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To my parents, to my sister.

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CONTENTS

LIST OF FIGURES

LIST OF TABLES

INTRODUCTION

The thesis of four chapters addresses a wide array of questions concerning banking regulation and the informational value of risk measures. In the first three chapters, I explore how regulation affects the behaviour of actors in different areas of financial markets. In the aftermath of the financial crisis, the public and academic outcry for a more stringent regulation was loud. However, the effect of a more stringent regulation is not clear-cut. On the one hand, stricter regulation ties the hands of actors in financial markets and thereby limits irrational or opportunistic behaviour. On the other hand, stricter regulation - if badly designed - might throw a spanner in the works of financial markets and might be exploitable. This thesis provides examples for both, areas in which a tighter regulation is needed as well as examples where increased regulation might have adverse effects.

In the first chapter, "Underreporting by Overdiversification? Strategic Usage of VaR Diversification", I examine whether and how banks use modelling freedom to underreport their exposure to market risk. Though earlier literature nearly unanimously finds that banks over- rather than understate their Value-at-Risk - a measure of market risk -, the financial crisis and a stricter regulation might have altered the relationship. Indeed, Begley et al. (2016) find that banks seemingly underreport their Value-at-Risk, if equity is low, but remain silent on the tools that allow banks to manage the VaR. This chapter proposes diversification - a reduction in the overall Value-at-Risk due to imperfect correlation between broad asset classes - as possible channel for underreporting. By combining reported broad asset class Value-at-Risks with observed correlation, I construct a counterfactual overall diversification as benchmark. To elicit possible underreporting, I examine how incentives to report a lower market risk affect the deviation from the counterfactual Value-at-Risk. I am able to show that banks report a higher diversification when they are weakly capitalised, but a lower diversification, if the potential penalty from underreporting is high. Finally, I show that backtesting exceptions - daily losses that exceed the Value-at-Risk - are more frequent if banks report a higher diversification relative to the benchmark. This chapter adds to the literature on the strategic usage of internal models by isolating a particular channel for underreporting market risk. Here, the regulator should adopt - and did indeed adopt while I was writing this chapter - a stricter regulation in the sense that the modelling freedom of banks is limited.

The second chapter, “How does the Dodd-Frank Act affect Issuer Ratings and Rating Reports?”, provides evidence for unintended and adverse consequences of tighter regulation. Against the backdrop of the apparent underestimation of the riskiness of asset-backed securities by credit rating agencies, the U.S. Congress passed the Dodd-Frank Act in 2010, which increased the liability of credit rating agencies for their ratings. The increased liability was intended to induce rating agencies to decide more faithfully about rating levels and changes. However, the existing literature documents a downwards bias rather than an increased accuracy of bond ratings as a reaction to the Dodd-Frank Act (Dimitrov et al., 2015). This chapter contributes to the literature in two ways. First, it analyses how the increased liability affects one of the main business lines of rating agencies: Issuer ratings. To evaluate possible effects of the Dodd-Frank Act, I use market-based risk measures - namely equity-implied, the credit default swap-implied and a failure probability based on a calibration of Hilscher and Wilson (2016) - as unaffected counterfactual to issuer ratings. Though I find a downwards bias in issuer ratings relative to the market-based counterfactuals, it is not robust to specification changes and the regressions appear to pick up a crisis effect rather than the impact of the Dodd-Frank-Act. For example, if I shorten the sample period from eight to four years or use a different function form of the macroeconomic control variables, the downwards bias either disappears or is of negligible magnitude. Second, the chapter looks at so far unexplored rating reports. Rating reports explain the rationale behind a rating decision by providing qualitative information and outlooks on the future of the company. After the Dodd-Frank Act, these reports contain more forward-looking words, but for lower rated issuers - for which ratings and rating reports have conceivably the highest importance - the wording is more ambiguous and the information content reduced. In this case, imposing a stricter regulation on an industry did not increase its efficiency, but rather devalued the information content of ratings in general.

The value of well-designed institutions and information for the financial markets is highlighted in the third chapter, "Credit Institutions, Ownership and Bank Lending in Transition Economies".[1] This chapter examines the transition of the banking sector in Eastern Europe from government control to private, often foreign ownership. It challenges the common perception that foreign ownership was the main driver behind the credit growth in the region and the contraction of lending after the crisis. Rather, a well-designed institutional setup mitigated the effect of the crisis. In particular, the empirical analysis shows that the crisis shock had a smaller impact on loan growth in countries with credit registers or bureaus for the recording of loans. This chapter shows that well-designed regulation for banking institutions is an important determinant of the success of a banking system.

Chapter 4 "Liquidity and Price Discovery in the CDS Market" looks at the speed of the price discovery, i.e. the speed with which new information is compounded into prices, of the credit default swap (CDS) market relative to the equity market.[2] CDS started to become popular in the early 2000s and rose to prominence during the financial crisis. On the one hand, CDS were heavily criticised as tool of malicious speculation, on the

[1] This chapter is joint work with Rainer Haselmann and Paul Wachtel. It is published in the Palgrave Handbook of European Banking.

[2] This chapter is joint work with Philipp Koziol.

other hand they were commonly used as a direct and timely measure of the riskiness of a borrower, for instance during the European debt crisis. However, at least for publicly traded companies, CDS are not the only security that prices in the probability of default of that company. The question, which security type prices new information earlier than the other, arises naturally and is important, since delayed pricing might open up arbitrage opportunities. Most of the literature on this topic focuses on the price discovery process of CDS relative to equity as the equity market is the largest and most liquid market besides CDS. Consequently, we study the price discovery process of CDS vis-à-vis equity in sample consisting of 530 firms and spanning from 2011 to 2013. In line with existing literature, we document an information flow from equity to CDS. However, entity-level analysis reveals that the results are driven by just around half of the firms and the magnitude of the information flow varies strongly, both between and within firms. We try to explain the differences in the price discovery process by differences in CDS liquidity and trading. Though price discovery appears to be affected by CDS liquidity and trading, the actual effect of the different measures varies widely between specifications.

CHAPTER 1

UNDERREPORTING BY OVERDIVERSIFICATION? STRATEGIC USAGE OF VAR DIVERSIFICATION

1.1 Introduction

Regulators increasingly allow banks to use internal models to calculate capital requirements. Banks have an incentive to design and calibrate these models in a capital-requirement minimizing way. For credit risk, Behn et al. (2016) have shown that banks use modelling leeway to reduce capital charges for loans. Begley et al. (2016) claim to have found a similar pattern for market risk. The capital requirements for market risk are calculated as multiple of the Value-at-risk (VaR, henceforth) of the trading portfolio, an upper bound for trading losses obtained by using internal models. Banks seemingly underreport their VaR if their equity ratio is low. Begley et al. (2016) measures under-reporting by the number of trading days on which trading losses exceed their VaR, the upper bound for losses. More of these so-called backtesting exceptions occurred when the equity ratio was low. This finding is surprising against the backdrop of earlier literature, which asserts that banks provide conservative estimates for their market risk exposure. For example, Perignon et al. (2008a) and Perignon and Smith (2010a) found that banks systematically overreport their VaR. This chapter examines one potential channel of possible underreporting, the diversification component in the VaR.

Broadly speaking, the diversification component is a reduction of the VaR due to non-perfect correlation between assets. For example, if a bank has a long position in two, imperfectly correlated assets, the probability that both assets incur severe trading losses on the same day is smaller than one. Hence, the VaR of holding both assets is smaller than the sum of the VaR of the single assets. Banks enjoy leeway in calculating this diversification effect. In the past, banks have reported an apparently conservative diversification effect and, hence, a higher VaR. For example, in its 2002 annual report, the Bank of America states that it does not "fully account for correlation among broad asset classes" to report a more conservative VaR. These conservative estimates provide the banks with some cushion for adverse economic development. If banks report a conservative VaR, they can either extend their trading operations without increasing the reported VaR or reduce the reported VaR while leaving their trading portfolio unchanged. In these cases, using the portfolio diversification does not translate into actual underreporting, but rather in less overreporting. However, as banks have increasingly reported a less conservative VaR, the diversification component could have been used to report a VaR that lies below the true VaR, to actually underreport market risk.

Diversification in absolute terms depends on three factors: The volatility of the returns, the level of asset holdings, and the correlation between the assets. In this chapter, I adopted a method proposed by Perignon and Smith (2010a) to calculate a hypothetical diversification component as a counterfactual to the reported diversification component. The approach takes the first two components - the volatility and level of asset holdings - as given, but relies on a counterfactual correlation matrix derived from market indices to calculate a counterfactual VaR. As no asset-level data is published by the banks, the analysis relies on the broad-asset classes VaR reported by the banks. A broad asset class VaR is the VaR of a sub-portfolio of the banks that is sensitive to particular market prices and rates. The Basel II regulation prescribes five broad asset classes: Equity, interest, credit, foreign exchange (FX, henceforth) and commodities. For example, the commodity VaR describes the possible losses that a bank could incur due to changes in the commodity prices. Likewise, the equity VaR reports possible losses of securities that are primarily sensitive to changes in stock prices. Put differently, this chapter neglects any potential underreporting in the single broad asset class VaR and focuses solely on the aggregation of the sub-VaRs. There is some anecdotal evidence that banks underreport the sub-VaRs, but without asset-level data, detecting this kind of underreporting proves to be difficult.[1]

Consider the following stylised example: A bank's trading portfolio is composed of 10 m USD equity VaR and 10 m USD credit risk. The undiversified VaR - the sum of the VaR of all broad asset classes - equals 20 m USD, but the bank reports a diversified VaR of 15 m USD, i.e. 25% of the undiversified VaR is offset by imperfect correlation between equity and credit risk. In this simple example, the assumed correlation between equity and credit risk can be backed out. Jorion (2006) has shown that the diversified VaR - given the VaR of the broad asset classes - can be expressed as $DVAR = \sqrt{V'RV}$ where V is the vector of broad asset class VaRs and R the correlation matrix. For this particular example, this expression reads as follows:

$$15 = \sqrt{\left(\begin{bmatrix}10\\10\end{bmatrix} \times \begin{bmatrix}1 & \rho\\ \rho & 1\end{bmatrix} \times \begin{bmatrix}10 & 10\end{bmatrix}\right)}$$

and one can solve for the correlation between equity and credit VaR: $\rho = 0.125$. To evaluate whether this implicitly reported correlation is on the high or low end, I compare the implied correlation with the correlation between two market indices that track equity and credit risk: The SP500 for equity and the Aaa-Baa credit spread for credit risk. Assume that the correlation between those two indices is 0.25 instead of 0.125. Plugging this value in the above expression yields a diversified VaR of 15.81 m USD rather than reported 15 m USD. In other words, relative to the benchmark of index correlation, the bank reports a diversified VaR that is 0.81 m USD lower than the benchmark suggests. Note that this approach does not rely on backing out the implied correlation between the different broad asset classes, but compares the reported diversified VaR with an alternative aggregation mechanism based on observable correlation.

[1]For example, Deutsche Bank was being investigated for not including certain interest rate bets in their VaR (Eaglesham, 2013a).

Table 1.1 provides a real-life example for the diversification effect. In April 2004, the Bank of Nova Scotia reported a diversified VaR of 8.2 m USD. The diversification component is sizeable. It offsets 38% of the undiversified VaR of 13.7 m USD. Comparing April 2004 with April 2003 reveals, that the diversification component as percentage of the undiversified VaR (diversification share) varies over time. In 2003, only 33% of the undiversified VaR was offset by broad asset class diversification effects whereas in 2004, the share rose to 40%. Using a correlation matrix based on market indices, I calculate a counterfactual diversified VaR of 8.68 m USD. Compared to this benchmark, the Bank of Nova Scotia underreports their exposure by 0.48 m USD or 5.8 percentage point of the reported VaR. This chapter examines whether such deviations from the benchmark are systematic and coincide with incentives to underreport market risk.

This chapter contributes to the literature in two ways. First, it extends the analysis of Perignon and Smith (2010a) and examines how VaR diversification is affected by the financial crisis. Second, it tests for a possible strategic usage of internal models. In particular, it proposes the diversification components as potential channel for the underreporting detected by Begley et al. (2016). Understanding the channels of underreporting is important as it provides the basis for improved regulation. If the diversification component is indeed used in a strategic manner, imposing more stringent rules on the deductibility of broad asset class diversification might also improve the informational value of the VaR.

The chapter finds significant and persistent deviations of the reported VaR from the benchmark VaR. Banks report a particularly low VaR if their leverage ratio is high and if the potential penalties for underreporting are high. However, the VaR bias does not react to changes in the regulatory capital ratios. In combination with the finding that backtesting exceptions appear to occur less frequently if banks overreport their VaR relative to the empirical benchmark, these results suggest that banks use the diversification component to strategically manage the reported VaR.

The remainder of the chapter is structured as follows. First, more information on the usage of the VaR in the regulatory context, on the modelling freedom of banks and on the calculation of the hypothetical VaR are provided. The second section describes the dataset and the evolution of the VaR bias. Third, the VaR bias is set into the context of possible strategic underreporting by banks to economize on equity capital.

1.2 Value-at-Risk: Regulatory Aspects and Empirical Counterfactual

1.2.1 VaR and Market Risk Capital Requirements

A VaR model gives thresholds that losses are not expected to be exceeded over a fixed time period with a certain probability. Technically speaking, the VaR is a low quantile of the distribution of trading gains and losses. Basel II prescribes a 99% threshold and 10 day holding period for the VaR models used for regulatory purposes. However, banks frequently use other holding periods (one day) and other probabilities (95%, 99.9%) for internal purposes. The capital requirement for the trading portfolio equals the diversified VaR times the so-called regulatory multiplier. By using the diversified rather than the undiversified VaR, increasing (decreasing) the diversification automatically reduces (increases) the capital requirements for the trading portfolio.

To disincentivise underreporting and for validation purposes, VaR models are backtested: If a bank incurs a loss larger than the VaR - a so-called backtesting exception - it is penalized by an increase of the multiplier that translates the VaR into capital requirements. Table 1.6 shows the increase of the multiplier. If the number of backtesting exceptions was below or equal to four in the last 250 trading days, the multiplier is equal to three. If more backtesting exceptions occurred, the multiplier increases gradually until it reaches four if ten or more backtesting exceptions were experienced and the bank is said to be in the "red" zone. The zone in between "green" and "red" is referred to as " yellow" zone. Note that the increase in the multiplier is not monotone: If the number of past exceptions in the last 250 trading days was 4, an additional exception increases the multiplier by 0.4 whereas if the number of past exceptions was 8, the increase would be 0.1.

In addition to the capital penalty due to an increased multiplier, banks face more severe regulatory scrutiny in the yellow and red zone. The supervisory framework explicitly states that the *"burden of proof in these situations should not be on the supervisor to prove that a problem exists, but rather should be on the bank to prove that their model is fundamentally sound."* (BIS, 1996b). In particular, increased regulatory scrutiny includes the provision of disaggregated VaR data on the trading-unit level.

1.2.2 Modelling Freedom

Allowing banks to account for diversification between asset classes has been subject to discussion ever since the introduction of VaR for regulatory purposes. The initial proposal in April 1995 did not permit banks to recognize correlation between asset classes for the calculation of the regulatory VaR. However, the actual amendment from January 1996 did allow banks to adjust their VaR for between asset class correlation (BIS, 1996a).

In the aftermath of the financial crisis, the Bank for International Settlement (BIS) repeatedly expressed its concern that banks miscalulate the diversification component. In May 2012, the BIS asserts that "*the current model-based approach may lead to sig-*

nificant over-estimation of overall portfolio diversification benefits across broad categories of exposures and consequent underestimation of the actual required capital". In the advent of market stress, correlation structures might change rapidly and cannot reliably be estimated using past data. A breakdown of the correlation structure might lead to dysfunctional hedges and disappearing diversification benefits. As a potential remedy, the BIS proposed constraining the modelling freedom of banks regarding the correlation structure. In particular, the BIS proposed that the trading portfolio should be divided into more granular, standardized sub-portfolios and the correlation between the sub-portfolios would be prescribed by the regulator.

Banks have a large set of modelling choices that affects the diversification component. These options can broadly be categorized by the frequency by which they can be altered. First, banks have an array of primarily time-invariant modelling choices. In particular, banks can choose whether they use the advanced Monte Carlo Method or the less complex historical simulation approach to calculate the VaR.[2] None of the banks in the sample did change the calculation method in the observation period. A second set of modelling choices can be altered at low frequency. Notably, banks can choose the length and weighting scheme of the sample period. The Basel regulation only constrains banks to the extent that the sample period must be at least one year. Banks are free to choose any weighting scheme as long as the weighted average time lags of the individual observations do not fall below six months. The third and final set of options contains tools that can frequently be changed and that are not publicly observable. First, banks update their parameters to calculate their VaR frequently. In fact, a survey by the BIS in 2013 revealed that many institutions updated the parameters used to calculate the VaR on a bi-weekly basis and some large institutes even exhibited a weekly update schedule (BIS, 2013). As estimates

[2] A further option is the scaling of the VaR to the ten-day holding period. Banks can either calculate their losses over a ten-day horizon directly or scale one-day losses to a ten day period. However, this options affects only the level of VaR, not the diversification component.

for parameters are highly variable and provide a band of possible parameters rather than point estimates, banks might use these re-calibrations in their favour. Second, banks might hedge open positions with securities that exhibit payoffs in tail events with probabilities below the VaR threshold, e.g. out-of-the-money options. Such securities might violate the sub- additivity assumptions of the VaR, i.e. the sum of the individual positions is actually larger than the total VaR of the portfolio (Danielsson, 2002a). In the latter case, the diversification component is only affected, if securities from other broad asset classes are used to hedge the risk. This chapter remains agnostic about the tools used to manage the diversification component, but assumes that banks have the opportunity to influence the level of diversification in their trading portfolios.

In a revision of the market risk framework in January 2016, the VaR model was replaced by a new risk metric: Expected shortfall (ES). After this revision, banks are no longer allowed to claim cross risk class diversification benefits (BIS, 2016).[3]

1.2.3 Counterfactual Diversification

The empirical diversification share is calculated following Jorion (2006) and Perignon et al. (2008a). Jorion (2006) has shown that the VaR can be written as a function of the VaRs of the broad asset classes and a correlation matrix thereof. Let V be a vector of the individual VaRs of the broad asset classes and R the correlation matrix, then the diversified VaR of bank i in quarter t is:

$$DVAR^{emp}_{i,t} = \sqrt{V'_{i,t} R_t V_{i,t}} \tag{1.1}$$

The correlation matrix R required to calculate $DVAR^{emp}_{i,t}$ is approximated by a corre-

[3]Though only adopted for regulatory purposes in early 2016, the concept of ES is not new. Acerbi and Tasche (2002) provides a theoretical comparison of ES and VaR, Yamai and Yoshiba (2005) a practical perspective.

lation matrix of returns of benchmark indices / rates as proposed by Perignon and Smith (2010a): To capture equity risk, I use the national stock market lead indices. Commodity risk is approximated by the Bloomberg Commodity Index.[4] Moody's Aaa-Baa credit spread is used to track credit risk. To mirror interest risk, I use the one-year constant maturity US bond yield for North American banks. For the European counterparts, I use the one-year constant maturity yield on German Bunds. Exchange rate risk is captured by the trade-weighted exchange rate of the domestic currency. To study the co-movement of the indices, the daily log returns are calculated as difference in the natural logarithm of the indices. Using the returns of the indices is equivalent to assuming that banks hold a net long position in this asset class. Although this assumptions appears reasonable, I discuss the validity in section 1.4.4.1 and test my results for robustness to this assumption.

I calculate several versions of the correlation matrix R. For the baseline results, I use a 250 day window, starting 250 days before the last day of the quarter and ending with the last day of the quarter. The choice of a 250 day window is in line with earlier literature (Perignon and Smith, 2010a) and reflects the minimum sample length of the Basel regulation (BIS, 1996a). A concern with this specification is that it - by using all available return data for a quarter - includes information that banks do not possess when determining their portfolio in the beginning of the quarter. For example, the correlation matrix R_t might be driven by the observations in the last month in the quarter. However, banks do not have this information for determining their portfolio in the first two month of the quarter. However, as correlation matrices are relatively stable over time and change only incrementally, the bias should not be large. In addition, the bias is further reduced by using the average quarterly VaR, rather than daily observations (such as the maximum VaR or the quarter-end VaR), but - to address this concern further - I calculate a different

[4]Formerly known as Dow Jones-AIG Commodity Index and Dow Jones-UBS Commodity Index.

version of the correlation matrix using a 250 day window ending with the last day before the quarter. As an alternative to the sample correlation, I use an dynamic conditional correlation (DCC) model as proposed by Engle (1999) and used by Perignon and Smith (2010a).

In essence, the DCC model is a univariate GARCH model that adjusts the correlations for time-varying volatility. This adjustment provides a better fit than the sample correlation, particularly in settings with abrupt changes (Engle, 2002). Methodologically, the DCC model strikes a balance between the flexibility of a univariate GARCH model and the computational complexity of multivariate GARCH models. This class of GARCH models is estimated in a two-step procedure. First, a univariate GARCH model is estimated. Second, the so-obtained estimates are used to calculate the correlation matrix. The first step yields the conditional covariance matrix $H_t = E(e_t e_t') = D_t R_t D_t$ where $e_t = r_t - E(r_t|t-1)$ represents the unexpected returns and D_t is a diagonal matrix with the conditional standard deviations on the main diagonal.[5] Formally, D_t reads:

$$D_t^2 = diag(\omega_i) + diag(\alpha_i) \circ (e_t e_t') + diag(\beta_i) \circ D_{t-1}^2$$

where $\circ$ denotes the element-by-element multiplier, and R_t is the conditional correlation matrix. R_t can be written as:

$$R_t = diag(Q_t)^{-\frac{1}{2}} \times Q_t \times diag(Q_t)^{-\frac{1}{2}}$$

Q_t is calculated as a function of the standardized residuals and two additional scalar parameters θ_1 and θ_2:

$$Q_t = R(1 - \theta_1 - \theta_2) + \theta_1(z_t z_{t-1}) + \theta_2 Q_{t-1}$$

[5]The description of the DCC procedure borrows heavily from Perignon and Smith (2010a) and Engle (2002)

with R being the unconditional correlation matrix of the standardized residuals. Intuitively, the DCC model adjusts the unconditional correlation matrix R for time variations in volatilities. Eventually, the DCC model generates a correlation matrix for each trading day. The quarterly DCC correlation matrix is calculated as the average of the daily DCC correlations from 250 days before the last day in the quarter to the last day in a quarter.

To quantify the extend of over-/underdiversification, the difference between the reported and empirical VaR is scaled by the reported VaR. Formally, I calculate:

$$VaR\ Bias_{i,t} = \frac{DVaR_{i,t}^{reported} - DVaR_{i,t}^{empirical}}{DVaR_{i,t}^{reported}} \tag{1.2}$$

The interpretation of $VaR\ Bias_{i,t}$ is straight-forward. If $VaR\ Bias_{i,t}$ is positive, the bank reports a higher VaR than the empirical diversification implies, i.e. the bank over-reports risk. Likewise, if $VaR\ Bias_{i,t}$ is negative, the empirical VaR is higher than the reported VaR, i.e. the bank underreports VaR relative to the empirical benchmark.

To make the evolution of the VaR more traceable and highlight the source of the bias, two additional variables are coded: The reported diversification and the empirical diversification share. Intuitively, the diversification shares - the percentage of the undiversified VaR that is offset by between broad asset class correlation - describe the percentage of the undiversified VaR, which is offset by the correlation between broad asset classes. The empirical diversification is obtained by subtracting the empirical VaR from the reported VaR. Then, the empirical and reported VaR diversification share is calculated as follows:

$$Diversification\ Share = \frac{Diversification\ in\ USD}{\sum_{i=1}^{5} VaR_i} \tag{1.3}$$

where i is an index for each of the five broad asset classes.

Overall, this approach is similar to the BIS proposal of narrowing down the modelling choices of the banks. Essentially, it compares the reported VaR to a counterfactual that is constrained to using only market-observable correlation.

1.3 Data

The dataset consists of three types of data: Quarterly VaR data, bank balance sheet data, and returns on the indices. Bank balance sheet data is obtained from SNL, and - if not available from SNL - from Datastream and the quarterly reports. Returns on the commodity risk index (Bloomberg Commodity Index, BCOM) and the national stock markets are taken from Bloomberg. The Aaa-Baa Spread of seasoned bonds is available on the FRED Database of the Federal Reserve Bank of St Louis. The trade-weighted exchange rates and the constant maturity government bonds were downloaded from the national central banks.

VaR data is hand-collected from the banks' annual and quarterly reports. Reporting of VaR information is coarse and the availability of VaR data restricts the sample to 16 banks (Perignon and Smith, 2010b).[6] To be included in the sample, banks must report the individual VaR components, the holding period and the confidence interval for at least 3 years. The sample consists of 16 banks and spans from 2002 to 2014.[7]

All banks in the sample report their VaR either as quarterly averages or year-to-date averages.[8] In addition to the averages, some banks report a wider array of summary

[6]The final sample includes the following banks: BNP Paribas, Bank of America Merrill Lynch, Bank of Montreal, Candian Bank of Commerce, Citigroup, Credit Suisse, Deutsche Bank, Goldman Sachs, ING, JPMorgan Chase, Bank of New York Mellon, Nordea, Royal Bank of Canada, Santander Bank, Bank of Nova Scotia, UBS.

[7]Data availability for VaR is very limited before 2002.

[8]In the latter case, the quarterly averages are backed out by recursively solving for the average VaR of bank i in year y and quarter N: $VaR_{i,y,N} = N * VaR^{avg}_{i,y,N} - \sum_{j=1}^{N-1} VaR_{i,y,j}$

statistics, such as minimum, maximum and quarter-end VaRs. Quarterly averages are the preferred measurement of the VaR, as the other measures that are essentially single-day snapshots are exposed to strong market movement (minimum and maximum) on a single day or window-dressing (quarter-end).

As described above, the incentive of banks to underreport risk depends on the level of equity. Scarcity of equity is measured in three specifications: The leverage ratio - shareholder equity over total assets (Eq/A) - and the regulatory capital ratio tier one (CET1 ratio) and the total regulatory capital ratio (CE ratio). The reason for using all three measures is threefold. First, the regulatory capital ratios might be partly endogenous since a lower VaR due to overdiversification increases the regulatory capital ratio by reducing the risk-weighted assets. This might lead to a downwards bias in the coefficient of regulatory capital ratios. Second, the regulatory ratios might be driven by regulatory changes. Namely the introduction and phase-in of Basel III during the observation period decreased regulatory ratios mechanically. Third, regulatory capital ratios might be a diluted measure of the capital ratio since the risk-weights assigned to the different assets do not necessarily reflect actual riskiness (Acharya et al., 2014). The leverage ratio is not driven by risk-weighting or regulatory changes, but has the disadvantage of being no real constraint for the bank. The Basel Regulation requires a minimum risk-weighted capital ratio, but no leverage ratio. Therefore, a bank with a high leverage might be far away from a binding equity constraint.

As an additional measure of capitalization, I resort to CDS spreads. CDS spreads are strongly linked to the default probability of the underlying reference entity and a proxy for the refinancing costs of the bank. High CDS spreads indicate a high probability of default and high funding costs. Like the leverage ratio, it does not reflect any regulatory threshold and is not subject to accounting changes, but rather reflects the market perception of the riskiness of a bank.

1.3.1 Summary Statistics

Table 1.3 displays summary statistics. The average bank in the sample has total assets of 1,140.22 bn USD and a regulatory capital ratio of 14.30%. The leverage ratio, defined as book equity over total assets (Eq/A), is much lower at around 5.89%. On average, banks were profitable with an average net income to total assets ratio of 0.15%.

On average, banks report a VaR of 133 m USD, but the range is large. The smallest reported VaR was 6.0 m USD by the Bank of New York Mellon in 2006q3. JP Morgan exhibited the highest VaR in the sample with 604.21 m USD.[9]

The *VaR Bias* is on average negative, indicating that the empirical VaR is generally larger than the stated VaR. Qualitatively, this implies that banks are underreporting their VaR relative to the empirical counterfactual. Quantitatively, the average baseline *VaR Bias* of -6.17 suggests that banks should increase their reported VaR by 6.17%, if the empirical correlation holds true for their portfolio. The VaR bias based on the alternative estimation window ending with the first day of the quarter, *Var Bias (alt)*, is slightly smaller with an average of -6.05. The VaR bias calculated based on the DCC correlations, *VaR Bias (DCC)*, is more negative on average (-8.42) and exhibits a smaller standard deviation and narrower range.

In unreported regressions, I examine the autocorrelation in the *VaR Bias*. All three variations of the *VaR Bias* are highly autocorrelated with a coefficient between 0.58 of

[9]VaR in currencies other than USD were converted using the quarter-end exchange rate. VaR reported at the 95% level were transformed into 99% VaR by assuming a normal distribution. Under this assumption, the 95% VaR can be converted into the 99% VaR by multiplying it with normal score of the 99% percentile (2.33) and dividing by the normal score of the 95% percentile (1.65).

the baseline *VaR Bias* and 0.78 for *VaR Bias (DCC)*.[10] Therefore, adjusting for autocorrelation in the dependent variable is paramount.

In order to be a valid counterfactual, the empirical and reported VaR should be positively but imperfectly correlated. Indeed, the stated VaR is highly correlated with all three empirical VaR measures. The correlation of the stated VaR is the strongest with VaR bias based on the alternative start dates (correlation coefficient: 0.91) and lowest with the DCC bias (0.88). As expected, the different empirical VaR bias measures are highly correlated among each other with no coefficients being lower than 0.9.

For the subsample of banks for which data on backtesting exceptions is available, the average number of exceptions is 0.6 per quarter. In 82 percent of the bank-quarter observations, banks were in the green zone, i.e. they had four or less backtesting exceptions in the last three quarters. Only four percent of the observations fall into the yellow zone, whereas 14 percent of the observations fall into the red zone.

1.3.2 Cross-sectional and Over Time Variation of the VaR Bias

The VaR bias varies both between banks and over time. Table 1.4 provides a break-down of the VaR bias by banks. Most banks exhibit a negative VaR bias on average, i.e. they report a lower VaR than the benchmark correlation would imply. In some cases, for instance the UBS, with an average bias of 31.9 pp, or the Bank of America, with a bias of -30.8, the bias is large and persistent. The differences are in line with the estimates of Perignon and Smith (2010a), who find differences in the diversification share, i.e. in the level of reported VaR, between -25 and 35 pp.

A persistent bias either suggests that the bank consistently under- or overreports

[10] Formally, I estimate the following equation: $VaR\ Bias_{i,t} = \alpha_i + \alpha_t + \beta \times VaR\ Bias_{i,t-1}$. In the text, I report β.

diversification or that the benchmark correlation matrix does not perfectly reflect the bank's trading portfolio. For example, it is conceivable that the bank holds a commodity portfolio that does not completely reflect the composition of the Bloomberg Commodity Index. In this case, the correlation of the commodity return vis-à-vis the other risk indices does not perfectly represent the true correlation of the bank's portfolio and leads to a VaR bias.

The variation of the aggregated VaR bias over time is explored in Figure 1.1, Figure 1.2 shows the individual development for each bank. Rather than the VaR bias, the source of the bias - the different diversification shares - are shown. Initially, the empirical diversification was lower than the reported diversification, but from 2004 to 2008, the empirical diversification exceeds the reported diversification. From 2008 onwards, the picture is reversed and the reported diversification exceeds empirical diversification. Translated into the VaR bias, the sample period breaks downs into roughly two periods. In the first period ranging from 2004 to mid-2007, banks, on average, provide a seemingly conservative estimate of their VaR. From mid-2007 onwards, the VaR bias is negative, i.e. banks overreport diversification and underreport VaR risk.

The trend in the average bias suggests a common factor for all banks. A possible common factor is the historic volatility that is fed into all banks' VaR models. As banks use time-series data as input for their VaR models - up to 5 years of past data - the current volatility may be much lower than the historic volatility levels. In this case, the reported VaR might be below the level that current volatility implies. Likewise, in periods with high volatility, the average volatility used in the models is smoothed by earlier periods with lower volatility. Indeed, eye-balling of Figure 1.3 suggests that periods of a high VaR bias, i.e. overreporting, coincide with a period of relatively low volatility.

To explore how changes in correlation might drive changes in the bias, I analyse how changes in the correlation matrix co-move with changes in the VaR bias. If sluggish adjustments to changes in the correlation matrix drive the VaR bias, one should observe larger biases when the changes to the correlation matrix are large. Changes in the correlation matrix are calculated by first summing up and then taking the square root of the squared difference of the correlation matrix used in the last period and the one used for the current year-quarter. It should be noted that this measure does not indicate whether there is "more" or "less" diversification between the different risk indices. Figure 1.4 shows a scatter plot of the absolute changes in the VaR bias and the change in the correlation matrix. Eye-balling suggests and (unreported) regression analysis finds only a very weak relationship between changes in the correlation matrix and changes in the VaR bias. I conclude that sluggish updating of the correlation matrix is not a major driver of the VaR bias.

1.4 Strategic Diversification

In this section, possible strategic considerations behind the VaR bias are examined. As outlined above, banks have both the tools as well as the incentives to strategically adjust the calculation of the VaR diversification. Banks face a trade-off between benefits of underreporting and its costs: Lower capital requirement today due to a higher reported VaR versus potential higher capital requirement tomorrow due to an increased multiplier. Both, the costs and benefits vary within a bank and over time. This variation of incentives is exploited to elicit possible strategic considerations behind the VaR bias.

The benefits today are driven by two factors: The scarcity of equity and the regulatory multiplier. The costs of having higher capital requirements today are increasing the scarcity of equity and increasing the regulatory multiplier. In other words, reducing the capital requirements today is more valuable, if the capital ratio is low and / or the regulatory multiplier is high. The benefits of having a higher equity ratio are manifold. First, low capital ratio could attract the attention of the regulator and might even trigger regulatory actions. Second, a lower capital ratio might reduce the credit rating and thereby increase the cost of capital. Therefore, the bias is expected to be higher, if the capital ratio is low. This reasoning condenses into the first hypothesis:

Hypothesis 1 *Banks underreport VaR relative to the benchmark VaR if their equity ratio is low.*

Banks benefit more from underreporting their VaR, if the regulatory multiplier is high as the "capital savings" from underreporting are a monotone function of the multiplier. The costs of under-reporting depend on the number of backtesting exceptions in the previous quarters. As shown in Table 1.6, the marginal costs of an additional exception, i.e. increase in the multiplier, vary with the number of past exceptions. For example, an additional backtesting exception incurs no increase in the multiplier, if the number of past exceptions lies between zero and three. However, if the number of past exceptions equals four, the multiplier jumps from 3.0 to 3.4, if an additional exception is observed. Note that this reasoning is distinct from the benefit considerations above. Above, the already prevalent costs of incurred exceptions are examined. Here, the effects of the marginal costs of an additional exception are in the focus. It is expected that banks report a higher VaR relative to the benchmark, if the penalty for an additional exception is high. Formally, the second hypothesis reads as follows:

Hypothesis 2 *Banks overreport VaR if the marginal costs of an additional exception are high and underreport their VaR if the regulatory multiplier is high.*

Finally, the VaR bias will be related to the number of backtesting exceptions. If the VaR bias is indeed used to over-/underreport market risk, a positive VaR bias should translate into a higher number of exceptions.

Hypothesis 3 *Backtesting exceptions occur more frequently if banks report a low VaR compared to the empirical benchmark.*

1.4.1 Hypothesis 1: Scarcity of Equity

The hypothesis that banks increase their capital ratios in times of low equity, the measures of over-/underdiversification and capital are related in the following regression equation:

$$
\begin{aligned}
VaR\ Bias_{i,t} = \ & \alpha_i + \alpha_t \\
& + \beta \times Capital\ Ratio_{i,t} \\
& + \kappa \times Bank\ Controls_{i,t} \\
& + \theta \times Market\ Controls_t + \epsilon_{i,t}
\end{aligned}
\tag{1.4}
$$

Bank controls include the log of total assets and the ratio of net income and total assets. To account for the persistent VaR biases at the bank-level and the common trend in aggregated VaR bias, bank fixed-effects (α_i) and year-quarter fixed effects (α_t) are included. Including the bank-fixed effects shifts the focus of the analysis towards within-bank variation. The year-quarter fixed effects account for common trends and extreme events, such as the collapse of Lehman Brothers. To further control for the effect of volatilities, the volatilities of the risk indices are included as independent variables.

The coefficient of interest is β. Recall that higher VaR bias indicates lower levels of diversification, i.e. overreporting of VaR. If β is positive, banks report a higher VaR if equity is not scarce. Recall that a positive coefficient does not immediately translate into underreporting. Banks might increase the diversification level (i.e. decrease the reported VaR), but still remain under the empirical diversification level.

Table 2.2 presents the results of the main specification (Equation 1.4). Column 1 to 3 show the results for different combinations of control variables. Adding control variables reduces the magnitude and significance only slightly. In column 4, standard errors are clustered at the year-quarter level rather than the bank-level. Using standard errors clustered at the bank-level generally provide less conservative estimates of the standard error. To account for the different sizes of the trading portfolios, I weigh the bank-quarter observations by the undiversified VaR in this quarter in column 5. Using the weights increases both magnitude and significance of β.

To tackle possible biases due to autocorrelation in the dependent variable, I include the lagged VaR bias as additional independent variable. As pointed out by Arellano and Bond (1991), including lagged dependent variables in a fixed-effects model might bias the estimates. To obtain consistent estimates, I adopted the general method of moments (GMM) approach suggested by Arellano and Bond (1991) and estimated the model in first differences and using past values of the dependent variable as instrument. Column 6 contains the results of the regression. The coefficient remains positive and significant at the 10% level. In terms of magnitude, the coefficient of 1.36 is substantially smaller than previous results.[11]

Depending on the specification, a one percentage point increase (decrease) in the leverage ratio is associated with an increase (decrease) in the VaR bias by 1.36 to 4.11 percentage points. The smallest effect of 1.36 is registered in the preferred Arellano-

[11]Both, the Sargan and Hansen Test do not reject the hypothesis of over-identification at any conventional level of significance. The Arellano-Bond test for autocorrelation for the AR(2) process does not reject the hypothesis of no autocorrelation. In other words, past values are endogenous from current values and are therefore valid instruments (p-value: 0.792). This holds true for every regression of this type in the chapter.

Bond specification. In terms of standard deviation, the effect is relatively small. A one standard deviation increase in *Eq/A* increases *VaR Bias* by 0.14 standard deviations. To grasp the economic magnitude, recall that the average diversified VaR equals 133.81 m USD. An *VaR Bias* by 1.36 pp would increase the VaR by only 1.81 m USD and the capital requirements by 5.46 m USD.[12]

1.4.1.1 Alternative Definitions of Equity Scarcity

Table 1.8 displays the results for the alternative specification of equity, the capital tier one ratio, the regulatory capital ratio and CDS spreads. Surprisingly, the regulatory capital ratios do not exhibit a significant co-movement with the VaR bias. In other words, the regulatory capital constraints do not drive overreporting of the VaR diversification. Regarding CDS spreads, the estimated coefficients are generally in line with the expectations, but insignificant in the case of the preferred specification with adjustment for autocorrelation (column 6). This finding suggests that market assessment rather than regulatory pressure incentivises banks to report a lower VaR.

1.4.1.2 Alternative Calculation of the VaR Bias

The results for the alternative specifications of the VaR bias, the alternative estimation window and the dynamic conditional correlations, are summed up in Tables 1.18 and 1.19. For *VaR Bias (alt)*, the results are virtually unchanged. An exception is the CDS spread that becomes strongly significant and negative in the Arellano-Bond specification in Table 1.18, Panel D, Column (6"). For *VaR Bias (DCC)* as dependent variable, the results are mixed. The leverage ratio is only significant if no volatility or bank controls are added or if the observations are weighted with the undiversified VaR. In the remaining

[12] I approximate the effect on the capital requirement by multiplying the average VaR with the estimated coefficient and the regulatory multiplier.

specifications, the leverage ratio does not explain variation of the *VaR Bias (DCC)*.

1.4.1.3 Subsamples

To elicit the drivers of the relationship, Equation 1.4 is adapted by including subsample dummies and interactions of the subsample dummy with the capital ratio. Table 1.9 contains the results for the subsamples.

First, possible differences between European and North American banks are analysed in column 1 of Table 1.9. The insignificance of the interactions suggests that there is no difference between banks that can be attributed to the geographic location.

Second, the sample is split by the calculation method of the VaR. Some banks use the so-called "historical simulation" approach, whereas others rely on the more advanced Monte Carlo method. Lazaregue-Bazard (2010a) points out two advantages of the Monte Carlo method: First, the Monte Carlo Method produces a larger number of possibles paths of the pre-specified distribution than other methods. Second, Monte Carlo simulations are more data-intensive and allow for a better modelling of extreme events. However, the insignificant coefficients do not indicate that the results are driven by banks using either calculation method.

Third, the size of the trading exposure might affect the bias for several reasons. Banks with a large trading portfolio might be under more scrutiny by the regulator than banks with a smaller portfolio. Higher regulatory scrutiny should decrease the bias. Likewise, banks with a large trading portfolio possibly devote more resources to the calculation of the VaR and might thereby reduce errors stemming from model quality. To assess the size effect, a dummy is coded that takes the value of one if the bank has an above mean VaR and zero if the bank's VaR is below the mean. The interaction term is negative and significant at the 10%-level. The negative sign implies that the relationship between the *VaR Bias* and equity scarcity is strongest for banks with a small VaR.

Fourth, the cost side of the trade-off is taken into consideration. The dummy *yellow* takes the value of one if the number of past backtesting exceptions was between five and nine, i.e. in the yellow zone of the regulatory multiplier. The increased multiplier makes maintaining a higher VaR more costly and thereby increases the incentives to reduce the reported VaR. The coefficient of the interaction term is negative and significant at the 10% level. The negative sign suggests that banks with a low capital ratio report a lower VaR, if having a higher VaR is more expensive in terms of equity.

Finally, possible changes of the relationship over time are examined in Table 1.9. The divergent literature on under-/overreporting of VaR might be rooted in banks underreporting risks in troubled times, but overreporting in calm times. Indeed, O'Brien and Szerszen (2014) find that VaRs were more conservative, but closer to the true values in the crisis period. Since the start of the financial crisis is ambiguous, I code a dummy for post 2007, 2008 and 2009 observations and interact the dummies with the leverage ratio (Eq/A). None of the interactions is significantly different from zero. Hence, it is concluded that the relation is not driven by particular time periods.

1.4.2 Hypothesis 2: Regulatory Multiplier

This section examines whether the shape of the penalty function translates into differences in the VaR bias. Note that unlike in the previous section, this specification focuses on the marginal costs of an additional rather than the already incurred increased penalty for past exceptions. Equation 1.4 is adapted in the following fashion:

$$
\begin{aligned}
\textit{VaR Bias}_{i,t} = \; & \alpha_i + \alpha_t \\
& + \beta \times \mathbb{1}[\textit{Past Exceptions} = n]_{i,t} \\
& + \gamma \times \textit{Bank Controls}_{i,t} \\
& + \kappa \times \textit{Market Controls}_t \\
& + \phi \times \textit{VaR Bias}_{i,t-1} + \epsilon_{i,t}
\end{aligned} \tag{1.5}
$$

where α_i and α_t are again bank and year-quarter fixed effects. Bank and market controls are the same as in Equation 1.4. $\mathbb{1}[PastExceptions = n]$ is a dummy variable that takes a value of one if the number of past exceptions in the previous quarter equals n. Since the largest differences in the marginal costs of additional exceptions occur around four backtesting exceptions in the previous three quarters, the analysis focuses on this threshold. Translated in terms of Equation 1.5, Hypothesis 2 translates into an expected positive β, if an additional exception leads to a penalty, i.e. an increase in the multiplier. I expect that the effect is stronger, if the increase in the multiplier is larger.

Table 1.6 shows the estimated coefficients for various specifications of the dummy. The results for four exceptions in the last three quarters is shown is column 4, the remaining columns report the results of placebo tests. In the first two columns, the dummy takes the value of one if the number of exceptions in the last three quarters is equal to one (column 1) or three (column 2). The coefficients of the dummies are small and not significant at any conventional level of significance. Column 3 examines whether being in the green zone affects the level of the VaR bias. Again, the coefficient is small and not significant. However, if the number of exceptions in the last three quarters equals four and the penalty for an additional exception is the highest, banks increase their reported VaR relative to the benchmark VaR by 12.53 pp of the reported VaR (p-value <0.05). Column 5 and 6 examine the VaR bias above the threshold of four exceptions. The negative coefficients suggest that banks report a lower VaR if the multiplier increases above the baseline of three, but none of the coefficients is significant at conventional levels. This effect of sitting on the boundary of four exceptions is of considerable economic magnitude: For an average bank, a 12.53 pp increase in the VaR translates into an increase in the capital charge of 50 m USD.

The positive coefficient of being at the boundary and non-existing effects of sitting above or below the threshold suggest that banks report a higher VaR if the marginal costs are high. Hypothesis 2 is therefore considered to be confirmed. However, it is unclear whether the penalty in form of the increased multiplier or the threat of higher regulatory scrutiny is ultimately responsible for the overreporting around the threshold.

1.4.2.1 Alternative Calculation of VaR Bias

Different calculation methods of the *VaR Bias*, namely the alternative estimation window and the dynamic conditional correlation, do not result in different results. Results are shown in Table 1.10. Crucially, the coefficient of $\mathbb{1}[\textit{Past Exceptions} = 4]$ remains positive and significant at the 5% level. All other dummy variables remain insignificant.

1.4.3 Hypothesis 3: Backtesting Exceptions

In this section, the connection between the VaR bias and the number of exceptions is explored. If the VaR bias is actually connected to underreporting, a negative bias should increase the number of exceptions.

Modelling the relationship between the VaR bias and backtesting exceptions is not straightforward. In particular, the data type of the backtesting exceptions is not clear-cut as the number of exceptions is neither a binary nor a genuine continuous variable. To avoid modelling biases, I use four different approaches to test the relationship between the VaR bias and the number of backtesting exceptions.

The first and most intuitive approach is a binary response model. In this case, the dependent variable is a dummy that takes the value of one if an exception occurs in a quarter. However, this option does not account for the number of exceptions in a quarter. To account for the number of exceptions, I employ a count regression model with the actual backtesting exceptions as dependent variable. The most commonly used count regression model, the Poisson regression, is not suited for the data: A key assumption of the Poisson regression is that the mean and the variance of the dependent variable are roughly equal. As shown in Table 1.3, even the standard deviation of the exceptions is more than three times as large as the mean. One remedy for this so-called "overdispersion" is the negative binomial regression. In essence, the negative binomial regression is a Poisson regression that explicitly models the overdispersion and uses narrower confidence intervals (Greene, 2008a). To strike a balance between the first and second approach, I code an ordinal variable that takes the value of zero if no exceptions occurs, one if only a single exception occur in a quarter and two if more than one exceptions occurs. In either specification of the dependent variable, adding fixed effects is problematic. First, adding year-quarter fixed effects effectively eliminates quarters in which no exceptions occurs and thereby nearly halves the number of observations. Second, adding fixed effects into a logistic regression might give rise to the incidental parameter problem, i.e. generates inconsistent estimates (Lancaster, 2000). This bias is particularly pronounced for panels with a limited length. As my dataset spans over 52 quarters for 12 banks, the bias should be limited. In addition, the negative binomial regression does not suffer from the incidental parameter problem. Finally, I adopt the approach of Begley et al. (2016) and standardize all continuous variables - including the number of backtesting exceptions

- to have zero mean and unit variance. This approach circumvents the aforementioned problem by removing the count character of the exceptions and allows Begley et al. (2016) to use OLS regressions techniques rather than the aforementioned models that explicitly account for the type of the dependent variable.

The results for the baseline specification of *VaR Bias* are reported in Table 1.7. The upper panel presents the results for the discrete models, the lower panel the coefficients of the Begley-type regressions. Overall, the results do lend very limited support for Hypothesis 3. Though the sign of the coefficient is - in line with the expectation - negative, i.e. suggesting that overreporting reduces the likelihood of an exception, it is not significant in any specification at any conventional level.

In the Begley-type regressions, the coefficients of *VaR Bias* are negative if any set of fixed effects added, but only significant if both year-quarter and bank fixed effects are added. The suggested magnitude of the effect is large. A one standard deviation increase in the *VaR bias*, i.e. an increase in overreporting, reduces the number of exceptions by 0.117 standard deviations. Overall, the support for Hypothesis 3 in the baseline specification is limited.

1.4.3.1 Alternative Calculation of the VaR Bias

As for Hypothesis 1 and 2, I estimate all specifications with the alternative estimation window and the DCC VaR Bias. The results are presented in Tables 1.11 and 1.12. The results for *VaR Bias (alt)* are slightly stronger in terms of magnitude and significance, the coefficients remain insignificant. Unlike for the first two hypothesis, the *VaR Bias (DCC)* generates significantly stronger results. In the discrete models, adding either year-quarter or bank fixed effects to the logistic regression generates significant, negative coefficients of the VaR Bias (DCC). The coefficient is not significant in the ordered logistic specification (Panel A, column 5), but significant at the 10% level in the negative binomial regression. Results for the Begley-type regression are very similar, yet slightly stronger.

The stronger results for *VaR Bias (DCC)* might stem from the superiority of the DCC model in capturing abrupt changes in returns. As shown in Figure 1.5, most of the exceptions occur during the financial crisis, i.e. in periods of large, unanticipated changes in the underlying indices. The sample correlations might not capture these movements as well as the DCC model does.

1.4.4 Robustness Tests and Additional Specification

1.4.4.1 Estimation Window and Short Positions

As outlined in the previous sections, banks differ in their VaR modelling and, in particular, in their time horizon they use for the VaR calculations. To account for these differences, I estimate the correlation using a shorter estimation window (150 days) and a longer one (400 days). Further, I will allow banks to have net short positions in a broad asset class. To model short positions, the returns of the asset class of which the bank is assumed to hold a short position are multiplied with minus one. In other words, the trading portfolio experiences a negative return, if the associated index increases.

Table 1.13 explores how different correlation assumptions affect the results for the scarcity of equity. It reports the coefficients of the Arellano-Bond specification with year-quarter and bank fixed effects as well the lagged bias. In column 1 and 2, the estimation window of the correlation matrix is lengthened to 400 trading days and shortened to 150 trading days. Both, shortening and lengthening the estimation window does not alter the results qualitatively. In columns 3-7, I allow for short positions in a broad asset class.

Allowing for a net short position in equity, foreign exchange and commodities leave the coefficient of the leverage ratio, Eq/A, positive and significant at the 10% level. However, if banks are assumed to be short in interest rate or credit risk VaR, the coefficient turns insignificant but remains positive.

Table 1.14 examines whether alternative estimation windows and short positions generate different results with regards to Hypothesis 2, i.e. that banks overreport if the costs of exceptions are high. For the sake of brevity, I only report the results for the crucial threshold of four exceptions in the last three quarters (column 4 in Table 1.6). Similar to the changes described in the previous paragraph, the coefficient turns insignificant if banks are assumed to be short in credit, interest rate and equity risk.

Finally, I test whether the results for Hypothesis 3 are affected. In particular, I re-estimate the logistic regression and the normalized, Begley-type regression with both sets of fixed effects with the VaR biases that allow for short positions and different estimation windows. For nearly every specification, the VaR bias does not significantly affect the number of back-testing exceptions.[13]

Overall, the results suggest that the assumption of a long position - especially in credit and interest rate risk - is crucial for the analysis. From the outset, it is unclear whether the assumption of a long position for the baseline specification is reasonable. In the tests above, I changed the assumptions that all banks have a long position in each asset class to the assumption that banks are long in all but one asset class. The reality, however, might be more complex. Some banks might hold a short position whereas other banks hold a long position. Likewise, a bank might be long in a broad asset class at some point in time, but long at another. The literature gives little guidance on the exposure

[13]Regressions unreported. VaR bias remains significant and negative in the logistic regression if banks are assumed to be short in equity or credit risk.

of banks to different risk classes. O'Brien and Berkowitz (2005) find that the exposure of six large dealer banks to certain risk classes varies only moderately over time and that all banks in the sample maintained a net long position in interest rate risk over the entire sample period. However, the sample of O'Brien and Berkowitz (2005) spans from 2000-2002 and might not capture the effect of the financial crisis and financial innovations, such as CDS. Using a larger and more recent dataset, Begenau et al. (2015) find - again using a factor model - that banks maintained not only a positive exposure to interest rate but also to credit risk, even after accounting for derivative exposure. Therefore, assuming a net long position in credit and interest rate risk might be a reasonable assumption, though the question can only be conclusively be answered using asset-level data.

1.4.4.2 Omitting Time Periods

As outlined above, VaR as a risk measure was subject to severe strain in the immediate aftermath of the financial crisis. In section 1.4.1.3, I examined whether the relationship between measures of equity scarcity and the VaR bias changes over time by adding interaction terms. As a robustness test, I take a different approach to elicit the importance of the crisis period for the identification of Hypothesis 1 by estimating the Arellano-Bond specification of Equation 1.4 for subsamples that exclude certain years. I start with dropping observations in a particular year (2004-2010) and conclude by excluding the entire immediate crisis period (2007-2010). Table 1.15 holds the results. If either all 2006 or 2007 observations are dropped, the leverage ratio is no longer a significant determinant of *VaR Bias*. Dropping other years or the entire crisis period strengthens the results. I conclude that much of the identification stems from the reaction of banks to the crisis in 2007.

1.4.4.3 Controlling for the Composition of the VaR

A further omitted variable is the composition of the VaR. The composition of the VaR has two aspects. First, the actual shares of the different sub-portfolios might matter. If - for example - market correlation captures the co-movement of the equity and commodity portfolio worse than co-movement of the equity and foreign exchange portfolio, the VaR bias should be larger for banks with a higher commodity portfolio. Second, the concentration of the total VaR in a certain sub-portfolio might matter. If - hypothetically - the entire VaR of a bank consists of credit risk, the potential diversification effect is zero by construction. If the total VaR is less concentrated in a single broad asset class VaR, the potential diversification benefits and thereby the potential VaR bias is larger.

To control for the first channel, the different shares of the sub-portfolios, I add the shares of the sub-portfolios on the total VaR as control variables. Adding the shares makes the results stronger in terms of magnitude and significance. To address the second potential channel, the concentration of the VaR, I code two variables. First, I calculate the Herfindahl-Hirschman-Index (HHI) of the shares of the sub-portfolios on the total VaR as the sum of the squared shares. The HHI is bounded between $\frac{1}{N}$ and 1, where N is the number of broad asset classes to which a bank has a non-zero exposure. Low values of the HHI indicate a low concentration, high values a high concentration. Second, I code a variable equalling the number of non-zero sub-portfolios. For example, if a bank has a non-zero exposure to all five broad asset classes, the variable takes a value of one. If a bank has, for instance, no exposure to credit risk but to all other exposures, the variable takes a value of four.[14] Adding these controls reduces the magnitude of the effect of the

[14]Note that the number of non-zero sub-portfolios might vary over time for a bank. Having a positive exposure in all or only four asset classes are nearly equally common with 313 and 316 bank-quarter observations, respectively. The remainder of 54 observations exhibits a count of three non-zero sub-portfolios.

equity ratio slightly: The coefficient drops from 1.355 (p-value: 0.05) to 0.793 (p-value: 0.06) if the HHI is added as control variable and to 0.976 (p-value: 0.09), if the number of non-zero sub-portfolios is included as regressor.[15]

1.4.4.4 Functional Form

Above, I used unscaled versions of the leverage and capital ratios. However, it is conceivable that the relationship between the dependent and independent variable is non-linear. I therefore re-estimate the core regressions of each hypothesis using different transformations of the independent variables. Notably, I use the log transformation and second order polynomial model.

In Table 1.16, I re-estimate the Arellano-Bond specification of Equation 4 for the different functional forms. In the first column of each panel, I report the coefficient of the linear model. The second column shows the coefficients of log-transformed capitalisation measures. In the third column, the squared capitalisation measure is used as dependent variable. The fourth column shows the results of the polynomial model with the linear and squared capitalisation measure.

Generally, the results are not driven by the functional form of the capitalisation measures. For the leverage ratio and the CDS spreads, the log-transformations generates stronger results in terms of significance. The coefficient of the squared regressors have the opposite sign as the linear term, but the linear effect dominates the squared effect for the entire range of the leverage ratio and the CDS spreads in the sample.[16] For the regulatory capital ratios (Panel B and C), the coefficient remains insignificant. One exception is the

[15]Results are not reported for the sake of conciseness.

[16]Given the coefficient of 5.64 of the linear component and -0.25 of the squared term suggests a net negative effect for values above 22.56. However, the largest observed leverage ratio is 13.88. For the CDS spread, the threshold for a net negative effect is 621 basis points and the highest observed CDS spread is 486 basis points.

logarithm *CET1 Ratio*, but the coefficient is small and only marginally significant.

1.4.4.5 Stress Tests

During the sample period, the regulators conducted a series of stress tests to assess the banks' ability to withstand the outfall of adverse economic developments. As the design of the stress tests varied between regions and over time in several dimensions, the stress tests might not be perfectly comparable. For example the stress tests might vary in the severity of the assumption of the economic development, the disclosure of bank-level data and the fail/pass threshold. However, either type of stress test puts the bank, its capitalisation and its internal models in the spotlight of the regulator. This increased scrutiny might provide additional incentives for banks to appear less risky then they actually are or induce caution in risk modelling. Further, as stress tests do not use the current balance sheet for the stress test, but rather the asset composition at the end of the previous fiscal year, banks have an incentive to report a lower VaR in the quarter that is used for the stress test calculations. As stress tests are announced well in advance, banks have the opportunity to adjust their risk positions in anticipation of the stress test. For example, the EBA 2014 stress test used the end-2013 balance sheets to calculate the scenarios, but the results were published in October 2014.

To evaluate a possible effect of stress tests, I examine the VaR bias in quarters in which stress test results are released and the quarters which serve as a reference or starting point for the stress test calculations. First, I code the variable *REFERENCE*, which takes a value of one, if the balance sheet of the bank in this quarter is used as starting point for the stress tests and zero otherwise. Second, I code a dummy variable, *RESULTS*, that takes the value of one, if stress test results for a bank are released in a quarter.[17] Defining those quarters is not as straight forward as it might seem at the first glance. Whereas stress tests by the European Banking Authority and the ECB examined only banks head-quartered in the European Union, the American counterpart, the Comprehensive Capital Analysis and Review (CCAR) includes also subsidiaries of foreign banks. For example, the Deutsche Bank is subject to both, the European stress tests as well as - by proxy of it subsidiary Deutsche Bank Trust Corporation - the CCARs. However, as the CCAR examine only the US American business division of a bank, I do not count stress tests of the division as stress tests for the entire bank. Third, I code a dummy, *FAIL*, variable that takes the value of one if a banks does not pass all elements of a stress test. Again, coding this variable is not straight-forward as the names of failing banks were not always reported.[18] Further, none of the European banks in the sample experienced a capital shortfall in any scenario. I therefore estimate the effect of *RESULTS* and *FAIL* for the combined EU-North America sample as well as individually for each region.[19]

Table 1.17 holds the results. The sign of *REFERENCE* in the full sample is positive, but the coefficient is not significant at any conventional level (column 1). The negative, yet insignificant coefficients of *RESULTS* in the full sample (column 2) suggests that banks overreport diversification, i.e. underreport their VaR by roughly 2.4 percentage points in quarters during which stress test results were released. To mitigate possible biases due to different designs, I estimate the effect separately for American banks (column 3 to 5) and European banks (column 6 and 7). The results suggest that the results are driven by

[17] In the US, stress test results were published in the second quarter of the years 2009 to 2014. In the EU, results were published in 2009q4, 2010q3, 2011q3 and 2014q4. In each case, the reference quarter was the last quarter in the previous year.

[18] For instance, the 2011 CCAR or the 2010 EBA stress do not disclose which banks did fail.

[19] The US stress test sample includes the Bank of America, the Citigroup, Goldman Sachs, JP Morgan and the Bank of New York Mellon. The European stress test sample consists of the Deutsche Bank, the ING Group, the Santander Bank, Nordea and the BNP. All European banks in the sample passed each of the stress tests. The Bank of America and the Citigroup in 2009, the Citigroup in 2012, Goldman Sachs and JP Morgan in 2013 and the Citigroup in 2014 did not pass all elements of the stress test.

US banks which underreport market risk by 21.10 percentage points in reference quarters and by 9.472 percentage points in announcement quarters relative to the VaR benchmark, whereas the European banks do not exhibit a pronounced pattern around stress tests. Interestingly, the negative coefficient of *RESULTS* and the positive coefficient of *FAIL* suggests that banks which do not pass a stress test do not underreport market risk as strongly as those banks that passed the test.[20]

The interpretation of the results is not clear-cut. It was expected that banks want to appear to be better capitalised during stress test periods in order to pass the test and to appear healthier to the public. The negative sign for *FAIL* could be the manifestation of an aversion against any further scrutiny by regulators and the market that would be attracted by a backtesting exception. However, as the number of observations is low, the tests have only limited power. As banks report their trading portfolios to the regulator, this question could be better addressed with micro data.

1.5 Conclusion

This chapter examines a channel of possible VaR underreporting, the diversification component. Past discussions about the diversification component and the removal for correlation effects from the most current regulation suggest that mis-calculations of the diversification indeed lead to underestimation of VaR. To control for variations in the correlation between asset classes, I construct a hypothetical VaR measure using a correlation matrix derived from public risk indices and the VaR breakdown reported by the banks using a methodology developed by Perignon and Smith (2010a).

[20] Banks might anticipate their failure in the stress test and might therefore report an even lower VaR in the reference quarter. However, failing banks do not exhibit a different behaviour in terms of the VaR bias in those quarter. The coefficient of the *FAIL*-specification is 14.45 with a p-value of 0.26.

I find persistent and systematic deviations of the reported VaR from the counterfactual benchmark. To examine whether banks strategically use their internal models to report a favourable VaR, I examine the reaction to time-varying incentives on the within bank variation of the bias. Banks report a lower VaR if their non-regulatory equity ratio is low and a higher VaR if marginal costs are high. The results are sensitive to some assumptions - such as the assumption of a long position in each asset class - and the modelling of the correlation between the broad asset classes. Overall, the results suggest that bank did use their modelling freedom to strategically report a lower VaR.

Tables

Table. 1.1: Example VaR Calculation

	Average for the three month ended		
Asset Class ($ USD millions)	April 30 2004	January 31 2004	April 30 2003
Interest Rate	7.0	8.8	5.9
Equities	4.5	5.4	4.0
Foreign Exchange	1.2	1.4	2.5
Commodities	1.0	1.0	0.5
Undiversified VaR	13.7	16.6	12.9
Diversification	(5.5)	(6.3)	(4.3)
Diversified VaR	8.2	10.3	8.6
Diversification Share	0.40	0.38	0.33

Values are taken from the second quarter report 2004. All values are in Canadian Dollar. Parentheses indicate negative values.

Table. 1.2: Penalty Function

Number of Exceptions	Multiplier	Zone
0-4	3.00	green
5	3.40	
6	3.50	
7	3.65	yellow
8	3.75	
9	3.85	
10+	4.00	red

The table describes the mapping from the VaR backtesting exceptions during the last 250 trading days into the regulatory multiplier, that is used to calculate the capital requirements for the trading portfolio.

Table. 1.3: Summary Statistics

	Obs	Mean	Std. Dev.	Min	Max
Diversified VaR	674	133.81	132.74	6.00	604.21
VaR Bias	674	-6.17	25.13	-74.97	47.08
VaR Bias (alt)	674	-6.05	25.06	-73.12	47.81
VaR Bias (DCC)	655	-8.42	19.89	-62.97	39.22
VaR Exceptions	469	0.52	1.88	0	12
Green	469	0.88	0.33	0	1
Yellow	469	0.03	0.18	0	1
Red	469	0.09	0.29	0	1
Eq/A	674	5.86	2.65	1.66	13.67
Capital Ratio	602	14.30	2.60	10.50	22.30
CET1 Ratio	617	11.15	2.59	7.10	18.40
CDS spread	530	87.05	72.28	4.71	486.77
Total Assets	674	1140.22	715.09	76.78	3652.90
Net Income	674	0.15	0.14	-0.46	0.41

Diversified VaR is the total, diversified VaR as stated in the quarterly and annual reports in USD million. *VaR Bias* is the relative difference between the reported and empirical VaR. The suffixes (alt) and (DCC) indicate different calculation methods of the counterfactual VaR. *VaR exceptions* is the number of quarterly backtesting exceptions. *Green*, *Yellow*, and *Red* are dummy variables that take the value of one if the number of incurred backtesting lies in the green, yellow or red zone and zero otherwise. *Eq/A* is the ratio of book equity and total assets in a quarter. *CET1 Ratio* and *Capital Ratio* are the core equity tier one and the capital ratio according to the prevailing Basel definition. *CDS Spread* is the 5y CDS senior, unsecured spread reported in basis points. *Net Income/Total Assets* is the net income in a quarter divided by *Total Assets* in that quarter. All values are transformed to USD using the quarter-end exchange rate.

Table. 1.4: VaR Bias by Bank

Bank	Mean	SD	Min	Max
BNP	-29.8	20.5	-82.2	8.9
Bank of America	-30.8	27.1	-77.4	17.8
Bank of Montreal	23.0	15.8	-15.1	45.2
Canadian Bank of Commerce	-17.4	27.9	-109.9	16.3
Citi	-12.2	10.3	-43.8	6.3
Credit Suisse	-10.7	17.2	-46.2	28.5
Deutsche Bank	-15.8	18.1	-63.9	7.6
Goldman	-0.4	11.3	-33.2	21.8
ING	-8.9	12.7	-38.8	9.6
JPMorgan	4.6	19.0	-44.7	45.4
Mellon	9.8	17.6	-27.1	50.6
Nordea	-20.4	17.8	-71.0	9.2
Royal Bank of Canada	-9.3	16.7	-36.7	53.1
Santander	-7.7	18.9	-61.9	31.8
Scotia	-6.7	12.4	-27.6	41.8
UBS	31.9	14.4	-12.1	50.0
Total	-5.5	25.1	-109.9	53.1

The table reports the *VaR Bias* as defined in Equation 1.2 in percentage points. Positive (negative) values indicate empirical VaR below (above) the reported VaR.

Table. 1.5: Equity Scarcity

	VaR Bias					
	(1)	(2)	(3)	(4)	(5)	(6)
Eq/A	3.17**	2.90**	3.04**	3.04***	4.11***	1.36*
	(0.01)	(0.04)	(0.03)	(0.00)	(0.00)	(0.05)
Undiversified VaR (log)		2.09	2.40	2.40	-1.64	-0.928
		(0.67)	(0.62)	(0.22)	(0.79)	(0.78)
Total Assets (log)		-3.27	-1.76	-1.76	2.87	-1.409
		(0.68)	(0.82)	(0.59)	(0.72)	(0.75)
Net Income/Total Assets		10.18	9.72	9.72	3.08	-1.510
		(0.12)	(0.17)	(0.11)	(0.70)	(0.53)
Observations	674	674	674	674	674	656
R-squared	0.31	0.32	0.32	0.66	0.66	
Weights	Equal	Equal	Equal	Equal	VaR	Equal
Vola Controls	No	No	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Bias	No	No	No	No	No	Yes
Cluster SE	Bank	Bank	Bank	Y-Q	Bank	Bank

The table reports the results of Equation 1.4. The volatility variables capture the annualized volatility of the risk indices in region of the bank's headquarters. *Undiversified VaR* is the sum of the broad asset class VaRs but net of diversification between them. The remaining variables are described in Table 1.3. Column 6 shows the coefficient of the Arellano-Bond estimation. P-values of the coefficients are reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

Table. 1.6: Effect of Marginal Costs on the *VaR Bias*

	VaR Bias					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}[\textit{Past Exceptions} = 0]$	-2.627					
	(0.36)					
$\mathbb{1}[\textit{Past Exceptions} = 3]$		-1.583				
		(0.76)				
$\mathbb{1}[\textit{Past Exceptions} < 5]$			1.561			
			(0.67)			
$\mathbb{1}[\textit{Past Exceptions} = 4]$				19.82**		
				(0.04)		
$\mathbb{1}[\textit{Past Exceptions} = 5]$					-19.06	
					(0.17)	
$\mathbb{1}[\textit{Past Exceptions} > 4]$						-4.180
						(0.55)
Observations	467	467	467	467	467	467
R-squared	0.368	0.366	0.366	0.370	0.374	0.367
Year-Quarter FE	Yes	Yes	yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	yes	Yes	Yes
Vola Controls	Yes	Yes	Yes	yes	Yes	Yes

The table reports the results of Equation 1.5. The independent variables are dummy variables that take the value of one if the backtesting exceptions in the three previous quarters satisfy the specified condition. Standard errors are clustered at the bank level. Standard Errors are clustered at the bank level. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

Table. 1.7: Predicting Outliers

Panel A: Discrete Models

	Exceptions					
	Dummy				Ordered	Count
	(1)	(2)	(3)	(4)	(5)	(6)
VaR Bias	-0.013	-0.013	-0.019	-0.019	-0.014	-0.008
	(0.34)	(0.22)	(0.10)	(0.16)	(0.54)	(0.20)
Observations	432	236	432	236	236	432
Model	Logit	Logit	Logit	Logit	Ologit	Neg Bin
Year-Quarter FE	No	Yes	No	Yes	Yes	Yes
Bank FE	No	No	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Vola Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Continuous Model

	Exceptions (z)			
	(1)'	(2)'	(3)'	(4)'
VaR Bias (z)	0.011	-0.055	-0.112	-0.117*
	(0.71)	(0.40)	(0.19)	(0.09)
Observations	432	432	432	432
R-squared	0.253	0.451	0.269	0.467
Year-Quarter FE	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Vola Controls	Yes	Yes	Yes	Yes

The table reports the results of tests for Hypothesis 3. In Panel A, the dependent variables are different specifications of the number of backtesting exceptions in a quarter. In column 1-4, the dependent variable is a dummy that takes the value of one of an exception occurred and zero otherwise. In column 5 ("Ordered"), the variable equals 2 if more than one exception occurred, one if one occurred and zero if none occurred. In column 6 ("Count"), the dependent variable is the actual number of backtesting exceptions. Variables amended with "(z)" are normalised to have zero mean and unit variance. Jackknife re-sampling is used to calculate the standard errors. P-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

Table. 1.8: Alternative Definition of Equity Scarcity

Panel A: Capital Ratio						
	VaR Bias					
	(1)	(2)	(3)	(4)	(5)	(6)
Capital Ratio	1.05	0.80	0.58	0.58	0.88	0.04
	(0.21)	(0.30)	(0.50)	(0.21)	(0.28)	(0.94)
Observations	601	601	601	601	601	587
R-squared	0.32	0.33	0.33	0.66	0.75	
Panel B: Capital Tier 1Ratio						
	VaR Bias					
	(1)'	(2)'	(3)'	(4)'	(5)'	(6)'
CET1 Ratio	0.83	0.71	0.37	0.37	0.96	0.49
	(0.36)	(0.41)	(0.71)	(0.56)	(0.26)	(0.30)
Observations	616	615	615	615	615	600
R-squared	0.30	0.31	0.32	0.66	0.77	
Panel C: CDS Spreads						
	VaR Bias					
	(1)"	(2)"	(3)"	(4)"	(5)"	(6)"
CDS spread	-0.05**	-0.06**	-0.07**	-0.07***	-0.08*	-0.03
	(0.03)	(0.01)	(0.02)	(<0.00)	(0.09)	(0.15)
Observations	535	527	527	527	527	515
R-squared	0.48	0.30	0.30	0.68	0.75	
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Bank	Bank	Bank	Y-Q	Bank	Bank
Weights	Equal	Equal	Equal	Equal	VaR	Equal

The table reports the results of Equation 1.4 for different measures of equity scarcity. The set of coefficients is the same as in table 2.2. A description of each variable can be found in Table 1.3. The weights applied in the sixth column are the undiversified VaRs are reported by the banks. Column 7 shows the coefficient of the Arellano-Bond estimation. P-values of the coefficients are reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

Table. 1.9: Subsamples

	VaR Bias						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Eq/A	4.192***	3.297**	7.081***	4.098	4.369**	4.264**	3.579**
	(0.00)	(0.04)	(0.00)	(0.14)	(0.02)	(0.02)	(0.02)
EU × Eq/A	0.333						
	(0.92)						
Monte Carlo × Eq/A		2.544					
		(0.24)					
Large VaR × Eq/A			-3.544*				
			(0.08)				
Yellow × Eq/A				-5.262*			
				(0.08)			
Post-2007 × Eq/A					-1.302		
					(0.34)		
Post-2008 × Eq/A						-1.440	
						(0.29)	
Post-2009 × Eq/A							-0.920
							(0.51)
Observations	674	674	674	343	674	674	674
R-squared	0.340	0.345	0.359	0.369	0.332	0.334	0.330
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vola Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table reports the results of Equation 1.4 with interaction of dummies with *Book Equity/Total Assets* (*Eq/A*). *Post-2007*, *Post-2008*,*Post-2009* and *Post-2010* are dummy variables that take the value of one for the quarter after the specified year. *EU* equals one for banks whose headquarters are located in Europe. *Monte Carlo* takes the value of one for banks that apply the Monte Carlo method to calculate the VaR. *Large VaR* is set to one if a bank's VaR is above the mean VaR in a quarter. *Yellow* equals one if the regulatory multiplier of the bank lies in the yellow zone. A description of the remaining variables can be found in Table 1.3. Standard errors are clustered at the bank level. P-values of the coefficients are reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

Table. 1.10: Effect of Marginal Costs on the VaR Bias

	VaR Bias (alt)					
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbb{1}[\textit{Past Exceptions} = 0]$	-2.039					
	(0.50)					
$\mathbb{1}[\textit{Past Exceptions} = 3]$		-2.549				
		(0.66)				
$\mathbb{1}[\textit{Past Exceptions} < 5]$			3.011			
			(0.47)			
$\mathbb{1}[\textit{Past Exceptions} = 4]$				18.98**		
				(0.04)		
$\mathbb{1}[\textit{Past Exceptions} = 5]$					-16.72	
					(0.22)	
$\mathbb{1}[\textit{Past Exceptions} > 4]$						-4.091
						(0.57)
Observations	467	467	467	467	467	467
R-squared	0.378	0.377	0.377	0.380	0.383	0.378

Panel B: VaR Bias (DCC)

	VaR Bias (DCC)					
	(1)'	(2)'	(3)'	(4)'	(5)'	(6)'
$\mathbb{1}[\textit{Past Exceptions} = 0]$	0.394					
	(0.89)					
$\mathbb{1}[\textit{Past Exceptions} = 3]$		-5.412				
		(0.40)				
$\mathbb{1}[\textit{Past Exceptions} < 5]$			-5.825			
			(0.32)			
$\mathbb{1}[\textit{Past Exceptions} = 4]$				16.05**		
				(0.04)		
$\mathbb{1}[\textit{Past Exceptions} = 5]$					-13.48	
					(0.22)	
$\mathbb{1}[\textit{Past Exceptions} > 4]$						-3.872
						(0.47)
Observations	467	467	467	467	467	467
R-squared	0.429	0.431	0.432	0.432	0.432	0.430
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Vola Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Bank	Bank	Bank	Bank	Bank	Bank

The table reports the results of Equation 1.5. The independent variables are dummy variables that take the value of one if the backtesting exceptions in the three previous quarters satisfy the specified condition. Standard errors are clustered at the bank level. Standard Errors are clustered at the bank level. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

Table. 1.11: Predicting Outliers - Alternative Start Date

Panel A: Discrete Models

	Exceptions					
	Dummy				Ordered	Count
	(1)	(2)	(3)	(4)	(5)	(6)
VaR Bias (alt)	-0.016	-0.015	-0.023*	-0.022	-0.017	-0.011
	(0.24)	(0.17)	(0.07)	(0.12)	(0.43)	(0.10)
Observations	432	236	432	236	236	432
Model	Logit	Logit	Logit	Logit	Ologit	Neg Bin
Year-Quarter FE	No	Yes	No	Yes	Yes	Yes
Bank FE	No	No	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Vola Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Continuous Model

	Exceptions (z)			
	(1)'	(2)'	(3)'	(4)'
VaR Bias (alt, z)	<0.000	-0.046	-0.136	-0.109*
	(>0.99)	(0.44)	(0.16)	(0.07)
Observations	432	432	432	432
R-squared	0.253	0.451	0.269	0.467
Year-Quarter FE	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Vola Controls	Yes	Yes	Yes	Yes

The table reports the results of tests for Hypothesis 3. In Panel A, the dependent variables are different specifications of the number of backtesting exceptions in a quarter. In column 1-4, the dependent variable is a dummy that takes the value of one of an exception occurred an zero otherwise. In column 5 ("Ordered"), the variable equals 2 if more than one exception occurred, one if one occurred and zero if none occurred. In column 6 ("Count"), the dependent variable is the actual number of backtesting exceptions. Variables amended with "(z)" are normalised to have zero mean and unit variance. Jackknife re-sampling is used to calculate the standard errors. P-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

Table. 1.12: Predicting Outliers - DCC Correlation

Panel A: Discrete Models

	Exceptions					
	Dummy				Ordered	Count
	(1)	(2)	(3)	(4)	(5)	(6)
VaR Bias DCC	-0.016	-0.021*	-0.020*	-0.027**	-0.022	-0.013**
	(0.34)	(0.06)	(0.10)	(0.04)	(0.29)	(0.03)
Observations	432	236	432	236	236	432
Model	Logit	Logit	Logit	Logit	Ologit	Neg Bin
Year-Quarter FE	No	Yes	No	Yes	Yes	Yes
Bank FE	No	No	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Vola Controls	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Continuous Model

	Exceptions (z)			
	(1)'	(2)'	(3)'	(4)'
VaR Bias DCC (z)	-0.056	-0.054	-0.132	-0.103*
	(0.32)	(0.30)	(0.12)	(0.05)
Observations	432	432	432	432
R-squared	0.259	0.452	0.275	0.468
Year-Quarter FE	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Vola Controls	Yes	Yes	Yes	Yes

The table reports the results of tests for Hypothesis 3. In Panel A, the dependent variables are different specifications of the number of backtesting exceptions in a quarter. In column 1-4, the dependent variable is a dummy that takes the value of one of an exception occurred an zero otherwise. In column 5 ("Ordered"), the variable equals 2 if more than one exception occurred, one if one occurred and zero if none occurred. In column 6 ("Count"), the dependent variable is the actual number of backtesting exceptions. Variables amended with "(z)" are normalised to have zero mean and unit variance. Jackknife re-sampling is used to calculate the standard errors. P-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

Table. 1.13: Short Positions, Hypothesis 1

	VaR Bias						
	Window		Short				
	Short	Long	Interest	Equity	FX	Credit	Commodity
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Eq/A	1.13*	1.02*	0.47	0.81*	0.91*	0.51	1.32***
	(0.08)	(0.09)	(0.40)	(0.07)	(0.10)	(0.44)	(0.01)
Total Assets (log)	-16.70***	-15.02***	-3.41	-1.92	-4.26	-2.87	-6.26*
	(0.00)	(0.00)	(0.18)	(0.48)	(0.33)	(0.41)	(0.07)
Net Income/Total Assets	6.49*	3.56	-1.91	4.97	4.13	0.21	7.75**
	(0.08)	(0.28)	(0.67)	(0.11)	(0.39)	(0.97)	(0.01)
Observations	658	658	658	658	658	658	658
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vola Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged bias	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Bank	Bank	Bank	Bank	Bank	Bank	Bank

The table reports the results of Equation 1.4 with different specifications of the VaR bias. In column one and two, the VaR bias has been calculated using a shorter and longer estimation window for the correlation of 150 and 400 days. In column 3-7, the VaR is calculated under the assumption the banks has a short position in the broad asset class specified in the second row. The regressions include the lagged *VaR Bias* and is estimated using the Arellano Bond approach. Standard errors are clustered at the bank-level. P-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

Table. 1.14: Short Positions, Hypothesis II

	Window		Short				
	Short	Long	Interest	Interest	FX	Commodity	Credit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\mathbb{1}[Past\ Exceptions = 4]$	17.52***	16.37***	1.074	1.179	20.26***	12.91***	6.106
	(0.01)	(0.00)	(0.91)	(0.86)	(0.00)	(0.00)	(0.23)
Observations	432	432	432	432	432	432	432
R-squared	0.682	0.699	0.711	0.742	0.702	0.673	0.643
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vola Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Bias	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table reports the results of Equation 1.5 with different specifications of the VaR bias, the independent variable. In column one and two, the VaR bias has been calculated using a shorter and longer estimation window for the correlation of 150 and 400 days. In column 3-7, the VaR is calculated under the assumption the banks has a short position in the broad asset class specified in the second row. The dependent variable is a dummy that takes the value of one if the number of backtesting exceptions in the three previous quarters equals 4.The regressions include the lagged *VaR Bias* and is estimated using the Arellano Bond approach. Standard errors are clustered at the bank-level. P-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

Table. 1.15: Omitting Time Periods

	VaR Bias							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Eq/A	1.355*	1.65**	1.25	1.15	1.45**	2.08***	1.94***	1.72**
	(0.05)	(0.04)	(0.11)	(0.19)	(0.03)	(0.01)	(0.00)	(0.03)
Year Dropped		2005	2006	2007	2008	2009	2010	2007-2009
Observations	656	612	605	601	598	596	593	483
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vola Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Bank	Bank	Bank	Bank	Bank	Bank	Bank	Bank

The table reports the results of Equation 1.4 for the full sample in column 1 and reduced samples in the remaining columns. The years that have been dropped from the sample are specified in the second line. The regressions include the lagged *VaR Bias* and estimated using the Arellano Bond approach. Standard errors are clustered at the bank-level. P-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

Table. 1.16: Functional Form

Panel A: Leverage Ratio

	VaR Bias			
	(1)	(2)	(3)	(4)
Leverage	1.35*			5.64**
	(0.06)			(0.04)
Leverage (log)		9.41**		
		(0.02)		
Leverage (squared)			0.05	-0.25*
			(0.21)	(0.10)
Observations	656	656	656	656

Panel B: Capital Ratio

	VaR Bias			
	(1')	(2')	(3')	(4')
Capital Ratio	0.02			-2.91
	(0.97)			(0.33)
Capital Ratio (log)		3.16		
		(0.60)		
Capital Ratio (squared)			0.03*	0.14
			(0.10)	(0.21)
Observations	587	587	587	587

Panel C: CET1 Ratio

	VaR Bias			
	(1")	(2")	(3")	(4")
CET1 Ratio	0.49			-2.91
	(0.29)			(0.33)
CET1 Ratio (log)		0.03*		
		(0.10)		
CET1 Ratio (squared)			-0.00	-0.14
			(0.37)	(0.21)
Observations	600	600	600	600
Year-Quarter FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Vola Controls	Yes	Yes	Yes	Yes
Lagged Bias	Yes	Yes	Yes	Yes

Panel D: CDS Spread

	VaR Bias			
	(1"')	(2"')	(3"')	(4"')
CDS Spread	-0.03			-0.10***
	(0.14)			(0.01)
CDS Spread (log)		-5.78**		
		(0.03)		
CDS Spread (squared)			0.05	0.00**
			(0.21)	(0.01)
Observations	600	600	600	600
Year-Quarter FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes
Vola Controls	Yes	Yes	Yes	Yes
Lagged Bias	Yes	Yes	Yes	Yes

The table reports the results of Equation 1.4 using different functional forms of the equity variables. The regressions include the lagged *VaR Bias* and estimated using the Arellano Bond approach. Standard errors are clustered at the bank-level. P-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

Table. 1.17: Effect of Stress Tests on the VaR Bias

	VaR Bias						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
REFERENCE	3.296		-21.10***			-10.39	
	(0.60)		(0.00)			(0.30)	
RESULTS		-2.404		-9.472***	-10.39***		-2.310
		(0.34)		(0.00)	(0.00)		(0.60)
FAIL					4.730**		
					(0.03)		
Observations	432	432	255	255	255	177	177
R-squared	0.775	0.774	0.799	0.798	0.799	0.785	0.781
Sample	US+EU	US+EU	US	US	US	EU	EU
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Vola Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Y-Q	Y-Q	Y-Q	Y-Q	Y-Q	Y-Q	Y-Q

The table reports the results of Equation 1.4 with additional dummy variables. *REFERENCE* equals one if the end-of-quarter balance sheet is used as reference for a stress test in that quarter t for bank i. *RESULTS* equals one if stress test results are published in that quarter t for a bank i. *FAIL* takes the value of one if a bank did not pass every component of the test. The US sample consists of the Citi Group, Goldman Sachs, J.P.Morgan and the Bank of New York Mellon. The EU sample includes the Deutsche Bank, ING, Banco Santander, Nordea and the BNP. The regressions include the lagged *VaR Bias* and estimated using the Arellano-Bond approach. Standard errors are clustered at the year-quarter level. P-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% level, respectively.

Table. 1.18: Equity Scarcity II: Alternative Estimation Window for *VaR Bias*

Panel A: Book Equity/Total Assets

	VaR Bias (alt)					
	(1)	(2)	(3)	(4)	(5)	(6)
Eq/A	3.11**	2.90**	3.01**	3.01***	4.16***	1.30*
	(0.01)	(0.04)	(0.03)	(<0.00)	(<0.00)	(0.06)
Observations	674	674	674	674	674	656
R-squared	0.32	0.32	0.33	0.66	0.74	

Panel B: Capital Ratio

	VaR Bias (alt)					
	(1')	(2')	(3')	(4')	(5')	(6')
Capital Ratio	1.12	0.94	0.74	0.74	1.02	0.25
	(0.16)	(0.20)	(0.37)	(0.11)	(0.14)	(0.62)
Observations	601	601	601	601	601	587
R-squared	0.33	0.34	0.34	0.66	0.75	

Panel C: Capital Tier 1 Ratio

	VaR Bias (alt)					
	(1")	(2")	(3")	(4")	(5")	(6")
CET1 Ratio	0.76	0.67	0.35	0.35	0.99	0.46
	(0.38)	(0.42)	(0.71)	(0.57)	(0.17)	(0.32)
Observations	616	615	615	615	615	600
R-squared	0.32	0.32	0.33	0.67	0.77	

Panel D: CDS Spreads

	VaR Bias (alt)					
	(1"')	(2"')	(3"')	(4"')	(5"')	(6"')
CDS spread (5y)	-0.06**	-0.07***	-0.08**	-0.08***	-0.09*	-0.04**
	(0.01)	(0.01)	(0.01)	(<0.00)	(0.08)	(0.05)
Observations	535	527	527	527	527	515
R-squared	0.48	0.30	0.30	0.68	0.75	
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Vola Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Bank	Bank	Bank	Y-Q	Bank	Bank
Weightening	Equal	Equal	Equal	Equal	VaR	Equal

The table reports the results of Equation 1.4. The vola variables capture the annualized volatility of the risk indices in region of the bank's headquarters. *Undiversified VaR* is the sum of the broad asset class VaRs but net of diversification between them. Column 6 shows the coefficient of the Arellano-Bond estimation. P-values of the coefficients are reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% level respectively.

Table. 1.19: Equity Scarcity III: DCC Correlation

Panel A: Book Equity/Total Assets

	VaR Bias (DCC)					
	(1)	(2)	(3)	(4)	(5)	(6)
Eq/A	2.03**	1.35	1.40	1.40	2.44**	0.58
	(0.05)	(0.28)	(0.26)	(0.10)	(0.03)	(0.42)
Observations	653	653	653	653	653	634
R-squared	0.21	0.22	0.23	0.55	0.51	

Panel B: Capital Ratio

	VaR Bias (DCC)					
	(1')	(2')	(3')	(4')	(5')	(6')
Capital Ratio	0.61	0.68	0.90	0.90	0.96	-0.26
	(0.56)	(0.39)	(0.31)	(0.25)	(0.15)	(0.62)
Observations	601	601	601	601	601	579
R-squared	0.23	0.23	0.24	0.45	0.52	

Panel C: Capital Tier 1Ratio

	VaR Bias (DCC)					
	(1")	(2")	(3")	(4")	(5")	(6")
CET1 Ratio	0.76	1.34	1.48	1.48*	-0.36	0.01
	(0.55)	(0.17)	(0.31)	(0.09)	(0.83)	(0.98)
Observations	616	615	615	615	615	580
R-squared	0.21	0.22	0.30	0.43	0.59	

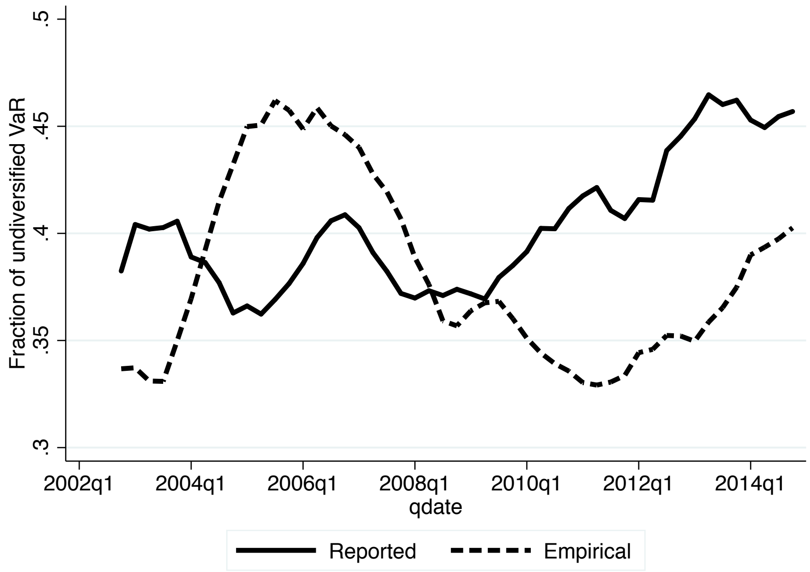
Panel D: CDS Spreads

	VaR Bias (DCC)					
	(1"')	(2"')	(3"')	(4"')	(5"')	(6"')
CDS spread (5y)	-0.02	-0.02	-0.10**	-0.10***	-0.06***	-0.03
	(0.63)	(0.53)	(0.02)	(0.01)	(0.00)	(0.28)
Observations	535	527	527	527	527	495
R-squared	0.44	0.37	0.44	0.51	0.60	
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Vola Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank Controls	Yes	Yes	Yes	Yes	Yes	Yes
Cluster SE	Bank	Bank	Bank	Y-Q	Bank	Bank
Weightening	Equal	Equal	Equal	Equal	VaR	Equal

The table reports the results of Equation 1.4. The vola variables capture the annualized volatility of the risk indices in region of the bank's headquarters. *Undiversified VaR* is the sum of the broad asset class VaRs but net of diversification between them. Column 6 shows the coefficient of the Arellano-Bond estimation. P-values of the coefficients are reported in parentheses. ***, **, and * denote significance at the 1%, 5% and 10% level respectively.

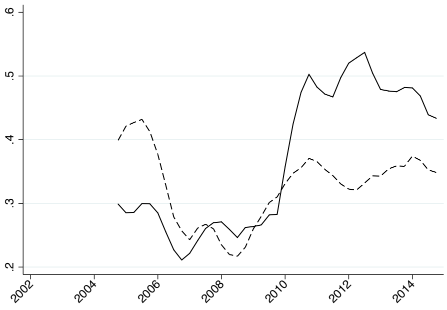
Figures

Figure 1.1: Aggregated Reported vs Empirical Diversification Share over Time

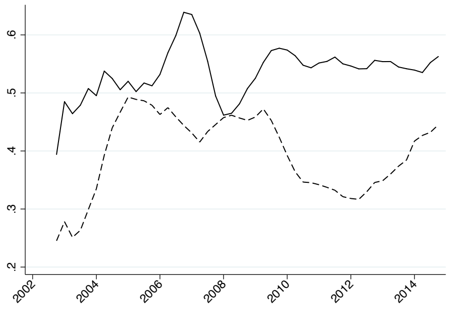


The figure depicts the evolution of the aggregate reported and empirical diversification share, i.e. the fraction of the undiversified VaR that is offset by between asset class correlation. The solid line represents the reported diversification, the dashed line the empirical counterpart. If the reported diversification is above (below) the counterfactual diversification, the bank underreports (overreports) its VaR relative to the benchmark.

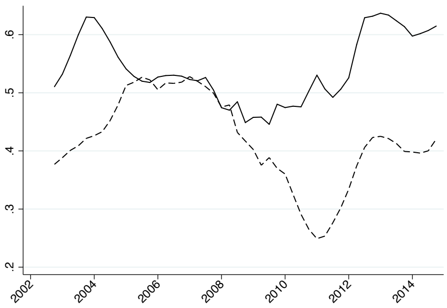
Figure 1.2: Difference Reported vs Empirical VaR - Bank Level



(a) Santander

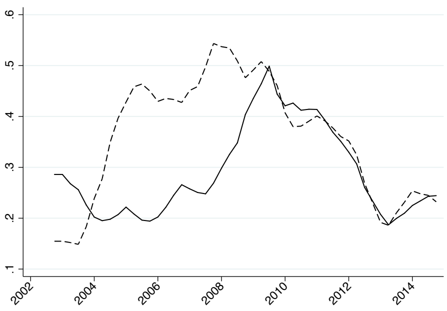


(b) BNP



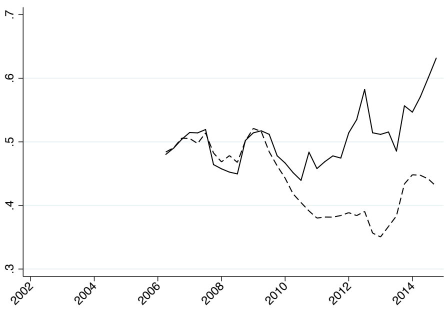
(c) Bank of America

(d) Bank of Montreal

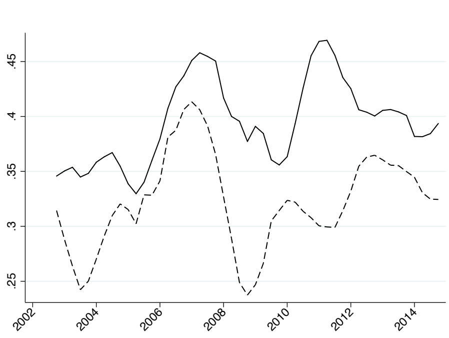


(e) Bank of New York Mellon

(f) Bank of Nova Scotia

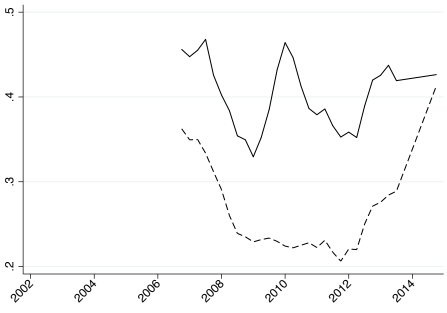


(g) Canadian Imperial Bank of Commerce

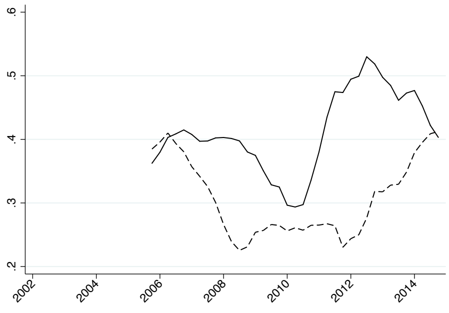


(h) Citigroup

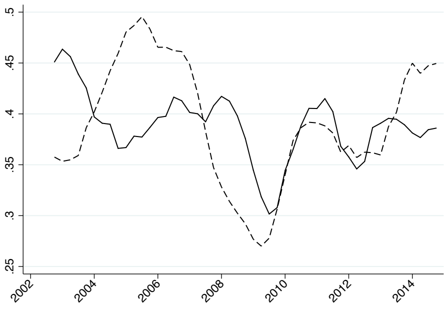
Figure 1.2: Difference Reported vs Empirical VaR - Bank level (cont.)



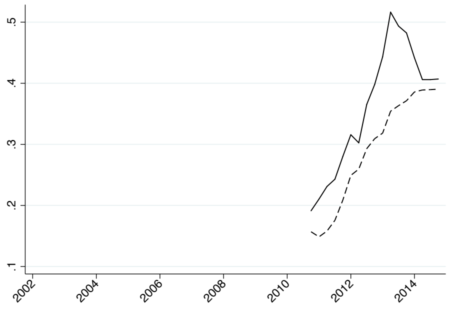
(i) Credit Suisse



(j) Deutsche Bank

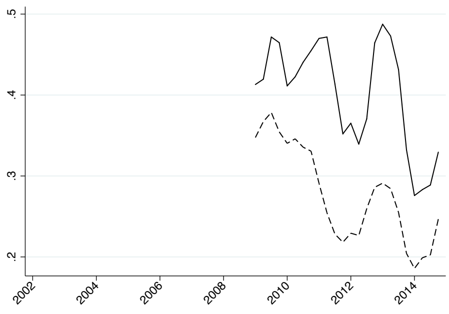


(k) Goldman Sachs

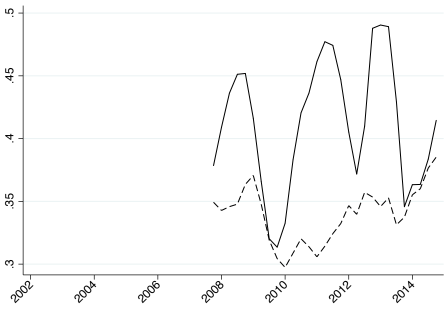


(l) ING

(m) JP Morgan



(n) Nordea

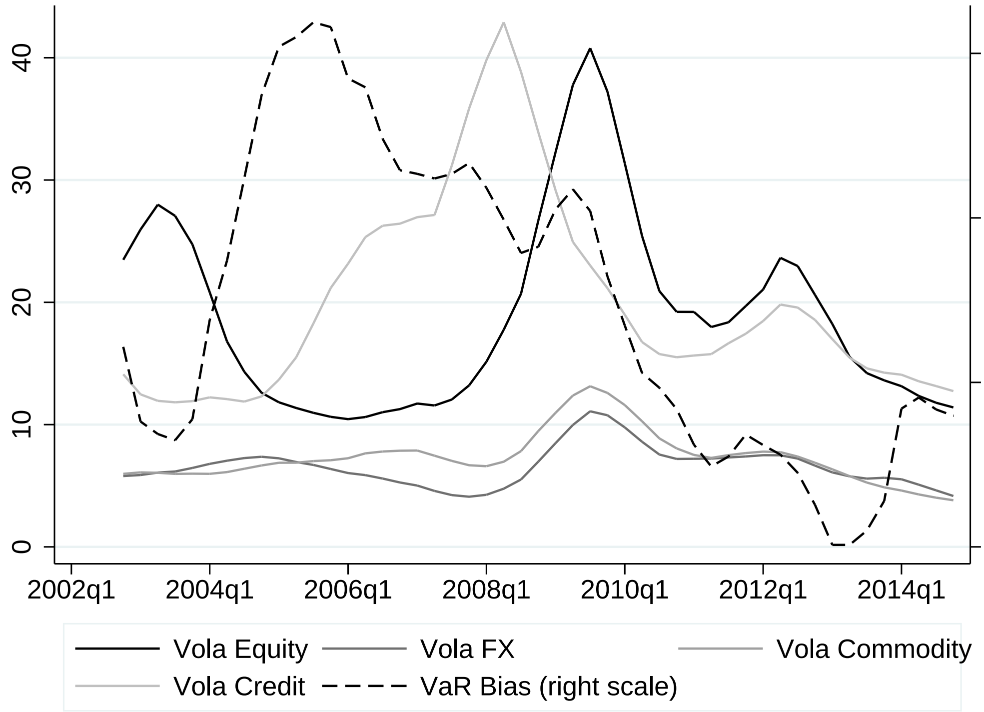


(o) Royal Bank of Canada

(p) UBS

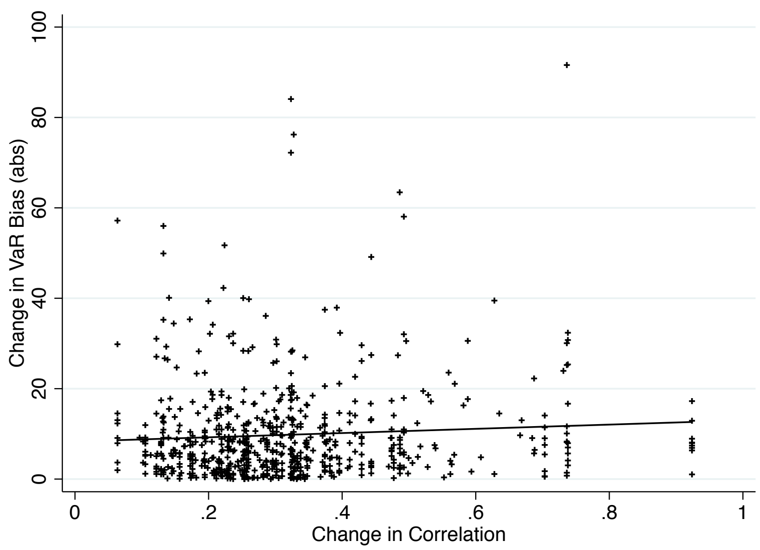
The figures depict the four month moving average of the reported and counterfactual diversification shares, i.e. the fraction of the undiversified VaR that is offset by between asset class correlation. The solid lines represent the reported diversification, dashed lines the empirical counterpart. If the reported diversification is above (below) the counterfactual diversification, the bank underreports (overreports) its VaR relative to the benchmark.

Figure 1.3: VaR Bias and Volatility over Time



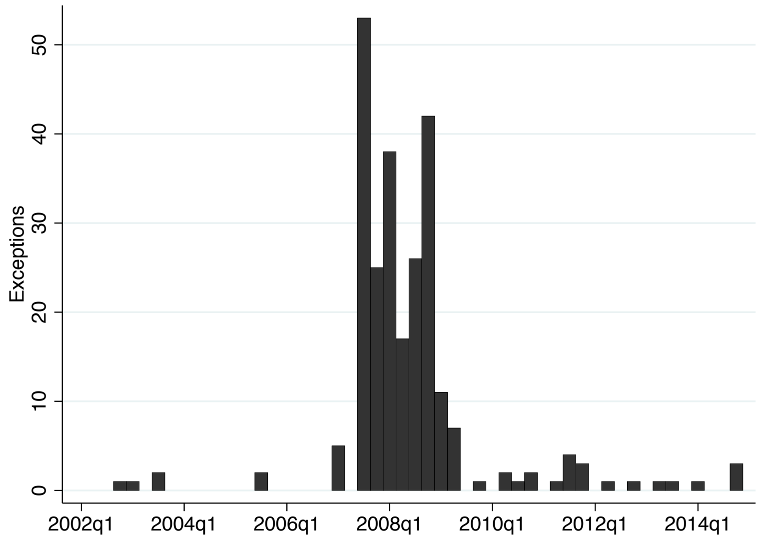
The figure plots the evolution of the four quarter moving average of the VaR bias and the volatility of the risk indices over time.

Figure 1.4: Changes in Correlation Matrix vs Changes in the VaR bias



The figure plots the absolute changes in the VaR bias on the y-axis against the changes in the empirical correlation matrix on the x-axis. Changes in the correlation matrix are calculated as the square root of the squared element-wise differences.

Figure 1.5: VaR Backtesting Exceptions



The total number of reported backtesting exceptions by all banks in the sample that report backtesting exceptions in a quarter.

CHAPTER 2

HOW DOES THE DODD-FRANK ACT AFFECT ISSUER RATINGS AND RATING REPORTS?

Credit rating agencies (CRAs) have been a long-standing subject of criticism. However, until the most recent financial crisis, they remained largely out of the regulatory scope. After they had severely misjudged the credit quality of structured finance products in the advent of the financial crisis, the Dodd-Frank Act (DFA) imposed a stricter regulation on CRAs. As one of the most important changes introduced by the regulation, CRAs no longer enjoy full protection from the freedom of speech for their ratings and are now more likely to be held liable for their ratings. The chapter provides insights on the effect of the new regulation in general and the increased liability in particular on one of the most important business lines of CRAs: Issuer ratings. Since the refinancing costs and thereby real investment decisions depend heavily on issuer ratings, understanding whether and how regulation might bias ratings is essential. The effect of increased liability on rating accuracy is ambiguous: On the one hand, it might induce a higher due-diligence effort by CRAs, on the other hand it might induce a downwards bias in the ratings as penalties are likely to occur only for overly optimistic ratings (Goel and Thakor, 2011). Two distinct approaches are taken to evaluate the impact of the new regulation. First, I assess whether CRAs are more conservative in the assignment of ratings after the Dodd-Frank Act (DFA) in the sense that they now assign lower ratings than before. Second, I take a novel approach and examine the information content of rating reports, which are brief explanations published by the CRAs that explain their rating decision.

To examine whether CRAs assign lower ratings after the DFA, I evaluate their ratings against market-based counterfactuals. If CRAs do indeed rate issuers lower to protect themselves against increased liability, they should lower their ratings relative to the market-based risk measures, which are unaffected by the regulation. Namely, I evaluate the rating levels against the equity-implied probability of default (PD), the CDS-implied PD and a PD calculated using the Campbell et al. (2008) failure score. This approach can be understood as an extension of Dimitrov et al. (2015), who look at bond ratings but do not explicitly control for the market assessment of risks. Like Dimitrov et al. (2015), I find a downward bias in the rating level - even after controlling for market-based risk measures. However, the results are not robust. For example, the effect vanishes if the sample period is shortened. In addition, I find little evidence that the lead-lag structure between ratings and the other risk measures is changed by the DFA. This part of the chapter connects to three strands of literature. First, it relates to the literature on the variation of ratings standards over time (Alp, 2013; Cheng and Neamtiu, 2009). Second, I build on prior work on the relationship between market-based risk measures and credit ratings (Hilscher and Wilson (2016)). Lastly and most importantly, I add to the literature on the effect of regulation on credit ratings (Dimitrov et al., 2015; Jankowitsch et al., 2015; Varmaz et al., 2015).

Furthermore, I provide a different perspective on the effects of regulation on ratings by looking a rating reports. Rating reports are published by CRAs and provide the rationale of a rating decision. To the best of my knowledge, the text at hand is the first to explore these reports. Looking at rating reports is interesting from several angles. Most importantly, it provides a novel perspective on the market reaction to rating changes. While a large strand of the literature assesses the information content of rating actions in general - see among others Hand et al. (1992); Norden and Weber (2004b); Fieberg et al. (2016), but relatively little has been done to explain market reactions. So far, the literature explains reactions either with anticipation by the market or by irrelevance of the rating itself. Rating reports and the information contained in them might explain the variation in the market reaction. As these reports are likely to be vital in any law suit against CRAs, they might provide valuable insight on how the regulation affects ratings and the reaction to ratings.

The increased liability for their ratings could incentivise CRAs to adopt a more careful language or publish more information of their due-diligence to provide as little attack surface as possible for law suits. A more careful or ambiguous language, in turn, decreases the informational value of the rating report in particular and rating decisions in general. My hand-collected sample consists of more than 14,000 reports on issuer rating actions published by Moody's between September 2006 and September 2014. Indeed, I find that the wording of reports appears to be more forward-looking and more cautiously worded after DFA. I explore the effects of the wording on market reactions approximated by the cumulative abnormal returns after the publication for a subset of 3,875 reports. I find that the wording of the reports does indeed explain the market reactions. Reports with a high fraction of forward-looking and precise words appear to be connected with higher informational value of the report.

The remainder of the chapter is organised as follows. In section 2.1, I describe the new regulation for the CRAs. The evolution of agency ratings vis-à-vis market counterfactuals is examined in section 2.2. Rating reports are investigated in section 2.3. Section 2.4 provides a conclusion.

2.1 The Regulation of Credit Rating Agencies

The existence of CRAs as private watchdogs dates back to the emergence of the railroad bond market in the U.S. at the turn of the last century (Sylla, 2002). Until recently, CRAs remained largely out of the focus of regulators. A summary of the regulation of CRAs before the recent financial crisis is provided by Coskun (2008). The "big bang" of the regulatory use of credit ratings in financial markets was the introduction of the Nationally Recognized Statistical Rating Organization (NRSRO) status in 1975, when the Securities and Exchange Commission (SEC) allowed broker-dealers to use credit ratings from NRSRO for the calculation of regulatory capital. In 1986, the SEC included references to NRSROs into the Investment Company Act and limited the possibility of portfolio managers to invest in securities with ratings from NRSROs below certain thresholds. Effectively, this regulation has created the institution of credit ratings as they are known today. It is noteworthy that there were no specific legal standards determining the qualification of a CRA as a NRSRO at this point. It was rather the experience of the SEC which led to the development of a few informal standards. Most importantly, a CRA had to be "nationally recognized" in the U.S., which effectively created entry barriers for new market participants in the rating market (Coskun, 2008, p. 270). With the lax regulation and protection from competition, the CRA business prospered in the decades following the adoption of the NRSRO standard.

The large accounting and auditing scandals at the beginning of the new millennium caused some doubts about the practice of CRAs and their role before the collapse of Enron and WorldCom. As the Sarbanes and Oxley Act in 2002 did overhaul the regulation of auditors but not of CRAs, the pressure on the government and regulators to review the role and function of credit ratings mounted. This renewed political interest in CRAs eventually led to the Credit Rating Agency Act in 2006. This reform created new standards for the qualification as a NRSRO. Specifically, it was the first legislation to require CRAs to disclose ratings performance, methodologies and potential conflicts of interest. Most importantly, the Credit Rating Agency Reform Act was intended to foster competition among CRAs by making it easier to apply for the NRSRO status.[1]

Finally, the overhaul of financial regulation following the outburst of the subprime

[1]It is debatable, whether competition increases the efficiency of the ratings market. Bolton et al. (2012) show that a duopoly or even a monopoly can be more efficient under the current standard of issuer-paid ratings, as more competition may also increase the incentive for rating-shopping.

crisis has profoundly affected the business of CRAs. CRAs have been accused of having produced inflated ratings for structured finance products, in particular mortgage-backed-securities (Ashcraft et al., 2010; Griffin and Tang, 2012). In July 2010, the DFA was introduced as a complete overhaul of U.S. financial regulation. As such, it contains specific new regulations regarding the business of CRAs.[2] The reforms in this area can be divided into two pillars. The first pillar is a sequel of the Credit Rating Agency Reform Act, as it consists of measures which are intended to increase the transparency of CRAs and strengthen the integrity of credit ratings as an institution in financial markets. The pillar-one rules directly assign CRAs to the supervision of the SEC, which has established an Office of Credit Ratings. Under these rules, CRAs must strengthen internal controls, implement compliance rules to manage conflicts of interest, fulfil specific requirements with regard to rating methodology and are subject to enhanced disclosure duties (PWC, 2010). Subsection C, Rule 932 of the DFA, requires that agencies report, *inter alia*, information about the credit rating uncertainty (e.g. limited data availability or bad data quality), limitations of the rating (i.e. whether certain risk types are not considered) and potential conflicts of interest. Moreover, the DFA goes one important step further as it is the first legislation to define specific fines and penalties, which the SEC can impose on CRAs if they fail to comply with the regulations. Most important for the empirical investigation of this chapter is the second pillar of the DFA rules for CRAs, which makes the agencies liable for their rating decisions. Before the introduction of the DFA, plaintiffs had to prove that CRAs had knowingly issued false ratings or recklessly neglected accuracy. Now, plaintiffs must only prove that the CRA has failed to conduct a "reasonable investigation" of the security (Dimitrov et al., 2015, p. 7). This is a substantial relaxation of the burden of proof, which effectively takes the shield of freedom of speech and expression away from

[2] A brief summary of the DFA regulation regarding CRAs is available on the SEC website: `https://www.sec.gov/spotlight/dodd-frank/creditratingagencies.shtml`

CRAs. Furthermore, the DFA makes CRAs liable as experts under Securities Act Section 11 for material misstatements/omissions relating to their ratings (Section 939G). This provides investors with a private right of action against CRAs in a similar fashion as such actions are possible against accountants and security analysts. The magnitude of the DFA became most visible in the asset-backed securities market. As a reaction to the increased liability, CRAs refused to allow issuers to include their ratings - which are required for a public ABS offering - in registration statements or prospectuses and thereby effectively froze the ABS market until this particular rule was suspended shortly after its introduction (Carbone, 2010; Brody, 2010). Though the regulation on issuer ratings is less severe, this example shows that CRAs do care about being liable for their ratings.

Regulatory changes for CRAs after the global financial crisis are not confined to the USA. In Europe, the European Commission conducted a thorough investigation of the development of the credit rating market from January 2007 onwards. However, newly introduced regulatory measures concern mainly competition, supervision and disclosure rather than liability. For example, the European Securities and Markets Authority was granted exclusive supervision powers over CRAs registered in the EU, including the subsidiaries of Fitch Ratings, Moody's and S&P. Crucially, no major regulatory change took place around July 2010 and the new European regulatory measures are minor compared to the DFA.[3]

In the following two sections I investigate the impact of the DFA as a comprehensive regulatory overhaul on the corporate policy of CRAs. Extending the work of Dimitrov et al. (2015), I begin with an analysis of the relations between alternative credit risk indicators (the counterfactual) and credit ratings. In section 2.3, I explore new territories and investigate the impact of the regulation on rating reports.

[3] An overview over the regulatory changes can be found on the website http://ec.europa.eu/finance/rating-agencies/index_en.htm.

2.2 Market Counterfactual

2.2.1 Literature Review and Hypothesis Development

Over the course of only a few years, CRAs have transitioned from being "lightly to highly regulated" (PWC, 2010). Especially the possibility of fines and penalties as well as the increased liability imposed from the DFA are expected to influence the rating policy of CRAs. In my investigation about the impact of the DFA on issuer ratings, I follow the literature on the variation of rating standards over time. This is a rather young, but quickly growing body of literature. Looking at ratings from 1985 to 2007, Alp (2013) finds that CRAs become more rigid after the introduction of the Sarbanes-Oxley Act. For given firm characteristics, the rating in 2007 was 1.5 notches lower than in 2002. This interpretation is supported by Cheng and Neamtiu (2009), who show that ratings are more accurate and less volatile after the introduction of the Sarbanes-Oxley Act. From a theoretical perspective, Opp et al. (2013) examine how rating-contingent regulation affects rating standards. Using a repeated game setup, Opp et al. (2013) show that regulatory usage of ratings decreases the informativeness of ratings if the advantage of having a favourable rating is high enough. **?** find that competitive pressure causes ratings inflation. Using the entry of Fitch to the rating market as a natural experiment, the authors are able to show that the incumbent agencies - Moody's and S&P - assign higher ratings in industries with a high Fitch market share. With regard to the DFA, Goel and Thakor (2011) from a theoretical and Dimitrov et al. (2015) from an empirical perspective discuss two hypotheses: First, the *disciplining hypothesis* suggests that ratings have become more accurate after the DFA in order to avoid penalties and lawsuits. Obviously, this was the intention of the regulatory overhaul. Second, the *risk avoidance hypothesis* implies that the regulation has an adverse effect on the quality of credit ratings by incentivising CRAs to produce downward biased ratings. The logic behind this presumption is that CRAs are now punished for ratings which are too optimistic, but not for ratings which are too pessimistic. For instance, assigning an investment grade rating to an issuer that defaults shortly afterwards is likely to be much more costly than denying a relatively sound firm an investment grade rating.

The accuracy of credit ratings, which is the variable of interest with respect to the Dimitrov et al. (2015) *disciplining hypothesis*, is usually examined using information about defaults and market reactions. Since data about corporate defaults is relatively hard to come by and also difficult to handle empirically, the literature focusses on the reactions of bond and stock prices to rating announcements (Dimitrov et al., 2015; Jankowitsch et al., 2015; Varmaz et al., 2015) before and after the introduction of DFA. Dimitrov et al. (2015) analyse the reaction of bond prices to rating changes and they report no evidence of increased bond rating informativeness after the introduction of the DFA. On the contrary, abnormal bond returns to rating changes are lower after the DFA than before. However, Jankowitsch et al. (2015) find that rating changes do evoke stronger market reactions after the introduction of the DFA. For the equity market, Bedeno et al. (2016) find that credit ratings have an increased information content in the aftermath of reputational shocks suffered by CRAs. Dimitrov et al. (2015) investigate the *risk avoidance hypothesis* using an ordered logistic regression model. Controlling for a number of firm-specific balance sheet and stock performance variables, they show that issue rating levels have decreased after the regulatory overhaul. Hence, they conclude that the introduction of the DFA has not improved the accuracy of ratings, but instead led to a downward bias of ratings and lower informational value of rating changes induced by the risk avoiding behaviour of CRAs.

The analysis of Dimitrov et al. (2015) suffers from two drawbacks. First, their logistic regressions lack adequate control variables for firm-specific credit risk. It is possible that the detected downward bias of credit ratings is a consequence of overall decreasing credit risk or the perception thereof and not an effect of the regulatory overhaul. I follow the relatively novel literature on the relationship between ratings and alternative, market-based credit risk measures in my assessment of the impact of the DFA on issuer ratings. The findings of this string of literature are twofold: Market-based measures tend to precede rating actions and preserve in large the ordering of riskiness implied by the ratings (Hull et al., 2004; Norden and Weber, 2004b). In other words, the market-based risk measure of a highly rated issuer is likely to indicate a lower riskiness than the one of a lower-rated rated issuer. I verify this relationship later in this chapter. Performance-wise, Hilscher and Wilson (2016) show that reduced form default risk models outperform credit ratings in forecasts of corporate defaults. Because of the substantial model risk and degrees of freedom in modelling credit risk, I control for firm-specific credit risk using several established credit risk models rather than relying on a single model. Namely, I evaluate the evolution of ratings against the development of the equity-implied PD, a failure probability calculated using a model of Campbell et al. (2008) with a calibration of Hilscher and Wilson (2016) and the CDS-implied PD. Second, the sample of Dimitrov et al. (2015) contains credit ratings from 2006-2012 and thereby encompasses the peak of credit risk during the financial crisis of 2008 and the following decline of credit risk. This pattern is illustrated in Figure 2.3 for issuer ratings and other measures of credit risk, which are explained in the subsequent section in greater detail. Moreover, the evolution of credit risk over time is closely related to the trend in several macroeconomic variables, which are graphically illustrated in Figure 2.3. The slump in Gross Domestic Product (GDP) growth in 2008 was accompanied by a drastic increase in the implied volatilities as measured by the CBOE Volatility Index (VIX), a common measure for the overall market volatility and often dubbed “fear index”. The years following 2009 constitute a period of normalisation. It is also noteworthy that financial markets have been extraordinarily influenced by unconventional monetary policy, so called credit easing, in this time period. These overriding factors are not satisfactorily addressed in the analysis of Dimitrov et al. (2015) and I provide a more explicit control for them. If not specified properly, a regression model might easily pick up a pre/post crisis effect rather than pre/post regulation effect.[4]

2.2.1.1 Hypothesis Development

This section puts the hypotheses of Dimitrov et al. (2015) to an enhanced test by relating both issuer credit rating levels and rating changes to several common credit risk measures. Bond or issue ratings, which are used by Dimitrov et al. (2015), are more suitable to investigate market reactions, as they are directly linked to the default risk of specific securities. I use issuer credit ratings because they reflect the long term default risk of firms (Standard & Poor's, 2016), which is conceptually closer to the alternative credit risk measures considered in this article. Plus, issuer ratings are not affected by security-specific idiosyncrasies - such as collateralization, covenants or maturities - that might drive the rating of a particular security. To assess the impact of the DFA, I test two hypotheses:

Hypothesis 1 *The DFA has caused a downward bias of issuer ratings (risk avoidance hypothesis)*

Hypothesis 2 *The DFA has prompted CRAs to produce credit ratings, which are more in line with alternative indicators of credit risk (disciplining hypothesis)*

Note that Hypothesis 1, $H1$, corresponds to Dimitrov et al. (2015) *risk avoidance*

[4] In general, CRAs claim that their ratings are "through the cycle", i.e. do not reflect the state of the business cycle, but rather focus on firm fundamentals. There is some literature, which supports this view (Altman and Rijken, 2006; Amato and Furfine, 2004; Löffler, 2013). However, as shown in Figure 2.3, there appears to be a cyclical pattern in the rating level.

hypothesis. As such, it is concerned with rating levels. If it holds true, we should observe lower rating levels after the introduction of the DFA, holding firm-specific credit risk and macroeconomic conditions constant. The second hypothesis, $H2$, provides a novel perspective on the impact of the DFA on credit ratings using rating changes. I estimate likelihoods of up- and downgrades based on changes of firm-specific credit risk to pinpoint which credit risk measures play an increased role in the rating decisions of CRAs after the regulatory overhaul. Rating changes are interesting from two perspectives: Anticipation of rating changes and reactions to rating changes.

Under $H2$, the *disciplining hypothesis*, I should observe changes to the lead-lag relationship between market-risk measures and credit ratings. With increased liability, CRAs might want to align their ratings faster with market-implied measures to avoid accusations of unjustified optimism. One would therefore expect that higher order lags of the market-implied risk measures have a lower impact on current rating changes.

2.2.2 Methodology

2.2.2.1 Credit Risk Measures

I employ several well-known credit risk measures as benchmark for agency ratings to elicit a potential effect of the regulatory overhaul. Specifically, I use the Merton (1974a) model, the risk neutral PDs implied by Credit Default Swaps (CDS) spreads, and the Campbell et al. (2008) failure score. As all three measures capture the same quantity as the issuer rating does - the probability that the rated firm is unable or unwilling to honour its obligations - and because they are unaffected by the DFA, they can serve as a counterfactual to agency ratings. These properties have been thoroughly evaluated in the literature. Wu et al. (2010) provide a comparative analysis of all of these measures. Hilscher and Wilson

(2016) and Bauer and Agarwal (2014) confirm the superior performance of the failure score over credit ratings. Further, these measures are also highly practice-oriented.

Equity-implied default probabilities are calculated using the Merton (1974a) model. According to the model, equity can be interpreted as a call option on equity and priced accordingly. In this context, the book value of liabilities (X_t) represents the strike price of the call option. The equity value is only positive if the value of assets ($V_{A,t}$) exceeds the book value of liabilities. Solving the model for the probability that equity has no value yields the following equation:[5]

$$Equity\ PD = N\left(-\frac{ln\frac{V_{A,t}}{X_t} + (\mu - 0.5\sigma_A^2)T}{\sigma_A\sqrt{T}}\right)$$

Note that the actual volatility of assets, σ_A, is not directly observable. I adopt the iterative method of Vassalou and Xing (2004) to pin down σ_A. The equity-implied probability of default is given through the cumulative normal density function, which is applied to the negative of the distance-to-default. T is the time horizon of the default probability. For all measures in this chapter, I normalise the PDs to describe the one-year-ahead default probability.

CDS-implied default probabilities are calculated by adopting Duffie (1999)'s constant hazard rate model. Assume that the probability of default in each period t is equal to $p(t) = 1 - e^{-\lambda t}$, with λ being the hazard rate. If fairly priced, the insurance against credit risk in form of the CDS should be equal to the expected loss. Writing the recovery rate as RR and the risk-free interest rate as r, the CDS spread can be written as:

$$CDS\ spread_t = \frac{\sum_0^t e^{rt}(e^{\lambda(t-1)} - e^{\lambda t})}{\sum_0^t e^{-(\lambda - r)t}}(1 - RR)$$

[5]A more detailed description of the model is provided by Vassalou and Xing (2004).

Observing the CDS spread, one can back-out the underlying hazard rate and thereby the default probability. I set the recovery rate (RR) equal to the conventional level of 40% and solve for λ numerically. CDS spreads are available for different tenors, restructuring clauses and seniorities. To mitigate the effect of liquidity on the spread, I pick the five year, senior CDS spreads with the modified restructuring clause as it represents the most liquid tenor, restructuring and seniority combination. Again, I annualize the implied *CDS PD* to make this measure comparable with the other models.

The failure score (F-Score) proposed by Campbell et al. (2008) is based on a large database on defaults, which are used to calibrate a logistic regression model with traditional accounting ratios and stock market data as explanatory variables. Note that this predictor reflects real-world PDs rather than the risk-neutral probabilities captured by asset prices. As I do not have access to the default data, I have to rely on a calibration of the model provided by Hilscher and Wilson (2016). All of the used accounting ratios and stock variables are well-documented and can easily be re-constructed using COMPUSTAT and CRSP databases. Hilscher and Wilson (2016) estimated the model of Campbell et al. (2008) for a set of rated, North American firms and a sample period ranging from 1986 - 2013.[6] As my sample is comprised of very similar firms and the summary statistics of the independent variables are similar to those of Hilscher and Wilson (2016), the obtained default probabilities are not a perfect, but a valid proxy for the real-world default probability. In the remainder of the chapter, the resulting probability of default is referred to as *CHS PD*. Appendix .1 contains a detailed description of the construction of this default measure and the summary statistics.

[6]More specifically, the calibration of column 4, rated-only in Table 2 of Hilscher and Wilson (2016) is used.

2.2.2.2 Identifying rating policy changes

I relate agency ratings to these benchmarks in an ordered logistic regression model to determine whether the introduction of the DFA prompted CRAs to assign lower issuer ratings relative to the benchmark. The rationale behind the benchmarking is the following: Unlike the agency ratings, the market-based risk measures are not affected by the regulation. If the regulation does indeed influence the assigned rating levels, the mapping of PDs into ratings should change. By using market perceptions of risk rather than mere balance sheet variables, I am able to control for trends in the default risk common to both ratings and my set of PDs, but not to the balance sheet variables. For example, lower ratings might reflect a more negative outlook on future development that is not yet captured by balance sheet variables. Further, more stringent ratings might not be the results of a tighter regulation, but rather of a general shift of the judgement of default risk. Therefore, looking at the evolution of ratings vis-à-vis other measures of default risk is of paramount importance to test my research hypotheses. To foster comparability with the literature, I use a similar specification as Dimitrov et al. (2015). Formally, the regression equation for the rating levels reads as follows:

$$\mathit{Numerical\ Rating}_{i,t+1} = \alpha + \beta \times \mathit{DFA}_t + \gamma \times \mathit{PD}_{i,t} + \rho \times K_{i,t} + \phi \times X_t + \epsilon_{i,t}. \tag{2.1}$$

Numerical Rating is a numerical transformation of the alphanumeric credit ratings with AAA=21, ..., CC=1 for every firm i in period t. *DFA* is a dummy which takes the value of one for every observation after July 2010 and zero otherwise. $PD_{i,t}$ is one of the three above specified credit risk measures. I estimate one separate version of Equation 2.1 for every credit risk measure. $K_{i,t}$ is the same set of firm control variables used by Dimitrov et al. (2015). The vector of macroeconomic control variables X includes the natural logarithm of the GDP, the VIX and the level of the S&P500. The coefficient of interest is β. If β is negative and significant, rating levels are lower after the DFA than before. As one firm might experience several rating changes in the sample, the standard errors are clustered at the firm level.[7] Unit of observation in this regression is firm-quarter. Though ratings are available at monthly frequency, the accounting ratios are not, I estimate Equation 2.1 using quarterly data. Ratings are collapsed to quarterly frequency by using the level of the first month in the quarter. To address possible endogeneity concerns, I use the forwarded value of the numerical rating as dependent variable.

Lastly, I investigate the impact of the DFA on the policy of CRAs in more detail using monthly data on upgrades and downgrades. The methodology closely follows the standard literature on rating predictability, i.e. the lead-lag relationship between credit ratings and other risk measures (Alsakka and ap Gwilym, 2010; Güttler and Wahrenburg, 2007; Milidonis, 2013). To test predictability, I regress the rating changes on lagged changes in the market-based risk measures ($\Delta Implied_{i,t-k}$). Formally, the model is captured by the following equation:

$$\begin{aligned} Rating\ Change_{i,t} = & \sum_{k=1}^{6} \kappa_k \times vRating\ Change_{i,t-k} + \sum_{k=1}^{6} \mu_k \times \Delta Implied_{i,t-k} \\ & + \sum_{k=1}^{6} \pi_k \times DFA_t \times \Delta Implied_{i,t-k} + \omega_{i,t} \end{aligned} \tag{2.2}$$

where $Rating\ Change_{i,t}$ is the change in the issuer rating by S&P of firm i in year-month t. The dependent variable can take five values. If the rating is lifted or reduced by two or more notches, $Rating\ Change_{i,t}$ is set to 2 and -2, respectively. Changes by one notch translate into a value of 1 for an upgrade and -1 for a downgrade. If the rating

[7] Clustering the standard errors at the year-month level or at the rating grade before the downgrade generates marginally stronger results.

remains unchanged in month t, *Rating* $Change_{i,t}$ is set to zero.[8]

$\Delta Implied_{i,t-k}$ is the absolute change in the implied PD measure. To control for possible autocorrelation in the dependent variables, the lags of *Rating* $Change_{i,t}$ are included. To elicit possible changes to the lead-lag relationship, the interaction of DFA_t and $\Delta Implied_{i,t-k}$ are added. If markets anticipate rating changes - or, alternatively, CRAs follow market sentiments - the implied PDs should increase before a downgrade and decrease before an upgrade. Hence, μ_k is expected to be negative. The coefficients of interest are π_k. If the interactions of the implied risk measure and the post DFA dummy *DFA* are significant and negative, the predictability of rating changes has increased. In essence, equation 2.2 tests the predictability of up- and downgrades by changes in the marked-implied risk measures, while controlling for possible autocorrelation in the dependent variable. Note that unlike in 2.1, all the data items which are required to estimate Equation 2.2 are available at monthly frequency. Hence, the unit of observation of Equation 2.2 is firm-month rather than firm-quarters . As before, standard errors are clustered at the firm-level.

2.2.3 Data

2.2.3.1 Sample Construction

My dataset combines credit ratings by Standard & Poor's (S&P) with balance sheet data, stock data and CDS spreads. Monthly ratings and quarterly balance sheet data are taken from COMPUSTAT. Stock data was provided by CRSP, CDS spreads by Markit. All data was downloaded via the Wharton Research Data Services (WRDS). My sample period spans from 2006 to 2014. Due to data availability of issuer ratings in COMPUSTAT,

[8]Looking only at actual downgrades centres the analysis on false negatives, i.e. rating changes that happen but are not predicted by the model, while excluding false positives, i.e. predicted, but non occurring rating changes.

the analysis is confined to North America. The sample is constructed as follows: First, all available firm-month rating observations were downloaded and merged with stock and balance sheet data. I drop all firm-month observations for which not all balance sheet and stock items were available. Notably, I thereby exclude all private firms from the sample and keep only publicly traded companies. Second, I add CDS spreads from Markit. Since CDS spreads are only available for a relatively small subsample, I keep observations with no CDS data, but provide the baseline results for both, the full sample and the reduced CDS sample. Finally, I drop firms with less than 12 observations, i.e. less than one year of observations, as well as all financial firms from the sample.

The full sample consists of 1,595 firms and 20,271 year-quarter observations, i.e. roughly 13 quarters or 3 years of data per firm. The CDS sample includes 448 firms and 9,613 year-quarter observations. The higher average number of observations per firm in the CDS sample can probably be attributed to the fact that firms with outstanding CDS contracts tend to be larger and therefore be better covered in databases and may have been existing for a longer time.

2.2.3.2 Descriptive Statistics

Table 2.1 provides summary statistics of key variables. For better readability, implied PDs are reported in basis points. The average numerical rating over the entire sample period is approximately 11.37, which corresponds to an alphanumerical rating grade between BBB+ und BBB. Figure 2.1 depicts the distribution of observed ratings levels, Figure 2.2 the distribution of rating changes. Most of the firms have a rating between BB-, the upper bound of the non-investment grade ratings, and AA-. Note that there are only a few observation at both ends of the rating scale. The equity-implied PD is approximately 6.57 basis points. Note that the distribution of equity-implied PDs is heavily skewed to the left and that the median equity-implied PD equals zero.[9] The average CDS-implied PD is 62.32 basis points. Unlike the equity-implied PDs, the CDS-implied PDs exhibit a less skewed distribution. The median CDS-implied PD is 13 basis points, roughly one quarter of the mean. *CHS PD* - the PD calculated using the methodology of Campbell et al. (2008) - is larger than both, the equity-implied PD and the CDS-implied PD with an average of 197.2 basis points for the full sample.

As a preliminary test, I report the pre- and post-DFA means of each variable. The average rating increases slightly from 11.18 to 11.57, indicating a lower average default risk. The implied PDs indicate a similar movement in default risk and dropped significantly. The strongest drop is registered for *Equity PD* and *CHS PD*, which are decreased by factor four. The drop in the CDS-implied PD is less pronounced. In order to detect a downwards bias in assigned ratings, adjustment to the ratings must be of smaller magnitude than the changes in the implied PDs.

To better understand the movement and co-movement of ratings and my benchmark PDs, Figure 2.3 plots their evolution over the sample period. During the financial crisis, the average rating drops by around 4% but recovers to the pre-crisis level by the end of 2011. The market-implied risk measures inversely mirror the development, but with a higher variability (Figure 2.3b). The average *CHS PD* and *CDS PD* rise to approximately 160% of the pre-crisis level in 2008 but drop sharply afterwards. Though the decline of the *CHS PD* is faster than the decline of *CDS PD*, the levels converge at the end of the sample period. *Equity PD* appears to lag behind the evolution of *CHS PD* and *CDS PD*. After an initial sharp drop, the *Equity PD* starts and keeps increasing as the other PD

[9] It is well known that the application of the cumulative normal density function used to calculate *Equity PD* leads to a miscalibration of this measure. In general, the distance-to-default tends to assume very high values (zero PDs) for relatively risk-free firms, but can drop considerably during equity market downturns even for very safe firms. For these reasons, the Merton (1974a) model usually delivers low PDs (Bharath and Shumway, 2008; Hillegeist et al., 2004).

measures drop.[10] The positive yet imperfect correlation between PDs suggests that all of my benchmark measures do capture - at least partly - the default risk of the issuer. Eye-balling of Figure 2.3c suggests that the changes in the rating level as well as the PD measures are correlated with the macroeconomic environment. Rating levels are low, if the GDP and the S&P500 are low and increase with the implied market volatility, captured by the VIX. This illustrates that the macroeconomic control variables are important in the context of this study and have to be treated with care.

To establish the implied PDs as valid counterfactual, I visualize the relationship between agency ratings and PDs in Figure 2.4. The figure depicts the average implied PD for each rating grade. To account for global time-varying effects, I follow Hilscher and Wilson (2016) and subtract the median rating grade PD of each month from the firm-specific PD. Figure 2.4 confirms that the relationship between ratings and CDS is stronger than the relationship between ratings and equity-implied PDs. The overlap between the PDs of the different rating grades is lower for *CDS PD* than for *Equity PD*. In particular, there appears to be no or little difference between *Equity PD* for investment-grade firms. Similarly, *CHS PD* exhibits starker differences between rating grades below the investment grade threshold. Despite the overlap, there appears to be an ordering of average PDs that reflects the rating grades. I conclude that the market-based measure are valid counterfactuals for the agency ratings.

[10] Explanations for this lagging behavior might be given by the distributional assumptions of the Merton (1974a) model and the iterative estimation procedure. Due to the assumption of the cumulative normal density function it takes a sustained decrease of equity prices to push relatively safe firms towards the default point. Moreover, as I use one year of equity returns to initiate the iterative estimation procedure, the high volatility observed during the financial crisis in 2008 passes through several iterations, leading to the increase of PDs in the aftermath of the crisis.

2.2.4 Results

2.2.4.1 Rating Level

Table 2.2 presents the results of the level regressions of Equation 2.1. The columns report the coefficients for different sets of control variables and samples. In column 1, no additional market-based PD is added, so the specification is equivalent to the Dimitrov et al. (2015) main model for issue ratings (see their Table 3). In column 2 and 3, *Equity PD* and *CHS PD* are added as additional controls. As CDS spreads are only available for a relatively small subsample, I verify that the baseline results do also hold in this subsample and estimate Equation 2.1 without additional PDs for this sample (column 4). Eventually, I add *CDS PD* as a control variable in column 5. The coefficient of *DFA*, β in Equation 2.1, is shown in the first row. In each specification, β is negative, i.e. suggests lower rating levels after the DFA. Quantitatively, the coefficient ranges between -0.310 to -0.417 depending on the added control variables and is larger than the -0.171 found by Dimitrov et al. (2015).[11] Transformed into odds, the coefficients of 0.310 and 0.417 suggest that the odds of obtaining a lower rating are between 1.36 and 1.51 times greater after the DFA. All of the firm control variables and the market-based risk measures have the expected sign or are not significant. McFadden's pseudo R^2 ranges between 0.209 and 0.305, which describes a good fit for an ordered logistic regression (McFadden, 1977).

A key assumption behind the ordered logistic regression - the so-called parallel regression assumption - is that the effect of the independent variables is the same across the different outcome levels. Put differently, one assumes that the effect of the regressors is the same for each of the possible outcomes. For example, the effect of an increase of 1 bp in *CDS PD* on the probability of an upgrade has to be the same for firms rated AA+

[11] Dimitrov et al. (2015) use an inverse transformation of the alphanumerical rating scale, i.e. AAA=1, ..., CC=21. Hence, to make their coefficient comparable to my estimates, I have to switch its sign from 0.171 to - 0.171.

and BBB+. For the particular setting of ratings, this assumption translates into equal distances between the rating grades. However, especially at the investment-speculative grade cut-off, this assumption is not entirely plausible. Further, as CRAs are more likely to be sued for an optimistic rather than a pessimistic model, they might adjust their policy primarily for lower rating grade (Goel and Thakor, 2011). I therefore conduct the so-called Brant Test. Technically, the Brant Test estimates a series of binary logistic regression models with the same set of regressors as in Equation 2.1. The dependent variables in those regressions are dummy variables that take a value of one if the rating is above a certain threshold and zero otherwise. The obtained coefficients are then tested for similarity.[12]

The coefficients of *DFA* in each of the binary logistic regressions are shown in Table 2.3. The Brant Test suggests that the parallel regression assumption is violated in all regressions in Table 2.2 at the 1% level, i.e. the effect of the DFA is not equal for all rating grades. While the effect of *DFA* is strongly negative for most rating levels, it switches the sign for very low and very high rating grades. However, as the number of observations at the extreme ends of the ratings scales is low, these coefficients should be treated with care. The coefficients tend to be more negative for low rating grades. This suggests that lower-rated rated issuers are less likely to be upgraded compared to higher rated issuers. Though there appears to be a jump at the investment grade threshold (BBB- to BB+), jumps in the coefficient of DFA between adjacent rating notches are not uncommon. To summarize, though the parallel regression assumption is violated and the effect of *DFA* is quantitatively different across rating notches, the qualitative result, rating levels are lower after the DFA, remains unchanged. The stronger effect at the lower rating grades hints towards the prevalence of the risk avoidance hypothesis.

[12]For more details see Long and Freese (2014).

Robustness tests and alternative specifications

The identification of the effect of the DFA hinges on the assumption that any pre/post differences in the rating levels, which are not explained by the set of regressors, can be attributed to the DFA. There is a number of developments which might have caused additional changes in the relationship between credit ratings and alternative risk measures. Most prominently, the pre-DFA period includes the financial crisis, whereas post-2010, the economy bounced back. To minimise the impact of such contaminating events, a three-pronged approach is taken. First, Equation 2.1 is estimated using a reduced sample of four instead of eight years centred around the DFA. Second, instead of the post-DFA dummy, I re-estimate Equation 2.1 with year-quarter dummies. This procedure is implemented by replacing the DFA dummy in Equation 2.1 with t dummy variables, one for every quarter.[13] Looking at the coefficients of the year-quarter dummies provides an alternative view on the potential effects of the DFA. If the DFA does indeed shift rating levels downward, the coefficients for the year-quarter dummies should drop to significant negative levels just after the introduction of the DFA or exhibit a downwards-sloping trend from the DFA onwards. I repeat this procedure for each of the implied PDs to elicit abnormal movements of the implied PDs and compare them to the movement of ratings. Third, like Dimitrov et al. (2015), I test the effect of a series of placebo treatments by shifting the commencement date of the DFA to the past and future.

Overall, the robustness tests cast considerable doubt on the detected relationship between rating levels and the DFA. Results for the shortened sample period are presented in Table 2.4. If the sample period is shortened, *DFA* becomes small and insignificant once any of the market-based measures are added as control variables. Figure 2.5 visualizes

[13] Note that adding fixed-effects to a non-linear model might result in biased estimates due to the incidental parameter problem. In brief, the incidental parameter problem states that adding fixed effects to a non-linear model might bias the estimators (Greene, 2004). Though this bias primarily arises if fixed effects for firms are added or in short panels, these results should be treated with care.

the estimated coefficients of the year-quarter dummies with confidence intervals for each quarter in the sample. Panel (a) of Figure 2.5 shows the results for the baseline rating model, the remaining panels show the coefficients for the implied PDs. For the rating levels and *Equity PD*, one can observe a pronounced spike in the coefficients during the crisis period and an inverse movement of the coefficients for the *CHS PD*. For *CDS PD*, the coefficients remain fairly constant after an initial increase. For each measure, the movement of the coefficients in the post-DFA period compared to the crisis period is muted. This raises the concern that *DFA* in the baseline specification captures a crisis effect rather than an effect of the new regulation. Finally, the placebo tests show that every hypothetical start date before July 2010 generates a negative coefficient of *DFA* (See Table 2.5). This might partially be attributable to anticipation as a first draft of the DFA was published in July 2009 and a revised version in December 2009. Indeed, the coefficient of *DFA* suggests, that the strongest differences arise if these dates are chosen as start date of the post period. However, a negative coefficient for the July 2008 start date - before any possible anticipation of the regulatory overhaul - suggests that other effects drive, at least partly, the differences in ratings levels.

Further specification concerns are of a more technical nature. First, adding the implied PD to the set of regressors might lead to multicollinearity. As the regressors explain default risk captured by credit ratings, they should also explain market-based measures of default risk. To check whether my results are driven by over-fitting, I re-estimate Equation 2.1 with just the market-implied PDs and macro controls. As shown in Table 2.6 (Panel A), the coefficients of *DFA* drop significantly. For instance, it decreases from -0.417 to -0.111 if only *Equity PD* is used as a regressor compared to the specification with the additional independent variables of Dimitrov et al. (2015). Note however, that the pseudo R^2 drops to 0.0477 and thereby below the threshold for a good fit (McFadden, 1977). For *CDS PD* the drop in the coefficient of *DFA* is less pronounced (-0.381 to -0.258) but still substantial. The fit of the model with *CDS PD* is still reasonable with a pseudo R^2 of 0.12. I conclude that multicollinearity might lead to an overstatement of the effect of the DFA, but does not change the results qualitatively. A further advantage of using only the implied PD measures and dropping the quarterly accounting ratios is that I can use firm-months as unit of observations instead of firm-quarters. Changing the unit of observations decreases the coefficient of *DFA* drastically. For *Equity PD* and *CHS PD*, the coefficient drops below 0.1 in absolute terms and even turns insignificant for *CHS PD*. Again, the CDS model provides the best fit and the coefficient drops from -0.258 to -0.164 (p-value: 0.096). I infer that, though the qualitative results carry over to the monthly specification, the magnitude in some cases is reduced to near economic inconsequentiality.

Second, I use a different variable to control for the business cycle. Namely, I swap the natural logarithm of nominal GDP used by Dimitrov et al. (2015) for the GDP growth rate. As shown in Figure 2.3c, the natural logarithm of the GDP shows a general upwards trend - with the exception of the dip in 2008. Using the GDP growth rate, which does not exhibit an upwards trend, as a control for the business cycle rather than the log GDP appears to be more natural. If the GDP growth rate is used, the coefficient of *DFA* turns positive or insignificant in each specification - except if *Equity PD* is included as independent variable (See Table 2.6, Panel B).

Third, I account for market sentiments in the implied PD measures by regressing them on the macro control variables and using the residuals as independent variable in 2.1. The results are virtually unchanged.[14] Overall, the specification tests hint towards a strong sensitivity of the results to modelling choices. Especially the dependence on a particular

[14]Results are not reported for the sake of conciseness. Crucial coefficient change at most after the third decimal place.

definition of the business cycle and sample length cast doubts over the effect detected in the baseline specification.

2.2.4.2 Rating Changes

In the following, I present the results regarding rating changes. Table 2.7 shows the estimation results for the changes model (Equation 2.2). Because increasing risk should yield decreasing ratings, the obtained coefficients should be negative. Odd columns report the results for the full sample. Even columns hold the results for a reduced, changes-only sample obtained by dropping all observations without changes. The first two columns present the results for the *Equity PD*. This variable has very low predictive power for rating changes. The obtained coefficients are small, mostly positive and most of the times they are insignificant. The first regressions yield very low pseudo R^2 (1.04% for the full sample and 4,91% for changes only sample), but fall in the range of comparable studies.[15]

The results for *CHS PD* (columns 3-4) and *CDS PD* (columns 5-6) are stronger and more in line with the expectations. All coefficients are negative or insignificant. The significance of higher order lags suggests that rating changes are indeed anticipated by the market up to five months in advance. Interactions between *DFA* and the PD-measures are negative and significant for the second lag of *CHS PD* and the fifth lag of *CDS PD*. The negative sign of these interactions suggests that a movement of the PD measure is more likely to trigger a rating change after the reform. In other words, the agency ratings appear to be more in line with market risk assessment after the introduction of the DFA. However, if the sample is split in pre- and post-DFA periods, the R^2 is larger in the pre- than in the post-period. Moreover, in unreported binary logistic regressions with upgrades

[15]Though the R^2 are in the region of Milidonis (2013) and Güttler and Wahrenburg (2007), they are below the threshold for a well-specified ordered logistic model, which according to McFadden (1977) shows R^2 of about 20%.

and downgrades as dependent variables rather than a common rating change variable, I find that the model predicts downgrades better than upgrades in terms of R^2, but none of the interaction coefficients is significant.[16] Overall, the evidence for an effect of the DFA on rating changes is weak. Only two significant interaction terms indicate that CRAs have adjusted their policy to be more in line with alternative credit risk measures, while the majority of interaction terms remains insignificant.

2.2.4.3 Interpretation of Results

The DFA as a legal reform of the financial market was supposed to strengthen the integrity of credit ratings as an important institution in financial markets. This chapter examined the effects of this reform on S&P issuer ratings. In the first part of the chapter, I find that - even after controlling for market assessment of default risk - issuer ratings appear to be lower after the DFA than before. However, this finding is not robust to specification changes: Shortening the sample period or using a different set of macroeconomic control variables as well as significant effects of placebo treatments cast questions, whether the baseline effect actually captures the impact of the DFA. The evidence for a changed predictability of agency ratings is weak, but suggests that agencies are more sensitive to changes in the market-implied PDs, even though the overall fit of the model deteriorates after the DFA.

This section cannot address all questions to complete satisfaction and leaves questions open for future research. First, the question how and whether the sensitivity of the specifications detected in the battery of robustness tests carries over to bond ratings and questions the results of Dimitrov et al. (2015). Second, the anticipation of rating changes should studied at daily frequency. As the section uses only monthly rating changes, the

[16] Results not reported for the sake of conciseness.

short-term adjustments of market sentiments around rating changes cannot be studied.

2.3 Rating Reports

The DFA might not only affect rating levels, but also qualitative information released by the agencies in rating reports. In fact, this effect is partly mechanical, because the DFA increased the disclosure requirement for CRAs. However, these additional disclosure requirements concern primarily technical details, such as the applied methodology or possible conflicts of interest. More importantly, the increased liability might alter the level of disclosure and framing of information which are private to the agencies or represented some sort of judgement. As in the previous chapter, the effect of increased liability on the information content is not clear-cut. On the one hand, CRAs might publish more and/or more precise information to justify their rating decision. On the other hand, CRAs might adopt defensive language to give as little leverage as possible to potential law suits. The first alternative corresponds to the *disciplining hypothesis* postulated in the previous chapter, the latter to the *risk avoidance hypothesis.* In this chapter, I analyse the qualitative information released by CRAs with their rating decision. For each decision - not only down- and upgrades, but also reviews, outlook changes, confirmations and assignments - CRAs publish a brief report outlining their reasoning behind the decision. I analyse a sample of more than 14,000 of those rating reports from Moody's with natural language processing tools to test for possible effects of the DFA on the wording and thereby, by proxy, on the information content of ratings reports. My sample includes not only reports on North American firms, but also reports on European issuers.[17] Note that the sample used in this chapter is entirely distinct from the one of the previous chapter.

An example of a rating report is provided in Appendix .2. On September 3, 2014, Moody's downgraded Frontier Communication Corporation, an American telephone com-

[17] I cannot differentiate between reports on Canadian and US firms. This might bias my results downwards as the ratings by Canadian subsidiaries of CRAs might not be affected by the DFA.

pany. The report opens with a brief summary of the action, that was taken, followed by a listing of the effects of the action on the different ratings. The most important part of the report is the rating rationale, an explanation of the reasons behind the action taken. The rationale contains information on the current development of Frontier Communications (e.g. "Frontier has posted modest broadband subscriber growth over the past several quarters") as well as a forward-looking analysis of possible developments (e.g. "...Frontier will continue to face price pressure..."). These statements are not merely descriptive, but reflect assessments of these information by Moody's. For example, Moody's considered the broadband subscriber growth as "modest", not as "weak" or "average". Similarly, Moody's considers a scenario of continuing price pressure as highly likely. This forecast could be framed more carefully by adding "most likely" or "probably". The toolbox of natural language processing allows me to detect and quantify such nuances in the wording and thereby enables me to examine changes in the wording over time.

The literature on the informational value of the wording of analyst reports is limited and, to the best of my knowledge, non-existing for rating reports. Most closely, this chapter relates to Huang et al. (2014), who examine the effect of the wording of sell-side analyst reports on abnormal stock performance around the publication date. The authors classify each sentence of the report along two dimensions. The first dimension is the polarisation of the sentence: Positive, negative or neutral. Second, the sentences are classified as either forward-looking or not forward-looking. The key finding is that wording sentiments do matter and that price reactions are magnified, if the sentiment is expressed in a forward-looking manner. In a broader sense, the chapter connects to the literature on the information content of corporate filings, see among others Kothari et al. (2009). The literature can be divided by their text classification approach. The first group uses machine learning algorithms - for instance Huang et al. (2014) and Li (2010).

In such an algorithm, a number of sentences in the sample are randomly selected and classified by hand. These classifications are then fed to the machine learning algorithm to classify the remaining sentences based on the similarity to the pre-classified sentences. The second group - including Kothari et al. (2009) - uses a dictionary-based technique, which assigns a sentiment to each word and classifies the text according to the frequency of certain word groups.

This chapter adds to the literature by looking at the so-far unexplored rating reports and using these reports to elicit effects of regulation on the information disclosure by CRAs. I find that the wording of the reports is more forward-looking and nuanced, but more vague for speculative-grade reports. As markets do value a more forward-looking wording but dislike vagueness, the overall effect of the DFA on the informational value is not clear-cut.

The remainder of this chapter is structured as follows. First, the methodology of detecting and quantifying changes is explained. The second section describes the download procedure of the rating reports and provides summary statistics. In the third section, a quantitative analysis of the impact of the DFA on the wording and the market reaction to the wording are examined.

2.3.1 Methodology

2.3.1.1 Language Classification

To detect changes in the language of rating reports, I employ several text analysis methods. Overall, I adapt two categories of classification measures: Frequency-based and sentiment-based measures.[18] Frequency-based measures examine the number and range of words

[18] For an introduction into practical text analysis see Miner et al. (2012) and Jockers (2014).

used in a text, for example measures of length and lexical complexity. Lexical complexity measures the range of different words used. They estimate the spectrum of word used, but they do not capture the "sophistication" of the words used. For example, the addition of the words "arcane" and "secretive" would affect the lexical complexity measures in the same way, though "arcane" is arguably a more sophisticated or complex word. The first frequency-based measure employed in this article is the *word count* of the report, measured by the number of words in the rating report. A longer report should - *ceteris paribus* - contain more information than a short one. For example, CRAs might provide more information to substantiate their decision or outline future scenarios in more detail. The second set of frequency-based measures contains two definitions of lexical complexity. All measures of lexical complexity relate the number of different words used ("tokens"[19]) to the total words of the text, but differ in the scaling of those components. Scaling is necessary as the number of different words used is decreasing in the length of the text. The reason behind the naturally decreasing lexical complexity is simple: Some words, such as articles or pronouns, occur naturally and repeatedly in each text and cannot be replaced by synonyms. As the literature does not identify a single superior definition of complexity, I use a simple and readily interpretable, but possibly biased measure, the type-token ratio (TTR) alongside a more modern, unbiased measure, the so-called "measure of lexical diversity" ($MTLD$). TTR is defined as the number of different words used in a text (V) divided by the total number of words (N): $TTR = \frac{V}{N} \times 100$. TTR is bounded between $\frac{100}{N}$ and 100. Larger values indicate a higher complexity. $MTLD$ accounts for the text length by splitting the text into so-called factors. A factor is defined as a sequence of words for which the TTR of that factor is above a certain threshold.[20] The $MTLD$ is then calculated as the total number of words divided by the number of factors. As for

[19]Broadly speaking, the linguistics literature refers to words as tokens. In the context of this article, I use the terms interchangeably.

[20]Most of the literature uses a TTR threshold of 76. I uphold this standard.

the TTR, higher values of $MTLD$ indicate a more complex text.[21]

However, the length or complexity of a rating report is likely to be an imperfect measure of the informational value of the reports as words do differ in their strength and connotation. Consider the following example: "Company A has been downgraded, because orders might decrease." and "Company A has been downgraded, because orders will decrease." Though both sentences have the same length and complexity, they differ significantly in their informational value as "might" and "will" suggest different levels of certainty. CRAs can modulate the precision of their predictions by varying their language, while leaving the lexical complexity unchanged. Such subtle differences in sentiments are not captured by the frequency-based measures. Therefore, I resort to the Loughran and McDonald (2011) dictionary, which provides a sentiment classification of words. In this context, a "sentiment" of a word is a particular connotation or subjectivity that capture the attitude of the text. For example, "brilliant" is likely to express a positive attitude whereas "apocalyptic" expresses probably a negative attitude. As the usage of words is highly situational, I use the specialised finance dictionary of Loughran and McDonald (2011) that provides sentiments of words along eight dimensions: Negative, positive, uncertainty, litigious, modal, superfluous, interesting and constraining. Two categories are of particular interest in this chapter: Uncertainty and modal. The class "uncertainty" collects words, which express ambiguity and vagueness (e.g., "approximate", "depend" or fluctuate"). Modal words describe, *inter alia*, probabilities.[22] Words classified as modal can fall into three sub-classes: strongly modal (e.g., "always", "definitely" or "never"), moderately modal (e.g., "can", "generally" or "usually"), and weakly modal (e.g., "almost", "could", "might" or "suggests"). In addition to the Loughran and McDonald (2011) dictio-

[21]Intuitively, a more complex text has less factors as the TTR is not dropping and thereby a higher $MTLD$. Note that the theoretical upper bound $MTLD$ is the number of words. It is achieved if only one factor can be observed, i.e. if the TTR never drops below the threshold.

[22]Other usages include obligations, permission, habits or tenses. However, with the exemption of the use in tenses, the alternative usages should be uncommon in rating reports.

nary, I use the classification of forward-looking words provided by Li (2010) and Huang et al. (2014). Words of this class are associated with the description of possible future developments and include words such as "envision", "anticipate" or "project". Rating reports with more forward-looking words should contain more information and be therefore more informative for forward-looking financial markets. Note that the classes are not mutually exclusive, i.e. a word can belong to several classes. For instance, "perhaps" and "maybe" are tagged as expressing uncertainty as well as being weakly modal.[23] To quantify the sentiment of the rating reports, I calculate the percentage share of words from every particular category (uncertainty, modal and forward-looking) and examine the development of this share over time. For instance, a report of 400 words and 10 words from the uncertainty category, *uncertainty* would equal $\frac{10}{400} \times 100 = 2.5\ pp$.

2.3.1.2 Empirical Identification

The identification of possible changes in the wording of rating reports proceeds in three steps. First, I explore differences over time in a simple regression framework with dummies for the post regulation period (*DFA*). It is conceivable that the DFA did not only affect ratings in North America (NA), but the global rating policy of the agencies. If this holds true, one should observe a change in the wording of the NA and European reports and not only of the NA ones. In a second step, the regression framework is extended to a difference-in-difference model by adding the interaction of a North America dummy (*NA*) and the post DFA dummy. Under the assumption that the new regulation affects only NA ratings, the coefficient of the interaction captures the treatment effect of the new regulation. Using the European reports as a counterfactual thereby serves as an additional control for unobserved, time-varying effects that are common to European and

[23]Out of the 297 words in the category "uncertainty", 26 are also weakly modal and two are moderately modal. None is strongly modal.

North American entities. In the third step, as the effect of increased liability is conceivably asymmetric, the effect on lower-rated rated issuers is examined in more detail. Lowly rated issuers are more likely to default and an erroneous rating decision has conceivably higher repercussions. Consequently, rating agencies have stronger incentives to frame the report more carefully for lower-rated rated issuers (Goel and Thakor, 2011). I therefore look at reports on ratings in the speculative grade region in greater detail by introducing a three-way interaction between the NA dummy, the DFA dummy and a speculative grade dummy (*spec*). The full-blown cross-sectional regression framework of step three reads as follows:

$$\begin{aligned} Text_i = \alpha_t &+ \beta \times NA_i + \gamma \times DFA_t + \delta \times spec_i \\ &+ \eta \times DFA_t \times NA_i + \theta \times DFA_t \times spec + \kappa \times NA_i \times spec_i \\ &+ \lambda \times DFA_t \times NA_i \times spec_i + \epsilon_i, \end{aligned} \tag{2.3}$$

where $Text_i$ is either a frequency-based or sentiment-based measure of rating report i. The unit of observation is a single rating report.[24] α_t are year-quarter fixed effects, NA is a dummy variable that takes the value of one for American rating reports and zero for European reports. As before, DFA_t is a dummy variable that takes the value of one for post-July 2010 reports and zero otherwise. X is a vector of control variables. To control for the macroeconomic environment, I include GDP growth and the inflation rate. Standard errors are two-way-clustered at the rating action and the year-quarter.[25] For step one and two, the respective interactions are dropped from Equation 2.3.

The coefficients of interest varies from step to step. In the first step without any

[24]Some reports refer to rating actions on the same issuer. However, as for most of the firms only one or two reports are in the sample, the within-firm variation cannot be exploited.

[25]The standard errors are adjusted as suggested by Cameron et al. (2011). Hence, I report the most conservative estimates. Clustering the standard errors only at the rating action or year-quarter level yields stronger results, but does not change the overall picture.

interactions, the coefficient of interest is γ, because it describes the difference in pre- and post-DFA averages. Under the assumption that Moody's adjust its rating policy not only in the US, but everywhere, γ describes the treatment effect of the DFA. In the second step, under the implicit assumption that the DFA affects only rating reports in NA, the treatment effect is captured by η. Specifically, η describes the pre-post change in the difference between NA and Europe of the text outcome variable. In the third step - if rating agencies only adjusted their wording for speculative grade ratings in NA - λ is the coefficient of interest. It describes how the difference between the wording of rating reports on speculative grade ratings in NA and Europe is altered by the DFA.

To test the parallel trend assumption, Equation 2.3 is estimated with interactions of year-quarter dummies with the NA dummy. The coefficients of these interactions capture the treatment effect individually for every year-quarter instead of an average treatment effect for the entire post-DFA period. If changes in pre-post differences are indeed driven by the DFA, one should observe a pronounced movement of the coefficients around the commencement date of the act. Formally, the following equation is estimated:

$$Text_i = \alpha_t + \beta \times NA_i + \gamma \times Post_t + \sum_{t=1}^{T} \mu_t \times quarter \times NA_i + \epsilon_i. \qquad (2.4)$$

For each of the text outcome variable $Text_i$, I plot the sequence of μ_t for the 15 trailing and 15 leading quarters to visually examine the parallel trend assumption.

Finally, I relate the stock market reactions to rating announcements with the wording of the associated rating reports. In a first step, I calculate the abnormal stock returns of the related issuer around the publication date of the report. I employ a standard market model and the event study methodology following Fama et al. (1969). I use an estimation window of 200 trading days closing 20 days before the publication of each report. The market return is approximated by the value-weighted return of the *CRSP* index. Formally, the market model reads as follows:

$$R_{i,t} = \alpha_i + \beta_i \times R_{m,t} + \epsilon_{i,t}, \tag{2.5}$$

where $R_{i,t}$ and $R_{m,t}$ denote the stock return of company i at trading day t and the return of the value-weighted CRSP index on trading day t, respectively. Abnormal returns are calculated as $\hat{AR}_{i,t} = R_{i,t} - \alpha_i + \beta_i \times R_{m,t}$ and cumulative abnormal returns as the sum of the abnormal returns around the event date: $CAR_{i,t} = \sum_{k=-j}^{l} \hat{AR}_{k,t}$. The nature of the setting constrains the choice of the event window. As this chapter focuses on the informational value of the report rather than the action, the event window opens with the publication of the report, i.e. $j = 0$. To avoid contamination with unrelated, overlapping events, I choose a narrow event window of three days, i.e. the event window closes two days after the publication (j=2). Note that $CAR_{j,t}$ is a directional measure in the sense that the sign indicates whether the new information is positive or negative. However, the primary interest of this chapter lies in the magnitude of the reaction and not in its direction. As the textual measure itself is not directional - an ambiguous language should reduce the information content of both downgrades and upgrades - I use the absolute value of the cumulative abnormal returns CAR^{abs} rather than the directional CARs.[26] In the second step, the absolute CARs are regressed on the wording variables derived above. Formally, I use the following cross-sectional regression framework:

$$CAR_i^{abs} = \alpha + \alpha_i + \beta \times Text_i + \gamma \times action + \delta \times spec_i + \epsilon_i, \tag{2.6}$$

where CAR_i^{abs} is the absolute cumulative abnormal return of the related issuer j and

[26]Consider for example the case of strong modal words. For reports on downgrades, a high fraction of strong modal words should lead to a more negative reaction. In contrast, if positive information - such as upgrades - are framed using a very strong language, CAR should be larger. Therefore, I use the absolute value of CAR as a measure for the magnitude of the reaction to the rating report as baseline specification.

$Text_i$ the text measure of the report. To control for apparent differences in CARs of the different rating actions, action-type fixed effects are included. Year-quarter fixed effects (α_i) absorb time-varying unobservable as well macroeconomic effects. In addition to this baseline specification, I estimate Equation 2.6 for downgrades and upgrades separately. In this subsamples, I do not have to take the absolute value of the CARs, because the expected direction of the CAR is the same for all reports in this sample.

2.3.2 Data

2.3.2.1 Sample Construction

Rating reports are publicly available on Moody's homepage. I obtain and process the reports in a three-step procedure. In the first step, the links to the single reports have to be collected. The collection starts with assessing Moody's homepage and setting search criteria, such that the results are narrowed down to reports on NA or European corporates. As Moody's does not allow for a bulk download of these reports and the homepage must be physically accessed to display the results, I resort to iMacros to navigate to the desired page and download the HTML code of this page in an automated process.[27] The links to the individual reports in the code are then isolated using R. In the second step, the HTML code of the single reports is downloaded using the *wget* function.[28]. In the third and final step, the HTML code containing the rating reports is parsed into R and the rating rationale is isolated. In particular, I remove disclaimers, notes on the methodology and disclosures, as these parts might mechanically be affected by the DFA due to increased disclosure requirements. Appendix .3 provides more detailed description on the three steps.

[27]More particular, I use the Firefox Plugin of iMacros. A more detailed description of iMacros can be found on `http://imacros.net/`

[28]The function is invoked via the Mac OS terminal. A description of the function can be found at `https://www.gnu.org/software/wget/`.

The title and text body of the reports are used to classify the report. First, I extract the rating action from the title. This is possible, since Moody's uses a narrow range of words in its title and a rigid structure. Each title starts with "Moody's", followed by a verb that signals the rating action. For example, the title always contains "downgrade" or "lowers", if the report describes a downgrade. Likewise, "raises" and "lifts" are used for upgrades.[29] Second, I classify a report as concerning a speculative or investment grade issuer. I conduct a word search in the text body for the alphanumeric rating grade in the main body. If the report contains any alphanumeric combination between *Aaa* and *Baa3*, it is classified as concerning an investment grade issuer. Likewise, it is classified as concerning a speculative grade issuer, if it contains any rating symbol *Ba1* and *C*.[30] Appendix .3 describes the classification algorithm in greater detail.

Matching the reports to stock data proves difficult, because the report does not contain an identifier other than the company name. Using the company name as an identifier is problematic, since databases differ significantly in the usage of abbreviations in the company name. For example, Moody's uses "LP" as abbreviation for a limited partnership, whereas CRSP uses "L.P.". Therefore, prior to merging, such abbreviations and type indicators are removed. Using these reduced company names, I am able to match 3,875 reports, roughly 35% of all NA reports, to a company in CRSP.[31]

[29]See Appendix .3 for a full list of the trigger words.

[30]To avoid misclassification, I require a leading and trailing space around each combination. To avoid confusion of the rating grade *A* with the capitalised indefinite article "A", I require that *A* is not preceded by punctuation mark.

[31]The matched sample is roughly representative for the full sample. The share of upgrades, outlooks and reviews is higher in the matched sample. Assignments, downgrades and confirmations are more frequent in the full sample. All differences lie in a range of five percentage points. The 3,875 reports concern 828 issuers.

2.3.2.2 Summary statistics

I choose a sample period of 33 quarters centred around the commencement of the DFA in 2010q3, i.e. four years before and after the commencement of the DFA. Overall, the sample includes 14,738 rating reports. 11,018 of those reports describe actions taken in NA and 3,720 actions taken in Europe.[32] The reports are, according to the type of action, classified into six categories: Assignment, confirmation, outlook, review, downgrade and upgrade. Assignments of ratings, i.e. the issue of a rating for a previously un-rated entity, account for the largest share of reports (4,238 reports). The second most common rating action in the sample are downgrades (3,602), which outweigh upgrades (1,835). Placing a rating under review (1,495 reports) or changing the outlook of a rating (2,951) are more common than confirmations of already assigned ratings (617). 2,527 of the reports concern a investment-grade rating and 10,172 reports a speculative grade rating. 1,464 reports mention both, an investment grade and a speculative grade rating.[33]

Table 2.8 provides summary statistics for the textual measures in the upper panel. On average, a rating report is approximately 400 words long.[34] Out of those 400 words, 12 words or 2.9 percent of the *word count* express uncertainty. The entire class of modal words accounts for 2.32 percent of the words, with strong modal words (*Modal 1*) being the largest subgroup with 1.45 percent. Weak modal words occur only three times less

[32]I exclude 448 corrections and addenda to reports from the sample but keep the report they refer to in order to avoid double counting. Further, I drop any report that concerns a particular issue rather than issuers (2,536 reports).

[33]There are several explanations for such double-classifications. First, the rating might change from an investment grade notch to a speculative grade notch (or vice versa). In this case, the alphanumeric notch abbreviation of both grades occur and the report is consequently tagged as investment grade and speculative grade report. Second, an issuer might have several outstanding issues with different ratings. Third, the classification process itself might be noisy. 715 reports did not contain any alphanumeric rating grade in the text body.

[34]Note the minimum of fifty words per report. Some of the reports could not properly be downloaded, processed or read in R. In those case, non or only a fraction of the words could be read. I therefore drop any report with less than fifty words. This criterion eliminates 86 reports, less than one percent of the sample. Including these reports weakens the results only marginally.

frequent with 0.55 percent. Forward-looking words according to Huang et al. (2014) are more frequent than any class defined by Loughran and McDonald (2011). On average, 5.82 percent of the words used in a report are forward-looking.

The lower panel of Table 2.8 lists summary statistics of the cumulative abnormal returns. Overall, the market reaction to a rating report is negative with a CAR of -0.19 pp. As expected, the reaction to a downgrade is negative (-1.05 pp) and marginally positive for upgrades (0.02 pp). This is in line with the literature that find a strong response to downgrades but little reaction to upgrades (See among others Hand et al. (1992)). The market reacts positively to assignments (0.15 pp), confirmations (0.04 pp) and outlook changes (0.02 pp). Reviews of ratings are perceived as negative (-0.22 pp) by the market.[35] Note that outlook changes and reviews are not directional in the sense that they can either indicate a more likely upgrade or downgrade.[36]

Table 2.9 shows the correlations between the key textual variables. As outlined above, the *word count* is negatively correlated with TTR but exhibits nearly zero correlation with the alternative lexical complexity measure, $MTLD$. Thus, $MTLD$ alleviates the problem of a mechanical negative relationship between length and complexity. Concerning the different word groups, several interesting observations can be made. First, the correlation between weak and strong modal words is almost zero. This suggests that weak and strong modal words are not *a priori* substitutes, i.e. Moody's did not use strong modal words to replace weak modal words and vice versa. Second, the correlation between strong modal words and uncertainty is negative. As strong modal words suggest high levels of certainty, the positive sign is expected. Third, the occurrence of forward looking words is positively

[35]The average market reactions are small. This is not entirely surprising as my event window does not capture stock movements in anticipations of rating changes. One of my major concerns was that the reports were made public a few days after the decision. However, Moody's asserted that the publication date of the report and the decision is the same.

[36]My classification procedure does not allow for a consistent detection of the "direction" of the outlook or review change.

correlated with the frequency of all modal measures and uncertainty. As all three classes - strong and weak modal, and uncertainty - express varying degrees of uncertainty, the positive correlation could be due to probabilities attached to different scenarios expressed by the forward-looking words. Put differently, if Moody's wants to provide more forward-looking information, they have to use modal words of sorts to describe the possibility attached to each scenario. Another reason for non-zero correlation might be that the overlap between the classes is mechanical: As described above, the classes are not disjunct. If a word occurs in both classes, a positive correlation is expected. For modal words, there is no overlap between strong and weak modal words, whereas there is considerable overlap between uncertainty and weak modal words.

Figure 2.6 depicts the evolution of the textual variables over time. Panel (a) shows the average word count per article. The number of words per report remained fairly stable in NA with around 400 words. Reports on European issuers are longer on average and increase over the observation period from 440 words in 2006q3 to roughly 500 words in 2014q3. The word count drops shortly after the DFA, but bounces back in the subsequent quarters. The *TTR* increases immediately after the DFA for European and NA issuers, indicating an increased lexical complexity. However, the alternative measure of complexity, *MLTD*, does not detect such a shift. Therefore, the increase in *TTR* can probably be attributed to the drop in length as shorter texts tend to mechanically exhibit a higher *TTR*. Strong and weak modal words follow an apparently similar upwards trend in both regions. *Uncertainty* fluctuates strongly before the DFA, but remain stable afterwards. There is a jump in the quarter of the DFA, but the movement is similar for NA and Europe and lies well within the variations observed in the pre-DFA period. As the other variables, *Forward* exhibits a similar pre-DFA trend but after the DFA, the fraction of forward-looking words in European reports drops sharply. Hence, changes in the difference of forward-looking words is attributable to a decrease in Europe rather than an increase in NA.

2.3.3 Results

2.3.3.1 Changes to the wording

Tables 2.10 and 2.11 show results of Equation 2.3. For each dependent variable, I estimate each of the three specifications described above. First, the regression includes only *NA* and *DFA* dummies. Second, the $NA \times DFA$ interaction is added. Third, the triple interaction $NA \times DFA \times spec$ and the lower order interactions are added.

As suggested by eye-balling, NA reports are shorter and all reports are longer after the DFA. However, the DFA does not have any unique effect on NA or speculative grade reports as the interaction of *NA* and *DFA* is insignificant. After the DFA, rating reports contain more complex wording, especially the reports on NA entities. These findings hold true for both measures of complexity, *TTR* and *MLTD*. For both, the post-DFA dummy and its interaction with the *NA* dummy is positive and significant. *TTR* is approximately 0.3 standard deviations higher after the DFA, *MLTD* increases by 0.44 standard deviations. In the specification with the $NA \times DFA$ interaction, the coefficient of *DFA* halves for *TTR* and turns insignificant for *MLTD*. I conclude that the increase of complexity is primarily driven by reports on NA issuers. The triple interaction is not significant, i.e. the effect is not unique to speculative grade issuers.

Regarding forward-looking words, no general change after the DFA can be detected. However, reports on NA issuers contain a higher fraction of forward-looking words. The $NA \times DFA$ interaction is positive and significant at the 1% level, whereas *DFA* in the specification without interactions is insignificant. In terms of magnitude, the coefficient of

0.99 of the interaction translates into an increase by 0.46 standard deviations. Again, the triple interaction $NA \times DFA \times spec$ is insignificant. Recall that the pre-post differences are likely to be driven by a drop in Forward in European reports rather than an increase in NA reports (See Figure 2.6).

For *uncertainty*, neither of the three specifications detects an effect of the DFA. Interestingly, the positive coefficient of *spec* in the specification without interactions suggests that rating agencies use a more ambiguous language in reports on issuers in the speculative grades.

Finally, I examine the effect of the DFA on modal words. For the sake of conciseness, I focus only on strongly and weakly modal words (*Modal 1* and *Modal 3*) and ignore the group of moderate modal words. Results of the intermediate group of moderately modal words lie between those of strong and weak modal words. Strong modal words are less common in speculative grade reports, whereas weak modal words are more common in these reports. However, *DFA* is not significant at any conventional level for both the fraction of weak and strong modal words. However, for both, the $NA \times DFA$ interaction is positive and significant. This suggests that after the DFA, reports on NA issuers contained more weak and more strong modal words. The general increase in the usage of modal words could reflect a more detailed discussion of future scenarios or a more careful description of the probability of the scenarios. Most interestingly, the triple interaction $NA \times DFA \times spec$ is negative for strong modal words (-0.38, p-value: 0.04) and positive for weak modal words (0.31, p-value: $<$0.00). Hence, rating reports on NA issuers in the speculative grade contain less precise and more weak modal words after the regulatory overhaul. Note that the coefficients are of comparable magnitude. From this similarity, it can be deduced that strong modal words have been replaced by weak modal words. Moody's appears to have used a more defensive wording for low rating grades.

In Figure 2.7, I visually test the parallel trend assumption and verify that the DFA is a possible explanation of pre/post differences (see Equation 2.4). For each textual outcome variable, I plot the sequence of μ_k around the DFA. If the regulatory reform does indeed affect the wording, μ_k is expected to change around the commencement of the DFA in 2010q3. Both complexity measures appear to increase after the DFA. For *MLTD*, a pronounced jump in 2010q3 can be observed whereas the increase in *TTR* is more gradual. For strong modal words and *uncertainty*, μ_k changes only little around the DFA. Contrarily, μ_k for weak modal and forward-looking words exhibit a strong increase right after the DFA. I conclude from the jumps that the reform is indeed a likely explanation for pre/post differences.

2.3.3.2 Market reactions

Results for the regression of the market reaction on textual variables are presented in Table 2.12 to 2.14. Table 2.12 holds the results of the non-directional regressions with CAR^{abs} as dependent variable, Tables 2.13 and 2.14 show the results of the directional regressions for the upgrade and downgrade sample.[37]

First, I test whether the DFA affects the market reaction to rating reports. As discussed, increased liability might decrease the informational value of rating decisions. Under the *risk avoidance hypothesis*, rating actions should become less informative as agencies might downgrade issuers as a precautionary measure and might be more reluctant to upgrade issuers to avoid law suits for underestimation of credit risk. Therefore, the market reaction should be lower in absolute terms. Indeed, Dimitrov et al. (2015) find this pattern for bond returns. In my sample, I can confirm this finding for abnormal stock returns. The results in Table 2.12 show that the overall magnitude of the reaction

[37] I re-run the estimation with winsorized *CARs*. Using the 1% or 5% winsorized *CARs* does not alter the results.

to rating reports CAR^{abs} is lower after the DFA.

Furthermore, the positive coefficient of *DFA* in Tables 2.13 and 2.14 has very different interpretations. For downgrades, this indicates that CAR is less negative, i.e. the market reaction to downgrades is more muted after the DFA. In contrast, a positive coefficient of *DFA* in the upgrade sample implies that reactions to upgrades are "more positive", i.e. the market reaction is stronger. This confirms the prevalence of the *risk avoidance hypothesis* from a stock market perspective. To verify that the level differences can indeed be attributed to the DFA, I use a similar procedure as before and regress the CAR on year-quarter dummies. If the DFA affects the CAR, the coefficients of the year-quarters should change around 2010q3, the commencement quarter of the DFA. Figure 2.8 depicts the sequence of coefficients for the full sample, downgrades and upgrades. Neither specification exhibits a pronounced jump or a switch in trends, which suggests that DFA is not necessarily the driver behind the differences in pre/post reactions to rating actions.

Lexical complexity, measured by TTR and *MLTD*, does not affect the market response to rating reports. The coefficients are virtually zero and not significant at conventional levels. A higher fraction of forward-looking words increases the non-directional, absolute CAR. A coefficient of 0.09 (p-value = 0.02) translates into an increase in CAR^{abs} by 0.12 standard deviations for a standard deviation increase in *forward*. Against the expectation, a higher *uncertainty* increases the market reaction. It was expected that the market reaction to a report should be smaller in absolute terms, if the wording of the reports is more uncertain. However, a one standard deviation increase in *uncertainty* leads to an increase in CAR^{abs} by 0.09 standard deviations. In line with the expectation, a higher fraction of strong modal words (*Modal 1*) boosts CAR^{abs}. Put again in terms of standard deviations, an increase of *Modal 1* by one standard deviation increases CAR^{abs} by 0.03

standard deviations. The fraction of weak modal words (*Modal 3*), does not impact CAR^{abs}. Overall, despite the significance, the quantitative effect is small, if measured by standard deviations.

For the upgrade and downgrade sample, I explore the directional effects of the textual measures. For downgrades, none of the variables affects the CAR. The market reaction to upgrades is more positive for reports with more strong modal and forward-looking words. Again the effect is small in terms of standard deviation. A one standard deviation increase in *Modal 1* and *Forward* increases the CAR by 0.1 and 0.08 standard deviations respectively. One interpretation of the disparities between up- and downgrades could be that the market does interpret downgrades as binary signal whereas upgrades are judged more carefully. On a more general note, it can be concluded that the wording of a report is a proxy for its informational value.

To test whether the reports are perceived differently after the DFA, I estimate Equation 2.6 with interactions of the textual measures and the DFA dummy. None of the interactions is significant and the coefficients of DFA do not change their sign. I conclude that the DFA impacts the way reports are worded, but not the way reports are perceived. Further, a test whether the interactions between the fractions of the different word classes affects the CARs yields no results. Put differently, the effect of e.g. forward-looking words is not conditional on the fraction of strong modal words.

2.3.3.3 Interpretation of results

The results hint towards more forward-looking and nuanced, yet more conservative wording of the reports after the DFA. A higher lexical complexity might reflect a more precise or situational use of words. Modal words, words expressing uncertainty and forward-looking words are more common in NA reports after the DFA relative to their European counterparts. Overall, the increase of words of those classes could reflect a stronger focus on future scenarios and a possible development of the issuer. This would lend support to the *discipling hypothesis* under which ratings are made more informative. Recall that for speculative grade issuers, strong modal words appear to be substituted by weak modal words, i.e. the level of precision of the language is reduced. This asymmetric effect lends support to the *risk avoidance hypothesis*.

However, not all of the word classes are relevant to the market. Of particular importance are strong modal words and forward-looking words. Higher abnormal returns for reports with a high fraction of strong modal and forward-looking words indicate that these reports contain more information than others. Combined with the finding of an increasing fraction of strong modal words, this suggests that the DFA increased the informational value of reports via the wording in general, but reduced information content in reports on speculative issuers. Like Dimitrov et al. (2015), I find that abnormal returns to rating actions are muted after the DFA. Though the DFA affects the informational value of the reports positively via the wording, this effect does not offset the general trend.

2.3.4 Limitations and Extension

The research on the wording of rating reports is still in its infancy and offers rich environment for future research. A potential route of future research is the analysis of the time-series variation of the wording. As detected by Alp (2013), rating standards vary considerably over time in reaction to regulation and economic conditions. This chapter focuses on a relatively narrow sample period of eight years, but older reports are available. Further, the analysis could be extended to reports from other agencies, such as Fitch or S&P. Several interesting questions could be addressed. First, one could examine whether the wording of reports of different CRAs for a particular issuer is similar. Split ratings - different ratings of a firm from different CRAs - are a well-documented phenomenon (Ederington, 1986; Baghai et al., 2014; Bongaerts et al., 2012). One possible avenue for future research is the extent to which such split ratings translate into different sentiments in the rating report. Second, the wording could be affected by the competitive environment of the ratings market (?). Future research could examine how the entry of Fitch to the rating markets affected the wording of the reports. Rating agencies might use more favourable wording in a contested sector to appease the issuer.

The first limitation is the absence of firm-level controls in the main reports sample. As the rating reports do not contain a firm identifier other than the name, merging the reports with stock and balance sheet data is difficult. Recall, that I am only able to merge stock data to a small subsample of the reports. However, adding stock and balance sheet data to the full sample would open additional routes for future research. For example one could analyse how the wording of the reports varies in the complexity of the firm or a sector. For instance, it is expected that reports for more opaque firms are longer and more important to the market. For my small sample, such explorations did not yield meaningful results.

Another limitation of the analysis the reliance on the dictionary and sentiments provided by Loughran and McDonald (2011) and Huang et al. (2014). As Loughran and McDonald (2011) themselves point out, the connotation of a word might be different in an alternative setting. The reports have been written based on a limited set of words and a very technical language which might be different from the language of the 10-k reports, which are used to calibrate the dictionary of Loughran and McDonald (2011). An alternative method which would not rely on a pre-defined dictionary would be a machine-learning algorithm as in Huang et al. (2014).[38]

2.4 Conclusion

This chapter examines the effect of the DFA on issuer ratings. A crucial aim of the new regulation was to improve the informational value of ratings. However, the existing literature - namely Dimitrov et al. (2015) - finds that the regulation did not achieve this aim. On the contrary, ratings have been found to be biased downwards and rating actions are perceived less informative after the DFA. This chapter paints a more nuanced picture. It confirms the finding of Dimitrov et al. (2015) for issuer ratings, though this result is highly specification-dependent.

Concerning the rating reports, I document a more forward-looking and nuanced wording after the DFA. For reports on speculative grade issuers, I find a substitution of strong modal by weak modal words, i.e. CRAs use a less precise languages for those reports that are most likely to trigger a law suit against them. I interpret these finding as evidence that CRAs do release more information in their reports but frame those information more carefully. The analysis of the CARs has shown that the market reacts to different wordings, especially to forward-looking and precise language. Hence, the overall effect of the DFA on the informational value is ambiguous. For highly rated issuer, the effect is likely to be positive as the reports contain more forward-looking information, for lower-rated rated issuer the less precise language probably reduces the informational value.

[38]A pre-requisite of the machine learning algorithm is the isolation of sentences in the reports. However, the splitting into sentences in R was error-prone. For example, decimal separators were recognized as punctuation marks. Other programs and languages, such as Python or C, provide a better splitting algorithm.

Tables

Table. 2.1: Summary Statistics

Variable	Obs	Mean				SD	Min	Max
		Full Sample	Pre DFA	Post DFA	sig			
Numerical rating	20,271	11.37	11.18	11.57	***	3.24	0	21
Equity PD	20,271	6.57	10.99	1.84	***	154.91	0.00	8565.99
CHS PD	13,156	197.20	409.63	104.40	***	920.73	1.04	10000.00
CDS PD	9,613	62.32	70.32	54.41	***	108.67	0.95	3454.31
OPERATING	20,271	3.45	0.03	0.03	***	2.13	-3.84	12.04
LT LEVERAGE	20,271	30.69	30.80	30.58		18.79	0.00	104.82
TD LEVERAGE	20,271	33.85	34.11	33.57	**	19.13	0.00	111.09
LOG MARKET	20,271	8.12	7.91	8.34		1.60	3.41	11.76
Beta	20,271	1.14	1.12	1.16	***	0.56	-0.03	2.90
SIGMA	20,271	0.38	0.45	0.31	***	0.24	0.11	1.59
INTEREST COVERAGE	20,271	7.37	7.33	7.41	***	18.46	-5.31	216.53
VIX	20,271	21.43	24.36	18.30	***	9.74	10.89	58.74
SP500	20,271	1350.22	1221.92	1487.68	***	280.14	757.13	2012.91
GDP (log)	20,271	9.63	9.58	9.69	***	0.07	9.53	9.78
GDP growth	20,271	1.18	0.39	2.02	***	1.84	-4.06	2.96

Numerical rating is the transformation of the alphanumeric rating scale, with AAA=21,...,D=1. *Equity PD* is the implied PD in the Merton model. *CHS PD* is the PD calibrated from Campbell et al. (2008) and Hilscher and Wilson (2016). *CDS PD* is the PD priced into CDS spreads. *OPERATING* is the operating margin, i.e. operating income before depreciation divided by total sales. *LT LEVERAGE*, the long-term debt leverage, is defined as total long-term debt divided by book value of equity. *TD LEVERAGE* is the total debt leverage, i.e. total debt divided by book value of equity. *LOG MARKET* is the natural logarithm of the market capitalisation, calculated as the number of shares outstanding times the share price at the end of a quarter. *Beta* is the CAPM beta estimated using the CRSP value-weighted index as benchmark. *SIGMA* is the standard deviation of daily stock returns within a quarter. *INTEREST COVERAGE* is obtained by dividing income before extraordinary items by the interest expenses. *VIX* is the CBOE Volatility Index, the implied volatility of the SP500 over the next 30-day period. *SP500* is the index value of the SP500 index. *VIX* and *SP500* are both available on daily frequency and are collapsed to quarterly frequency by taking the average. *GDP (log)* is the natural logarithm of nominal GDP. *GDP growth* is the growth rate of the nominal GDP.

Table. 2.2: Rating Levels before an after the Dodd-Frank Act

	Numerical Rating				
	(1)	(2)	(3)	(4)	(5)
DFA	-0.376***	-0.417***	-0.310***	-0.383***	-0.381***
	(<0.00)	(<0.00)	(<0.00)	(<0.00)	(<0.00)
Equity PD		-0.00581***			
		(<0.00)			
CHS PD			-0.324***		
			(<0.00)		
CDS PD					-5.647***
					(<0.00)
OPERATING	10.26***	9.275***	6.316**	14.56***	5.186
	(<0.00)	(<0.00)	(0.02)	(<0.00)	(0.12)
LT LEVERAGE	-4.571***	-4.667***	-3.566***	-9.258***	-6.753***
	(<0.00)	(<0.00)	(<0.00)	(<0.00)	(<0.00)
TD LEVERAGE	1.391	1.776**	0.756	5.091***	4.765***
	(0.11)	(0.04)	(0.45)	(0.01)	(0.01)
LOG MARKET	1.056***	1.010***	1.056***	1.182***	0.841***
	(<0.00)	(<0.00)	(<0.00)	(<0.00)	(<0.00)
Beta	-0.214***	-0.0940	-0.325***	-0.360***	-0.255**
	(<0.00)	(0.12)	(<0.00)	(<0.00)	(0.03)
SIGMA	-3.392***	-2.753***	-2.732***	-3.575***	-0.865***
	(<0.00)	(<0.00)	(<0.00)	(<0.00)	(<0.00)
INTEREST COVERAGE	0.00237	0.00111	0.00574	0.00918	0.0112*
	(0.40)	(0.70)	(0.28)	(0.10)	(0.06)
Observations	20,271	20,271	13,156	9,613	9,613
Sample	Full	Full	Full	CDS	CDS
Macro Controls	Yes	Yes	Yes	Yes	Yes
Market Controls	Yes	Yes	Yes	Yes	Yes
CDS Liquidity Controls	No	No	No	No	Yes
Pseudo R2	0.209	0.219	0.217	0.214	0.305

This table shows the results of the ordered logistic regression for numerical ratings, Equation (2.1). The baseline model is equivalent to the model proposed by Dimitrov et al. (2015). In each case, the dependent variable is the numerical transformation of the alphanumeric S&P issuer rating. *CHS PD* is the PD calibrated from Campbell et al. (2008) and Hilscher and Wilson (2016). *CDS PD* is the PD priced into CDS spreads. To make the coefficients more traceable, the common logarithms of the PDs are used as independent variables. *OPERATING* is the operating margin, i.e. operating income before depreciation divided by total sales. *LT LEVERAGE*, the long-term debt leverage, is defined as total long-term debt divided by book value of equity. *TD LEVERAGE* is the total debt leverage, i.e. total debt divided by book value of equity. *LOG MARKET* is the natural logarithm of the market capitalisation, calculated as the number of shares outstanding times the share price at the end of a quarter. *Beta* is the CAPM beta estimated using the CRSP value-weighted index. *SIGMA* is the standard deviation of daily stock returns in a quarter. *INTEREST COVERAGE* is obtained by dividing income before extraordinary items by interest expenses. Standard errors are clustered at the firm level. P-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, 10% levels.

Table. 2.3: Parallel Regression Assumption

	Coefficient of *DFA*			
	Additional Controls			
Rating above	None	Equity PD	CHS PD	CDS PD
B-	-0.119	-0.303	-0.037	0.590
B	-0.638	-0.544	-0.753	0.777
B+	-0.643	-0.592	-0.741	-0.202
BB-	-0.588	-0.598	-0.811	-0.546
BB	-0.568	-0.531	-0.714	-0.482
BB+	-0.724	-0.606	-0.827	-0.596
BBB-	-0.508	-0.405	-0.629	-0.405
BBB	-0.358	-0.125	-0.458	-0.253
BBB+	-0.371	-0.235	-0.444	-0.618
A-	-0.440	-0.306	-0.617	-0.679
A	-0.268	-0.389	-0.446	-0.320
A+	-0.418	-0.880	-0.416	-0.860
AA-	-0.075	-0.380	0.069	-0.705
AA	-0.099	0.045	0.125	-0.556
AA+	0.018	0.010	0.301	-0.829

The table shows the coefficients of the DFA dummy in the set of logit regressions for the parallel regression test. In each regression the dependent variable is a dummy that a rating is above the rating grade specified in the first column. The first row shows the coefficients of the regressions without market counterfactual. In column 2-4, I include the equity-implied, CHS PD, and the CDS-implied PD as additional controls.

Table. 2.4: Shorten Sample Period

	Numerical Rating				
	(1)	(2)	(3)	(5)	(6)
DFA	-0.120***	-0.049	0.056	-0.072	-0.021
	(0.01)	(0.30)	(0.26)	(0.20)	(0.81)
Equity PD		-0.006***			
		(<0.00)			
CHS PD			-0.323***		
			(<0.00)		
CDS PD					-5.736***
					(<0.00)
Observations	10,683	10,683	9,221	5,021	5,021
Sample	Full	Full	Full	CDS	CDS
Firm Controls	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes
Market Controls	Yes	Yes	Yes	Yes	Yes
CDS Liquidity Controls	No	No	No	No	Yes
Pseudo R2	0.214	0.221	0.215	0.215	0.303

This table shows the results of the ordered logistic regression for numerical ratings, Equation (2.1), using a reduced sample period from July 2008 to July 2012. In each case, the dependent variable is the numerical transformation of the alphanumeric S&P issuer rating. *CHS PD* is the probability of default calibrated from Campbell et al. (2008) and Hilscher and Wilson (2016). *CDS PD* is the probability of default priced into CDS spreads. To make the coefficients more traceable, the common logarithms of the PDs is used as independent variables rather than the actual PDs. The same set of firm controls as in Table 2.2 are included but not reported. Standard errors are clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, 10% level.

Table. 2.5: Hypothetical Commencement of the Dodd-Frank Act

	Coefficient of the Post-Treatment Dummy				
	Additional implied PD				
Hypothetical Start Date		Equity PD	CHS PD		CDS PD
2008 July	-0.431***	-0.590***	0.161	-0.213***	-0.375***
	(0.00)	(0.00)	(0.37)	(0.01)	(0.00)
2009 July	-1.066***	-1.190***	-0.892***	-0.881***	-0.755***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
2009 December	-1.013***	-1.056***	-0.880***	-0.938***	-0.682***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
2010 July	-0.376***	-0.417***	-0.310***	-0.383***	-0.381***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
2011 May	0.0459	-0.143***	0.0244	-0.0372	-0.291***
	(0.32)	(0.00)	(0.66)	(0.49)	(0.00)
2011 July	0.138***	-0.202***	0.0549	0.125**	-0.316***
	(0.01)	(0.00)	(0.41)	(0.04)	(0.00)
2012 July	0.317***	-0.0557	0.440***	0.499***	0.171**
	(0.00)	(0.36)	(0.00)	(0.00)	(0.04)
Sample	Full	Full	Full	CDS	CDS

This table shows the coefficient of the DFA dummies from different hypothetical commencements of the DFA. The hypothetical starting date is specified in the first column, the remaining columns show the coefficients for different sets of control variables specified in the header. Note that the coefficient of commencement date July 2010 correspond to the coefficients in Table 2.2.

Table. 2.6: Specification Tests

Panel A: PD-only Regression & Monthly Frequency						
			Numerical Rating			
	(1)	(2)	(3)	(4)	(5)	(6)
DFA	-0.111***	-0.0701*	-0.119*	-0.0821	-0.258**	-0.164*
	(0.01)	(0.07)	(0.06)	(0.16)	(0.01)	(0.09)
Equity PD	-0.0108***	-0.0106***				
	(<0.00)	(<0.00)				
CHS PD			-2.500***	-2.407***		
			(<0.00)	(<0.00)		
CDS PD					-7.211***	-6.859***
					(<0.00)	(0.259)
Observations	24,944	72,672	13,818	37,664	7,394	20,752
Frequency	Quarterly	Monthly	Quarterly	Monthly	Quarterly	Monthly
Firm Controls	No	No	No	No	No	No
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes
Market Controls	Yes	Yes	Yes	Yes	Yes	Yes
CDS Liquidity Controls	No	No	No	No	No	No
Pseudo R2	0.0477	0.0442	0.120	0.113	0.244	0.233

Panel B: Alternative Control for the Business Cycle					
			Numerical Rating		
	(1')	(2')	(3')	(4')	(5')
DFA	0.0180	-0.203***	0.215***	0.184***	1.244***
	(0.71)	(0.00)	(0.00)	(0.01)	(0.00)
Equity PD		-0.00591***			
		(0.00)			
CHS PD			-0.286***		
			(0.01)		
CDS PD					-5.166***
					(0.00)
Observations	20,271	20,271	13,156	9,613	9,613
Sample	Full	Full	Full	CDS	CDS
Firm Controls	Yes	Yes	Yes	Yes	Yes
Macro Controls	Yes	Yes	Yes	Yes	Yes
Market Controls	Yes	Yes	Yes	Yes	Yes
CDS Liquidity Controls	No	No	No	No	Yes
Pseudo R2	0.212	0.223	0.220	0.216	0.298

In the upper panel, the results Equation 2.1 without firm controls, i.e. just the PD measure and market controls are shown. In odd columns, the unit of observations are firm-quarters. In even columns, the unit of observations is firm-months. In the lower panel, I control for the macroeconomic environment using the GDP growth rate rather than the log of the nominal GDP. Standard errors are clustered at the firm level. P-values are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, 10% level.

Table. 2.7: Lead-Lag Relationship between S&P Issuer Ratings and Implied PDs

	Numerical Rating (1)	Numerical Rating (2)		Numerical Rating (3)	Numerical Rating (4)		Numerical Rating (5)	Numerical Rating (6)
ΔEquity PD			ΔCHS PD			ΔCDS PD		
t-1	0.001	0.006	t-1	-2.789***	-2.310***	t-1	-4.728***	-7.197***
	(0.002)	(0.005)		(0.584)	(0.833)		(0.626)	(1.479)
t-2	0.004**	0.004	t-2	0.072	-0.128	t-2	-0.892	-2.627**
	(0.002)	(0.005)		(0.658)	(1.281)		(0.825)	(1.310)
t-3	0.000	0.003	t-3	-2.086***	-1.874*	t-3	-2.289***	-1.801
	(0.002)	(0.008)		(0.549)	(0.983)		(0.755)	(1.648)
t-4	-0.006***	-0.021***	t-4	-1.630**	-3.260**	t-4	-3.862***	-8.000***
	(0.002)	(0.006)		(0.674)	(1.530)		(0.652)	(1.699)
t-5	-0.001	0.002	t-5	-1.671***	-1.893*	t-5	-1.856***	-0.355
	(0.001)	(0.005)		(0.626)	(1.150)		(0.685)	(1.849)
t-6	-0.003*	-0.009**	t-6	-1.609***	-3.792**	t-6	-3.251***	-4.301***
	(0.001)	(0.004)		(0.574)	(1.750)		(0.626)	(1.436)
ΔEquity PD × DFA			ΔCHS PD × DFA			ΔCDS PD × DFA		
t-1	-0.004	-0.012	t-1	1.317*	-0.013	t-1	-1.787	-2.687
	(0.003)	(0.008)		(0.755)	(1.229)		(1.269)	(3.009)
t-2	-0.008***	-0.019**	t-2	-2.928***	-4.084***	t-2	-1.994	-4.267
	(0.003)	(0.009)		(0.774)	(1.478)		(1.583)	(3.369)
t-3	-0.002	-0.009	t-3	-0.232	-0.467	t-3	-0.629	-2.014
	(0.002)	(0.012)		(0.682)	(1.114)		(1.640)	(3.562)
t-4	0.006***	0.021**	t-4	1.293	2.608	t-4	1.389	4.383
	(0.002)	(0.009)		(0.794)	(1.788)		(1.348)	(3.154)
t-5	-0.003	-0.008	t-5	-0.058	-1.279	t-5	-2.975**	-10.746***
	(0.002)	(0.008)		(0.710)	(1.326)		(1.438)	(3.305)
t-6	0.003	0.008	t-6	-0.768	0.380	t-6	1.424	-0.515
	(0.002)	(0.009)		(0.690)	(1.981)		(1.378)	(3.074)
Observations	62,027	1,653		53,791	1,147		26,745	535
Sample	Full	Changes only		Full	Changes		Full	Changes
Pseudo-R2	0.0104	0.0491		0.0242	0.0990		0.0443	0.159

The table shows the results of Equation 2.2. Unit of observations are firm-month. Odd columns contain results for the full sample ("Full"), even columns the results for the reduced sample ("Changes only"). In the reduced sample, only firm-month in which the rating changed are considered. Standard errors are clustered at the firm level. ***, **, and * denote significance at the 1%, 5%, 10% level.

Table. 2.8: Changes in the Frequency-based Measures

Panel A: Textual Variables					
	Observations	Mean	Std. Dev.	Min	Max
Word Count	14,738	403.12	176.56	50	2870
TTR	14,738	47.65	6.71	17.04	82.95
MLTD	14,113	88.29	23.44	24.22	225.70
Uncertainty	14,738	2.90	1.29	0	10.11
Modal 1	14,738	1.45	1.08	0	8.26
Modal 2	14,738	0.32	0.47	0	5.06
Modal 3	14,738	0.55	0.54	0	5.59
Forward	14,738	5.83	2.14	0	20.20
Spec	14,738	0.79	0.41	0	1
GDP growth	14,738	0.95	1.93	-4.29	3.61
Inflation	14,738	2.08	1.15	-0.27	3.71
Panel B: Cumulative Abnormal Returns					
	Observations	Mean	Std. Dev.	Min	Max
Overall	3,875	-0.19	5.72	-33.35	32.28
Overall (absolute)	3,875	3.7	4.3	0.0	33.3
Assignment	925	0.15	3.86	-24.11	16.77
Confirmation	156	0.04	4.84	-27.56	19.03
Downgrade	783	-1.04	7.31	-33.35	29.31
Outlook	881	0.03	5.04	-24.33	32.28
Review	537	-0.22	8.11	-30.98	27.27
Upgrade	593	0.02	3.94	-22.38	17.42

Word Count is the number of different words in the report. *TTR*, the type-token-ratio is the ratio of different token (words) and total words. *MLTD*, the "measure of textual lexical diversity developed by McCarthy and Jarvis (2010), calculates the complexity dynamically rather than relying on aggregate words counts. For each variable, a higher value indicates a more complex language. *Modal 1* and *Modal 3* are the fractions of strong (e.g. "always" or "never") and weak (e.g. "almost" or "might") modal words in the reports as described in Loughran and McDonald (2011). *Uncertainty* is the fraction of words in the report that Loughran and McDonald (2011) classify as expressing uncertainty. *Forward* is the fraction of forward-looking words as classified in Huang et al. (2014). Panel B shows the cumulative abnormal returns in percentage points for the overall sample and a breakdown by the different rating action.

Table. 2.9: Correlation Matrix of Lexical Variables

	Word Count	*TTR*	*MLTD*	*Uncertainty*	*Modal 1*	*Modal 3*	*Forward*
Word Count	1						
TTR	-0.73	1					
MLTD	0.05	0.42	1				
Uncertainty	-0.06	0.08	0.10	1			
Modal 1	0.01	0.04	0.06	-0.05	1		
Modal 3	-0.10	0.15	0.17	0.77	$<$0.00	1	
Forward	-0.05	0.09	0.13	0.28	0.46	0.38	1

The table shows the pairwise correlation coefficients. *Word Count* is the number of different words in the report. *TTR*, the type-token-ratio is the ratio of different token (words) and total words. *MLTD*, the "measure of textual lexical diversity developed by McCarthy and Jarvis (2010), calculates the complexity dynamically rather than relying on aggregate words counts. For each variable, a higher value indicates a more complex language. *Modal 1* and *Modal 3* are the fractions of strong (e.g. "always" or "never") and weak (e.g. "almost" or "might") modal words of the total word count in the report. *Uncertainty* is the fraction of words in the report that Loughran and McDonald (2011) classify as expressing uncertainty. *Forward* is the fraction of forward-looking words as classified in Huang et al. (2014).

Table. 2.10: Changes in the Wording I

	Frequency			TTR			MLTD			Forward		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
spec	36.53	36.53	15.36	-1.12***	-1.12***	-0.30	-2.21	-2.17	-0.93	-0.21**	-0.21**	-0.33***
	(0.14)	(0.13)	(0.45)	(0.00)	(0.00)	(0.41)	(0.15)	(0.17)	(0.29)	(0.03)	(0.01)	(0.00)
NA	-64.98***	-61.74***	-69.86***	0.10	-0.41	0.64**	2.00*	-1.83	1.55	0.16	-0.22***	-0.16
	(0.00)	(0.00)	(0.00)	(0.57)	(0.24)	(0.03)	(0.09)	(0.12)	(0.42)	(0.35)	(0.01)	(0.11)
DFA	-36.46***	-29.90*	-54.50	1.97***	0.93***	0.74*	10.45***	2.48	1.13	0.22	-0.54	-0.79
	(0.00)	(0.05)	(0.12)	(0.00)	(0.00)	(0.07)	(0.00)	(0.44)	(0.77)	(0.28)	(0.30)	(0.19)
$DFA \times NA$		-8.54	1.82		1.36**	1.40***		9.98***	7.70*		0.99***	1.03**
		(0.62)	(0.97)		(0.05)	(0.00)		(0.00)	(0.06)		(0.00)	(0.02)
$DFA \times spec$			36.81			0.27			1.73			0.38**
			(0.30)			(0.65)			(0.17)			(0.04)
$NA \times spec$			14.59			-1.44***			-4.27*			-0.04
			(0.41)			(0.00)			(0.09)			(0.73)
$DFA \times NA \times spec$			-20.78			-0.17			2.28			-0.15
Observations	14,738	14,738	14,738	14,738	14,738	14,738	14,113	14,113	14,113	14,820	14,820	14,820
R-squared	0.07	0.07	0.07	0.623	0.624	0.63	0.270	0.273	0.27	0.087	0.091	0.09
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Action FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table presents the results of equation 2.3. *TTR*, the type-token-ratio is the ratio of different token (words) and total words. *MLTD*, the "measure of textual lexical diversity developed by McCarthy and Jarvis (2010), calculates the complexity dynamically rather than relying on aggregate words counts. For each variable, a higher value indicates a more complex language. *Forward* is the number of forward-looking words as classified in Huang et al. (2014) *Post* is a dummy variable that takes a value of one of post July 2010 observations and zero otherwise. *NA* is a dummy variable that takes a value of one for reports on North American companies and zero for European ones. *spec* takes a value of one for reports that mention a below investment grade notch, i.e. a rating below Baa3. We include macro controls (real GDP growth and inflation), year-quarter fixed effects, action FE and a dummy for ratings of notes rather than issuer ratings. Unit of observation is a rating report. Standard errors are reported in parenthesis and are two-way clustered at the year-quarter and the rating action level. To account for a potentially low number of cluster, the standard errors are adjusted as suggested by Cameron et al. (2011). ***, **, and * denote significance at the 1%, 5%, 10% level.

Table. 2.11: Changes in the Wording II

	Modal 1			Modal 3			Uncertainty		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
spec	-0.20***	-0.20***	-0.10	0.16***	0.16***	0.10	0.33***	0.33***	0.19
	(0.00)	(0.00)	(0.31)	(0.00)	(0.00)	(0.13)	(0.00)	(0.00)	(0.11)
NA	0.25***	0.16**	0.19***	-0.01	-0.13***	-0.03	0.33***	0.31***	0.10
	(0.00)	(0.02)	(0.01)	(0.83)	(0.00)	(0.56)	(0.00)	(0.00)	(0.21)
DFA	-0.02	-0.20	-0.26	0.17*	-0.08	-0.13	0.07	0.02	0.12
	(0.84)	(0.24)	(0.30)	(0.06)	(0.16)	(0.16)	(0.56)	(0.84)	(0.48)
$DFA \times NA$		0.23**	0.52***		0.33***	0.06		0.06	0.03
		(0.02)	(0.00)		(0.00)	(0.62)		(0.23)	(0.84)
$DFA \times spec$			0.11			0.05			-0.14
			(0.47)			(0.69)			(0.57)
$NA \times spec$			-0.07			-0.10			0.29***
			(0.39)			(0.14)			(0.00)
$DFA \times NA \times spec$			-0.38**			0.31***			0.09
			(0.04)			(0.00)			(0.63)
Observations	14,738	14,738	14,738	14,738	14,738	14,738	14,738	14,738	14,738
R-squared	0.111	0.111	0.11	0.149	0.150	0.15	0.105	0.105	0.11
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Action FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table presents the results of equation 2.3. *Uncertainty* is the number of words in the report that Loughran and McDonald (2011) classify as expressing uncertainty. *Modal 1* and *Modal 3* are the number of strong (e.g. "always" or "never") and weak (e.g. "almost" or "might") modal words in the reports . *Post* is a dummy variable that takes a value of one of post July 2010 observations and zero otherwise. *NA* is a dummy variable that takes a value of one for reports on North American companies and zero for European ones. *spec* takes a value of one for reports that mention a below investment grade notch, i.e. a rating below Baa3. We include macro controls (real GDP growth and inflation), year-quarter fixed effects, action FE and a dummy for ratings of notes rather than issuer ratings. Unit of observation is a rating report. Standard errors are reported in parenthesis and are two-way clustered at the year-quarter and the rating action level. To account for a potentially low number of cluster, the standard errors are adjusted as suggested by Cameron et al. (2011). ***, **, and * denote significance at the 1%, 5%, 10% level.

Table. 2.12: Market Reaction to Rating Reports - Full Sample

	CAR^{abs}						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DFA	-5.24***	-5.24***	-5.24***	-5.29***	-5.24***	-5.28***	-5.30***
	(<0.00)	(<0.00)	(<0.00)	(<0.00)	(<0.00)	(<0.00)	(<0.00)
TTR		<-0.00					
		(0.90)					
MLTD			<-0.00				
			(0.62)				
Uncertainty				0.14**			
				(0.02)			
Modal 1					0.10**		
					(0.04)		
Modal 3						0.08	
						(0.21)	
Forward							0.09**
							(0.02)
Observations	3,875	3,875	3,809	3,875	3,875	3,875	3,875
R-squared	0.18	0.18	0.18	0.19	0.19	0.18	0.19
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Action FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table presents the results of Equation 2.6: $CAR_i^{abs} = \alpha + \alpha_i + \beta \times Text_i + \gamma \times action + \delta \times spec_i + \epsilon_{i,t}$. *Modal 1* and *Modal 3* are the number of strong (e.g. "always" or "never") and weak (e.g. "almost" or "might") modal words in the reports. *Uncertainty* is the number of words in the report that Loughran and McDonald (2011) classify as expressing uncertainty. *Forward* is the number of forward-looking words as classified in Huang et al. (2014). I include year-quarter and action fixed effects. Unit of observation is a rating report. Standard errors are reported in parenthesis and are clustered at the year-quarter level. To account for a potentially low number of cluster, the standard errors are adjusted as suggested by Cameron et al. (2011). ***, **, and * denote significance at the 1%, 5%, 10% level.

Table. 2.13: Market Reaction to Downgrades

	CAR						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DFA	15.08***	15.07***	14.21***	15.05***	14.86***	14.93***	14.54***
	(<0.00)	(<0.00)	(<0.00)	(<0.00)	(<0.00)	(<0.00)	(<0.00)
TTR		-0.07					
		(0.20)					
MLTD			0.03*				
			(0.05)				
Uncertainty				0.07			
				(0.82)			
Modal 1					0.19		
					(0.25)		
Modal 3						0.17	
						(0.60)	
Forward							0.12
							(0.46)
Observations	783	783	780	783	783	783	783
R-squared	0.07	0.07	0.07	0.07	0.07	0.07	0.07
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table presents the results of Equation 2.6: $CAR_i = \alpha + \alpha_i + \beta \times Text_i + \gamma \times action + \delta \times spec_i + \epsilon_{i,t}$. *Modal 1* and *Modal 3* are the number of strong (e.g. "always" or "never") and weak (e.g. "almost" or "might") modal words in the reports. *Uncertainty* is the number of words in the report that Loughran and McDonald (2011) classify as expressing uncertainty. *Forward* is the number of forward-looking words as classified in Huang et al. (2014). I include year-quarter and action fixed effects. Unit of observation is a rating report. Standard errors are reported in parenthesis and are clustered at the year-quarter level. To account for a potentially low number of cluster, the standard errors are adjusted as suggested by Cameron et al. (2011). ***, **, and * denote significance at the 1%, 5%, 10% level.

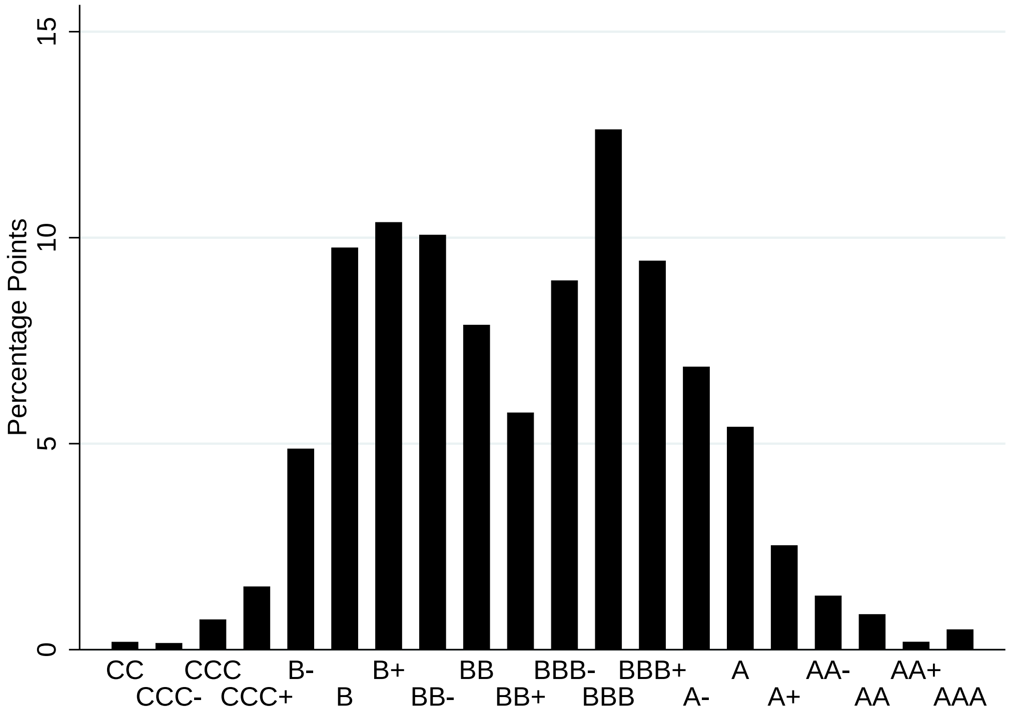
Table. 2.14: Market Reaction to Upgrades

	CAR						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
DFA	6.88***	6.82***	6.27***	6.81***	6.78***	6.82***	6.70***
	(<0.00)	(<0.00)	(<0.00)	(<0.00)	(<0.00)	(<0.00)	(<0.00)
TTR		-0.06*					
		(0.06)					
MLTD			0.02*				
			(0.07)				
Uncertainty				0.10			
				(0.30)			
Modal 1					0.38***		
					(0.01)		
Modal 3						0.08	
						(0.60)	
Forward							0.14*
							(0.06)
Observations	593	593	562	593	593	593	593
R-squared	0.07	0.08	0.08	0.07	0.08	0.07	0.08
Macro Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

The table presents the results of Equation 2.6: $CAR_i = \alpha + \alpha_i + \beta \times Text_i + \gamma \times action + \delta \times spec_i + \epsilon_{i,t}$. *Modal 1* and *Modal 3* are the number of strong (e.g. "always" or "never") and weak (e.g. "almost" or "might") modal words in the reports. *Uncertainty* is the number of words in the report that Loughran and McDonald (2011) classify as expressing uncertainty. *Forward* is the number of forward-looking words as classified in Huang et al. (2014). I include year-quarter and action fixed effects. Unit of observation is a rating report. Standard errors are reported in parenthesis and are clustered at the year-quarter level. To account for a potentially low number of cluster, the standard errors are adjusted as suggested by Cameron et al. (2011). ***, **, and * denote significance at the 1%, 5%, 10% level.

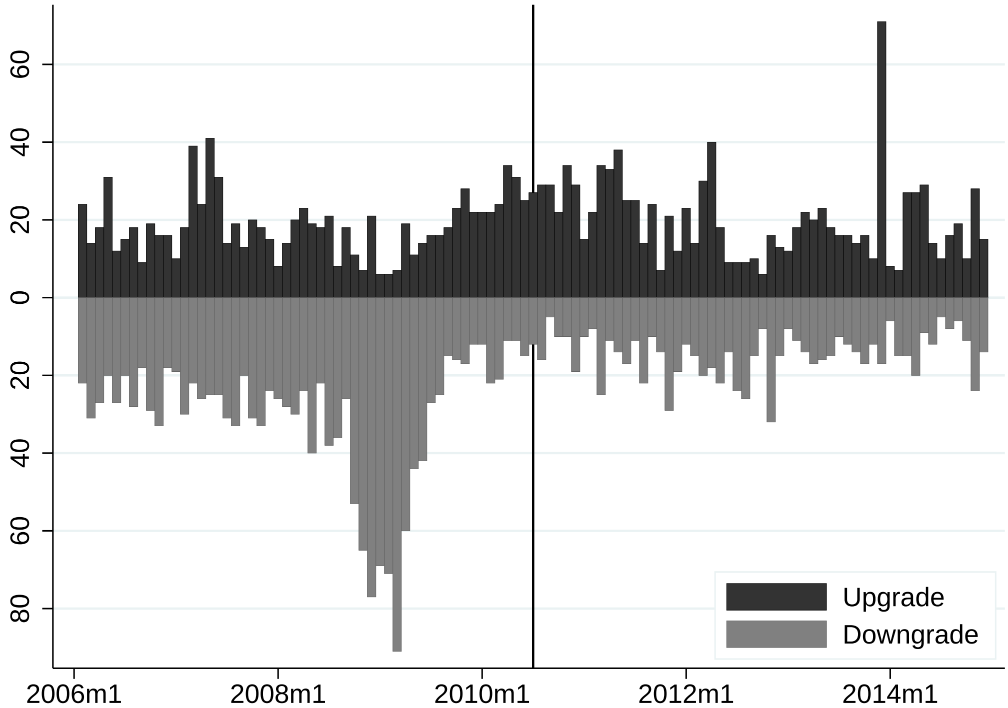
Figures

Figure 2.1: Distribution of Assigned Ratings



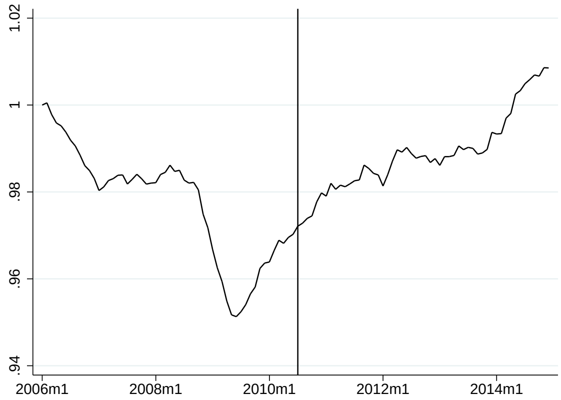
The figure plots the fraction of the different rating grades of the total firm-month observations in percentage points.

Figure 2.2: Rating Changes over Time

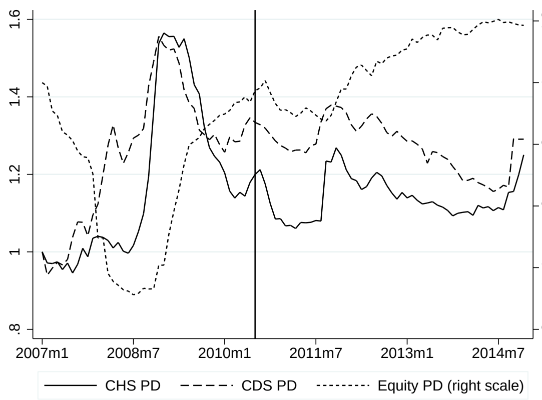


The graphs plots the number of upgrades and downgrades per month. The black bars describe the number of downgrades, the grey bars the number of downgrades.

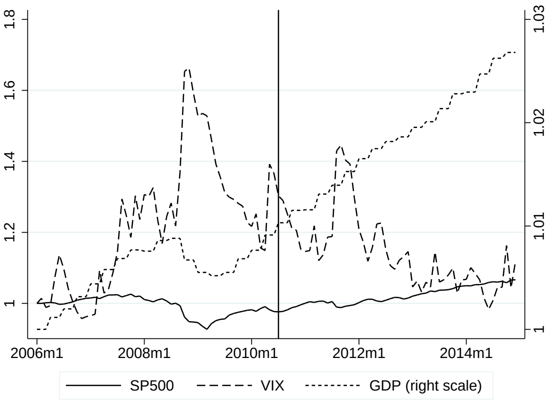
Figure 2.3: Evolution of S&P Issuer Ratings, Implied PDs and Macro Controls



(a) S&P Issuer Rating



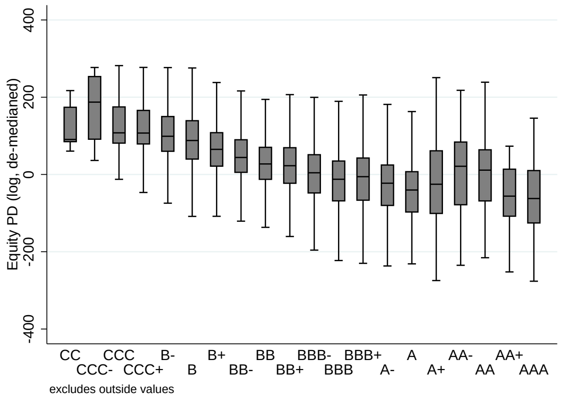
(b) Implied PDs



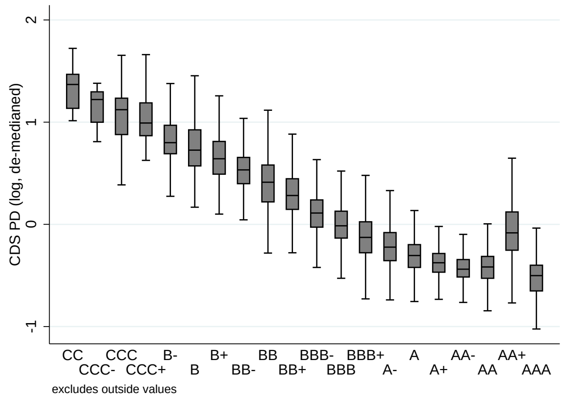
(c) Macro Controls

The figures depict the evolution of S&P issuer rating, implied PD and macro controls over time. All variables are normalised to 2006m1 or 2007m1 values. Due to limited data availability for CDS-implied PDs, the plot for the implied PDs starts in 2007m1. All variables - with the exceptions of the ratings - are logged.

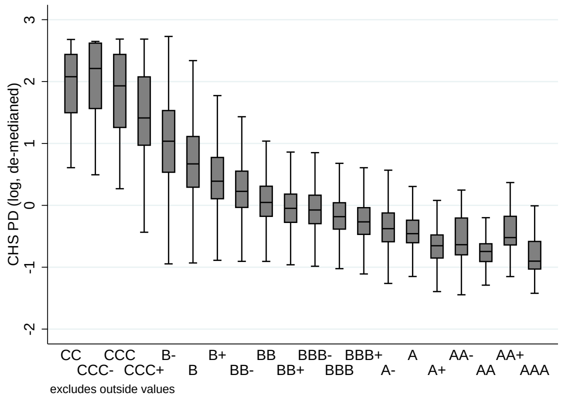
Figure 2.4: Credit Risk over Credit Rating Grades



(a) Equity



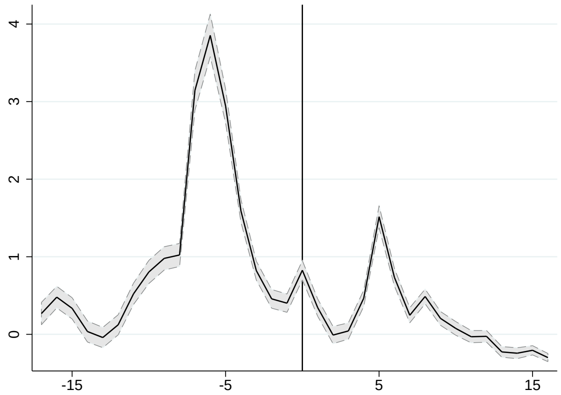
(b) CDS



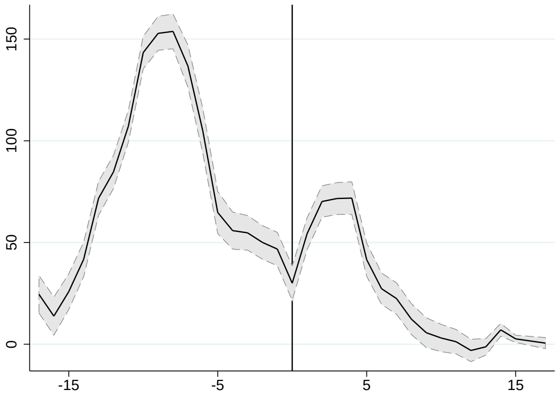
(c) CHS

This figure plots the percentiles of the de-medianed 12-month CHS failure probability, equity- and CDS-implied probabilities of default, annualized (10th, 25th, median, 75th, 90th of the distribution), by S&P credit ratings. The failure probability is the annualized and is de-medianed using the overall monthly median failure probability.

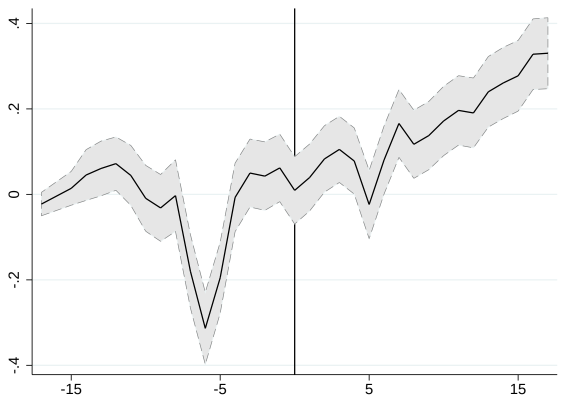
Figure 2.5: Year-quarter Effects around the DFA



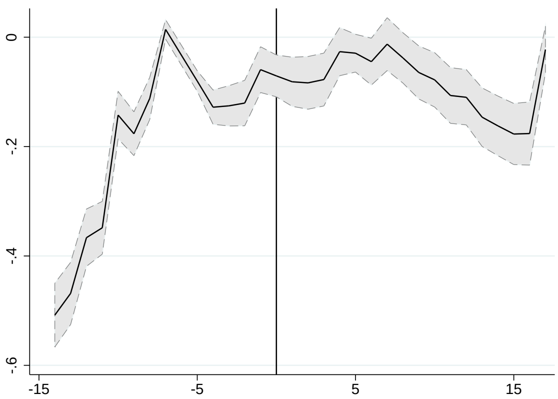
(a) S&P Issuer Ratings



(b) Equity PD



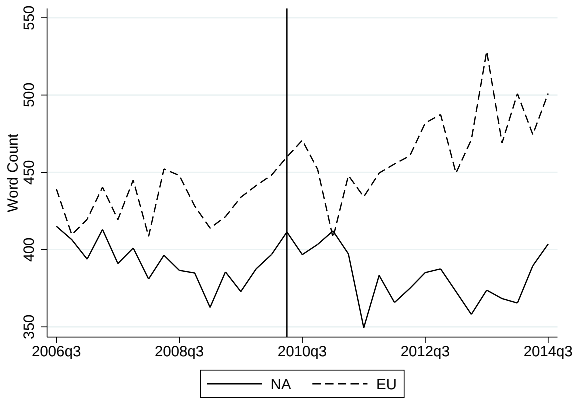
(c) CHS PD



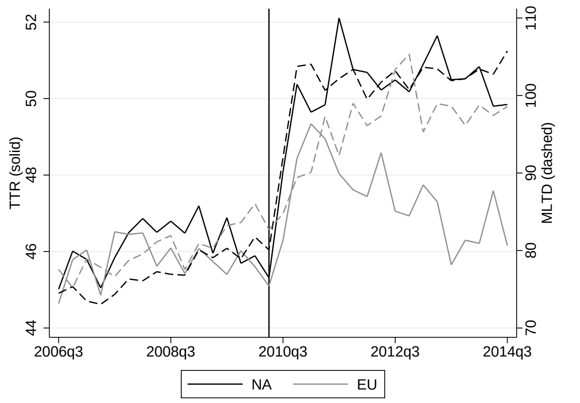
(d) CDS PD

This figure plots coefficients of the year-quarter dummies added to Equation 2.1 without *DFA* and any PD measure on the y-axis. For the PD measures as dependent variable, the coefficients κ originate from the following equation: $PD_{i,t} = \alpha + \kappa \times YQ_t + \rho \times K_{i,t} + \epsilon_{i,t}$, where YQ_t is a vector with the year-quarter dummies. The vertical line indicates 2010q3, the quarter of the commencement of the DFA. The y-axis shows the year-quarters relative to the DFA.

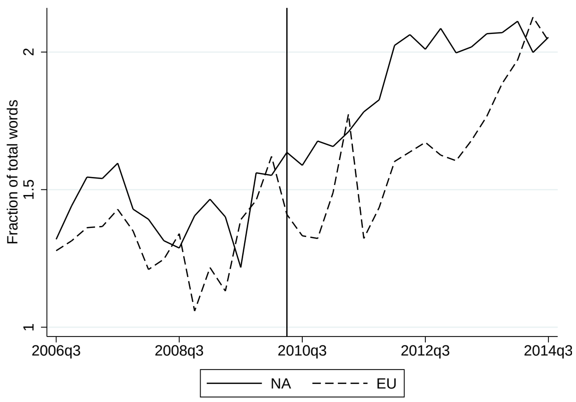
Figure 2.6: Evolution of Textual Variables over Time



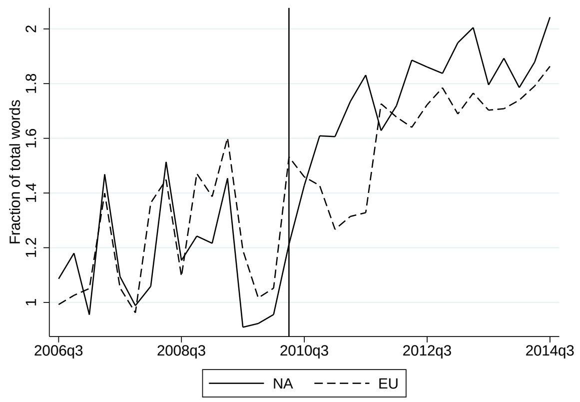
(a) Word Count



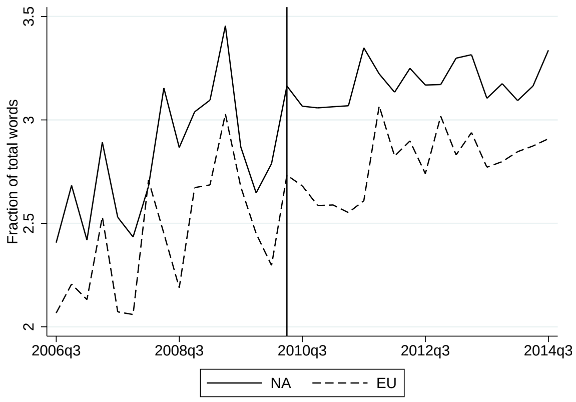
(b) Complexity



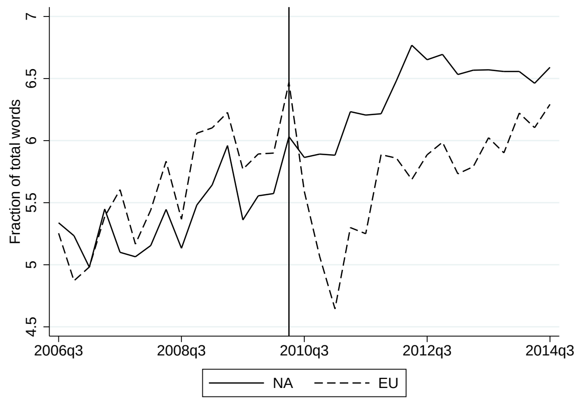
(c) Modal 1



(d) Modal 3



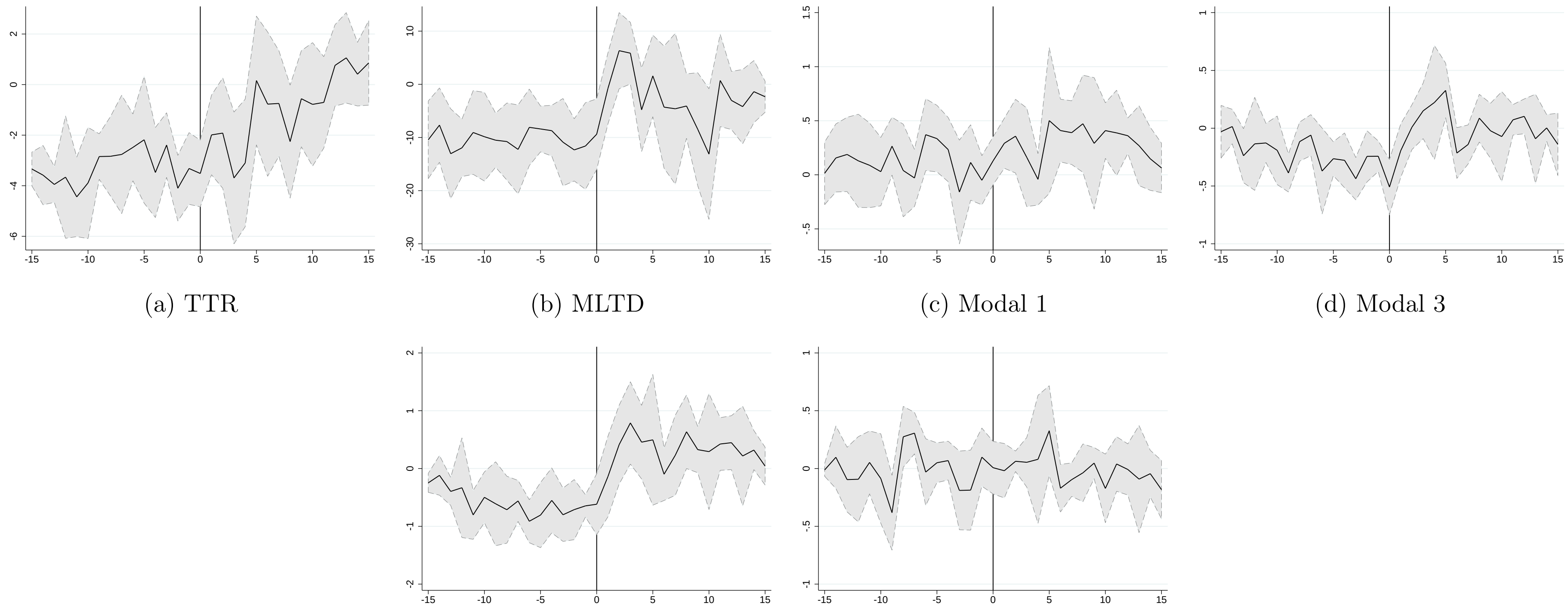
(e) Uncertainty



(f) Forward

The figures depict the evolution of quarterly average over time. The values for North American reports are shown in red, the European ones in blue. *Word Count* is the number of different words in the report. *TTR*, the type-token-ratio is the ratio of different token (words) and total words. *CTTR* is the same ratio but the nominator is the log of different words. *MLTD*, the "measure of textual lexical diversity developed by McCarthy and Jarvis (2010), calculates the complexity dynamically rather than relying on aggregate words counts. For each variable, a higher value indicates a more complex language. *Modal 1* and *Modal 3* are the number of strong (e.g. "always" or "never") and weak (e.g. "almost" or "might") modal words in the reports. *Uncertainty* is the number of words in the report that Loughran and McDonald (2011) classify as expressing uncertainty. *Forward* is the number of forward-looking words as classified in Huang et al. (2014). The variants of these variables labelled *scaled* are the ratio of number of words of that category and *Word Count*.

Figure 2.7: Parallel Trend Assumption for Textual Variables

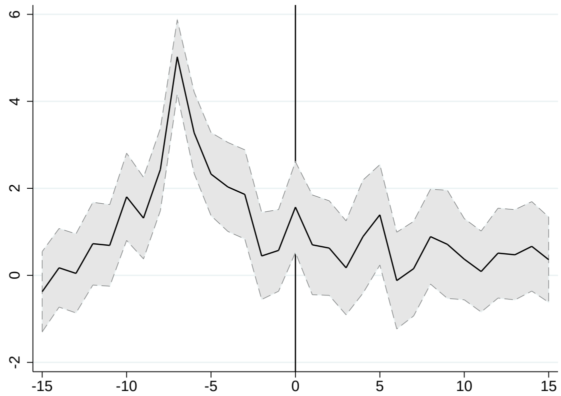


(a) TTR (b) MLTD (c) Modal 1 (d) Modal 3

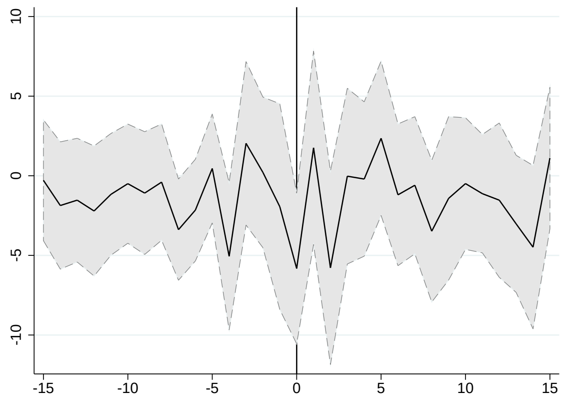
(e) Forward (f) Uncertainty

The figure shows the sequence of μ_t, the coefficients the interactions of the NA-dummy with the year-quarter dummies in equation 2.4 on the y-axis. Negative (positive) values on the x-axis indicate quarters before (after) the commencement of the Frank-Dodd Act in 2010Q3. The vertical line highlights the commencement of the DFA in 2010q3. The dashed lines describe the 95% confidence interval. *Word Count* is the number of different words in the report. *TTR*, the type-token-ratio is the ratio of different token (words) and total words. *MLTD*, the "measure of textual lexical diversity developed by McCarthy and Jarvis (2010), calculates the complexity dynamically rather than relying on aggregate words counts. For each variable, a higher value indicates a more complex language. *Modal 1* and *Modal 3* are the number of strong (e.g. "always" or "never") and weak (e.g. "almost" or "might") modal words in the reports. *Uncertainty* is the number of words in the report that Loughran and McDonald (2011) classify as expressing uncertainty. *Forward* is the number of forward-looking words as classified in Huang et al. (2014).

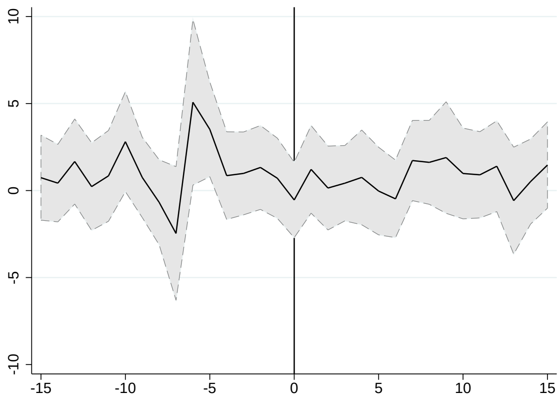
Figure 2.8: Parallel Trend Assumption for Abnormal Returns



(a) Full Sample (CAR^{abs})



(b) Downgrades (CAR)



(c) Upgrades (CAR)

The figure shows the sequence of μ_t, the coefficients of the year-quarter dummies of $CAR_i = \alpha_t + \gamma \times action + \sum_{t=1}^{T} \mu_t \times quarter + \epsilon_i$ on the y-axis. Negative (positive) values on the x-axis indicate quarters before (after) the commencement of the Frank-Dodd Act in 2010Q3. In Panel (a), the full sample is used and the dependent variable is the absolute cumulative abnormal return following the publication date. Panel (b) and (c) are based on the downgrade and upgrade subsample, respectively. The dependent variable is the unaltered CAR. The vertical line highlights the commencement of the DFA in 2010q3. The dashed lines describe the 95% confidence interval.

.1 Campbell et al. (2008)'s Default Probability

This appendix describes the contruction of *CHS PD* and borrows significant parts from Campbell et al. (2008). I first construct the regressors used by Campbell et al. (2008) and Hilscher and Wilson (2016) based on the description of Campbell et al. (2008), second I use a set of coefficients estimated by Hilscher and Wilson (2016) to obtain *CHS PD*.

The regressors are defined as follows:

$$
\begin{aligned}
RSIZE_{i,t} &= \log \frac{Firm\ Market\ Equity_{i,t}}{Total\ S\&P500\ Market\ Value_{i,t}} \\
EXRET_{i,t} &= \log(1 + R_{i,t}) - \log(1 + R_{S\&P500,t})) \\
NITA_{i,t} &= \frac{Net\ Income_{i,t}}{Total\ Assets_{i,t}} \\
TLTA_{i,t} &= \frac{Total\ Liabilities_{i,t}}{Total\ Assets_{i,t}} \\
NIMTA_{i,t} &= \frac{Net\ Income_{i,t}}{Firm\ Market\ Equity_{i,t} + Total\ Liabilities_{i,t}} \\
TLMTA_{i,t} &= \frac{Total\ Liabilities_{i,t}}{Firm\ Market\ Equity_{i,t} + Total\ Liabilities_{i,t}} \\
CASHMTA_{i,t} &= \frac{Cash\ and\ Short\ Term\ Investments_{i,t}}{Firm\ Market\ Equity_{i,t} + Total\ Liabilities_{i,t}} \\
MB_{i,t} &= \frac{Firm\ Market\ Equity_{i,t} + Total\ Liabilities}{Total\ Assets_{i,t}}
\end{aligned}
$$

As Campbell et al. (2008), I use the COMPUSTAT Data44 for total assets, Data69 for net income, and Data54 for total liabilities. To measure the volatility of a firm's stock returns, we use a proxy, centred around zero rather than the rolling three-month mean, for daily variation of returns computed:

$$
SIGMA_{i,t-1,t-2} = \left(252 * \frac{1}{N-1} \sum_{k \in (t-1,t-2,t-3)} r_{i,k}^2 \right)^{\frac{1}{2}}
$$

PRICE is the log of price per share winsorized above \$15. All regressors are winsorized at the 1% level. However, winsorizing is not crucial for my results.

The coefficients used to transform to predict the failure probability are taken from column 4 in Table 2 of Hilscher and Wilson (2016). In this specfication, the sample consisted only of rated firms and the ranges from 1986 to 2013. Out of all reported specifications in Campbell et al. (2008) and Hilscher and Wilson (2016), this sample overlaps most with my sample. Specifically, I use the following calibration to calculate to odds ratio:

$$\begin{aligned}
\textit{Failure Score}_{i,t} = & -12.68 - 23.50 \times NIMTAAVG_{i,t} + 2.74 \times TLMTA_{i,t} - 12.19 \times EXRETAVG_{i,t} \\
& + 1.33 \times SIGMA_{i,t} - 0.29 RSIZE_{i,t} - 2.09 \times CASHMTA_{i,t} \\
& + 0.09 \times MB_{i,t} + 0.17 \times PRICE_{i,t}
\end{aligned}$$

Eventually, *CHS PD* is calculated as $\textit{CHS PD}_{i,t} = \exp(\textit{Failure Score}_{i,t})$. To validate the construction of the variables, Table 15 provides a comparison of the summary statistics of my full sample with those of Campbell et al. (2008). A comparison with Hilscher and Wilson (2016) would have been preferred since their calibration is used for the calculation of *CHS PD*, but they do not provide summary statistics of those variables in their sample. Firms in my full sample appear to be somewhat more profitable in terms of NIMTA and EXRET. They are also larger, measured by RSIZE, and exhibit a higher Market-to-Book ratio. The larger size of the firms in my sample could also be the driver behind the lower volatility (SIGMA). As I only consider rated firms, which are conceivably larger than unrated ones, the difference in size is expected. The standard deviations in my sample are also comparable to those of Campbell et al. (2008). Overall, the differences between the samples appear to be small and do not hint towards a miscalculation of any variables.

Table. 15: Comparison of Summary Statistics

Panel A: Summary Statistics of Campbell et al. (2008)					
	Mean	Median	Std.Dev.	Min	Max
NIMTA	0.000	0.006	0.023	-0.069	0.028
TLMTA	0.445	0.427	0.280	0.036	0.923
EXRET	-0.011	-0.009	0.117	-0.243	0.218
RSIZE	-10.456	-10.570	1.922	-13.568	-6.773
SIGMA	0.562	0.471	0.332	0.153	1.353
CASHMTA	0.084	0.045	0.097	0.002	0.358
MB	2.041	1.557	1.579	0.358	6.471
PRICE	2.019	2.474	0.883	-0.065	2.708
Panel B: Summary Statistics of the full sample					
	Mean	Median	Std.Dev.	Min	Max
NIMTA	0.011	0.017	0.032	-0.159	0.079
TLMTA	0.473	0.457	0.204	0.045	0.983
EXRET	0.000	0.002	0.031	-0.121	0.096
RSIZE	-8.341	-8.343	1.637	-12.804	-4.549
SIGMA	0.386	0.320	0.241	0.112	1.593
CASHMTA	0.059	0.038	0.064	0.000	0.391
MB	2.412	1.829	1.342	0.341	7.123
PRICE	2.534	2.708	0.438	0.377	2.708

The table presents the summary statistics of Campbell et al. (2008) and the respective counterparts of their variables in my sample. All variables are defined as described above.

.2 Sample Rating Report

Moody's downgrades Frontier to Ba3

New York, September 03, 2014 – Moody's Investors Service ("Moody's") has downgraded Frontier Communications Corporation's ("Frontier"; or the company"") Corporate Family Rating ("CFR") to Ba3 from Ba2 primarily as a result of the increased leverage from debt incurred to finance the $2 billion acquisition of AT&T's Connecticut wireline assets. As part of this rating action, Moody's has also lowered Frontier's Probability of Default Rating ("PDR") to Ba3-PD from Ba2-PD and assigned Ba3 ratings to each of the two tranches of senior unsecured notes issued today, which will be used to finance the acquisition. Additionally, Moody's has affirmed Frontier's SGL-1 speculative grade liquidity rating. This concludes Moody's review initiated on December 17, 2013. The outlook is stable.

Moody's has taken the following rating actions:

Frontier Communications Corporation ...

...Corporate Family Rating, downgraded to Ba3 from Ba2

...Probability of Default Rating, downgraded to Ba3-PD from Ba2-PD

...Senior Unsecured Notes, downgraded to Ba3 (LGD4) from Ba2 (LGD4)

...Senior Unsecured Shelf, downgraded to (P)Ba3 from (P)Ba2

...Speculative Grade Liquidity Rating, affirmed at SGL-1

...Outlook, changed to Stable from Rating under Review

...New Senior Unsecured Regular Bond/Debenture, Assigned Ba3 (LGD4)

...New Senior Unsecured Regular Bond/Debenture, Assigned Ba3 (LGD4)

RATINGS RATIONALE

Frontier's Ba3 CFR reflects its large scale of operations, its strong and predictable cash flows and high margins. These factors are offset by the company's challenged competitive position versus cable operators, its declining revenues and the possibility that the company may not have the flexibility or discipline to continue to adequately invest in network modernization.

The change to Ba3 from Ba2 reflects Moody's view that Frontier's debt-financed acquisition of AT&T Inc's local wireline business in the state of Connecticut will result in leverage above 3.75x (Moody's adjusted) until at least 2017. Moody's had previously identified leverage of 3.75x as the upper limit of Frontier's Ba2 rating. Further, Moody's views the debt-financed acquisition as a departure from Frontier's prior conservative financial policy and discipline which, in Moody's view, was focused on debt reduction. Moody's believes that the acquisition will improve Frontier's scale, adding an estimated $1.25 billion of revenue for FYE2014, nearly 1.4 million additional households and about 1 million additional residential and commercial customers. The acquisition will also add an asset with high broadband penetration to Frontier's coverage area. However, Moody's believes that the incremental EBITDA and cost synergies will not materially reduce leverage for the next several years.

Frontier has posted modest broadband subscriber growth over the past several quarters, yet revenues continue to fall as voice revenues decline faster than the growth from broadband. Over a longer time horizon, the headwind from voice disconnects will moderate and Frontier may return to growth. Further, we believe that Frontier's margins will remain strong because does it not offer a facilities-based triple play bundle and does not have to absorb the low margin pay TV product. However, we also believe that Frontier's network architecture limitations and lower broadband speeds may limit its ability to take market share and could force the company to compete more aggressively on price. Because of this, we believe that Frontier will continue to face price pressure in both its residential and small business customer segments.

Moody's could lower Frontier's ratings further if leverage were to exceed 4.25x (Moody's adjusted) or free cash flow turns negative, on a sustained basis. Also, the ratings could be lowered if the company's liquidity becomes strained or if capital spending is reduced below the level required to sustain the company's market position.

Moody's could raise Frontier's ratings if leverage were to be sustained comfortably below 3.75x (Moody's adjusted) and free cash flow to debt were in the mid single digits percentage range.

The principal methodology used in these ratings was Global Telecommunications Industry published in December 2010. Other methodologies used include Loss Given Default for Speculative-Grade Non-Financial Companies in the U.S., Canada and EMEA published in June 2009. Please see the Credit Policy page on www.moodys.com for a copy of these methodologies.

Frontier is an Incumbent Local Exchange Carrier headquartered in Stamford, CT. Following the company's merger with a company spun out of Verizon Communications' northern and western operations (Spinco) in a reverse Morris Trust transaction, Frontier became the fifth largest wireline telecommunications company in the US.

REGULATORY DISCLOSURES

For ratings issued on a program, series or category/class of debt, this announcement provides certain regulatory disclosures in relation to each rating of a subsequently issued bond or note of the same series or category/class of debt or pursuant to a program for which the ratings are derived exclusively from existing ratings in accordance with Moody's rating practices. For ratings issued on a support provider, this announcement provides certain regulatory disclosures in relation to the rating action on the support provider and in relation to each particular rating action for securities that derive their credit ratings from the support provider's credit rating. For provisional ratings, this announcement provides certain regulatory disclosures in relation to the provisional rating assigned, and in relation to a definitive rating that may be assigned subsequent to the final issuance of the debt, in each case where the transaction structure and terms have not changed prior to the assignment of the definitive rating in a manner that would have affected the rating. For further information please see the ratings tab on the issuer/entity page for the respective issuer on www.moodys.com.

For any affected securities or rated entities receiving direct credit support from the primary entity(ies) of this rating action, and whose ratings may change as a result of this rating action, the associated regulatory disclosures will be those of the guarantor entity. Exceptions to this approach exist for the following disclosures, if applicable to jurisdiction: Ancillary Services, Disclosure to rated entity, Disclosure from rated entity.

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.3 Sample Construction Rating Reports

Rating reports were obtained from Moody's homepage (https://www.moodys.com). Under the tab "Ratings & Research", Moody's publishes, *inter alia*, credit opinions, issuer reports and rating news. Ratings reports fall under the category of ratings news and, unlike most other publications are freely available to the public. The search is further narrowed down by confining the region to "North America" and "Europe" and consider only "Corporates" and "Financial Institutions" (i.e. excluding structured finance, the public sector and project-related ratings). Finally, we look only at reports in English.

The results of this search are return on a series of webpages, each containing ten reports satisfying the set conditions. Figure A.1 shows a screenshot of this page. The first challenge is access each of the pages that contain the results. Note that result pages must be physically be visited in a browser to contain the links to the reports. If the results pages are downloaded without browser, for example by directly parsing the result pages to wget, the html code does not contain the links. I therefore resorted to iMacros, a Firefox plugin, to access and save the result pages individually. This approach exploits the structure of the addresses of the result pages. A typical result page looks as follows: $https : //www.moodys.com/researchandratings/viewall/issuer - research/rating - action/$[...]$/0/i/$[...]$/ - /rra$ The "i" in the URL indicates the number of the results page. For example, the ten first rating reports are contained on results page one and i = 1, the second batch of rating reports are listed on results page two and i = 2. Therefore, the following simple loop over i in iMacros accesses each results page and saves the html code:

1. VERSION BUILD=8970419 RECORDER=FX
2. TAB T=1
3. URL GOTO=`https://www.moodys.com/[...]/rating-action/[...]/0/!LOOP/[...]`
4. SAVEAS TYPE=HTM FOLDER=/path/FILE=!LOOP

where !LOOP is the loop variable.

The such obtained html codes are imported into R using the "readLines"-command. Lines containing a link to a report are identified by the href attributes at the beginning of the line. Figure A.2 provides an example for the bit of the code that contains a link to report. By looping over the saved result page html codes, the links to all reports are collected as comma separated value s (csv).

In the second step, the *wget* function is invoked via the Mac OX Terminal using the following command: "wget -i download-file-list.txt", where "download-file-list.txt" is the list of the links to all the reports obtained in step 1. This command downloads all the webpages with the reports and stores them locally.

Finally, I isolate the actual rating report from the html code and non-report text items like disclaimers in the following procedure. In this process, the common structure of all rating reports and the similar wording is exploited. Each element of the structure can be identified by a particular word sequence as described below.

Figure A.1: Downloading the Reports, Step 1

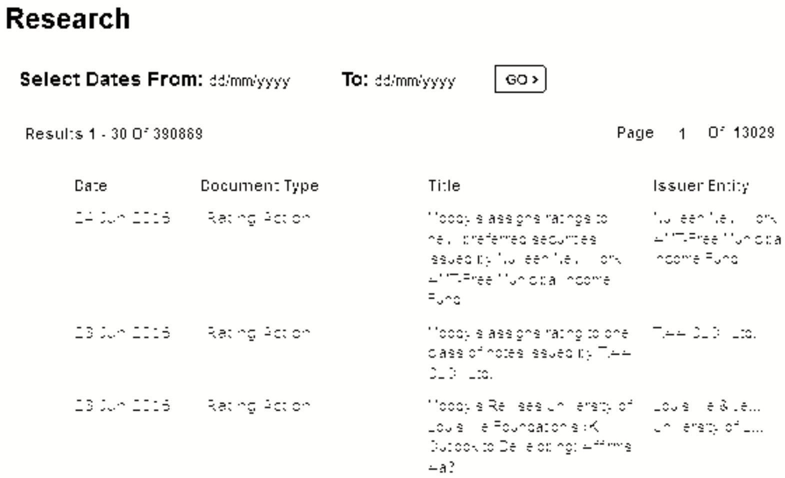


Figure A.2: Downloading the Reports, Step 2

```
</td><td>
    <a href ='/credit-ratings/Jefferson-City-of-Combined-Utilities-WI-credit-rating-903395467'
</td></tr><tr class="mdcResearchDocItem"><td>
    <input type="hidden" value='PR_903425188' class="mdcDocumentId" /><img
        src='/_layouts/Mdc/Images/lock.png' alt="" class="mdcHide" />
</td><td class="mdcResearchDateValue">
    23 Jun 2016
</td><td class="mdcResearchDocTypeValue">
    Rating Action
```

1. Title, identified by “Rating Action:"
2. Date, identified by “Global Credit Research"
3. Summary, no unique identifier
4. Ratings Rationale, identified by “RATINGS RATIONALE"
5. Methodology, identified by “The principal methodology used"
6. Regulatory disclosure, identified by “REGULATORY DISCLOSURES"
7. Addresses, identified by “Corporate Finance Group"
8. Disclaimer, identified by “All rights reserved."

A rating report might not contain each of the elements but the sequence of elements is always the same. Therefore, the following procedure uses the aforementioned structure to isolate the ratings rationale:

1. Removal of the html commands using the “bracketX"-function of the qdap package. This function removes all string that are enclosed in angled brackets, i.e. all html commands.
2. Isolation of the title of the report. The line containing the title of the report can be identified by the sequence “Rating Action:". If no title line can be identified, the report is dropped from the sample. In each html file that contains the sequence “Rating Action:", this sequence uniquely identifies a line, i.e. there is no ambiguity about the title. All lines preceding the title line are dropped.
3. Removal of the summary. The justification of the rating change is always placed under the headline “RATINGS RATIONALE". By dropping all lines before the line containing “RATINGS RATIONALE".

4. Removal of methodology, disclosure, addresses and disclaimer by dropping all lines behind the identifying sequences outlined above.

Once the rating rational is isolated, the rating action is classified by rating action and rating grade. The type of rating action is identified by the wording of the title. Moody's uses a fixed set of words associated with each rating action. Downgrades are identified by the verbs "downgrades" and "lowers", upgrades by "upgrades", "raises" and "lifts". Rating actions are classified as "outlook" changes or "reviews" if the title includes "outlook" or "under review", respectively. Moody's might affirm ratings amid important corporate events, such as mergers or substantial issues. Such affirmations are identified by "affirms" or "confirms". Finally, Moody's might issue a new rating, e.g. for a bond issue. The title of new assignments includes either "rates" or "assigns". Note that the different rating actions are not necessarily exclusive. For example, a downgrade might be accompanied by change of the outlook. For the classification by rating grade, the ratings rationale is scanned for the alphanumeric rating grades. For each rating grade, I code a dummy that takes the value of one if the alphanumeric code occurs and zero if not.

APPENDIX A

CREDIT INSTITUTIONS, OWNERSHIP AND BANK LENDING IN TRANSITION ECONOMIES

A.1 Introduction

The transition of banking sectors in Central and Eastern Europe in the first 15 years of transition was nothing short of remarkable. When the Communist regimes fell, none of the transition countries had a functioning financial system that could provide intermediary services. Most observers at the time assumed that the development of market-based banking systems would take many years. However, by the early years of the 21st century, the transition of banking sectors in Central and Eastern Europe (though not in many countries of the former Soviet Union) was largely complete. For the most part, the countries in the region have market oriented banks that utilize modern banking technologies and are largely independent of direct government influence.

Why and how did this remarkable success story take place? Early in the transition period, observers attributed the improvements to banking reforms - recapitalizations and privatization - and, importantly, the early entry of foreign banking (Bonin et. al., 1998 and 2005; Bonin and Wachtel, 1999). Foreign bank entry though it was resisted at first, began in the mid-1990s and was a catalyst for change. In this view, the rapid transition of the banking sector can be attributed to foreign owners who brought modern technology, market oriented decision making, independence from vested interests and competition.

By 2000, foreign banks owned a majority of bank assets in virtually every transition country and almost all of the assets in several countries. Credit expanded very rapidly in the region in the years prior to the global financial crisis. There are many reasons for this but importantly the foreign ownership of banks facilitated and spurred these credit booms. If the domestic deposit base was small or growing slowly, foreign owned banks were able to fund their expansion with cross border flows (see De Haas and van Horen 2016). Foreign banks could shift liabilities to their foreign subsidiaries with loans deposits, make equity investments and facilitate flows from other home country entities. Moreover, the expansion of credit in the transition countries had one particular characteristic, lending to households expanded much more rapidly than lending to any other sector.

The global financial crisis challenged the idea that foreign banks were in every respect a positive influence. All of a sudden, the parent banks from large countries were under intense pressure to deleverage and increase liquidity. They could reduce or even pull back financing to their transition country subsidiaries. In this view foreign bank ownership could magnify the impact of the global real sector shock on the transition countries. Foreign ownership which had been a catalyst for financial sector development for a decade was now, perhaps, the source of fragility. Financial systems in transition countries were particularly vulnerable to the crisis shock. Surprisingly, there were only two transition countries with systemic bank crises in 2009 - Latvia and the Ukraine - and two more with near systemic problems - Hungary and Russia.

The experience of the last 15 years - a credit boom that created financial fragilities which amplified the crisis shock - indicates that foreign bank ownership might be a mixed blessing. The question is essentially an empirical one and we will see below that the evidence in the literature, though mixed, tends to absolve the foreign banks. Foreign banks may have amplified the transmission of the crisis shock to transition countries but in most instances they retained their commitment to these secondary home markets and foreign subsidiaries. More importantly, we argue that the banking sectors in transition economies withstood the crisis shock because they had developed their own solid institutions - an effective supervisory structure and legal framework.

There is more to the story behind the success of banking in transition countries than foreign ownership. The quality of institutions in the financial sector plays a major role in fostering the development of the banking sector. The significance of legal institutions, regulatory structures and the institutional infrastructure for financial relationships was overlooked in the early transition years. This is not surprising because economists did not pay much attention to the role of institutions in economic growth until the late 1990s. For example, La Porta, Lopez-de-Silanes, Shleifer, and Vishny (1997) argued that better creditor rights are associated with better developed credit markets in a large cross-section of countries. This law and finance literature developed quickly to show how improved legal structures are associated with better financial development (Djankov, McLiesh and Shleifer (2007)), fewer loan covenants (Qian and Strahan (2007)) and better corporate investment decisions (Giannetti (2003)).

The story of banking in transition countries is as much the story of institution building as it is a story of foreign ownership. Our view of transition banking is that institutions are key. Modern market oriented banking systems emerged when institutional structures were in place. This included a reliable legal framework for the conduct of banking business, a framework for regulation and the conduct of monetary policy and the end of direct or implicit government influence on banking activity. Foreign banks were interested in entering the markets when these conditions were in place.

To summarize, most transition countries experienced credit booms which were followed by the global financial crisis shock. The presence of foreign banks which was pervasive by this time might have exacerbated credit booms and the impact of the crisis. Nevertheless, the banking sectors in transition countries were very resilient. Our hypothesis is that the degree of resilience to the boom and crisis shocks related primarily to the quality of domestic institutions and policy decisions.

The transition in Central and European from a command to a market economy has been an important laboratory for the so-called law and finance literature which was emerging toward the end of the 1990s. Literature on the region examined specific legal arrangements relevant to financial development. For example, Dahan (2000), Pistor (2004) and Pistor, Raiser, and Gelfer (2000) described how creditor rights have been introduced in these countries. Haselmann, Pistor and Vig (2010) documented the changes in creditor rights that occurred in the transition countries as the World Bank and the EBRD advised countries to adopt legislation. They construct indicators of the strength of collateral law and bankruptcy law and relate them to the growth of lending. Their results indicate that better creditor rights are associated with more lending and the existence of good collateral law has a stronger impact on lending than the strength of bankruptcy protections, probably because collateral law is a prerequisite for introducing protections to creditors in bankruptcy proceedings. In related work, Haselmann and Wachtel (2010) showed that legal differences result in differences in loan composition. Good collateral law results in more private credit formation and more lending to SMEs as opposed to large firms. Finally, good creditor rights seem to be especially important for foreign banks and therefore more of them will enter if creditor rights are good.

In addition to the legal framework for lending, banks rely on credit information in order to make credit judgments. Credit information effects lending for several reasons (see Japelli and Pagano 1993). First, if banks have more information on borrowers, they are better able to access the credit worthiness and price loans accordingly. Second, information sharing reduces the market power of banks over borrowers as information is "stored" outside the bank. Information sharing might have a more pronounced effect in countries with weak creditor protection since enforcement of the contract is costly.

The empirical literature lends support to the hypothesis that information sharing increases lending, and decreases credit spreads and default rates. Jappelli and Pagano

(2002) and Djankov et al. (2007) find a positive correlation between information sharing and lending to the private sector and a negative correlation with default rates. Brown et al. (2009) confirm this finding with firm-level data for Eastern Europe: firms in countries with more information sharing have easier access to credit and pay lower interest rates. The effect is larger for countries with weak creditor protection suggesting that credit registers can serve as a substitute for underdeveloped legal systems.

In this chapter we provide a brief survey of banking in the transition economics. The discussion takes us through the first decade - the 1990s - when commercial banks emerged, and the 2000s, the era of foreign bank ownership. Our emphasis in on the structure of banking - the emergence of foreign banking - and the role of institutions.

It is difficult to distinguish the influence of good institutions from the influence of foreign bank ownership because they emerged at the same time and clearly influenced each other. However, the crisis provides a quasi-experimental context for evaluating the role of ownership and institutions. We present some suggestive econometric results that test whether foreign ownership and good institutions enable banking systems to withstand the crisis shock. Specifically, we will show that a well-functioning credit information systems can help dampen the impact of financial crisis on the financial sector.

The crisis originated in the American mortgage markets so it can be viewed as an external or exogenous shock for the transition countries. The shock resulted in an increase in uncertainty about the future of the real economy and a general increase in credit risks. If credit information systems help overcome such uncertainties by providing idiosyncratic information on individual borrowers we would expect that markets that have a better creditor information system would be more resilient to the shock.[1]

[1] As already noted, many transition countries were experiencing a credit boom prior to the crisis so the crisis might to have some extent been endogenous to the region. We would still expect countries with better credit institutions to bounce back from the shock more rapidly.

Our empirical investigation examines the volume of lending and its composition among the major sectors: households, non-financial corporations and government. The extent of information asymmetry and uncertainty around the crisis event varies for different types of borrowers. It should be larger for SME borrowers as compared to large borrowers and for corporate borrowers compared to the government. We use data on credit institutions from the World Bank and find that the quality of institutions, especially the coverage of credit information systems affects post-crisis loan volume.

A.2 Transition Banking: The First Decade

In the early years of transition, banking sectors consisted of state owned banks that were competing with newly privatized banks and new entrants in a system largely devoid of effective regulation. The state owned banks, at the behest of the government, continued to lend to loss-making state owned enterprises and even privatized banks continued lending to their old customers, which led to the rapid growth of bad loan portfolios. New entrants, so-called Greenfield banks, took advantage of loose oversight to take on risky and too often shady deals. The collapse of trading relationships with the Soviet Union and the absence of any other markets led to large transition recessions while at the same time the liberalization of prices and large government deficits resulted in episodes of hyperinflation.

The first transition development was the creation of banking institutions where none had existed before (see Hasan, Bonin and Wachtel 2015). Some centrally planned economies had advanced industrial enterprises which were in some instances internationally competitive but none had banks that resembled those in developed countries. The planning framework had no place for banks or financial intermediaries. Capital was allocated by plan and the role of the banks, usually a national mono-bank, was just to provide a payments system and accounting mechanism for transactions among enterprises. Thus, a first step in transition was to create banks by separating the mono bank into a central bank and one or more state owned commercial banking entities.[2]

Commercial banks were created before functioning regulatory structures were in place and before the relationship between state owned enterprises and banks were restructured. As a result, every one of the transition countries experienced at least one banking crisis in the early 1990s that required the re-nationalization of banks that had been privatized, widespread losses to depositors and the recapitalization of state owned banks by the government. These experiences point to the importance of institution building, in this case both the structure of banks and the regulatory framework.

At the start of transition, governments were reluctant to allow foreign ownership of banks as a matter of national pride. The banking system - the overseer of the nation's money - was an important symbol of sovereignty; the monetary system was viewed as a national treasure that should not be subject to foreign control. By the mid-1990s attitudes began to change with the realization that foreign strategic investors in banks were, like any other foreign direct investment, a fixed investment (in this instance bank capital) and a source of technology transfers (see Claessens et al. (2001)). The first such deal was the sale of Budapest Bank, a state owned bank with a serious bad loan problem, to GE Capital in 1995. That opened the floodgates and by 2000, a majority of bank assets were in foreign owned institutions in Czech Republic, Hungary, Poland, Bulgaria, Croatia, and the three Baltic countries. The only exceptions in central and Eastern Europe were Slovakia, Romania, Serbia and Slovenia; by 2005, Slovenia was the lone exception where

[2] This simplification abstracts from the differences among transition countries. Yugoslavia, for example, established somewhat independent commercial banks in the 1950s; Hungary always had a foreign trade bank and savings bank. Similarly, there were differences in the way commercial banks were created. Bulgaria granted every office of the central bank a universal banking license in 1990 while neighbouring Romania created one state owned commercial bank.

government policy limited foreign participation in banking.[3] Small countries such as Estonia, Lithuania, Slovakia and Croatia seem to maintain their sovereignty even as over 90% of bank assets are in entities controlled by foreigners.

Foreign banks brought modern banking technology and products and introduced arm's length relationships between banks and their loan customers.[4] Further, improved banking practices spilled over from the foreign owned institutions to the domestic banks including state owned institutions. However, the emphasis on the catalytic effect of foreign bank ownership overlooks the role of institutions. Foreign entry would not have occurred without improvements in the institutional structure. The introduction of banking laws and regulatory structures were often due to foreign influences starting in the 1990s. USAID, the World Bank, EBRD, EU Phare all provided support and expertise for writing legislation (see Pistor, Raiser and Gelfer, 2000). Foreign influence increased when six transition countries began accession talks with the EU in 1998.

Basic institutions such as a banking law, accounting standards and regulatory authorities were introduced in the 1990s. However, it often took some time before an arm's length relationships developed between regulators and the banks. Further, it took additional time for the legal structures used in banking to emerge, including reliably functioning court systems for commercial disputes, credit information systems and laws regarding the use and taking of collateral.

In Hungary, the first country to welcome foreign bank ownership, legislation in 1992 introduced modern banking law, international accounting standards and a new bankruptcy

[3]Slovenia suffered a serious banking crisis in 2013 and then began to relax ownership restrictions.

[4]For example, the banking systems skipped the use of paper checks and were early adopters of electronic payments systems. On the asset side, banks imported credit scoring models from their parents.

law.[5] The sale of Budapest Bank took place in late 1995, after the legal reforms.[6] In the Czech Republic, an ambitious program of voucher privatisation of enterprises started in 1991, before corporate governance reforms and capital market regulations were in place. The program was soon enveloped in scandals involving bank sponsored privatization funds and lending to bank controlled enterprises. By 1998 bad loans were about one-quarter the size of Czech GDP. Enterprise and legal reforms started around 1999 as the Czech Republic entered serious negotiations with the EU on accession. Bank restructuring and reprivatisation began soon thereafter. In 1999 foreign banks owned about one-quarter of Czech bank assets and two-thirds in Hungary. By 2005, foreign ownership was about 90% in both countries. Foreign ownership in both instances followed institutional reforms.

A.3 Transition Banking After 2000

In the decade prior to the financial crisis, GDP growth in the transition economies was faster than growth in developing Asia (with the exception of India and China) and credit markets deepened substantially. The credit expansion was largely driven by capital inflows, particularly bank flows from Western Europe and external debts (borrowing by banks and by sovereigns). There were a number of reasons why the flows were large including the global savings glut, confidence in the transition economies generate by EU accession and the expectation that Euro adoption would follow, demand generated by structural reforms.

The credit boom and the shift in the composition of lending from non-financial busi-

[5] Foreign entry developed much more slowly in the former Soviet Union (other than the Baltics) where legal and regulatory institutional developments lagged those in Central and Easter Europe.

[6] The sale was controversial because the government agreed to take back bad loans that might be uncovered after the sale.

ness to households in the 12 transition countries in our sample are shown in Figure 1.[7] In all of the countries shown the share of lending going to households has increased over the last decade and in many instances the share is as large at the share going to non-financial businesses. The foreign banks brought credit scoring models which were easily applied to household lending but not readily adopted for lending to enterprises. Further the banks had only recently cleaned up loan losses and reduced lending to large unprofitable state owned enterprises. Lending to enterprises, particularly newer or smaller enterprises, is often relationship based. Household lending took off before bank - enterprise client relationships had time to develop. Commenting on developments in Polish banking, Wiesiolek and Tymoczko (2015, p. 315) conclude that:

> The model of banking which involved promoting loans for households (mostly housing loans) on a large scale was imported from headquarters before a culture of cooperation with enterprises had sufficient time to emerge. As a consequence, households rather than enterprises have become the most important clients of banks . . . .

Another feature of lending was that by 2008 lending denominated in foreign currencies exceeded 50% of all loans in some countries (e.g. Hungary, Bulgaria, Croatia, Romania; see Bonin (2010).

By the time of the crisis, foreign banks were a pervasive presence in all the countries in our sample except Slovenia and the Ukraine.[8] The differential impact of the crisis does not seem to be related to the foreign bank share of assets or loans which are in most instances little changed after the crisis. There are small declines which might reflect tighter lending standards in the post-crisis period by foreign banks.

GDP dropped sharply in almost every country when the crisis started and in most instances it rebounded after a year. Movements in private credit after the crisis differed

[7]The 12 transition countries are Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Romania, Slovakia, Slovenia and the Ukraine.

[8]The foreign share of bank assets in each country in 2008 is shown in Table 1.

from place to place. For example, in Poland, there was a short sharp decline in credit that was quickly reversed and credit was back on trend by 2010. In Slovakia the impact of the crisis on GDP was small and credit continued to grow. However, in Romania and Hungary the credit slowdown was long lasting and five years after the crisis, credit had not reached it prior peak. In Hungary, Slovenia, the Ukraine and the Baltic States credit growth in the post-crisis years has been negative.

The share of lending going to households increased before the crisis and then tended to level off at about 40% of all lending in most countries. In most countries, the share of lending going to government and to financial corporations together was below 20% so any increase in the household share was at the expense of lending to non-financial business. Lending to households was concentrated in mortgage lending in Poland and Hungary in particular. In Hungary, the largest type of lending was mortgages dominated in foreign currency which led to both maturity and currency mismatch on bank balance sheets and a banking system that was particularly vulnerable during the crisis. The only counties where the share of lending to the non-financial business sector has increased since the crisis are Romania, Slovakia and Hungary all of which experienced declines in total lending.

The impact of the financial crisis on the transition countries was severe as demand for their exports dropped quickly after the crisis shock. Further, there was immediate concern that financial crises would ensue as capital inflows halted suddenly. From the very start of the crisis there was concern that banking customers in the transition economies where most financial services were provided by foreign banks would suffer. Popov and Udell (2012) use survey data on small and medium enterprises in the region to investigate the transmission of the crisis shock through credit supply to SMEs. They find that SMEs report larger credit constraints in areas where the local banks' parents were more severely affected by the crisis. According to De Haas et al. (2015), the contraction in credit by foreign bank subsidiaries in transition countries occurred earlier and was deeper than that of domestic banks during the crisis years of 2008 and 2009. These studies indicate that the developed country financial crisis was quickly transmitted to the transition countries through a foreign bank ownership channel.

The fear of transmission of the financial crisis to the transition economies led immediately to a broad international policy response known as the Vienna Initiative. The Vienna Initiative was an unusual private-public, multilateral response to the crisis. As the global crisis was deepening in January 2009, the international financial institutions (including the EBRD, IMF and the EIB) and the private foreign parent banks in the region reached an agreement to cushion the effects of the shock. The banks agreed to maintain their exposures to the transition countries and recapitalize banks as necessary while the IFIs offered support of 33 billion Euros to maintain bank stability. Among the larger transition countries, Hungary, the Ukraine, Poland and Romania all opened lending arrangement with the IMF. These efforts contributed to the post-crisis recovery of banking and credit creation in the region.

The discussions that led to the Vienna Initiative began in November 2008.[9] There was good reason for concern that the global crisis would be transmitted to and magnified in the region because of the extensive foreign ownership. Thinking about foreign bank ownership which had been widely supportive since the late 1990s was quickly reversed. In the IMF's retrospective view:

> Many western banks in emerging Europe operate their subsidiaries as if they are branches, with risk management centralized at the group level and local supervisors relying on parent banks? home supervisors to monitor the changes in the risk profile of their foreign affiliates. Foreign-owned banks can often evade regulatory measures,

[9]The large foreign banks originated the idea of a coordinated approach, which resulted in the Vienna Initiative, in a letter expressing concern for the financial stability of the region sent to the European Commission in November 2008.

> including by switching from domestic to cross-border lending or by switching lending from banks to non-banks, such as leasing institutions (owned by foreign-owned banks). Foreign-owned banks are also less likely to be influenced by domestic monetary policy measures, such as the raising of domestic interest rates. Often, these banks are systemically important in the host country although only a small part of the overall bank group. (Bakker and Klingen, 2012, pp. 21-22).

The evidence is that the Vienna Initiative was successful; De Haas et al. (2015) found that banks that participated in the Vienna Initiative were less likely to contract credit in the region than banks that did not participate. This is particularly important because De Haas and Van Lelyveld (2014) found that around the world multinational bank subsidiaries curtailed credit growth during the crisis much more than domestic banks.

Nonetheless, Epstein (2014) argues that it was the business models of the banks themselves rather the Vienna Initiative intervention that mitigated the effects of the crisis. The foreign parent banks in the regions were committed to their longer-term objectives of maintaining market share and reputation in their "second-home" markets. Further Bonin and Louie (2105) show that the six large multinational banking groups with transition subsidiaries maintained their commitment to the region during both the global financial crisis and the Eurozone crisis.

For more than a decade, differences in banking performance among transition countries was often attributed to the beneficial presence of foreign banks. The crisis experience dispelled that notion; there was evidence that foreign ownership transmitted or magnified the crisis shock. Nevertheless, most countries in the region demonstrated a great deal of resilience in face of the crisis shock albeit with the help of the Vienna Initiative. Bonin (2010) notes that countries with and without extensive foreign ownership were affected by the crisis and argues that other factors were at work. For example, Slovenia, with little foreign ownership but serious macro-economic imbalances suffered a banking crisis.

Hungary on the other hand with extensive foreign ownership was severely affected by the crisis. In order to stem capital outflow and maintain financial sector stability, the Hungarian central bank had to raise its base lending rate by 300 basis points at the end of 2008. However, the problem in Hungary was the extent of lending in foreign currency and bank portfolios with both maturity and currency mismatch. Bank regulators probably and mistakenly assumed that foreign bank parents would absorb all risks. This is as much a failure of domestic bank supervision and poor risk management by banks. In the post-crisis period, Hungarian authorities have tried to develop macro-prudential policy tools to prevent a recurrence. A few south eastern European countries, particularly Croatia, used macro prudential tools prior to the crisis to rein in a credit boom with some limited success.[10] Poland performed well during the crisis despite extensive foreign ownership. Poland's banking system was less concentrated than elsewhere and more competitive with diverse foreign ownership and little foreign currency lending. Lending in the Ukraine declined and more recently some Russian banks have replaced risk-adverse owners from the West. Banking experience after the crisis was diverse and seems to have more to do with domestic policy and the quality of regulation than the extent of foreign ownership.

In the next section we discuss how institutional characteristics effect the banking system's ability to withstand a crisis shock. Our hypothesis is that the crisis shock increased uncertainty about lending; it should have a lesser effect when good institutional structures provide a shock absorber.

[10] A variety of interventions were used to curb types of lending or reduce capital inflows. See Dimova et al (2016).

A.4 Credit Information Systems in Transition Countries

The literature on law and finance cited earlier emphasizes the importance of legal institutions. Clearly defined property rights, contract law, a commercial code and a court systems that can adjudicate disputes fairly, quickly and without corruption are essential for a modern business economy. There are many nations around the world where many of these things are missing but they are in place in most of the transition countries partly as a result of reforms that were required to secure EU membership. The World Bank's Doing Business surveys introduced in 2003 have become a standard source for measures of the general context for business activity (see Besley (2015)). Generally, the transition countries score well on the Doing Business indicators. The average overall doing business distance to the frontier (a value of 100 representing best practices) for the 12 countries in our empirical analysis was 74.5 in 2014, only a few points below the average for OECD countries.

The two principal roles of banks are the provision of deposits used as the transactions medium and the financial intermediation by providing credit to deficit units. The ability to provide credit efficiently relies on the existence of institutions that support lending operations. For our empirical investigation, we are particularly interested in the data on credit institutions from the Doing Business Surveys.[11] There are data on the existence and functioning of both public credit registries and private credit bureaus that maintain data bases on payment history and credit outstanding for both enterprises and individuals. All of the 12 transition countries in our empirical analysis have one or the other and five have both. The existence of credit information is just the first step, it has to be available and

[11] For a description of the World Bank's methodology regarding data on getting credit see: http://www.doingbusiness.org/methodology/getting-credit.

usable to lenders.

The World Bank Doing Business reports also provide an summary index, the "Depth of Credit Information", which is based on responses to questions regarding the availability of credit information and another summary index, the "Strength of Legal Rights" which measures legal rights of lenders in regard to collateral and in bankruptcy.[12] Table 1 shows the 2008, pre-crisis, value of the indicators and also the asset-weighted market share of foreign banks for the 12 countries in our empirical analysis below.

The quality of credit information systems differs among countries. Some countries, such as Lithuania and Bulgaria, scored well on the "Depth of Credit Information" index while Latvia, Slovenia and the Ukraine have scores of zero indicating the absence of any formal credit information systems. Cross-country variation is the "Strength of Legal Rights" index, though substantial, is less pronounced. In 2008, index values range from 4 out of 10 in Slovakia to 10 out of 10 in Latvia and an overall average of approximately 7. Interestingly, the indicators are uncorrelated. The correlation between the 2008 values of two indices is 0.15. Most notably, Latvia has a weak credit registry with very little coverage and a maximal score on the "Strength of Legal Rights" index. In addition, both indices have only a weak correlation with the foreign bank share.[13] The correlation of the foreign bank asset share in 2008 with the depth of credit index is 0.21 and with the strength of legal rights index it is 0.01.

Coverage by registers and bureaus varies among those countries, which have such an institution in place. Coverage is measured as the number of entities in the database

[12]The questions in each index are found under the aforementioned link.

[13]The foreign bank lending shares were calculated by combining the "Bank Ownership Database" (see Claessens and Van Horen (2015) with Bankscope data. The highest consolidation level in Bankscope and the ownership data base were merged by index number or by name. Unmatched banks were dropped if their loans was below 1% in every year. Ownership of the others was determined from annual reports, press articles and self-descriptions on the homepages.

plus the number of credit inquiries for which there was no entry, all as a ratio to the adult population. For private credit bureaus in 2008, the coverage ranges from 3% in the Ukraine to 72% in Croatia with an overall mean of 28%. Coverage by public registers ranges 1% in Slovakia to 31% in Bulgaria with an overall mean of 4%.[14]

The credit information systems are not the only potentially relevant institutional structures in which the countries differ. We also find variation regarding the enforcement of contracts (measured by length in days required and the costs of enforcement as per cent of the claim) and the insolvency system (measured by the recovery rate and the costs of the procedure as a per cent of the estate).

We turn next to an empirical examination of the influence of these indicators on bank lending and the resilience of lending to the crisis shock.

A.5 Empirical Analysis

We use a panel data for our 12 transition countries for the period 2004-14 to examine the effects of institutional quality and the extent of foreign ownership on the volume of bank lending. The global financial crisis presents an opportunity to examine how good institutions cushion the effects of the shock. We treat the global financial crisis as an exogenous shock and examine how lending is affected during the crisis.[15] Specifically, we relate the pre-crisis characteristics of the financial sector to the strength of lending after

[14] Some of the large differences can be attributed to the scope of the register or bureau. In some countries with low values coverage is restricted to firms.

[15] The crisis originated in the US and was quickly transmitted around the world. See also Behn, Haselmann and Wachtel (2016).

the crisis shock. The regression framework for the analysis is shown by:

$$\log(\text{Loan Volume})_{i,t} = \alpha_i + \alpha_t + \delta * \text{Institution}_{i,2008} * \text{Crisis}_t + \theta * \text{Controls}_{i,t} + \epsilon_{i,t} \tag{A.1}$$

The dependent variable is the log of the volume of loans to a particular sector in current Euros in country i in year t. The coefficient of particular interest is δ, the coefficient on the interaction of the crisis indicator, Crisis_t which has a value of one post-2008 and a measure of institutional quality, $\text{Institution}_{i,2008}$, in the pre-crisis year (2008). A positive δ indicates that institutional quality cushioned the effect of the financial crisis on loan volume.

Other variables on the right hand side are fixed effects for both countries and years and macro and banking sector controls. To control for economic development, we include real GDP growth and inflation from the IMF World Economic Outlook. We control for possible effects the Vienna Initiative with a variable that reflects the influence of the policy initiative in each country. We identify the banks in each country that participated in the Vienna Initiative or are owned by a bank that participated in the Vienna Initiative. The control variable is the asset-weighted share of these "Vienna-Parent"-banks in each country.[16]

Estimates of equation (1) are in Table 2. Since the existence of asymmetric information might vary considerably between different sectors, institutions may play a very different role for different borrowers. In order to learn about this we present separate regressions for lending to households, non-financial businesses and the government sector, as well as total lending. We present results for the coverage of credit institutions and for the foreign bank share. Other measures of institutional quality did not have any significant impact.

[16] The bank asset data are from Bankscope.

Estimates use OLS and the standard errors are clustered by country.

To identify the effect of the institutional variables on lending, we use the crisis shock as a quasi-experiment. That is, we examine whether there is a differential reaction in lending in response to the shock depending on the quality of institutions, e.g. the extent of coverage of the credit register. As noted earlier, the failure of Lehman Brothers in September 2008 and the subsequent strain on the global financial system did not originate in Eastern Europe and can therefore be considered exogenous. The coefficient δ in equation (1) describes how much of the shock was absorbed by the institutional variable. Intuitively, δ describes how lending in countries with good pre-crisis institutions fared compared to countries with poor institutions.

In order to measure the effectiveness of credit institutions we apply the coverage of private credit bureaus as explanatory variable in panel A and the coverage of public credit registers in panel B. With regards to aggregate lending, we find that well-functioning credit information institutions measured as public registers are able to cushion the effects of the crisis. More specifically, once the crisis shock hit the Eastern European economies, aggregate lending decreased by 12 percent less as a response to the shock in a country where the coverage of the public credit register is by 10 percentage points higher relative to another country. When we measure the quality of credit institutions by the coverage of private credit bureaus we do not find a significant impact on aggregate lending.

Looking at the different sectors reveals a more distinct pattern. High bureau coverage increases lending to households post crisis whereas high register coverage increases lending to non-financial corporations. Reason for this asymmetric effect is possibly the different scope of bureaus and registers: bureaus tend to focus on individuals whereas registers primarily collect information on firms. We conclude that the availability of creditor information mitigated the effects of the financial crisis.

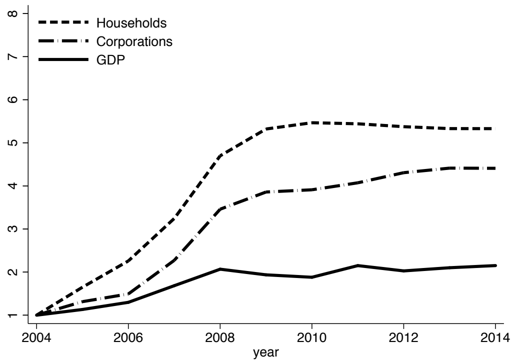
In Panel C, we look at the effect of foreign banks on the post crisis reaction. We find that the presence of foreign banks did not shield countries from the effect of the crisis. On the contrary, the negative interaction coefficients suggests that countries with a high presence of foreign banks recovered more slowly after the crisis shock.

We also test a series of other institutional measures - for example the duration of the insolvency procedure or the costs of contract enforcement - but none of these variables has a systematic influence on the post-crisis reaction of lending.

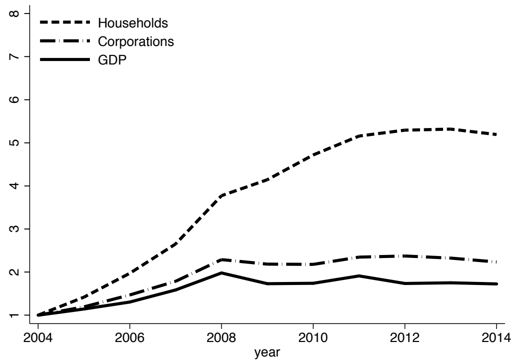
A.6 Conclusion

Early studies of transition banking starting in the late 1990s tended to emphasize the importance of foreign bank entry. The literature on the law and finance nexus was just emerging at that time and the importance of institutional development in transition banking was not appreciated at first. In addition, measurement of institutional quality is difficult and the World Bank data on specific institutional characteristics was not collected until after 2003. Economics tends to emphasize things that can be measured. Changes in ownership provided concrete data while institutional change is harder to measure. With the limited data available, our regression framework gives some broad indication of the role of institutions on lending in transition countries and shows that institutions - particularly credit institutions - can mitigate the effects of the crisis. During the global financial crisis, foreign ownership was a burden mitigated by Vienna Initiative, while good credit institutions were a cushion.

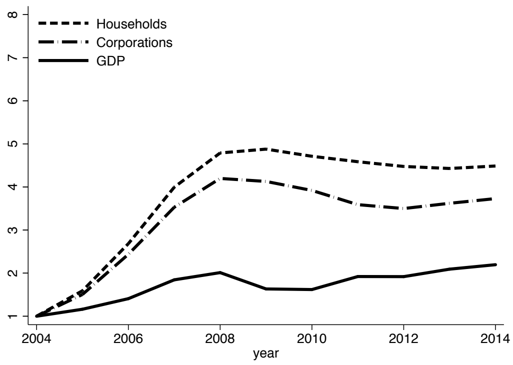
Figure A.1: Household and Business Lending and GDP, 2004-2014



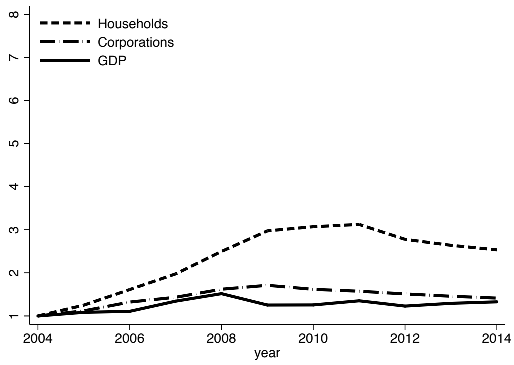
(a) Bulgaria



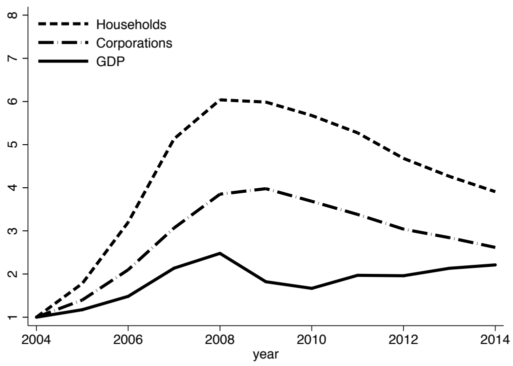
(b) Czech Republic



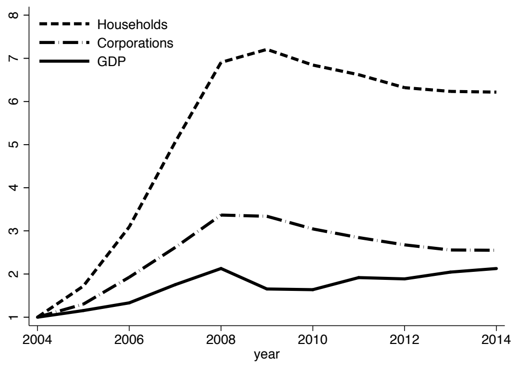
(c) Estonia



(d) Hungary

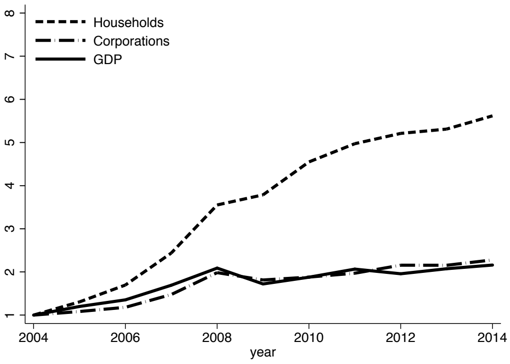


(e) Latvia

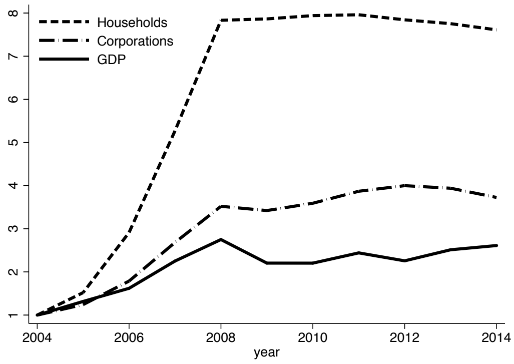


(f) Lithuania

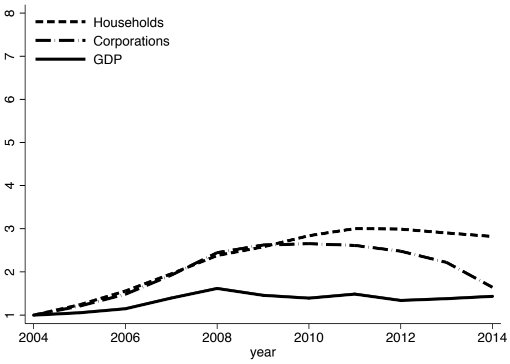
Figure A.1: Household and Business Lending and GDP, 2004-2014 - continued



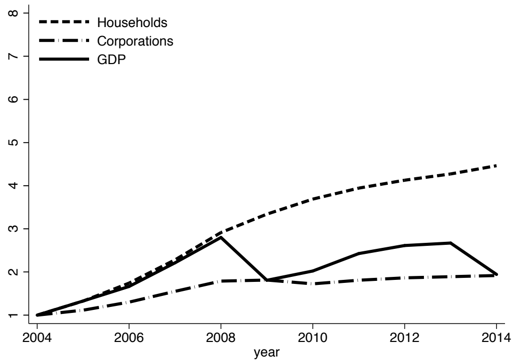
(g) Poland



(h) Romania



(i) Slovenia



(j) Ukraine

The figure depicts the development of loans to households, non-financial corporations and nominal GDP normalized to 1 in 2004. The data is from the European Central Bank (ECB) and, if not available from the ECB, from the national central banks. For non-Euro currencies, the loan volume is converted into EUR using the average exchange rate in that month. The development for Slovakia and Croatia are not shown due to limited data availability in 2004.

Table. A.1: Institutional and Bank Data in 2008

	Bulgaria	Croatia	Czech Republic	Estonia	Hungary	Latvia	Lithuania	Poland	Romania	Slovakia	Slovenia	Ukraine
Credit Information												
Depth of Credit Information Index	6	3	5	5	5	0	6	5	4	4	0	0
Credit Bureaus	5%	72%	65%	21%	10%	0%	7%	50%	25%	40%	0%	3%
Credit Registers	31%	0%	5%	0%	0%	4%	9%	0%	5%	1%	3%	0%
Strength of Legal Rights Index	9	7	6	6	7	10	5	8	9	8	4	9
Bankruptcy & Insolvency Law												
Enforcement Length (Days)	564	561	653	425	335	279	210	830	537	565	-	387
Enforcement Costs (% of Claim)	24%	14%	33%	17%	15%	16%	24%	19%	20%	26%	19%	44%
Recovery Rate	32%	30%	21%	39%	38%	35%	49%	34%	29%	45%	47%	9%
Insolvency Costs (% of Estate)	9%	15%	15%	9%	15%	13%	7%	15%	9%	18%	8%	42%
Foreign Banks												
Share of Foreign Bank	84%	91%	85%	98%	84%	66%	92%	76%	88%	99%	31%	51%
Share Vienna	41%	54%	45%	89%	40%	48%	64%	15%	56%	20%	43%	6%

The 2008 value is displayed. *Depth of Credit information*, *Coverage private bureau*, *Coverage public register*, and *Strength of Legal Rights Index* are taken from the annual Worldbank "Doing-Business" Survey. *Depth of Credit Information* is an index ranging from 0 to 8. Likewise, the *Strength of Legal Rights Index* from 0 to 12. Larger index values indicate more and deeper information on borrower in the credit register or better protection of lenders and borrowers. *Enforcement Length (Days)* is the time to resolve a dispute, counted from the moment the plaintiff files the lawsuit in court until payment. This includes both the days when actions take place and the waiting periods between. *Enforcement Costs (% of Claim)* are the cost in court fees and attorney fees, where the use of attorneys is mandatory or common, expressed as a percentage of the debt value. *Recovery Rate* calculates how many cents on the dollar secured creditors recover from an insolvent firm at the end of insolvency proceedings. *Insolvency Costs (% of Estate)* are the average cost of insolvency proceedings. *Share of Foreign Bank* is the asset-weighted market share of foreign banks. *Share Vienna* is the fraction of banks whose parents participated in the Vienna Initiative. Description of the credit information, and bankruptcy and insolvency law partly taken from the Worldbank "Doing Business" report.

Table. A.2: The Effect of Credit Information and Foreign Bank Ownership on Lending

	Panel A: Bureau Coverage			
		Loans to		
	Total	Households	Business	Government
	(1)	(2)	(3)	(4)
Crisis * Bureau	0.002	0.007***	0.002	0.000
	(0.003)	(0.002)	(0.002)	(0.011)
Observations	121	121	121	121
R-squared	0.81	0.94	0.86	0.31
	Panel B: Register Coverage			
		Loans to		
	Total	Households	Business	Government
	(1')	(2')	(3')	(4')
Crisis * Register	0.012***	0.001	0.013***	0.044***
	(0.003)	(0.003)	(0.002)	(0.008)
Observations	121	121	121	121
R-squared	0.83	0.92	0.88	0.42
	Panel C: Foreign Banks			
		Loans to		
	Total	Households	Business	Government
	(1")	(2")	(3")	(4")
Crisis * Foreign	-0.003***	-0.003***	-0.007**	-0.007**
	(0.001)	(0.001)	(0.003)	(0.003)
Observations	121	121	121	121
R-squared	0.81	0.92	0.87	0.33

The table reports δ of equation 1: $\log(\text{Loan Volume})_{i,t} = \alpha_i + \alpha_t + \delta * \text{Institution}_{i,2008} * \text{Crisis}_t + \theta * \text{Controls}_{i,t} + \epsilon_{i,t}$. Each specification includes country and year fixed effects and macro control variables (as described in the text). Loans to Businesses exclude loans to financial corporations. *Bureau* is the number of individuals and firms listed in the largest credit bureau as percentage of adult population. *Register* is the number of individuals and firms listed in the credit register as percentage of adult population. *Foreign* is the asset-weighted market share of foreign banks. *Crisis* is a post-crisis dummy which is equal to one post 2008. Standard errors are adjusted for clustering at the country level and reported in parenthesis. Note: * indicates statistical significance at the 10% level, ** at the 5% level and *** at the 1% level.

APPENDIX B

LIQUIDITY AND PRICE DISCOVERY IN THE CDS MARKET

B.1 Introduction

Credit default swaps (CDS) are one of the most successful financial innovation of the last decades. Even though the size of the CDS market nearly halved in the aftermath of the financial crisis, the global outstanding volume is still approximately one fourth of the US bond market.[1] The basic mechanism of a CDS is that of an insurance against default of an entity: If the reference entity of the CDS contract defaults, the holder of a CDS receives a payment. Therefore, a CDS can be understood as an insurance against the credit risk of a certain company. Credit risk or, put differently, the probability of default of a firm is not uniquely priced in CDS, but also in equity prices. As shown by Merton (1974a), equity can be understood as a put option on the assets with a strike price of the nominal value of debt. If the value of the firm's assets fall below the nominal value of debt - if the firm is in default - equity is wiped out. Hence, the value of equity depends on the probability of default.[2] Thereby, CDS and equity are priced based on a similar set of fundamentals of the firm. Therefore, one expects that new information about the reference entity is simultaneously priced in the CDS and equity market since otherwise arbitrage opportunities might arise. However, there is an extensive literature on the lead-lag relationship between CDS and equity returns documenting delayed pricing of new information in the CDS spreads.

Our aim is to examine whether the lead-lag relationship varies over time or across entities and how CDS liquidity and trading affects the price discovery process. In general, we expect that information is more timely priced into CDS spreads if the market is more liquid and when the trading activity is high. To this end, we merge weekly data

[1] According to the Securities Industry and Financial Markets Association, the total US outstanding bond market debt was 39,885 bn USD in the forth quarter of 2013. The gross notional of single-name CDS was 10,731 bn USD.

[2] Carr and Wu (2011) describes the strong similarities between an out-of-the-money American put option and a CDS.

of outstanding CDS volume and transactions with daily CDS and equity returns. Our sample consists of 530 entities, the observation period spans from 2011 to 2013. To assess the price discovery of CDS vis-à-vis equity, we adopt the methodology of Hilscher et al. (2013) and regress current CDS returns on lagged equity returns. Our results are in line with earlier research as far as we document an information flow from equity to CDS on an aggregate level. Looking on the entities individually, we find that the aggregate results are driven by only half of the firms in the sample. For the other half, equity returns do not predict CDS returns. In addition, we document a stark variation of the information flow not only between entities but also over time. Though liquidity and trading appears to affect the price discovery process, the effect is highly specification depended and no single variable can be pinned down that drives the process.

The remainder of the chapter is organized as follows: The second section reviews the relevant literature. Section 3 describes the the methodology and the dataset. Results are presented in section 4. The robustness of the results is tested in the fifth section. The sixth and final section concludes.

B.2 Literature

This chapter connects to three strands of literature. First, we extend the literature on the price discovery in related security markets, namely the CDS and equity market. Second, we connect to the literature on CDS trading in as far as we examine the effect of trading on price discovery. Third, we build on the extensive literature on the non-credit risk components of CDS spreads to form our hypothesis.

The literature on the lead-lag relationship finds that equity returns predominantly lead CDS returns. Notable exceptions are Acharya and Johnson (2007) and Qiu and Yu (2012), who find that information flow from CDS to equity - especially for reference entities with a high probability of default and on days with a credit events. The leadership of CDS over equity in the price discovery process is interpreted as insider trading by informed dealer banks on the CDS market, which have private information on the creditworthiness of an entity. Later studies, namely Norden and Weber (2007), Hilscher et al. (2013), Forte and Lovreta (2013), and Augustin et al. (2014), find evidence that information flow from the equity to the CDS market. Though the findings of those papers point in the same directions, the methodologies vary. Forte and Lovreta (2013) use a structural model to extract credit spreads from equity and CDS rather than using returns. Exploiting the co-integration relationship between the CDS- and equity-implied credit spreads, they employ a vector autocorrection model to calculate information shares à la Hasbrouck (1995) and Gonzalo and Granger (1995). Norden and Weber (2007), and Hilscher et al. (2013) use an approach which does not rely on structural models to extract credit spreads. Instead of credit spreads, they analyse the lead-lag relationship between equity and CDS returns in a linear regression model. Regarding the price discovery of CDS vis-Ãă-vis the bond market, the existing literature - to the best of our knowledge unanimously - find that CDS lead the price discovery (Blanco et al., 2005; Palladini and Portes, 2011; Mayordomo et al., 2014; Forte and Pena, 2009; Augustin et al., 2014). Higher standardization of CDS contracts compared to bonds is identified as main reason for the price discovery leadership.

Subrahmanyam et al. (2014), and Boehmer et al. (2015) show that the possibility of CDS trading has an impact beyond the mere introduction of a possibly redundant asset. Subrahmanyam et al. (2014) demonstrate that firms become more likely to file for bankruptcy once CDS on them become available. Boehmer et al. (2015) shows that the equity market quality - returns show a stronger autocorrelation and the price process is more noisy - deteriorates if CDS contracts on the firm are traded. A more policyorientated discussion of the impact of CDS trading and its role in the financial crisis can be found in Stulz (2010).

The literature on the drivers of the lead-lag relationship is limited. Forte and Lovreta (2013) finds some variation in the price discovery using a sample of 92 European firms from 2002-2008. In their sample, the stock market dominates the CDS market more strongly during a period of financial distress, whereas the CDS market has the same or even higher information share during tranquil times. A high CDS bid-ask spread reduces the information share of CDS . Likewise, Hilscher et al. (2013) and Augustin et al. (2014) show that the relationship between CDS and equity is stronger for entities with a higher credit rating - a finding in line with the prediction of Merton (1974a), that asserts that the sensitivity of an option to changes in the value of the underlying is increasing in the moneyness of the option. In addition, Hilscher et al. (2013) link price discovery to investor inattention. As investors have only limited attention and trade in the CDS market primarily for liquidity reasons and have little open positions, they will pay less attention to the CDS market than to the equity market. Indeed, Hilscher et al. (2013) find that around earning announcement - when CDS traders are likely to pay more attention - information are much faster incorporated into CDS spreads. Narayan et al. (2014) find that the stock market leads the CDS market, especially for investment grade firms. Furthermore, the authors document some heterogeneity between different sectors and over time using the Gonazalo-Granger information share methodology of measuring contributions to price discovery.[3] For industrials, the stock market contributes 70% of the information to the price discovery process, while the average for all firms lies around 60%. Even for the sector with the lowest contribution of the stock market, health care, the contribution of the stock market of 52,9% is higher than the contribution of the CDS

[3]See Yan and Zivot (2010) for a discussion of the differences of co-integration-based price discovery measures.

market. The results from estimating the contribution to the price discovery with sample with different market capitalization suggest, that firms with a higher market capitalization generally exhibit a higher contribution of the stock market.[4]. We extend this literature by explicitly examining differences in the price discovery process within and between entities as well as the impact of a series of CDS liquidity and trading measures.

The trading activity of CDS contracts has received only limited attention in the literature. One of the first paper examining the structure of the CDS market is Chen et al. (2011). They find that most reference entities exhibit a very low trading activity and that trading tends to be clustered in time and is possibly event-driven. We confirm the finding of Chen et al. (2011) and document a high within entity variation of CDS trading. The network structure of the CDS market is explored by Peltonen et al. (2014). First, they find that the CDS market is structured similar to the interbank market, i.e. exhibit a "small world" structure. Second, the network structure varies between entities in terms of size, activity and concentration. Oehmke and Zawadowski (2016) examine the linkage between the CDS and bond market. CDS provide an alternative trading venue for hedging and speculation in the underlying bond. This venue is more frequently used if bond market of that entity is fragmented and negative CDS-bond basis, i.e. if the CDS spread is below the bond spread. Finally, Gündüz et al. (2013) provides insights on how the order flow affects the CDS spreads. Their finding is twofold. First, they document that CDS spreads increase (decrease) if trader buy (sell) protection. Second, dealers appear to have significant pricing power as they demand higher prices from buy-side investors than from other dealer. Overall, the literature finds that the CDS market is far from being a perfect market but is rather categorized by market frictions and time-varying trading.

[4]Note that the description in the article of Narayan et al. (2014) of the size groups is not clear cut. The main body of the article suggests that lower bin number indicate a higher market capitalization, whereas the table description states that the bin labelled "Size 1" contains the "smallest sized firms, while the largest sized firms are in size 10" (Narayan et al., 2014, Page 174)

A large body of literature analyses non-credit risk components of CDS spreads. Overall, the literature is unanimous in acknowledging a substantial liquidity component in CDS spreads. Bongaerts et al. (2011) provide a model an equilibrium asset pricing which explicitly considers the over-the-counter features of the CDS market. The model is used to decompose CDS returns into credit risk, liquidity premium and other components. For CDS of all rating categories and CDS bid-ask spread levels, liquidity explains a substantial part of CDS returns. Hence, the authors conclude, CDS cannot be used as a frictionless measure of default risk. Similar to Bongaerts et al. (2011), Tang and Yan (2013) find that approximately one third of a the change in the CDS spread can be explained by supply-demand imbalance and CDS liquidity. Arakelyan and Serrano (2012) find that the number of contributors has a positive effect on CDS spreads, i.e. a CDS spread increase coincides with an increase in the number of contributors. As a superior measure of CDS illiquidity, the authors single out the number of contributors, i.e. the number of dealer banks and CDS broker that submit books which are used to calculate the CDS spread . The interaction of liquidity and spread changes are examined by Qiu and Yu (2012).They find that liquidity is generally higher if the transaction demand is higher. However, liquidity provision - measured by the number of quote providers - is reduced in the advent of a credit event. In other words, the non-credit risk component is likely to be larger in times, when one wants a clean measure of credit risk.

B.3 Data & Methodology

B.3.1 Dataset

B.3.1.1 CDS Position and Transaction data

The Depository Trust & Clearing Corporation (DTCC), a US-based clearing house, publishes the outstanding positions as well as the associated transaction data for the 1,000 entities with the highest outstanding positions on a weekly basis from October 2008 onwards. By its own account, DTCC captures 98% of the global CDS transactions. We collect DTCC data from April 2011 to December 2013. DTCC provides two measures for the market size for a reference entity: Net and gross notional amounts. The gross notional amount equals the sum of all outstanding CDS contracts. This measure is likely to be diluted by industry practices and overestimates the size of the CDS market: Often, CDS traders do not terminate a contract when they want to reduce a position but take an offsetting position. Offsetting trades bloat the gross notional amount even though they reduce the actual net CDS positions. The offsetting trades are excluded in the second measure of market size, the net notional amount. In the net notional, only contracts of net protection buyers are counted. Intuitively, the net notional amount can be understood as the maximum amount of payments which had to be made in case of credit event (Oehmke and Zawadowski, 2016). We - like Oehmke and Zawadowski (2016) - use therefore the net notional amount rather than the gross notional amount as a cleaner measure of size for the individual reference entity. All reference entities which are not among the 1000 reference entities over the entire observation period are dropped to allow for a focus on the within-entity variation.

For each entity, the DTCC provides weekly information on new trades, assignments (transfer of existing contracts to a third party), terminations of existing contracts and matured contracts.[5] In addition, to the aforementioned transaction data, the DTCC publishes data on risk transfers from August 2010 onwards. Risk transfers excludes transactions which did not result in a change in the market risk position of the market participants and are not market activity. In particular, trade compressions - aggregation of existing contracts into fewer contracts that keep the net risk position of each party unchanged - and replacements of expiring contracts does not enter the risk transfers.[6] Risk transfers include primarily new trades between two parties, termination and assignment of existing contracts. Risk transfers (*Transfer*) include therefore information which are not included in the other transaction measure since one does not know ex ante whether, e.g. a new trade was made to replace a maturing one (which would not result in a change in the risk position) or whether a market participant opened a new position. To account for the different dimension of transactions, we select two of the available transaction measures with different interpretations. First, we use risk transfers. Risk transfers can be best understood as a turnover variable which measures by how much actual risk positions changed. If no change in risk positions occurs, CDS quotes might not or only sluggishly be updated and, hence, not reflect all information as there is no need for dealer banks to adjust their spreads. Note that we do not observe whether a risk transfer results in a increase or decrease in the total outstanding risk. Our second measure, the maturing volume of CDS *Matured* is more linked to inattention than to turnover. If a CDS contract matures and the investor wants to leave his risk position unaltered, a new CDS contract must be agreed upon. Most likely, the investor and the dealer will use all available information to price the new contract, i.e. they allocate more of their scarce attention his CDS portfolio. We expect that CDS returns are more informative and reflect new information faster in

[5]A detailed explanation of the size and transaction data can be found in DTCC (2011). Before February 2013, transactions were only reported if there occurred more than 50 trades in a particular week. This restriction was dropped in February 2013 and from then on all transaction independent from the number of trading instances are reported.

[6]This procedure is similar to netting of CDS positions. But unlike to netting that weights contracts against each other, trade compression actually alters the contracts, e.g. by terminations.

periods of high risk transfers and maturing volume. To make the measures comparable across entities, we scale both, *Transfer* and *Matured* by the *Net Notional.*

B.3.1.2 CDS Spreads and liquidity measures

We match the DTCC data with CDS spreads and liquidity variables from Markit, a financial service provider primarily owned by dealer banks. Markit is widely used by CDS market participants and academia, because its data is considered to be of higher quality than data of alternative providers (Qiu and Yu, 2012; Mayordomo et al., 2014). CDS spreads are available for different tenors, seniorities and restructuring clauses.[7] In our study, we use the five year tenor of senior, unsecured debt since it is the most liquid tenor-seniority combination (Chen et al., 2011). Concerning the restructuring clause, we use the "no restructuring" clause" (XR) for US entities, the "modified-modified restructuring" (MM) clause for European entities and the "full restructuring" (CR) clause for entities in Asia, Australia and New Zealand.[8] Note that the CDS spreads provided by Markit are quoted spreads rather than transaction prices. CDS returns CDS are calculate as the difference in the natural logarithm of the spread. Positive returns an increase in the spread and thereby in the market perception of the default risk of the entity.

From April 2011 onwards, Markit provides four daily liquidity measures: the number of quotes, the number of active dealer, composite depth and the bid-ask spread. To make the CDS bid-ask spread (*CDS BAS*) comparable across entities, we normalized the absolute bid-ask spread by the CDS spread.[9] In an over-the-counter market, high bid-ask spreads could have several reasons. First, the bid-ask spread could be driven by high

[7] The restructuring clause of a CDS contract defines which events - e.g. actual default, delayed payments or restructuring of debt - constitute a default and thereby trigger a payment.

[8] Our choice corresponds to regional preferences of Thompson Reuters Datastream. Likewise, Slive et al. (2013) use the "no restructuring" clause for US Dollar contracts and "modified-modified" for contracts denominated in Euro.

[9] Markit actual provides longer time series but they are not available in the database of the Bundesbank.

inventory costs. Since - as Chen et al. (2011) pointed out - dealer tend not to hedge new CD positions immediately, a high bid-ask spread could be used to compensate dealers for high inventory costs. Second, dealer could set high bid-ask spreads to deter informed trader à la Acharya and Johnson (2007). In either case, a high bid-ask spread makes timely pricing of new information in CDS spreads less likely.

Quotes count *(QC)* is the number of unique quotes for an entity at a given day. A quote is defined as a different bid and/or ask value from the same source within the same hour, or a same bid and ask value from the same source within different hours. A new quotes signals the arrival of new information. Therefore, a high frequency of quotes indicates that the dealers rapidly react to new information and adjust their quotes to avoid arbitrage strategies. A low frequency of quotes could be explained by high transactions costs which prevent arbitrage strategies and thereby the demand for CDS contracts in the first place. Overall, we expect that observations with a higher number of quotes exhibit a lower information flow from equity to CDS.[10]

The dealers count *(DC)* is the number of distinct dealer making a quote for an entity at a given day. We use dealers count as a measure of market distortion due to limited competition and overall liquidity provision. One would expect that a higher competition between dealers fosters timely pricing of new information in the CDS market. Several mechanism are conceivable. Under higher competition dealer might be forced to reduce bid-ask spreads and attract more traders to the CDS market. Alternatively, dealer - which are in most cases large banks - might have private information and use these information to price CDS (Acharya and Johnson, 2007; Qiu and Yu, 2012). Both described channels have the same implication: the higher the number of dealers, the lower is the informational dominance of the equity market compared to the CDS market.

[10]Note that quotes are not binding. Commonly, they only serve as a starting point for negotiations for transaction prices (Biswas et al., 2014).

Composite depth *(Depth)* is the number of the of contributors whose books of record are used to calculate the five year price (Markit,2014). Contributors could not only be dealer but also non-dealer investment banks or CDS broker (Qiu and Yu, 2012). The number of contributors is higher for a) larger firms and firms with a larger stock turnover, b) firms just at the cut-off between investment- and speculative-grade and c) firms with more banking relationships (Qiu and Yu, 2012). Intuitively, the higher number of contributors for reasons a) and b) can be attributed to a higher hedging demand and uninformed trading. If a company has many bank relationships, many banks - potential dealers - have private information about the firm and might use them to price CDS. Thereby, CDS might reflective information more timely than equity (Acharya and Johnson, 2007; Qiu and Yu, 2012).

B.3.1.3 Stock data and control variables

In addition to the firm-specific variables, we collect data on the VIX from the FRED database of the Federal Reserve Bank of St Louis. The VIX, which equals the VIX is the three-month implied volatility of S&P500 index options, is a common measure for the market volatility and risk aversion. If - as Chen et al. (2011) suggests - dealers do not hedge their CDS positions immediately, they are exposed to inventory risk. The inventory risk is likely to be larger in times of high market volatility and dealers might be deterred from writing new CDS contracts or might set high bid-ask spreads. We therefore expect that more information flows from the equity market to the CDS market during periods of high market volatility. To control further for risk aversion and risk perception, we add the spread between Moody's seasoned Baa corporate Bond yield and the seasoned Aaa corporate bond yield to our sample.

Share prices are obtained from Datastream. Again, returns are calculated as th the difference in the natural logarithm of the stock price.[11] A positive equity returns signals an increase in the stock price and a decrease in the default risk of the firm.

B.3.1.4 Descriptives statistics

The final dataset includes 530 different reference entities. The observation period stretches from April 2011 to December 2013 with a maximum of 713 trading days per reference entity. For each entity, we have a minimum of 240 daily observations. As per 27th December 2013, the sample covers 50 % of the entire net notional amount reported by the DTCC. Financials (21.5 %), consumer good (16%) and consumer services (15%) are the most common sectors in the sample. Approximately 52 % of the reference entities are located in the Americas, 33% in Europe. The average firm in our sample has total assets of 1,850 m USD million and a book value of equity of 517 m USD.

On average, the *Net Notional* amount of a reference entity is slightly above 1,000 m USD, i.e. above the average book value of the liabilities. The standard deviation is high and observed net notional ranges from 54 to 12,723 m USD. Absolute risk transfer amounts on average to 130 m USD. To make this measure of turnover comparable across entities, we scale the absolute transfers by the size of the CDS market for that entity. Relative to the size of the CDS market, the risk transfer amounts to just above 13% of the net notional. Risk transfers, on average, are larger than the matured volume. Roughly 11% of the *Net Notional* or, in absolute terms, 91 USD million mature each week.

The average *CDS spread* with the regional preferred restructuring clause is 182 basis points. Figure A.4 depicts the development of the average CDS spread and key liquidity and trading measures over time. The average CDS spread lies around 150 basis points in April 2011, increases to nearly 250 in late 2011 and than slowly decreases over time

[11] To exclude outliers, we winsorize CDS and equity returns at 0.1% level.

to roughly 130 in late 2013. In terms of implied default probabilities, a CDS spread of 180 basis point corresponds - assuming a recovery rate of 40% - to an annualized default probability of 2.9%.

The contemporaneous correlation between CDS returns is - as expected - negative (-0.28) as a positive CDS return signals an increase in the credit risk but a positive equity return a decrease in the default risk. Both, equity and CDS returns, are autocorrelated though the pattern is more pronounced for CDS returns (See Figure A.1). The correlation coefficients between the contemporaneous equity and CDS return with the first lag are 0.03 and 0.12, respectively. Figure A.2 depicts the cross-correlation of equity and CDS returns. The correlation of contemporaneous CDS returns with past equity returns is stronger than vice versa. The correlation coefficient of the contemporaneous equity returns and past CDS returns drops to zero for the first lag.

Looking at the liquidity measure of the CDS market, we find that approximately six out from a maximum of 15 dealers are active and 35 quotes are made for five year senior CDS contracts.[12] On average, the CDS spread was calculated based on books from more than six contributors. The bid-ask spread of CDS, normalised by the spread, is above 50%, whereas the bid-ask spread for equity, normalised by the price, amounts to 0.2%.[13]

Liquidities measures do not show a consistent pattern over time (See Figure A.4). Some measures indicate an increasing liquidity over time, for example the composite depth, whereas, *inter alia*, a decreasing dealers count hints towards a decrease in liquidity. The composite depth rises from below five to approximately 6.5 in late 2011 and stays at this level for the rest of the observation period. Contrary, the average dealers count

[12] As per June 2011, DTCC lists 17 clearing dealer: Bank of America Merrill Lynch, Barclays, BNP Paribas, Clayon, Citigroup, Credit Suisse, Deutsche Bank, Goldman, Sachs, HSBC, JPMorgan Chase, Morgan Stanley, Natixis, Nomura, Royal Bank of Scotland, Société Générale, UBS, and UniCredit.

[13] We conservatively remove bid and ask prices which have been incorrectly reported. In most of those cases, the decimal was wrongly placed.

decreases from eight to six at a steady rate. Though visually the quotes count appears to be highly correlated with the dealers count, it follows a distinct path. The average drops from around 40 to 25 in early 2012 and then recovers to 40 in late 2013. The CDS Bid-Ask Spread, normalised by the CDS spread, rises from around 40% to more than 55% of the CDS spread (dashed line in Figure A.4, Panel (d)). Since we used a normalised bid-ask spread, the results could be driven by the changes in the CDS spread. Indeed, the unscaled CDS bid-ask spreads displays a different pattern: it jumps in 2011 from 50 basis point to over 90. Afterwards it gradually decreases to 55 basis points (solid line in Figure A.4, Panel (d)). Risk transfers relative to the *Net Notional* are relatively flat over the sample period.

Overall, the liquidity and trading characteristics vary significantly between the entities and over time. Though the variation of liquidity measures is primarily driven by between-entity variation, there is a substantial within-entity variation. In Table B.2, I show the decomposition of the overall standard deviation in between entity and within entity variation. For the composite depth, the CDS bid-ask spread, dealers count, and quotes count, the within-entity variation lies between 60% and 85% of the between entity-variation. For risk transfers, both absolute and relative, the within-entity is larger than the between-entity variation. To visualise the between-entity variation, Figure A.3 plots the distribution of the averages of selected liquidity variables over the entities. Eye-balling suggests stark differences between entities. In particular, a few entities exhibit a much larger *net notional* and number of quotes then the average entity does. For risk transfers and composite depth, the distribution is more even but range of values is still substantial.

As expected, the liquidity and trading measures are correlated. Table B.3 shows the pairwise correlation coefficients for the different liquidity and trading measures. Regarding the sign, the correlation coefficients are generally in line with expectations. The positive correlation coefficients between *Depth*, *DC*, and *QC* and the negative correlations coefficient of those variables with both versions of the *BAS CDS* suggest, that all liquidity measures point in the same direction. However, none but one of the correlation coefficients exceed 0.5 in absolute terms. This suggest that though the liquidity measures point in the same directions, they capture information not contained in other variables.[14] Note that even though the dealers count and composite depth appear quantitatively similar in absolute numbers, the correlation between the measures is relatively low with approximately 0.3. A higher *net notional* and higher risk transfers are generally associated with with a more liquid CDS market. The matured volume is only weakly correlated with the other variables. This weak correlation was expected as the maturity of a contract is pre-defined in the contract and therefore exogenous to current market conditions.

B.3.2 Methodology

To assess the predictability of returns, we adopt the methodology used by Hilscher et al. (2013) and regress contemporary CDS returns on past equity returns. The main regression equation reads as follows:

$$Ret_{i,t}^{CDS} = \alpha_i + \sum_{j=1}^{J} \beta_j \times Ret_{i,t-j}^{Eq} + \gamma \times Ret_{i,t-1}^{CDS} + \epsilon_{i,t} \tag{B.1}$$

$Ret_{i,t}^{\mathrm{CDS}}$ and $Ret_{i,t}^{\mathrm{Eq}}$ are the CDS and equity returns of firm i at time t, respectively. The intercept (α_i) is allowed to vary at the reference entity level. For our main results, we use the first ten lags of equity returns, i.e. $J = 10$, to predict contemporaneous CDS returns. If information is compounded simultaneously in the CDS and equity market, the lagged equity returns should not explain current CDS returns, i.e. $\beta_j = 0 \forall j > 0$.

[14] A more formal analysis of the interaction of different liquidity measures, particularly the CDS bid-ask spread, the dealer count and Wojtowicz (2014)

Results for different lag structures are provided as robustness checks. The lagged CDS returns is included to account for autocorrelation. Like Hilscher et al. (2013), we cluster the standard errors by date. I refer to the sum of the coefficient of lagged equity returns as cumulative effect of equity on CDS in the remainder of the chapter.

To explore the effect of CDS liquidity and trading, I estimate Equation B.1 for a number of different samples. First, we pool all observations and obtain a single vector of β_j for the full sample to obtain baseline results, which are comparable to those of Hilscher et al. (2013). Then, to elicit effects of liquidity and trading, we sort the observations into subsamples based on liquidity and trading measures. The subsample are generated by sorting the daily observations of each entity into five quintiles according to their liquidity and trading activity.[15] Higher quintile numbers indicate higher values of the split variable. For example, liquidity quintile 1 contains the days with lowest 20% of the observation of each entity. Note that, since the sorting takes place on the entity level, absolute values in higher quantile can actually be lower than values in lower quintiles on an aggregate level. These regressions by quintile serve as a preliminary test for - possible non-linear - effects of CDS liquidity and trading on price discovery. Second, we allow the coefficients to vary on a entity level by estimating Equation B.1 for each entity individually. By doing so, we get a sequence of β_j from Equation B.1 for each entity and can analyse how between entity differences in β_j can be explained by average CDS liquidity and trading. We refer to results obtained from those sample as "entity-level results". Third, we allow the coefficients to vary not only between entities but also over time. Time-varying coefficient are obtained by splitting the observation period in sub-periods of 120 trading days. By shifting the estimation window by 20 trading days - roughly on trading month - in each

[15]By sorting the observation on the entity level, we look at the effect of within entity variation in liquidity and trading. We also try sorting in the full sample rather than on the entity level as well as sorting into a different number of quantiles but the qualitative implications are unaffected.

step, we obtain a maximum of 33 sub-periods per reference entity.[16] As highlighted in the previous section, liquidity and trading does not only vary between entities but also strongly over time. By using different estimation windows for a entity, we obtained a number of β_j, t for each entity and are now able to examine how they co-move with liquidity and trading variables.

To assess the variation in the price discovery between entities and over time, we quantify deviations from our expectation that equity returns do not explain current CDS returns. We code two variables. First, the variable *Significance* indicates whether past equity returns actually exercise a significant influence on contemporaneous equity returns. *Significance* is coded as a dummy and takes the value one if the hypothesis that the sum of the coefficient of the lagged returns is equal to zero is rejected at the 10% level. Formally, we test the null hypothesis $\sum_{j=1}^{J} \beta_j = 0$ against the alternative $\sum_{j=1}^{J} \beta_j \neq 0$.

Second, we quantify the deviation from the expectation by summing up the coefficients of past equity returns. Since one expects a negative correlation between equity and CDS returns, we multiply the coefficient with minus one to make magnitude more readily interpretable: A larger cumulative effect can be interpreted as a stronger impact of past equity returns on CDS returns. If the sum of the coefficient is against the expectations larger than zero, we set the cumulative effect to zero. Formally, the magnitude is calculated as $Magnitude = \max\left[0, -\sum_{j=1}^{J} \beta_j\right]$. Though *Magnitude* has no ready or intuitive interpretation, we interpret a larger *Magnitude* as an indicator for a stronger information flow from equity to CDS as the deviation from the null hypothesis of $\sum_{j=1}^{J} \beta_j = 0$ is larger.

To evaluate the determinants of our two measures of price discovery, we regress both,

[16] We also try non-overlapping estimation window. Our main results are not affected by the choice of overlapping estimation windows. If anything, the results for the overlapping windows are weaker.

Significance and *Magnitude*, on a series of liquidity and trading measures. For *Significance*, we estimate a probit model of the following form:

$$P(\mathit{Significance}_{i,t} = 1) = \Phi\left(\alpha + \delta \times \mathit{liquidity}_{i,t} + \mu \times \mathit{trading}_{i,t} + \kappa \times \mathit{Significance}_{i,t-1} + \epsilon_{i,t}\right) \tag{B.2}$$

where $liquidity_{i,t}$ and $trading_{i,t}$ are vectors with the liquidity and trading measures. For each variables in those vectors, we first estimate a univariate regression and, second, the multivariate regression with all variables in $liquidity_{i,t}$ and $trading_{i,t}$. Equation B.2 is adapted to the different samples as follows. For the entity level regressions, the time subscripts are dropped and the intercept does not vary between entities. Explanatory variables are average over the different estimation periods: For the entity level regressions, the average over the entire sample period is taken; for the rolling sample, the variables are average only over the estimation window of 120 days. To control for the macroeconomic environment, we add the aforementioned control variables - the VIX and the credit risk spread - to all regression based on the rolling sample. $\mathit{Significance}_{i,t-1}$ is included to control for autocorrelation in the dependent variable that occurs by design in this setup.

In a similar fashion, we regress *Magnitude* on the same set of variables. As for *Significance*, we show the regression equation for the rolling sample setup. The equation on an entity level, the intercept does not vary between entities and the time subscripts are dropped.

$$\mathit{Magnitude}_{i,t} = \alpha + \delta_i \times \mathit{liquidity}_{i,t} + \mu_i * \times \mathit{trading}_{i,t} + \kappa \times \mathit{Magnitude}_{i,t-1} + \epsilon_{i,t} \tag{B.3}$$

where $liquidity_{i,t}$ and $trading_{i,t}$ are same vectors of the liquidity and trading measures as in the probit specification. For the rolling estimation window, we also use different combinations of window and entity fixed effects to account for unobservable effects and shift the focus of the regression on the within-entity variation. As the series of the magnitudes for each entity is autocorrelated by design, we include $Magnitude_{i,t-1}$ to control for this autocorrelation. Heteroscedasticity-consistent standard errors are used. Again, we include the VIX and the credit risk spread as control variables in each specification that does not include window fixed effects.

Finally, we examine the fractional response to assess the speed with which CDS spreads react to new information (Hilscher et al., 2013). The fractional response is defined as the share of the CDS return at time t relative to the sum of returns from t to t+10. Formally, the fractional is defined as: $Fractional\ Response_{i,t} = \frac{Return^{CDS}_{i,t}}{\sum_{s=t}^{t+10} Return^{CDS}_{i,s}}$. To ensure that the fractional response takes only values between zero and one, the fractional response takes the value of 1 if the return at time t is larger than the sum of returns from t to t+10. If the return at time t has the opposite sign as the sum of returns from t to t+10, the fractional response takes the value of 0. Intuitively, the fractional response describes the speed with which new informations are incorporated in CDS spread. A high fractional responds hints towards fast incorporation of new information, a low fractional response towards a more sluggish adjustment. Since the fractional response is bounded between zero and one, we are able to use the following linear probability model:

$$Fractional\ Response_{i,t} = \Phi\left(\alpha_i + \delta_i \times liquidity_{i,t} + \mu_i * \times trading_{i,t} + \epsilon_{i,t}\right) \tag{B.4}$$

Again, we subsequently add different sets of entity and week fixed effects to focus on within entity variation rather than across entity differences. However, using fixed effects in a non-linear model might lead to biased estimators due to the incidental parameter problem. However, as the bias is most pronounced in short panels with firm fixed effects, the bias should not be serious in our setup. Nevertheless, the results should treated with care. Standard errors are clustered at the entity level. Unlike the first approach, the fractional response measure does not assess the speed of information vis-à-vis a related security market but rather examines whether CDS exhibit some sort of "momentum" or pronounced autocorrelation in the return pattern.

B.4 Results

B.4.1 Pooled Results

Table B.4 holds our baseline results of Equation B.1. Past equity returns do have predictive power for contemporary CDS returns. Vice versa, CDS returns have only very limited predictive power for contemporary CDS returns. The overall, untransformed cumulative effect of past equity returns is -0.390 and 0.068 for past CDS returns. The qualitative implications do not change if fewer lagged returns are taken into account: If only the first five lags are considered, the effect for past equity returns is -0.31, for lagged CDS returns the effect is 0.097. In other words, the first five lags account for roughly 80% of the cumulative effects - $\sum_{j=1}^{J} \beta_j$ in Equation B.1 - and the last 5 lags account for the remaining 20% of the cumulative effect of equity on CDS. Quantitatively, these estimates for the full sample are very similar to those of Hilscher et al. (2013).

Table B.5 provides first insights in the impact of liquidity and trading on the price discovery process. We estimate Equation B.1 for subsamples with different liquidity quantiles. Equity returns exercises a stronger influence on CDS returns for entities for observations for the low liquidity quantiles. For instances, the observations with in the lowest liquidity percentile of the CDS bid-ask spread exhibit a cumulative effect of 0.350 whereas the entities of the highest percentile 0.241. We also find strong differences for the composite depth: The observation in the percentile with the highest composite depth, the cumulative effect amounts to -0.428 compared to -0.390 of the full sample. This patterns of increased information value of equity returns can be found for all trading measures. Those differences suggest - against our predictions - that past equity is more informative in times of high liquidity. The cumulative effect does not exhibit a switching behaviour in the sense that the cumulative effect tends to be either or increasing or decreasing in the liquidity and trading quintiles.

The different sequences of β_j for high and low liquidity quintiles are visualised in Figure A.5. In each panel, we plot the cumulative effect for the high and low liquidity quintile of the specified variable individually. For most variables, the difference in the β_j's is persistent in the sense that the difference between the β_j of the first lagged equity return is preserved over the 10 lag horizon and in most cases the difference in increasing in the number of lag. Notable exceptions are the dealer count and the bid-ask spread. For the dealer count, the difference in β_j is small and the cumulative effect of the high liquidity percentile is sometimes larger and sometimes smaller than that of the low liquidity percentile. For the bid-ask spread, this pattern is even more pronounced. From the plots, we conclude that - though the differences are existent from lag one onwards - that a certain number of lags in needed to generate consistent differences between the high and low liquidity and trading percentiles.

Since the number of dealers and contributors is very small - recall that for single entity there are never more than 15 active dealers and more than 12 contributors per day - the marginal dealer or contributor might bring valuable and noticeable information to the CDS market. To elicit the effect of the marginal dealer and contributors, we estimate Equation B.1 separately for days on which a dealer/contributor left or entered the market. Figure A.6, Panel A depicts the cumulative effect of equity on CDS for the days on which an additional dealer (dashed line) or an additional contributor (dotted line). An additional dealer does no effect on the magnitude of the effect of equity on CDS. Two explanations are possible. Either the additional dealer does not bring new information to the market or our estimation is biased. Since we do not know whether the dealer at time t-1 and t are the same, we cannot exclude the possibility that a dealer leaves the market at the same time as a new dealer arrives. In this case, a dealer with new information enters the market, but our aggregate measure indicate no change. Unexpectedly, an increase in the number of contributors increases the predictability of CDS returns by equity returns. A possible explanation by hedging behaviour by traders (Qiu and Yu, 2012): CDS Traders observe changes in the equity market and want to adjust their CDS portfolio. Thereby, the increased hedging demand leads to a higher composite depth but also to a delayed response in the CDS spread relative to stock prices. An second explanation is more technical: The entry of a new contributor is associated with a larger return in absolute terms.[17] Assuming a constant variance of stock returns, the coefficients should be larger values if the dependent variable can take larger values and the variance of the independent variables remains unchanged. Finally, I examine whether the model works differently for positive and negative CDS returns. Indeed, Panel B of Figure A.6 reveals that higher lags of equity returns have an impact for positive CDS returns, i.e. increases in the default risk but virtually none for negative CDS returns, i.e. decreases in default risk. One possible explanation for this finding is that CDS traders make use of negative stock market information, but do not price positive information from the stock market in the CDS spreads. Again, this suggests that the leadership of in the price discovery process is more nuanced than suggested by the baseline results in Table B.4.

As described above, we run the regression in a rolling estimation window of 120 trading days. Figure A.7 depict the evolution of the cumulative effect of past equity returns on CDS returns over time. At the beginning of the sample period, the magnitude is around

[17] I test this hypothesis in an ordered logistic regression model with quantiles of the absolute returns as dependent and the number of contributors as dependent variable. The coefficient of the composite depth is positive suggesting that a higher number of contributors leads to larger, absolute returns

0.4, rises to 0.7 and then dwindles to almost zero in late 2012. In 2013, the the magnitudes fluctuates around the mean of 0.28. To avoid possible biased due to overlapping estimation windows, we also estimate the cumulative effect for non-overlapping estimation windows (dashed line in Figure A.7). The results are virtually unchanged. We conclude that the relationship between equity and CDS returns does not only vary between entities - as discovered by the sample splits - but also over time.

B.4.2 Entity Level

To analyse cross-sectional differences between the entities, we estimate Equation B.1 individually for each reference entity. Only for roughly 54% of the 530 entities, the past equity returns exercise a statistically significant influence on the contemporary CDS returns at the 10% level. In other words, the pooled results of the previous section appear to be driven by approximately half the sample whereas the remaining half does not exhibit a robust pattern between CDS and lagged equity returns.

Table B.6 reveals the drivers of the differences in *Significance* in the first two columns. Column 1 holds the results for the univariate regressions. High CDS bid-ask spreads reduce the likelihood that equity leads CDS. This can be viewed as confirmation of our hypothesis that high bid-ask spreads reduce arbitrage opportunities and therefore the incentive to quickly adjust CDS spreads and stock prices to new information priced in the other security. The coefficients of the size and trading activity proxies generally suggest, that equity is less likely to lead CDS if the outstanding amount is large and trading activity is high. Against the expectation, a higher dealer of quotes count does not decrease the probability that equity leads CDS returns in the univariate regressions. Finally, we examine how the variance of stock and CDS returns affect the relationship. For firms with a high (low) standard deviation in CDS (equity) returns, past equity returns are less likely to lead CDS returns. In the multivariate regression (column 2), most regressors - with the exception of the bid-ask spread, the quotes count, relative transfers, the absolute matured volume and the standard deviations of returns - lose their significance.

As for the *Significance*, we find substantial heterogeneity of the magnitude between the entities. Figure A.8 depicts the distribution of the effect over the entities. The cumulative effect of equity on CDS ranges from zero to 1.5. In Panel (b) of A.8, the distribution of the cumulative effect of CDS on equity is plotted. As for the full sample, the information flow in this direction is smaller in magnitude and is often - against the expectation - positive. We run all our estimations also for an information flow from CDS to equity but without meaningful results. Therefore, and for the the sake of conciseness and clarity, we do not report the results for the flow from CDS to equity. Columns 3 and 4 of Table B.6 examines the determinants of the magnitude. The results are inconclusive. In the univariate regressions, higher CDS spreads increase the size of the coefficient of past returns. As for size and trading activity, the magnitude is lower for entities with a high volume of outstanding CDS contracts but higher for entities with a more active market, i.e. high relative transfers and maturing volume. Again, the standard deviations exercise a strong effect on the magnitude suggesting a partly mechanical relationship as described above.

Overall, the regressions on the entity level suggest that liquidity and trading activity does matter for the price discovery process though the results are not always in line with expectations. This is not entirely surprising since the regressors show substantial within entity variation - as shown in Table B.2 - that is not captured in this specification, which uses averages of the liquidity and trading variables over the entire sample period.

B.4.3 Rolling Estimation Window

In the two previous section, we documented a substantial heterogeneity both, between entities and over time. In this section, we focus on within-entity heterogeneity. As outlined in section B.3.2, we estimate Equation B.1 for each entity in rolling, overlapping estimation windows.

Out of the 14,044 observations of $Significance_{i,t}$, only 31.9% are actually significant at the 10% level. The lower percentage is not surprising given the already low number of entities which exhibit a statically significant relationship in the first place and the reduced number of observations per regression compared to the entity level, that should increase the variance mechanically. For virtually all of the entities (492 out of 530), $Significance_{i,t}$ takes a value for some of the rolling estimation window. For 486 of the entities, $Significance_{i,t}$ changes its value at least once from estimation window to estimation window. On an aggregate level, the fraction of entities for which $Significance_{i,t} = 1$ is highest at the beginning of the observation period in mid-2011 with around 40 percent. Afterwards, the fraction drops to roughly 25% and remains stable afterwards.

Table B.7 sheds light on the determinants of $Significance_{i,t}$. Equity returns are more likely to lead CDS returns in periods of high liquidity - measured by the bid-ask spread and the dealer and quotes count - and high relative transfers, a high CDS spread and high relative transfers. However, in the multivariate specification, none of the variables remains significant. Recall that each of the regressions includes the lagged value of $Significance_{i,t}$, standard deviations of equity and CDS returns and the aforementioned market variables as controls.

Columns 3-8 of Table B.7 holds the results for the magnitude regressions for various sets of fixed effects. In the specification without firm and window fixed effects, only the composite depth exercises a consistent and - as expected - negative effect on the magnitude. The quotes count and the matured volume are marginally significant at the 10%-level, but only in the univariate specification. Adding firm fixed effects - and thereby accounting for time-invariant firm unobservables - renders the dealers count and *Net Notional* insignificant. However, the positive sign of the dealers count suggests that more information flow from the CDS to the equity market if the CDS market is more dealers are active. The negative sign of *Net Notional* is in line with the expectations and suggests a reduced information flow from equity to CDS in periods of a relatively large CDS market. Adding window fixed effects, alters the picture to an extent (columns 7 and 8 of Table B.7): The dealer count remains significant but the *net notional* is no different from zero at any conventional level of significance. Instead, the relative risk transfers exercise a positive effect on the magnitude. Again, this finding is in contradiction to our expectations as it suggests a higher information flow from equity to CDS if the trading activity on the CDS market is higher. [18]

B.4.4 Fractional Response

The results for the fractional response are shown in Table B.8. Recall that we expect a positive sign for all liquidity and trading measures except the CDS bid-ask spread. For the set of liquidity measures, the results are in line with this expectation though the bid-ask spread is not significant in the baseline specification without any fixed effect. For the trading and size measures, the results are less clear cut. Market size (*net notional*) and relative transfers exhibit a positive sign. Contrary, absolute risk transfers as well as absolute and relative maturing volume reduce the speed with which information are incorporated in CDS spreads. Again, most variables do not remain significant in the

[18] A likely explanation for the stark impact of the window fixed effects is the decreasing time trend in the *Net Notional*. The risk transfers remain fairly stable over the observation period.

multivariate specification. Adding entity fixed effects (columns 3 and 4) to the makes the coefficients larger but do not make signs flip. Adding week fixed effects renders both, absolute and relative maturing volume as well as relative transfers insignificant.

Overall, the analysis of the fractional response suggests that liquidity - all measures except the bid-ask spread - the absolute size, and relative transfers increase the speed with which information are incorporated in CDS spreads.

B.5 Robustness Tests

In our analysis, we made assumptions - for example on the number of lags or the specifications of our prediction Equation B.1 - which might drive our results. This section provides a number of robustness test. First, we vary some modelling assumptions and check whether those changes alter the results. Second, we compare our results qualitatively to those of Qiu and Yu (2012), who propose a methodology that allows to identify effects of liquidity and trading that does not rely on sample splits or varying estimation windows.

B.5.1 Vector Autoregressive Model

Instead of including only the first lag of CDS returns for the prediction of CDS and equity returns in equation B.1, one can estimate the cumulative effect in a full-blown Vector Autoregressive Model (VAR) specification. We estimate the following system:

$$\begin{aligned} \mathrm{Ret}_{i,t}^{CDS} &= \alpha_{CDS} + \sum_{i=1}^{10} \beta_{CDS,i}^{CDS} \mathrm{Ret}_{i,t-i}^{CDS} + \sum_{i=1}^{10} \beta_{Eq,i}^{CDS} \mathrm{Ret}_{i,t-i}^{Eq} + \epsilon_{i,t}^{CDS} \\ \mathrm{Ret}_{i,t}^{Eq} &= \alpha_{Eq} + \sum_{i=1}^{10} \beta_{Eq,i}^{Eq} \mathrm{Ret}_{i,t-i}^{Eq} + \sum_{i=1}^{10} \beta_{CDS,i}^{Eq} \mathrm{Ret}_{i,t-i}^{CDS} + \epsilon_{i,t}^{Eq} \end{aligned} \tag{B.5}$$

The estimation is carried out on the entity level and for the rolling estimation windows. Analogous to the definitions above, we generate the variables *Significance* and *Magnitude*. *Significance* takes the value of one, if the hypothesis $\sum_{i=1}^{10} \beta_{Eq,i}^{CDS} = 0$ is rejected at the 10% level and zero otherwise. *Magnitude* is defined as $max(0, -\sum_{i=1}^{10} \beta_{Eq,i}^{CDS})$.

Generally, the VAR model suggests a lower number of significant relationships. Only for 229, instead of 256, entities, equity returns predict CDS returns at the 10% level. As on the entity level, we observe a drop in the number of significant observations from 4,475 to 3,955. The *magnitudes* generated by the VAR specification are similar to those of our main specification for the information flow from equity to CDS (rank-correlation of 0.79). For the rolling estimation window, the rank correlation of *Significance* is 0.72.

To check whether the determinants of price discovery are dependent on the modelling assumptions in Equation B.1, we regress *Significance* and *Magnitude* generated by the VAR model on our liquidity and trading measure. Tables B.9 and B.10 present the results for the entity level and rolling window regressions. The estimated coefficients for the entity-level sample are partly different (especially for the relative transfers and relative maturing volume), but the general picture of the determinants fo the price discovery process does not change. For the rolling sample, the VAR approach yields even less significant regressors.

B.5.2 Different Lag Structure

The choice of ten lags in Equation B.1 is to an extend arbitrary. As much of the cumulative effects occurs in the first five lags, we run all regressions with five instead ten lags. The results of the five-lag specification are similar to our main findings. Regarding *Significance*, the five-lag specification suggests a higher number of significant relationships. On the entity level, past equity returns predict contemporaneous CDS returns in 300 instead of 256 out of a possible 530 cases. A high rank-correlation of 0.76 indicates, that the magnitudes generated by the VAR model are similar to the magnitudes of our main specification. For the rolling estimation window, the rank correlation for *Significance* is 0.58 and the number of significant observations drops from 4,475 to 3,821.

Table B.11 and B.12 examines the determinants of price discovery for the 5-lag specification. For significance at the entity level, keeping only the first five lags makes all trading and size variables insignificant whereas they remain similar for the magnitude regressions. A similar pattern can be detected for the rolling estimation window with the notable exception that relative transfers are no longer significant but the maturing volume is. As in the VAR specification, none of the variables exercises a significant, consistent influence on the magnitude of the information flow.

B.5.3 Qiu & Yu Methodology

Qiu and Yu (2012) examine the price discovery process amid worsening credit conditions. The effect of worsening credit conditions is captured in the following regression:

$$\begin{aligned} R^{CDS}_{i,t} = \alpha &+ \sum_{k}^{5} \big(b_k + b_k^D (Credit\ Condition\ Dummy)_{i,t}\big) * Ret^{CDS}_{i,t-k} \\ &+ \sum_{k}^{5} \big(c_k + c_k^D (Credit\ Condition\ Dummy)_{i,t}\big) * Ret^{Eq}_{i,t-k} \end{aligned} \tag{B.6}$$

The advantage of this is that the liquidity measure does not have to aggregated to examine the effect on the price discovery process. We adapt this specification is as far as we replace the credit condition dummy with a liquidity dummy. The liquidity dummy takes the value of 1 if $R^{CDS}_{i,t}$ falls in the highest of three liquidity terciles for entity i.[19] Results of the regression are presented in Table B.13.

The past CDS returns exercise a positive influence and past equity returns a negative effect on current CDS returns. The positive effect of past CDS returns were expected due to the autocorrelation exhibited by CDS returns. The negative effect of past equity effect hints - as in our baseline specification - towards a sluggish incorporation of new information in CDS spreads. Against our working hypothesis, a high liquidity - in particular the composite depth and the net notional amount - to increase the autocorrelation in the CDS returns as the additional CDS effect is positive and thereby exacerbates the already positive CDS effect. Contrary, a high dealer count appears to reduce the autocorrelation, i.e. shows a negative additional CDS effect. CDS liquidity and trading does not appear the way past equity predict CDS returns. For every measure - except the maturing volume - the additional equity effect is not different from zero at any conventional level of significance. For both specification of the maturing volume, the additional stock effect more than offsets the normal equity effect. This hints towards inattentive CDS traders that only use information from other security markets if their attention on the CDS market is required.

B.6 Conclusion

We examined the influence of trading and liquidity measures on the price discovery in the CDS vis-à-vis the equity using a large sample of firms from 2011 to 2013. In line with the existing literature, we find an information flow from equity to CDS rather than vice versa. We add to the literature by documenting strong difference in the lead-lag

[19] Again, we try different sorting methodologies - a higher number of quantiles and an across entity sorting into the quantiles - but the results do not change

relationship over time and between entities. As possible determinant of the relationship, we examine a number of liquidity and trading measures to isolate variables that signal high or low informational value of CDS returns. Our results are not clear-cut and do not point towards a single liquidity measure as main driver of the lead-lag relationship. Though liquidity and trading appears to matter for the price discovery process, the actual effect of the different measures is specification-depended.

Table. B.1: Summary Statistics

		Depth	CDS BAS	Dealer Count	Quotes Count	Spread	Net Notional	Transfer	Transfer (relative)	Matured	Matured (relative)
2011	Observations	93816	90585	93476	93476	91460	19108	17237	17237	5395	5391
	Mean	5.66	0.43	6.67	32.87	193.33	992.76	128.70	0.12	56.85	0.04
	Std. Dev.	1.86	0.23	3.76	33.38	178.67	925.76	176.28	0.11	263.57	0.16
2012	Observations	125720	121438	124924	124924	122792	24720	21350	21335	10346	10320
	Mean	6.57	0.49	6.28	34.25	202.61	888.02	116.47	0.12	147.87	0.17
	Std. Dev.	1.72	0.33	3.65	33.60	189.90	839.74	169.28	0.13	489.53	0.48
2013	Observations	113172	109322	111329	111329	111262	24798	21755	21355	22233	22230
	Mean	6.54	0.56	5.76	38.57	149.89	777.79	127.49	0.16	73.53	0.10
	Std. Dev.	1.61	0.35	3.28	34.59	143.38	740.34	190.49	0.19	340.11	0.37
Overall	Observations	332708	321345	329729	329729	325514	68626	60342	59927	37974	37941
	25% percentile	5.00	0.30	3.00	10.00	71.02	370.11	21.71	0.04	0.00	0.00
	Mean	6.31	0.50	6.21	35.32	181.98	877.35	123.93	0.13	91.41	0.11
	75% percentile	7.00	0.61	9.00	52.00	222.46	1107.06	151.92	0.17	0.00	0.00
	Std. Dev.	1.77	0.32	3.58	33.96	173.63	835.47	179.24	0.15	379.61	0.39

CDS BAS is the CDS bid-ask spread scaled by the CDS spread of the entity and the unscaled version of the CDS bid-ask spread. *(Depth)* is the number of the of contributors whose books of record are used to calculate the price. *DC* and *QC* are the number of dealers and quotes for a 5-year CDS contract on a trading day. *Spread* is the spread of a 5-year, senior unsecured CDS spread. *Net Notional* is the volume of outstanding net CDS positions. *Transfers* is the volume of CDS trades that leads to a change in the net position of a market participant. *Matured* is the volume of maturing CDS contract. The scaled versions *Transfer* and *Matured* are obtained by dividing the absolute volume by the *Net Notional*. *Equity BAS* is the bid-ask spread of the stock, scaled by the stock price. *Equity TO* is the value of the traded shares.

Table. B.2: Variance Decompositions

	Variance		
	Overall	Between	Within
Depth	1.77	1.38	1.17
CDS BAS	0.32	0.27	0.17
DC	3.58	2.92	2.14
QC	33.96	26.32	21.41
Spread	174.84	165.23	96.63
Net	928.82	865.06	268.29
Transfer	186.92	116.58	142.20
Transfer (relative)	0.15	0.05	0.14
Matured	349.75	47.41	346.04
Matured (relative)	0.35	0.06	0.34

This table shows the decomposition of the variance into in within- and between-entity variation. The within- and between-entity variation does not add up to total variation due to the unbalanced panel. The fourth row shows the within-variation relation to the between variation. A description of the variables can be found in the notes of Table B.1.

Table. B.3: Correlation Matrix

	CDS BAS	CDS BAS (unscaled)	Depth	DC	QC	Spread	Net Notional	Transfer	Transfer (relative)	Matured	Matured (relative)
CDS BAS	1										
CDS BAS (unscaled)	-0.001	1									
Depth	-0.176	-0.126	1								
DC	-0.337	-0.259	0.33	1							
QC	-0.302	-0.183	0.184	0.677	1						
Spread	-0.401	0.764	-0.017	0.005	0.105	1					
Net Notional	-0.323	-0.242	0.245	0.466	0.455	-0.01	1				
Transfer	-0.302	-0.104	0.212	0.377	0.437	0.119	0.56	1			
Transfer (relative)	-0.142	0.081	0.08	0.134	0.209	0.19	0.009	0.642	1		
Matured	-0.042	-0.012	0.088	0.035	0.018	0.013	0.099	0.073	-0.001	1	
Matured (relative)	0.04	0.06	0.051	-0.069	-0.066	0.016	-0.059	-0.034	-0.01	0.737	1

This table shows pairwise correlation between liquidity and trading measures. A description of the variables can be found in the notes of Table B.1.

Table. B.4: Baseline Estimates

Panel A: Equity on CDS

γ_0	γ_{-1}	γ_{-2}	γ_{-3}	γ_{-4}	γ_{-5}	γ_{-6}	γ_{-7}	γ_{-8}	γ_{-9}	γ_{-10}
-0.388	-0.142	-0.080	-0.046	-0.040	-0.002	-0.037	-0.003	-0.022	-0.007	-0.011
(<0.00)	(<0.00)	(<0.00)	(<0.00)	(<0.00)	(<0.00)	(0.59)	(<0.00)	(0.41)	(<0.00)	(0.15)
				$\sum_{j=1}^{5} \gamma_j = -0.310$					$\sum_{j=1}^{10} \gamma_j = -0.390$	

Panel A: Equity on CDS

γ_0	γ_{-1}	γ_{-2}	γ_{-3}	γ_{-4}	γ_{-5}	γ_{-6}	γ_{-7}	γ_{-8}	γ_{-9}	γ_{-10}
-0.305	0.013	0.007	0.044	0.016	0.015	-0.008	-0.001	-0.024	0.012	-0.007
(<0.00)	(<0.00)	(<0.00)	(<0.00)	(<0.00)	(<0.00)	(<0.00)	(<0.00)	(0.61)	(<0.00)	(<0.00)
				$\sum_{j=1}^{5} \gamma_j = 0.097$					$\sum_{j=1}^{10} \gamma_j = 0.068$	

This table shows the sequence of coefficients for Equation B.1: $Ret_{i,t}^{CDS} = \alpha_i + \sum_{j=1}^{J} \beta_j \times Ret_{i,t-j}^{Eq} + \gamma \times Ret_{i,t-1}^{CDS} + \epsilon_{i,t}$. In Panel A, contemporary CDS returns are regressed on past equity returns. In Panel B, the roles of equity and CDS returns in Equation B.1 are reversed. The coefficients of the constant and the own lagged return are not reported for the sake of conciseness. Robust p-value are reported in parentheses.

Table. B.5: Sample Splits

Quartile	Low Liquidity & Trading 1	2	3	High Liquidity & Trading 4	5
Depth	-0.294**	-0.282**	-0.298	-0.343	-0.428***
	(0.05)	(0.03)	(0.35)	(0.40)	(<0.00)
CDS BAS	-0.35	-0.32	-0.323	-0.313	-0.241***
	(0.22)	(0.97)	(0.91)	(0.74)	(<0.00)
DC	-0.332	-0.277**	-0.285*	-0.318	-0.378**
	(0.44)	(0.03)	(0.08)	(0.92)	(0.03)
QC	-0.332	-0.345	-0.309	-0.296	-0.317
	(0.54)	(0.22)	(0.57)	(0.23)	(0.87)
Spread	-0.302	-0.224***	-0.246***	-0.308	-0.411***
	(0.37)	(<0.00)	(<0.00)	(0.60)	(<0.00)
Net	-0.269***	-0.26***	-0.254**	-0.317	-0.424***
	(0.01)	(<0.00)	(0.02)	(0.87)	(<0.00)
Transfer	-0.218***	-0.264***	-0.299	-0.363*	-0.395***
	(<0.00)	(0.01)	(0.27)	(0.09)	(<0.00)
Transfer (relative)	-0.217***	-0.287	-0.299	-0.389***	-0.369*
	(<0.00)	(0.11)	(0.29)	(<0.00)	(0.07)
Matured	-0.322				-0.592***
	(0.63)				(<0.00)

The table displays the cumulative effect for samples with different liquidity and trading activity. The sample was split as follows: For each entity, the quantile 1 contains the observations that exhibit the lowest liquidity or trading activity. A description of the variables can be found in the notes of Table B.1. We test whether the cumulative effect of the subsample (-0.310) is different from the entire sample. P-values are reported of this test are parentheses. For *Matured*, there was not sufficient variation as for a lot of entities, no or only a small number of contracts mature in a week. Quartile one is estimated using all observation with zero maturing volume, quartile five with all observations with a positive maturing volume. ***, **, and * denote significance at the 1%, 5% and 10% level respectively.

Table. B.6: Determinants of Price Discovery, Entity Level

	Significance		Magnitude	
	Univariate	Multivariate	Univariate	Multivariate
Depth	-0.072*	-0.024	0.008	0.014
	(0.07)	(0.68)	(0.58)	(0.42)
CDS BAS	-0.63***	-1.435***	-0.005	0.211*
	(<0.00)	(<0.00)	(0.94)	(0.06)
DC	-0.008	-0.006	0.001	0.032***
	(0.68)	(0.88)	(0.85)	(0.01)
QC	0.002	0.009**	0.00	-0.002
	(0.29)	(0.04)	(0.87)	(0.11)
Spread	0.055*	-0.054	0.038***	0.031*
	(0.09)	(0.37)	(<0.00)	(0.06)
Net Notional	-0.137**	0.152	-0.075***	-0.182***
	(0.05)	(0.48)	(0.01)	(<0.00)
Transfer	-1.216**	-0.511	-0.128	1.206**
	(0.01)	(0.78)	(0.35)	(0.02)
Transfer (relative)	-1.269	-4.14**	0.985***	-0.591
	(0.21)	(0.05)	(<0.00)	(0.31)
Matured	-4.361***	-9.482***	-0.501	-0.341
	(<0.00)	(<0.00)	(0.15)	(0.68)
Matured (relative)	-1.655*	0.656	0.75***	0.446
	(0.08)	(0.64)	(<0.00)	(0.18)
SD CDS Returns	-44.376***	-38.726***	-6.235*	-7.348*
	(<0.00)	(<0.00)	(0.08)	(0.07)
SD Equity Returns	8.567*	16.561**	6.399***	4.856*
	(0.07)	(0.02)	(<0.00)	(0.07)

The table presents results from Equation B.2 on the entity. The dependent variable in the first four columns is *significance*. *Significance* is coded as a dummy, which takes the value of 1 if the first ten lags of equity (CDS) returns predict CDS (equity) returns and zero otherwise. The dependent variable in the remaining four columns is *magnitude*. *Magnitude* is the sum of the coefficient of the lagged returns. Columns labelled "univariate" contains coefficients of the univariate regression of the dependent variable on the independent variable specified in the first column. Columns labelled "multivariate" display coefficients of the multivariate regression of the dependent variable on all regressors specified in the first columns. A description of the independent variables can be found in the notes of Table B.1. ***, **, and * denote significance at the 1%, 5% and 10% level respectively. Each regression is estimated using robust standard errors.

Table. B.7: Determinants of Price Discovery, Rolling

	Significance		Magnitude					
	Univariate	Multivariate	Univariate	Multivariate	Univariate	Multivariate	Univariate	Multivariate
Depth	0.016	0.015	-0.012***	-0.017**	0.003	0.001	0.006	-0.005
	(0.10)	(0.31)	(0.00)	(0.01)	(0.80)	(0.94)	(0.68)	(0.78)
CDS BAS	-0.177***	-0.029	0.009	-0.001	0.077	0.143	0.098*	0.174
	(0.00)	(0.72)	(0.72)	(0.99)	(0.12)	(0.23)	(0.06)	(0.16)
DC	0.013***	-0.004	0.002	0.003	0.028***	0.046***	0.021**	0.034***
	(0.01)	(0.68)	(0.29)	(0.55)	(0.00)	(0.00)	(0.01)	(0.01)
QC	0.002***	0.001	0.005*	0.001	0.002*	-0.002	0.001	-0.001
	(0.00)	(0.15)	(0.06)	(0.14)	(0.05)	(0.24)	(0.22)	(0.30)
Spread	0.024***	0.013	-0.001	-0.007	0.011	0.001	0.008	-0.007
	(0.00)	(0.28)	(0.70)	(0.17)	(0.32)	(0.96)	(0.49)	(0.65)
Net Notional	0.274	0.025	-0.066	-0.26	-0.318**	-1.313***	-0.021	-0.546
	(0.17)	(0.95)	(0.45)	(0.15)	(0.04)	(0.00)	(0.90)	(0.11)
Transfer	0.024	-0.004	-0.007	-0.024	0.008	-0.165**	-0.016	-0.115
	(0.14)	(0.91)	(0.32)	(0.18)	(0.86)	(0.02)	(0.74)	(0.14)
Transfer (relative)	0.244**	-0.231	-0.036	0.109	0.187	1.07***	0.274*	0.835***
	(0.04)	(0.48)	(0.45)	(0.41)	(0.23)	(0.00)	(0.06)	(0.00)
Matured	-0.067	-0.039	-0.075*	-0.083	-0.166*	-0.16	-0.053	0.006
	(0.53)	(0.82)	(0.07)	(0.17)	(0.07)	(0.22)	(0.60)	(0.97)
Matured (relative)	-0.08	-0.102	-0.013	0.017	-0.037	0.019	-0.018	-0.024
	(0.10)	(0.17)	(0.57)	(0.61)	(0.33)	(0.71)	(0.63)	(0.63)
Market & Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Window FE	No	No	No	No	No	No	Yes	Yes
Entity FE	No	No	No	No	Yes	Yes	Yes	Yes

The table presents results from Equation B.2 in the rolling sample. The dependent variable in the first two columns is *significance*. *Significance* is coded as a dummy, which takes the value of 1 if the first ten lags of CDS returns predict equity returns and zero otherwise. The dependent variable in the remaining four columns is *magnitude*. *Magnitude* is the sum of the coefficient of the lagged returns. Columns labelled "univariate" contains coefficients of the univariate regression of the dependent variable on the independent variable specified in the first column. Columns labelled "multivariate" display coefficients of the multivariate regression of the dependent variable on all regressors specified in the first columns. A description of the independent variables can be found in the notes of Table B.1. ***, **, and * denote significance at the 1%, 5% and 10% level respectively. Each regression is estimated using robust standard errors.

Table. B.8: Determinants of the Fractional Response

	Fractional Response					
	Univariate	Multivariate	Univariate	Multivariate	Univariate	Multivariate
Depth	0.016***	-0.002	0.03***	-0.003	0.029***	0.004
	(<0.00)	(0.84)	(<0.00)	(0.82)	(<0.00)	(0.77)
CDS BAS	0.009	0.084	0.038***	0.017	-0.011	-0.058
	(0.32)	(0.13)	(<0.00)	(0.87)	(0.37)	(0.65)
DC	0.008***	0.012**	0.021***	0.026***	0.017***	0.023**
	(<0.00)	(0.02)	(<0.00)	(<0.00)	(<0.00)	(0.03)
QC	0.001***	-0.002*	0.002***	<0.00	0.001***	<0.00
	(<0.00)	(0.06)	(<0.00)	(0.94)	(<0.00)	(0.81)
Spread $\left(\times\frac{1}{100}\right)$	-0.01***	<0.00	-0.024***	<0.00	-0.016***	<0.00*
	(<0.00)	(0.31)	(<0.00)	(0.13)	(<0.00)	(0.09)
Net Notional	0.108***	0.072	0.149***	0.09	0.063***	0.009
	(<0.00)	(0.59)	(<0.00)	(0.53)	(<0.00)	(0.96)
Transfer	-0.006**	-0.033	-0.056***	0.074	-0.013	-0.028
	(0.03)	(0.23)	(<0.00)	(0.33)	(0.32)	(0.79)
Transfer (relative)	0.041***	0.114	0.143***	0.092	0.051***	0.145
	(<0.00)	(0.40)	(<0.00)	(0.51)	(<0.00)	(0.38)
Matured	-0.066***	-0.118**	-0.056***	-0.092	0.022	-0.068
	(<0.00)	(0.04)	(<0.00)	(0.11)	(0.41)	(0.31)
Matured (relative)	-0.072***	0.025	-0.073***	0.026	0.006	0.001
	(<0.00)	(0.65)	(<0.00)	(0.64)	(0.88)	(0.99)
Entity FE	No	No	Yes	Yes	Yes	Yes
Week FE	No	No	No	No	Yes	Yes

This table examine the drivers of the fractional response as described in Equation B.4. A description of the independent variables can be found in the notes of Table B.1. $\left(\times\frac{1}{100}\right)$ indicates that a dependent variable has been divided by 100 to make to coefficient more traceable. ***, **, and * denote significance at the 1%, 5% and 10% level respectively. Each regression is estimated using robust standard errors.

Table. B.9: Robustness Test: Vector Autoregression, Entity Level

	Significance		Magnitude	
	Univariate	Multivariate	Univariate	Multivariate
Depth	-0.113***	-0.039	0.012	-0.004
	(0.01)	(0.49)	(0.50)	(0.81)
CDS BAS	-0.178	-0.93***	-0.165*	-0.357***
	(0.42)	(0.01)	(0.05)	(<0.00)
DC	-0.041**	-0.049	0.006	-0.009
	(0.03)	(0.22)	(0.42)	(0.45)
QC	<0.00	0.009**	<0.00	<0.00
	(0.82)	(0.04)	(0.18)	(0.69)
Spread	0.026	-0.034	-0.019**	-0.009
	(0.43)	(0.59)	(0.05)	(0.65)
Net Notional	-0.175**	-0.264	0.085***	0.155*
	(0.02)	(0.26)	(<0.00)	(0.08)
Transfer	-1.28**	2.225	0.46***	-0.699
	(0.01)	(0.23)	(<0.00)	(0.31)
Transfer (relative)	-2.367**	-5.911***	-0.032	0.085
	(0.03)	(0.01)	(0.92)	(0.91)
Matured	-3.794***	-5.336*	0.715*	-0.875
	(<0.00)	(0.09)	(0.05)	(0.25)
Matured (relative)	-0.453	0.92	-0.964***	0.113
	(0.66)	(0.55)	(<0.00)	(0.76)
SD Ret_i^{CDS}	-25.147***	-17.624*	16.805***	17.069***
	(<0.00)	(0.06)	(<0.00)	(<0.00)
SD Ret_i^{Eq}s	4.78	9.502	-3.976***	-6.339***
	(0.35)	(0.23)	(0.01)	(<0.00)

The table presents results derived from an vector autoregressive model with 10 lags on the entity level. The dependent variable in the first two columns is *Significance*. *Significance* is coded as a dummy, which takes the value of 1 if the first ten lags of CDS returns predict equity returns and zero otherwise. The dependent variable in the remaining four columns is *Magnitude*. *Magnitude* is the sum of the coefficient of the lagged returns. Columns labelled "univariate" contains coefficients of the univariate regression of the dependent variable on the independent variable specified in the first column. Columns labelled "multivariate" display coefficients of the multivariate regression of the dependent variable on all regressors specified in the first columns. A description of the independent variables can be found in the notes of Table B.1. ***, **, and * denote significance at the 1%, 5% and 10% level respectively. Each regression is estimated using robust standard errors.

Table. B.10: Robustness Test: Vector Autoregression, Rolling Sample

	Significance		Magnitude					
	Univariate	Multivariate	Univariate	Multivariate	Univariate	Multivariate	Univariate	Multivariate
Depth	0.015	0.028	-0.033	-0.055	-0.111*	0.009	-0.069	-0.035
	(0.51)	(0.65)	(0.13)	(0.24)	(0.06)	(0.93)	(0.24)	(0.73)
CDS BAS	-0.27**	-0.228	-0.348***	-0.572**	-1.022***	-2.499**	-0.763**	-1.9
	(0.03)	(0.54)	(<0.00)	(0.02)	(<0.00)	(0.03)	(0.02)	(0.10)
DC	0.01	-0.044	0.021*	0.064*	0.053	0.012	-0.023	-0.041
	(0.38)	(0.35)	(0.07)	(0.09)	(0.16)	(0.89)	(0.55)	(0.68)
QC	0.001	0.003	0.005***	-0.01	0.01**	-0.009	0.007	-0.006
	(0.30)	(0.72)	(<0.00)	(0.24)	(0.03)	(0.61)	(0.16)	(0.75)
Spread $\left(\times\frac{1}{100}\right)$	0.052**	-0.004	0.003	-0.059	0.102**	-0.225*	0.121**	-0.199
	(0.01)	(0.95)	(0.85)	(0.19)	(0.05)	(0.06)	(0.01)	(0.14)
Net Notional	-0.081	-0.345	0.508	1.818	1.254	2.768	1.947**	4.687**
	(0.88)	(0.86)	(0.22)	(0.19)	(0.12)	(0.12)	(0.02)	(0.02)
Transfer	0.002	-0.01	0.013***	0.03	-0.014	0.025	-0.034	0.008
	(0.63)	(0.72)	(<0.00)	(0.27)	(0.57)	(0.59)	(0.19)	(0.87)
Transfer (relative) $\left(\times\frac{1}{100}\right)$	0.017	0.029	0.081**	-0.099	0.078	-0.313	0.074	-0.324
	(0.54)	(0.87)	(0.02)	(0.64)	(0.56)	(0.22)	(0.59)	(0.26)
Matured $\left(\times\frac{1}{100}\right)$	-0.042	0.082	-0.03	-0.042	-0.071	-0.102	-0.012	-0.101
	(0.18)	(0.27)	(0.25)	(0.39)	(0.15)	(0.18)	(0.79)	(0.19)
Matured (relative)	-0.157	-0.724*	-0.274***	0.119	-0.272*	0.166	-0.165	0.271
	(0.24)	(0.07)	(0.01)	(0.60)	(0.08)	(0.68)	(0.10)	(0.46)
Market & Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Window FE	No	No	No	No	No	No	Yes	Yes
Entity FE	No	No	No	No	Yes	Yes	Yes	Yes

The table presents results derived from an vector autoregressive model with 10 lags for the rolling sample. The dependent variable in the first two columns is *significance*. *Significance* is coded as a dummy, which takes the value of 1 if the first ten lags of CDS returns predict equity returns and zero otherwise. The dependent variable in the remaining four columns is *magnitude*. *Magnitude* is the sum of the coefficient of the lagged returns. Columns labelled "univariate" contains coefficients of the univariate regression of the dependent variable on the independent variable specified in the first column. Columns labelled "multivariate" display coefficients of the multivariate regression of the dependent variable on all regressors specified in the first columns. A description of the independent variables can be found in the notes of Table B.1. $\left(\times\frac{1}{100}\right)$ indicates that a dependent variable has been divided by 100 to make to coefficient more traceable. The coefficients of $Significance_{i,t-1}$ and $Magnitude_{i,t-1}$ are not reported but smaller than one in every specification. ***, **, and * denote significance at the 1%, 5% and 10% level respectively. Each regression is estimated using robust standard errors.

Table. B.11: Robustness Test: Five Lags, Entity Level

	Significance		Magnitude	
	Univariate	Multivariate	Univariate	Multivariate
Depth	-0.039	-0.04	-0.019*	-0.015
	(0.33)	(0.48)	(0.06)	(0.14)
CDS BAS	-0.655***	-0.859***	-0.001	-0.15***
	(<0.00)	(0.01)	(0.97)	(<0.00)
DC	0.021	-0.034	-0.002	-0.005
	(0.26)	(0.40)	(0.70)	(0.45)
QC	0.007***	0.01**	0	0.002**
	(<0.00)	(0.02)	(0.41)	(0.02)
Spread	0.06*	-0.159***	-0.01**	-0.018**
	(0.07)	(0.01)	(0.04)	(0.05)
Net Notional	0.005	-0.145	0.045**	0.068
	(0.93)	(0.49)	(0.02)	(0.23)
Transfer	0.423	1.434	0.052	-0.168
	(0.37)	(0.38)	(0.51)	(0.55)
Transfer (relative)	1.368	-1.674	-0.539***	-0.345
	(0.18)	(0.38)	(<0.00)	(0.25)
Matured	-1.101	-4.152	0.181	-1.082*
	(0.34)	(0.19)	(0.37)	(0.08)
Matured (relative)	-2.083	-0.932	-0.729**	0.199
	(0.11)	(0.62)	(0.04)	(0.44)
SD CDS Returns	-19.337**	-25.503***	2.781	-0.853
	(0.01)	(<0.00)	(0.20)	(0.71)
SD Equity Returns	20.63***	35.21***	-1.373	2.646*
	(<0.00)	(<0.00)	(0.15)	(0.08)

The table presents results derived from Equation B.1 with a five lags on the entity level. The dependent variable in the first two columns is *significance*. *Significance* is coded as a dummy, which takes the value of 1 if the first ten lags of CDS returns predict equity returns and zero otherwise. The dependent variable in the remaining four columns is *magnitude*. *Magnitude* is the sum of the coefficient of the lagged returns. Columns labelled "univariate" contains coefficients of the univariate regression of the dependent variable on the independent variable specified in the first column. Columns labelled "multivariate" display coefficients of the multivariate regression of the dependent variable on all regressors specified in the first columns. A description of the independent variables can be found in the notes of Table B.1. ***, **, and * denote significance at the 1%, 5% and 10% level respectively. Each regression is estimated using robust standard errors.

Table. B.12: Robustness Test: Five Lags, Rolling Sample

	Significance		Magnitude					
	Univariate	Multivariate	Univariate	Multivariate	Univariate	Multivariate	Univariate	Multivariate
Depth	-0.009	0.041	-0.005**	-0.002	0.023**	0.002	0.027**	<0.00
	(0.42)	(0.14)	(0.04)	(0.68)	(0.02)	(0.82)	(0.01)	(0.98)
CDS BAS	-0.193***	0.162	-0.027**	-0.028	0.006	-0.069	0.016	-0.056
	(<0.00)	(0.23)	(0.02)	(0.16)	(0.87)	(0.19)	(0.67)	(0.32)
DC	0.012**	0.015	0.001	0.008**	<0.00	0.011	-0.002	0.009
	(0.04)	(0.48)	(0.66)	(0.02)	(0.97)	(0.24)	(0.75)	(0.37)
QC	0.002***	-0.002	0.001***	-0.002**	<0.00	-0.002	<0.000	-0.001
	(<0.00)	(0.55)	(0.01)	(0.03)	(0.49)	(0.10)	(0.53)	(0.33)
Spread (×100)	0.047***	0.045*	0.002	0.005	0.002	0.01	0.002	0.012
	(<0.00)	(0.07)	(0.37)	(0.24)	(0.77)	(0.48)	(0.84)	(0.44)
Net Notional	0.362	0.949	0.014	-0.019	0.036	0.143	0.026	0.351
	(0.11)	(0.23)	(0.85)	(0.86)	(0.81)	(0.60)	(0.87)	(0.25)
Transfer	<0.00	0.01	0.002	-0.001	<0.000	-0.001	-0.001	0
	(0.80)	(0.41)	(0.19)	(0.61)	(0.92)	(0.85)	(0.79)	(0.94)
Transfer (relative) (×100)	0.021	-0.043	0.003	0.011	0.015	0.007	0.014	-0.011
	(0.13)	(0.59)	(0.49)	(0.43)	(0.20)	(0.79)	(0.27)	(0.72)
Matured (×100)	-0.032**	-0.033	-0.003	-0.004	-0.001	-0.004	-0.002	-0.002
	(0.01)	(0.28)	(0.26)	(0.42)	(0.83)	(0.65)	(0.75)	(0.84)
Matured (relative)	-0.117**	0.112	-0.012	0.017	-0.012	0.037	-0.012	0.041
	(0.03)	(0.39)	(0.28)	(0.37)	(0.62)	(0.25)	(0.64)	(0.26)
Market & Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Window FE	No	No	No	No	No	No	Yes	Yes
Entity FE	No	No	No	No	Yes	Yes	Yes	Yes

The table presents results derived from Equation B.1 with a five lags in the rolling sample The dependent variable in the first two columns is *significance*. *Significance* is coded as a dummy, which takes the value of 1 if the first ten lags of CDS returns predict equity returns and zero otherwise. The dependent variable in the remaining four columns is *magnitude*. *Magnitude* is the sum of the coefficient of the lagged returns. Columns labelled “univariate” contains coefficients of the univariate regression of the dependent variable on the independent variable specified in the first column. Columns labelled “multivariate” display coefficients of the multivariate regression of the dependent variable on all regressors specified in the first columns. A description of the independent variables can be found in the notes of Table B.1. The coefficients of $Significance_{i,t-1}$ and $Magnitude_{i,t-1}$ are not reported but smaller than one in every specification. ***, **, and * denote significance at the 1%, 5% and 10% level respectively. Each regression is estimated using robust standard errors.

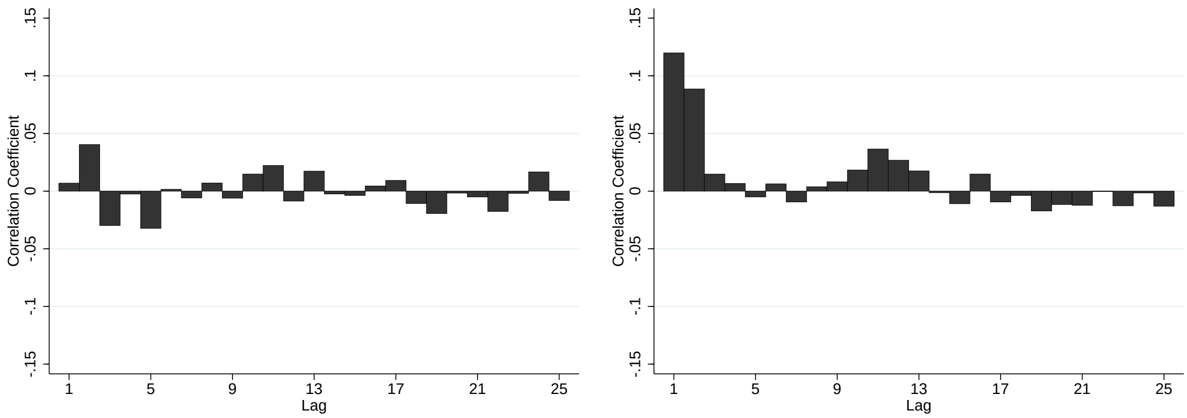
Table. B.13: Price Discovery à la Qiu and Yu (2012)

	Depth	CDS BAS	Dealer Count	Quotes Count	Spread	Net Notional	Transfer	Transfer (relative)	Matured	Matured (relative)
CDS Effect	0.097***	0.119***	0.139***	0.12***	0.129***	0.101***	0.131***	0.12***	0.127***	0.127***
$\left(\sum_{k=1}^{5} c_k\right)$	(0.10)	(0.12)	(0.14)	(0.12)	(0.13)	(0.10)	(0.13)	(0.12)	(0.13)	(0.13)
Equity Effect	-0.19***	-0.194***	-0.198***	-0.186***	-0.193***	-0.183***	-0.194***	-0.192***	-0.2***	-0.201***
$\left(\sum_{k=1}^{5} b_k\right)$	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Additional CDS Effect	0.073***	0.025	-0.036*	0.015	-0.008	0.055***	-0.009	0.014	-0.029	-0.025
$\left(\sum_{k=1}^{5} c_k^D\right)$	(0.00)	(0.28)	(0.09)	(0.47)	(0.68)	(0.01)	(0.65)	(0.52)	(0.32)	(0.40)
Additional Equity Effect	0.00	0.008	0.029	-0.009	0.004	-0.013	0.011	0.006	0.267***	0.291***
$\left(\sum_{k=1}^{5} b_k^D\right)$	(0.74)	(0.70)	(0.22)	(0.67)	(0.87)	(0.51)	(0.62)	(0.78)	(0.00)	(0.00)
Obs	248,849	246,538	247,852	247,852	248,849	248,849	248,849	248,849	248,849	248,849
R^2	0.040	0.038	0.038	0.038	0.037	0.038	0.038	0.038	0.041	0.039

This table provides a summary of the results of following regression: $R_{i,t}^{CDS} = \alpha + \sum_k^5 \left(b_k + b_k^D (\textit{High Liquidity Dummy})_{i,t}\right) * R_{i,t-k}^{CDS} + \sum_k^5 \left(c_k + c_k^D (\textit{High Liquidity Dummy})_{i,t}\right) * R_{i,t-k}^{Equity}$. Below the sum of coefficient, the p-value of the hypothesis that the sum of the coefficient is zero is displayed. ***, **, and * denote significance at the 1%, 5% and 10% level respectively. Standard errors are clustered at the date level.

Figures

Figure A.1: Autocorrelation of Equity and CDS Returns

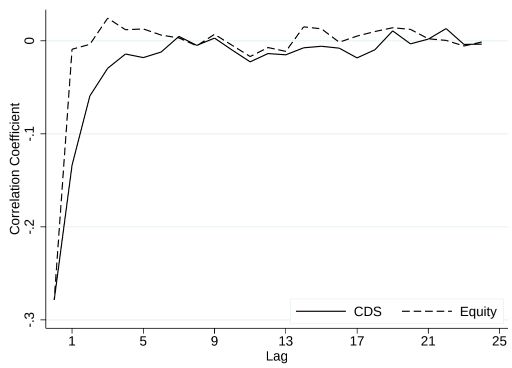


(a) Equity

(b) CDS

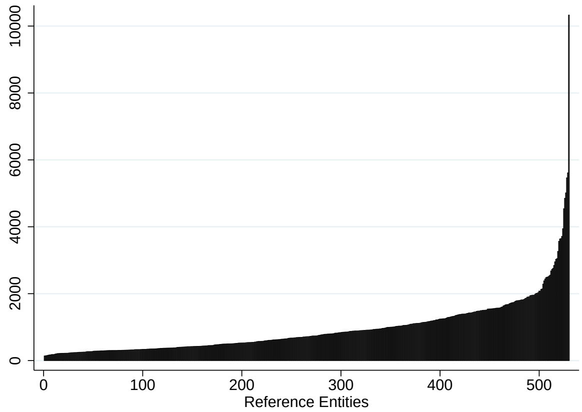
The figure depicts the average autocorrelation of equity and CDS returns. Each bar represents a correlation coefficient of the contemporaneous returns with a lagged return. Average autocorrelations are obtained by first calculating the the autocorrelation for each reference individually and, second, averaging these coefficients.

Figure A.2: Cross-correlation of Equity and CDS Returns

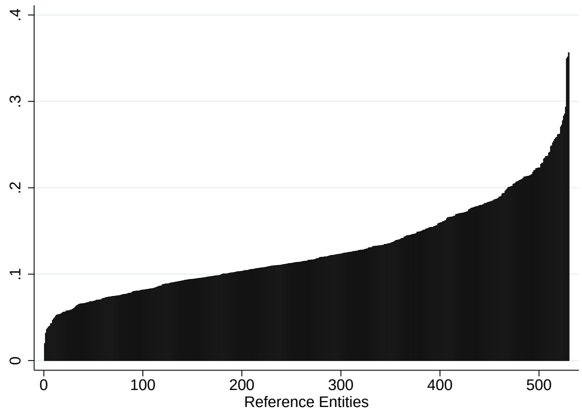


The figure shows the cross-correlation coefficients of contemporary CDS (solid line) and equity (dashed line) return with past equity and CDS return. Average cross-correlations are obtained by first calculating the the autocorrelation for each reference individually and, second, averaging these coefficients.

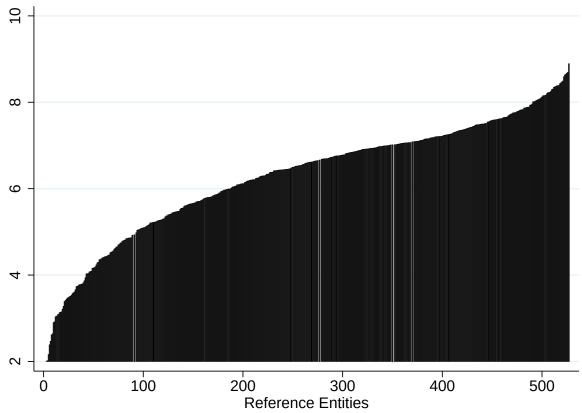
Figure A.3: Heterogeneity in Liquidity between Entities



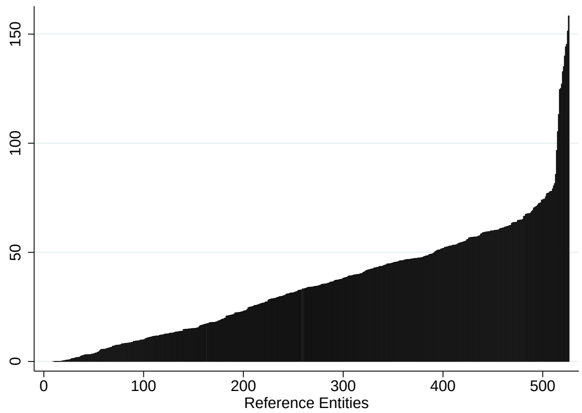
(a) Net Notional



(b) Risk Transfer



(c) Composite Depth

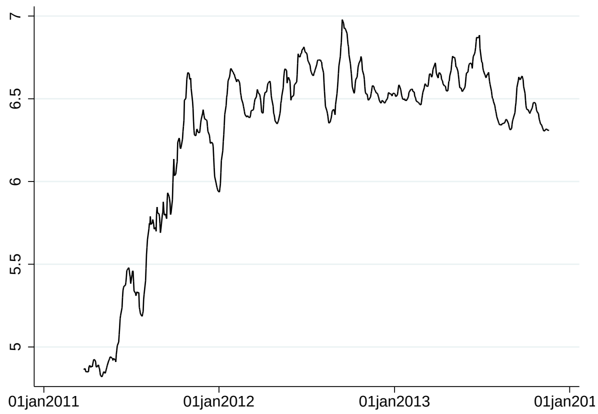


(d) Quotes Count

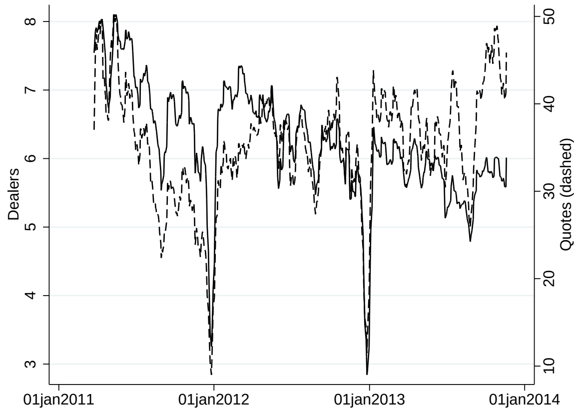
The figures depicts the between-entity variation of several measures of CDS trading and liquidity. The data points for each entity are obtained by taking the mean over the entire sample period. Sorting of the entities varies between the panels. *Net Notional* is the net outstanding volume in USD million. *Risk Transfer* are trades that resulted in a change of the individual risk position scaled by the *Net Notional*. *Composite Depth* is number of unique contributors to the mean spread calculation process. *Quotes Count* is the number of unique quotes on a trading day.

Figure A.4: Variation over Time

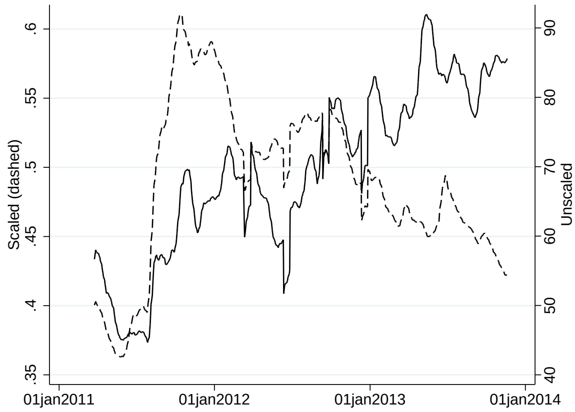
(a) CDS spread



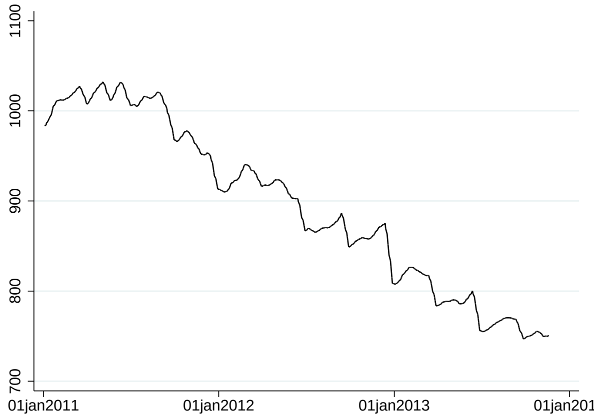
(b) Composite Depth



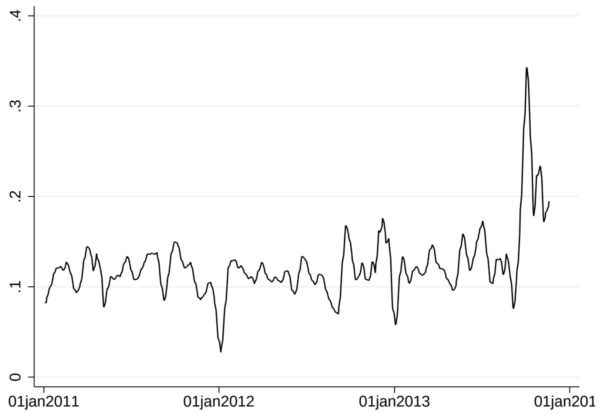
(c) Dealer and Quotes Count



(d) Bid-Ask Spread



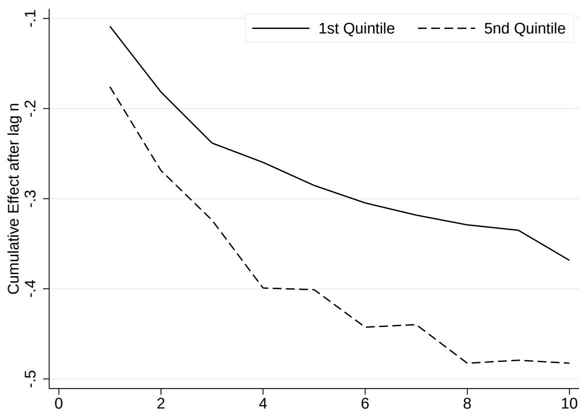
(e) Net Notional



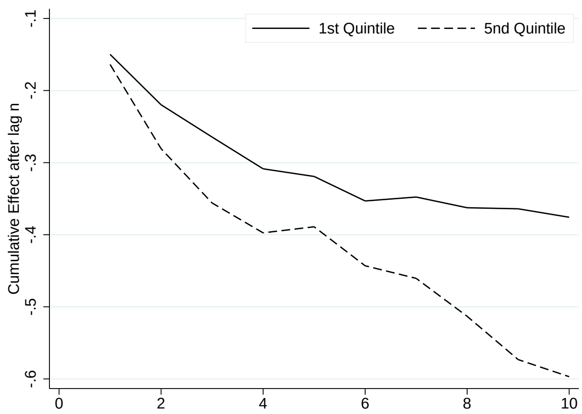
(f) Risk Transfer

The figures depicts the variation of several measures of CDS trading and liquidity over time. All variables are depicted using a moving average of 11 days. *CDS Spread* is the quoted CDS spread of the 5-year tenor and the restructuring clause specified in the text. *Dealer Count* and *Quotes Count* are the numbers of unique dealers and quotes on a trading day. *Composite Depth* is number of unique contributors to the mean spread calculation process. *Bid-Ask spread* is the quoted bid-ask spread absolute and scaled by the *CDS spread*. *Net Notional* is the net outstanding volume in USD million. *Risk Transfer* are trades that resulted in a change of the individual risk position scaled by the *Net Notional*.

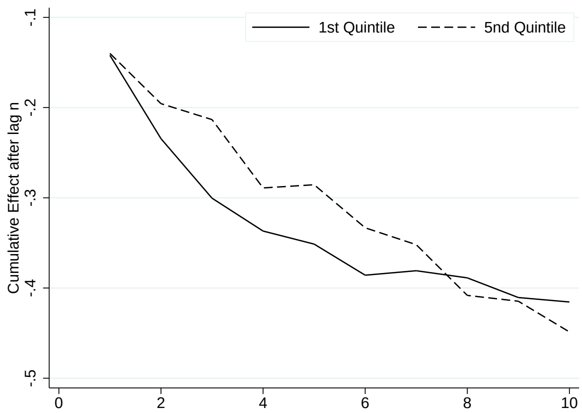
Figure A.5: Sample Splits I



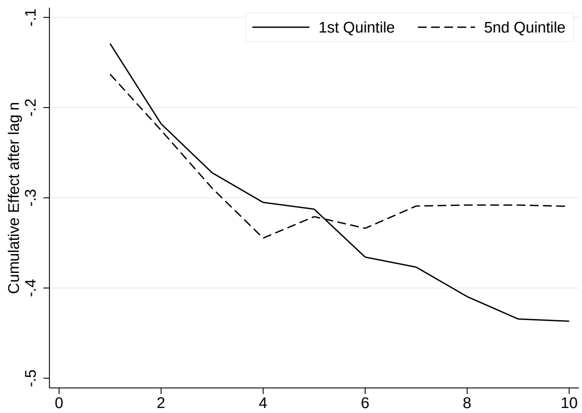
(a) Negative / Positive Returns



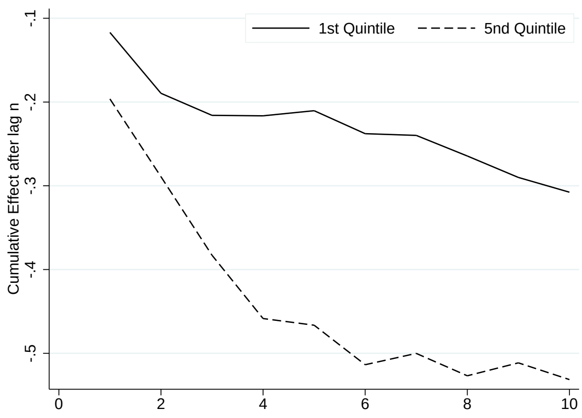
(b) Composite Depth



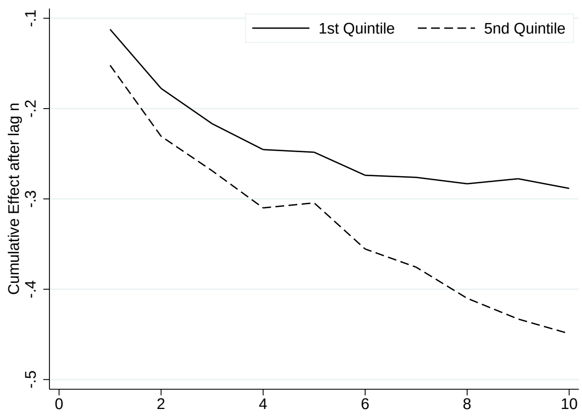
(c) Dealer Count



(d) Bid-Ask Spread



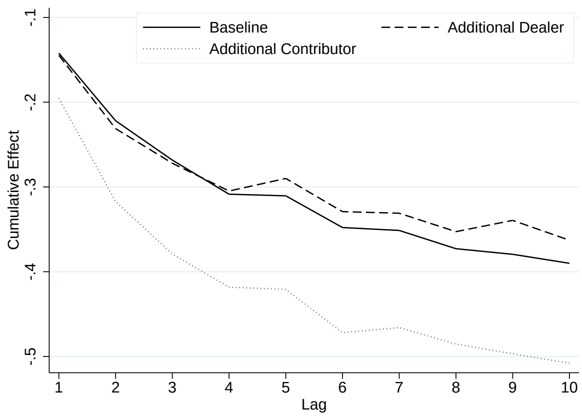
(e) Net Notional



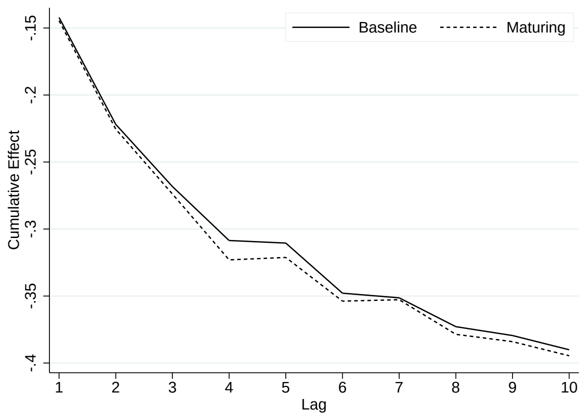
(f) Risk Transfer

The figure shows the cumulative effects of equity on CDS for different liquidity and trading quantiles. The lines depict the cumulative sum of the coefficient of lagged equity returns from the equation B.1: $Ret_{i,t}^{CDS} = \alpha_i + \sum_{j=1}^{10} \beta_j \times Ret_{i,t-j}^{Eq} + \gamma \times Ret_{i,t-1}^{CDS} + \epsilon_{i,t}$. Solid lines show coefficients that are estimated based on those observations of $Ret_{i,t}^{CDS}$ that fall in the lowest quintile of the variables specified below. Dashed lines are based on observations that fall in the highest quintile of the specified variable.

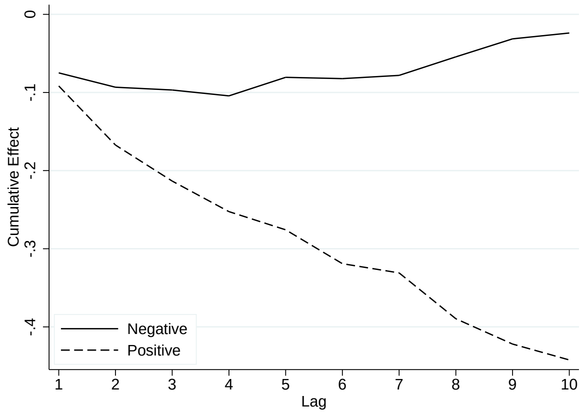
Figure A.6: Sample Splits II



(a) Additional Dealer and Contributor



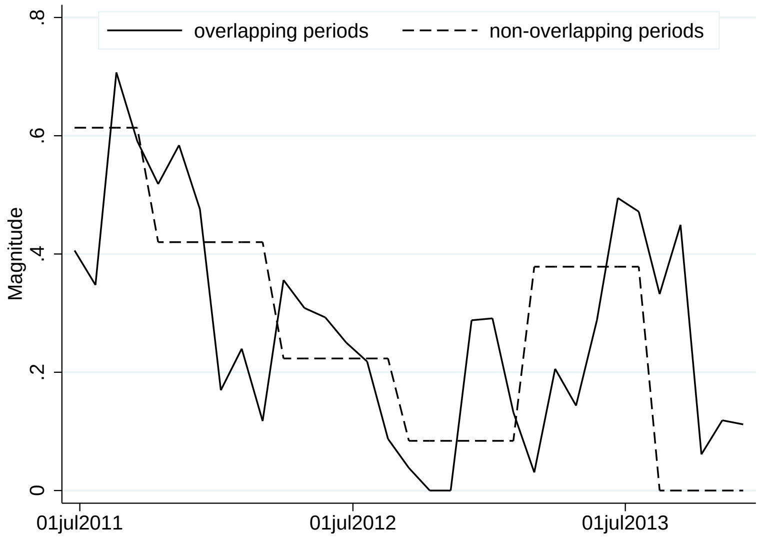
(b) Maturing and Non-Maturing



(c) Positive and Negative CDS Returns

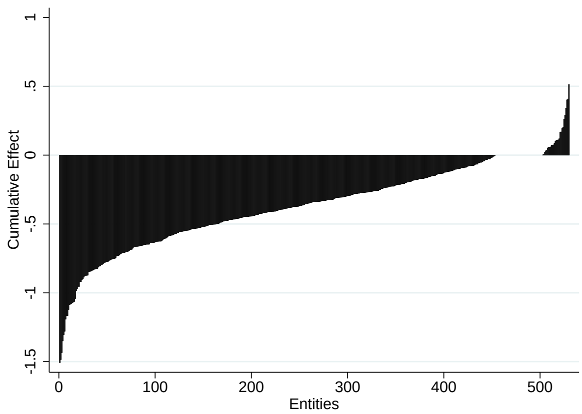
The figure shows the cumulative effects of equity of equity on CDS for different samples. The lines depict the cumulative sum of the coefficient of lagged equity returns from the equation B.1: $Ret_{i,t}^{CDS} = \alpha_i + \sum_{j=1}^{10} \beta_j \times Ret_{i,t-j}^{Eq} + \gamma \times Ret_{i,t-1}^{CDS} + \epsilon_{i,t}$.In panel (a), the dashed and dotted lines show the sequence of β_j for $Ret_{i,t}^{CDS}$ during which the reported number of contributors (dotted) or dealer banks (dashed) increases. In panel (b), the short-dashed line depicts the cumulative effect for CDS returns on week in which CDS contracts matured. Panel (c) compares the coefficients lagged equity returns for positive and negative $Ret_{i,t}^{CDS}$ separately.

Figure A.7: Variation of the Cumulative Effect of Equity on CDS over Time

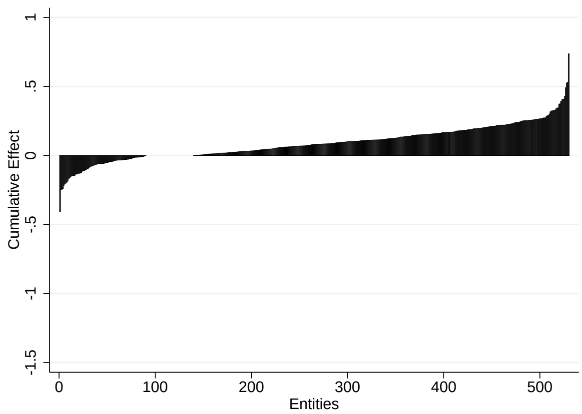


The figure depicts the cumulative effect in the pooled sample over time. The solid line shows the cumulative effect obtained by using overlapping estimation windows of 120 days. The dotted line shows the cumulative effect for non-overlapping time periods.

Figure A.8: Distribution of the Cumulative Effect



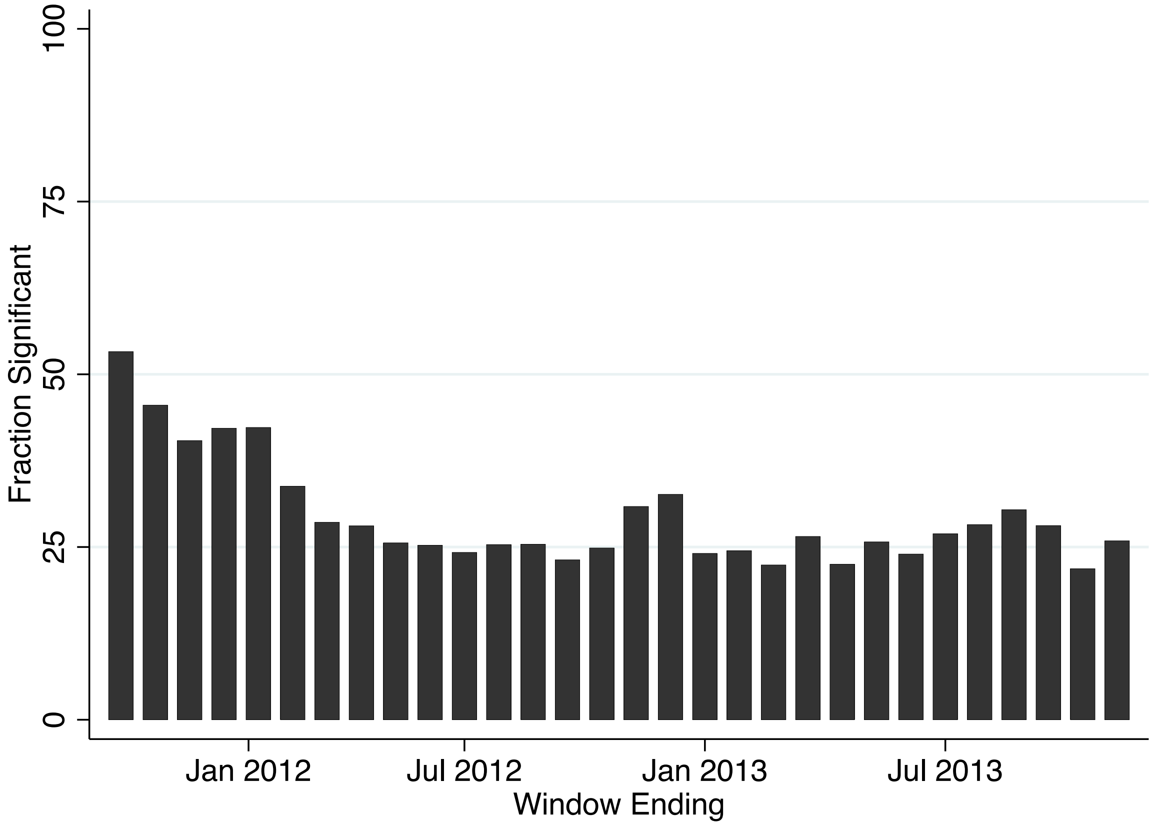
(a) Equity on CDS



(b) CDS on Equity

This figure depicts the distribution of the cumulative effect of equity on CDS on Panel (a) and CDS on Equity on Panel (b) over the entities. The cumulative effect is calculated as the sum of the coefficient of lagged equity (CDS) returns in the regression: $Ret_{i,t}^{CDS} = \alpha_i + \sum_{j=1}^{10} \beta_j \times Ret_{i,t-j}^{Eq} + \gamma \times Ret_{i,t-1}^{CDS} + \epsilon_{i,t}$, i.e. the cumulative effect equals $\sum_{j=1}^{10} \beta_j \times Ret_{i,t-j}^{Eq}$ For Panel (b), the roles of equity and CDS returns are reversed.

Figure A.9: Fraction of Predicting Relationships



This figure depicts the fraction of entities for which equity returns do predict CDS returns in Equation, i.e. $Significance_{i,t} = 1$, in percentage points.

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