Analyse von Ausfallrisiken und Heilungschancen eines Bankportfolios aus deutschen mittelständischen Unternehmen

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Zusammenfassung

Im Artikel in Modul 1 wird ein umfangreicher Datensatz mit Jahresabschluss- und Ausfallinformationen deutscher, mittelständischer Unternehmen analysiert. Diese Daten, welche als typisch für ein Firmenkreditportfolio einer Großbank zu sehen sind, werden als Basis genutzt, um ein firmenspezifisches Verlustprognosemodell zu entwickeln. Unter Verwendung dieses Modells können signifikante firmenspezifische und makroökonomische Risikotreiber identifiziert und Ausfallrisiken über einen Mehrjahreshorizont prognostiziert werden. Über das zeitspezifische Verhalten der ermittelten Ausfallwahrscheinlichkeiten werden mehrperiodige Portfolioverlustverteilungen für bankspezifische Kreditportfolien geschätzt. Die Analysen basieren auf einem Datensatz aus 5.930 deutschen, mittelständischen Unternehmen. Zu diesen Unternehmen werden über einen Zeitraum von 2002 bis 2007 insgesamt über 23.000 Jahresabschlüsse analysiert. Die Ergebnisse können als Grundlage zur Entwicklung von Handlungsstrategien dienen, um Kreditportfolioverluste über mehrere Perioden realistischer bewerten zu können.

Im Artikel in Modul 2 wird die Heilung von ausgefallenen Unternehmen analysiert und es werden beobachtbare Heilungsereignisse in die Ausfallprognose von kleinen und mittleren Unternehmen integriert. Aufgrund der zusätzlichen heilungsspezifischen Informationen wird ein neues Informationsset genutzt, um individuelle Ausfall- und Heilungsereignisse vorauszusagen. Dies ist ein neuer Ansatz innerhalb der Kreditrisikoanalyse, welcher unserer Meinung nach bislang nicht verfolgt wurde. Es werden unterschiedliche firmenspezifische und makroökonomische Ausfall- und Heilungsereignis beeinflussende Risikotreiber identifiziert. Die Schätzungen werden mittels des firmenspezifischen Datensatzes entwickelt. Aufgrund des signifikanten Einflusses auf das Ausfallrisiko sowie die Ertragserwartung der Bank bezüglich eines geheilten Unternehmens scheint es elementar für das Risikomanagement diese zusätzlichen Informationen in die Kreditrisikoanalyse zu integrieren.

Im Artikel in Modul 3 wird die Belastbarkeit der Kundenbeziehung zwischen einer kreditgebenden Bank und ihren Kreditnehmern, bestehend aus kleinen und mittleren Unternehmen, in einer Stresssituation analysiert. Wir fokussieren uns auf Firmen eines Kreditportfolios, welche einen Ausfallgrund aufweisen und untersuchen den Einfluss unterschiedlicher qualitativer und quantitativer Faktoren auf die Kündigungswahrscheinlichkeit der Kundenbeziehung. Die Ergebnisse werden auf Basis des firmenspezifischen Datensatzes entwickelt. Unsere Ergebnisse zeigen, dass eine Bank höchstwahrscheinlich die Kreditbeziehung kündigen wird, wenn sie überzeugt ist, dass es keinerlei Zahlungen bezüglich des Kredites geben wird. Ist die Zahlung dagegen lediglich einige Zeit verzögert, ist eine Kündigung wenig wahrscheinlich. Darüber hinaus stabilisiert ein großer Einbezug der Gesellschafter des Unternehmens, gemessen an der Eigenkapitalquote, die Kundenbeziehung nachhaltig. In makroökonomischer Hinsicht haben ein geringes Zinsniveau sowie ein wirtschaftlicher Aufschwung stabilisierenden Einfluss auf die Kundenbeziehung.

Abstract

The paper in module I evaluates a large database consisting of financial statements and default information regarding German small- and medium-sized firms. The databank can be seen as a typical major bank SME credit-portfolio. The data is applied in order to develop a firm specific loss-prediction model. The model identifies significant firm-specific and macroeconomic risk-drivers and allows multi-period loss-predictions. Based on the individual time-specific behavior of the determined default-probabilities, a multi-period loss-prediction regarding a bank-specific credit portfolio is estimated. The databank consists of 5,930 German SME with information from over 23,000 financial statements from January 2002 to December 2007. The findings can be applied as a basis for the development of strategies in order to evaluate multi-period credit-portfolio risk more realistic.

The paper in module II evaluates the resurrection event regarding defaulted firms and incorporates observable cure events in the default prediction of SME. Due to the additional cure-related observable data, a completely new information set is applied to predict individual default and cure events. This is a new approach in credit risk that, to our knowledge, has not been followed yet. Different firm-specific and macroeconomic default and cure-event-influencing risk drivers are identified. The estimations are developed based on the firm-specific database. Due to the significant influence on the default risk probability as well as the bank's possible profit prospects concerning a cured firm, it seems essential for the risk management to incorporate the additional cure information into the credit risk evaluation.

The paper in module III evaluates the resilience of the relationship between a lending bank and its SME borrowers in a stressed situation. We focus on firms in a credit portfolio which triggered a default event and investigate the interdependencies between the cancelation of the relationship and different qualitative and quantitative influence factors. The findings are developed based on the firm-specific database. We find that the relationship is most likely canceled if the bank is convinced that it will not get paid any more regarding its outstanding loans. On the other hand, if the payment is only delayed for some time, a cancelation of the relationship is less likely. Furthermore, the commitment of the firm's owner, measured in the equity quote, seems to be essential for the robustness of the relationship. Also macroeconomic influence factors are identified. A low interest rate and an economic upturn are in general a relationship-supporting environment.

Schlagwörter

Kreditportfolio, Verlustprognose, Mehrjahreshorizont, Heilungswahrscheinlichkeit, Kundenbeziehungskündigung

Keywords

credit portfolio, loss prediction, multi-period, cure-probability, relationship-cancelation

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Zusammenfassung

1 Motivation

Die vergangenen Jahre der Finanzmarkt- und Schuldenkrise haben eindrucksvoll gezeigt, wie wichtig es für Finanzinstitute ist, Kreditportfolien hinsichtlich ihrer Risikostruktur realitätsnah beurteilen zu können. Das richtige Management von Kreditportfolien durch genaue Identifikation und Prognose von Verlustrisiken kann überlebenswichtig sein für Banken und hat somit weitreichende ökonomische Relevanz. Entsprechend umfangreich sind die Forschungsansätze im Bereich der Kreditrisikoanalyse, siehe hierzu beispielsweise Altman und Saunders (1997), Jarrow und Turnbull (2000), Bluhm et al. (2003) oder Albrecht (2005).

Die verwendeten Modelle erstrecken sich inzwischen von der Scoring-basierten Analyse eines einzelnen Schuldners, siehe Altman (1968) und Ohlson (1980), bis hin zu umfangreichen Kreditportfoliomodellen, welche auf den Ansätzen der strukturellen Modelle oder der Reduktionsmodelle basieren, siehe Merton (1974, 1977), Black und Scholes (1973), Jarrow und Turnbull (1995), Jarrow et al. (1997) sowie Hillegeist et al. (2004). Zudem sind in den vergangenen Jahren auch komplexe Modelle zur Prognose mehrjähriger Kreditrisiken entstanden, siehe Hamerle et al. (2007), Duffie et al. (2007) und Duffie et al. (2009).

Der überwiegende Teil der Forschung befasst sich mit dem angloamerikanischen Raum und stützt sich bei der Modellentwicklung auf eine Datenbasis bestehend aus börsengehandelten Firmenanleihen beziehungsweise Finanzdaten US-amerikanischer Unternehmen, welche häufig börsennotiert sind und deren Informationspolitk entsprechend umfangreich ist, siehe Hillegeist et al. (2004), Das et al. (2007) oder Duffie et al. (2009). Hierbei stellt sich die Frage, ob sich diese Modelle reibungslos auf Kreditportfolien mit Schuldnern aus dem deutschen Mittelstand adaptieren lassen, oder ob es hier nicht auch eigene, wichtige Zusammenhänge unterschiedlicher Risikotreiber zu beachten gilt. Diese Frage ist für alle Banken von elementarer

Bedeutung, welche Kreditportfolien bestehend aus deutschen Mittelständlern besitzen, da bei einer kritiklosen Übernahme der auf US-amerikanischen Daten beruhenden Modelle bestimmte Portfoliorisiken gegebenenfalls nicht korrekt abgebildet werden. Hierdurch könnten die jeweiligen Kreditinstitute, je nach Prognose, zu viel eigene Mittel für das Kreditportfoliorisiko binden oder, im anderen Extremfall, relevante Ausfallrisiken nicht genügend absichern. Insbesondere im traditionell verschwiegenen deutschen Mittelstand stellt die Erarbeitung von passenden Risikomodellen eine Herausforderung da. Der deutsche Mittelstand, welcher überwiegend aus familiengeführten Unternehmen besteht, ist seit jeher relativ zurückhaltend bezüglich finanzspezifischer Informationen. Die externe Finanzierung erfolgt nicht durch Börsennotierungen sondern primär durch Bankkredite, wodurch öffentliche Publizitätspflichten grundsätzlich entfallen. Folglich ist die Datenbasis, welche als Grundlage für Risikomodelle, die sich auf ein Portfolio aus Schuldnern des deutschen Mittelstandes beziehen, dienen kann, entsprechend begrenzt, siehe Deutsche Bundesbank (2010). Zudem sind Ausfallereignisse relativ selten. Kaiser und Szczesny (2003) und Hamerle et al. (2007) haben sich der Risikoanalyse mittelständischer Unternehmen gewidmet und hierbei auf öffentlich zugängliche Daten zurückgegriffen, welche die jeweiligen Unternehmen freiwillig zur Verfügung gestellt haben. Bei freiwillig zur Verfügung gestellten Daten wird jedoch, insbesondere bei den informationspolitisch zurückhaltenden deutschen Unternehmen, nur ein ausgesuchter Teil des gesamten deutschen Mittelstandes analysiert.

Diese Arbeit nutzt eine umfangreiche Datenbasis mit einer Fülle an Informationen über den kompletten Querschnitt des deutschen Mittelstandes. Der Datensatz wurde von der Dresdner Bank AG im Frühjahr 2008 zur Verfügung gestellt und beinhaltet umfangreiche mehrjährige Finanzinformationen aus über 23.000 Jahresabschlüssen von 5.930 deutschen, mittelständischen Unternehmen. Die erfassten Daten erstrecken sich über einen Zeitraum von Januar 2002 bis zum Dezember 2007. Darüber hinaus sind umfangreiche Ausfalldaten zu 1.243 Unternehmen verfügbar. Der Datensatz kann als ein typisches Bankportfolio aus Firmenkunden gesehen werden, da alle Kunden erfasst wurden, deren Daten in das für die Kreditentscheidung notwendige Programm eingegeben wurden. Diese Fülle an Informationen zum deutschen Mittelstand war der Wissenschaft bislang weitgehend unzugänglich. Der Datensatz dient u.A. als Basis, um das mehrperiodige Intensitätsmodell von Duffie et al. (2007) direkt auf den deutschen Mittelstand anzuwenden und so ein entsprechendes Kreditrisikomodell abzuleiten. Hierdurch ist es möglich, eine Mehrperiodenausfallprognose, basierend auf signifikanten, firmenspezifischen und makroökonomischen Risikotreibern, für ein Kreditportfolio aus deutschen, mittelständischen Firmenkunden vorzunehmen.

Das so entwickelte Kreditrisikomodell kann Banken, welche Kreditportfolien aus deutschen Mittelständlern haben, als Grundlage zur Entwicklung von Strategien zur Minimierung von Portfoliorisiken dienen. Durch die realistischere Analyse der Ausfallrisiken und die Optimierung des entsprechenen Chance-Risikoprofils können Erträge im Verhältnis zum Risiko maximiert werden.

Ein besonderes Ereignis im Bereich der Kreditausfallanalyse ist die Gesundung (Cure Event) des ausgefallenen Unternehmens. Mit der Analyse von Gesundungen beschäftigt sich die Kreditriskoliteratur in den letzten Jahren zunehmend intensiver. Hierbei werden überwiegend Modelle verwendet, in denen nicht beobachtbare Cure Events genutzt werden, um Verzerrungen bei Schätzungen mit sehr vielen zensierten Ereignissen zu vermeiden. So nutzen beispielsweise Mo und Yau (2010) und Tong et al. (2012) diese Modellierung, um Ausfälle bei Krediten im Privatkundenbereich besser schätzen zu können. Aber auch in der Kreditrisikoanalyse des Firmenkundengeschäftes findet die Berücksichtigung von Gesundungen in der Modellierung zunehmend Beachtung, siehe Yildirim (2008) und Topaloglu und Yildirim (2009).

Die Nutzung von Kreditrisikomodellen, welche die Gesundung berücksichtigen, ermöglicht nicht nur Vorhersagen, wann ein Schuldner ausfällt, sondern auch, ob er ausfällt. Der derzeitige Einbezug nicht beobachtbarer Cure Events führt jedoch dazu, dass die

Modelle hinsichtlich ihrer Definition des Cure Events variieren können. Ein möglicher Lösungsansatz ist die Berücksichtigung von beobachtbaren Gesundungen, also dem Wegfall des Ausfallgrundes ohne Verlust für die Bank. Der in dieser Arbeit verwendete Datensatz beinhaltet neben den umfangreichen Finanzinformationen auch eine Vielzahl von ausfallspezifischen Informationen. So ist etwa der weitere Verlauf der ausgefallenen Unternehmen dokumentiert. Hierbei werden auch Gesundungen dokumentiert. Somit ermöglicht die Datenbank eine explizite Analyse von beobachtbaren Gesundungen. Beobachtbare Cure Events werden derzeit bestenfalls indirekt durch die komplette Wiederherstellung des Unternehmens ohne Verlust in der Kreditrisikoanalyse berücksichtigt, siehe Calabrese und Zenga (2010). Für eine explizite Aufnahme in die Kreditrisikoanalyse sprechen mehrere Gründe: Wenn ein ausgefallenes und gesundetes Unternehmen lediglich als nicht ausgefallen gilt, bleiben höchstwahrscheinlich elementare Informationen unberücksichtigt, welche bei näherer Beobachtung zur Optimierung des Chance-Risikoprofils einer Bank beitragen könnten. Darüber hinaus bedeutet ein erfolgreicher Heilungsprozess nicht nur keinen Verlust für die Bank, sondern ist häufig mit einem zusätzlichen Ertragspotential verknüpft. Meist sind höhere Kreditkonditionen vereinbart worden und das geschärfte Risikobewusstsein des Kunden dürfte zusätzliche Potentiale, beispielsweise durch Absicherungsgeschäfte bei Währungs- oder Zinsrisiken, eröffnen. Auch der Anteil am gesamten Ertragsvolumen, welches mit einem Firmenkunden erwirtschaftet wird, dürfte nach einer Gesundung vornehmlich auf die am Heilungsprozess aktiv beteiligten Bankpartner aufgeteilt sein und sich nicht auf weitere, außenstehende Finanzinstitute verteilen. Zudem kennen sich die beteiligten Parteien nach einem so einschneidenden Ereignis meist deutlich intensiver, was zu einer verbesserten Informationspolitik führen kann. Auch die professionelle Herbeiführung der Gesundung durch Zukauf von Krediten von Unternehmen in der Restrukturierungsphase mit entsprechendem Abschlag auf den Nominalbetrag bietet zusätzliches Ertragspotential, wenn eine entsprechende Expertise in einer bankinternen Restrukturierungseinheit vorhanden ist.

Um diese Potentiale erfassen und steuern zu können ist eine tiefergehende Analyse von beobachtbaren Cure Events und deren Integration in die Verlustrisikoanalyse notwendig. Die ausfall- und heilungsspezifischen Informationen werden in dieser Arbeit verwendet, um sowohl Verlustpotentiale von Kreditportfoliorisiken zu identifizieren als auch Chancenpotentiale durch die Analyse sichtbarer Cure Events zu berücksichtigen. Dies ist ein neuer Ansatz, welcher meiner Ansicht nach bislang noch nicht analysiert worden ist. Das in dieser Arbeit entwickelten Cure After Default Model (CADM) kann als Grundlage genutzt werden, um ein Kreditportfolio aus deutschen, mittelständischen Unternehmen hinsichtlich bestehender und zukünftiger Ausfallrisiken und Heilungschancen einzuschätzen und zu bewerten.

Wenn die Kreditaufnahme eines Firmenkunden nicht durch kurzfristige Projektierung über einen Broker abgewickelt wird, sondern mit einer engen Kundenbeziehung zwischen Bank und Kreditnehmer einhergeht, kann dies positive Effekte für den Kreditgeber wie auch den Schuldner haben. Die unterschiedlichen Aspekte dieser engen Kreditbeziehungen werden in der wissenschaftlichen Literatur als Relationship Lending bezeichnet, siehe Boot und Thakor (2000). Generell kann die Kundenbeziehung positive Auswirkungen für beide Partner haben. Für die kreditgebende Bank ist eine enge Beziehung zwischen Bank und Kreditnehmern häufig die Basis für einen umfassenden Informationstransfer. Der Kreditgeber ist durch den Einblick in die finanzielle Situation des Schuldners in der Lage, einen Informationsvorsprung zu generieren und Insiderwissen im Kreditmarkt aufzubauen, siehe Schenone (2010). Die enge Kreditbeziehung ist häufig Ausgangsbasis für weitere Produktansätze, welche zusätzliche Ertragspotentiale generieren, siehe La Torre et al. (2010). Aus einer entsprechenden Informationshistorie können mit der Zeit zunehmend anspruchsvollere Kreditrisikoeinschätzungen einzelner Schuldner vorgenommen werden, siehe Sharpe (1990). Für den Kreditnehmer kann durch das Rating, aber auch durch das bloße Engagement eines Kreditinstitutes, eine positive Signalwirkung im Markt enstehen, siehe James (1996). Eine Vielzahl weiterer Aspekte der bestehenden Kreditbeziehung wie der Einfluss der Kreditbeziehung auf den Unternehmenswert oder die Höhe und die Kosten der Kreditfinanzierung wurden bislang ausführlich in der Relationship Lending-Literatur evaluiert, siehe Fama (1985), Berger und Udell (1995) und Elyasiani und Goldberg (2004).

Etwas seltener findet sich der Einfluss einer engen Kundenbeziehung auf die Situation von Unternehmen in einer finanziellen Notsituation. Dies ist vermutlich damit zu begründen, dass Ausfallereignisse bei Firmenkunden ein relativ seltenes Ereignis sind und die Datengrundlage entsprechend eingeschränkt ist. James (1996) und Berlin (1996) haben in diesem Zusammenhang herausgefunden, dass eine enge Kreditbeziehung zu einer Bank einen positiven Einfluss auf die Refinanzierungssituation von Unternehmen im Restrukturierungsprozess haben kann.

Neben den harten finanziellen Informationen spielen gerade im Relationship Lending auch die kundenspezifischen weichen Informationen eine wichtige Rolle. Insbesondere diese über einen längeren Zeitraum erworbenen weichen Informationen können für ein Kreditinstitut von besonderem Wert sein, siehe Berger und Udell (2002).

Die untersuchten Bereiche in der Relationship Lending-Literatur haben im Wesentlichen gemeinsam, dass sie Einflussfaktoren einer bestehenden Kundenbeziehung analysieren. Die Frage, was die Kundenverbindung selbst aufrecht erhält, wird hierbei nicht evaluiert. Dies ist bemerkenswert, da die meisten der genannten Vorteile im Falle einer Kündigung verloren gehen würden. Somit ist die Stärke und Nachhaltigkeit der Beziehung eine elementare Voraussetzung für den Erfolg der Kundenbeziehung. Diese Arbeit widmet sich unter Anderem der Fragestellung, welche qualitativen und quantitativen Einflussfaktoren eine bestehende Kundenbeziehung stärken und welche eher zu einer Aufkündigung der Beziehung führen. Hierbei liegt der Fokus nicht auf einer einvernehmlichen Kündigung beider Partner, sondern auf der einseitigen Kündigung während einer Stresssituation. Eine solche Stresssituation ergibt sich definitionsgemäß dann, wenn ein Firmenkunde für den Kreditgeber als ausgefallen gilt. Als Basis für die Analyse dient ein umfangreicher Datensatz deutscher, mittelständischer Unternehmen, welcher 144 beobachtete Kündigungen unter 1.243 Unternehmen in Stresssituationen beinhaltet. Darüber hinaus werden weitere qualitative Informationen über den Ausfallgrund und den weiteren Verlauf der ausgefallenen Unternehmen ausgewertet. Die gewonnenen Erkenntnisse können zum besseren Verständnis beitragen, wie Banken ihre Kundenbeziehungen bewerten und von welchen Faktoren die Robustheit der Beziehungen in Extremsituationen abhängen. Ein besseres Verständnis dieser Zusammenhänge kann Kreditgeber und Kreditnehmer in die Lage versetzen, die diversen Vorteile des Relationship Lending langfristig und auch über Krisen hinweg zu nutzen.

2 Themenüberblick

Die Dissertation setzt sich insgesamt aus drei einzelnen Artikeln zusammen.
Der Fokus des ersten Artikels liegt primär auf der Identifikation relevanter, ausfallbeeinflussender Variablen sowie der Ableitung eines mehrperiodigen Verlustprognosemodells. Die Entwicklung des Modells erfolgt auf Basis eines umfangreichen Firmenkundenportfolios, welches als repräsentativ für ein typisches Bankportfolio, bestehend aus mittelständischen, deutschen Firmenkunden, angesehen werden kann. Es wird ein aktuelles Mehrperiodenausfallprognosemodell von Duffie et al. (2007) auf den umfangreichen Datensatz angewendet und so ein Kreditportfoliomodell zur Mehrperiodenverlustprognose aus den historischen Daten des Firmenkundenportfolios abgeleitet. Insbesondere die mit 1.243 Beobachtungen relativ große Anzahl von beobachteten Ausfallereignissen macht die Entwicklung des Ausfallprognosemodells interessant. Es werden verschiedene firmenspezifische und makroökonomische Ausfallrisikotreiber identifiziert, welche über einen autoregressiven Prozess erster Ordnung in ihrer zukünftigen Entwicklung beschrieben werden. Auf dieser Basis erfolgt die Prognose der Verlustrisikokennzahlen Value at Risk, Expected Loss und Expected Shortfall für mehrere Jahre.

Der zweite Artikel intensiviert den Fokus auf die ausgefallenen Unternehmen in dem Firmenkundenkreditportfolio. Hierbei wird der aktuell in der Literatur diskutierte Bereich der Cure Events im Zusammenhang mit der Kreditrisikoanalyse beleuchtet. Im Gegensatz zu den überwiegend mit unbeobachtbaren Cure Events arbeitenden Modellen in der Literatur, welche primär zur Problemlösung bei Datensätzen mit einer großen Anzahl von zensierten Ereignissen Verwendung finden, werden in der vorliegenden Arbeit beobachtbare Cure Events analysiert. Beobachtbare Cure Events werden derzeit vonehmlich indirekt über die Rückgewinnungsquote in den Risikomodellen berücksichtigt. Eine explizite Identifizierung und Einarbeitung in die Ausfallmodellierung erscheint jedoch sinnvoll, da ein Cure Event nicht lediglich den Wegfall des Ausfallgrundes und eine Vermeidung von Verlusten bedeutet, sondern sich die gesamte Chance-Risikostruktur bezüglich des jeweiligen Firmenkunden ändert. Während Ausfallrisiken durch einen intensivierten Informationsaustausch nach einer erfolgreichen Restrukturierung eher sinken dürften, erhöhen sich gleichzeitig diverse Ertragspotentiale, zum Beispiel durch höhere Margen und weiteres Cross-Sell-Potential. Der zu Verfügung gestellte Datensatz beinhaltet den Ausfallgrund der Unternehmen sowie den weiteren Verlauf der Restrukturierung und erlaubt somit die explizite Analyse von beobachtbaren Cure Events. Unterschiedliche firmenspezifische und makroökonomische Risikotreiber werden hinichtlich ihrer Signifikanz und Einflusstärke auf die individuellen Heilungschancen der ausgefallenen Unternehmen mittels eines bivariaten Probit Sample Selection Modells untersucht. Darauf aufbauend wird ein neuartiges Kreditausfallmodell entwickelt, welches beobachtbare Cure Events direkt in die Ausfallanalyse integriert: das Cure After Default Model. Dieses Modell identifiziert firmenspezifische und makroökonomische Risikotreiber für Ausfall- und Heilungswahrscheinlichkeiten deutscher, mittelständischer Unternehmen.

Im dritten Artikel wird der Einfluss verschiedener qualitativer und quantitativer Einflussfaktoren hinsichtlich ihrer Auswirkung auf die Stabilität der Kundenbeziehung zwischen Bank und ausgefallenen Schuldnern analysiert. Zu den unterschiedlichen qualitativen Einflussfaktoren zählen zum Beispiel die Einschätzung des Kreditgebers hinsichtlich der Rückzahlungswahrscheinlichkeit, eine vorläufige Zinslosstellung oder ein Zahlungsverzug. Die untersuchten quantitativen Einflussfaktoren sind firmenspezifische Finanzinformationen aus den Jahresabschlüssen der Unternehmen sowie makroökonomische Größen. Die jeweiligen Faktoren werden auf Interdependenzen bezüglich der Kündigung der Geschäftsbeziehung untersucht. Es wird ein Modell geschätzt, welches die Einflussstärke der signifikanten Variablen im Hinblick auf die Kündigung aufzeigt. Durch Identifikation der signifikanten Treiber werden qualitative und quantitative Rahmenbedingungen ermittelt, welche bei einer Kündigung der Geschäftsbeziehung wirken.

3 Datengrundlage

Der verwendete Datensatz beinhaltet ein Portfolio aus insgesamt 5.930 deutschen, mittelständischen Firmenkunden der Dresdner Bank AG[1]. Die Informationen wurden im Frühjahr 2008 zur wissenschaftlichen Analyse in anonymisierter Form vom Bereich Firmenkunden sowie der zuständigen Risikoabteilung bereitgestellt. Insgesamt werden 23.894 Jahresabschlüsse für den Zeitraum vom 01.01.2002 bis zum 31.12.2007 analysiert. Das Portfolio kann als repräsentativ für ein bankspezifisches Kreditportfolio angesehen werden, da die Daten keiner Vorselektion unterliegen. Es werden alle Kunden erfasst, deren Daten in das für die Kreditentscheidung notwendige Risikosystem eingegeben wurden. Zu den vorliegenden Informationen zählen mehrjährige Finanzdaten aus der Gewinn- und Verlustrechnung (GuV) und der Bilanz sowie Informationen zur Branche und gegebenenfalls Ausfallindikatoren mit dazugehörigen Ausfallgründen. Insgesamt liegen Ausfallinformationen zu 1.243 Unternehmen vor, wobei die ersten Ausfälle im Jahr 2003 registriert werden. Da

[1] Die Dresdner Bank AG wurde im Sommer 2008 von der Commerzbank AG übernommen.

dass genutzte Risiko- und Bilanzanalysemodell im Jahreswechsel 2002/2003 initialisiert wurde, liegen für 2002 ausschließlich gesunde Unternehmen vor. Es werden nur Geschäftsjahre in die Analyse einbezogen, die 12 Monate umfassen. Sowohl Rumpfgeschäftsjahre als auch Eröffnungsbilanzen werden nicht mit einbezogen. Die analysierten Finanzinformationen basieren ausschließlich auf Einzelabschlüssen. Konsolidierte Zahlen wurden nicht verwendet, da der Fokus auf den Kreditgeber gerichtet ist und allein der Eintritt eines Ausfallgrundes bereits - zumindest bürokratischen - Aufwand für die Bank bedeutet, auch wenn es sich dabei nur um ein Gruppenunternehmen eines Konzerns handelt, bei dem letztendlich ein Mutterunternehmen nach einer gewissen Zeit aushelfen könnte. Die drei wesentlichen Informationsbereiche des Datensatzes der mittelständischen Unternehmen - Finanzdaten, Brancheninformationen und Ausfallinformationen - werden in den nachfolgenden Abschnitten erläutert.

3.1 Finanzdaten

Die Jahresabschlussdaten des Datensatzes beinhalten folgende Finanzinformationen: Umsatz, EBITDA[2], EBITA[3], Bruttoergebnis, Nettoergebnis, kurzfristiges Fremdkapital, langfristiges Fremdkapital, langfristige Rückstellungen, Eigenkapital, Anlagevermögen sowie Umlaufvermögen.

In der nachfolgenden Tabelle 1 werden deskriptive Statistiken, welche die firmenspezifischen Variablen des Datensatzes veranschaulichen, dargestellt. In der Tabelle wird die durchschnittliche Höhe der einzelnen Werte über die sechs Jahre des gesamten Beobachtungszeitraums hinweg dargestellt. Die Daten beziehen sich auf Durchschnittswerte für jedes der insgesamt im Zeitablauf untersuchten 5.930 Unternehmen. Es wird das arithmetische Mittel, der Median sowie das 25%- und das

[2]Earnings before interest, taxes, depreciation and amortization; auf deutsch: Ergebnis vor Zinsen, Steuern, Abschreibungen auf Sachanlagen und Amortisation von immateriellen Wirtschaftsgütern.

[3]Earnings before interest, taxes and amortization; auf deutsch: Ergebnis vor Zinsen, Steuern und Amortisation von immateriellen Wirtschaftsgütern.

Tabelle 1: Durchschnittswerte der beobachteten Variablen bezüglich aller Firmen über den Gesamtbetrachtungszeitraum von 2002 bis 2007 in tausend Euro ($N = 5.930$, Anzahl der beobachteten Firmen innerhalb des Gesamtbetrachtungszeitraum).

Variable	Arithm. Mittel	25%-Quantil	Median	75%-Quantil
Umsatz	93.311	2.870	12.667	36.867
EBITDA	4.421	77	571	2.141
EBITA	2.222	-13	261	1.230
Bruttoergebnis	4.124	4	282	1.524
Nettoergebnis	1.461	0	145	882
Kurzfristiges Fremdkapital	35.890	1.522	4.338	12.314
Langfristiges Fremdkapital	11.625	12	731	3.436
Langfristige Rückstellungen	6.663	0	91	853
Eigenkapital	23.142	214	1.369	5.840
Anlagevermögen	38.225	434	2.371	9.698
Umlaufvermögen	38.349	1.372	4.711	14.132

75%-Quantil der jeweiligen Variablen veranschaulicht.

Der Median des Umsatzes der Unternehmen liegt im Durchschnitt der Jahre bei rund 13 Mio. Euro, das 25%-Quantil liegt bei 3 Mio. Euro und das 75%-Quantil bei 37 Mio. Euro. Nach der umsatzspezifischen Definition des statistischen Bundesamtes gehören die betrachteten Firmen somit durchschnittlich zum Bereich der kleinen und mittleren Unternehmen (KMU) der deutschen Wirtschaft. [4] Der Median des EBITDA liegt bei rund 0,6 Mio. Euro bei einem Wert von rund 0,08 Mio. im 25%-Quantil und 2,1 Mio. Euro im 75%-Quantil. Eine ähnliche Spannweite ist beim EBITA zu erkennen. Hier liegt der Median bei 0,26 Mio. Euro, wobei das 75%-Quantil einen Wert von 1,2 Mio. Euro aufweist und im 25%-Quantil ein negativer Wert von -13 Tsd. Euro zu erkennen ist. Setzt man, bezogen auf den jeweiligen Median, das Bruttoergebnis ins Verhältnis zum Umsatz so ist eine Rendite von durchschnittlich 2,2% festzustellen. Der Median des kurzfristigen Fremdkapitals liegt im Durchschnitt bei etwa 4,3 Mio. Euro. Beim langfristigen Fremdkapital liegt der Median deutlich niedriger bei 731 Tsd. Euro. Der Median der langfristigen Rückstellungen liegt bei 91 Tsd. Euro. Auffällig ist weiterhin, dass über 25% der Unternehmen in den betrachteten

[4] Umsatzdefiniton KMU: 2 bis 50 millionen Euro.

Jahren langfristige Rückstellungen von 0 Euro aufweisen. Sowohl das arithmetische Mittel des Anlagevermögens als auch das des Umlaufvermögen liegen beide bei rund 38 Mio. Euro. Die Unterschiede werden bei der Betrachtung des Medians deutlich. Der Median des Anlagevermögens ist mit 2,37 Mio. Euro im Durchschnitt über die einzelnen Jahre rund halb so hoch wie der des Umlaufvermögens mit etwa 4,71 Mio. Euro.

3.2 Branchendaten

Die unterschiedlichen Branchen sind in Hauptbranchen und Unterbranchen unterteilbar. Die Gliederung der Branchen entspricht dem Schema des Statistischen Bundesamtes. Die 5.930 Unternehmen des Datensatzes lassen sich insgesamt in 851 Branchen und Unterbranchen aufteilen. Um die Interpretation zu vereinfachen, wurden die Unterbranchen auf die jeweiligen Hauptbranchen konsolidiert. Hierdurch reduziert sich die Anzahl der Branchen auf 56. Diese Branchen sind, zusammen mit der Anzahl der dazugehörigen Unternehmen, mit abnehmender Firmenanzahl in Tabelle 2 dargestellt. Die mit 1.125 Firmen größte Anzahl an Unternehmen kommt in der Branche Handelsvermittlung und Großhandel vor. Diese Branche beinhaltet unter anderem Großhandel von Nahrungsmitteln, Getränken, Maschinen, Baustoffen, Textilien, pharmazeutischen, medizinischen und orthopädischen Erzeugnissen, Mineralölerzeugnissen, Erzen und Metallen sowie chemischen Erzeugnissen. Am zweithäufigsten sind Unternehmen der Branche Erbringung von wirtschaftlichen Dienstleistungen vertreten. Die 611 Unternehmen dieser Branche verteilen sich auf Unterbranchen wie zum Beispiel Architektur- und Ingenieurbüros, Werbung, Management von Holdinggesellschaften, Unternehmensberatung sowie Wach- und Sicherheitsdienste. Mehr als die Hälfte der Unternehmen sind in den ersten sechs Branchen Handelsvermittlung und Großhandel, Erbringung von wirtschaftlichen Dienstleistungen, Maschinenbau, Grundstücks- und Wohnungswesen, Herstellung von Metallerzeugnissen und Baugewerbe tätig.

Tabelle 2: Konsolidierte Branchen der Unternehmen aus der Datenbank mit der Anzahl an vorkommenden Firmen. Dargestellt in absteigender Anzahl der Unternehmen.

Branche	Firmenanzahl
Handelsvermittlung und Großhandel	1.125
Erbringung von wirtschaftl. Dienstleitungen	611
Maschinenbau (inkl. Wartung, Reparatur)	457
Grundstücks- und Wohnungswesen	448
Hv Metallerzeugnissen	239
Baugewerbe	234
Kraftfahrzeughandel, Instandhaltung und Reparatur von KFZ, Tankstellen	211
Einzelhandel	201
Hilfs- und Nebentätigkeiten für Verkehr und Verkehrsvermittlung	178
Hv chemischen Erzeugnissen	173
Ernährungsgewerbe	156
Hv Gummi- und Kunststoffwaren	146
Metallerzeugung und -bearbeitung	122
Hv Kraftwagen und Kraftwagenteilen	114
Hv Medizin-, Mess-, Steuer- und Regelungstechnik, Optik, Uhren	112
Glasgewerbe, Hv Keramik, Verarbeitung von Steinen und Erden	94
Schifffahrt	92
Hv Geräten zur Elektrizitätserzeugung, -verteilung	90
Verlagsgewerbe, Druckgewerbe, Vervielfältigung von bespielten Bild-, Ton- und Datenträgern	85
Datenverarbeitung und Datenbanken	82
Papiergewerbe	78
Hv Möbeln, Schmuck, Musikinstrumenten, Sportgeräten, Spielwaren	77
Gesundheits-, Verterinär- und Sozialwesen	74
Elektrizitäts- und Gasversorgung	69
Textilgewerbe	61
Kultur, Sport und Unterhaltung	57
Hv Rundfunk- und Nachrichtentechnik	49
Abwasser- und Abfallbeseitigung	43
Erbringung von sonstigen Dienstleistungen	42

Fortsetzung auf der nächsten Seite

Tabelle 2: Konsolidierte Branchen der Unternehmen aus der Datenbank mit der Anzahl an vorkommenden Firmen. Dargestellt in absteigender Anzahl der Unternehmen. Forts.

Branche	Firmenanzahl
Sonstiger Fahrzeugbau	38
Holzgewerbe (ohne Hv Möbeln)	36
Vermietung beweglicher Sachen ohne Bedienungspersonal	34
Gewinnung von Steinen und Erden, sonstiger Bergbau	33
Bekleidungsgewerbe	26
Landverkehr	26
Gastgewerbe	25
Erziehung und Unterricht	25
Banken, Finanzdienstleistungen	23
Recycling	21
Interessenvertretungen sowie kirchliche und sonst. Vereinigungen (ohne Sozialwesen, Kultur)	19
Nachrichtenübermittlung, Post, Telefon, Rundfunk, Fernsehen	17
Hv Leder, Lerderwaren, Schuhe	14
Landwirtschaft und Jagd	13
Hv Büromaschinen, Datenverarbeitungsgeräten und -einrichtungen	12
Mit Kredit- oder Versicherungswesen verbundene Tätigkeiten	12
Kokerei, Mineralölverarbeitung	8
Wasserversorgung	6
Tabakverarbeitung	5
Kohlenbergbau und Torfgewinnung	3
Luftfahrt	3
Forschung und Entwicklung	3
Privatpersonen	3
Gewinnung von Erdöl und Erdgas	2
Forstwirtschaft	1
Versicherungsgewerbe	1
Gesetzliche Sozialversicherung und Arbeitsförderung	1

3.3 Ausfalldaten

Von den 5.930 Unternehmen in der Datenbank fallen im Gesamtbetrachtungszeitraum von Januar 2002 bis Dezember 2007 insgesamt 1.243 aus. Als ausgefallen gilt ein Unternehmen, welches mindestens einen Ausfallgrund aufweist. Ausfallgründe sind beispielsweise 90 Tage Zahlungsverzug, Abschreibungen oder Insolvenz. Für das Jahr 2002 sind nur nicht ausgefallene Unternehmen vorhanden. Die ersten Ausfälle werden im Jahr 2003 registriert, da das Risikosystem aus dem die Daten stammen erst gegen Ende des Jahres 2002 aktiviert wurde. Es sind 2.779 Jahresabschlüsse von ausgefallenen Unternehmen verfügbar. Dies bedeutet, dass im Durchschnitt 2,2 Jahre an Jahresabschlussdaten zur Verfügung stehen. Bei den 4.687 nicht ausgefallenen Firmen sind im Durchschnitt Finanzdaten für 4,5 Jahre vorhanden. Darüber hinaus sind Informationen über die weitere Entwicklung nach dem Ausfall vorhanden. Hierbei wird zwischen fünf verschiedenen Ausprägungen unterschieden: Cured bedeutet, dass der Ausfallgrund ohne Verlust für die Bank entfallen ist. Write-off bedeutet, dass ein Teil oder das Gesamtengagement abgeschrieben wurde. Worked-out bedeutet, dass die Kreditlinie gestrichen wurde und die Sicherheitenverwertung eingetreten ist. Distressed-sold bedeutet, dass das Kreditengagement mit Verlust verkauft wurde. Die fünfte Ausprägung lautet Unknown, was bedeutet, dass die weitere Entwicklung nach dem Ausfall nicht bekannt ist. Insgesamt kommen 333 Firmen mit Cured vor, 269 mit Write-off, 244 mit Unknown, 239 mit Worked-out und bei 158 ist die Entwicklung Distressed-sold genannt. Die genannten Ausfallinformationen werden in Tabelle 3 veranschaulicht.

Zu den verfügbaren Ausfallinformationen zählen auch die Ausfallgründe. Hierbei sind Mehrfachnennungen durchaus die Regel. In Tabelle 4 sind die untersuchten Ausfallgründe mit der jeweiligen Anzahl an Nennungen aufgeführt.

Die Bezeichnung Free-of-interest-state bedeutet, dass das Unternehmen keine fälligen Zinsen für ausstehende Kreditlinien zahlt. Payment-unlikely ist kein hartes Kriterium, sondern eher eine Einschätzung des Gläubigers, dass eine bestimmte Zah-

Tabelle 3: Ausprägungen der unterschiedlichen Entwicklungen.

Ausprägung	Anzahl der Unternehmen
Cured	333
Write-off	269
Unknown	244
Worked-out	239
Distressed-sold	158
Nicht ausgefallen	4,687
Summe	5,930

Tabelle 4: Ausprägung der Ausfallgründe der ausgefallenen Firmen in der Datenbank mit der Anzahl der Beobachtungen. Mehrfachnennungen sind möglich.

Ausprägung	Anzahl an Beobachtungen
Free-of-interest-state	238
Relationship-cancelation	144
Payment-unlikely	58
Settlement	238
Non-accrued	115
Depreciation	2
90-day-delayed-payment	35
Specific-provision	562
Troubled-debt-restr	9
Provision	236
Bankruptcy	1

lungen unwahrscheinlich ist. Wenn verschiedene kreditspezifische Zahlungen nicht geleistet wurden, wird dies mit Non-accrued vermerkt. Zahlungen, die seit mindestens 90 Tagen überfällig sind, sind mit 90-day-delayed-payment gekennzeichnet. Die Kündigung der Geschäftsbeziehung wird durch Relationship-cancelation gekennzeichnet und Probleme bei der Restrukturierung durch Troubled-debt-restr. Diese Bezeichnung kommt mit lediglich 9 Beobachtungen relativ selten vor. Gleiches gilt für die Bezeichnung Depreciation, welche Abschreibungen auf die Kreditlinie erfasst und lediglich zweimal vorkommt, ebenso wie die Insolvenz des Unternehmens, welche mit Bankruptcy gekennzeichnet ist und einmal registriert wird. Wenn ein Kredit nicht restrukturiert werden konnte und nur teilweise, beispielsweise durch Sicherheitenverwertung, zurückgeführt wurde, ist die Bezeichnung Settlement zu finden. Wenn bei einem Kredit eine Einzelwertberichtigung vorgenommen wurde, ist dies durch Specific-provision gekennzeichnet. Eine generelle Rückstellungsbildung wird mit Provision bezeichnet.

4 Ausblick und zukünftige Forschung

Die vorliegende Arbeit vermittelt einen ersten Eindruck bezüglich der Relevanz von Cure Events in der Kreditrisikomodellierung. Die entwickelten Modelle basieren auf einem Datensatz aus deutschen, mittelständischen Unternehmen. Cure Events treten aber auch bei deutlich kleineren oder deutlich größeren in- und ausländischen Unternehmen auf. Die Analyse von Datensätzen mit spezifischen Informationen zu beobachtbaren Cure Events aus diesen Bereichen würde eine höchst interessante Vergleichsmöglichkeit bezogen auf die vorliegenden Ergebnisse ermöglichen. Hierbei wäre es zudem erstrebenswert, auf längere Zeitreihen zugreifen zu können. Da es naturgemäß größerer Zeitintervalle bedarf, bis nach einem Ausfallereignis ein Cure Event sichtbar wird, würde eine längere Beobachtungszeit beim vorliegenden Datensatz unter Umständen die Anzahl der Unternehmen mit unbekanntem Status zugunsten der Grundgesamtheit der Cure Events verringern.

Eine deutliche Ausweitung des Beobachtungszeitraums der historischen Daten würde zudem die Integration von zufälligen Effekten in die Modellschätzung ermöglichen. Über die zufälligen Effekte könnten unbeobachtbare, makroökonomische Einflüsse erfasst werden, welche nicht explizit über die untersuchten Modellvariablen Berücksichtigung finden. Die Verwendung der zufälligen Effekte könnte bei der Ermittlung der Risikotreiber sowohl der Ausfallwahrscheinlichkeiten als auch der Heilungswahrscheinlichkeiten und der Kündigungswahrscheinlichkeiten eine sinnvolle Erweiterung sein.

Schließlich wäre es eine vielversprechende Erweiterung, die im ersten Artikel vor-gestellte Mehrperiodenausfallprognose auf das Cure After Default Model aus dem zweiten Artikel anzuwenden. Somit könnte das Ausfallrisiko eines Kreditportfolios unter Berücksichtigung der möglichen Cure Events für mehrere Perioden prognostiziert werden. Hierdurch könnten mehrjährige Prognosen für Ausfälle und deren Heilungsoptionen in mittelständischen Kreditportfolien vorgenommen werden. Die so ermittelten Erkenntnisse könnten von Banken beispielsweise genutzt werden, um die Steuerung und Strategiefestlegung ihres Risikomanagements zu präzisieren.

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Modul I

Mehrperiodenausfallprognose eines Bankportfolios aus deutschen mittelständischen Unternehmen

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Modul II

Cure Events in Default Prediction

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Working Paper

Abstract

This paper evaluates the resurrection event regarding defaulted firms and incorporates observable cure events in the default prediction of SME. Due to the additional cure-related observable data, a completely new information set is applied to predict individual default and cure events. This is a new approach in credit risk that, to our knowledge, has not been followed yet. Different firm-specific and macroeconomic default and cure-event-influencing risk drivers are identified. The significant variables allow a firm-specific default risk evaluation combined with an individual risk reducing cure probability. The identification and incorporation of cure-relevant factors in the default risk framework enable lenders to support the complete resurrection of a firm in the case of its default and hence reduce the default risk itself. The estimations are developed with a database that contains 5,930 mostly small and medium-sized German firms and a total of more than 23,000 financial statements over a time horizon from January 2002 to December 2007. Due to the significant influence on the default risk probability as well as the bank's possible profit prospects concerning a cured firm, it seems essential for the risk management to incorporate the additional cure information into the credit risk evaluation.

1 Introduction

1.1 Motivation

In credit risk evaluation the influence of cure events is gaining more and more attention. Recent literature stated that survival models, which incorporate cure events, are used to improve the prediction of default events. In these models a fraction of cured or immune borrowers is identified in order to deal with heavy censoring due to rare default events. With this approach, one can not only predict when a borrower defaults but also if he defaults at all. This is a big benefit to the existing ordinary survival analysis. These methods were, for example, used by Mo and Yau (2010) and Tong et al. (2012) to predict defaults among personal loan portfolios. Cure models are also used to predict the default of corporate bonds or the bankruptcy of the firms itself, see Yildirim (2008) and Topaloglu and Yildirim (2009). One significant element in these models is that the cure events are unobserved and thus depend on different definitions of long-term survivorship. Differing definitions of cure events might reduce the comparability of these models and the findings most likely depend on the number of cure events created on the basis of these definitions.

An alternative way to evaluate the cure event occurrence is the use of observable cure events. Those events are observed among credit defaults when a default is triggered which does not generate a loss for a lender due to a successful resurrection. The use of observable cure events in the default prediction is a new approach in credit risk that, to our knowledge, has not been followed yet.

Usually observable cure events are treated indirectly as a 100% recovery, see Calabrese and Zenga (2010). Nevertheless, there are several reasons to evaluate observable cure events separately and introduce them in the default prediction rather than in the recovery estimation: an observable cure event has a significant impact on the defaulted firms in a credit portfolio because cured firms are no longer defaulted and are treated as "living" firms. Hence, the influence of this cure event is essential within the evaluation of default risk and is consequently an event that, if identified, should rather be explicitly incorporated in the default prediction than only indirectly measured by the estimation of the recovery rate. Default prediction models that incorporate the cure event are not only capable of predicting when a borrower defaults, but also if he defaults. If a fraction of defaultable firms in a bank's credit portfolio can be linked with a high cure probability this should reduce the equity costs of the expected portfolio loss.

Furthermore, if a defaulted firm is cured it is a special situation for both parties, the firm as well as the bank. The firm faced a default trigger and hence was most likely in a financial struggle, which might even lead to bankruptcy, while the bank had to deal with a possible loss due to significant depreciations as well as the loss of a business relationship and its potential yield due to various cross-sell prospects. The cure event leads to a complete new situation. If the business relationship is maintained, it most probably becomes stronger than ever because both cope with this special situation while other partners might have reduced or cut the relationship with this firm. Both partners know each other even better after a successful recovery which might reduces asymmetric information. The bank suffered no loss in a cure event. In addition, it might gain a higher potential yield due to higher interest concerning the loans or more cross-sell, for example, because of the customers desire to reduce operative risks, such as commodity price risks or interest risks, with derivative products. Customer and bank become more aware concerning default-driving indicators of the firm which might reduce the probability of a further default event regarding the cured firm. Hence, the profit concerning a cured firm might be higher than ever, while the default probability is reduced after the turnaround and the relationship becomes strengthened.

Banks usually have a special "intensive care" unit which treats firms in financial struggle in order to bring about a turnaround situation and thus generate a cure event. If the resurrection expertise of these units is high enough, the profit of these units can be maximized by buying external default events, e.g., loans of struggling firms, in order to create cure events. Predominantly, these loans are bought with a significant discount on the nominal amount. Independent of the intensity of the following relationship with those borrowers, there is a high short-term profit upside related to the extent of the discount.

Therefore, a cure event is much more than a recovery of 100% regarding the outstanding loans; it is an indicator for a reduced credit portfolio risk, a sophisticated "intensive care" unit and enhanced, short- as well as long-term, profit prospects.

If one could identify the risk drivers concerning the default and the resurrection of a firm, it could be possible to identify the probability of a firm being cured. If we know a firm's cure probability as well as its default probability it is possible to estimate the probability of the firm of being "immune" for a certain time period. With this additional information, it might be possible to make more accurate loss predictions. Important information concerning the default and cure events could be recognized by these models, which might lead to lower costs or reveal, so far unseen, risk potentials.

To reach the event of being cured, a firm has to face the event of default first. The resurrection of a firm is an observable and loss-influencing but nevertheless mostly unevaluated event. Data concerning cure events is rare and predominantly only known to banks. Nevertheless, a cure event might contain a lot of borrower-specific and risk-specific information and a separate evaluation of a firms resurrection through a cure probability model might cover this information. Our study can make use of bank-internal information regarding 1,243 default events and 333 cure events among the defaulted firms.

The following sections start with a brief overview of the existing topic-concerned literature. Then, based on the credit portfolio data, a default model is developed that treats the firms, which are cured after their default event, as not-defaulted. This model can be seen as a plain default model which does not incorporate cure-relevant information by different cure-related risk drivers. The influence of the cure event is covered by the reduction of the number of defaulted firms. Since this model only recognizes the definite default events, it is called the Definite Default Model (DDM). In the next step, the handling of mixture cure model events which are used to handle heavy censoring are elucidated. A widely used survival analysis model is discussed, which includes a subject's probability of being cured. It is shown that the model can be seen as a combination of a certain cure probability model and the DDM. In a further step, the approach is modified so that it incorporates observable cure events. The cure event is only observable when the default event is observed and, therefore, the influence of the not-defaulted firms is not evaluated, for example, by linear regression. Hence, a sample selection bias could be generated, see Heckman (1979). In order to omit this bias, the significant influence factors are evaluated with a bivariate Probit sample selection model, see Boyes et al. (1989) and Greene (1998). The new model consists of two main parts: a default probability model and a cure probability model, both developed based on the entire financial database. This new developed model is called the Cure After Default Model (CADM).

1.2 Literature Review

Earlier credit-risk-related scientific literature was written in the mid-1960s and focused on the default risk of single borrowers. Basic work was done by Beaver (1966, 1968a,b). At the end of the 1960s Altman (1968) defined a scoring model evaluating credit risk on the basis of financial data: the Z-Score. A later generation of scoring models is the O-Score, evaluated by Ohlson (1980) based on logistic regression. An overview of the credit risk modeling on single loan basis can be found in Altman and Saunders (1997).

In the following years scientific work turned its focus from the single loan to the evaluation of credit risk regarding loan portfolios. Two main approaches in the credit risk literature are used as the basis for the evaluation of credit portfolio models:

the structural model approach and the intensity model approach. The pioneers of the structural models were Merton (1974, 1977) and Black and Scholes (1973). In their option-pricing approach, a firm's assets follow a geometric Brownian motion and the default probability is only driven by the firm's distance-to-default. The portfolio model used in Basel II as well as the Portfolio Manager^{TM} model from Moodys and the Credit Metrics^{TM} from JP Morgan Chase are examples of the use of the structural model approach. The intensity or reduced form models are based on the individual default intensity process of a borrower. Conditional on the realization of the intensity the number of defaults up to time t are independent Poisson-distributed events. Basic work is done by Jarrow and Turnbull (1995), Jarrow et al. (1997), Lando (1998) and Hillegeist et al. (2004). The portfolio model Credit Risk+^{TM} from Credit Suisse Financial Products uses this approach. Hybrid models that use a combination of both approaches can be found in Duffie and Lando (2001) and Madan and Unal (2000). On overview concerning the intensity model approach can be found in Jarrow and Turnbull (2000) and Bluhm et al. (2003)[1]. A quite new development in literature is the multi-period prediction with credit risk models, see Duffie et al. (2007) and Duffie et al. (2009).

Besides the multi-period prediction the recent credit risk literature pays more and more attention to the cure event in default prediction. Due to the fact that a default event is a very rare event, the applied survival analysis for default evaluation faces a high amount of censored observations which can distort the findings. The problem of heavy censoring among the observed subjects is well known in medicine and is routinely solved by the use of mixture cure models, where the patients are considered cured if they are immune concerning the evaluated disease, see Farewell (1982), Kuk and Chen (1992) and Hughes (1999). Mixture cure models are widely used among clinical trials and separate the data generally into a cure fraction and a fraction of not-cured subjects, see Peng and Dear (2000), Sy and Taylor (2000), Corbière and Joly (2007) and Lai and Yau (2009). It is common to model both groups, the

[1]Cp. Bluhm et al. (2003), p. 55-164.

immune subjects in the cure fraction as well as the fraction of not-immune subjects, conditional on some covariate vectors in order to explain the two distributions. The covariate vectors can consist of the same covariates, but not necessarily. Some covariates may affect the possibility of being cured but may not have any influence on the timing of the event of interest and vice versa, see Yu and Peng (2008) and Zhang and Peng (2009). The use of mixture cure models is a quite new aspect in the credit-default-related literature. However, the cure event takes part in a wide range of credit default risk evaluation models. In several credit scoring models this approach is used in combination with personal loan data recently, see, for example, Beran and Djaidja (2007), Mo and Yau (2010) and Tong et al. (2012). However, the approach can also be found concerning the credit risk analysis regarding the bond market or firms. Yildirim (2008) used the mixture cure model approach with random effects to model long-term survivorship concerning the default estimation of commercial mortgage backed securities. He considered that a reasonable contingent of the observed securities will never default during the duration and thus distorts the results of the survival analysis without cure fraction. The correlation between the securities is captured through the introduction of three independent random effects concerning region, property type and loan level. Topaloglu and Yildirim (2009) used a mixture cure model in order to predict the default of publicly traded US firms. They concluded that in this case the common assumption in the survival analysis, where every subject will eventually reach the event of interest, is too pessimistic for the economic framework.

1.3 Main Contributions

The introduction of cure events in credit risk modeling generates a wide range of additional options for superior models. The latest work in the credit literature, e.g., Tong et al. (2012), used mixture cure models to enhance the performance of survival analysis concerning default risk modeling. This approach uses the unobserved cure event to deal with heavy censoring in the default data. We follow an alternative way to evaluate the cure event with the utilization of observable cure events. The idea that a cure event can be reached after the default is observed can be found in Ambrose and Capone Jr. (1996) where different foreclosure alternatives are modeled concerning mortgage obligations. But in this model the cure probability is given exogenously without further evaluation. In our paper the cure probability is not given exogenously. A main focus is due to the evaluation of the cure-specific influence factors and the estimation of individual firm-specific cure probabilities.

Predominantly, if a cure event is observed by a bank then the firm is treated as not-defaulted, see Basel Committee on Banking Supervision (2005). An indirect influence of a cure event is usually recognized by the estimation of the recovery rate as 100% recovery, see Renault and Scaillet (2004) and Calabrese and Zenga (2010). Recent literature indicated that the recovery rate is strong related to the default risk, see Bade et al. (2011), Pykthin (2003) and Qi and Yang (2009). Nevertheless, a cure event is much more than a recovery of 100% regarding the outstanding loans, it is an indicator for reduced credit portfolio risk and enhanced short- as well as long-term profit prospects. Hence, the cure event should be recognized by the default prediction. We develop a default risk model that applies this approach in order to be capable not only of predicting when a default occurs but also whether it occurs or not.

A cure event is only observable among defaulted firms; therefore, the influence of not-defaulted firms on a firm's probability of being cured is ignored without further modifications. The estimation of resurrection influencing risk drivers might lead to biased findings because non-randomly selected samples are used, see Heckman (1976, 1979). We use a bivariate Probit sample selection estimator to estimate the cure-related drivers and omit a sample selection bias, see Boyes et al. (1989), Greene (1998) and Lee et al. (2004).

The models, which are predominantly discussed in the literature, are nearly all developed based on bond issues or personal loan data, while the developed model in this paper is based on firm-specific information. Our database contains a lot of information over a representative sample of the cross-section concerning German SMEs. The database is not preselected. Hence, it includes every firm that is a Dresdner Bank[2] customer and whose financial data is listed in a risk program necessary for a loan decision. The database can be seen as an example for a typical bank credit portfolio of corporate customers.

The default prediction models DDM and CADM, which are developed in this paper, both use a default probability model in order to cover a firm's default-influencing risk drivers. In addition, the CADM uses a cure probability model, based on observed cure events.

2 Cure and Default Models

In this section different credit risk approaches are developed followed by the description of the applied estimation methods. The first described model, the definitive default model, treats the cured firms as not-defaulted and excludes them from the fraction of defaulted firms. Cure-specific information is not incorporated by risk drivers and the default risk is evaluated based on the remaining "definitive" default events. After that the mixture cure model, a survival model which incorporates long-term survivorship, will be elucidated. It can be seen as a combination of a cure probability model and the DDM.

Then the cure event evaluation in the mixture cure model is modified, so that it can be applied regarding an SME-specific credit portfolio including observed cure events after the default event. A cure model is constructed, which allows cure-relevant risk drivers and their influence to be identified. Following this, the cure model is combined with a default model in order to allow cure events among the defaulted

[2] The firm-specific data was provided by Dresdner Bank AG in spring 2008. Dresdner Bank AG was taken over by the Commerzbank AG in summer 2008.

firms. The parameters of the default model and the cure model are estimated simultaneously via a bivariate Probit sample selection model. The combination of the cure model and the default model is called the Cure After Default Model.

2.1 Risk Management without Cure Events: The Definite Default Model

It is common in credit risk evaluation that cured firms are no longer treated as defaulted firms, see Basel Committee on Banking Supervision (2005). Hence the cure event is indirectly recognized, but it is not separately modeled and evaluated. In order to construct a plain model that uses this approach, the Definite Default Model is derived. In the DDM the cured firms are treated as not-defaulted. The DDM is used in the following to compare the CADM with a standard credit risk approach. A default model is estimated, which uses only the definitely defaulted firms as observed default events. Through this model different firm-specific and macroeconomic risk drivers are identified. The risk drivers are based on known financial data of the previous time period. The default intensity λ of a firm i ($i = 1, ..., N$) for one time period t ($t = 1, ..., T$) is described by the following equation:

$$\lambda(U_{i,t-1}, V_{t-1}) = e^{-(\zeta + \beta \cdot U_{i,t-1} + \theta \cdot V_{t-1})}. \tag{1}$$

$U_{i,t-1}$ is a vector of observable one-year time-lagged firm-specific risk drivers. The vector V_{t-1} includes different observable one-year time-lagged macroeconomic variables that influence all firms at the same intensity and depend only on the time period. ζ is a constant, β and θ are vectors of the different parameters of the covariables to be estimated. The coherence between the one-year default intensity and the one-year default probability is as follows:

$$PD_i(t) = 1 - e^{-\lambda(U_{i,t-1}, V_{t-1}) \cdot 1}, \tag{2}$$

see Cleves et al. (2004)[3]. Based on these probabilities the individual defaults can be predicted. The approach is illustrated in Figure 1.

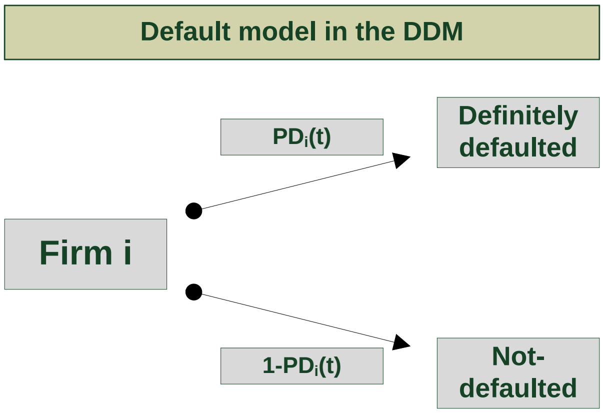

Figure 1: Influence of the default probability in the Definite Default Model. Depending on the individual default probability the firms in the portfolio either default during the observed time period or they survive the time period.

2.2 Risk Management with Unobserved Cure Events: The Mixture Cure Model

Mixture cure models (MCM) are applied in order to deal with heavy censoring in the survival analysis. These models were recently used in the credit risk framework in order to enhance credit scoring models as well as for models used to evaluate defaultable bonds or the bankruptcy of firms. MCM themselves are not a new statistical scope; they are common in medical science, for example, for evaluating diseases within clinical trials such as cancer or for the research of survival studies. Due to medical advancements it is common that a significant part of the observed patients in the clinical trials are long-term survivors. In some cases, a cure fraction becomes imperative because a heavy censoring even in long-term periods may contort the results of survival analysis trials. These models are a mixture of the normal group of subjects at risk, which either experiences death or is censored, and a group of cured long-term survivors. This analysis method allows both modeling of timing

[3]Cp. Cleves et al. (2004), p. 16 and 222-224.

and modeling of the probability of the event of interest at the same time. Furthermore, it is possible to explain timing and probability through different risk drivers and to estimate them separately via parametric, semi-parametric or non-parametric models. An implicit condition of this model type is a sufficient long data history because a cured person can normally not be identified in the short run, see Yu and Peng (2008).

The MCM consists of a cure fraction and a latency survival model. The probability that a subject i ($i = 1, ..., N$) belongs to the cured fraction in time period t ($t = 1, ..., T$) is often measured through logistic regression:

$$PC_i(t) = \frac{e^{z_{i,t-1}}}{1 + e^{z_{i,t-1}}}, \tag{3}$$

where $z_{i,t-1}$ is a state matrix composed of covariate parameters, see Farewell (1982). In order to maintain consistency in notation, we use one-period time-lagged variables $t-1$, while most of the cited work uses the notation t.

In the survival model several risk drivers determine the default probability. In order to include a cured fraction in the survival model the marginal survival function $S_i^m(t)$ and the marginal density function $f_i^m(t)$, indicated by an upper 'm', are modeled as:

$$S_i^m(t) = PC_i(t) + (1 - PC_i(t)) \cdot S(x_{i,t-1})^l, \tag{4}$$

$$f_i^m(t) = (1 - PC_i(t)) \cdot f(x_{i,t-1})^l, \tag{5}$$

where $S(x_{i,t-1})^l$ is the latency survival function and $f(x_{i,t-1})^l$ is the latency density function of the model that includes a cure fraction, indicated by an upper 'l'. The state matrix $x_{i,t-1}$ contains several risk drivers. These risk drivers can be the same as in $z_{i,t-1}$ but they do not have to be. In order to separate this model from a model without a cure fraction as well as from the cure probability model generated through logistic regression, it is called the latency model. Without a cure fraction the model is reduced to a standard survival model, see Corbière and Joly (2007) and Yu and

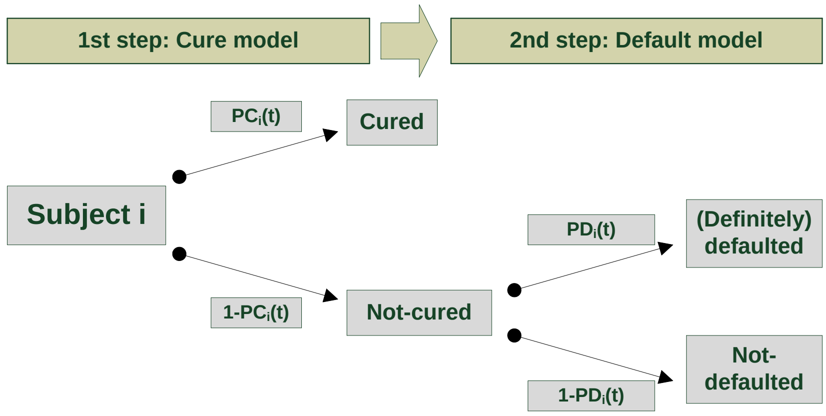

Figure 2: Relation between the different steps regarding the Mixture Cure Model, cp. Topaloglu and Yildirim (2009). First the cure fraction is predicted and separated, among the remaining subjects defaults are predicted in the second step.

Peng (2008). Figure 2 shows the relation between the different fractions.

2.3 Risk Management with Observed Cure Events: The Cure After Default Model

If one extends the mixture cure approach so that it fits in a default prediction environment with observed cure events after the default event, several modifications have to be made.

Firstly, the assumption that there is a fraction of borrowers in a credit portfolio, which is not connected with any default risk and will never default is dropped. In the CADM every firm has a certain default probability and the possibility of being cured is only relevant for those firms, which triggered a default event. This is due to the fact that only after an observed default event can a firm be cured. This assumption seems to be more intuitive and is also underlined by the empirical observations concerning the recent financial crisis of 2008 as well as the ongoing crisis in 2011/2012. There seems to be no group of borrowers that are not under risk. Every credit agreement is currently at risk, even if it is a very unlikely one.

Secondly, from an empirical point of view only defaulted firms are able to become cured. In order to incorporate this fact in the model, the two steps of the MCM are changed: in a first step, a default model is used to calculate the firm's individual default probability in order to predict the default events. In a second step, a cure probability model is used to calculate the firm's individual cure probability in order to predict the cure events among the predicted defaults. The order of the two steps in the CADM now displays the empirical circumstances of resurrection in the credit-default environment.

Thirdly, the change of the order of the two steps has major implications on the default probability as well as on the cure probability model: if the cure event was not separated previously, one has to apply a default probability model that recognizes all default events, even if the firms might be cured afterwards. Hence, the DDM is not appropriate and a new default probability has to be estimated that counts every default event as a default, independent of its further deployment. In the new default model of the CADM, similar to the DDM, different firm-specific and macroeconomic risk drivers are identified. The risk drivers are based on known financial data of the previous time period.

Fourthly, the logistic regression used in the MCM concerning the cure probability model incorporates only the narrow sample of defaulted firms and ignores the rest of the firms in the credit portfolio, because the cure event is only observable when the default event is observed. Nevertheless, the not-defaulted firms have a certain default probability. The exclusion of the not-defaulted firms would neglect this influence and might generate a sample selection bias, see Heckman (1976, 1979). A bivariate Probit sample selection model is used to omit a possible bias, see Boyes et al. (1989), Greene (1998) and Lee et al. (2004). The model is used to predict individual cure probabilities $PC_i(t)$ for the firms, whereas different one-year time-lagged firm-specific and macroeconomic influence factors are evaluated as influence factors.

After considering the described modifications a new credit default model that includes cure-specific risk drivers besides the default influencing ones is created: The Cure After Default Model. The CADM is visualized in Figure 3.

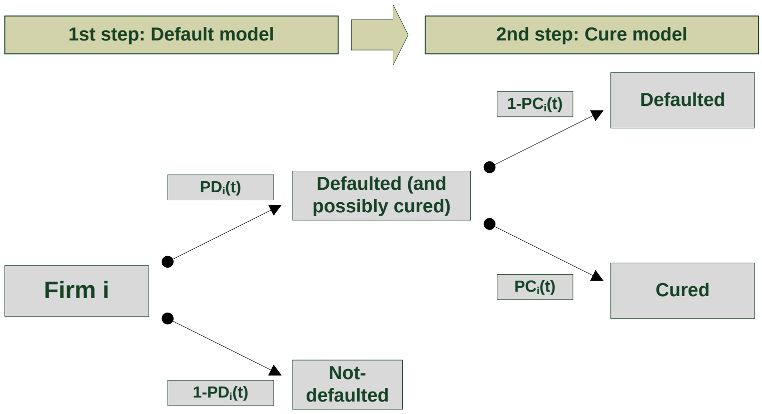

Figure 3: Relation between the two steps in the Cure After Default Model. In the first step the individual default probability is used to predict default events among the firms in the portfolio. In the second step the individual cure probability among the defaulted firms is used to predict cure events.

The default model in the CADM incorporates all observed default events, independent of the further deployment, because the cure event is introduced after the default model. The definition of the default event is the only difference concerning the default model of the DDM, which reduces the number of default events by the fraction of cured firms.

The firms cure probability is relevant for the second step and is used to identify significant variables that influence a firm's probability of being cured. With the cure-related risk drivers it is possible to calculate a firm's individual cure probabilities in order to predict cure events among the predicted default events in the credit portfolio. This model introduces all resurrection-related information concerning the individual borrowers.

2.4 Estimation of the Default- and Cure-Related Parameters

2.4.1 Estimation of the Parameters for the DDM

The probability distribution of firm-specific defaults, that are needed for the distribution of portfolio loss, are based on individual firm-specific default probabilities. The default probabilities are calculated by a model with observable firm-specific and macroeconomic risk drivers. The correlation is induced by the macroeconomic variables, see Yamaguchi et al. (2002) and Duffie et al. (2007).

An accelerated-failure-time model is used. The estimated findings, therefore, have to be interpreted as follows: covariables with a positive parameter delay the time until a default occurs. They protect the firm against a possible default. Covariables with a negative value accelerate the time until a default occurs. In order to receive the findings of a proportional hazard model, one can simply change the algebraic sign of the estimated parameters, see Cleves et al. (2004)[4].

The observable firm-specific and macroeconomic variables of the years 2002 to 2006 are the input data of the default model. The variables are one-year time-lagged. The financial data of the year 2007 is not applied, because defaults are not available for the year 2008. The covariables are assumed to be constant within the different time periods, they change only from year to year. The time homogenous description refers only to the respective time period. Over the different time periods the variables change and become time dependent.

Annual financial statements and accordingly subsequent derived ratings have always been in the main focus when default probabilities for individual firms are calculated, see Altman (1968), Beaver (1966, 1968a,b), and Ohlson (1980). Duffie et al. (2007) used for the evaluation of a default model based on US American industrial firm's three-month treasury interest rates as macroeconomic influence factors. Also the GDP is evaluated as a potential influence factor. In our paper we use different quotes derived from the annual financial statements of the firms in the credit portfolio as well as the sales and total capital as proxy for the firm size. The 12-month EURIBOR and the German annual GDP growth rate are used to capture macroeconomic influences.

The logarithmized firm-specific covariates ln(Sales) and ln(Total Capital) are mentioned in units of a thousand euros. The evaluated variables measured in quotes are Gross Profit, Long-term Liabilities, Current Liabilities, Long-term Provisions

[4] Cp. Cleves et al. (2004), p. 13-16, 123-127, 200-212 and 215-224.

and Equity in relation to the Total Capital and Fixed Assets in relation to Total Assets. Also the evaluated macroeconomic variables 12-month EURIBOR and annual growth rate of the German GDP are one-year time-lagged. In this estimation method the cured default events are mentioned as not-defaulted. The remaining default events are defined as definite default events and are captured in the estimation procedure through the dummy variable *dd*. The parameters are estimated through the maximum likelihood method. The likelihood function is applied to the individual firm i ($i = 1, ..., N$) at the time intervals t ($t = 1, ..., T$). The likelihood function is:

$$L = \prod_{t=1}^{T} \prod_{i=1}^{N_t} [(f(U_{i,t-1}, V_{t-1}))^{dd_{it}} \cdot (S(U_{i,t-1}, V_{t-1}))^{1-dd_{it}}], \tag{6}$$

whereas $U_{i,t-1}$ is a vector of firm-specific covariates and V_{t-1} is a vector of macroeconomic variables. The binary dummy variable dd_{it} ($dd_{it} \in \{0, 1\}$) indicates if the respective firm has a definite default event within the observed time interval ($dd_{it} = 1$) or if it survives the observed time interval ($dd_{it} = 0$). By inserting the relation

$$f(U_{i,t-1}, V_{t-1}) = \lambda(U_{i,t-1}, V_{t-1}) \cdot S(U_{i,t-1}, V_{t-1}) \tag{7}$$

into equation (6), it follows:

$$L = \prod_{t=1}^{T} \prod_{i=1}^{N_t} [(\lambda(U_{i,t-1}, V_{t-1}) \cdot S(U_{i,t-1}, V_{t-1},))^{dd_{it}} \cdot (S(U_{i,t-1}, V_{t-1}))^{1-dd_{it}}] \tag{8}$$

$$\iff \qquad L = \prod_{t=1}^{T} \prod_{i=1}^{N_t} (\lambda(U_{i,t-1}, V_{t-1},))^{dd_{it}} \cdot (S(U_{i,t-1}, V_{t-1}))^{1}. \tag{9}$$

The maximization is done using a Newton-Rhapson algorithm, see Blossfeld et al. (1986)[5], Miller (1981)[6] as well as Yamaguchi et al. (2002). The 1,243 default events are reduced to 922 observed default events due to missing data. These observed default events are further reduced to 657, because the 265 cured firms are not treated

[5]Cp. Blossfeld et al. (1986), p. 67-76.
[6]Cp. Miller (1981), p. 16-20.

as defaults. The estimations are made with the NLMIXED procedure of the program SAS.

2.4.2 Estimation of the Parameters for the CADM

As in the MCM a cure fraction exists in the CADM. A substantial difference is that this cure fraction is not a fraction of subjects which will never experience the event of interest but it is a fraction of firms, related to all defaulted firms, that could recover without any loss for the bank. One main advantage compared to the MCM is the identifiability of the cured fraction because these cure events are definitely observable.

An additional challenge compared to the MCM is the possible sample selection bias due to the sample reduction from the N firms in the portfolio to the reduced sample of defaulted firms. In order to avoid a possible bias a bivariate Probit sample selection model is used, see Heckman (1976, 1979), Greene (1998) and Boyes et al. (1989).

The standard Heckman model consists of the two dependent variables d_{it} and c_{it}. Their corresponding parameters are estimated via a linear equation. One dependent variable, c_{it} is only observable if a second dependent variable, the binary default indicator variable $d_{it} \in \{0, 1\}$, has the outcome 1, hence a default occurred. The observable indicator d_{it} has the outcome 0 if the not-observable metric variable d^*_{it} falls below a specific threshold:

$$d^*_{it} = \alpha^{H_d} \cdot x^{H_d}_{i,t-1} + u^{H_d}_{it} \tag{10}$$

$$d_{it} = \begin{cases} 1 & \text{if } d^*_{it} > 0 \\ 0 & \text{if } d^*_{it} \leq 0 \end{cases} \tag{11}$$

where α^{H_d} is a parameter vector for the covariates to be estimated. The state matrix $x^{H_d}_{i,t-1}$ contains several one-year time-lagged risk drivers. $u^{H_d}_{it}$ is the residual error term.

In our evaluated model also the dependent variable c_{it} is a binary variable, because its outcome is 1 if the defaulted firm is cured afterwards and 0 if it is not-cured. The standard Heckman method is not appropriate concerning this special case, because of the fact that the outcome of the second equation is binary. In order to handle the Heckman model with two binary dependent variables, we apply a bivariate Probit sample selection model, see Boyes et al. (1989), Lee et al. (2004). In the case of $d_{it} = 1$, c_{it} is an observable binary indicator that has the outcome 0 if the not observable metric variable c^*_{it} falls below a specific threshold and 1 otherwise:

$$c^*_{it} = \alpha^{H_c} \cdot x^{H_c}_{i,t-1} + u^{H_c}_{it}, \qquad \text{if } d_{it} = 1 \tag{12}$$

$$c_{it} = \begin{cases} 1 & \text{if } c^*_{it} > 0 \qquad \text{and } d_{it} = 1 \\ 0 & \text{if } c^*_{it} \leq 0 \qquad \text{and } d_{it} = 1 \end{cases} \tag{13}$$

where α^{H_c} is a parameter vector for the covariates to be estimated. The state matrix $x^{H_c}_{i,t-1}$ contains several one-year time-lagged risk drivers. $u^{H_c}_{it}$ is the residual error term. The error terms $u^{H_d}_{it}$ and $u^{H_c}_{it}$ are jointly normal distributed with a mean of 0, a standard deviation of 1 and a correlation ρ^H. The outcome of c_{it} and d_{it} is either 0 or 1, hence, three combinations are possible: $d_{it} = 0$, $d_{it} = 1$ and $c_{it} = 0$ as well as $d_{it} = 1$ and $c_{it} = 1$. This leads to:

1. If no default occurred:

$$Pr\left(d_{it} = 0\right) = 1 - \Phi\left(\alpha^{H_d} \cdot x^{H_d}_{i,t-1}\right) \tag{14}$$

2. If a default occurred and the firm is not-cured:

$$Pr\left(d_{it} = 1, c_{it} = 0\right) = \Phi\left(\alpha^{H_d} \cdot x^{H_d}_{i,t-1}\right) - \phi\left(\alpha^{H_d} \cdot x^{H_d}_{i,t-1}, \alpha^{H_c} \cdot x^{H_c}_{i,t-1}, \rho^H\right) \tag{15}$$

3. If a default occurred and the firm is cured:

$$Pr\left(d_{it}=1, c_{it}=1\right) = \phi\left(\alpha^{H_d}\cdot x_{i,t-1}^{H_d}, \alpha^{H_c}\cdot x_{i,t-1}^{H_c}, \rho^H\right) \tag{16}$$

where Φ denotes the cumulative distribution function for the standardized univariate normal distribution and ϕ denotes the cumulative distribution function of the standardized bivariate normal distribution with correlation ρ^H, see Boyes et al. (1989). The likelihood of the model can be written, conditional on the identified covariates, as:

$$\begin{aligned} L = \prod_{t=1}^{T}\prod_{i=1}^{N_t} \left(1-\Phi\left(\alpha^{H_d}\cdot x_{i,t-1}^{H_d}\right)\right)^{1-d_{it}} \cdot \\ \left(\Phi\left(\alpha^{H_d}\cdot x_{i,t-1}^{H_d}\right) - \phi\left(\alpha^{H_d}\cdot x_{i,t-1}^{H_d}, \alpha^{H_c}\cdot x_{i,t-1}^{H_c}, \rho^H\right)\right)^{d_{it}\cdot(1-c_{it})} \cdot \\ \left(\phi\left(\alpha^{H_d}\cdot x_{i,t-1}^{H_d}, \alpha^{H_c}\cdot x_{i,t-1}^{H_c}, \rho^H\right)\right)^{d_{it}\cdot c_{it}} . \end{aligned} \tag{17}$$

For the maximization of the function a quasi-Newton-Raphson algorithm is used. The estimations are made simultaneous with the QLIM procedure of the program SAS. From the 1,243 defaulted firms 711 are observed in the estimation due to missing data or unknown occurrence after the default event. Regarding these firms 250 are cured ($c_{kt}=1$) and 461 are not-cured ($c_{kt}=0$).

3 Descriptive Statistics

3.1 Origin of the Database

The data was provided for scientific evaluation in anonymous form by the corporate banking and risk controlling divisions of Dresdner Bank AG in spring 2008. The database contains multi-year data from balance sheets and profit and loss statements concerning a total number of 5,930 German firms as well as 1,243 observed default events. Triggers for a default event are, for example, 90-day-delayed-payment, notice of relationship-cancelation through the bank and bankruptcy. Concerning the defaulted firms information regarding the deployment in the bank is available, for example, if the exposure is written off, if the credit was sold with discount or if the default could be handled without loss for the bank. The firms are predominantly not listed on a stock market. The observed firms range over many different branches. In total 23,894 financial statements over a period from 01.01.2002 to 31.12.2007 were evaluated. The financial data is solely taken from individual financial statements. Consolidated financial statements are not used on purpose within the modeling. This is due to the fact that the default event, from the lender's point of view, is in the main focus and thus it is not relevant if there exists a mother firm which could solve some of the problems after a while because alone the fact that there is a problem, as, for example, a delayed payment of at least 90 days, generates bureaucratic effort and a loss for the lender becomes likely.

The database concerning the financial statements include: branch, sales, EBITDA[7], EBITA[8], gross profit, net profit, current liabilities, long-term liabilities, long-term provisions, equity, fixed assets as well as current assets. Furthermore, only financial data that relies on a 12-month time period are used. Shortened financial years and opening balance sheets are not used. If for one firm several default events are mentioned, the first is used as the relevant default event.

In this paper the following units are applied concerning the firm-specific information from the database: the quotes of gross profit to total capital, current liabilities to total capital, long-term liabilities to total capital, long-term provisions to total capital, equity to total capital and fixed assets to total assets as well as current assets to total assets. In addition, the logarithmized total capital and the logarithmized sales are used. The logarithmized values are based on units of a thousand euros. The logarithmization is done in order to smooth the data and hence generate more comparable findings with the estimated quotes.

[7]Earnings before interest, taxes, depreciation and amortization.

[8]Earnings before interest, taxes and amortization.

3.2 Default Information

From the total of 5,930 firms in the database 1,243 firms defaulted in the period from January 2002 to December 2007. For the year 2002 only not-defaulted firms are mentioned in the database and the first defaults are observed in January 2003, because the used risk and accounting system was activated in the turn of the year 2002/2003. A total of 2,779 years of balance sheet data are counted among these defaulted firms. That means that on average 2.2 years per firm are known. Regarding the 4,687 not-defaulted firms on average 4.5 years per firm are known. The further deployment in the bank after the default of the firms is also part of the data. Five possible occurrences are mentioned: Cured means that the problem with the firm could be removed without any loss for the bank, Write-off means that some part or all of the exposure had to be expensed, Worked-out means that the loan agreement is canceled and the securities had to be disposed to cover the outstanding liabilities, Distressed-sold means that the loans had been sold with loss. The fifth calibration is Unknown, which means that the further development after the default event is not definitely known. Concerning the calibration of the defaulted firms in the database 333 firms are Cured, 269 are Write-off, 244 are Unknown, 239 are Worked-out and 158 are mentioned as Distressed-sold. These facts are summed up in Table 1.

Table 1: Calibration status of all firms in the database with the total number of annual financial statements for each of the specifications.

Calibration	Number of Firms	Number of Balance Sheet Years
Cured	333	688
Write-off	269	635
Unknown	244	675
Worked-out	239	481
Distressed-sold	158	300
No default	4,687	21,115
Sum	5,930	23,894

4 Empirical Findings

4.1 Definite Default Model

In Table 2 the findings concerning the parameter estimation of the default model with definite default events are shown. Three different variants are distinguished; the first contains only a constant and the macroeconomic variables, the second variant includes all evaluated variables, and the third variant is the final default model of the DDM. In addition, the hazard rate is mentioned. It indicates a covariable's influence on the default intensity if its value is changed by one unit, given that all other variables remain unchanged, see Cleves et al. (2004)[9].

One should keep in mind that the coefficients are depending on their units. For example, the 12-month EURIBOR is mentioned in percent while the ln(Sales) is mentioned in logarithmized units of a thousand euros. Therefore, the hazard rate indicates the influence of these variables on a firms default intensity by the change of one percent point or one logarithmized unit of a thousand euros, respectively. The quotes are mentioned as ratios, for example, 0.23. A change by one unit could be seen, for example, as a change from 0 to 1. If one would like to interpret the quote's influence in percent points, one needs to divide the parameter and the standard error by 100. The significance would remain unchanged, see Cleves et al. (2004)[10].

Variant 1 contains only a constant and the macroeconomic variables. All estimated parameters are significant, the parameter for the constant and the GDP at 1% and the one for the 12-month EURIBOR at the 10% level. The hazard rate regarding the constant is 8.04%[11]. Concerning the GDP the hazard rate indicates that an increase of about one percentage point reduces the default intensity by 54%. The same increase would reduce the intensity by 18% regarding the 12-month EURIBOR.

[9]Cp. Cleves et al. (2004), p. 13-16, 123-127 and 215-224.

[10]Cp. Cleves et al. (2004), p. 125-127.

[11]657 default events are observed in the estimation. The estimated basic hazard rate is much higher than the average number of default events because the influence of the macroeconomic variables is not at 0 value. If the weighted average value of the macroeconomic variables is used, the average default rate is at 1.4%.

Table 2: Estimation of the parameters concerning the Definite Default Model, separated in three different variants. Variant 1: default model solely with a constant and the macroeconomic variables, Variant 2: default model with all evaluated variables, Variant 3: final default model of the DDM. (Standard deviations in parentheses)

Covariate	Variant 1		Variant 2		Variant 3	
	Parameter	Hazard Rate	Parameter	Hazard Rate	Parameter	Hazard Rate
Constant	2.5209*** (0.2659)	0.0804	3.6415*** (0.5064)	0.0262	4.0564*** (0.4354)	0.0173
ln(Sales)			0.1870*** (0.0283)	0.8294	0.1848*** (0.0258)	0.8313
Gross Profit / Total Capital			0.2338*** (0.0450)	0.7915	0.2286*** (0.0434)	0.7957
Current Liabilities / Total Capital			-2.1349*** (0.4271)	8.4562	-2.1447*** (0.4262)	8.5395
Long-term Liabilities / Total Capital			-2.0779*** (0.4363)	7.9877	-2.0711*** (0.4283)	7.9336
Long-term Provisions / Total Capital			-1.0533* (0.6159)	2.8671	-1.0630* (0.6148)	2.8950
Equity / Total Capital			0.7677*** (0.2572)	0.4641	0.7705*** (0.2567)	0.4628
Fixed Assets / Total Assets			0.0303 (0.1725)	0.9702		
ln(Total Capital)			-0.1388*** (0.0351)	1.1489	-0.1365*** (0.0328)	1.1463
GDP	0.7844*** (0.0842)	0.4564	0.7304*** (0.0857)	0.4817	0.8297*** (0.0607)	0.4362
12-month EURIBOR	0.2074* (0.1257)	0.8127	0.2073 (0.1280)	0.8128		

*significant at 10%, **significant at 5% , ***significant at 1%

The second variant of the Definite Default Model includes all reviewed covariates in the database. The estimated parameters for the variables Fixed Assets to Total Assets and 12-month EURIBOR are not significant. The constant and the parameters for the macroeconomic variable GDP and the firm-specific variables Current and Long-term Liabilities and Gross Profit in relation to Total Capital respectively as well as the ln(Sales) and ln(Total Capital) are significant at the 1% level. The parameter for the variable Long-term Provisions to Total Capital is significant at 10%. Due to the enhanced number of explaining variables the basic hazard rate is reduced to 2.6%. A negative algebraic sign can be seen concerning Current Liabilities to Total Capital, Long-term Liabilities to Total Capital, Long-term Provisions to Total Capital and ln(Total Capital).

The third variant is derived from the second one and is the applied default model in the DDM. The remaining significant parameters are unchanged in significance and influence direction. The hazard rate concerning the constant reduces from 2.62% to 1.73%.

The negative influence of the Long-term Provisions to Total Capital could be interpreted as the effect that firms, which have the need for provision building for imminent losses or uncertain liabilities, have, on average, a lower financial strength. The negative influence of the Current and Long-term Liabilities to Total Capital indicates that firms within the observed portfolio with a quite high value concerning the liability quotes have to pay a relative high amount of interest on average, are less flexible concerning an expansion of the credit lines for necessary investments or an spontaneous recognition of market chances.

The positive influence of the Gross Profit to Total Capital underlines the intuitive assumption that a high profit means a high financial strength, flexibility and it is an indicator for a well-working market strategy. The positive influence of the Equity to Total Capital might be due to a higher financial flexibility and stability of firms with a high amount of equity.

The variables ln(Sales) and ln(Total Capital) can both be seen as proxies for the size of a firm. Hence, the opposing influence of these parameters is somewhat surprising at first glance. Taking the influence direction into account one can say that firms, which are bigger concerning their sales, have a lower default probability because of their market influence and have a higher bargaining power, whereas firms which are bigger concerning their assets might have a lower flexibility, cannot react in time if changes in important markets are developing and thus fail in these situations more often.

The positive influence of the GDP can be explained by the fact that in economic upturns a lower number of firms fails due to the high market demand.
In general, one can state that firms with relatively high sales, gross profit and equity and a quite low position of current and long-term liabilities, long-term provisions and total capital have a pretty good chance of surviving, especially when the economy is in upturn and the GDP is relative high.

4.2 Cure After Default Model

The findings concerning the parameter estimation of the covariates regarding the bivariate Probit sample selection model are shown in Table 3. Variant 1 contains the default model for the probability of selection among all N firms as well as the cure model with sample correction concerning the defaulted firms. Hence the selection part of variant 1 is the default model of the CADM and the cure part of Variant 1 is the cure model of the CADM. Variant 2 is the cure model without sample correction concerning the defaulted firms. In order to compare the findings of the sample selection part of the CADM with the default model of the DDM, the algebraic sign of the parameters has to be switched. In the default model of the DDM an accelerated failure time model is used. Hence, a default probability enhancing variable is indicated by a negative algebraic sign of its estimated parameter because it reduces the time to the default event. In the sample selection part the parameters of the regression are estimated by Probit. $d_{it} = 1$ indicates a default event, hence a positive-valued parameter indicates a default event supporting variable. The selection part of the CADM and the default model of the DDM evaluate similar things: default event influencing variables. All estimated firm-specific and macroeconomic parameters in the selection part are identical in their significance and influence direction with the respective parameters in the default model of the DDM. This fact underlines the robustness of the identified risk-driving variables in the selection part of the CADM.

Table 3: Estimation of the bivariate Probit sample selection model of the CADM, separated in two different variants. Variant 1 contains the estimated parameters concerning the probability for the default event and the estimated parameters regarding the sample corrected cure model, variant 2 contains via logistic regression with Probit link function estimated parameters without sample correction. (Std. Errors in parenthesis)

Covariate	Variant 1		Variant 2
	Selection Part	Cure Part	
Constant	-1.0477*** (0.2057)	1.5169* (0.8069)	0.7017* (0.4226)
ln(Sales)	-0.0941*** (0.0133)	0.0916** (0.0426)	0.0647* (0.0385)
Gross Profit / Total Capital	-0.3916*** (0.0534)		
Current Liabilities / Total Capital	0.6690*** (0.1429)	-0.9418** (0.3978)	-0.6083** (0.3012)
Long-term Liabilities / Total Capital	0.5483*** (0.1496)	-0.7515* (0.4155)	-0.4152 (0.3169)
Long-term Provisions / Total Capital		-1.4465** (0.6856)	-1.2793* (0.7135)
Equity / Total Capital	-0.48027*** (0.1088)		
ln(Total Capital)	0.0663*** (0.0162)	-0.1394*** (0.0472)	-0.1287*** (0.0493)
GDP	-0.2608*** (0.0385)		
12-month EURIBOR	-0.1575*** (0.0592)		

*significant at 10%, **significant at 5% , ***significant at 1%

4.2.1 Default-Related Parameter Estimates of the CADM

Concerning the selection part of the model in variant 1, the constant as well as the estimated parameters of the macroeconomic and firm-specific risk drivers are significant at the 1% level. The estimated parameters have a negative value concerning the constant and the firm-specific covariables ln(Sales), Gross Profit to Total Capital and Equity to Total Capital as well as the macroeconomic covariables growth rate of the German GDP and 12-month EURIBOR. The estimated parameters regarding the Current Liabilities to Total Capital, Long-term Liabilities to Total Capital and ln(Total Capital) have a positive algebraic sign. A relative high value concerning the variables Gross Profit to Total Capital, Equity to Total Capital, ln(Sales), growth rate of the German GDP and 12-month EURIBOR has a positive effect on a firms survival probability. A high value concerning the variables Current Liabilities to Total Capital, Long-term Liabilities to Total Capital and ln(Total Capital) has a negative impact. A higher Gross Profit to Total Capital is an indicator for financial strength and a sustainable business model with high margins. Firms with a quite high Equity to Total Capital can face short-term-loss situations without much effort, they have a better standing in loan negotiations and have a higher financial stability. For firms with relatively high short- and long-term liability positions, it might be more difficult to get more liabilities form their borrowers. Hence, possible short-term opportunities can not be realized with further credit. In addition, there is a higher dependence concerning their borrowers and a loss situation can soon end up in bankruptcy. As discussed concerning the findings of the default model regarding the DDM, the variables ln(Sales) and ln(Total Capital) can both be seen as proxies for the size of a firm. The findings suggest that firms with relative more sales have a lower default probability because of their market influence and a higher bargaining power. Whereas firms which are bigger concerning their assets might have a lower flexibility and cannot react in time in situations of important market developments and thus more often fail in these situations. The GDP has a significant positive influence on a firms survival probability. In addition, the parameter of the 12-month EURIBOR turns out to be significant with a positive influence on a firm's survival probability, too. The positive influence of the GDP can be explained by the fact, that in a prosperous economic environment a lower number of firms fails because inefficiencies regarding the business model are not punished instantly by the market. The positive influence of the 12-month EURIBOR might be due to the enhancing interest rate especially at the top of an economic upturn, induced by the central banks in order to omit an overheating of the economy.

4.2.2 Cure-Related Parameter Estimates of the CADM

Comparing the cure part of variant 1 with variant 2 one can see that the cure model without sample correction would miss to identify the cure-relevant variable Long-term Liabilities related to Total Capital. Furthermore, the estimated parameters concerning the variables ln(Sales) and Long-term Provisions to Total Capital have a much lower significance. Therefore, the sample selection in the model would miss to identify a cure-relevant variable and lead to a weaker model, if not corrected through the applied Heckman sample selection method. This is due to the fact that the cure part of the model contains only observable information regarding a smaller fraction of the evaluated firms in the data, because only defaulted firms can become cured. The estimation of variant 2 is only based on the non-randomly selected small sample of defaulted firms. Hence, the influence of the not-defaulted firms, which indeed have a certain probability of default, is completely missed by the logistic regression in variant 2. The applied bivariate Probit sample selection method of variant 1 includes also the influence of the not-defaulted firms in order to omit a sample selection bias, see Heckman (1976, 1979) and Boyes et al. (1989).

The probability of being cured in the evaluated model is solely depending on firm-specific influence factors since the GDP and the 12-month EURIBOR are only significant in the selection part. The estimated parameter for the variable ln(Total Capital)is significant on the 1% level, the parameters for Long-term Liabilities to Total Capital as well as the constant are significant on the 10% level and the parameters for the ln(Sales), the Current Liabilities and the Long-term Provisions to Total Capital are significant on the 5% level. The ln(Total Capital) and the parameters regarding the variables Current Liabilities, Long-term Liabilities and Long-term Provisions to Total Capital have a negative influence on the probability of being cured, while the ln(Sales) support a cure event. A relatively low debt position may enhance the flexibility and be helpful for the restructuring of the credit agreements and thus enhances the probability to cure a firm. This could be the reason for the negative influence of the variables Current and Long-term Liabilities to Total Capital. Furthermore, one can assume that there was a good reason to undertake the provisions concerning uncertain risks although not all risks are covered. If a firm has a high financial risk potential due to court proceedings or charges then the probability of being cured after a default event is very low. The restructuring of bigger firms might be more complex. Usually, multiple lenders have to find common agreements. The financial analysis as well as the implementation of a new strategy needs preparation and time. Hence, cure attempts fail more often, which is indicated by the negative influence of the ln(Total Capital), and this can be seen as a proxy for a firm's size. Another proxy for a firm's size can be the ln(Sales). Concerning this variable bigger firms tend to have a higher cure probability. This might be due to the fact that a firm that is bigger than others concerning its sales might be an important player in the market with some significant influence. Furthermore, firms with higher sales might have a higher probability of being cured because even a slight cost reduction during the restructuring phase would enhance instantly the margins and, therefore, the profitability.

4.2.3 Influence of the Default Probability

The individual default probabilities for two firms regarding the CADM and the DDM are shown in Figures 4 and 5 for two exemplary firms from the credit portfolio. Firm A has on average a relative low default probability and firm B has on average a relative high default probability. The one-year default probabilities are predicted for the years 2003 to 2007 based on the known data of the years 2002 to 2006 that are applied in the two estimation methods. The default probabilities for firm A are generally lower than those of firm B regarding all evaluated time periods. This holds for both models. The CADM predicts a higher default probability than the DDM for both firms. The difference between the default probabilities of the models is increasing with the level of the predicted default probability. Firm A and

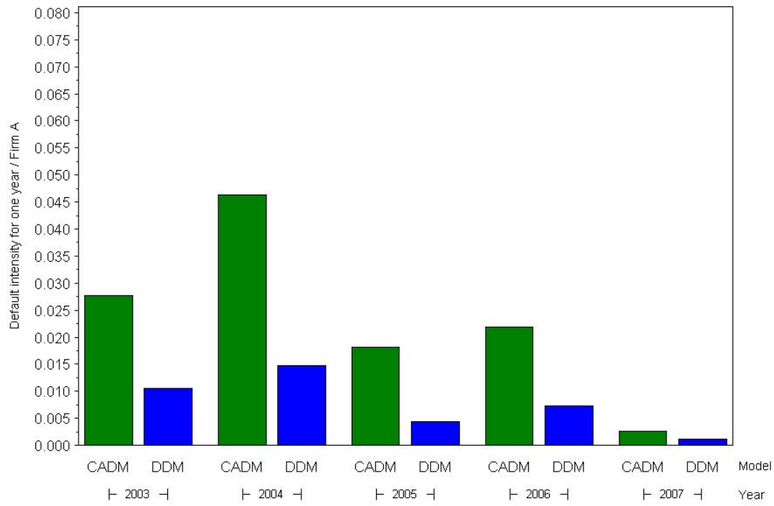

Figure 4: Individual default probabilities of firm A regarding the CADM and DDM. Predicted probabilities for the years 2003 to 2007.

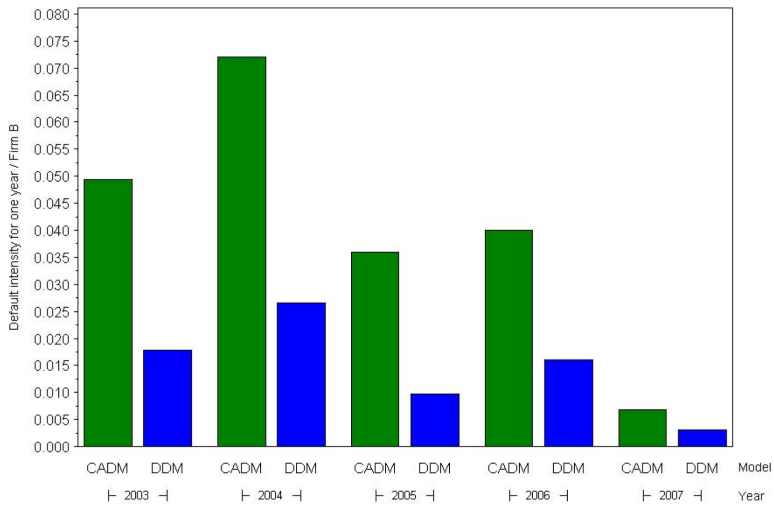

Figure 5: Individual default probabilities of firm B regarding the CADM and DDM. Predicted probabilities for the years 2003 to 2007.

B face a strong probability increase between 2003 and 2004 regarding the CADM. The probability of default for firm A increases from 2.75% in 2003 to 4.6% in 2004 and for firm B from 4.8% to nearly 7.25%, respectively. The default probability of the DDM shows the same behavior on a lower level and increases by nearly 40%. After a significant default probability reduction regarding the year 2005 a second increase can be seen for both firms and both models for the year 2006. The default probabilities concerning the year 2007 are on a relative low level, between 0.1% and 0.3% for firm A and between 0.25% and 0.5% for firm B. The difference between

Table 4: Distributions of the default probabilities regarding all firms in the credit portfolio of the years 2003 to 2007. The default probabilities are displayed concerning the CADM and the DDM. In addition, the CADM-related cure probabilities of all defaulted firms in the different years are mentioned.

			Arithmetic Mean	Median	25% Quantil	75% Quantil
2003	CADM	Default Prob.	0.0457	0.0386	0.0253	0.0575
		Cure Prob.	0.6063	0.6108	0.5627	0.6554
	DDM	Default Prob.	0.0174	0.0147	0.0093	0.0218
2004	CADM	Default Prob.	0.0613	0.0529	0.0351	0.0758
		Cure Prob.	0.6184	0.6175	0.5601	0.6644
	DDM	Default Prob.	0.0234	0.0195	0.0123	0.0294
2005	CADM	Default Prob.	0.0293	0.0238	0.0150	0.0361
		Cure Prob.	0.6273	0.6251	0.5852	0.6665
	DDM	Default Prob.	0.0080	0.0066	0.0042	0.0101
2006	CADM	Default Prob.	0.0363	0.0298	0.0191	0.0443
		Cure Prob.	0.6134	0.5972	0.5722	0.6814
	DDM	Default Prob.	0.0142	0.0116	0.0073	0.0175
2007	CADM	Default Prob.	0.0064	0.0046	0.0025	0.0075
		Cure Prob.	0.6213	0.5988	0.5757	0.6381
	DDM	Default Prob.	0.0026	0.0021	0.0013	0.0032

the predicted default probabilities of the DDM and the CADM vanishes on this low probability level. The general higher default probabilities in the CADM are due to the fact that some of the defaulted firms face a cure event and, therefore, reduce the number of defaulted firms in a further step while the DDM only predicts defaulted firms that are not-cured afterwards.

The distributions of the default probabilities of the complete credit portfolio regarding the DDM and the CADM are shown in Table 4. In addition, the CADM-related cure probabilities of the defaulted firms are shown over the different time periods. The predicted default and cure probabilities are based on the known data of the years 2002 to 2006.

The development of the portfolio-based default probabilities in Table 4 is quite similar to the already stated individual probabilities of firm A and firm B in Figure 5. The default probabilities concerning the CADM are generally on a significant higher level than the probabilities of the DDM. From the year 2003 to 2004 an

increase can be stated regarding both methods. The mean of the default probability rises from 4.57% to 6.13% regarding the CADM and from 1.74% to 2.34% regarding the DDM. In 2005 the mean reduces to 2.93% and 0.8%, respectively. In 2006 the default probabilities are increasing once more to 3.63% and 1.42% regarding the DDM. Finally in 2007 a sharp decrease can be stated. The mean reduces to 0.64% concerning the CADM and to 0.26% concerning the DDM.
The CADM-related cure probabilities do not show the up- and downturns of the default probabilities. The mean of the cure probabilities is at a constant range between 61% and 63% over the different time periods. This indicates that on average nearly two third of the defaulted firms can be cured. In addition, if one takes the cure probabilities into account, the relative high difference between the default probabilities concerning the two models nearly vanishes. Hence, the two models are predicting nearly the same default probability on the "net" definite default level. The main advantage of the CADM is that it enables a bank to identify which firms will most likely be cured with no loss. For example, it could be better to predict ten defaulted firms which can possibly be cured and it is known that the two firms with the highest earning upside for the bank will most likely be cured than to have five definitely defaulted firms with high and low earning upsides for the bank and no option concerning the cure probabilities. The CADM generates on average a 2.5 times higher default probability but it also presents a lot of additional information concerning the defaulted firms as well as the chance of a cure event. If the predicted defaults are reduced by the predicted cured firms, the defaults are on nearly the same level. Hence, no additional loss is predicted but rather a lot of additional information. A bank could use the cure probability concerning the predicted defaults to ensure that the right ones will become cured. The bank gets the information if a defaulted borrower with high earning prospects due to cross-sell will probably become cured. This information allows "cherry picking" among the defaulted firms and thus might enhance the earning prospects. Furthermore the

"intensive care" performance can be measured directly and thus it can be optimized in order to enhance the cure probabilities of all defaulted firms. The CADM ensures a more detailed risk management and might enhance the earning upsides of a bank because the cure probability of defaulted firms with high earning prospects is known and individual treatments based on that information can be managed.

5 Conclusion

In this paper the Cure After Default Model is developed in order to incorporate the possibility of a cure fraction in a credit default prediction model. The CADM identifies different default probability and cure probability influencing variables and uses the default- and cure-related information. The findings of the CADM are compared to the Definite Default Model which treats the defaulted firms that are cured as never defaulted and ignores cure-event-influencing risk drivers.

Concerning the Definite Default Model significant parameters are estimated regarding the variables ln(Sales) and ln(Total Capital) as well as Gross Profit, Current and Long-term Liabilities, Long-term Provisions and Equity to Total Capital and the German GDP growth rate. Concerning the influence direction of the covariates, with the exception of the additional variable Long-term Provisions to Total Capital and the excluded 12-month EURIBOR, the findings are nearly equal to those of the default model of the CADM. The CADM combines a default probability model with a cure probability model. The parameter estimation concerning the cure probability is done with a bivariate Probit sample selection model. Due to the included cure probability model the firm-specific variable ln(Sales) can be identified as significant, cure probability enhancing variable. The firm-specific variables Current and Long-term Liabilities to Total Capital as well as Long-term Provisions to Total Capital and the ln(Total Capital) can be identified with a strong negative influence on the cure probability.

The findings indicate that the treatment of the possibility of being cured within a default prediction model has a significant influence on the default risk, hence it seems to be very important for the risk management to incorporate the possibility of being cured and its additional information into the credit risk modeling. The findings and interpretations should sensibilize for potential future default risks through their results.

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Modul III

Why does a Major Bank Cancel its Relationship with a Borrowing Firm? Empirical Findings from a Major Bank's SME Credit Portfolio

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Working Paper

Abstract

In this paper we evaluate the resilience of the relationship between a lending bank and its SME borrowers in a stressed situation. We focus on firms in a credit portfolio which triggered a default event and investigate the interdependencies between the cancelation of the relationship and different qualitative and quantitative influence factors. The findings are developed based on a major bank's credit portfolio that contains 5,930 mainly small- and medium-sized German firms. A total of 1,243 default events are observed over a time period from January 2002 to December 2007. Among the defaulted firms 144 relationships are canceled. The default reasons as well as the further deployment of the defaulted firms are documented in the database. We find that the relationship is most likely canceled if the bank is convinced that it will not get paid any more regarding its outstanding loans. On the other hand, if the payment is only delayed for some time, a cancelation of the relationship is less likely. Furthermore, the commitment of the firm's owner, measured in the equity quote, seems to be essential for the robustness of the relationship. Also macroeconomic influence factors are identified. A low interest rate and an economic upturn are in general a relationship-supporting environment.

1 Introduction

1.1 Motivation

A sustainable relationship between bank and borrower is the foundation for every aspect of the cooperation. In a stable and intensive relationship both partners can gain significant benefits. Based on different maintained long-term relationships a bank can build a sophisticated credit risk expertise. With a sufficient information history regarding several borrowers, the lender is capable of using this information advantage in order to evaluate the general credit risk of the individual borrower, see, e.g., Sharpe (1990). Also the borrower is capable of generating significant advantages based on a strong relationship with the bank. Reliable funding should enable sustainable financing and hence reduce risks of mid- and long-term projects. In addition, a firm might benefit from the bank's information advantage in credit risk evaluation, for example, through lower interest payments and reduced collateral requirements in long-term relationships, see Berger and Udell (1995).

Furthermore, a maintained and intensive relationship is a key aspect for the bank to reach several additional earning upsides, for example, due to cross-sell potential. Predominantly the relationship is first established based on a loan agreement and later the bank attempts to collect not only earnings due to the credit line but also on fee-based products that are free from credit risk and thus have a significant leverage on the earning prospects, see La Torre et al. (2010).

The importance of the relationship is further displayed by the fact that in the case of a default event regarding a borrower, this situation does not necessarily lead to a cancelation of the relationship. As we will see, several defaulted firms have maintained their relationship with the bank and can get cured afterwards. Furthermore, if the business relationship between a bank and a specific borrower is strong enough to cope with the special situation of a default event while other bank partners might have to reduce their exposure or cut the relationship with the firm, new opportunities might be available for the involved partners. A strong relationship might support the exchange of information regarding the special challenge of surrendering in a financial struggle and ease the path towards resurrection. In addition, a new potential yield due to higher interest concerning the restructured loans or more cross-sell could be generated. New cross-sell prospects might be created, for example, because of the customer's desire to reduce operative risks, such as commodity price risks or interest risks, with derivative products, see Berlin (1996).

On the contrary, a relationship cancelation negates the possibility of a defaulted firm to become cured with no loss for the bank and eliminates all above-named potential benefits. Furthermore, in the case of relationship cancelation the bank's accumulated soft information regarding the borrower is probably lost, see Berger and Udell (2002). Hence, it should be in the interest of both partners, the bank as well as the borrower, to maintaining the relationship. This leads to the question of which occurrences initiate such a hard step as a cancelation of the relationship. While the maintained relationship and its influence on lender and borrower is extensively evaluated in the relationship lending literature, the framework of influence factors that might support or prevent the cancelation of the relationship between a lending major bank and borrowing small- and medium-sized firms in a stressed situation has only been scarcely elucidated in this research area, see Elyasiani and Goldberg (2004).

One predominant assumption in the relationship lending literature is that major banks are reluctant to establish a relationship with SMEs due to the diffuse information policy of these customers. The high standardization level in major banks seems to conflict with the necessary individuality level concerning SMEs relationships. Hence, predominantly small regional banks with flexible and short decision-making processes are present in this market niche, see Berger and Udell (1998) and Elyasiani and Goldberg (2004). In this paper, an SME credit portfolio regarding a major German bank is evaluated. The existence of this evaluated data already indicates that larger, international-operating banks are also interested in relationships with SMEs. We evaluate the dependencies of a relationship cancelation with several other qualitative factors, for example, delayed payments or provision building and quantitative factors from the firm's financial statements, for example, the quotes of equity or liabilities. We focus on cancelations in stressed situations in order to evaluate the robustness-influencing factors of the relationship. A stressed situation is defined as a situation where the borrowing firm has triggered a default event. Data concerning defaulted firms are rare and predominantly only known to banks. The database in this paper includes a total of 1,243 default events and 144 relationship cancelations among the evaluated firms. Concerning the defaulted firms, besides the default reason also the further deployment is available. The full information data is available concerning 886 defaulted firms and 104 relationship cancelations.

The database contains a great deal of information over the whole cross-section concerning German SMEs. It is not preselected, which means that it includes every firm that is a Dresdner Bank[1] customer and whose financial data is listed in a risk program necessary for a loan decision. Hence, the database can be seen as representative for a typical major bank credit portfolio of German SMEs. Contrary to, for example, US American SMEs, German SMEs are predominantly not listed on a stock market and are rather reluctant to divulge financial information. External financing is mostly accomplished through bank loans, see Deutsche Bundesbank (2010).

In the following sections, first an overview regarding the literature and the main contributions of our paper are given. Second, the model is described, followed by the estimation process. After that some descriptive statistics concerning the balance sheet data as well as further relationship-cancelation-related information of the SME in the evaluated credit portfolio are shown. Finally, the empirical findings concerning the significant influence factors are described, followed by a conclusion.

[1]The firm-specific data were provided by Dresdner Bank AG in spring 2008. Dresdner Bank was acquired by Commerzbank AG in summer 2008.

1.2 Literature Review

The relationship lending literature evaluates a wide range of influence factors and impacts concerning the concurrence regarding borrowers and lenders. A prevalent argument is that relationship lending is applied by banks in order to evaluate firms with reluctant information policies concerning their credit worthiness. These borrowers are predominantly small and medium-sized enterprises. The necessary information concerning the SME has to be gathered individually over a relatively long period regarding each individual borrower. Hence, small regional banks with flexible and short decision-making processes should have an advantage in this market niche, see Berger and Udell (1996, 1998).

Recent literature stated that larger banks are also increasingly interested in relationship lending and thoroughly capable of producing significant value regarding the SME market. For example, Berger and Udell (2006) showed that larger banks do not necessarily have a comparative disadvantage concerning relationship lending compared to small, regional banks. The strategic position depends mainly on the used lending technology and internal organization. The impact of changes in the banking industry on the relationship lending, for example, due to consolidation, technological advancement or a change of regulatory conditions are evaluated by Berger and Udell (2002). They found that small banks have an advantage in relationship banking due to their lower hierarchical structure and clearer organization. In the case of mergers the advantage vanishes with increasing size and new smaller banks take the place of the market.

La Torre et al. (2010) found, based on the evaluation of small, medium-sized and major banks in 12 countries, that all kinds of banks are increasingly serving SME borrowers with relationship lending, because of potential cross-sell regarding fee-based financial products. Furthermore, bigger financial institutions can gain upsides due to economies of scale and scope. The increasing competition in the banking market and its influence on the relationship lending was evaluated by Boot and Thakor

(2000). They stated that in the case of a fast development of the banking industry with increasing competitive pressure among the operating banks, relationship lending is being focused on more. On the contrary, increasing competition in the bond market is reducing the appearance of relationship lending.

Credit default events are predominantly mentioned indirectly in the relationship lending literature. Berlin (1996) found that for small, medium-sized and large firms in financial distress a strong relationship is supportive concerning the probability of resurrection. If these firms do not only rely on private lending based on relationship but also on public financing they have a lot more problems in the restructuring phase, due to reluctant bank partners. James (1996) showed that the success of the restructuring process depends mainly on the bank's participation intensity as well as the capital structure regarding public and private claims.

The value of the relationship between borrower and lender was, for example, evaluated in Fama (1985). It is shown that borrowers are willing to pay higher interests for relationship lending than for financing alternatives on the public market. Petersen and Rajan (1994) found that a close relationship between borrower and lender is connected with a significant value. Furthermore, if more than one lender is included, the interest rates tend to go up while the availability of credit lines is shortened. Sharpe (1990) showed that banks have an information advantage due to the cumulated loan market information regarding the history of their long-term customers. They can generate significant rents from this information asymmetry, see Schenone (2010). Furthermore, Stanton (2002) showed that a bank's profitability can be enhanced if the relationship lending is focused on larger credit exposures.

The long-term history of different borrowers allows a bank to calculate sophisticated ratings and evaluate the individual credit risks, see Machauer and Weber (1998). The asymmetric information was also evaluated by Dass and Massa (2011), based on empirical information concerning US American firms. They found, that with increasing relationship intensity, measured by loan size and insider potential of the bank, not only the information advantage of the lender is increasing but also the corporate governance of the borrower is improving. In addition, the information advantage, which can be achieved by relationship lending, can generate a positive signaling effect regarding third parties. For example, James and Wier (1990) found that an established borrowing relationship between a bank and a firm can generate a significant valuation upside if the firm offers stocks on a public market during an initial public offering.

The length of the engagement is also a widely discussed area in the relationship literature, but with different and sometimes divergent findings. For example, Degryse and van Cayseele (2000) found, based on information concerning European banks and SMEs, that the duration has an enhancing effect on the interest rate and simultaneously an decreasing effect on collateral. A contrary influence is found concerning the scope of the relationship, which is measured in other financial products that are connected with sensitive information. Then again, for example, Berger and Udell (1995) and Brick and Palia (2007) showed that borrowers pay lower interest rates with enhancing duration of the relationship. Furthermore, with increasing relationship time the necessary collateral is decreasing.

The relationship lending is predominantly evaluated among banks and corporations in the Anglo-Norman area. Nevertheless, some work was also carried out concerning the German banking industry: for example, Elsas and Krahnen (1998) and Elsas (2005) evaluated the relevant determinants of relationship lending between German universal banks and SMEs. Their main focus was on the evaluation of the so-called "Hausbank" status, a position where a bank is one of the most important bank partners for the firm. They found that the "Hausbank" status does not depend on the length of the relationship but rather on the number of bank relationships that the firm has as well as the total credit exposure of the respective bank. Furthermore, it was shown that the "Hausbank" is a reliable financing partner also in the case of a negative rating development of the respective firm. These findings were also found by Lehmann and Neuberger (2001). In addition, Lehmann and Neuberger (2001) evaluated the social behavior and interaction between the acting persons on both sides. They found that this social effect significantly influences the availability and conditions of the loans.

A general overview concerning the relationship lending literature can be found in Elyasiani and Goldberg (2004).

1.3 Main Contributions

If a firm's loan funding is not done by a broker through a single transaction but instead provided by a financial intermediary, for example a bank, which has a close and maintaining business connection, then it is a matter of relationship lending, see Boot and Thakor (2000). A huge part of the relationship literature is focused on maintaining relationships in normal situations. A great deal of work was done concerning the influence of relationship lending on interest rates, credit availability, ratings, collateral, firm value etc., see, e.g., Fama (1985), Elsas (2005), Sharpe (1990), James and Wier (1990) or Elyasiani and Goldberg (2004).

The strong connection between the bank and the borrowing firm regarding relationship lending is not only based on quantitative information that can be found, for example, in a firm's financial statements, but also soft facts about the borrower are available in a close relationship. Those soft facts are a relevant information resource for a bank. Few papers evaluated this qualitative information, which can be accumulated by the bank concerning the borrower over a longer time horizon such as social influence factors or the behavior of the acting persons on both sides, see Berger and Udell (2002) and Elyasiani and Goldberg (2004). In addition, the relationship in a distressed situation has rarely been focused on, perhaps due to the scarcer data concerning defaulted firms. The influence of the relationship on the restructuring process among firms in financial distress was, for example, evaluated by James (1996) and Berlin (1996). The research in this area is mainly based on the availability of loans in the refinancing process.

Our paper focuses on both scarcely evaluated research areas. We elucidate a framework around the relationship between a major bank and its SME borrower and focus on quantitative as well as soft qualitative influence factors that might support or destroy the relationship in a stressed situation. Hence, we ask the question of under which circumstances a bank cancels the relationship regarding a defaulted SME borrower. In addition, we shift the focus from loan availability to the identification of relevant influence factors concerning the robustness of the individual relationship itself. Our findings regarding this question are straightforward: We find a qualitative and quantitative framework of influence factors which, depending on their occurrence, can support a maintaining relationship or lead to a cancelation of the relationship. The qualitative factors are in turn related to the bank's valuation of future earning prospects: delayed payments are tolerated, whereas the cancelation of interest payment is most likely followed by the cancelation of the relationship. Furthermore, the quantitative variable Equity to Total Capital indicates that a high commitment of the firm's owner generally supports the relationship. In addition, it is shown that a low interest rate and an economic upturn, measured by the 3-month EURIBOR and the one-year growth rate of the German GDP, enhance the probability of a relationship being maintained between the bank and its borrower in a stressed situation. Our findings indicate that the knowledge of the bank concerning the individual borrower leads to a specific tolerance level concerning the on-time payment of interests, in particular when the owner is also involved with a relatively high amount of equity. Although a 90-day-delayed-payment triggers a default event, the lender often accepts the delayed payment and does not apply a hard cut. As long as there is certainty that the interest will be payed the relationship is not in danger. This holds even more during macroeconomic environments with low interest rates and high economic growth.

2 The Relationship Model

2.1 Model Construction

In this paper we evaluate influence factors regarding the cancelation of the relationship between a major bank and an SME borrower. Our focus is not on amicable cancelations by both partners, but rather on cancelations by the bank in stressed situations. A stressed situation is defined as a situation in which the borrower triggered a default reason. Since we focus on those firms where a default event is triggered, the evaluated cancelation-specific data are only observable among the small sample of defaulted firms. A simple linear regression could be done among the defaulted firms in order to find dependencies between the relationship cancelation and potential influence factors. However, this approach would only incorporate the small sample of firms that triggered a default reason and it would ignore the remaining not-defaulted firms in the credit portfolio. Since the not-defaulted firms also have a certain default probability based on macroeconomic and firm-specific risk drivers, the exclusion of these firms would neglect their influence and might generate a sample selection bias, see Heckman (1976, 1979).

We apply a certain variant of the Heckman model to solve the supposed problem of sample selection bias. In general, the Heckman model consists of two dependent variables and their corresponding parameters are estimated via a linear equation. The first variable is applied to incorporate the influence regarding the complete available sample, hence in our case, all firms in the SME credit portfolio. This sample consists of firms that are not-defaulted as well as the defaulted ones. In our case, the first variable is represented by the binary variable d_{it} which indicates through the outcome 0, if the firm i ($i = 1, \ldots, N$) is not-defaulted in time period t ($t = 1, \ldots, T$) and through the outcome 1, if the firm i is defaulted in time period t. Since also the not-defaulted firms have a certain default probability they have to be considered with this individual probability concerning the regression among the defaulted firms. Through the occurrence of a default event concerning a specific firm, this firm is selected in the smaller sample of defaulted firms. Only among the sample of defaulted firms are the evaluated cancelation-specific variables observable. Here the second dependent variable, rc_{it} is applied. Since we want to evaluate, which influence factors significantly influence the cancelation of the relationship between the bank and the borrower in a stressed situation, we have to make a regression concerning the depending variable relationship cancelation and the data among the defaulted firms we are interested in. The second regression can only be done if the firm is defaulted, hence, only if d_{it} has the outcome 1, because the evaluated data is predominantly only observable among the reduced sample of defaulted firms. In that case, the relationship cancelation can be evaluated. In our case, the variable, rc_{it} is also a binary one and indicates with the outcome 1 if the relationship between the borrower i is canceled in period t or if the relationship of borrower i and the bank is still maintained in period t.

In order to introduce the influencing risk drivers in the estimation, the following regressions are done:

$$d^*_{it} = \alpha^{H_d} \cdot x^{H_d}_{i,t-1} + u^{H_d}_{it} \tag{1}$$

$$rc^*_{it} = \alpha^{H_{rc}} \cdot x^{H_{rc}}_{i,t-1} + u^{H_{rc}}_{it}, \qquad \text{if } d_{it} = 1, \tag{2}$$

where d^*_{it} and rc^*_{it} are not-observable metric variables that depend on the value of the evaluated, significant default-related and relationship-related risk drivers, respectively. α^{H_d} and $\alpha^{H_{rc}}$ are parameter vectors for the related covariates to be estimated. The state matrix $x^{H_d}_{i,t-1}$ contains several one-year time-lagged default-related firm-specific and macroeconomic risk drivers. The state matrix $x^{H_{rc}}_{i,t-1}$ contains several one-year time-lagged relationship-related firm-specific and macroeconomic risk drivers. $u^{H_d}_{it}$ and $u^{H_{rc}}_{it}$ are the residual error terms. The error terms are jointly normally distributed with a mean of 0, a standard deviation of 1 and a correlation ρ^H. The standard Heckman model states that if the not-observable metric variable d^*_{it} falls below a specific threshold, the observable indicator d_{it} has the outcome 0 and

1 otherwise:

$$d_{it} = \begin{cases} 1 & \text{if } d_{it}^* > 0 \\ 0 & \text{if } d_{it}^* \leq 0 \end{cases} \tag{3}$$

In the standard Heckman model the second dependent variable is assumed to be a metric one. Nevertheless, in our evaluated model rc_{it} is also a binary variable, because its outcome is 1 if the relationship between the bank and the individual firm is canceled and 0 if it is not-canceled. Hence, the standard Heckman model is not appropriate for the case of two binary variables and we have to use a slightly modified model variant. We use a bivariate Probit sample selection model to handle the estimation, see Lee et al. (2004), Greene (1998) and Boyes et al. (1989). If a default event occurs, indicated by $d_{it} = 1$, rc_{it} is an observable binary indicator regarding the status of the relationship between the bank and the borrower that has the outcome 0 if the not-observable metric variable rc_{it}^* falls below a specific threshold and 1 otherwise:

$$rc_{it} = \begin{cases} 1 & \text{if } rc_{it}^* > 0 \qquad \text{and } d_{it} = 1 \\ 0 & \text{if } rc_{it}^* \leq 0 \qquad \text{and } d_{it} = 1 \end{cases} \tag{4}$$

The default-related risk drivers and the relationship-related variables are simultaneously identified within the estimation of the bivariate Probit sample selection model, see Boyes et al. (1989).

2.2 Estimation of the Model Parameters

In the applied bivariate Probit selection model the outcome of the dependent variables is either 0 or 1. Consequently, three combinations are possible: the firm is not-defaulted ($d_{it} = 0$), the firm is defaulted and the relationship is not-canceled ($d_{it} = 1$ and $rc_{it} = 0$) as well as the case of a defaulted firm with canceled relationship ($d_{it} = 1$ and $rc_{it} = 1$). Hence, the following probabilities are possible:

1. Firm i does not default in time period t:

$$Pr\left(d_{it}=0\right)=1-\Phi\left(\alpha^{H_d}\cdot x_{i,t-1}^{H_d}\right) \tag{5}$$

2. Firm i defaults in time period t and the relationship is not-canceled:

$$Pr\left(d_{it}=1, rc_{it}=0\right)=\Phi\left(\alpha^{H_d}\cdot x_{i,t-1}^{H_d}\right)-\phi\left(\alpha^{H_d}\cdot x_{i,t-1}^{H_d}, \alpha^{H_{rc}}\cdot x_{i,t-1}^{H_{rc}}, \rho^{H}\right) \tag{6}$$

3. Firm i defaults in time period t and the relationship is canceled:

$$Pr\left(d_{it}=1, rc_{it}=1\right)=\phi\left(\alpha^{H_d}\cdot x_{i,t-1}^{H_d}, \alpha^{H_{rc}}\cdot x_{i,t-1}^{H_{rc}}, \rho^{H}\right). \tag{7}$$

Φ indicates the cumulative distribution function for the standardized univariate normal distribution. ϕ indicates the cumulative distribution function of the standardized bivariate normal distribution with the correlation denoted by ρ^H, see Boyes et al. (1989). The above-named probabilities lead to the likelihood of the sample selection model. It can be written, conditional on the evaluated covariates, as follows:

$$\begin{aligned} L=\prod_{t=1}^{T}\prod_{i=1}^{N_t}&\left(1-\Phi\left(\alpha^{H_d}\cdot x_{i,t-1}^{H_d}\right)\right)^{1-d_{it}}\cdot \\ &\left(\Phi\left(\alpha^{H_d}\cdot x_{i,t-1}^{H_d}\right)-\phi\left(\alpha^{H_d}\cdot x_{i,t-1}^{H_d}, \alpha^{H_{rc}}\cdot x_{i,t-1}^{H_{rc}}, \rho^{H}\right)\right)^{d_{it}\cdot(1-rc_{it})}\cdot \\ &\left(\phi\left(\alpha^{H_d}\cdot x_{i,t-1}^{H_d}, \alpha^{H_{rc}}\cdot x_{i,t-1}^{H_{rc}}, \rho^{H}\right)\right)^{d_{it}\cdot rc_{it}}. \end{aligned} \tag{8}$$

The variables for the state matrix $x_{i,t-1}^{H_d}$ consist of one-year time-lagged default-related firm-specific and macroeconomic risk drivers. The state matrix for the relationship-related variables, $x_{i,t-1}^{H_{rc}}$, consist of the evaluated one-year time-lagged quantitative firm-specific and macroeconomic risk drivers as well as different qualitative firm-specific risk drivers. A quasi-Newton-Raphson algorithm is used for the maximization of the likelihood function, see Lee et al. (2004), Greene (1998) and

Boyes et al. (1989). The 144 observed relationship cancelations are reduced to 104 observed relationship cancelations due to missing data. The estimations are done simultaneous with the QLIM procedure of the statistic program SAS.

2.3 Evaluated Risk Drivers and Expected Influences

The evaluated information concerning the default probability part of the model is the logarithmized sales and the logarithmized total capital as well as the quotes gross profit, long-term liabilities, current liabilities and equity in relation to the total capital. The default-related influence of different firm-specific information from the firm's financial statement as well as the balance sheet data have been evaluated several times since the credit-scoring models were invented by Altman (1968) and Ohlson (1980). The evaluated macroeconomic data is the 3-month EURIBOR and the annual growth rate of the German GDP. The influence of interest rates and the GDP growth on the default probability was, for example, evaluated by Duffie et al. (2007).

Regarding the influence direction of the evaluated default-related variables, we assume a default-probability-reducing effect concerning the firm-specific variable Gross Profit to Total Capital and Equity to Total Capital as well as the macroeconomic variable GDP and a default-probability-enhancing effect regarding the variable Long-term Liabilities to Total Capital and Current Liabilities to Total Capital. Concerning the variables ln(Sales) and ln(Total Capital) as well as the 3-month EURIBOR both influence directions are ex ante seen as possible.

The evaluated information concerning the relationship cancelation part of the model are the quantitative firm-specific and macroeconomic data and qualitative information concerning the development of the defaulted firms. The evaluated qualitative data include the specification Free-of-interest state, Payment-unlikely, Non-accrued, 90-day-delayed-payment, Bankruptcy, Troubled-debt-restructuring, Depreciation, Settlement, Specific-provision and Provision. Those variables are binary, hence they have the outcome 0 if they are not observed and 1 if they occur as a default trigger or after the triggered default, respectively. These variables do not necessarily lead to the cancelation of the relationship, but they are supposed to influence the relationship between the bank and the borrower. Qualitative influence factors in the relationship lending were, for example, evaluated by Berger and Udell (2002) and Elyasiani and Goldberg (2004). Concerning the influence direction of the qualitative variables, we assume a negative influence on the relationship regarding Bankruptcy and Troubled-debt-restructuring because these states indicate a heavy disturbance of the firm's financial health with direct, most likely negative, influence on the relationship. On the contrary, the variable 90-day-delayed-payment is not necessary connected with deeper problems and might even be generated out of a firm's carelessness. Hence, this variable might be a minor default trigger and should predominantly be found in the relationship maintaining defaults. It is assumed to have a positive influence. Concerning the other qualitative variables no specific influence direction is assumed. In addition, the quantitative firm-specific and macroeconomic variables of the selection part are also evaluated in the relationship cancelation part of the model. We thereby assume ex ante that the variables, which have a default-probability-reducing effect, have a positive influence on the relationship. Quantitative influence factors are evaluated in the relationship literature by Berger and Udell (1998) and Brick and Palia (2007). In addition, we evaluate some credit-amount-related information, because several literature states a significant dependence between the total credit amount and the relationship lending, for example, see Stanton (2002) and Petersen and Rajan (1994). The credit-amount-related information is: the total value of long-term liabilities, the total value of current liabilities, the sum of the total value of long-term and current liabilities, the logarithmized total value of long-term liabilities, the logarithmized total value of current liabilities and the logarithmized sum of the total value of long-term and current liabilities. Concerning the size of the exposure no specific influence direction is expected ex ante. A high exposure is often connected with a more sophisticated evaluation of the firm and a larger number of involved persons regarding the bank's decision making which might lead to a better information exchange and a deeper understanding of the firm's situation. In addition, when a high credit exposure is at stake, the bank might be more interested in an active role within the restructuring process. This might support a maintained relationship. On the contrary, a high exposure with delayed or canceled payments generates a lot of opportunity costs. If the bank was to annul the relationship, take the money and invest it in the credit market, it might be better of. Hence, the bigger the exposure, the bigger the opportunity costs and a cancelation might become more likely.

3 Descriptive Statistics

3.1 Origin of the Database

All evaluated firm-specific data were provided in anonymous form by Dresdner Bank AG in spring 2008. The database contains balance sheet and profit and loss information from 23,894 financial statements. The evaluated time period was 01.01.2002 to 31.12.2007. A total number of 5,930 German firms are observed as well as 1,243 default events. Regarding the defaulted firms, information concerning the default reason and the further deployment in the bank is available. The firms in the portfolio are spread over a wide range of different branches and almost all firms are not listed on a stock exchange. Only financial data from individual financial statements are observed. The financial statements are explicitly not evaluated in a consolidated form: Since every triggered default event by a single firm is instantly connected at least with some certain kind of bureaucratic effort for the lender, it is not relevant if a potential mother firm could cure the default reason after some time.

Regarding the financial statements, information is available concerning: branch, sales, EBITDA[2], EBITA[3], gross profit, net profit, current liabilities, long-term liabilities, long-term provisions, equity, fixed assets as well as current assets. Regarding the financial statements, only data that is available for a 12-month time period are applied. Hence, shortened financial years and opening balance sheets are excluded. If one firm has triggered several default events at different time intervals, the first-mentioned default is used as the relevant one.

3.2 Balance Sheet Information

In the following tables descriptive statistics concerning the firm-specific variables are presented in order to elucidate the major bank's SME portfolio.

In Tables 1 to 3 the arithmetic mean, the median as well as the 25%- and the 75%-quantile of the respective variable are shown for every year in thousands of euros. In addition, the total number of observed firms on which the average values rely is mentioned for each of the six years. The highest number of firms is observed within the first two years 2002 and 2003 with a total of 4,771, while within the year 2007 with a total of 2,706 the lowest number of firms is observed. Changes in the total number of observed firms appear due to default events and censoring. There are also possible changes due to missing data.[4] Over all time periods from 2002 to 2007 a total of 1,243 default events were observed. The average value of the respective variables over the complete time series is shown in Table 4. The data shown in this table rely on the average values concerning all of the mentioned 5,930 firms in the database, thus resulting in positions after the decimal point. This is due to the fact that the variables in the database are mentioned in units of a thousand euros while Table 4 refers to average values concerning a various number of years.

[2]Earnings before interest, taxes, depreciation and amortization.

[3]Earnings before interest, taxes and amortization.

[4]The 4,471 observed firms in the years 2002 and 2003 are not necessarily the same. There are definitely some firms that are mentioned in 2002 and where financial statements are missing in 2003 as well as there are firms mentioned the first time in 2003. The total number of observed financial statements in 2002 is 4,529 and in 2003 it is 4,518. Due to incomplete data 58 financial statements are excluded in 2002 and 47 in the year 2003.

Table 1: Average value of the observed variables from the financial statements of the years 2002 and 2003 in thousand euros (N_t = Number of observed firms within the respective year t)

Variable	$N_{2002} = 4,471$				$N_{2003} = 4,471$			
	Arithm. Mean	25%-quantile	Median	75%-Quantile	Arithm. Mean	25%-Quantile	Median	75%-Quantile
Sales	57,093	2,879	12,464	35,572	70,374	3,014	13,081	38,658
EBITDA	2,739	60	541	2,112	3,115	75	605	2,192
EBITA	1,056	-54	225	1,082	1,295	-32	265	1,198
Gross profit	4,224	-18	201	1,228	2,785	2	262	1,395
Net profit	3,093	-1	94	751	1,423	0	123	837
Current liabilities	26,559	1,463	4,233	12,213	28,377	1,507	4,347	12,460
Long-term liabilities	12,920	0	852	4,047	11,292	0	704	3,757
Long-term provisions	4,960	0	88	918	5,600	0	100	982
Equity	16,699	169	1,194	5,353	18,806	216	1,431	6,029
Fixed assets	33,228	475	2,501	9,937	33,320	489	2,639	10,614
Current assets	25,435	1,411	4,774	14,050	28,941	1,422	4,741	14,150

Table 2: Average value of the observed variables from the financial statements of the years 2004 and 2005 in thousand euros (N_t = Number of observed firms within the respective year t)

Variable	$N_{2004} = 4,237$				$N_{2005} = 4,382$			
	Arithm. Mean	25%-Quantile	Median	75%-Quantile	Arithm. Mean	25%-quantile	Median	75%-Quantile
Sales	99,490	3,309	14,430	43,811	78,789	3,234	13,964	42,499
EBITDA	5,479	108	725	2,657	4,679	103	697	2,527
EBITA	3,581	1	388	1,606	2,798	5	373	1,588
Gross profit	5,325	40	455	1,978	4,825	58	485.5	2,050
Net profit	1.594	0	237	1,171	2,453	5	240	1,210
Current liabilities	37,105	1,506	4,471	13,017	31,083	1,444	4,238	12,452
Long-term liabilities	12,215	0	506	3,211	11,137	0	409	2,884
Long-term provisions	7,608	0	121	1,064	6,191	0	98	972
Equity	24,386	281	1,708	6,862	19,412	318	1,738	6,939
Fixed assets	41,162	454	2,595	10,922	37,448	415	2,366	10,055
Current assets	48,065	1,440	5,238	15,203	29,215	1,429	4,999	14,874

Table 3: Average value of the observed variables from the financial statements of the years 2006 and 2007 in thousand euros (N_t = Number of observed firms within the respective year t)

Variable	$N_{2006} = 3,627$				$N_{2007} = 2,706$			
	Arithm. Mean	25%-Quantile	Median	75%-Quantile	Arithm. Mean	25%-Quantile	Median	75%-Quantile
Sales	122,495	3,961	16,923	49,036	147,715	5,790	21,796	62,294
EBITDA	5,873	170	873	3,128	6,311	254	1,148	4,012
EBITA	2,902	29	485	1,955	2,216	67	700	2,666
Gross profit	4,437	86	627	2,598	2,628	102	830	3,222
Net profit	2,100	15	361	1,612	567	13	451	1,963
Current liabilities	47,382	1,613	5,077	14,202	55,414	2,226	6,430	17,428
Long-term liabilities	12,973	0	450	3,156	16,509	0	565	3,659
Long-term provisions	7,761	0	109	1,054	8,149	0	135	1,158
Equity	30,217	396	2,063	8,030	35,744	559	2,652	9,220
Fixed assets	49,040	503	2,735	10,384	56,710	724	3,439	11,975
Current assets	47,544	1,763	5,966	17,277	57,095	2,436	7,663	20,795

Table 4: Average value of the observed variables of all firms during the complete time period from 2002 to 2007 in thousand euros ($N = 5,930$, Number of observed firms within the complete time period)

Variable	Arithm. Mean	25%-Quantile	Median	75%-Quantile
Sales	93,311	2,870	12,667	36,867
EBITDA	4,421	77	571	2,141
EBITA	2,222	-13	261	1,230
Gross profit	4,124	4	282	1,524
Net profit	1,461	0	145	882
Current liabilities	35,890	1,522	4,338	12,314
Long-term liabilities	11,625	12	731	3,436
Long-term provisions	6,663	0	91	853
Equity	23,142	214	1,369	5,840
Fixed assets	38,225	434	2.371	9.698
Current assets	38,349	1,372	4,711	14,132

The sales median of the firms fluctuates between 12.5 and 14.5 million euros in the years 2002 to 2005 and enhances in the following years up to 17 and accordingly 22 million euros. The all-year average is located around 13 million euros with a 25%-quantile of 3 million euros and accordingly 37 million euros at the 75%-quantile. Concerning the sales-specific definition of the German Federal Statistical Office the observed firms belong on average to the division of small and medium-sized enterprises of the German economy.[5] Small and medium-sized enterprises are playing an important role in the German economy and politics. In this division 50% of all German employees are located, see Jung (2010). The strong increase in sales within the years 2006 and 2007 is a clear indicator for the enhanced business activity in the German SME division during the economic upturn and thus underlines its importance for the German economy. It should be mentioned that during the calculation of the average values the first years gain a lot of influence because of their high number of observed firms within the observed portfolios.

The EBITDA median is growing constantly over the years from 0.5 million up to 1.2 million euros, except for the years 2004 and 2005 when it remains nearly constant. The behavior of the EBITA median is analogous: it increases from 0.2 up to 0.7 million euros. Similar behavior can be stated for the gross profit and the net profit medians which increase from 0.2 million up to 0.8 million and accordingly from 0.1 million up to 0.5 million euros. If one calculates the gross profit/sales ratio it can be seen that the average rate of return enhances over the years from 1.6% up to 3.8%. This might be an indicator that in an economic upturn significant higher margins can be achieved in the markets.

The median concerning the current liabilities has a value around 4.3 million euros during the first four years and increases in the years 2006 and 2007 up to 5.1 million and accordingly to 6.4 million euros. On average the median has a value of 4.3 million, see Table 4. Concerning the long-term liabilities the median reduces during the periods 2002 to 2005 from around 0.9 million down to 0.4 million euros and in-

[5] Sales-specific definition SME: 2 to 50 million euro.

creases in the following two years up to 0.6 million euros. The long-term provision's median alternates during the complete time horizon between 90 thousand and 140 thousand euros. Noticeable also is the fact, that during the time periods over 25% of the firms possess long-term liability and long-term provision values of zero euros. The equity position of the firms is improving during the observed time periods. The median increases from an initial 1.2 million up to 2.7 million euros. The average value lies at 1.4 million euros.

Both the fixed assets' median and the median of the current assets are fluctuating around 2.5 million and accordingly 5 million euros during the time periods from 2002 to 2005. Within the year 2006 the values grow to 2.7 million and 6 million euros and finally reach 3.4 million and accordingly 7.7 million euros in the year 2007. The average values over the complete time period are located at 2.4 million and 4.7 million euros.

3.3 Default Deployment

Default events are observed concerning 1,243 firms in the credit portfolio in the time period from January 2002 to December 2007. In the year 2002 no default is observable in the database. The first defaults are observed in January 2003, because the bank's risk and accounting system was activated at the turn of the year 2002/2003. A total of 2,779 years of balance sheet data are counted among the defaulted firms, while 21,115 years of balance sheet data are available regarding the 4,687 not-defaulted firms. Five possible specifications regarding the firm's further deployment after the default are mentioned in the data: the firms that are resurrected without any loss for the bank are referred to Cured, Write-off means that some part or all of the exposure had to be expensed, Worked-out indicates that the securities had to be disposed to cover the outstanding liabilities and Distressed-sold means that the loans had been sold with a certain haircut. The fifth specification is Unknown, which means that the further development after the default event is not definitely known. In the database 333 firms are Cured, 269 are Write-off, 244 are Unknown, 239 are Worked-out and 158 are mentioned as Distressed-sold. The stated facts are shown in Table 5.

It should be mentioned, that a defaulted firm with a canceled relationship cannot get cured afterwards.

3.4 Default Reasons

In Table 6 the evaluated default reasons are shown with their number of occurrences among the defaulted firms. The default reason is known for 1,017 defaulted firms. Multiple reasons can be mentioned concerning a single default event.

The cancelation of the relationship between the bank and its borrower is mentioned 144 times among the defaulted firms. The occurrence is mentioned as Relationship-cancelation. The specification Free-of-interest-state means that the defaulted firm does not pay any interest on its outstanding loans. Payment-unlikely is not a hard fact, it is rather an assessment of the bank concerning the loan and interest re-payment probability of a defaulted firm. If some of the amortization and interest payments regarding a loan are delayed the specification Non-accrued is used. More than 89 days in delayed payment results is mentioned by the specification 90-day-delayed-payment. If some problems concerning the restructuring of the outstanding loans are observable, the specification is Troubled-debt-restructuring. The findings

Table 5: Specification status of all firms in the database with the total number of annual financial statements for each of the specifications.

Specification	Number of Firms	Number of Balance Sheet Years
Cured	333	688
Write-off	269	635
Unknown	244	675
Worked-out	239	481
Distressed-sold	158	300
No default	4,687	21,115
Sum	5,930	23,894

Table 6: Default reasons of the defaulted firms in the database with the individual percentage among the defaulted firms and the total number of observed relationship cancelations per observed specification.

Default Reason	Number of Occurrences	Percentage among the Defaulted Firms	Observed Cancelations	Percentage of the Canceled Relationships
Relationship-cancelation	144	11.59	144	100.00
Free-of-interest-state	238	19.15	143	99.31
Payment-unlikely	58	4.67	0	0.00
Non-accrued	115	9.25	16	11.11
90-day-delayed-payment	35	2.82	8	5.56
Troubled-debt-restructuring	9	0.72	0	0.00
Bankruptcy	1	0.08	0	0.00
Settlement	238	19.15	144	100.00
Depreciation	2	0.16	0	0.00
Specific-provision	562	45.21	94	65.28
Provision	236	18.99	12	8.33

concerning this specification should be interpreted with caution, because it is only observable 9 times. This holds also for the depreciation of a borrowers loan and the firms filing for bankruptcy since the specification Depreciation is mentioned only twice and Bankruptcy is mentioned only once. If a troubled credit agreement is only partly repaid or the reclamation of collateral is mentioned, the status is called Settlement. If the single credit of a defaulted borrower is reduced in its mentioned value, due to credit-risk-related valuation methods, this is recognized by Specific-provision. A general provision building for expected losses due to a troubled credit arrangement is mentioned by the specification Provision.

One can see that most of the relationship cancelations are observable among Free-of-interest-state, Settlement and Specific-provisions. Furthermore, all of the observed relationship cancelations are also connected with Settlement, hence a total of 94 maintained relationships have the status Settlement. The specifications Payment-unlikely, Troubled-debt-restructuring, Bankruptcy and Depreciation are all only observed among maintained relationships.

4 Empirical Findings

4.1 Parameter Estimates

The findings concerning the estimated parameters of the bivariate Probit sample selection model are shown in Table 7. From the 1,243 defaulted firms only 886 are considered in the estimation due to missing data. A total of 104 of the remaining default events have a canceled relationship ($rc_{it} = 1$) and 782 have a maintained relationship ($rc_{it} = 0$). Table 7 shows the final model. In addition, the relationship-specific findings without sample correction are shown. The not-corrected model parameters are estimated via a logistic regression with a Probit link function.

All parameters concerning the probability of sample selection are significant on the 1% level. A positive value is estimated concerning the parameters of the Current Liabilities to Total Capital, Long-term Liabilities to Total Capital, ln(Total Capital) and the macroeconomic covariable 3-month EURIBOR. The positive value indicates that higher values of the variables lead to a higher probability of selection. Hence, those variables have a negative influence on the survival probability of the firms. The estimated parameters of the constant and the firm-specific covariables ln(Sales), Gross Profit to Total Capital and Equity to Total Capital as well the macroeconomic covariable growth rate of the German GDP turn out to have a negative algebraic sign. A negative value indicates a lower selection probability with higher values regarding the covariates. Hence, these variables have a positive influence on the survival probability.

A quite high value concerning the Gross Profit to Total Capital indicates a dominant market strategy and financial strength. If a firm's Equity to Total Capital is on a high level, it can face short-term loss situations without much effort. Furthermore, it indicates a higher financial stability and leads to a better standing in loan negotiations. Regarding firms with high short- and long-term liability positions the extension of the credit lines become more and more difficult due to reluctant lenders.

Table 7: Estimation of the model parameters. Variant 1 contains the estimated parameters concerning the probability for the selection and the estimated parameters regarding the identified significant relationship-related variables. Variant 2 contains the via logistic regression with a Probit link function estimated relationship-related parameters without sample correction. (Std. Errors in parenthesis)

Covariate	Variant 1		Variant 2
	Selection Part	Sample-Corrected Relationship Part	Not-Sample-Corrected
Constant	-1.8148*** (0.1719)	-5.7947*** (0.6470)	-6.7705*** (0.9239)
ln(Sales)	-0.0862*** (0.0126)		
Gross Profit/ Total Capital	-0.4324*** (0.0512)		
Current Liabilities/ Total Capital	0.5366*** (0.1291)		
Long-term Liabilities / Total Capital	0.4681*** (0.1351)		
Equity / Total Capital	-0.5663*** (0.0995)	-0.8031*** (0.2147)	0.0296 (0.4153)
ln(Total Capital)	0.0540*** (0.0149)		
GDP	-0.3906*** (0.0320)	-0.7060*** (0.1373)	-0.8991*** (0.2304)
3-month EURIBOR	0.3135*** (0.0472)	1.1763*** (0.2536)	1.8646*** (0.3227)
Free-of-interest-state		2.4447*** (0.3613)	4.1931*** (0.3508)
Non-accrued		-0.7135*** (0.2428)	-1.1884*** (0.3721)
90-day-delayed-payment		-0.9026*** (0.3171)	-2.0201*** (0.3992)

*significant at 10%, **significant at 5% , ***significant at 1%

Hence, possible short-term opportunities cannot be realized with further credit. In addition, the dependence concerning their borrowers is enhancing with the credit lines and a loss situation can soon end up in insolvency. The covariables ln(Sales) and ln(Total Capital) can be used as proxies for a firm's size. The findings indicate, that firms with higher sales have a lower default probability. This might be due to a greater market share and more bargaining power. On the opposite side, the negative algebraic sign of the parameter ln(Total Assets) indicates that firms have a lower survival probability with a higher amount of assets. A higher total asset position might be attended by a lower flexibility. Those firms cannot react in time if changes in important markets are developing and thus on average more often fail in these situations. The parameter of the 3-month EURIBOR has a positive value, hence a higher interest rate has a negative impact of a firm's survival probability. If the interest rates turn up the refinancing costs concerning new loans as well as loans on variable interest basis are growing, too. If those costs cannot be compensated the firm's business model loses efficiency and a default becomes more likely. The growth rate of the GDP has a significant positive influence on a firm's survival probability. The positive influence of the GDP can be explained by the fact, that in economic upturns a lower number of firms fails due to the high market demand.

Regarding the relationship-cancelation-related parameter estimations one can see, that the findings concerning the sample-corrected and the not-sample-corrected variant differ. Especially regarding the variable Equity to total Capital the differences are obvious, because the not-sample-corrected model fails to identify this significant variable. Hence, without correction, a sample selection bias is most likely. This can be explained by the fact that relationship-related information is only observable concerning the small fraction of defaulted firms. The influence of the not-defaulted firms in the credit portfolio, which have a certain probability of default, is completely missed by the logistic regression in the variant 2 in Table 7. The applied bivariate sample selection method also incorporates the influence of the not-defaulted firms in order to omit a sample selection bias, see Heckman (1976, 1979), Boyes et al. (1989) and Greene (1998). Both methods identify the relationship-relevant variables Free-of-interest state, Non-accrued, 90-day-delayed-payment, GDP and 3-month EURIBOR. The significance level of these parameters is at the 1% level in both divisions. In addition, the parameter of the variable identified in the sample-corrected model Equity to Total Capital is significant at the 1% level.

It should be mentioned that regarding the relationship-cancelation-related evaluation all variables concerning the credit amount have turned out to be not significant. Hence, the stability of the relationship between a bank and its defaulted borrower seems to be indifferent concerning the total credit exposure of the borrowing SME. The significant variables create an interesting picture concerning the lenders behavior regarding the relationship with its individual borrowers as well as the influence of macroeconomic circumstances. The identified variable Free-of-interest state has a significant strong positive influence on the probability for the cancelation of the relationship. The estimated parameter is significant at the 1% level. Hence, if it is obviously stated that the lender will not be paid any more interest for the outstanding credits, this has a highly negative influence on the relationship between lender and borrower.

If the payment is not completely canceled but only late for some time, indicated by the negative parameters regarding the variables Non-accrued and 90-day-delayed-payment, the relationship is not burdened much. Both parameters are significant at the 1% level. The highest negative influence is found concerning the variable 90-day-delayed-payment. The occurrence of delayed payments seems to be tolerated to some extent concerning the bank's SME portfolio.

Another relationship-supporting influence can be stated concerning the variable Equity to Total Capital. A high equity quote can be seen as a strong commitment of the firm's owner. High equity positions are not necessarily connected with liquidity. Hence, a high Equity to Total Capital position seems more a positive signaling by the owner, because equity itself cannot guarantee the payment of any bill. The owner of the firm will most likely invest more energy in the support of the firm when his equity share is high. The signaling enhances the trust between borrower and lender and thus strengthens the cooperation. This might be the reason why the bank tends to maintain the relationship more often if a firm's equity position is relative high.

The macroeconomic environment is displayed in the model by the variables GDP and 3-month EURIBOR. Regarding those variables both parameters are significant at the 1% level. The GDP has a positive influence on the relationship. In an economic upturn the relationship is more often maintained, which might be due to the generally higher chances for all firms in the economy to prosper and thus return to profitability and liquidity. A negative influence of the interest rate is indicated by the high positive value of the parameter regarding the 3-month EURIBOR. Hence, with higher interest rates the bank tends more often to cancel the relationship with its defaulted SME borrower. Higher interest rates have two main effects on the relationship: First, the firm faces higher refinancing costs and is probably not capable of paying these additional interests when it is in an financial struggle. Hence, the restructuring process is interrupted and the relationship becomes weaker. Second, the bank's opportunity costs, for example, regarding the delayed or not-paid interest are growing. Hence, it becomes more reasonable to cancel the relationship, maybe even with a loss, and invest the money in the capital market.

The findings indicate that the relationship between a major bank and an SME borrower is most likely canceled if the bank is convinced that it will not get paid any more for the outstanding loans. However, if the payment is only deferred for some period of time and not completely stopped, the relationship cancelation is less likely. The bank seems to accept that a borrower might sometimes be late concerning its payments. In addition, a positive signaling by the firm's owner as a risk taker, indicated through a high equity involvement, further strengthens the relationship. In general, a prosperous economy and low interest rates, which indicate a likable turnaround of the defaulted firm, are a relationship-supporting environment. Hence, the earning prospects for the bank regarding its loans to the individual SME as well as risk-related facts seems to be essential for the robustness of the relationship.

5 Conclusion

In this paper the robustness of the relationship between a major bank and an SME borrower in a stressed situation is evaluated. A stressed situation is defined as a situation in which the borrowing firm has triggered a default event. Different qualitative and quantitative factors are evaluated concerning their influence on the strength of the relationship. Based on SME credit portfolio data, a model is found that incorporates the significant risk driving variables regarding the relationship.
We apply a bivariate Probit sample selection model for the estimation. The evaluated database contains 144 observed relationship cancelations as well as multi-year data from balance sheets and profit and loss statements concerning a total number of 5,930 German small and medium-sized firms and 1,243 triggered default events. A trigger for a default event is, for example, 90-day-delayed-payment, Specific-provision or Bankruptcy.
We find out that the qualitative variables 90-day-delayed-payment and Non-accrued have a significant negative effect regarding the probability of a relationship cancelation while the variable Free-of-interest-state has a significant probability-enhancing effect regarding the cancelation of the relationship. This indicates that delayed payments are tolerated by the bank while a complete cancelation of interest payments is most likely followed by the cancelation of the relationship between the bank and the borrowing firm. In addition, we find a significant, relationship-supporting influence concerning the firm-specific variable Equity to Total Capital. This variable can be seen as proxy for the commitment of the owner regarding his firm. Hence, if the owner has a high equity involvement regarding the defaulted firm, the bank is inclined to maintain the relationship with its borrower. Finally, a significant macroeconomic influence can be stated by two variables. The economic growth, measured by the variable German one-year GDP growth rate, has a significant relationship-supporting influence, while the interest rate, measured by the variable 3-month EURIBOR, has a contrary influence direction. The findings indicate that the re-

lationship between a bank and an SME borrower retains its robustness in stressed situations where a default trigger is observed as long as the bank gets paid for its loans and the owner is a seriously involved risk taker. The relationship continuation is further supported by a macroeconomic environment with low interests and high economic growth rates. The findings can be applied by banks and borrowers for a better understanding of their relationship and in order to gain benefits from the relationship even in difficult situations.

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