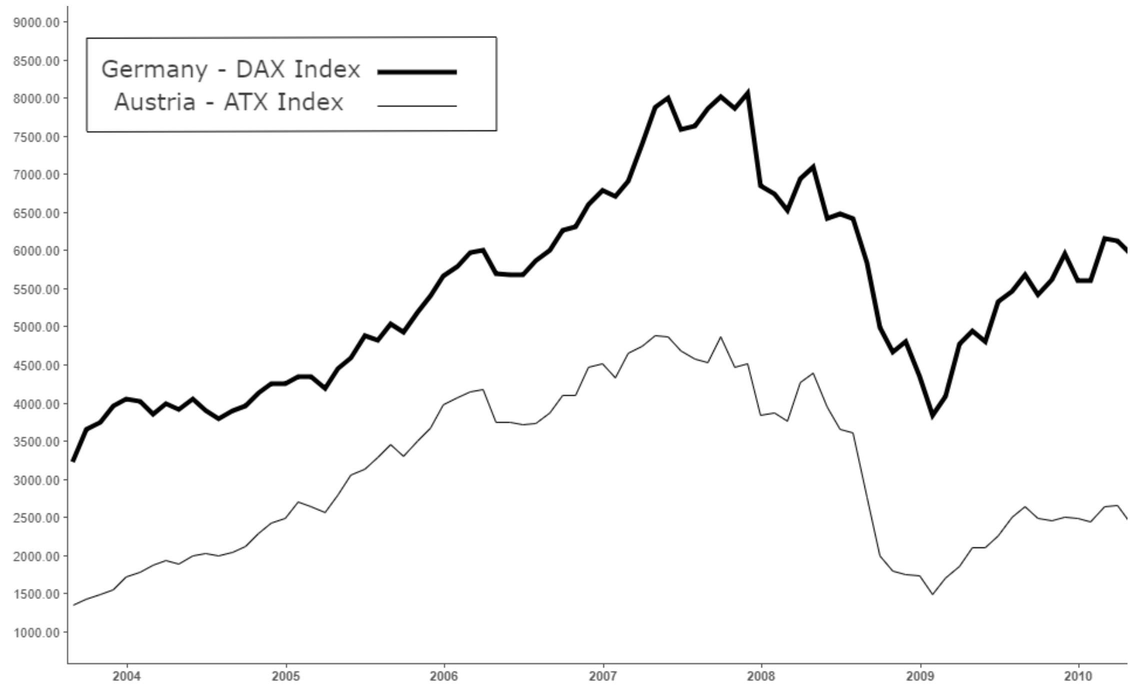
Appendix - For Online Publication – Figures

Figure A.1: Standardized Average Credit Rating of German Firms over Time (Longer Pre-treatment Period)



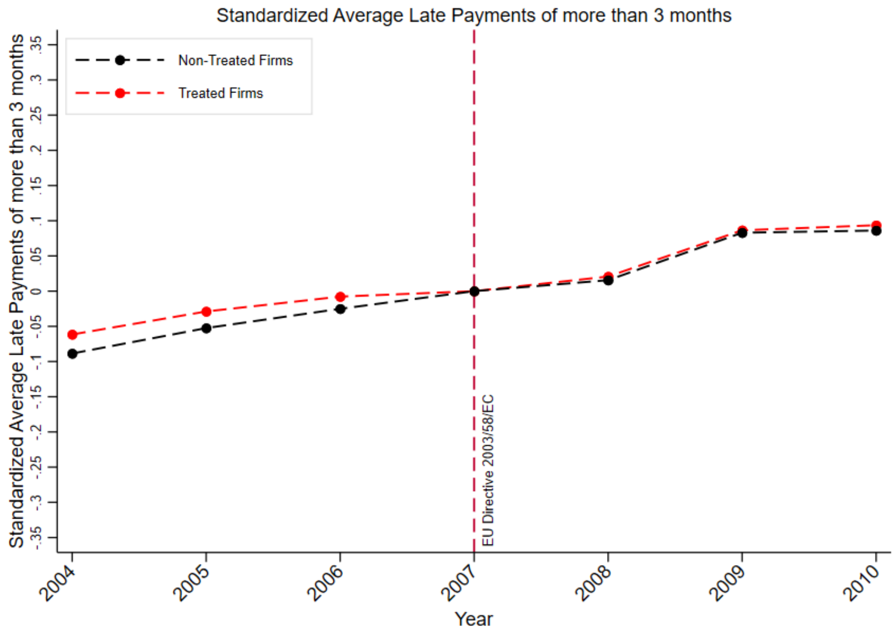
This figure shows the standardized average credit ratings over time for the Treated and Non-Treated firms for the period 1999 to 2010. *Treated* firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. The credit rating index ranges from 100 (good rating) to 500 (bad rating). A higher (lower) value indicates that the credit rating gets worse (better).

Figure A.2: German DAX index and Austria ATX Index over Time.



This figure shows the German DAX Index and the Austrian ATX index over the period 2004 to 2010.

Figure A.3: Changes in Late Payments of More than 3 Months over Time



This figure shows the standardized average of late payments of more than 3 months over time for the Treated and Non-Treated firms. *Treated* firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. The payment behavior variable range from 0 (No late payments) to 1 (Significant late payments of at least 3 months). A higher (lower) value indicates that the payment behavior gets worse (better).

Appendix - For Online Publication – Tables

Appendix Table A.1: Matching

Variable	Number of Treated firms	Mean	Number of Non-Treated Firms	Mean	Significance
Panel A: Before Matching					
Average Log Age	195,945	2.901	6,160	2.422	p < 0.001
Average Log Employees	195,945	2.030	6,160	1.985	p < 0.002
Average Log Productivity x 1000	195,945	11.994	6,160	12.159	p < 0.001
Panel B: After Matching					
Variable	Number of Treated firms	Mean	Number of Non-Treated Firms	Mean	Significance
Average Log Age	5,791	2.850	5,791	2.822	p < 0.204
Average Log Employees	5,791	2.018	5,791	1.991	p < 0.164
Average Log Productivity x 1000	5,791	12.002	5,791	12.025	p < 0.184

Notes: This table reports mean values of firm characteristics for the treated and non-treated groups, averaged over the pretreatment period. We employ a nearest neighbor propensity score matching to find comparable firms. Since our pool of untreated firms is larger than the pool of treated firms, we turn the typical matching procedure around. Hence, for each untreated firm, we search for the treated firm with the closest propensity score.

The propensity score is calculated by regressing the untreated variable on the pretreatment average of age, employees, and productivity. We also force untreated firms to be match to treated firms that operate in the same industry (2 nace digit code) and region (16 regions), have the same payment behavior reported by suppliers (29 categories, ranging from paying on time to severe late payments), and whether the firm privately disclosed financial statements to the CRA before the law. Due to the common support restriction, 261 firms drop out the sample. After matching, there are on average no significant differences between age, employees, and productivity. Since we also forced treated and untreated firms to be exactly the same in several dimensions, there are also no difference in terms of region, industry, payment behavior, and if they disclose financial statements in the pre-treatment period through private channels or not.

Appendix Table A.2: The Impact of Financial Statement Disclosure on Credit Ratings – Creditreform index translated to S&P Index

	(a)	(b)	(c)	(d)	(e)	(f)
Dependent Variable: Credit Rating translated to S&P index						
Treated x Post	0.268***	0.149***	0.221***	0.275***	0.276***	0.269***
	(0.043)	(0.039)	(0.039)	(0.043)	(0.044)	(0.049)
Treated	0.866***					1.001***
	(0.035)					(0.054)
Log Age	-0.351***	-0.449***	-0.352***	-0.641***	-0.565***	-0.366***
	(0.014)	(0.064)	(0.057)	(0.099)	(0.104)	(0.017)
Log Employees$_{(t-1)}$	-0.540***	-0.209***	-0.160***	-0.213***	-0.182***	-0.613***
	(0.010)	(0.011)	(0.009)	(0.029)	(0.030)	(0.013)
Log Productivity$_{(t-1)}$	-0.131***	-0.067***	-0.050***	-0.072***	-0.060***	-0.145***
	(0.007)	(0.006)	(0.006)	(0.019)	(0.020)	(0.007)
Method	OLS (Xia, 2014)	OLS (Xia, 2014)	OLS (Xia, 2014)	OLS (Xia, 2014)	OLS (Xia, 2014)	Ordered Logit (Dimitrov et al., 2015)
Firm fixed effects	No	Yes	Yes	Yes	Yes	No
Industry fixed effects	Yes	Implied	Implied	Implied	Implied	Yes
Region fixed effects	Yes	Implied	Implied	Implied	Implied	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Payment Behavior fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Industry Time Trends	No	No	Yes	No	Yes	No
Controls x Post	No	No	Yes	No	Yes	No
R^2	0.623	0.846	0.848	0.879	0.881	0.215
N	808,942	808,942	808,942	42,608	42,608	808,942

Notes: Column (a) to (e) presents OLS regressions of firms' credit ratings, and in column (f) we present an Ordered Logit Model. We translated the credit rating index of Creditreform to the rating scale of S&P using the Creditreform's conversion table (Creditreform, 2017). Following prior literature, a numerical value is assigned to each rating on a notch basis as follows: AAA = 1, AA+ = 2, AA = 3, AA- = 4, A+ = 5, A = 6, A- = 7, BBB+ = 8, BBB = 9, BBB- = 10, BB+ = 11, BB = 12, BB- = 13, B+ = 14, B = 15, B- = 16, CCC+ = 17, CCC = 18, CCC- = 19, CC = 20, C = 21, and D = 22 (Xia, 2014). Treated firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. *Post* is dummy variable equal to 1 for all firms for the years after 2007, i.e. the period when financial statements of treated firms became publicly available. The credit rating index range from 1 (good rating – AAA rating) to 22 (bad rating – D rating). A positive (negative) coefficient indicates that the credit rating gets worse (better). In columns (a) to (c) and (f) we use the full sample, and in columns (d) and (e) we use the matched sample (see Appendix Table A.1 for more details on the matching procedure). Heteroscedasticity-robust standard errors are clustered at the credit rating office level. Robust standard errors appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively. Variable definitions are provided in section IV.A.

Appendix Table A.3: The Impact of Financial Statement Disclosure on Credit Ratings – Alternative Sample –Including Firms that Voluntary Disclosed to the Public

	(a)	(b)	(c)	(d)	(e)
Dependent Variable: Credit Rating					
Treated x Post	5.431***	2.946***	4.319***	5.829***	5.842***
	(0.693)	(0.650)	(0.642)	(0.838)	(0.787)
Treated	14.766***				
	(0.540)				
Log Age	-6.199***	-5.641***	-5.050***	-9.256***	-8.435***
	(0.259)	(1.204)	(0.998)	(1.854)	(2.012)
Log Employees$_{(t-1)}$	-10.021***	-4.110***	-2.848***	-2.690***	-1.755***
	(0.204)	(0.198)	(0.165)	(0.647)	(0.612)
Log Productivity$_{(t-1)}$	-2.326***	-1.176***	-0.826***	-0.933**	-0.845*
	(0.141)	(0.119)	(0.110)	(0.411)	(0.446)
Firm fixed effects	No	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Implied	Implied	Implied	Implied
Region fixed effects	Yes	Implied	Implied	Implied	Implied
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Payment Behavior fixed effects	Yes	Yes	Yes	Yes	Yes
Industry Time Trends	No	No	Yes	No	Yes
Controls x Post	No	No	Yes	No	Yes
R^2	0.630	0.847	0.850	0.878	0.880
N	900,297	900,297	900,297	44,977	44,977

Notes: This table presents OLS regressions of firms' credit ratings. This analyses is similar as the results presented in Table 2, but we include both treated and non-treated firms that voluntarily disclosed information to the public before the law change. *Treated* firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. *Post* is a dummy variable equal to 1 for all firms for the years after 2007, i.e. the period when financial statements of treated firms became publicly available. The credit rating index ranges from 100 (good rating) to 500 (bad rating). A positive (negative) coefficient indicates that the credit rating gets worse (better). In columns (a) - (c) we use the full sample, and in columns (d) and (e) we use the matched sample (see Appendix Table A.1 for more details on the matching procedure – in this matching procedure, we additional match firms on if they voluntary disclosed in the pre-period or not). Heteroscedasticity-robust standard errors are clustered at the credit rating office level and are presented in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively. Variable definitions are provided in section IV.A.

Appendix Table A.4: The Impact of Financial Statement Disclosure on Credit Ratings: Impact over Time

	(a)	(b)	(c)	(d)	(e)
Dependent Variable: Credit Rating					
Treated x Year dummy 2004	-0.399	1.023	0.681	-0.337	-0.196
	(0.781)	(0.786)	(0.792)	(1.067)	(1.058)
Treated x Year dummy 2005	-0.124	0.530	0.124	0.108	0.074
	(0.737)	(0.731)	(0.720)	(1.005)	(0.993)
Treated x Year dummy 2006	-0.863	0.093	-0.106	-0.376	-0.427
	(0.806)	(0.681)	(0.680)	(0.896)	(0.890)
Treated x Year dummy 2008	3.341***	2.171***	3.073***	3.258***	3.227***
	(0.709)	(0.734)	(0.726)	(1.080)	(1.043)
Treated x Year dummy 2009	7.481***	5.474***	6.545***	7.148***	6.979***
	(1.018)	(0.944)	(0.959)	(1.218)	(1.195)
Treated x Year dummy 2010	7.792***	5.283***	6.677***	8.032***	8.129***
	(1.117)	(1.097)	(1.119)	(1.586)	(1.525)
Treated	15.054***				
	(0.757)				
Log Age	-6.224***	-5.815***	-4.986***	-9.661***	-8.664***
	(0.270)	(1.163)	(0.978)	(1.909)	(1.947)
Log Employees$_{(t-1)}$	-9.724***	-3.949***	-2.741***	-3.697***	-2.897***
	(0.194)	(0.202)	(0.160)	(0.577)	(0.578)
Log Productivity$_{(t-1)}$	-2.059***	-1.062***	-0.680***	-1.253***	-0.998**
	(0.149)	(0.117)	(0.110)	(0.376)	(0.419)
Firm fixed effects	No	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Implied	Implied	Implied	Implied
Region fixed effects	Yes	Implied	Implied	Implied	Implied
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Payment Behavior fixed effects	Yes	Yes	Yes	Yes	Yes
Industry Time Trends	No	No	Yes	No	Yes
Controls x Post	No	No	Yes	No	Yes
R^2	0.628	0.847	0.850	0.879	0.881
N	808,942	808,942	808,942	42,608	42,608

Notes: This table presents the dynamics of the treatment effect over time. Treated firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. *Year Dummy 200X* is dummy variable equal to 1 for all firms in our sample for the year it indicates. The credit rating index range from 100 (good rating) to 500 (bad rating). A positive (negative) coefficient indicates that the credit rating gets worse (better). In columns (a) - (c) we use the full sample, and in columns (d) and (e) we use the matched sample (see Appendix Table A.1 for more details on the matching procedure). Heteroscedasticity-robust standard errors are clustered at the credit rating office level. Robust standard errors appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively. Variable definitions are provided in section IV.A.

Appendix Table A.5a: Alternative Control group: Placebo Test - Austria

	(a)	(b)	(c)	(d)	(e)
Dependent Variable: Credit Rating					
Placebo Treated x Post	-0.095	-0.397	0.450	1.048	0.988
	(0.573)	(0.451)	(0.471)	(1.027)	(0.975)
Placebo Treated	9.362***				
	(0.531)				
Log Age	-4.522***	-3.826***	-3.635***	-6.102***	-4.332***
	(0.139)	(0.358)	(0.363)	(1.200)	(0.898)
Log Employees$_{(t-1)}$	-7.591***	-2.384***	-1.947***	-4.095***	-4.063***
	(0.116)	(0.190)	(0.199)	(0.811)	(0.871)
Log Productivity$_{(t-1)}$	-1.297***	-0.393***	-0.256**	-1.706***	-1.465***
	(0.100)	(0.115)	(0.121)	(0.436)	(0.399)
Firm fixed effects	No	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Implied	Implied	Implied	Implied
Region fixed effects	Yes	Implied	Implied	Implied	Implied
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Payment Behavior fixed effects	Yes	Yes	Yes	Yes	Yes
Industry Time Trends	No	No	Yes	No	Yes
Controls x Post	No	No	Yes	No	Yes
R^2	0.690	0.914	0.915	0.937	0.938
N	194,812	194,812	194,812	22,473	22,473

Notes: This table presents OLS regressions of Austrian firms' credit ratings. *Placebo Treated* firms are *Austrian* firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements *before and after* 2007. Non-treated firms are *Austrian* firms with the legal forms OHG or KG that were required *neither before nor after* 2007 to disclose financial statements. *Post* is a dummy variable equal to 1 for all firms for the years after 2007, i.e. the period when financial statements of treated firms became publicly available. The credit rating index range from 100 (good rating) to 500 (bad rating). A positive (negative) coefficient indicates that the credit rating gets worse (better). In columns (a) - (c) we use the full sample, and in columns (d) and (e) we use the matched sample (see Appendix Table A.1 for more details on the matching procedure). Heteroscedasticity-robust standard errors are clustered at the credit rating office level and are presented in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively. Variable definitions are provided in section IV.A.

Table A.5b: Alternative Control Group: German Setting vs. Austria Setting – Difference-in-Difference-in-Differences

	(a)	(b)	(c)	(d)	(e)
Dependent Variable: Credit Rating					
Treated x Post x Germany	6.803***	4.222***	3.056***	5.305***	5.182***
	(0.788)	(1.003)	(1.036)	(1.318)	(1.292)
Treated x Post	-0.184	-0.490	1.806**	0.876	0.956
	(0.414)	(0.739)	(0.767)	(1.005)	(0.986)
Treated	9.037***				
	(0.936)				
Germany x Post	-0.377	-0.871	-0.231	-1.149	-0.521
	(1.655)	(1.468)	(1.628)	(1.466)	(1.552)
Germany x Treated	5.560***				
	(1.150)				
Germany	-8.659***				
	(2.739)				
Log Age	-6.352***	-5.112***	-4.452***	-8.123***	-6.171***
	(0.281)	(0.820)	(0.625)	(1.138)	(0.996)
Log Employees$_{(t-1)}$	-9.482***	-3.687***	-2.693***	-3.778***	-3.257***
	(0.208)	(0.199)	(0.147)	(0.490)	(0.486)
Log Productivity$_{(t-1)}$	-2.040***	-0.980***	-0.721***	-1.404***	-1.134***
	(0.185)	(0.124)	(0.100)	(0.303)	(0.319)
Firm fixed effects	No	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Implied	Implied	Implied	Implied
Region fixed effects	Yes	Implied	Implied	Implied	Implied
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Payment Behavior fixed effects	Yes	Yes	Yes	Yes	Yes
Industry Time Trends	No	No	Yes	No	Yes
Controls x Post	No	No	Yes	No	Yes
R^2	0.632	0.858	0.860	0.899	0.901
N	1,003,754	1,003,754	1,003,754	65,081	65,081

Notes: This table presents OLS regressions of firms' credit ratings. *Treated* firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. *Germany* is a dummy variable equal to 1 for all firms within Germany, and 0 for firms within Austria. *Post* is a dummy variable equal to 1 for all firms for the years after 2007, i.e. the period when financial statements of German treated firms became publicly available. The credit rating index ranges from 100 (good rating) to 500 (bad rating). A positive (negative) coefficient indicates that the credit rating gets worse (better). In columns (a) - (c) we use the full sample, and in columns (d) and (e) we use the matched sample (see Appendix Table A.1 for more details on the matching procedure). Heteroscedasticity-robust standard errors are clustered at the credit rating office level and are presented in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively. Variable definitions are provided in section IV.A.

Appendix Table A.5c: Alternative Control group: German Limited Liability firms vs. Austria Limited Liability Firms

	(a)	(b)	(c)	(d)	(e)
Dependent Variable: Credit Rating					
Treated x Post	6.450***	3.351***	2.800***	2.041***	1.718***
	(0.178)	(0.166)	(0.171)	(0.262)	(0.256)
Treated	-3.116***				
	(0.163)				
Log Age	-6.432***	-5.008***	-4.380***	-3.896***	-3.573***
	(0.062)	(0.254)	(0.284)	(0.395)	(0.417)
Log Employees$_{(t-1)}$	-9.508***	-3.713***	-2.689***	-3.226***	-2.451***
	(0.054)	(0.109)	(0.112)	(0.194)	(0.199)
Log Productivity$_{(t-1)}$	-2.045***	-0.979***	-0.710***	-0.800***	-0.553***
	(0.046)	(0.056)	(0.059)	(0.109)	(0.113)
Firm fixed effects	No	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Implied	Implied	Implied	Implied
Region fixed effects	Yes	Implied	Implied	Implied	Implied
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Payment Behavior fixed effects	Yes	Yes	Yes	Yes	Yes
Industry Time Trends	No	No	Yes	No	Yes
Controls x Post	No	No	Yes	No	Yes
R^2	0.627	0.855	0.857	0.872	0.873
N	967,134	967,134	967,134	251,823	251,823

Notes: This table presents OLS regressions of firms' credit ratings. *Treated* firms are *German* firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are *Austrian* firms with the legal forms GmbH or GmbH Co. KG that were required before and after 2007 to disclose financial statements. *Post* is a dummy variable equal to 1 for all firms for the years after 2007, i.e. the period when financial statements of German treated firms became publicly available. The credit rating index ranges from 100 (good rating) to 500 (bad rating). A positive (negative) coefficient indicates that the credit rating gets worse (better). In columns (a) - (c) we use the full sample, and in columns (d) and (e) we use the matched sample (see Appendix Table A.1 for more details on the matching procedure). Heteroscedasticity-robust standard errors are clustered at the credit rating office level and are presented in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively. Variable definitions are provided in section IV.A.

Appendix Table A.6a: The Impact of Financial Statement Disclosure on Firms' Payment Behavior

	(a)	(b)	(c)	(d)	(e)
Dependent Variable: Payment Behavior					
Treated x Post	0.181	0.100	0.233	-0.198	-0.183
	(0.198)	(0.176)	(0.186)	(0.232)	(0.234)
Treated	-0.735***				
	(0.157)				
Log Age	-0.922***	-0.132	0.216	-1.306**	-1.309**
	(0.087)	(0.378)	(0.361)	(0.538)	(0.595)
Log Employees$_{(t-1)}$	-1.404***	-0.085*	-0.150***	0.098	-0.047
	(0.053)	(0.047)	(0.052)	(0.166)	(0.172)
Log Productivity$_{(t-1)}$	-0.609***	-0.246***	-0.209***	-0.266**	-0.226**
	(0.039)	(0.037)	(0.039)	(0.105)	(0.105)
Firm fixed effects	No	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Implied	Implied	Implied	Implied
Region fixed effects	Yes	Implied	Implied	Implied	Implied
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry Time Trends	No	No	Yes	No	Yes
Controls x Post	No	No	Yes	No	Yes
R^2	0.068	0.601	0.602	0.632	0.634
N	808,942	808,942	808,942	42,608	42,608

Notes: This table presents OLS regressions of firms' payment behavior. *Treated* firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. *Post* is a dummy variable equal to 1 for all firms for the years after 2007, i.e. the period when financial statements of treated firms became publicly available. The payment behavior variable range from 1 (best payment behavior category) to 29 (worst category). A positive (negative) coefficient indicates that the payment behavior gets worse (better). Using an ordered probit model instead of OLS, we also find an (insignificant) effect on our main variable of interest. In columns (a) - (c) we use the full sample, and in columns (d) and (e) we use the matched sample (see Appendix Table A.1 for more details on the matching procedure). Heteroscedasticity-robust standard errors are clustered at the credit rating office level and are presented in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively. Variable definitions are provided in section IV.A.

Appendix Table A.6b: The Impact of Financial Statement Disclosure on the Credit Analyst's Opinion about Firms' Creditworthiness

	(a)	(b)	(c)	(d)	(e)
Dependent Variable: Credit Analyst Opinion					
Treated x Post	1.922***	1.365***	1.629***	1.721***	1.768***
	(0.169)	(0.160)	(0.161)	(0.167)	(0.165)
Treated	0.634***				
	(0.120)				
Log Age	-0.086*	0.196	0.736***	-0.911**	-0.443
	(0.052)	(0.221)	(0.220)	(0.383)	(0.355)
Log Employees$_{(t-1)}$	-0.837***	-0.179***	0.068*	-0.035	0.051
	(0.033)	(0.039)	(0.040)	(0.128)	(0.126)
Log Productivity$_{(t-1)}$	-0.352***	-0.103***	-0.006	-0.001	0.078
	(0.023)	(0.024)	(0.021)	(0.083)	(0.092)
Firm fixed effects	No	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Implied	Implied	Implied	Implied
Region fixed effects	Yes	Implied	Implied	Implied	Implied
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Payment Behavior fixed effects	Yes	Yes	Yes	Yes	Yes
Industry Time Trends	No	No	Yes	No	Yes
Controls x Post	No	No	Yes	No	Yes
R^2	0.296	0.690	0.692	0.720	0.722
N	808,942	808,942	808,942	42,608	42,608

Notes: This table presents OLS regressions of the credit analysts opinion. *Treated* firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. *Post* is a dummy variable equal to 1 for all firms for the years after 2007, i.e. the period when financial statements of treated firms became publicly available. The analyst opinion contains out of 6 main categories range from 10 (best credit opinion category) to 60 (the worst category). A positive (negative) coefficient indicates that the credit analyst opinion gets worse (better). Using an ordered probit model instead of OLS, we also find a statistically significant positive effect on our main variable of interest. In columns (a) - (c) we use the full sample, and in columns (d) and (e) we use the matched sample (see Appendix Table A.1 for more details on the matching procedure). Heteroscedasticity-robust standard errors are clustered at the credit rating office level and are presented in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively. Variable definitions are provided in section IV.A.

Appendix Table A.6c: The Impact of Financial Statement Disclosure on the Credit Ratings while Controlling for the Credit Analyst Opinion

	(a)	(b)	(c)	(d)	(e)
Dependent Variable: Credit Rating					
Treated x Post	-0.154	-0.076	0.436	0.618	0.672
	(0.463)	(0.441)	(0.436)	(0.607)	(0.608)
Treated	12.796***				
	(0.375)				
Log Age	-6.020***	-9.872***	-10.477***	-12.108***	-11.472***
	(0.136)	(0.492)	(0.449)	(1.261)	(1.443)
Log Employees$_{(t-1)}$	-5.947***	-2.990***	-2.579***	-3.032***	-2.795***
	(0.088)	(0.130)	(0.117)	(0.478)	(0.482)
Log Productivity$_{(t-1)}$	-0.712***	-0.763***	-0.650***	-1.151***	-1.149***
	(0.078)	(0.073)	(0.078)	(0.291)	(0.316)
Additional Control: Credit Analyst Opinion Fixed Effects	Yes	Yes	Yes	Yes	Yes
Firm fixed effects	No	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Implied	Implied	Implied	Implied
Region fixed effects	Yes	Implied	Implied	Implied	Implied
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Payment Behavior fixed effects	Yes	Yes	Yes	Yes	Yes
Industry Time Trends	No	No	Yes	No	Yes
Controls x Post	No	No	Yes	No	Yes
R^2	0.810	0.900	0.901	0.918	0.919
N	808,942	808,942	808,942	42,608	42,608

Notes: This table presents OLS regressions of firms' credit ratings. *Treated* firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. *Post* is a dummy variable equal to 1 for all firms for the years after 2007, i.e. the period when financial statements of treated firms became publicly available. The credit rating index range from 100 (good rating) to 500 (bad rating). A positive (negative) coefficient indicates that the credit rating gets worse (better). In columns (a) - (c) we use the full sample, and in columns (d) and (e) we use the matched sample (see Appendix Table A.1 for more details on the matching procedure). Heteroscedasticity-robust standard errors are clustered at the credit rating office level and are presented in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively. Variable definitions are provided in section IV.A.

Appendix Table A.7. - Accuracy Model: Type I and Type II errors

	Probit Model	Probit Model	Probit Model	Probit Model
Dependent Variable:	*Type II Errors*	*Type II Errors*	*Type I Errors*	*Type I Errors*
Treated x Post x Credit Opinion		0.008***		0.007
		(0.003)		(0.006)
Treated x Post	0.449***	0.021	-0.110	-0.292
	(0.029)	(0.083)	(0.069)	(0.197)
Credit Opinion x Treated		0.037***		-0.008
		(0.002)		(0.005)
Credit Opinion x Post		-0.015***		-0.010
		(0.003)		(0.006)
Treated	0.356***	-0.774***	0.071	0.293*
	(0.018)	(0.054)	(0.049)	(0.158)
Credit Opinion		0.045***		0.009*
		(0.002)		(0.005)
Log Age	-0.085***	-0.101***	-0.076***	-0.076***
	(0.002)	(0.003)	(0.007)	(0.007)
Log Employees$_{(t-1)}$	-0.261***	-0.219***	0.065***	0.064***
	(0.002)	(0.003)	(0.006)	(0.006)
Log Productivity$_{(t-1)}$	-0.068***	-0.048***	0.005	0.005
	(0.002)	(0.002)	(0.005)	(0.005)
Firm-fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes
Payment Behavior fixed effects	Yes	Yes	Yes	Yes
Pseudo R^2	0.356	0.469	0.191	0.191
N	808,942	808,942	808,942	808,942

Notes: This table presents probit estimations and linear probability models of the likelihood of a type one or type two error. We define type-one errors as firms that default, but received an investment grade (i.e. credit rating < 301) in the year that they default, and we define type two-errors as firms that received a speculative grade (i.e. credit rating > 301) but did not default in that year. We use all firm-year observations of firms that either default or do not default during our sample period. *Treated* firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. *Post* is dummy variable equal to 1 for all firms for the years after 2007, i.e. the period when financial statements of treated firms became publicly available. Heteroscedasticity-robust standard errors are clustered at the credit rating office level. Robust standard errors appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively. Variable definitions are provided in section IV.A

Appendix Table A.8: The Impact of Financial Statement Disclosure on Credit Ratings across Quantiles – S&P index

Quantiles:	(a) 10%	(b) 25%	(c) 50%	(d) 75%	(e) 90%
Credit Rating Value at the Quantile:	*CR: A*	*CR: BBB+*	*CR: BBB-*	*CR: BB*	*CR: BB-*
Dependent Variable: Credit Rating translated to S&P index					
Treated x Post	0.020	0.008	0.442***	0.366***	0.563***
	(0.049)	(0.079)	(0.077)	(0.054)	(0.054)
Log Age	-0.759***	-0.874***	-0.587***	-0.480***	-0.353***
	(0.115)	(0.137)	(0.158)	(0.118)	(0.078)
Log Employees$_{(t-1)}$	-0.210***	-0.209***	-0.224***	-0.108***	-0.062*
	(0.053)	(0.050)	(0.049)	(0.038)	(0.037)
Log Productivity$_{(t-1)}$	-0.172***	-0.087***	-0.050*	0.010	0.026
	(0.034)	(0.021)	(0.027)	(0.030)	(0.024)
Pseudo Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Region fixed effects	Yes	Yes	Yes	Yes	Yes
Payment Behavior fixed effects	Yes	Yes	Yes	Yes	Yes
Pseudo-R^2	0.631	0.656	0.665	0.661	0.635
N	42,608	42,608	42,608	42,608	42,608

Notes: This table presents quantile regressions of firms' credit ratings. We translated the credit rating index of Creditreform to the rating scale of S&P following Creditreform's conversion table (Creditreform, 2017b). Following prior literature, a numerical value is assigned to each rating on a notch basis as follows: AAA = 1, AA+ = 2, AA = 3, AA- = 4, A+ = 5, A = 6, A- = 7, BBB+ = 8, BBB = 9, BBB- = 10, BB+ = 11, BB = 12, BB- = 13, B+ = 14, B = 15, B- = 16, CCC+ = 17, CCC = 18, CCC- = 19, CC = 20, C = 21, and D = 22 (Xia, 2014). We estimate quantile regressions with pseudo firm-fixed effects using the Mundlak-Chamberlain device as proposed by Wooldridge (2010). Time-invariant variables are included in the model, but not reported. Treated firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. *Post* is dummy variable equal to 1 for all firms for the years after 2007, i.e. the period when financial statements of treated firms became publicly available. The credit rating index range from 1 (good rating – AAA rating) to 22 (bad rating – D rating). A positive (negative) coefficient indicates that the credit rating gets worse (better). We use Parente-Santos Silva clustered-standard errors as proposed by Wooldridge (2010), which are presented in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively. Variable definitions are provided in section IV.A.

Appendix A.9: Impact of Disclosure Regulation on Credit Ratings: Shift in bank behavior

	Coordination Cost Story (Hertzberg et al., 2011)		Shift from Relationship Approaches to Transactional Approaches (Breuer et al., 2017)	
	Subsample of Firms with a Single Lender	Subsample of Firms with Multiple Lenders	Subsample of Young Firms	Subsample of Old Firms
Dependent variable: credit rating				
Treated x Post	3.027***	3.849***	4.103***	3.781***
	(1.083)	(0.808)	(1.064)	(0.769)
Log Age	-6.512***	-7.548***	-2.588*	-8.965*
	(1.146)	(1.248)	(1.345)	(5.223)
Log Employees$_{(t-1)}$	-3.886***	-4.445***	-3.783***	-4.293***
	(0.243)	(0.290)	(0.222)	(0.294)
Log Productivity$_{(t-1)}$	-1.059***	-1.466***	-0.851***	-1.352***
	(0.129)	(0.167)	(0.125)	(0.150)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Implied	Implied	Implied	Implied
Region fixed effects	Implied	Implied	Implied	Implied
Payment Behavior fixed effects	Yes	Yes	Yes	Yes
R^2	0.825	0.855	0.824	0.853
N	380,795	302,675	404,908	404,034

Notes: This table presents OLS regressions of firms' credit ratings. In column 1, we only observations from firms that have a single relationship lender. In column 2, we use observations from firms that have multiple lenders. In column 3 and 4, we split the sample on the median age (13 years). Column 3, looks at the 50% youngest firms, and column 4, on the 50% oldest. *Treated* firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. *Post* is dummy variable equal to 1 for all firms for the years after 2007, i.e. the period when financial statements of treated firms became publicly available. The credit rating index range from 100 (good rating) to 500 (bad rating). A positive (negative) coefficient indicates that the credit rating gets worse (better). All models include an intercept that is omitted in the table. Heteroscedasticity-robust standard errors are clustered at the firm level. Robust standard errors appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively. Variable definitions are provided in section IV.A.

Appendix A.10: Impact of Disclosure Regulation on Credit Ratings: Alternative Explanations: Shift in Competition

	Change in Competition (Breuer 2018; Bernard 2016)			
	Subsample of firms in high competitive industries	Subsample of firms in low competitive industries	Subsample of firms in ex-ante low disclosure industries	Subsample of firms in ex-ante high disclosure industries
Dependent variable: credit rating				
Treated x Post	3.841***	4.239***	3.463***	3.979***
	(0.854)	(0.894)	(0.777)	(0.972)
Log Age	-7.334***	-4.010***	-4.907***	-6.596***
	(1.063)	(1.395)	(1.016)	(1.438)
Log Employees$_{(t-1)}$	-4.404***	-3.879***	-4.207***	-3.899***
	(0.274)	(0.245)	(0.259)	(0.246)
Log Productivity$_{(t-1)}$	-1.091***	-1.277***	-1.690***	-0.764***
	(0.154)	(0.149)	(0.207)	(0.110)
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed ef9*fects	Yes	Yes	Yes	Yes
Industry fixed effects	Implied	Implied	Implied	Implied
Region fixed effects	Implied	Implied	Implied	Implied
Payment Behavior fixed effects	Yes	Yes	Yes	Yes
R^2	0.868	0.884	403,990	404,952
N	405,378	403,564	0.855	0.838

Notes: This table presents OLS regressions of firms' credit ratings. In column 1 and 2, we have calculated the herfindahl index, and have split on the median of this index. In column 3 and 4, we have split the sample on the median of the share of firms that voluntarily disclosed in the pre-period within an industry-district. To calculate the share of firms that voluntarily disclosed to the public within each industry and region, we take the sum of publicly listed firms and the 5% of limited liability firms that voluntarily disclosed to the public, and divide this number by the total number of firms active with an industry and region in the pre-period. *Treated* firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. *Post* is dummy variable equal to 1 for all firms for the years after 2007, i.e. the period when financial statements of treated firms became publicly available. The credit rating index range from 100 (good rating) to 500 (bad rating). A positive (negative) coefficient indicates that the credit rating gets worse (better). All models include an intercept that is omitted in the table. Heteroscedasticity-robust standard errors are clustered at the firm level. Robust standard errors appear in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively. Variable definitions are provided in section IV.A.

Appendix A.11: Switchers around the law change

Years	Switching from Non-Treated to Treated Firms	Switching from Treated to Non-Treated Firms
2004	0.315%	0.266%
2005	0.187%	0.137%
2006	0.209%	0.154%
2007	0.187%	0.140%
2008	0.154%	0.146%
2009	0.224%	0.182%
2010	0.187%	0.151%

Notes: This table presents descriptive statistics on the percentage of treated and non-treated firms in the database that switch from treated to non-treated firms, and from non-treated to treated firms during our time period of interest. Treated firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements from 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements.

Appendix Table A.12: Additional Fixed Effects and Firm-Time Trends

	(a)	(b)	(c)	(d)	(e)
Dependent Variable: Credit Rating					
Treated x Post	7.130***	4.721***	2.967***	6.364***	4.014**
	(0.625)	(0.563)	(0.925)	(0.950)	(1.680)
Treated	14.045***				
	(0.527)				
Log Age	-6.192***	-6.053***	-8.149**	-9.580***	-1.753
	(0.259)	(0.797)	(3.735)	(2.045)	(10.987)
Log Employees$_{(t-1)}$	-9.507***	-3.971***	-0.767***	-3.744***	-0.358
	(0.176)	(0.160)	(0.243)	(0.816)	(1.527)
Log Productivity$_{(t-1)}$	-2.108***	-1.139***	-0.899***	-1.444***	-1.848***
	(0.122)	(0.101)	(0.159)	(0.540)	(0.634)
Firm fixed effects	No	Yes	Yes	Yes	Yes
Industry x Region x Year fixed effects	Yes	Yes	Yes	Yes	Yes
Payment Behavior fixed effects	Yes	Yes	Yes	Yes	Yes
Firm Time Trends	No	No	Yes	No	Yes
Controls x Post	No	No	Yes	No	Yes
R^2	0.678	0.864	0.950	0.933	0.976
N	808,942	808,942	808,942	42,608	42,608

Notes: This table presents OLS regressions of firms' credit ratings while controlling for industry-region-time-fixed effects and and/or firm-time trends. *Treated* firms are firms with the legal forms GmbH or GmbH Co. KG that were obliged to disclose financial statements after 2007 and did not disclose financial statements beforehand. Non-treated firms are firms with the legal forms OHG or KG that were required neither before nor after 2007 to disclose financial statements. *Post* is a dummy variable equal to 1 for all firms for the years after 2007, i.e. the period when financial statements of treated firms became publicly available. The credit rating index range from 100 (good rating) to 500 (bad rating). A positive (negative) coefficient indicates that the credit rating gets worse (better). In columns (a) - (c) we use the full sample, and in columns (d) and (e) we use the matched sample (see Appendix Table A.1 for more details on the matching procedure). Heteroscedasticity-robust standard errors are clustered at the credit rating office level and are presented in parentheses. ***, ** and * indicate a significance level of 1%, 5%, and 10%, respectively. Variable definitions are provided in section IV.A.