Credit risk refers to the risk that the value of a portfolio or an individual security changes due to unexpected changes in the credit quality of issuers. This thesis contributes to the empirical literature on credit risk by means of four studies. The empirical results are not only important by themselves, they may also provide guidance to future empirical research.

Rating agencies are important institutions in today’s financial markets. They provide counterparty credit risk information to financial market participants. However, surveys reveal that market participants believe that agency ratings adjust slowly to changes in corporate credit quality. This is confirmed by studies that compare agency rating changes to benchmark measures of corporate credit quality. Moreover, studies on announcement returns typically find significant return reactions surrounding announcements of deteriorating credit quality.

To better understand the rating process Chapter 2 first gives an overview of Moody’s watchlist and outlook assignments, resolutions and resolution periods. Within our sample period, ranging from October 1991 to February 2005, 36 (31) percent of observed downgrades (upgrades) were preceded by a watch for downgrade (upgrade). The corresponding
numbers in case of negative (positive) outlooks are 16 (10) percent. More than 2/3 (2/5) of the times a company was subjected to a watch (outlook) it eventually experienced a rating change in similar direction.

On average resolution periods are in line with Moody’s intentions for watches and outlooks, being 90 days and 18 to 36 months, respectively. However, resolution periods of watches for downgrade and negative outlooks are generally more concentrated at the lower end of the empirical frequency distribution. These short resolution periods result in a relatively high fraction of actual downgrades as well.

Watches and outlook assignments are by and large equally divided between investment- and speculative-grade issuers, with the exception of watches for downgrades. In the latter case the number of assignments in the investment-grade category are almost twice as large. This is surprising given the fact that the number of downgrades is almost equally divided between investment- and speculative-grade issuers.

Estimating pooled window abnormal returns (WAR) surrounding rating agency announcements reveals that WARs are largest and most significant in case of negative announcements. We observe similar return patterns across negative announcement types. A significant part of the negative total abnormal return materializes prior to the announcement day window. Typically, we obtain a movement in the opposite direction in the post-announcement window, especially in case of downgrades and negative outlooks.

To more accurately assess the information content of announcements, we subsequently estimate point-in-time default prediction models along the lines of Altman and Rijken (2005)(2006). These models do not suffer from possible conservatism in information provisioning by rating agencies. From these models we obtain so called credit model ratings.
Summary

This allows us to distinguish between confirmed and unconfirmed announcements. We define an announcement as confirmed if we observe a credit model rating change in similar direction within a one year period prior to the actual announcement. When no credit model rating change, or even an opposite tendency, is observed, the rating change is classified as unconfirmed.

Conditioning on credit model precedence, we find no significant positive post-announcement returns if announcements are unconfirmed. This indicates that new information is fully absorbed once it is revealed. On the other hand, significant positive post-announcement returns typically materialize when announcements are in line with pre-announcement point-in-time credit quality deteriorations. This suggests a pre-announcement excessive response once market participants’ concerns about specific companies grow. Formal rating agency announcements might then predominantly resolve underlying uncertainty, which puts the market at ease.

These results are robust to several modifications, such as: conditioning on credit model ratings assigned strictly outside the event window only; excluding company WARs that were smaller (larger) than the 10 (90) percent quantile of empirical WAR distributions; and excluding announcements if they were preceded by an announcement in similar direction within the pre-announcement event window. Results are not unduly driven by differences in sample composition in terms of investment- and speculative-grade issuers either.

Finally, in case of downgrades, we find that pre-announcement return reactions are intimately related to watchlist precedence. Pre-announcement negative abnormal returns are less severe when downgrades are preceded by watchlist additions. Assigning a watch
for downgrade to a specific company already leads to a significant negative abnormal return reaction once the watchlist addition is announced.

Contrary to pooled estimates, Chapter 2 more accurately assesses the information content of rating agency announcements. Furthermore, enhanced insight into the information revelation process by means of outlooks, watches, and rating changes reveals interesting directions of future research.

For example, in the theoretical model of Boot, Milbourn and Schmeits (2006) the watchlist predominantly serves as a monitoring device. Firms hit by a negative shock are more inclined to exert effort to restore credit quality once a credit watchlist procedure is present (i.e., monitoring by rating agencies).

One empirical implication of Boot et al. (2006) is that the likelihood of being put on the watchlist is most valuable for firms of intermediate credit quality. This might explain why the number of investment-grade firms receiving a watch for downgrade is relatively large as compared to speculative-grade firms. Moreover, negative return reactions related to watches for downgrade and potential successive downgrades may depend on the company’s effectiveness of recovery effort. If chances of restoring credit quality are high (e.g., management ability), the negative response upon watchlist addition (downgrades) should be relatively low (high).

Chapter 3 looks at the relation between corporate governance and both firm value and credit quality. Past experience has shown that weak governance can be an important driver of default risk (e.g., Enron’s default in 2001). Corporate governance refers to the set of mechanisms that direct and control management activities within companies.
The analysis in the chapter is confined to shareholder rights and blockholders, defined as shareholders owning 5 percent or more of a company’s stock.

From a theoretical point of view there can be a positive or negative relationship between the presence of large shareholders and value, see Bhojraj and Sengupta (2003). The shared benefits hypothesis suggests that a large shareholder is beneficial to all of the company’s stakeholders. Large shareholders may mitigate the agency problem between management and stakeholders as a group. The private benefits hypothesis states that large shareholders can have a detrimental impact. If blockholders pursue their own objectives, they might expropriate value from other stakeholders, like debt holders. When blockownership is more dispersed these effects can be strengthened or weakened.

Given that the shared benefits hypothesis prevails, less blockholder concentration makes it harder to internalize positive externalities. Less blockholder concentration can also lead to free-riding problems. On the other hand, when blockholders threaten to sell their stock following bad results, small blockholders have a larger incentive to trade ex-post to discipline management, see Edmans and Manso (2011).

Given that the private benefits hypothesis prevails, small blockholder are less affected by negative externalities associated with their behavior. This strengthens the negative impact of blockholder presence. On the other hand, multiple small blockholders may be inclined to monitor each others behavior, reducing the negative impact on firm value and credit quality.

Using a large dataset of about 3,500 U.S. firm year observation from 1996-2001, we find a negative relation between aggregate blockholding and firm value. This is in line with the private benefits hypothesis. It is also in line with results of Barclay and Holderness
(1989), Nenova (2003) and Dyck and Zingales (2004), that confirm the possible existence of private benefits of control.

The sample reveals that blockholding by multiple blockholders, especially outside blockholders, is a widespread phenomenon in the U.S.. To capture dispersion we make use of a scaled Herfindahl concentration measure. Unlike an unscaled Herfindahl measure, this allows us to disentangle the impact of aggregate blockholding and blockholder dispersion.

We consistently obtain a negative relation between blockholder dispersion and firm value. The results are robust to a variety of model specifications, including controlling for shareholder rights. In line with this result, we obtain a negative relation between blockholder dispersion and credit quality.

With respect to shareholder rights we find opposite results. Shareholder rights are positively related to firm value, but negatively related to debt quality. This suggests that a shift in balance of power towards shareholders is considered as a negative signal by credit rating agencies.

The theoretical model provided in Chapter 3 shows that less blockholder concentration might aggravate the private benefits hypothesis in two ways. First, the smaller ownership stake of blockholders in control enhances their failure to internalize negative externalities. This negative effect may be stronger than the potential positive effect of monitoring by blockholders that are not in control. Second, even if blockholders are aware of their mutual incentives to divert resources, they might have no economic incentive to obstruct each others attempt to extract private benefits. This may make blockholders better off compared to the monitoring or collusion case, with a larger negative effect on firm value.
Interpreting the results we have an obvious caveat in mind. Endogeneity is frequently an important concern in empirical work. It might well be that causality at least partially runs from firm value to block dispersion. Existing empirical studies on blockholders generally do not address endogeneity. Becker, Cronqvist, and Fahlenbrach (2011) have recently tried to cope with it using the method of instrumental variable estimation. They use the number of individuals with high net worth relatively to the number of corporate headquarters incorporated in a particular state as an instrument. Wealthy non-management individual blockholders, the only subcategory of blockholders considered, might be more willing to invest in locally familiar corporations. However, their study excludes other blockholder types (e.g., mutual funds and money managers), that constitute the largest part of the blockholder sample. Though it is certainly not straightforward, the lack of suitable instruments is an important missing element which might be addressed in future empirical research.

In Chapter 4 we look more closely at the identification of systematic credit risk factors. Ideally systematic credit risk factors are perfectly represented by observable variables. Das et al. (2007) reject that defaults in an intensity-based setting are independent conditional on the evolution of common observable risk factors, the so called doubly stochastic framework.

Apart from observable covariates, several studies have recently incorporated latent factors within different model specifications, see Duffie, Eckner, Horel, and Saita (2009), Koopman, Lucas, and Schwaab (2008a), Koopman, Lucas, and Monteiro (2008b), Koopman, Kräussl, Lucas, and Monteiro (2009). These latent factors make an important, if
not dominant contribution to systematic credit risk modeling.

Chapter 4 looks at three related questions regarding interpretation, distributional assumptions and significance of latent factors in credit risk modeling.

First, latent factors seem predominantly of importance at peaks and troughs of the credit cycle, see Koopman et al. (2009). These are periods when macroeconomic variables typically take their lowest or highest values as well. We find that including relevant variables in a nonlinear way has no bearing on latent factor significance. We double check the latter finding using a simulation study. This confirms that it is unlikely that empirical results have been driven by a failure to incorporate nonlinearities adequately. The estimation methodology has no problem in identifying latent factors and nonlinear responses to observed variables separately.

Second, we examine whether or not skewness and excess kurtosis should be incorporated within latent factor specifications. Christodoulakis, Batiz-Zuk, and Poon (2009) examine skewness and excess kurtosis of the systematic- or idiosyncratic factor within a Vasicek (1987) single factor setting. The authors find that specifying skewed normal systematic factors provides a better description of empirical credit loss distributions than Gaussian models. Given our data set, we find no statistical evidence to incorporate skewness and excess kurtosis within latent factor specifications.

Third, we look at goodness-of-fit tests to assess whether doubly stochastic models with frailty components are adequately specified. Along the lines of Das et al. (2007) we switch from calendar time to intensity time. Intensity time is measured in units of aggregated (across companies) integrated (across calendar time) transition intensities.

We first consider Fisher’s dispersion test. We find that the number of defaults per
(intensity) time bin \( c \) are independently Poisson(\( c \)) distributed only if a latent factor specification is considered. In line with Das et al. (2007), this will not be the case when only observable covariates are included. On the other hand, the inter-arrival test proposed by Prahl (1999) provides no convincing evidence of exponentially i.i.d. inter-default times.

Simulating and re-estimating default intensity models with latent components reveals that Prahl’s test is somewhat over-sized, while Fisher’s test is under-sized. We also find that Fisher’s test is sensitive to model misspecification. There is a large chance the test will be rejected when the data generating process contains a latent component while the latent process is not part of the estimation model. On the other hand, it is not trivial to specify latent processes that could not be captured reasonably well by a simple autoregressive process, in terms of not rejecting Fisher’s dispersion test. This means the test has low power in distinguishing between alternative latent specifications.

Overall, given empirical estimation results, Gaussian latent factor models seem indispensable ingredients in empirical credit risk modeling. At the same time, it is obviously important to devise powerful testing procedures to assess whether doubly stochastic models with frailty components are adequately specified.

Chapter 5 studies short- and long-run dynamics of speculative-grade bond yields. Averaging historical time series on loss given default and default probabilities of different rating categories reveals that investors in corporate debt require a spread over the risk-free rate in excess of expected default losses, see Altman and Bencivenga (1995), Amato and Remolona (2003), Hull, Predescu, and White (2005). Nonetheless, we still expect that a unit change in expected default loss would be fully reflected in corporate bond yields in
the long-run.

As a result the chapter takes a different perspective. Instead of looking at historical averages, we study the time series behavior of bond yields. We obtain cointegration relations between speculative-grade bond yields, Treasury yields and estimated default losses. In line with research on historical averages, the cointegration relations reveal that average excess returns of corporate bonds over Treasuries increase when ratings decrease.

The estimated default loss coefficient is close to one when, in case of the cointegration relation of the B rated yield series, it is possible to use rating specific default rates to estimate default losses. This implies that default loss changes are fully incorporated in yields in the long-run. Estimated coefficients on the default loss variable are understated (overstated) when we are forced to use speculative-grade default rates that overestimate (underestimate) rating specific default rates related to the bond yield series considered.

Short-term dynamics are subsequently captured by error-correction models. The magnitude and significance of coefficients associated with cointegration equation residuals give an additional indication of the importance of long-run equilibria. Besides bond liquidity and changes in expected default loss, short-run dynamics of speculative-grade yields are driven by changes in short rates and stock market volatility. We also find a clear January effect with respect to speculative-grade bond yields. This can most likely be ascribed to market participants trying to prevent high-yield debt from officially appearing within financial documentation (i.e., window dressing).

Splitting bond indices up in terms of maturity ranges, we obtain similar long-run dynamics across rating categories given a specific maturity range. Nonetheless, short maturity bonds generally respond more vigorously to changes in default losses.
Summary

Short-run adjustment to long-run errors depends on the maturity range considered. Consistent with Merton (1974), we also obtain dissimilarities across maturity ranges with respect to changes in the short-rate and stock market volatility. The impact of other explanatory variables is more or less uniform within specific rating categories.