Four Essays on Debt Securitization and Entrepreneurial Finance

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Vorwort

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Contents

List of Tables

List of Figures

Summary

This dissertation consists of four independent research papers which I wrote participating in the doctoral program "Quantitative Economics and Finance" at the University of Konstanz. The first three papers address debt securitization that has become more and more popular in the financial industry since the early 1990s. A subset of securitization transactions are collateralized debt obligations or 'CDOs'. In these transactions, part of the credit risks associated with a portfolio of loans or bonds is transferred from originating banks to investors buying the tranches of the CDO. The tranches differ in seniority, risk exposure and credit spread. Some of the credit risk remains with the originating bank. The first paper investigates the securitization design, in particular the risk-sharing between banks and investors and how it is linked to the underlying portfolio quality. The second paper analyzes tranche pricing and identifies CDO- and tranche- features that imply additional credit spreads. The crisis in the US mortgage market beginning in mid 2007 led to large losses in another class of securitizations: residential mortgage backed securities (RMBS). This triggered the research question of the third paper: under what circumstances would a moratorium on securitized mortgage interest rates be beneficial for originating banks and RMBS-tranche investors? In the context of industrial organization, the fourth paper also touches the topic of risk sharing, as it analyzes the conflict between optimal matching of entrepreneurial partners and income risk sharing. The paper examines effects on welfare and industry-wide capital usage of 'incubators' fostering small entrepreneurial partnerships at the expense of optimal risk sharing. The present chapter serves as an introduction to the dissertation and summarizes the main findings.

Chapter 1 is joint work with Günter Franke, University of Konstanz, and Markus Herrmann, HSBC London, and addresses the question how collateralized debt obligation transactions are designed. The originator designs the transaction so as to maximize her benefit subject to requirements imposed by investors, regulators and rating agencies. An important issue in these transactions is the information asymmetry about the quality of securitized loans or bonds between the originator and the investors. Investors are concerned about buying lemons and, therefore, insist on credit enhancements which mitigate potential problems of information asymmetry due to adverse selection and moral hazard. First Loss Positions are the most important enhancement. We analyze the optimal size of the First Loss Position in a model and the actual size in a set of European collateralized debt obligation transactions. We find that the asset pool quality, measured by the weighted average default probability and the diversity score of the pool, plays a predominant role for the transaction design. Characteristics of

the originator play a minor role. A lower asset pool quality induces the originator to take a higher First Loss Position and, in a synthetic transaction, a smaller Third Loss Position. Assuming a lognormal distribution for the default loss rate of the underlying portfolio we find that the First Loss Position bears on average 86 % of the expected default losses. This loss share is largely independent of the asset pool quality. However, it is significantly higher for bond transactions. The loss share and the asset pool quality strongly affect the rating and the credit spread of the lowest rated tranche.

Chapter 2 analyzes the premia of tranches in synthetic CDO-transactions. These premia are credit spreads on top of the risk free interest rate and compensate investors for the expected annualized default loss and for the risk of default losses. Focusing on the second component, the pure risk aversion premium, the paper estimates the relative risk aversion implied by the credit spreads and the loss distributions of 215 differently rated tranches of 59 European CDO transactions. A pricing kernel approach is applied, using the aggregate loss rate as the systematic risk factor. Estimated relative risk aversion is significantly lower for mezzanine tranches which are more exposed to default risks. This may be caused by market segmentation, i.e. less risk averse investors predominantly buying the more risky tranches and vice versa. A higher weighted average default probability of the portfolio induces higher average tranche risk and lowers the estimated relative risk aversion. This effect is strongest for the senior tranches and smaller for the mezzanine tranches. Better diversification allows the originator to transfer more risk to investors at relatively moderate risk premia. Controlling for expected losses of tranches, better portfolio diversification reduces the risk premia for the lowest two rated tranches of a transaction. Higher tranches are relatively unaffected by variations in portfolio diversification as they are well protected against information asymmetries by the first loss piece and two or more rated junior tranches. Controlling for tranche rating, the relative risk aversion estimates are higher for the lowest rated tranche of a given transaction. This hints at additional compensation for the lowest rated tranches, presumably for the associated information problems.

Chapter 3 is joint work with Julia Hein, University of Konstanz, that was motivated by the US mortgage market crisis. Banks' lending standards have been criticized to have contributed to the crisis. Especially problematic appears the use of adjustable rate mortgages that start with fairly low interest rates which are later replaced by higher rates. The interest rate reset poses a payment shock to debtors and causes additional defaults, in particular if house prices have already declined. Several policy options have been discussed to mitigate the current mortgage crisis. We analyze an interest rate freeze on adjustable rate mortgages as one possible reaction. We study the implications on residential mortgage backed securities (RMBS) sold briefly after origination. We examine shifts in the underlying portfolio's discounted cash flow distributions as well as changes in the payment profile of RMBS-tranches, taking into consideration feedback effects on house prices. For investors of rated tranches we show that relatively moderate positive effects of a rate freeze on foreclosures and house prices can outweigh the negative effect of lower interest income. The owners of the First Loss Position are more likely to suffer from the freeze. Here, stronger feedbacks on house prices are needed to assure a net benefit from an interest rate freeze.

Chapter 4 is joint work with Oliver Fabel, University of Vienna, on industrial organization. In an economy, innovative projects can either be carried out by small entrepreneurial partnerships or within large industrial firms. The existence of an "incubator" organization, such as the *Silicon Valley* network, can improve the matching of individuals in teams and, thus, foster the entrepreneurial sector. However, the industrial sector loses these professional elites and there is less risk sharing in the economy. We investigate the effects of incubators on welfare and capital input and derive ambiguous results: only societies whose members exhibit relatively low degrees of risk-aversion are likely to benefit from the improved matching. We argue that this helps to explain why technology or science parks require persistent public support in Europe whereas they emerge as efficient institutions in the US.

Zusammenfassung

Die vorliegende Dissertation besteht aus vier unabhängigen Forschungspapieren, die im Rahmen des Promotionsprogramms "Quantitative Economics and Finance" an der Universität Konstanz erstellt wurden. Die ersten drei Papiere behandeln die Verbriefung von Kreditrisiken, deren Bedeutung in den letzten zwei Jahrzehnten stark zugenommen hat. Eine Klasse von Verbriefungstransaktionen sind sogenannte collateralized debt obligations, kurz CDOs, die sich auf das Kreditrisiko von Portfolios bestehend aus Bankkrediten oder Anleihen beziehen. In einem CDO wird ein Teil dieses Risikos von der verbriefenden Bank weitergegeben an Investoren, die die Tranchen des CDOs erwerben. Die Tranchen unterscheiden sich nach Seniorität, Risiko und Zinsaufschlag. Ein Teil des Kreditrisikos verbleibt bei der Bank. Das erste Papier untersucht die Ausgestaltung von Verbriefungstransaktionen. Es geht insbesondere auf die Risikoteilung zwischen Investoren und verbriefender Bank ein und darauf, wie diese mit der Qualität des zugrundeliegenden Portfolios zusammenhängt. Das zweite Papier analysiert die Preisgestaltung der Tranchen und untersucht, welche Eigenschaften der CDO-Transaktion oder der einzelnen Tranche zusätzliche Prämien motivieren. Die Krise des amerikanischen Hypothekenmarkts seit Mitte 2007 hat zu großen Verlusten bei Hypothekenverbriefungen geführt, bei sogenannten residential mortgage backed securities, kurz RMBS. Dies motivierte die Fragestellung des dritten Papiers: unter welchen Umständen hilft ein partieller Zinserlass für Schuldner schlechter Bonität den verbriefenden Banken und den RMBS-Investoren? Das vierte Papier geht ebenfalls auf Risikoteilung ein, aber im Kontext der Industrieökonomik. Das Risiko unternehmerischer Aktivität kann entweder in industriellen Großfirmen aufgeteilt werden, oder in kleinen partnerschaftlich organisierten Firmen. Das Papier analysiert die Wohlfahrtseffekte, die von 'Inkubatoren' ausgehen, welche die kleinen Partnerschaften fördern zu Lasten der besseren Risikoteilung in Großfirmen. Das vorliegende Kapitel fasst die wichtigsten Ergebnisse der Dissertation zusammen.

Kapitel eins entstammt einer gemeinsamen Arbeit mit Günter Franke, Universität Konstanz und Markus Herrmann, HSBC London, und untersucht die Ausgestaltung von Verbriefungstransaktionen. Die verbriefende Bank maximiert bei der Transaktionsgestaltung ihren Ertrag unter den Nebenbedingungen, die Investoren, Regulierungsbehörden und Ratingagenturen an sie stellen. Informationsasymmetrien zwischen Bank und Investoren bezüglich der Qualität des verbrieften Portfolios spielen hierbei eine wichtige Rolle. Investoren fürchten schlechte Kredite im Portfolio und bestehen daher auf zusätzlichen Verlustschutz, um die Probleme aus Informationsasymmetrien, d.h. adverse Selektion und moral hazard, zu dämpfen. Die Einrichtung einer Erstverlustposition, die Investoren bis zu einer Schwelle vor Ausfällen im Portfolio abschirmt, ist die wichtigste solcher Maßnahmen. Wir leiten zunächst die optimale Größe der Erstverlustposition in einem theoretischen Modell her und überprüfen die Ergebnisse anschließend empirisch auf einem Datensatz europäischer CDOs. Die Qualität des verbrieften Portfolios, gemessen an der gewichteten mittleren Ausfallwahrscheinlichkeit und der Streuung des Portfolios, spielt eine herausragende Rolle in der Ausgestaltung der Transaktionen. Eigenschaften der verbriefenden Bank haben dagegen kaum Einfluss. Schlechtere Portfolioqualität führt zu größeren Erstverlustpositionen und im Falle synthetischer Transaktionen ferner zu kleineren Drittverlustpositionen, die bei der Bank verbleiben. Wir unterstellen eine lognormale Verteilung der Portfolio-Ausfallrate und errechnen, dass die Erstverlustposition durchschnittlich 86% der erwarteten Verluste abdeckt. Dieser Anteil ist weitgehend unabhängig von der Qualität des Portfolios. In Transaktionen, die sich auf Anleiheportfolios beziehen, ist er allerdings signifikant höher. Auch wirkt er sich stark auf das Rating und den Zinsaufschlag der untersten gerateten Tranche aus, ebenso wie die Portfolioqualität.

Im zweiten Kapitel werden die Prämien untersucht, die auf Tranchen von synthetischen CDO-Transaktionen gezahlten werden. Diese Prämien werden als Zinsaufschlag über den risikofreien Zins hinaus gezahlt und entschädigen die Investoren für die erwarteten Kreditausfälle und das Ausfallrisiko. Das Kapitel analysiert die zweite Komponente, die reine Ausfallrisikoprämie. Aus Zinsaufschlag und Ausfallrisiko einer Tranche wird die der Prämienfindung zugrundeliegende relative Risikoaversion geschätzt. Dies geschieht für 215 Tranchen aus 59 verschiedenen CDO-Transaktionen. Dabei wird ein *pricing kernel*-Ansatz angewandt, wobei die Gesamtverlustrate der Ökonomie als systematischer Risikofaktor eingeht. Für mezzanine Tranchen, die mehr Ausfallrisiko tragen, werden signifikant niedrigere relative Risikoaversionen geschätzt. Dies deutet auf Marktsegmentierung hin, also darauf, dass risikobereitere Investoren überwiegend riskante Tranchen erwerben und umgekehrt risikoscheue Investoren risikoarme Tranchen. Eine höhere mittlere Ausfallwahrscheinlichkeit im Portfolio führt im Mittel zu riskanteren Tranchen und senkt die geschätzte relative Risikoaversion. Dieser Effekt ist bei den oberen Tranchen stärker ausgeprägt als bei den mezzaninen. Bei besser gestreuten Portfolios kann die verbriefende Bank mehr Risiko an die Investoren abgeben, und dies zu relativ niedrigen Prämien. Kontrolliert man für den erwarteten Verlust der Tranchen, so senkt eine bessere Streuung im Portfolio die Risikoprämien der untersten beiden gerateten Tranchen. Die oberen Tranchen reagieren dagegen kaum auf Änderungen in der Streuung, da sie durch mehrere geratete Tranchen und die Erstverlustposition gegen Informationsasymmetrien abgeschirmt werden. Kontrolliert man für das Rating der Tranchen, so zeigt sich eine höhere geschätzte Risikoprämie in der untersten gerateten Tranche der jeweiligen Transaktionen. Dies weist auf zusätzliche Zinsaufschläge für diese Tranchen hin, vermutlich als Entschädigung für die hier besonders starken Auswirkungen asymmetrischer Information.

Kapitel drei entstammt einer gemeinsamen Arbeit mit Julia Hein, Universität Konstanz, die durch die amerikanische Hypothekenkrise motiviert wurde. Laxer Kreditvergabe amerikanischer Banken wird häufig eine Mitschuld an der Krise zugesprochen. Besonders problematisch erscheinen im Licht der Krise spezielle Hypothekenkredite, deren recht niedriger Eingangszinssatz nach ein bis zwei Jahren deutlich ansteigt. Der Zinssprung dieser *adjustable rate mortgages* stellt für die Schuldner einen Zahlungsschock dar. Dies führt insbesondere im Umfeld bereits gesunkener Hauspreise zu zusätzlichen Kreditausfällen. In der Politik wurden mehrere Vorschläge diskutiert, wie die Auswirkungen der Krise abzumildern wären. Wir untersuchen die Handlungsoption eines partiellen Zinserlasses, bei dem auf den Zinssprung der adjustable rate mortgages verzichtet wird. Insbesondere analysieren wir die Auswirkungen auf Verbriefungen solcher Hypotheken. Der Zahlungsstrom des zugrundeliegenden Portfolios verändert sich, da weniger Zinsen anfallen, aufgrund des ausbleibenden Zahlungsschocks allerdings auch weniger Kredite ausfallen. Letzteres kann in einer positiven Rückkopplung auch dazu beitragen, den Immobilienmarkt zu stabilisieren. Wir untersuchen den Nettoeffekt auf die Tranchen der Verbriefungen und zeigen, dass die mezzaninen und oberen Tranchen bereits bei moderaten Rückkopplungseffekten von dem Zinserlass profitieren. Die Halter der Erstverlustposition trifft der Zinserlass stärker, sie profitieren nur, wenn sich die Immobilienpreise dank des Zinserlasses deutlich stabilisieren.

Kapitel vier entstammt einer gemeinsamen Arbeit mit Oliver Fabel, Universität Wien, aus dem Feld der Industrieökonomik. In einer Ökonomie können innovative Projekte entweder in kleinen partnerschaftlich organisierten Unternehmen durchgeführt werden oder in industriellen Großunternehmen. Eine Organisation wie das Netzwerk rund um das *Silicon Valley* kann wie ein "Inkubator" für Kleinunternehmen wirken, indem es die Partnersuche erleichtert, also das *matching* der Partner verbessert. Bei diesem Prozess verliert allerdings der industrielle Sektor die fähigsten Mitarbeiter und weniger Personen profitieren von der Risikoteilung in Großunternehmen. Die Auswirkungen auf Wohlfahrt und Kapitaleinsatz sind daher nicht eindeutig. Gesellschaften mit schwach ausgeprägter Risikoaversion profitieren, da der Vorteil des besseren matchings dominiert. Bei höherer Risikoaversion überwiegen dagegen die Nachteile aus der schlechteren Risikoteilung. Dies ist unserer Ansicht nach einer der Gründe, warum Technologieparks in Europa weniger erfolgreich sind als in den USA.

Chapter 1

Information Asymmetries and Securitization Design

1.1 Introduction

Over the last 20 years the volume of securitizations has grown tremendously. The global volume of securitization issuance was estimated to be roughly 270 bn USD for 1997 and about 2100 bn USD for 2006 (HSBC (2007)). The recent subprime-crisis depressed the issuance volume. Securitizations were accused of fostering intransparancy of bank risks which dried out the liquidity in the interbank market. Whether the intransparancy was generated by the securitizations or by the complexity of structured investment vehicles investing in securitization bonds, is an unsettled empirical question. It is also controversial whether securitizations have positive or negative effects on financial stability. In any case, many financial intermediaries use securitizations for their management of default risks. Despite of this, there is amazingly little research on securitizations. This paper looks at a subset of securitization-transactions, called collateralized debt obligation (CDO)-transactions which can be collateralized loan obligation (CLO)- or collateralized bond obligation (CBO)-transactions. In the former case a bank typically securitizes part of its loan portfolio. In the latter case the originator of the transaction, a bank or an investment manager, buys bonds, and sometimes in addition some loans, pools them in one portfolio and sells the portfolio to investors.

This paper analyzes important aspects of the design of CDO-transactions. Given information asymmetries between banks and investors about the quality of securitized loans or bonds, investors are concerned about buying lemons and, therefore, insist on credit enhancements in securitizations which mitigate potential problems of information asymmetry. If a bank, for example, securitizes the payment claims of many loans granted to small and medium sized enterprises, then investors know little about these obligors, relative to the bank. This provides room for adverse selection and moral hazard of the bank. Since investors penalize the bank for information asymmetries, she therefore attempts to mitigate their effects. In a perfect capital market these problems would not exist. Therefore securitization research needs to focus on market imperfections to understand the design of securitization transactions. Information asymmetries, costs of financial distress, costs of equity capital, other regulatory costs and liquidity premiums appear to be important as well as transaction and management costs. The latter include the costs of setting up (internal costs of the originator, fees of lawyers, rating agencies, custodians etc.) and managing the transaction after the setup. They are incurred by the originator and the investors buying the securities. Thus, various costs pose a barrier to securitization. It makes sense only if these costs are overcompensated by benefits. These may come from better risk allocation across agents, a reduction of the bank's cost of required equity capital, other regulatory costs and funding costs. Moreover, the transfer of default risks in a securitization gives the bank the option to take other risks.

The purpose of this paper is to add to the understanding of the design of securitization transactions by analyzing credit enhancements. The most important credit enhancements are contractual obligations of the originator and third parties to bear default losses of the asset pool underlying the transaction. In all transactions there exists a First Loss Position (FLP). It absorbs all default losses up to a limit, equal to its volume. Investors only bear default losses beyond the FLP. The higher the FLP, the more are investors protected against default losses and, hence, against problems of information asymmetries. In synthetic transactions, investors usually bear only part of the default losses beyond the FLP. They take a limited second loss position (SLP) and the originator takes the third loss position (TLP) by not selling the super-senior tranche. She may buy protection against the losses of the TLP through a senior credit default swap. Similarly, the originator need not retain the FLP, but may sell part or all of it to third parties. It is not publicly known to what extent the originator retains the risks of the FLP and the TLP.

The market imperfections mentioned above pose a challenge to the originator of a transaction. How should she design the transaction so as to maximize her net benefit? In particular, given the quality of the underlying asset pool (loans/bonds) serving as collateral for a transaction, how large should the FLP be so as to mitigate problems of information asymmetry? Should the transaction be structured as a true sale- or a synthetic transaction so as to allow for a TLP? How large should be the TLP? These questions can only be answered taking into consideration the needs of the originator and those of investors. They insist on a solid design of the transaction so as to protect them against potential losses due to information asymmetries. We try to answer these questions by, first, analyzing the optimization problem of the originator and deriving hypotheses about an optimal design. Second, we investigate a set of European securitization transactions to test these hypotheses. In the empirical analysis, we also investigate the lowest rated bond tranche sold to investors. This tranche can be viewed as the mirror of the FLP since the FLP determines the protection of the lowest rated tranche against default losses. Therefore the characteristics of the lowest rated tranche help to understand the choice of the FLP.

To our best knowledge, this study is the first to analyze the impact of the quality of the securitized asset pool and originator characteristics on the transaction design. The design is the outcome of an optimization model. *The optimal design of a transaction is a function of the asset pool quality, of the attitudes of investors and rating agencies* *and of the characteristics of the originator.* This function is investigated in this paper. We assume that this function is the same for all CDO-securitization transactions and, thus, exogenous to the originator. Her job is to design the transaction according to this function because there is no way for her to do better.

The main findings of the paper can be summarized as follows. First, a theoretical model shows that the FLP should be inversely related to the quality of the securitized asset portfolio. The FLP should increase when the portfolio quality declines. The quality of the securitized asset portfolio is measured by its weighted average default probability (WADP) and by Moody´s diversity score (DS). A lower WADP and/or a higher DS improve the asset pool quality. The empirical evidence confirms that the FLP increases when the asset pool quality declines. We interpret this as evidence that a lower portfolio quality reinforces problems of asymmetric information which are mitigated by a higher FLP.

Second, the qualitative finding that a lower asset pool quality raises the FLP does not tell us how the FLP is quantitatively determined. Therefore, we investigate two transformations of the asset pool quality into loss sharing characteristics, assuming a lognormal distribution for the default loss rate of the underlying portfolio. The first characteristic is the share of expected default losses absorbed by the FLP, called the loss share. The second characteristic is the probability that all default losses are fully borne by the FLP, i.e. investors are not hit. We denote it as the support-probability of the FLP. (1 - support-probability) is the probability that investors are hit by default losses. In particular, it is the probability that the lowest rated tranche, i.e. the tranche with the lowest rating, is hit. Its rating is determined by this probability according to S&P.

A simple optimization model illustrates how the loss share and the support-probability react to changes in asset pool quality. Empirically, it turns out that the share of expected default losses, with a mean of 86 %, is independent of the asset pool quality. This indicates that a share of 86 % is the guideline for the market which may be influenced to some extent by other considerations. A constant share of the expected default loss implies for the lognormal model that the support-probability of the FLP depends inversely on the WADP and, surprisingly, also inversely on the DS. This is confirmed by the empirical findings. These findings give us a rather precise understanding of how the market copes with information asymmetries in securitizations.

Third, the FLP resp. its loss share together with asset pool quality are quite powerful in explaining empirically the rating and the credit spread of the lowest rated tranche. But the credit spread of the lowest rated tranche is better explained by its rating, its maturity and the date at which the transaction is arranged. This underlines the important role of the rating agencies.

Fourth, the attractiveness of a synthetic relative to a true sale transaction increases with the portfolio quality. Hence, TLPs are more likely for transactions with better portfolio quality. Better quality implies a lower default risk of the super-senior tranche, given its size, making it less attractive for the originator to buy protection on this tranche through selling it or buying a super-senior default swap. The preference for synthetic transactions is stronger for originators with a better rating. Presumably, for highly rated originators funding through standard bonds is cheaper than through true sale transactions. Retention of the super-senior tranche is in strong contrast to the literature which argues that the originator should sell the least information-sensitive tranche. The size of the super-senior tranche, i.e. the size of the TLP, *increases* with the portfolio quality, in contrast to the size of the FLP which is *inversely related* to portfolio quality. This indicates the different nature of the FLP and the TLP. The FLP appears to be important for investor protection while the TLP does not and, therefore, is driven by other considerations.

Fifth, surprisingly, characteristics of the originator like her total capital ratio, Tobin´s Q and other variables which proxy for her securitization motives, add little to the explanatory power of the regressions. This indicates that the design of securitization transactions depends little on these characteristics. Essentially, rating agencies and investors appear to be the dominant forces.

The paper is structured as follows. In section 2 the relevant literature is discussed. In section 3 we model the originator's optimization problem and derive hypotheses about her choice of the transaction design. The empirical findings are presented in section 4 and discussed in section 5. Section 6 concludes.

1.2 Literature Review

The design of a CDO-transaction regarding the handling of information asymmetries is a complex task. In order to relate it to the literature, we first characterize CDO-transactions. Depending on her motives, the originator selects a set of loans or/and bonds[1] as the underlying asset pool of the transaction. In a static deal, this set is determined at the outset. In a dynamic (managed) deal, this set changes over time

[1]The bonds may include a few tranches of other securitization transactions or structured finance products.

depending on the originator's policy. In a true sale transaction, all loans/bonds are sold without recourse to the special purpose vehicle which issues an equity tranche (=FLP) and various tranches of bonds to investors. The originator can freely use the proceeds from issuing the tranches including the sold part of the equity tranche. In a synthetic transaction the originator retains ownership of the loans/bonds and transfers part of the default risk through a junior credit default swap to the special purpose vehicle. This swap covers default risks beyond a threshold, excluding the default risk of the TLP. This threshold implies a FLP of the originator. The coverage of default risks by the swap is limited by the face value of the bonds issued by the SPV. Often the issued bond-tranches cover only a small fraction of the nominal value of the underlying portfolio so that the originator retains a large super-senior tranche and its associated default risk unless this risk is protected through a super-senior credit default swap. Hence, the super-senior tranche represents a TLP which is only hit if the SLP of investors is fully exhausted by default losses. In contrast to a true sale transaction, the originator does not receive the issuance proceeds in a synthetic transaction. These need to be invested in AAA-securities or other almost default-free assets. In all transactions, the originator decides about the choice of the asset pool, the size of the FLP, the tranching of the bonds to be issued. If the originator opts for a synthetic transaction, he also decides about the TLP. These decisions are taken by the originator in close collaboration with the involved rating agencies and leading investors.

In the following we summarize the literature related to these issues. There exists a variety of papers modelling the optimal design of financial contracts. Several papers show the optimality of first loss positions (FLP). In the absence of information asymmetries, Arrow (1971) [see also *Gollier* and *Schlesinger* (1996)] analyzes the optimal insurance contract for a setting in which the protection buyer is risk averse, but the protection sellers are risk neutral. If the protection sellers bound their expected loss from above, then a FLP of the protection buyer is optimal. This follows because optimal risk sharing entails an upper limit of the realized loss borne by the risk averse protection buyer. *Townsend* (1979) considers risk sharing between a risk averse entrepreneur and investors in the presence of information asymmetries about the entrepreneur's ability to pay. If the entrepreneur fully pays the investors' claim, then she incurs no other costs. If she does not fully pay claiming that she lacks the necessary funds, then this claim needs to be verified. If the state verification cost is borne by the entrepreneur, the optimal contract is a standard debt contract: The entrepreneur fully pays the fixed claim when her company earns sufficient funds. Otherwise she prefers to pay the lower state verification cost and impose some loss on the investors. This is basically the same as taking a FLP.

In a related model of *Gale* and *Hellwig* (1985), both, the entrepreneur and investors, are risk neutral. However, the entrepreneur can only bear limited losses in order to stay solvent. Again, a standard debt contract turns out to be optimal implying a FLP of the entrepreneur.

In the previous two papers information asymmetries are resolved through state verification. The more recent literature distinguishes between information-sensitive and -insensitive securities. Information-insensitive securities are subject to little information asymmetries, in contrast to information-sensitive securities. *Boot* and *Thakor* (1993) argue that a risky cash flow should be split into a senior and a subordinated security. The senior security is information-insensitive and can be sold to uninformed investors while the subordinated security is information-sensitive and should be sold to informed investors. This allows the seller of the cash flow to raise the sales revenue. *Riddiough* (1997) extends this reasoning by showing that loan bundling allows for pool diversification which softens information asymmetries. Moreover, the holder of the junior security should control changes in the loan portfolio because she primarily bears the consequences.[2]

DeMarzo and *Duffie* (1999) analyze the security-design assuming a tradeoff between the retention cost of holding cash flows and the liquidity cost of selling information-sensitive securities. They also prove that a standard debt contract is optimal and that an issuer with very profitable investment opportunities retains little default risk in a securitization transaction. In a recent paper *DeMarzo* (2005) shows that pooling of assets has an information destruction effect since it prohibits the seller to sell asset cash flows separately and, thereby, optimize asset specific sales. But pooling also has a beneficial diversification effect. Tranching then allows to create more and also less information-sensitive claims and to sell the more liquid information-insensitive claims. This model is generalized to a dynamic model of intermediation. Summarizing these papers, they demonstrate the optimality of a FLP and argue that the senior information-insensitive tranches should be sold to investors. This is in strong contrast to synthetic transactions in which the least information-sensitive tranche, the TLP, is not sold.

Plantin (2003) shows that sophisticated institutions with high distribution costs buy and sell the junior tranches leaving senior tranches to retail institutions with low distribution costs. *David* (1997) asks how many tranches should be issued. Tranches are sold to individual and institutional investors. The latter buy tranches to hedge their

[2] *Gorton* and *Pennacchi* (1995) consider a bank which optimizes the fraction of a single loan to be sold and the guarantee against loan default through a repurchase agreement.

endowment risk. Hence tranches should be differentiated so as to allow the different groups of investors an effective hedging.[3]

There are only a few empirical studies related to securitizations. *Childs*, *Ott* and *Riddiough* (1996) investigate the pricing of Commercial Mortage-Backed securities and conclude that the correlation structure of the asset pool and the tranching are important determinants of the launch spreads of the tranches. *Higgins* and *Mason* (2004) find that credit card banks provide implicit recourse to asset-backed securities to protect their reputation. *Cebenoyan* and *Strahan* (2004) document that banks securitizing loans hold less capital than other banks and have more risky assets relative to total assets. *Downing* and *Wallace* (2005) analyze securitizations of commercial mortgage backed securities and find that FLPs are higher than what might be expected looking at the actual performance of mortgages. According to *Downing*, *Jaffee* and *Wallace* (2006) participation certificates sold to special purpose vehicles are on average valued less than those not sold. *Franke* and *Krahnen* (2006) find that securitization tends to raise the bank's stock market beta indicating more systematic risk taking. *Cuchra* and *Jenkinson* (2005) analyze the number of tranches in securitizations and conclude that the number increases with sophistication of investors, with information asymmetry and with the volume of the transaction. Finally, *Cuchra* (2005) analyzes the launch spreads of tranches in securitizations and finds that ratings are very important determinants besides of general capital market conditions. He also finds that larger tranches command a lower spread indicating a liquidity premium.

1.3 The Originator's Optimization and Hypotheses

The focus of this paper is the design of CDO-transactions in the presence of information asymmetries and other market imperfections. If the originator would ignore the reactions of investors and rating agencies to information asymmetries in the design of securitization transactions, then she might end up paying very high credit spreads. Therefore she prefers to mitigate information asymmetry induced problems by credit enhancements, in particular by setting up a First Loss Position. The optimal design of a transaction depends on the quality of the underlying asset pool, the originator characteristics and the attitudes of investors and rating agencies. While the originator chooses asset pool quality, her characteristics, attitudes of investors and those of rating

[3] *Glaeser* and *Kallal* (1997) show that more information may increase information asymmetries. Hence limiting information disclosure may improve liquidity of asset-backed securities in the secondary market.

agencies are exogenously given. The function relating the *optimal* design of a transaction to asset pool quality is driven by these exogenous factors. We assume that this function is the same for all CDO-transactions and exogenously given. Every originator chooses the optimal transaction design according to this function. The purpose of this paper is to find out important properties of this function. We, therefore, analyze a simple model to determine these properties theoretically and then a set of European CDO-transactions to determine them empirically.

In this section, first, we relate information asymmetries to asset pool quality. Second, we present some general results on the relationship between asset pool quality and loss sharing between investors and the holders of the FLP. Third, we present a simple optimization model of the originator to derive her optimal monitoring effort and her choice of the FLP. Fourth, we derive various hypotheses about the optimal transaction design which are tested later on a set of European transactions.

1.3.1 Information Asymmetries and Asset Pool Quality

Transferring default risks through a securitization transaction is always subject to problems of information asymmetries between the originator and investors. The originator knows more about the quality of the loans underlying the transaction because she has close contact to the obligors. Moreover, she decides about her effort of monitoring the obligors and enforcing her loan claims. This effort is not observable by investors adding to the information asymmetry. Therefore credit spreads include a penalty for adverse selection and moral hazard problems. To model these information asymmetries, we distinguish between the published and the true quality of the underlying asset pool.

Asset pool quality is measured in different dimensions. One measure of the average quality of the loans is the weighted average default probability (WADP) of the loans. The higher WADP, the higher are the expected default losses of the asset pool. The second measure of asset pool quality is a measure of asset pool diversification. The intra- and interindustry-diversification of the loan portfolio can be summarized in a diversity measure as done in Moody´s Diversity Score (DS). This score can be interpreted as the diversification-equivalent number of equally sized loans whose defaults are uncorrelated. A third characteristic of the asset pool quality is the weighted average loss given default of the loans. Loss given default is measured by (1-recovery rate). The recovery rate of a loan is the fraction of its par value denoting the present value of all future payments on this defaulted loan discounted to the date of default. Initially the par value of the loan approximately equals its market value so that the loss given default applies equally to the par and the market value. Since we cannot get reliable data on the weighted average loss given default for most CDO-transactions, we assume that this characteristic is the same across all CDO-transactions.[4] Moreover, to simplify modelling we assume that the loss given default is non-random. Hence we characterize asset pool quality by the two determinants WADP and DS.

The rating agencies publish information on the asset pool quality. We assume that rating agencies do their best to publish unbiased information. Investors believe this so that they consider the published information as the best predictor of the true asset pool quality. But they know that the true quality differs from the published quality by a noise term ϵ,

$$\text{published asset pool quality} = \text{true asset pool quality} + \epsilon.$$

We define the standard deviation of the noise term, $\sigma(\epsilon)$, as quality uncertainty and assume that it is inversely related to the true asset pool quality. The intuition for this is that errors in estimating WADP are likely to be *proportional* to the true WADP. If the true WADP is very small (high), then errors in estimating WADP are likely to be small (high). We also assume that $\sigma(\epsilon)$ is inversely related to the true DS. As pointed out by *DeMarzo* (2005) and others, a high DS reduces information asymmetries because the idiosyncratic risks of the assets tend to be diversified away.[5] The lower the DS, the stronger is idiosyncratic default risk relative to systematic default risk. The effects of idiosyncratic risks are almost by definition harder to analyze and to predict than those of systematic risk, because idiosyncratic risks are much more diverse and less well understood. Hence we believe that there are good reasons to assume an inverse relation between asset pool quality and quality uncertainty.

Higher quality uncertainty creates more potential for adverse selection and moral hazard, because these activities are more difficult to discover when the quality risk is stronger. For example, moral hazard of the originator in monitoring loan performance which adds to $\sigma(\epsilon)$, is harder to discover for loans of low quality because these loans often are more exposed to hardly observable, idiosyncratic risk factors than high quality loans. Therefore, higher uncertainty about asset pool quality should reinforce problems of information asymmetries.

In the following, the two asset pool characteristics WADP and DS are always under-

[4] Only for a few Spanish transactions we have some data which we then use in our empirical study.

[5] *De Marzo* (2005) argues that stronger diversification makes securitization of asset pools more attractive relative to liquidating assets separately because diversification reduces information asymmetries.

stood as the published characteristics. Investors assume that these characteristics are unbiased estimates of the true characteristics, but are aware of the quality uncertainty-dependent potential for adverse selection and moral hazard.

1.3.2 General Relationship between Asset Pool Quality and Loss Sharing

Investor scepticism, driven by information asymmetries, can be reduced by raising the FLP. The economic rationale behind the FLP is similar to that behind the deductible in insurance business. The higher the deductible, the more damages are borne by the insured, the weaker are her incentives for adverse selection and moral hazard, the less important are problems of information asymmetries for the insurer.

The FLP can take different forms. In a true sale transaction, the originator may retain, for example, all or part of the most junior tranche of the securities, i.e. the equity tranche, which is most information-sensitive. The FLP may be an initial FLP which is a fixed commitment of the originator to absorb the first default losses up to a given limit. The initial FLP may be supplemented by a reserve account in which interest surplus (interest revenue from the asset pool minus interest expense on tranches) accrues over time and which then serves to absorb default losses. Hence an originator may substitute part of the initial FLP by a reserve account. This would reduce regulatory equity capital requirements. In a synthetic transaction, the FLP equals the threshold of the junior credit default swap between the originator and the investors. The latter being protection sellers cover only default losses exceeding the threshold, up to the limit given by the face value of issued tranches. The SPV is the intermediary of this swap.

In the following, we discuss the relation of loss sharing between investors and the holders of the FLP to asset pool quality. Without loss of generality, we analyze securitization transactions with an underlying asset pool of a par value of 1 €. Hence the default loss of the pool equals the loss rate.

Loss sharing between investors and the holders of the FLP can be measured in a naive way by the size of the FLP. This measure does not take into account the asset pool quality. We would like to know more precisely the functional relationship between the FLP and the two main determinants of the quality of the asset pool, WADP and DS. This would improve our understanding of how the capital market copes with information asymmetries. We search for an empirically testable model which maps WADP and DS into an economically meaningful loss sharing characteristic. Ideally speaking, this loss sharing characteristic should describe the equilibrium loss sharing as a function of WADP and DS. Since investors are concerned about risk and expected return, it is natural to look at two loss sharing characteristics, one being a measure of sharing expected losses and the other one being related to the probability that investors are hit by default losses.

The first measure, the share of expected default losses borne by the FLP, s, is defined as the expected loss borne by the FLP, divided by the expected loss of the asset pool. s is called the *loss share*. The higher this share is, the smaller are the potential effects of information asymmetries on investors. Although this measure does not consider risk explicitly, the risk of the loss rate distribution is implicitly taken into account as it determines the loss share (see the following Lemma 1 a).

The second measure of loss sharing is the probability that all losses are fully covered by the FLP. (1$-$ this probability) is the probability that investors are hit by default losses. We define the *support-probability of the FLP* as the cumulative probability of the asset pool-loss rate distribution at the loss rate which equals the FLP (in percent of the par value of the asset pool). If, for example, the FLP is 4 percent and the associated cumulative probability of the loss rate distribution is 80 percent, then with 80 percent probability the FLP fully absorbs all losses. Investors then incur losses with 20 percent probability. According to S&P, this probability determines the rating of the tranche with the lowest rating. The higher this probability, the lower is the rating of this tranche, the more investors are exposed to default risks, the more afraid investors may be of information asymmetry. This measure of loss sharing addresses default risk by quantile considerations as does the value at risk which is commonly used by banks to assess tail risk.

First, we analyze the relationship between the loss share and true portfolio quality. As a primer, we characterize the impact of a change in asset pool quality on the loss share. This impact depends on the direct impact of the asset pool quality on loss allocation and on the indirect impact through the originator´s adjustment of her monitoring effort and of the FLP. The following lemma characterizes the direct impact of a change in WADP resp. DS on the loss allocation. A decline in DS, holding WADP constant, can be perceived as a mean preserving spread in the loss rate distribution of the asset pool so that the two cumulative probability distributions intersect once. An increase in WADP, holding DS constant, can be perceived as a first order stochastic dominance shift in the loss rate distribution. Lemma 1a) and b) are proved in Appendix 1.8.1, Lemma 1c) in Appendix 1.8.2.

Lemma 1 *Consider a securitization transaction, given the size of the FLP and the originator´s effort.*

a) A mean preserving spread of the loss rate distribution, induced by a decline in asset pool diversification, implies a lower expected loss for the FLP and a higher expected loss for the sold tranches (including the TLP in case of a synthetic transaction). Hence it reduces the share in expected losses of the asset pool borne by the FLP.

b) A first order stochastic dominance shift in the loss rate distribution, induced by an increase in the weighted average default probability of the asset pool, implies a higher expected loss for the sold tranches (including the TLP in case of a synthetic transaction) and for the FLP.

c) Given a lognormal loss rate distribution, an increase in the weighted average default probability reduces the share in expected losses of the asset pool borne by the FLP if the FLP is equal or greater than the expected loss of the asset pool.

The lemma shows that a decline in asset pool diversification redistributes the expected loss from the FLP to investors (and the TLP in case of a synthetic transaction) while an increase in the weighted average default probability hurts both, the FLP and the investors (including the TLP in case of a synthetic transaction). Whether the loss share increases with WADP, depends on the shape of the probability distribution. A simple probability distribution is the lognormal distribution. This was also used by Moody´s (2000). It implies a positive probability of a loss rate above 1 which in reality is impossible. But this probability is very small for realistic assumptions. Consider a transaction in which the average default probability of loans is high with 20 percent and the DS is low with 10. Then the cumulative probability of the implied lognormal distribution at a loss rate of 1 is 99.9 percent. In typical transactions this probability would be higher. Therefore the lognormal approximation should be quite good.

For each securitization transaction we derive the lognormal distribution as follows (see Appendix 1.8.2). The expected loss rate of the asset pool is λ WADP with λ being the loss given default of the loans. λ is assumed to be exogenously given and non-random. We assume that all claims in the asset pool have the same loss rate variance S^2 derived from a binomial model of default or non-default,

$$S^2 = \lambda^2 \, WADP(1\text{-}WADP).$$

We divide S^2 by the DS to derive the variance of the loss rate of the asset pool. Given this variance and the expected loss of the asset pool, we derive the mean and the standard deviation σ of the lognormal distribution as shown in Appendix 1.8.2. Then applying the Black-Scholes methodology, for each transaction the share of expected losses, borne by the FLP, s, is given by

$$s = N(h) + \frac{FLP}{\lambda WADP}(1 - N(h + \sigma)) \tag{1.1}$$

$$\text{with } h = \frac{\ln \frac{FLP}{\lambda WADP}}{\sigma} - \frac{\sigma}{2}$$

$$\text{and } \sigma^2 = \ln\left(1 + \frac{\frac{1}{WADP} - 1}{DS}\right).$$

The support-probability of the FLP, $\gamma(FLP)$, is given by the value of the normal distribution function at the standardized $\ln(FLP)$,

$$\gamma(FLP) = N(h + \sigma). \tag{1.2}$$

$N(.)$ and $n(.)$ denote the standard normal distribution function resp. the standard normal probability density function.

Returning to Lemma 1c), an increase in WADP reduces the loss share if the FLP is equal to or greater than the expected loss rate. This is a weak condition which is mostly satisfied. Hence, given the FLP and the originator´s effort, the loss share usually goes down when WADP increases.

Second, we analyze the support-probability of the FLP associated with the loss rate distribution as another measure of loss sharing. Again we state a lemma which describes the effects of changes in the asset pool quality on this support-probability, given the FLP and the originator´s effort. For changes in WADP, the proof follows immediately from a graph of the respective cumulative probability distributions. For changes in DS, look at Figure 1.4 in Appendix 1.8.1.

Lemma 2 *Consider a securitization transaction, given the size of the FLP and the originator´s effort.*

a) A mean preserving spread of the loss rate distribution, induced by a decline in asset pool diversification, reduces (increases) the support-probability of the FLP *if the FLP is higher (smaller) than the loss rate at which the two cumulative probability distributions intersect. Given a lognormal loss rate distribution, the latter condition holds if and only if*[6]

$$FLP \geq \lambda WADP \sqrt{1 + \frac{\frac{1}{WADP} - 1}{DS}}.$$

b) *A first order stochastic dominance shift in the loss rate distribution, induced by an increase in the weighted average default probability of the asset pool, reduces the support-probability of the FLP.*

Not surprisingly, Lemma 2 states that a higher WADP lowers the support-probability of the FLP. Also a deterioration of the asset pool quality given by a lower DS lowers the support-probability if the FLP is higher than the loss rate at which the two cumulative probability distributions intersect. For a lognormal distribution, the latter condition is satisfied if the FLP clearly exceeds the expected loss rate of the underlying portfolio. As will be shown later in the empirical part, the FLP usually satisfies the condition in Lemma 2. Therefore Lemma 2 implies that a deterioration of the asset pool quality has similar qualitative effects on the support-probability of the FLP as on the share of expected losses (Lemma 1).

Since the loss share and the support-probability are two different loss measures which might govern the size of the FLP, it is important to understand the relationship between both. This is given by the next lemma proved in Appendix 1.8.3.

Lemma 3 *Assume a lognormal loss rate distribution. Suppose that upon a change in the portfolio quality, the First Loss Position is changed so that its loss share remains the same. Then, given the originator´s effort, the support-probability of the FLP is inversely related to the weighted average default probability and to the diversity score, if and only if* $h < n(h+\sigma)/(1-N(h+\sigma))$. *Also,* $\partial FLP/\partial WADP < 1$ *if* $FLP \leq WADP$.

Lemma 3 gives a surprising result. Given a constant loss share and the condition $h < n(h+\sigma)/(1-N(h+\sigma))$, the support-probability of the FLP declines if one measure of portfolio quality, the WADP, worsens, but it also declines if the other measure of portfolio quality, the DS, *improves*. The condition $h < n(h+\sigma)/(1-N(h+\sigma))$ clearly holds if the FLP does not exceed the expected loss rate because then $h < 0$. But for a very high FLP h would be rather high while $n(h+\sigma)/(1-N(h+\sigma))$ converges to 0.

[6]For proof see Appendix 1.8.2.

Then the support-probability of the FLP would increase with the DS. As will be shown in the empirical part, the condition $h < n(h+\sigma)/(1-N(h+\sigma))$ is always satisfied in our sample.

From Lemma 3 it is easy to derive the effects of changes in WADP and DS on the loss share holding the support-probability of the FLP constant. Since the loss share and the support-probability increase with the FLP, we have the following

Corollary 1 *Given the conditions in Lemma 3, but holding the support-probability instead of the loss share constant, a higher weighted average default probability and a higher diversity score raise the loss share.*

1.3.3 Modelling the Optimal First Loss Position

The Model Setup

Next we present a simple model for the originator´s optimization problem and derive her optimal effort and the optimal FLP. When structuring a securitization transaction, the originator maximizes her net benefit. Her gross benefit in a CLO-transaction may be summarized by the decline in the costs of required equity capital and other regulations and possibly the decline of funding costs. The decline in default risks enables the originator to take new risks. Then the value of these new activities contributes to the gross benefit. The costs of securitization transactions include the setup and management costs, the credit spreads paid to investors, the costs of credit enhancements and reputation costs. The latter costs are incurred if investors suffer from default losses and attribute them to bad management of the originator. Investors would then charge higher spreads in future transactions.

In a CBO-transaction, the originator also maximizes her net benefit. However, often she purchases the asset pool and securitizes it simultaneously, retaining part of the risks through a FLP. Apart from these risks, the net benefit in such a transaction is an arbitrage profit. This explains why these transactions are often called arbitrage transactions.

The preferred size of the FLP depends on the benefits and costs of a FLP incurred by the originator. First, consider the benefits. If the originator retains the most junior tranche, she saves the high credit spread including, perhaps, a complexity premium on this tranche due to high costs of required sophisticated management. A higher FLP may also strengthen investor confidence in the overall transaction so that they charge a lower penalty for information asymmetry on all sold tranches. This is likely to be true because a higher FLP reduces the investors´ share in default losses. Therefore, investors may be more confident in the overall transaction, the higher is the FLP. Second, the cost of the FLP is the cost of the required regulatory/economic capital, apart from management costs.

We illustrate the originator´s choices by a simple model. To motivate this model, first we argue why we do not use a signalling model. Signalling models help to analyze the behavior of economic agents in the presence of adverse selection problems. These problems also exist in securitization transactions. Hence it would be natural to explore a signalling model explaining the choices of the originator such that she would be motivated to signal the true properties of the transaction[7]. The main properties from the perspective of the investors are the portfolio quality, the FLP and the originator´s effort in monitoring and servicing the underlying loans. The latter is unobservable, but it is important for the evaluation of the portfolio quality. The FLP is specified in the offering circular. Hence the crucial properties are the WADP (and the loss given default) and the DS of the underlying portfolio describing its quality. But these are estimated by the rating agencies, not by the originator. They are responsible for estimating and communicating the portfolio quality. They should also forecast the originator´s effort and incorporate it in their estimates of the portfolio quality. Therefore a signalling model would have to model the behavior of the rating agencies. This is beyond the scope of this paper.

Instead, this paper analyzes a simple model of the originator which ignores strategic behavior of investors and of the originator. She faces a cost function and chooses FLP and effort to minimize the overall cost in a true sale-transaction. The cost function is

$$E(l(e)) + C(FLP) + (a + r)(1 - s)E(l(e)) + g(e) \ . \tag{1.3}$$

This cost is composed of the expected loss of the asset pool, $E(l(e))$, the regulatory/economic cost of the FLP-risk, $C(FLP)$, the penalty imposed on the originator for problems associated with information asymmetry, $(a+r)(1-s)E(l(e))$, and the cost of the originator´s effort, $g(e)$. e denotes the originator´s effort in monitoring obligors

[7] A signalling model might provide a hypothesis quite different from our hypothesis. We shall show that the size of the FLP should be higher, the lower the quality of the asset pool is. Bester (1987) showed that borrowers may signal their quality to lenders through the amount of collateral. Since the expected cost of the collateral, borne by the borrower, is inversely related to her default probability, the expected cost of a collateral is inversely related to the borrower quality. Therefore high quality borrowers are ready to provide large collateral while low quality borrowers are not. Applying the same logic to the FLP in a securitization transaction, the signalling model would indicate that the size of the FLP increases with the quality of the asset pool.

and collecting debt claims. Effort is scaled such that $g(e)$ is a linearly increasing function. We assume that there is a minimal effort e_{min} such that $e \geq e_{min}$. The higher the effort is, the smaller is the expected loss.$E(l(e))$ is a declining, convex function since losses can never become negative. Its negative slope increases with WADP because then there is more to be gained through more effort. For modelling, we assume that a higher effort reduces the expected loss such that the loss distribution improves by first order stochastic dominance. Investors and rating agencies cannot observe the effort. But they are assumed to correctly predict the originator´s effort. Therefore in equation (1.3) e is the correctly anticipated effort.

In the cost function the expected loss $E(l(e))$ is fully attributed to the originator. The motivation for this is that even though the investors bear part of the losses, they charge the originator for these losses so that eventually she has to bear these losses. We assume that investors base their behavior on the asset pool quality communicated by the rating agencies, but they are aware of quality uncertainty.

Investors charge the originator a penalty for problems of information asymmetries. Since investors are only exposed to default losses according to their loss share, it is assumed that the penalty is based on the expected loss borne by investors, $(1-s)E(l(e))$. The penalty factor is composed of an ex-ante penalty factor a and an ex-post penalty factor r. a and r are known to investors and the originator. Splitting the penalty factor into two parts is motivated by the sequential decision making of the originator. After the sale of the tranches the originator decides about her effort. Investors may provide an incentive for a strong effort by charging ex post a reputation cost if they actually have to bear default losses. We model the actual reputation cost as $r\ max(0, l(e) - FLP)$ so that the expected reputation cost is $r(1-s)E(l(e))$. The originator can reduce this cost through a higher effort which, however, generates a higher effort cost. r is constant, irrespective of portfolio quality, because investors are assumed to charge reputation costs proportional to their realized loss.

Before the tranches are sold, the originator decides about the FLP. The credit spreads charged by the investors include the ex-ante penalty $a(1-s)E(l(e))$. The ex-ante penalty factor a is also assumed to be constant. Since the penalty is charged on the investors´ loss, a high a motivates the originator to choose a high FLP which, however, raises her cost of economic capital. Overall, the model includes two mechanisms by which investors can reduce their expected loss, the ex ante-penalty and the ex post-reputation cost. The higher a and r are, the stronger are the incentives for the originator to reduce the investors´ expected loss through the choice of FLP and effort.

The cost of the equity capital required by the FLP, $C(FLP)$, depends on the regulatory/economic capital associated with the FLP. In the new banking regulation of Basle II the regulatory capital required for the FLP is equal to the FLP. In our model the bank as an originator uses economic capital, defined as the value at risk of the FLP. If the originator sells part of the equity tranche, then the buyer would also use economic capital as a measure of risk. The value at risk equals for a standardized par value of 1 € of the transaction volume,

$$VaR(FLP) = l(q) - expected\ loss\ of\ the\ FLP$$

with $l(q)$ being the loss rate quantile associated with the exogenously given quantile probability q, used for the VaR. This probability is usually below 1 percent. In all CDO-transactions the probability that the FLP is fully absorbed by losses is higher than 1 percent. Therefore $l(q)$ equals FLP. Hence,

$$VaR(FLP) = FLP - expected\ loss\ of\ the\ FLP.$$

The cost function, $C(FLP)$, starting in the origin, is assumed to be linear in the $VaR(FLP)$. This is supported by the observation that banks often require a fixed rate of return on economic capital, for example, 20 percent. Since most CDO-transactions have a maturity of 5 to 7 years, the cost of the FLP has to be aggregated and discounted over these years. For simplicity, we assume that the present value of this cost equals 100 percent per € of the $VaR(FLP)$. Then the cost function (1) simplifies to

$$\begin{aligned} &E(l(e)) + FLP - sE(l(e)) + (a+r)(1-s)E(l(e)) + g(e) \\ &\quad = FLP + (1+a+r)(1-s)E(l(e)) + g(e)\ . \end{aligned} \tag{1.4}$$

In the cost function, we ignore transaction costs because we assume for simplicity that they are independent of the transaction design. Moreover, we ignore potential benefits of funding costs for the originator because these do not exist in synthetic transactions and are of little relevance for the optimal choice of effort and FLP in true sale transactions. We will address the funding cost issue later on when discussing true sale versus synthetic transactions.

The Optimal Effort

Given the quality of the asset pool, the originator faces two choices, the size of the FLP and her effort to monitor the obligors and collect the outstanding debt claims. Since the effort is chosen after the setup of the transaction and the sale of tranches, we first consider the optimal effort choice. e^* minimizes the subsequent cost function

(1.5), given the asset pool quality and the FLP. Hence $e^* = e^*(FLP)$. Knowing this function, before the sale of tranches the originator optimizes the FLP which translates into an optimal loss share s^*.

The originator optimizes her effort after the setup of the transaction and the sale of the tranches. Then the cost of the originator, still dependent on her effort choice, equals her expected loss, $sE(l(e))$, the variable part of the cost of economic capital, $-sE(l(e))$, her expected reputation cost, $r(1-s)E(l(e))$, and the effort cost $g(e)$. The first two terms cancel. Hence the originator minimizes

$$r(1-s)E(l(e)) + g(e). \tag{1.5}$$

This equation shows that the optimal effort is determined by its impact on the expected loss of the investors, not by its impact on the expected loss borne by the FLP. This rather surprising result is driven by the assumption that the present value of the equity cost declines 1 to 1 with the expected loss borne by the FLP. Hence, if $r = 0$, there is no reputation cost and the originator´s effort is minimal. Now assume $r > 0$. Let g‘ denote the constant marginal effort cost. Then the FOC for the effort, given an interior solution, is

$$r\frac{\partial(1-s)E(l(e))}{\partial e} + g' = 0. \tag{1.6}$$

The higher r, the higher is the optimal effort. Actually, r could be set so that the optimal effort would equal the first best effort, given by the FOC, $\partial E(l(e))/\partial e + g' = 0$.

How does the optimal effort depend on the FLP and on the quality of the underlying portfolio? By definition,

$$(1-s)E(l(e)) = \int_{FLP}^{1} (1-FLP)f(l(e))dl \tag{1.7}$$

with $f(l(e))$ being the probability density function of the portfolio loss rate l , given effort e. Hence from the FOC,

$$g' = -r\int_{FLP}^{1} (1-FLP)\frac{\partial f(l(e))}{\partial e}dl \tag{1.8}$$

For an interior solution of the optimal effort, the sensitivity of the optimal effort with respect to some parameter p, $\partial e^*/\partial p$, is given by

$$\frac{\partial e^*}{\partial p} = \frac{\frac{\partial}{\partial p}\int_{FLP}^{1} (1-FLP)\frac{\partial f(l(e^*))}{\partial e}dl}{\frac{\partial^2}{\partial e^2}[(1-s)E(l(e))]} \tag{1.9}$$

with the denominator being positive.

First, consider the effect of an increase of the FLP on the optimal effort. From (1.9) it follows that the numerator on the right hand side of (1.9) then equals - $\partial F(FLP, e^*)/\partial e$ with $F(FLP, e^*)$ being the cumulative probability of the loss rate distribution at $l = FLP$, given effort e^*. Hence $F(FLP, e^*)$ is the support-probability of the FLP. Since a higher effort implies a first order stochastic dominance improvement of the loss rate distribution, by Lemma 2b), $\partial F(FLP, e^*)/\partial e > 0$ so that the optimal effort is inversely related to the FLP. This surprising result is again due to the fact that a higher effort serves to reduce the expected loss borne by investors. This loss is, ceteris paribus, smaller, the higher is the FLP. If $FLP \to 0$, then the expected loss borne by investors approaches $E(l(e))$. Hence the originator´s effort would be maximal.

Second, consider an increase in WADP. Given WADP, $-\int_{FLP}^{1}(1-FLP)\frac{\partial f(l(e^*))}{\partial e}dl$ is positive since an effort increase lowers the expected loss of investors. If WADP increases, then there is more to be gained from an effort increase. Hence the numerator of (1.9) is positive and the optimal effort increases. Third, if the diversity score declines, then from Lemma 1a) $(1-s)E(l(e))$ also increases so that the same reasoning applies and the optimal effort increases. This proves

Proposition 1 *The optimal effort of the originator declines, ceteris paribus, if the First Loss Position increases. It increases if the quality of the asset portfolio declines.*

The Optimal First Loss Position

Next, we analyze the choice of the FLP. Since the optimal effort is chosen in a subsequent step, $e^* = e^*(FLP)$. Therefore the optimization of the FLP has to take into consideration the impact of the FLP on the optimal effort. The originator minimizes the overall cost

$$FLP + (1 + a + r)(1 - s)E(l(e^*)) + g(e^*) \qquad s.t. e^* = e^*(FLP). \tag{1.10}$$

First, suppose $r = 0$. Then the originator chooses the minimal effort. Differentiating (1.10) with respect to FLP gives the optimal size of the FLP

$$0 = 1 - (1 + a)(1 - F(FLP^*, e_{min})). \tag{1.11}$$

The higher the adverse selection penalty parameter a is, the higher is the optimal FLP. This is intuitive because a higher FLP reduces the loss borne by investors and hence the adverse selection penalty. Moreover, for $r = 0$, from (1.11) it follows that the support-probability of the optimal FLP is independent of the portfolio quality. By Lemma 2, given the FLP and effort and the condition in Lemma 2a), this support-probability goes down if WADP increases or DS declines. Hence in order to retain the same support-probability of the optimal FLP, the optimal FLP has to go up. This is also in line with intuition. A lower portfolio quality induces a higher FLP.

For a lognormal distribution it follows from Corollary 1 that an increase in WADP or DS raises the loss share s if the support-probability of the FLP is held constant and if the conditions in Lemma 3 hold.

These results are summarized in

Proposition 2 *Assume that the reputation cost parameter r is zero. Then*

a) the support-probability of the optimal FLP is independent of the portfolio quality,

b) the optimal FLP increases if the weighted average default probability of the asset pool increases or, given the condition of Lemma 2 a), the diversity score declines,

c) the optimal loss share s increases if the weighted average default probability or the diversity score increases, subject to the conditions in Lemma 3.

It should be noted that according to statement b) the optimal FLP increases if portfolio quality declines, but according to statement c) the optimal loss share increases with WADP, but also increases if the DS increases. Hence, Proposition 2 shows that in the absence of reputation costs the optimal loss share does not react unanimously to a deterioration in portfolio quality.

Now suppose $r > 0$. Given an interior solution for the optimal effort, the FOC (1.6) applies. Hence, the optimal FLP is given by

$$0 = 1 - (1 + a + r)(1 - F(FLP^*, e^*) - \frac{g'}{r}\frac{\partial e^*}{\partial FLP}) + g'\frac{\partial e^*}{\partial FLP}. \qquad (1.12)$$

This can be rewritten as

$$(1 + a + r)(1 - F(FLP^*, e^*)) + \left|\frac{\partial e^*}{\partial FLP}\right| g'(\frac{1 + a}{r} + 2) = 1 \qquad (1.13)$$

This FOC shows the interaction effect between effort and FLP. $\partial e^*/\partial FLP$ is negative (Proposition 1). Hence the more sensitively the optimal effort reacts to the FLP, the smaller $F(FLP^*, e^*)$ must be, implying ceteris paribus a smaller optimal FLP.

But a smaller FLP implies a higher optimal effort. Hence the more sensitively effort reacts to the FLP, the smaller is the optimal FLP and the higher is the optimal effort. The intuition for this result is the substitution between FLP and effort for investor protection. Investors are protected by a high FLP, but also by strong effort. Both mechanisms substitute for each other such that a high FLP induces a low effort and vice versa.

In order to get some insight into the reaction of $|\partial e^*/\partial FLP|$ to asset pool quality, first, consider a very good asset pool quality. Then the optimal effort equals the minimal effort so that the sensitivity $\partial e^*/\partial FLP = 0$, regardless of the level of the reputation cost parameter r. Second, assume a low portfolio quality and a high reputation cost parameter, then the optimal effort will be high indicating a high sensitivity $|\partial e^*/\partial FLP|$. Hence we observe a sensitivity increase, moving from high to low asset pool quality. Whether there exists a monotonic relation between $|\partial e^*/\partial FLP|$ and asset pool quality, depends on effort productivity and the cost parameters a and r. In any case, Proposition 2c) no longer holds. From the FOC (1.13), a lower asset pool quality reduces the support-probability of the FLP if it raises the sensitivity. If this increase is strong enough, then the decline in the support-probability of the FLP is strong enough to reduce the optimal loss share s^*. This proves

Corollary 2 *The optimal loss share of the originator is inversely related to the quality of the asset pool if the absolute sensitivity of the optimal effort to the First Loss Position is strongly inversely related to the asset pool quality.*

1.3.4 Hypotheses For Loss Sharing

From the preceding analysis, we now derive testable implications. Proposition 2 b) shows that the optimal FLP is inversely related to asset pool quality, given no reputation costs. This relation remains true if the reputation cost parameter r is positive, but the effort increase following a deterioration of asset pool quality does not fully compensate for the increase in problems of information asymmetry. Therefore we state the general hypothesis

Hypothesis 1 *The FLP is higher, the lower the quality of the asset pool.*

Regarding the more refined measures of loss sharing, Corollary 2 shows that the optimal loss share may be positively or negatively related to asset pool quality, depending on marginal effort productivity and on the cost parameters a and r. Since we neither know marginal productivity nor the cost parameters, we state the null-hypothesis

Hypothesis 2 *The optimal share of expected losses, borne by the FLP, is independent of WADP and DS.*

The alternative null-hypothesis 3 rests on the assumption that there are no reputation costs. Then we obtain from Proposition 2a)

Hypothesis 3 *The optimal support-probability of the FLP is independent of the quality of the asset pool.*

The optimization model discussed in the previous subsection is based on true sale-transactions. In a synthetic transaction the originator retains the super-senior tranche and thus has a TLP. This tranche would also be affected by changes in the DS or the WADP. But since the probability is very small that the super-senior tranche incurs a loss, the preceding results for true sale transactions are likely to remain valid also for synthetic transactions. Therefore hypotheses 2 and 3 are equally tested on synthetic transactions.

Hypotheses 1 to 3 are the core hypotheses on loss sharing. In the following we derive hypotheses about the impact of some other transaction characteristics on loss sharing. Hypotheses 1 to 3 are based on the conjecture that loss sharing is driven by the extent of information asymmetries. These might be stronger in CLO- than in CBO- transactions, controlling for WADP and DS. Loans are often given to small or medium sized firms whose identity is not revealed to investors while bond issuers are revealed and often are big firms or governments with publicly available information. Therefore CLO-transactions might offer more potential for adverse selection than CBO-transactions, controlling for WADP and DS. Also moral hazard problems might be stronger in CLO-than in CBO-transactions. In a CLO-transaction the originator remains the servicer of the loans so that the loan sale generates a moral hazard problem. In a CBO-transaction, the originator is not the servicer of the bonds eliminating the associated moral hazard on her side. Yet there may exist a moral hazard problem of the trustees in the bond issues. But these risks are diversified given many different bond trustees while the servicer risk in the CLO-transaction is not diversified (see also deMarzo (2005)). Therefore CLO-transactions may invoke more investor skepticism than CBO-transactions, given the same WADP and DS. Originators may respond to this by higher FLPs in CLO-transactions. This motivates

Hypothesis 4 *Given the same quality of the asset pool, loss sharing through the FLP is higher in CLO- than in CBO- transactions.*

Hypothesis 4 makes a statement on the optimal FLP in CLO- and CBO-transactions, given the same asset pool quality. This qualification may be problematic. If investors charge higher credits spreads for portfolios with lower diversification, then it pays for the originator to put together a well diversified asset portfolio. In a CLO-transaction this is easy for a bank with a large loan portfolio. Therefore we conjecture that the loan portfolio in a CLO-transaction will show a high DS. The situation is different for CBO-transactions. In a CBO-transaction the originator has to buy the bonds for the asset pool. This is often costly since the bond market is rather illiquid. Therefore we hypothesize that loan portfolios are better diversified.

Hypothesis 5 *The diversity score of the asset pool is higher in CLO- than in CBO-transactions.*

If Hypothesis 5 is correct, then the better diversification of CLO-transactions may render FLPs in CLO-transactions smaller than in CBO-transactions.

The originator faces the choice between a static and a dynamic (managed) transaction. In a static transaction the original asset pool cannot be changed subsequently by the originator. In contrast, the originator may change the asset pool in a dynamic transaction subject to constraints specified in the offering circular. She may replenish the pool after repayment of some assets or substitute new for existing assets. This induces another moral hazard problem which can be mitigated by a higher FLP. This motivates

Hypothesis 6 *Given the same quality of the asset pool, loss sharing through the FLP is higher in managed than in static transactions.*

A higher FLP retained by the originator reduces her opportunities for taking new risks. Therefore an originator with better investment opportunities should take a smaller FLP. As argued by *De Marzo* and *Duffie* (1999), she would transfer more default risks, the more valuable her real options are.

Hypothesis 7 *Banks with more valuable real options reduce loss sharing through the FLP.*

1.3.5 Hypotheses about the Lowest Rated Tranche

Closely related to the loss sharing through the FLP are the properties of the lowest rated tranche, i.e. the most subordinate tranche sold to investors. This tranche is hit by default losses only if FLP[8] is completely exhausted by default losses. The higher the FLP, the higher is the loss sharing of the FLP. According to S&P, (1-support probability) determines the launch or initial rating (= rating at the issue date) of the lowest rated tranche. According to Moody´s, the expected loss per invested € of a tranche determines its rating. Therefore not only the loss sharing of the FLP matters, but also the size (thickness) of the tranche. Given the FLP, a thicker tranche implicitly includes part of better tranches so that the expected loss per invested € is lower. Therefore, the size of a tranche might also matter for its rating. Hence, given the loss rate distribution of the asset pool, the rating (credit spread) of the lowest rated tranche should be related positively (inversely) to the loss sharing of the FLP and the size of the tranche. This motivates

Hypothesis 8 *The rating (the credit spread) of the lowest rated tranche is positively (inversely) related to the quality of the underlying asset pool, the loss sharing of the FLP and to the size of this tranche.*

Cuchra (2005) finds that credit spreads of tranches are strongly determined by their ratings relative to other factors like capital market conditions and type of collateral asset. In order to find out whether investors rely more on the factors given in hypothesis 8 than on the rating, we test

Hypothesis 9 *The credit spread of the lowest rated tranche is better explained by its rating and its maturity than by the factors given in hypothesis 8.*

Maturity of the transaction should also matter because the credit spread is paid annually while the rating is based on the lifetime of the transaction.

Cuchra (2005) also finds that the credit spread of a tranche is inversely related to its \$-volume indicating an inverse relation between the tranche´s liquidity premium and its volume. Therefore we also test

Hypothesis 10 *The credit spread of the lowest rated tranche is inversely related to its €-volume.*

[8] In some transactions, there exists more than one non-rated junior tranche. Then all these tranches together define the size of the FLP.

1.3.6 Hypotheses about the Choice Between a True Sale- and a Synthetic Transaction

While loss sharing in a true sale-transaction is determined by the FLP, in a synthetic transaction the FLP and the TLP determine loss sharing. Usually a synthetic transaction is partially funded, i.e. the volume of securities sold is only a (small) fraction of the volume of the asset pool. The originator often retains part of the FLP *and* a large super-senior tranche being a TLP. If she does not buy protection against the default risk of the super-senior tranche, then she takes this TLP. Investors take a second loss position (SLP) through their tranches. The TLP reduces the default losses borne by the SLP. But in contrast to the FLP, the TLP does not reduce the probability that investors are hit by default losses. Since the TLP is only hit by default losses, when the SLP is completely exhausted by default losses, there is little protection of investors through the TLP. Conversely, the SLP provides strong protection for the TLP. Therefore, investors should neither care much about the existence of a TLP nor about whether the originator retains the risk of the super-senior tranche. The latter is anyway not publicly known. Hence the previous discussion about the choice of the FLP does not apply to the choice of the TLP.

The choice between a true sale- and a synthetic transaction involves a choice between a) selling vs. not selling the super-senior tranche, and b) funding vs. no funding footnoteAnother aspect relates to balance sheet effects. Until 2004, in a true sale transaction the securitized assets disappear from the originator's balance sheet while they do not in a synthetic transaction. Thus, a true sale transaction allows to "improve" the balance sheet. The new accounting standards imply for many true sale transaction that the assets need to be shown on the originator´s consolidated balance sheet.. In a true sale-transaction the originator may freely use the proceeds from issuing tranches, while in a synthetic transaction the proceeds need to be invested in almost default-free bonds. Thus, synthetic transactions in general provide no funding for the originator.

Whether it pays for a bank to sell the super-senior tranche, depends on the quality of this tranche and the credit spread required by investors. The quality depends on the size of the super-senior tranche. The smaller it is, the larger are the subordinated tranches, the better is the quality of the super-senior tranche. Holding its size constant, the better the quality of this tranche, the smaller is its risk, making it more attractive for the originator to retain this tranche. The tranche-quality is positively related to the asset pool quality. Hence, strong asset pool quality would support retention of the super-senior tranche. This motivates

Hypothesis 11 *Synthetic transactions are preferred to true sale transactions for asset pools with high quality.*

Similarly, holding the risk of the non-securitized super-senior tranche constant, its size grows with the quality of the asset pool. Hence, the bank can retain a larger super-senior tranche, the better is the asset pool quality. This motivates

Hypothesis 12 *In a synthetic transaction the size of the non-securitized super-senior tranche (Third Loss Position) increases with the quality of the asset pool.*

If this hypothesis is correct, then investors may interpret the size of the non-securitized super-senior tranche as a positive signal about the quality of the underlying portfolio.

Retaining the super-senior tranche is, however, in strong contrast to some papers discussed in section 1.2 which argue that the originator should sell the least information-sensitive tranche because it suffers least from information asymmetries. The super-senior tranche is the least information-sensitive tranche. Hence synthetic transactions pose a puzzle. The explanation of this puzzle may hinge on the funding cost. The originator may consider the credit spread on a super-senior tranche as high relative to its default risk so that she prefers not to sell this tranche. This is plausible, in particular, if the bank regards the asset pool quality as very high, but rating agencies do not share this view[9]. We hypothesize that banks with a very good rating have little incentive to use CDO-transactions for funding purposes since they can obtain funds at low credit spreads anyway. This is impossible for banks with a weak rating. For them it may be cheaper to obtain funds through a true sale transaction than through stand alone-borrowing. In a true sale transaction the strong collateralisation and the bankruptcy-remoteness of the special purpose vehicle render the bank's rating rather unimportant. These arguments support

Hypothesis 13 *Synthetic [true sale] transactions are preferably used by banks with a strong [weak] rating.*

These hypotheses will be tested in the following.

[9] The originator may buy protection against default losses of this tranche through a super-senior credit default swap. Casual observation suggests that banks often do not buy this protection because they feel that it is too expensive.

1.4 Empirical Findings

The hypotheses stated above will be tested on a set of European CDO-transactions. We only consider multi tranche-transactions because single tranche-transactions are usually initiated by investors. The quality of the asset pool plays a pivotal role in our hypotheses. Therefore it is essential to have the same type of quality measure for all transactions. Moody's uses two important measures of asset pool quality, one being the weighted average rating factor of the assets in the pool and the other one being their diversity score (DS). We include in our data set all European CDO-transactions from the end of 1997 to the end of 2005 for which we know Moody's DS and can derive the WADP.[10] Most transactions were completed in the years 2000 to 2005. Information about transactions is taken from offering circulars, from pre-sale reports issued by Moody's and from transaction reports of the Deutsche Bank-Almanac. Our European CDO-sample of multi-tranche deals includes 169 observations. This sample represents a fraction of about 50 % of all European CDO-transactions in the observation period.

1.4.1 Measuring Asset Pool Quality

The expected default loss of the asset pool equals the weighted average default probability times the loss given default. Since we mostly do not have transaction specific information on loss given default, we assume λ to be 50 percent with exceptions mentioned subsequently. In a recent study Acharya et al (2007) document recovery rates for various loans and bonds in the US. They find an average recovery rate of 81 percent for bank loans, 59 percent for senior secured, 56 percent for senior unsecured, 34 percent for senior subordinated and 27 percent for subordinated debt instruments, each figure with a standard deviation of more than 26 percent. The average recovery rate is slightly above 50 percent. For 2 transactions with secured loans we use $\lambda = 25$ percent. For some recent mezzanine transactions in which the underlying loans are subordinated and unsecured, we use $\lambda = 100$ percent as the rating agencies do.

Moody's assigns each asset a rating factor and then takes a weighted average. This rating factor equals 1 for all AAA-claims regardless of maturity. For claims with another rating, the rating factor depends on the maturity and denotes the idealized probability of default for this rating class divided by the idealized probability of default for AAA-claims of the same maturity. We use Moody's tables to translate the weighted

[10] We include a few transactions without a rating from Moody´s where the average quality of the underlying assets is known and also their diversification.

average rating factor into the weighted average default probability (WADP). If Moody's does not publish a weighted average rating factor, we use the published average rating of the asset pool and translate it into the WADP using Moody´s tables.

Moody's diversity score (DS) measures the diversification of the assets within and across industries, taking into account also variations in asset size. The DS is defined as the number of claims of equal size and uncorrelated defaults which gives the same standard deviation of the loss rate distribution as that actually observed. The DS is defined by Moody´s as

$$DS = \sum_{k=1}^{m} G \left\{ \sum_{i=1}^{n_k} min \left\{ 1, F_i/\overline{F} \right\} \right\}.$$

m denotes the number of industries, n_k the number of claims against obligors in industry k, F_i the par value of claim i and the average par value of all claims. $G(y)$ is an increasing concave function with a maximum of 5 attained at $y = 20$. Hence, the maximum diversity score within an industry is 5. The diversity score ranges between 1 and 135. Thus, a DS of 1 indicates "no diversification" and a DS of 135 indicates "excellent diversification".

The DS has been criticized on different grounds (see *Fender* and *Kiff* 2004). The main weaknesses of the formula are, first, that the industry specific diversity scores are added, and second, that there is no transparent derivation of the G-formula. The first weakness implies that implicitly Moody´s DS assumes that defaults of obligors of different industries are uncorrelated. Therefore, in 2000 Moody´s started to use an *adjusted DS*. The adjusted DS explicitly takes into account asset correlations between industries. We also use the adjusted DS if we have enough information to derive it. We use the information on the par values of claims across industries to take into account the diversification across industries. This allows us to use the following formula for the adjusted DS (see *Fender* and *Kiff* 2004)

$$ADS = \frac{n^2}{n + \rho_{ext} n(n-1) + (\rho_{int} - \rho_{ext}) \sum_{k=1}^{m} n_k(n_k - 1)}.$$

As argued by *Fender* and *Kiff*, the ADS is quite close to Moody´s DS if $\rho(in) = 20$ percent and $\rho(ex) = 0$ percent. The formula for the adjusted DS shows that a positive $\rho(ex)$ clearly reduces the adjusted DS. Therefore the adjusted and Moody´s DS can be quite different. For example, consider a transaction with 15 industries and 10 loans of equal size in each industry, assuming $\rho(in) = 20$ percent. Then the adjusted DS with $\rho(ex) = 0$ percent equals about 54. But the adjusted diversity score with $\rho(ex) = 2$ resp. 4 percent would be about 27 resp. 18. This is just $\frac{1}{2}$ resp. $\frac{1}{3}$.

In their simulation tools for deriving loss rate distributions of asset pools Moody´s and S&P usually assume that the asset correlation of obligors of the same industry is around 20 percent while the asset correlation of obligors of different industries is around 5 percent or below. Therefore when we use the adjusted diversity score, we assume an intra-industry asset correlation $\rho(in)$ of 20 percent and an inter-industry asset correlation $\rho(ex)$ of 2 percent. Alternatively, we also use inter-industry correlations of 0 and 4 percent.

We know Moody´s DS for all 169 transactions. But we have information about industry diversification only for 92 transactions. This is mainly due to the managed transactions. For these transactions various criteria for replacing existing claims through new claims are specified in the offering circulars, but mostly not industry specific. Therefore we cannot derive the adjusted DS for these transactions. Hence we use Moody´s DS for analyzing the full sample and, in addition, the adjusted diversity score for analyzing the reduced sample.

1.4.2 Descriptive Statistics and Methodology

First, we present some descriptive statistics. The sample includes 169 transactions. Table 1.1 shows their distribution across CLO/CBO- and true sale/synthetic transactions and the distribution across years. In the sample 57 percent of the transactions are CBO-transactions, 54 percent are synthetic. This is an astonishing percentage in view of the literature which argues that the least information-sensitive tranches should be sold. This tranche is the super-senior tranche which is rarely sold in synthetic transactions.

	True sale	Synthetic	$\sum$
CLO	30	43	73
CBO	48	48	96
$\sum$	78	91	169

Year	1997	1998	1999	2000	2001	2002	2003	2004	2005
number of transactions	1	1	12	26	40	42	16	19	12

Table 1.1: The upper part shows the number of transactions in the sample differentiating CLO- and CBO-transactions as well as true sale- and synthetic transactions. The lower part shows the distribution of transactions across years.

From the 169 transactions, 136 are arranged by banks and 33 by investment firms. The latter buy existing bonds and securitize them. 15 of these 33 transactions are classified as CLO-transactions, although the originating investment firms buy bonds and existing loans and securitize them. Therefore we reclassify these 15 CLO-transactions as CBO-transactions. Thus, 33 CBO-transactions, i.e. $\frac{1}{3}$ of the CBO-transactions, are originated by investment firms, all other transactions by banks.

	CLO - ts	CLO - synth	CBO - ts	CBO - synth
WADP - mean	7.5%	3.8%	13.2%	1.9%
WADP - std.	7.5%	3.1%	9.8%	3.2%
DS - mean	87	89	34	56
DS - std.	46	30	11	26
FLP - mean	6.1%	2.9%	12.1%	3.6%
FLP std.	4.8%	1.5%	6.2%	2.6%
TLP - mean	-	80%(86%)	-	87%
TLP - std.	-	23%(7%)	-	7%
Ratinglast- mean	-9.4	-11.7	-9.1	-8.0
Ratinglast - std.	2.8	1.9	3.8	3.0
CSL- mean	244bp	475bp	373bp	270bp
CSL - std.	184bp	206bp	254bp	150bp

Table 1.2: The table shows the means and standard deviations of transaction characteristics differentiating CLO and CBO-transactions as well as true sale (ts) and synthetic (synth) transactions. WADP and Moody's DS are the weighted average default probability and Moody's diversity score of the asset pool. FLP is the initial size of the FLP, TLP the non-securitized senior tranche as a percentage of the asset pool volume in synthetic transactions, ratinglast and CSL the launch rating resp. the launch credit spread of the most junior rated tranche. The bracketed numbers for TLP in CLO-transactions are obtained if three fully funded Geldilux-transactions are excluded.

Table 1.2 presents the means and standard deviations of

- WADP, the weighted average default probability of the assets in the pool,
- DS, Moody's diversity score of the asset pool,
- FLP, the initial size of the first loss position as a percentage of the volume of the asset pool,

– TLP, third loss position, i.e. the volume of the non-securitized senior tranche as a percentage of the volume of the asset pool in synthetic transactions,

– the rating of the lowest rated tranche. Rating is always captured by an integer variable which equals -1 for a AAA-rating and declines by 1 for every notch, with -16 for a rating of B-. A higher integer indicates a better rating.

– CSL, the initial (= launch) credit spread on the lowest rated tranche[11].

The data are presented separately for true sale-/synthetic and CLO/CBO- transactions.

Table 1.2 indicates several interesting properties. The mean weighted average default probability is much higher for true sale than synthetic transactions. Also the mean is clearly higher for synthetic CLO- than synthetic CBO-transactions. On average, CLO-transactions are much better diversified than CBO-transactions supporting hypothesis 5. The average size of the FLP is higher for true sale than for synthetic transactions, and within these subsets the FLP is higher for CBO- than for CLO-transactions.

Comparing the average size of the FLP with the average expected loss which is about half of the WADP, the average FLP clearly exceeds the average expected loss as assumed in Lemma 1c). Also the averages satisfy the condition in Lemma 2a). The condition $h < n(h+\sigma)/(1-N(h+\sigma))$ in Lemma 3 always holds, based on an adjusted diversity score with $\rho(ex) = 2$ percent. The average size of the FLP is smaller than the average WADP except for synthetic CBO-transactions, suppporting the last condition in Lemma 3.

The TLP in synthetic transactions is, on average, about 87 % of the asset pool volume with a standard deviation of only 7 % for CLO **and** for CBO-transactions if we exclude three atypical Geldilux-transactions. These transactions are the only fully funded synthetic CLO-transactions, i.e. TLP is zero. Including these transactions lowers the average TLP of synthetic CLO-transactions to 80 %.

The overall mean of the rating of the lowest rated tranche is between BBB and BBB-. There is one transaction with only one rated tranche (AAA) and also one transaction with a tranche rated B-. Thus, there is strong variability in the rating of the lowest rated tranche. The rating (credit spread) of the lowest rated tranche is, on average, lowest (highest) for synthetic CLO-transactions which have underlying portfolios with strong quality.

[11]Most tranches are floating rate notes. In the few cases of fixed rate notes we take the difference between the coupon and the swap rate of the same maturity as the credit spread.

In the following we test the hypotheses derived in section 1.3. Originator characteristics may affect loss sharing. Therefore we distinguish banks and investment firms as originators, and, include various characteristics of originating banks in our empirical analysis. These characteristics are largely unknown for investment firms, but they matter presumably little for the design of transactions originated by them. These firms arrange transactions solely for arbitrage purposes. The involved choices should be largely determined by market conditions imposed by investors and rating agencies, not by characteristics of the investment firm.

Banks pursue different objectives in their securitization activities. A bank may want to reduce its default risk and, hence, the equity capital requirements. The need for such a transaction may depend on the level of its equity capital relative to its risk-weighted assets, on its profitability and on its options for taking other risks. Therefore these characteristics might affect the transaction design. Similarly, a bank may want to lower its funding costs through a true sale-securitization. The need for doing this may be related to its funding opportunities using standard debt instruments. Since the costs of these instruments depend on the bank´s rating, this should also be true for the strength of the funding motive in securitizations.

In order to account for the impact on securitization decisions of these bank-internal considerations, in the regressions we include as additional regressors data on the originating banks which proxy for these considerations. These data are

- data on equity capital relative to risk weighted assets: the tier 1-capital ratio and the total capital ratio,
- capital structure data: equity/total assets,
- asset structure data: loans/total assets,
- profitability data: the return on average equity capital in the transaction year, the average return over the years 1994 to 2004, and the standard deviation of these returns as a proxy for profitability risk,
- Tobin´s Q to proxy for the bank´s profitability and also for its growth potential as evaluated by the capital market,
- the bank´s rating to proxy for its funding motive.

These bank characteristics are obtained from the Bank Scope Database.

Since these characteristics are not available for investment firms and also for some banks, for each characteristic we attach a residual dummy RD of 1 to those originators for whom the characteristic is not known and a residual dummy RD of 0 otherwise. Then the regression is of the type

$$y = a + bx_1 + c(1 - RD)\Delta x_2 + dRD + \epsilon. \tag{1.14}$$

x_1 denotes the vector of explaining variables not being originator characteristics, b the vector of regression coefficients, Δx_2 the bank characteristic minus its average in the sample and ϵ the usual error term. This approach implies that for the banks with a known characteristic the variation in this zero-mean characteristic is taken into consideration while for the other originators no variation is assumed. d can be interpreted as the product of the average (unknown) characteristic and the corresponding "true" regression coefficient. Hence a higher average would be automatically compensated by a lower "true" regression coefficient and, thus, is irrelevant. If Δx_2 or RD does not add to the explanatory power of the regression, then it is eliminated.

1.4.3 The Quality of the Asset Pool

The quality of the underlying asset pool is a core variable in most hypotheses. Therefore, we first try to improve our understanding of what drives the quality of the asset pool. In particular, we ask two questions. First, does the originator follow a homogeneous quality policy, i.e. is a low (high) weighted average default probability (WADP) associated with a high (low) diversity score (DS)? Second, do originator characteristics affect the choice of asset pool quality? Under a homogeneous quality policy, both quality indicators would be highly correlated. Regressing ln Moody´s DS only on WADP shows a negative, highly significant regression coefficient. But the explanatory power, measured by R^2, is only 9.3 %. The reason is evident from Fig. 1.1 a). It appears that for asset pools with WADP below 0.1 there is no relation between WADP and Moody´s DS. For asset pools with WADP above 0.1, Moody´s DS is rather low indicating low quality of the pool. Hence there is partial support for homogeneous quality choice. Looking at the adjusted DS and WADP in Fig. 1.1 b) confirms even more that there is no systematic relation between both quality measures.

Therefore, we now check which originator characteristics affect WADP and DS. In each subsequent regression we include a constant, but we never show it in the following tables which display the regression results. The first column of Table 1.3 shows that WADP depends strongly on the originator type represented by a dummy of 1 if the originator is an investment firm and 0 otherwise. On average, investment firms clearly

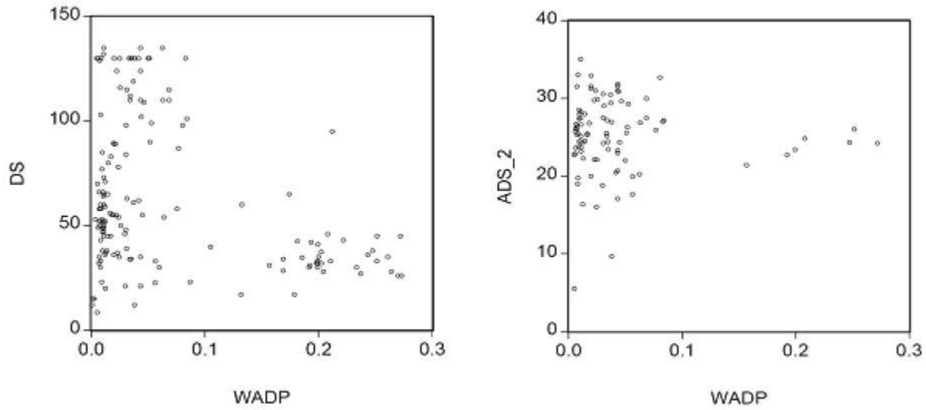

Figure 1.1: Left hand side (Fig. 1.1 a) shows for 169 transactions Moody´s diversity score DS and the weighted average default probability WADP. Right hand side (Fig. 1.1 b) shows for 92 transactions the adjusted diversity score DS with $\rho(ex) = 0.02$ and the weighted average default probability WADP.

choose a higher WADP than banks. Possibly asset pools with a higher WADP offer more potential for arbitrage profits in a CBO-transaction. As shown in the second column, WADP tends to be lower in synthetic transactions represented by a dummy of 1 if the transaction is synthetic and 0 otherwise. Finally, WADP tends to increase with the bank´s total capital ratio indicating that banks with a strong equity buffer take more default risks. Tobin´s Q has no significant impact.

Looking at the characteristics explaining Moody´s diversity score, remember that WADP explains only very little. Hence the third column of Table 1.3 indicates that a substantial part of the variation in DS can be explained by the CBO-dummy which is 1 for a CBO-transaction and 0 otherwise. CBO-transactions tend to be much less diversified as can be seen already in the descriptive statistics in Table 1.2. This might, however, be driven more by the relative ease to put together a large loan portfolio than by information asymmetries. Hypothesis 5 is clearly supported by the data.

For the DS it does not matter whether the originator is a bank or an investment firm. As indicated by the last column in Table 1.3, high diversity scores tend to be observed in synthetic transactions indicating a low risk of the super-senior tranche with a given size. The regression coefficient is weakly significant. Finally, DS tends to increase with the total capital ratio of the originating bank. The explanation of this finding may be that well capitalized banks lend to more obligors so that their loan portfolio is better diversified. Other bank characteristics do not appear to affect the choice of WADP and DS. This indicates that the choice of the asset pool is largely driven by market factors and less by internal considerations of the originator.

Explained variable	Weighted average default probability(%)		Inverse ln Diversity Score	
Weighted average default probability (%)	-	-	0.001 (0.0079)	0.0006 (0.17)
Inverse ln diversity score	17.0 (0.17)	16.7 (0.19)	-	-
Investment firm-dummy	11.6 (0.0000)	8.83 (0.0000)	-	-
CBO-dummy	-	-	0.043 (0.0000)	0.040 (0.0000)
Synthetic dummy	-	-5.37 (0.0000)	-	-0.018 (0.0580)
ΔTotal capital ratio	-	1.41 (0.0014)	-	-0.008 (0.0188)
ΔTobin's Q	-	-1.20 (0.126)	-	-
Adjusted R^2	0.371	0.486	0.265	0.350

Table 1.3: The table displays the coefficients (Newey-West heteroscedasticity adjusted p-values in brackets) of OLS-regressions explaining the weighted average default probability (WADP) and log diversity score of the asset pool. The investment firm-dummy is 1 if an investment firm is the originator and 0 otherwise. The CBO-dummy is 1 for a CBO-transaction and 0 otherwise. The synthetic dummy is 1 for a synthetic transaction and 0 otherwise. ΔTotal capital ratio is the total capital ratio of the originating bank in the transaction year minus the average total capital ratio in the sample (see equation (1.14)). The adjusted R^2 is shown in the last row.

These findings are partly confirmed by the subsample of 92 transactions for which we can derive the adjusted diversity score with $\rho(ex) = 2$ percent. The overall explanatory power of the subsample is smaller regardless of whether Moody´s DS or the adjusted DS is used. If we use the inverse ln adjusted DS to explain WADP, then its coefficient is negative and significant, however. The other explanatory variables in the second regression of Table 1.3 retain their coefficient signs, but are less significant. Regressing the inverse ln adjusted DS on WADP and the CBO-dummy shows no significant coefficient of WADP, but a significant positive coefficient of the CBO-dummy. The synthetic dummy is significant as before but ΔTotal capital ratio loses significance.

1.4.4 The Extent of Loss Sharing

Now the main hypotheses of the paper on loss sharing will be tested. First, we look at the size of the FLP. Hypothesis 1 states that the size of the FLP is inversely related to the quality of the asset pool. First, we OLS-regress the size of the FLP on the WADP and $1/\ln DS$. The reason for including $1/\ln DS$ is that the relationship between the FLP and diversification is likely to be nonlinear since the marginal benefit of diversification should decline. The first regression in Table 1.4 confirms this conjecture. The WADP of the asset pool has a strongly significant positive impact on the FLP, its regression coefficient is smaller than 1. This is expected if the loss share is independent of the asset pool quality and FLP is smaller than WADP (Lemma 3).The impact of the diversity score on FLP is clearly negative. Given the high adjusted R^2 of 54.5 %, Hypothesis 1 is strongly supported.

Next, we include in the regression the Synthetic dummy. Its coefficient is significantly negative indicating that synthetic transactions have smaller FLPs. Investors may view the synthetic structure as a signal of low risk because the super-senior tranche is not sold. This may allow the originator to choose a smaller FLP retaining the same published portfolio quality. In order to test hypotheses 4 and 6, we add the CBO- and the dynamic-dummy. The latter is 1 for a managed (dynamic) transaction and 0 otherwise. Results are not shown in Table 1.4. Both dummies turn out to be insignificant so that hypotheses 4 and 6 are falsified. The lack of significance of the dynamic-dummy may be due to the strict rules on replenishment/substitution of loans/bonds in offering circulars. Also it does not matter for the size of the FLP whether a bank or an investment firm is the originator.

Hypothesis 7 claims that originators with more valuable real options should prefer lower FLPs. Including Tobin´s Q as a proxy for the bank´s real options does not add to the explanatory power of the regression, thus falsifying the hypothesis. The same negative results are obtained for other bank characteristics.

Next, we look at other loss sharing measures. Hypotheses 2 and 3 claim that the share of expected losses borne by the FLP resp. the support-probability of the FLP are invariant to the asset pool quality. In order to test these hypotheses, we assume that the loss rate distribution is lognormal (for details see Appendix 1.8.2).

This parametric approach to estimating the lognormal loss rate distribution is done

Explained variable	First Loss Position (%)		
WADP of asset pool (%)	0.387	0.303	0.293
	(0.0000)	(0.0000)	(0.0000)
Inverse ln diversity score	49.80	43.40	43.34
	(0.0015)	(0.0033)	(0.0035)
Synthetic dummy	-	-2.82	-2.87
		(0.0004)	(0.0004)
Adjusted R^2	0.545	0.587	0.593

Table 1.4: This table displays the coefficients (Newey-West heteroscedasticity adjusted p-values in brackets) of OLS-regressions explaining the size of the FLP. WADP is the weighted average default probability of the asset pool. The synthetic-dummy is 1 for a synthetic transaction and 0 otherwise. The adjusted R^2 is shown in the last row.

for each of the 92 transactions for which we can derive the adjusted diversity score. For the 92 transactions we, first, derive the adjusted DS 2, i.e. the adjusted DS with $\rho(ex) = 2$ percent. Then the implied share of expected losses, s, has a mean of 86.1 percent and a standard deviation of only 8.4 percent. This indicates that the FLP takes a very high share of the expected losses. It also indicates that the loss share varies only little. For the support-probability $\gamma(FLP)$ the mean is 87.62 percent and the standard deviation 14.7 percent. This mean is also quite high. Since the inter-industry correlation is controversial, we add the figures for $\rho(ex) = 0$ percent and for 4 percent. In accordance with Lemma 1, the average share of expected losses declines from 91.6 to 82.3 percent if $\rho(ex)$ increases from 0 to 4 percent. In accordance with Lemma 2, the average support-probability declines from 88.25 to 87.57 percent if $\rho(ex)$ increases from 0 to 4 percent. Surprisingly, the average loss share clearly reacts to the assumed inter-industry correlation, while the support-probability is almost constant. This indicates that the cumulative lognormal distributions, generated by different inter-industry correlations, intersect at loss rates which are only slightly smaller than the FLP.

We now run linear regressions to explain s resp. $\gamma(FLP)$ by the explanatory variables we used before. The results are shown in Table 1.5. Regressing the share s on WADP and on the inverse log adjusted DS 2 it turns out that WADP is completely insignificant, while the coefficient of the inverse adjusted DS 2 is positive and significant. However, the explanatory power of the regression is only about 5.6 percent. *Hence we conclude that neither WADP nor DS can explain the variation in the share s.* This finding supports Hypothesis 2 claiming that the loss share is independent of asset pool quality.

	Share of expected losses (%)		Support probability (%)	
WADP(%)	-0.124 (0.30)	-0.128 (0.34)	-1.99 (0.0000)	-2.00 (0.0000)
Inverse ln ADS2	61.7 (0.0145)	41.1 (0.0718)	64.1 (0.0625)	43.2 (0.15)
CBO-dummy	-	5.91 (0.0006)	-	5.99 (0.0002)
Adjusted R^2	0.056	0.164	0.596	0.632

Table 1.5: This table displays the coefficients (Newey-West heteroscedasticity adjusted p-values in brackets) of OLS-regressions explaining the share of expected losses taken by the FLP resp. the support-probability of the FLP. WADP is the weighted average default probability of the asset pool. Inv ln ADS2 is the inverse log adjusted diversity score assuming a default correlation between industries of 2 percent. The CBO-dummy is 1 for a CBO-transaction and 0 otherwise. The sample is restricted to 92 transactions for which ADS2 can be derived. The adjusted R^2 is shown in the last row.

In terms of Proposition 2 and Corollary 2 this suggests that the originator faces both, adverse selection and reputation costs. The second column of Table 1.5 shows the regression results adding the CBO-dummy. The regression coefficient is positive and significant indicating that in CBO transactions the FLP absorbs a higher share of expected losses. Since CBOs tend to be less diversified, the adjusted DS 2 turns almost insignificant. Even though the explanatory power of the regression increases, it is still modest.

Next, we run the same regressions for the support-probability of the FLP, $\gamma(FLP)$. Using only WADP and the adjusted DS 2 for explanation, both turn out to be highly significant. And this regression has a rather impressive explanatory power of 60 %. Thus, Hypothesis 3 is invalidated. These findings are not surprising in view of the previous finding that the loss share is independent of the asset pool quality. Lemma 3 then implies that the support-probability should clearly react to the asset pool quality. Comparing this support-probability regression with that of the expected loss share shows that the latter much better characterizes the market norm. The support-probability depends on the asset pool quality, while the loss share does not. Thus, the market norm appears to mitigate information asymmetry problems not through a constant support-probability, but much more through a constant share of expected losses borne by the FLP.

Returning to the first regression of the support-probability, surprisingly both regression coefficients have different signs. While a higher WADP reduces the support-probability $\gamma(FLP)$, a deterioration in the adjusted DS raises the probability. The explanation for this surprising result is also provided by Lemma 3. It states that given a constant loss share, the support-probability of the FLP declines if the WADP or the DS increases. Thus, this finding corroborates the finding that the loss share is independent of the portfolio quality. Adding the CBO-dummy turns the DS insignificant while the dummy coefficient is significantly positive. Summarizing, the observation that the support-probability can be explained much better than the share of expected losses through the regressions, indicates that originators much closer adhere to the constant loss share-strategy than to the constant support-probability strategy. The constant share strategy appears to be a good approximation to what is actually observed in the market.

It should be noted that a loss share which is independent of asset pool quality does not imply that the share is constant. The originator may still vary the rating of the lowest rated tranche within close limits. This would raise the explanatory power of the regressions, but also create an endogeneity problem. Adding originator characteristics as regressors in the regressions of Table 1.5 does not improve explanatory power. Hence loss sharing appears to be driven by market factors, not by originator characteristics.

The assumption of a lognormal loss rate distribution is sometimes criticized. If one simulates the loss rate distribution of a loan portfolio, often the distribution is slightly better approximated by a gamma distribution than by a lognormal distribution. Therefore we run a robustness check using a two parameter gamma distribution. For each transaction the expected loss rate and the variance $\sigma^2(l)$, based on the adjusted DS with $\rho(ex) = 2$ percent, are translated into the parameters of a gamma distribution. While the share of expected losses assuming a lognormal distribution has a mean of 86.1 percent, this mean is 84.3 percent assuming a gamma distribution. A linear regression of the lognormal-based share on the gamma-based share shows an R^2 of 93.5 percent. Regarding the support-probability of the FLP, $\gamma(FLP)$, its lognormal-based mean is 87.6 percent, while its gamma-based mean is 85.7 percent. A linear regression of the gamma-based $\gamma(FLP)$ on the lognormal-based $\gamma(FLP)$ has an R^2 of 98.9 percent.

Hence it it not surprising that the regression results are similar. Regarding the share of expected losses taken by the FLP, the same coefficients are significant/insignificant taking the gamma distribution instead of the lognormal distribution. The significant coefficients have the same sign. And also there is no dominance of one over the other distribution in terms of the R^2s. The same statements are true comparing the regressions of the gamma-based $\gamma(FLP)$ and the lognormal-based $\gamma(FLP)$. Hence we conclude that in terms of the regression results there is no noticeable difference between a lognormal and a gamma distribution.

1.4.5 Properties of the Lowest Rated Tranche

The lowest rated tranche should clearly reflect the loss sharing of the FLP and the asset pool quality. Hence we want to know which measure of loss sharing best explains the properties of the lowest rated tranche. Therefore we now analyze two important properties of the lowest rated tranche, its launch rating and its launch credit spread. Since we can derive the adjusted diversity score for only 92 transactions, the sample is again based on 92 observations for the regressions explaining the rating of the lowest rated tranche. The regressions explaining the launch credit spread of the lowest rated tranche are based on 82 observations, since we do not know the credit spread of the lowest rated tranche for all 92 transactions.

First, we try to explain the rating of the lowest rated tranche. Hypothesis 8 states that the rating of this tranche should be driven by the quality of the asset pool, the loss sharing of the FLP and the size of the tranche. Although rating is a discrete variable, we use OLS since we have 16 rating classes. The first regression in Table 1.6 strongly supports hypothesis 8 using FLP itself as a measure of loss sharing. Since the FLP strongly depends on WADP and ln ADS2, we include in the regression FLP-residual, i.e. the residual from an OLS-regression of FLP on WADP and ln ADS2. This assures that the coefficients of WADP and ln ADS2 are not biased through the impact of these variables on FLP. The coefficients of WADP, FLP-residual and tranche size have the expected signs and are strongly significant. The explanatory power of this regression is quite high with 70 percent. Replacing FLP by the share of expected losses lowers the explanatory power somewhat, this effect is stronger using instead the support probability of the FLP. As the second regression in Table 1.6 shows, FLP appears to be an incomplete measure of loss sharing. Adding the share of expected losses-residual raises the explanatory power to 73 percent. This residual is from am OLS-regression of the share of expected losses on the FLP because the share is determined by the FLP, while WADP and ADS2 are largely irrelevant. The high explanatory power indicates that the rating of the lowest rated tranche is affected by both, the FLP and the loss share. In both regressions the coefficient of ln ADS2 is negative. This can be explained by Lemma 3. Controlling for the share of expected losses, the support-probability of the FLP is inversely related to the DS. The same is true of the rating of the lowest rated tranche reflecting that the rating of S&P depends on the support-probability.

Originator characteristics appear to be irrelevant.

Next, we analyze the determinants of the credit spread of the lowest rated tranche. As regressors we use the same variables that we used to explain the rating of the tranche. In addition, we include the maturity of the transaction and also the issue date because the ratings are usually "through the cycle ratings", i.e. they do not change with the current phase of the business cycle. Therefore the date may proxy for this phase and for changes in the market´s risk aversion. Since the business phase moves up and down in the sample period, we include the date and its square in the regressions. The date is an integer variable equal to 0 for the last quarter of 1997 and increases by 1 for each successive quarter. The third column of Table 1.6 shows the regression results. The adjusted diversity score turns out to be irrelevant, as does the FLP once we include the share of expected losses. The maturity of the transaction is also irrelevant. This is not surprising given its correlation with WADP of 62.4 %. The regression explains almost 50 percent of the variation in the credit spread. As expected, the signs of the regression coefficients are precisely opposite to those in the rating regressions supporting hypothesis 8. The strong impact of the issue date is given by a parabola with a maximum around 2002 which represents a trough in the business cycle. One would expect the IBOXX-spread, defined by the average yield of BBB-bonds over government bonds, to better reflect market sentiment than the mechanical date. Substituting for the date by the IBOXX-spread reduces the explanatory power of the regression considerably, however.

The negative coefficient of the tranche size seems consistent with hypothesis 10 supporting a liquidity premium effect in line with the findings of *Cuchra* (2005). But this conclusion is presumably misleading because the explanatory power of the regression shrinks to 41.7 % if we replace the size of the lowest rated tranche (in percent of the transaction volume) by its €-amount. Hence we conclude that thickness drives the negative sign, not €-volume. Hypothesis 10 is not supported.

Hypothesis 9 claims that the credit spread of the lowest rated tranche can be better explained by its rating and its maturity than by the characteristics analyzed so far. This claim is strongly supported by the fourth regression in Table 1.6. Squared rating, maturity and issue date explain 65 % of the variation in the credit spread, much more than the third regression. We use squared rating instead of rating because there is a strong convexity relating the credit spread to rating. Maturity has a significant, positive coefficient as expected. Including other regressors in the last regression does not improve explanatory power. This is perhaps not surprising given that the rating itself depends strongly on the portfolio quality, loss sharing of the FLP and the size

Explained variable	rating of the lowest rated tranche		credit spread of the lowest rated tranche (bp)	
Weighted average default probability (%)	-0.13 (0.0000)	-0.08 (0.0175)	12.21 (0.0000)	- -
Ln ADS2	-3.78 (0.0006)	-3.93 (0.0000)	-	-
FLP - Residual	0.70 (0.0000)	0.60 (0.0080)	-	-
Ln size of lowest rated tranche	0.91 (0.0000)	0.90 (0.0000)	-69.4 (0.0003)	-
Share of expected losses - Residual	-	0.10 (0.0216)	-	-
Share of expected losses (%)	-	-	-9.24 (0.0012)	-
Squared Rating of lowest rated tranche	-	-	-	-3.00 (0.0000)
Maturity	-	-	-	22.2 (0.0219)
Date of issue	-	-	63.4 (0.0001)	57.2 (0.0000)
Date of issue squared	-	-	-1.68 (0.0000)	-1.43 (0.0000)
Adj. R^2	0.700	0.732	0.494	0.650

Table 1.6: This table displays the results from OLS-regressions explaining the rating and the credit spread of the lowest rated tranche (p-values in brackets, heteroscedasticity adjusted in OLS regressions). WADP is the weighted average default probability of the asset pool. Ln ADS2 is the log adjusted diversity score assuming a default correlation between industries of 2 percent. FLP-Residual is the residual of an OLS regression of FLP on WADP and ln ADS2. Ln size of lowest rated tranche is the logarithm of the percentage size of this tranche. Share of expected losses-residual is the residual of an OLS regression of Share of expected losses on FLP. Maturity is the maturity of the transaction. Date of issue refers to the date at which the transaction is launched. Regarding the rating, the sample is restricted to 92 transactions for which ADS2 can be derived. Regarding the credit spread the sample is restricted to 82 transactions for which ADS2 can be derived and the credit spread of the lowest rated tranche is known. The adjusted R^2 is shown in the last row.

of the tranche. Overall, hypothesis 9 is supported by the findings. Again, originator characteristics appear to be irrelevant.

1.4.6 The Choice Between True Sale- and Synthetic Transactions

As discussed above, the choice between true sale- and synthetic transactions is a joint choice of a funding strategy and of taking/not taking a TLP. Hypothesis 13 claims that originators with a good rating are not interested in funding through securitization. A probit regression of the synthetic-dummy on the originator's rating supports this hypothesis. We include two regressors, the originator rating minus the average originator rating in the sample, and a dummy for those originators for which we do not have a rating. The first regression in Table 1.7 shows that the originator rating has a significant, positive impact on the probability of synthetic transactions, while the originators without a rating appear to prefer a true sale transaction. For them refinancing through true sale appears to be preferable. These findings provide strong support for hypothesis 13.

Hypothesis 11 states that synthetic transactions are preferred for high quality asset pools. This hypothesis is strongly supported as can be seen from the second regression in Table 1.7. The explanatory power of the regression can be clearly improved by including also the originator rating and the corresponding dummy for those originators for which a rating is not known (third regression).

In the last regression we test for the effects of other variables. It turns out that the explanatory power can be improved by also including the originator´s Tobin´s Q and her total capital ratio. But now DS is no longer significant. This may be explained by the correlations between ln DS and the new regressors, Tobin´s Q (-0.19) and the total capital ratio (0.24). A high total capital ratio indicates a low cost to the originator of retaining the super-senior tranche. The negative coefficient of Tobin´s Q tells us that it may not pay for originators with attractive outside options to retain the risk of a TLP.

Next we analyze the size of the TLP in synthetic transactions. Since we only look at synthetic transactions, the determinants of the TLP-size are not necessarily the same as those of the choice between synthetic and true sale transactions. We exclude here the three fully funded Geldilux-transactions which are atypical. For two other transactions we do not know the TLP-size leaving us with 86 observations. According to hypothesis

Explained variable	Synthetic dummy			
Weighted average default probability (%)	-	-0.11 (0.0000)	-0.10 (0.0000)	-11.69 (0.0000)
Inverse ln diversity core	-	-6.71 (0.0050)	-6.86 (0.0085)	-3.39 (0.24)
ΔOriginator's rating	0.225 (0.0033)	-	0.22 (0.0107)	0.30 (0.0020)
Originator rating-dummy	-1.54 (0.0000)	-	-1.29 (0.0002)	-1.33 (0.0001)
ΔTobin's Q		-	-	-0.93 (0.0010)
ΔTotal capital ratio				0.211 (0.0570)
McFadden R^2	0.190	0.265	0.362	0.424

Table 1.7: This table shows the coefficients (with p-values in brackets) of binary probit regressions explaining the synthetic-dummy, This variable is 1 for a synthetic transaction and 0 otherwise. ΔOriginator's rating is the originator´s rating minus the average originator rating in the sample (see equation(1.14)). ΔTobin´s Q and ΔTotal capital ratio are defined analogously. The originator rating-dummy is 1 for originators without a rating and 0 otherwise. The last row shows the McFadden R^2.

Explained variable	Size of the third loss position (%)	
Weighted average default probability (%)	-0.015 (0.0000)	-0.015 (0.0000)
Ln diversity score	0.14 (0.0000)	0.14 (0.0001)
Inverse ln diversity score	1.56 (0.0007)	1.47 (0.0017)
Investment firm-dummy	-	-0.06 (0.0007)
Adjusted R^2	0.576	0.588

Table 1.8: This table displays the coefficients (Newey-West heteroscedasticity adjusted p-values in brackets) of OLS-regressions explaining the size of the third loss position in synthetic transactions. The investment firm-dummy is 1 if the originator is an investment firm and 0 otherwise. The adjusted R^2 is shown in the last row.

12, the TLP-size increases with the quality of the asset pool. This is clearly true for the WADP. The WADP alone explains already 48 % of the variation in the TLP-size (not shown in Table 1.8). Including DS clearly improves the explanatory power as shown in the first regression of Table 1.8. The impact of ln DS is u-shaped. For small diversity scores up to about 28 the TLP-size declines with the diversity score, but for higher diversity scores it increases.[12] There are only a few transactions with a diversity score below 28. Therefore, the general picture is that the TLP-size increases with the diversity score. Thus, hypothesis 12 is clearly confirmed. The explanatory power of the regression can be improved slightly by including the investment firm-dummy (last column in Table 1.8). The coefficient is negative indicating that investment firms tend to retain smaller TLPs.

Comparing our findings for the size of the FLP and of the TLP, the differences are striking. While the FLP-size reacts inversely to asset pool quality, the TLP increases with asset pool quality. This indicates that both are driven by different motives. The FLP serves to mitigate problems of information asymmetries, but the TLP does not. The TLP-size appears to be driven by the effects of the TLP on the originator´s risk and return. The originator prefers a large TLP if its default risk is low. Then it does not pay to sell this risk to investors because they would charge a relatively high credit spread.

1.4.7 Robustness Tests

A potential critique of OLS-regressions to explain the FLP and the TSP is that these variables are constrained to the (0;1)-range. The distribution of the regression residuals turns out to be fairly symmetric, with little excess kurtosis. As a robustness test we transform the FLP and the TSP so that the transformed variable varies between plus and minus infinity. The regression results basically stay the same. Therefore we do not present the results of the transformation.

The discussion about the best way to measure the diversity score has led us not only to consider the DS published by Moody´s, but also to consider the adjusted DS based on default correlations between industries of 0, 2 resp. 4 percent. The regression results are similar even though our sample shrinks to 92 observations. Sometimes the results are stronger for the adjusted DS with 4 percent inter-industry correlation. This is

[12]For $Z(DS) = 0.14 \ln DS + 1.56/\ln DS$ we get $Z(20) = 0.940$, $Z(28) = 0.935$, $Z(60) = 0.954$, $Z(90) = 0.977$, $Z(120) = 0.996$. Hence, the non-securitized senior tranche would increase on average by 4.2 % of the par value of the asset pool if the DS increased from 28 to 90.

surprising but may indicate that in former years 4 percent inter-industry correlation was assumed to be realistic.

There might exist an endogeneity problem regarding the choice of asset pool quality as analyzed in Table 1.3. The choice of WADP and DS might be interdependent. We check for endogeneity through a two stage least squares regression (2SLS). First, consider the dependence of *WADP on DS.* As shown before, the diversity score is much higher in CLO- than in CBO-transactions while WADP is similar in both types of transactions. Therefore, we use the CBO-dummy as an instrumental variable. In a 2 SLS inverse ln diversity score is regressed, first, on the CBO-dummy, the synthetic dummy *Syn,* Δ*Tobin´s Q and* Δ*total capital ratio* (see equation (1.14)). Second, WADP is regressed on the estimate of *inverse ln DS, e(1/ln DS)*, the investment firm dummy *ID* and the same other variables except for the CBO-dummy. The estimation results are

$$\begin{aligned} WADP &= \underbrace{29.9e(1/lnDS)}_{0.29} + \underbrace{8.86ID}_{0.0000} - \underbrace{5.05Syn}_{0.0004} \\ &\quad + \underbrace{1.54\Delta tot\ cap\ ratio}_{0.0015} - \underbrace{1.39\Delta Tobin's\ Q.}_{0.102} \end{aligned}$$

This result is very similar to that of the second regression in Table 1.3 in which the WADP is OLS regressed on the same variables. Hence, even though the originator chooses WADP and DS simultaneously, this does not appear to significantly affect the explanation of WADP.

Then we turn the exercise around to explain ln diversity score. As shown above, transactions originated by investment firms clearly have a higher WADP, without having a clear impact on the diversity score. Therefore we use the investment firm-dummy as an instrumental variable for WADP. Hence in a 2SLS, we first regress the WADP on the investment firm-dummy, the CBO dummy, the synthetic dummy and Δtotal capital ratio. Second, ln diversity score is regressed on the estimate of WADP and the same other variables except for the investment firm-dummy. The estimation results are

$$\begin{aligned} 1/lnDS &= \underbrace{0.0009e(WADP)}_{0.294} + \underbrace{0.04CBO}_{0.0000} \\ &\quad - \underbrace{0.015Syn}_{0.2073} - \underbrace{0.009\Delta tot\ cap\ ratio.}_{0.0130} \end{aligned}$$

This result is very similar to that of the fourth regression in Table 1.3 in which *inverse ln DS* is OLS regressed on the same variables. Hence, the simultaneous choice of WADP and DS by the originator also does not appear to significantly affect the explanation of *inverse ln DS.*

In the other regressions, we see little potential for endogeneity. The regressions try to answer the question how asset pool quality affects loss sharing through FLP and TLP, given exogenous originator characteristics and attitudes of investors and rating agencies. These attitudes together with asset pool quality determine the choice of the loss sharing. Including a CBO-dummy as regressor does not create endogeneity because CLO- and CBO-transactions represent two different types of transactions. Including a Synthetic-dummy is more prone to endogeneity problems. But as Table 1.7 indicates, the choice between true sale and synthetic transactions itself is driven by asset pool quality and originator characteristics. Regarding the rating and the credit spread of the lowest rated tranche, any reasonable economic model needs to take into consideration its size and loss sharing as explaining variables.

1.5 Discussion

The general presumption of this paper is that information asymmetries are stronger for asset pools with lower quality. Therefore the originator faces penalties for information asymmetries which are mitigated by her choice of effort and of the FLP. In synthetic transactions the originator also takes a TLP. Lemmas 1 to 3 characterize the impact of asset pool quality on default losses borne by investors and the holders of the FLP. Propositions 1 and 2 characterize the optimal effort and the optimal FLP. While a lower asset pool quality induces a higher FLP, its impact on the loss share and on the support-probability of the FLP depends on the size of the adverse selection and reputation cost parameters a and r as well as on the marginal productivity of effort.

This paper investigates the impact of asset pool quality on some important aspects of the transaction design, given the attitudes of investors and rating agencies and originator characteristics. In almost all regressions asset portfolio quality, measured by the weighted average default probability and the diversity score, plays a strong role. Originator characteristics play only a weak role if at all. In the following, we discuss the empirical findings. The impact of both asset pool quality variables on other originator choices is not homogeneous in the sense that a higher WADP always has the same impact as a lower DS. Therefore we discuss both quality measures separately. The main empirical findings are summarized in Fig. 1.2. The arc relating two variables indicates which variable has an impact on the other one. (+), (-) indicates a positive resp. a negative impact.

Asset pool quality has an impact on all choices shown in Fig. 1.2 except for the share of expected losses borne by the FLP. As stated in Hypothesis 1, low asset pool quality makes it attractive for the originator to offer a high FLP to mitigate problems of information asymmetries. This is clearly supported by the findings. The two more refined measures of loss sharing between the originator and the investors are the share of expected losses borne by the FLP and the support-probability of the FLP. The share of expected losses, derived from WADP and DS, turns out to be largely independent of both quality measures, supporting Hypothesis 2. It appears that this share with a mean of 86 percent and a low standard deviation of 8.4 percent represents the strong guideline for choosing the FLP. In contrast, the support-probability of the FLP reacts inversely to the weighted average default probability and to the diversity score invalidating Hypothesis 3. This inhomogeneous impact of the two quality measures is not surprising in view of Lemma 3.

These findings also shed some light on the relevance of adverse selection and moral hazard effects. Given our model, Proposition 2 indicates that in the absence of reputation costs the support-probability of the FLP should be independent of the asset pool quality. In the presence of substantial reputation costs, the share of expected losses borne by the FLP may decline with portfolio quality. For moderate reputation costs, the share of expected losses could be invariant to portfolio quality. Since this invariance is found in the data, this finding is consistent with a market in which both, adverse selection and reputation costs, exist. This is in line with intuition.

The FLP is lower in synthetic transactions, controlling for asset pool quality. Strong asset pool quality makes a synthetic transaction more attractive relative to a true sale transaction supporting Hypothesis 11. Hence a synthetic transaction may signal strong asset pool quality so that investors demand a smaller FLP, given the published asset pool quality. In synthetic transactions, the originator usually takes a TLP which appears to *grow* with asset pool quality supporting Hypothesis 12. This is in strong contrast to the FLP which *inversely reacts* to asset pool quality. This indicates that the purposes of the FLP and the TLP are quite different. While the FLP serves to mitigate information asymmetry problems, the TLP appears to be driven by the originator motive to avoid high default risks.

Loss sharing through the FLP is not higher in CLO- than in CBO-transactions, invalidating Hypothesis 4. Our conjecture that information asymmetries are stronger in CLO-transactions may be wrong. The generally higher diversity score in CLO-transactions renders idiosyncratic default risks rather unimportant supporting Hypothesis 5. Also, loss sharing through the FLP is not higher in managed than in static transactions despite of stronger moral hazard concerns invalidating Hypothesis

6. This may be due to the stringent conditions for management resp. replenishment. Hypothesis 7 claiming lower loss sharing through FLPs for originators with higher Tobin´s Q is also not supported by the data.

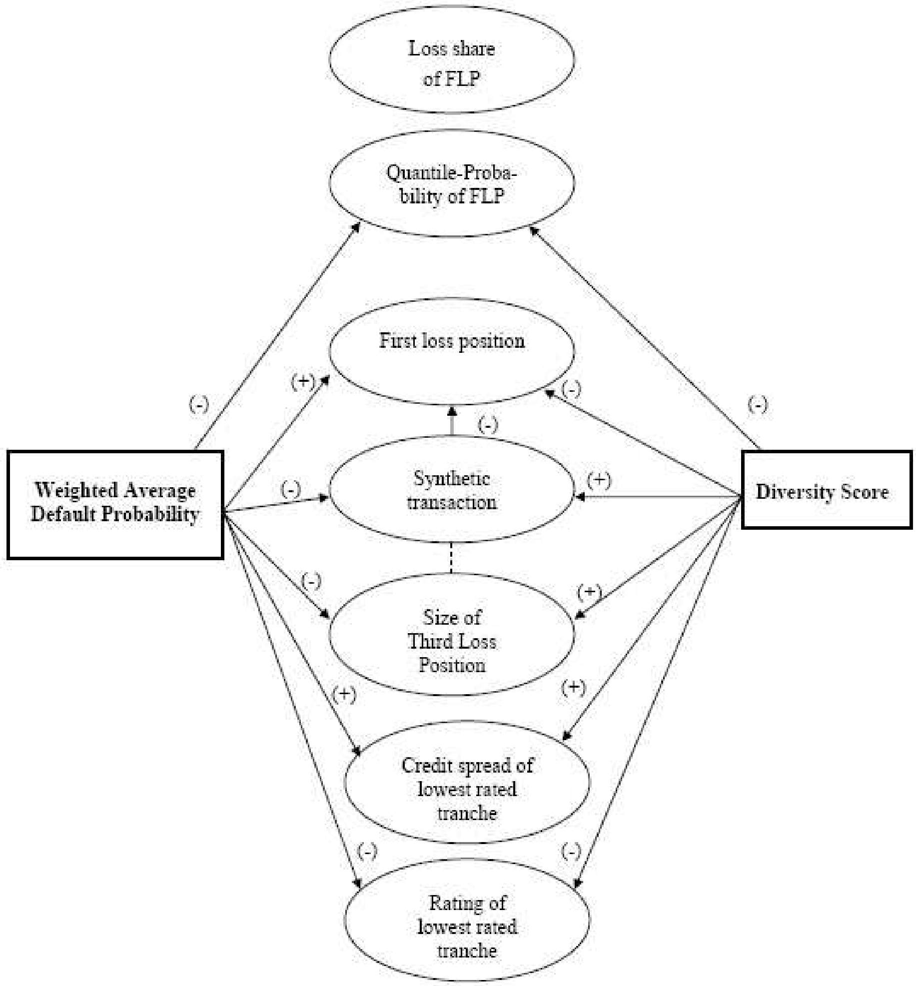

Figure 1.2: It summarizes the empirical impact of the asset pool quality on other transaction characteristics.

The properties of the lowest rated tranche reflect asset pool quality and the size of the subordinated FLP. It turns out that the rating of this tranche can be explained to a large extent by the asset pool quality, the FLP and the tranche size supporting Hypothesis 8. Including the share of expected losses improves the explanatory power of the regression. The DS negatively affects the rating in line with Lemma 3. The credit spread of the lowest rated tranche is explained best by WADP, the share of expected losses, the tranche size and the issue date, if rating is excluded. Thus, Hypothesis 8 is partly supported. The issue date is quite important for this spread reflecting changing market sentiment and risk aversion.

But the credit spread of the lowest rated tranche is much better explained by its squared rating, the maturity of the transaction and the issue date, supporting Hypothesis 9. Adding other regressors does not improve the explanatory power of the regression. Investors may believe that rating agencies have much better information for valuing this very information-sensitive tranche and, hence, attach a high significance to the rating. Hypothesis 10, claiming a liquidity premium effect of the tranche volume on the credit spread, is not supported.

Finally, we discuss the impact of bank characteristics. Regarding asset pool quality, Tobin´s Q has no effect. Banks with a high total capital ratio appear to prefer asset pools with high WADP *and* high DS. It may be that banks with a high total capital ratio can afford to grant loans with high default probabilities and mitigate the high default risk of the loan portfolio through strong diversification. A high Tobin´s Q appears to render synthetic transactions less attractive relative to true sale transactions. It might be that an originator with a high Q is not interested in retaining the senior tranche with low credit risk since she has attractive real options. A high total capital ratio makes synthetic transactions more attractive, perhaps because the originators, not being plagued by capital regulation, may not worry about the default risk of the TLP.

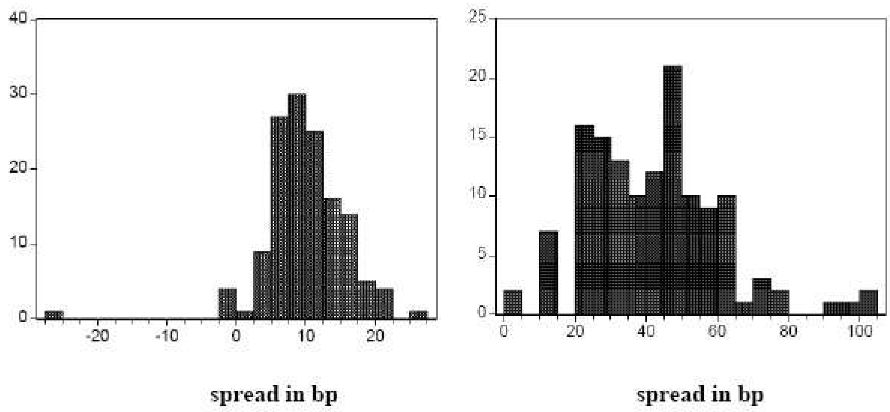

Figure 1.3: The left histogram shows the credit spreads over EURIBOR/LIBOR of 137 European bank bonds with a maturity of at least 5 years, rated AA- or better, issued between 2000 and 2005. Data are obtained from DEALSCAN. The right histogram shows the credit spreads over EURIBOR/LIBOR of the 135 AAA-rated CDO-tranches of our securitization sample.

A better originator rating renders synthetic transactions more attractive due to the funding motive. Otherwise this rating appears irrelevant. The funding motive helps to explain the puzzle that the least information-sensitive tranche is not sold to investors in a synthetic transaction. Fig. 1.3 displays two histograms, the left one shows credit spreads over EURIBOR/LIBOR of European bank bonds with a maturity of at least 5 years, rated AA- and better, issued between 2000 and 2005. The right histogram shows the credit spreads of only AAA-rated CDO-tranches of our sample. The mean credit spread of the bank bonds is 9.9 basis points, while it is 40.6 basis points for the AAA-tranches. The minimum (maximum) spread of the bank bonds is -27 (+25) basis points, while it is +1 (+100) basis points for the AAA-tranches. These figures clearly show that the credit spreads of highly rated bank bonds are often lower than those on AAA-tranches. Thus, funding through a true sale transaction likely implies a higher funding cost for highly rated banks than issuing standard bonds combined with a synthetic transaction. Possibly highly rated banks have a very good reputation which is not adequately reflected in their rating. This argument is also supported by the recent discussion of a proposal of Moody´s to upgrade the big banks because they might be too big to fail. Conversely, a AAA-tranche in a securitization transaction may face some investor scepticism because securitization transactions are relatively new instruments and there is no reliable history on their performance. Therefore a standard bond of a highly rated bank may be subject to fewer problems of information asymmetries than a AAA-tranche of a securitization transaction.

1.6 Conclusion

This paper investigates how problems of information asymmetries are dealt with in collateralised debt obligations through loss sharing arrangements. Market imperfections such as information asymmetries, regulatory costs, funding costs, transaction and management costs are likely to play a role in the transfer of default risks. The originator optimizes the design of the securitization transaction so as to maximize her benefit. This paper analyzes, in particular, the relation of the First Loss Position and, in synthetic transactions, the Third Loss Position to the quality of the underlying asset pool and the originator characteristics.

Using a sample of European transactions, asset pool quality is measured by its weighted average default probability and its diversity score. A higher default probability lowers the quality, while a higher diversity score improves it. Asset pool quality should be inversely related to information asymmetry and have a strong impact on the transaction design. It turns out that the First Loss Position is strongly inversely related to asset pool quality. Hence this position serves to mitigate information asymmetry problems. This position also is the most information-sensitive tranche which should not be sold to investors. The general guideline for the market appears to be that the First Loss Position should cover a high share of the expected default losses, independent of the asset pool quality. The support-probability of the First Loss Position, i.e. the probability that the First Loss Position absorbs all losses, is inversely related to the weighted average default probability and the diversity score of the asset pool.

Asset pool quality positively affects the originator´s preference for a synthetic transaction. More than half of the transactions are synthetic in which the originator does not sell the large information-insensitive super-senior tranche. This tranche represents a Third Loss Position of the originator unless she covers its default risk through a senior credit default swap. The size of the Third Loss Position increases with the quality of the asset pool, in strong contrast to the First Loss Position. Hence the Third Loss Position does not serve to mitigate information asymmetry problems. Retaining this position is in strong contrast to the literature which argues that the originator should sell the least information-sensitive tranche. Selling this tranche does not achieve a substantial risk transfer, but may involve transaction costs and relatively high credit spreads so that the originator may consider this funding mechanism as too expensive. This appears to be true in particular for originators with a good rating.

The rating of the lowest rated tranche which is protected through the subordinated First Loss Position, is inversely related to the weighted average default probability *and* the diversity score of the asset pool and improves with loss sharing of the First Loss Position. Not surprisingly, the same variables affect the credit spread of the lowest rated tranche, but with opposite signs. Credit spreads are, however, better explained by the tranche ratings indicating that investors believe in superior information of rating agencies.

Bank characteristics have a surprisingly small impact on these choices. This indicates that choices are largely driven by attitudes of investors and rating agencies and much less by originator motives. The findings of this paper should be considered a first step. Clearly more empirical research is needed to better understand the design of CDO-transactions.

1.7 References

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1.8 Appendix

1.8.1 Proof of Lemma 1a) and b)

a) A mean preserving spread is a second order stochastic dominance shift in the probability distribution of the loss rate, holding the mean constant. Let $F_1(l)$ and $F_2(l)$ denote the cumulative probability distribution before resp. after the mean preserving spread. A necessary and sufficient condition for a second order stochastic dominance shift is that $F_2(l)$ intersects $F_1(l)$ once from above. Let $\bar{l}$ denote the loss rate at the intersection. This is illustrated in Fig. 1.4.

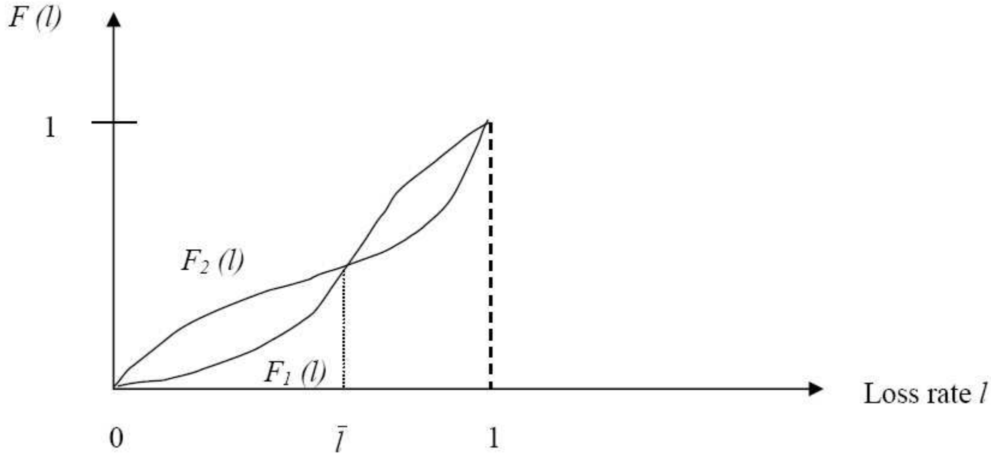

Figure 1.4: The cumulative probability distribution of the loss rate $F_2(l)$, obtained from $F_1(l)$ by a mean preserving second order stochastic dominance shift, intersects $F_1(l)$ once from above at $l = \bar{l}$.

First, we show that the expected loss of the FLP is smaller under $F_2(l)$ than under $F_1(l)$. Suppose that the size of the FLP is smaller than $\bar{l}$. For $l \geq \bar{l}$, the loss of the FLP always equals FLP. For $l \leq \bar{l}$, $F_1(l)$ first order stochastically dominates $F_2(l)$. Hence the expected loss of the FLP is smaller under $F_2(l)$. Therefore the expected loss of the sold tranches must be higher, holding the mean constant.

Now suppose that the size of the FLP is higher than $\bar{l}$. Then, for $l \leq \bar{l}$, investors do not bear any losses. For $l \geq \bar{l}$, $F_2(l)$ first order stochastically dominates $F_1(l)$. Hence the sold tranches incur a higher expected loss under $F_2(l)$ so that the FLP bears a smaller expected loss.

b) A first order stochastic dominance deterioration in the loss rate distribution is characterized by $F_1(l) \geq F_2(l); \forall l$. This implies a higher probability of a complete loss of the FLP. Since a first order stochastic dominance deterioration is equivalently characterized by replacing l through $l + \epsilon(l)$ with $\epsilon(l) \geq 0$ for every l, it follows that the FLP and the sold tranches incur higher expected losses.

1.8.2 Proof of Lemma 1c) and 2a)

The parameters of the lognormal loss rate distribution

Let denote

$\lambda =$ average loss given default across loans,

$\pi =$ WADP = average probability of default,

$S =$ average standard deviation of the loss rate across loans,

$\sigma =$ standard deviation of the lognormally distributed portfolio loss rate, $\sigma = \sigma(\ln l)$,

$\mu =$ expectation of the lognormally distributed portfolio loss rate, $\mu = E(\ln l)$,

$F_i =$ par value of loan i, divided by the par value of all loans; $i = 1, \ldots, n$,

$\rho_{ij} =$ asset correlation between loan i and loan j.

Then the expectation of the portfolio loss rate equals

$E(l) = \lambda\pi$,

the average standard deviation of the loan loss rate across loans, S, is given by

$$S^2 = (0 - \lambda\pi)^2(1 - \pi) + (\lambda - \lambda\pi)^2\pi = \pi(1 - \pi)\lambda^2 \qquad (1.15)$$

Then the variance of the portfolio loss rate is obtained by dividing through the DS,

$$S^2 = \sum_{i=1}^{n}\sum_{j=1}^{n} S^2\rho_{ij}F_iF_j = S^2\sum_{i=1}^{DS}\left(\frac{1}{DS}\right)^2 = S^2/DS. \qquad (1.16)$$

The latter part of the equation follows from the definition of the diversity score. It is the number of equally sized loans whose defaults are uncorrelated which generates the same variance of the portfolio loss rate.

Now assume that the portfolio loss rate is lognormally distributed. Then

$$S_p^2 = [E(l)]^2 \lfloor \exp \sigma^2 - 1 \rfloor \tag{1.17}$$

so that

$$\begin{aligned}\sigma^2 &= \ln\left[1 + \left(\frac{S_p}{E(l)}\right)^2\right] \\ &= \ln\left[1 + \frac{\frac{1}{\pi} - 1}{DS}\right].\end{aligned} \tag{1.18}$$

For μ we obtain

$$\begin{aligned}\mu &= \ln E(l) - \frac{\sigma^2}{2} \\ &= \ln(\lambda\pi) - \frac{1}{2}\ln\left[1 + \frac{\frac{1}{\pi} - 1}{DS}\right]\end{aligned} \tag{1.19}$$

From these equations we obtain the sensitivities

$$\frac{\partial \mu}{\partial \ln \pi} = 1 + \frac{1}{2}\frac{1}{1 + \pi(DS - 1)} > 0 \tag{1.20}$$

$$\frac{\partial \mu}{\partial \ln DS} = \frac{1}{2}\frac{1 - \pi}{1 + \pi(DS - 1)} > 0 \tag{1.21}$$

$$\frac{\partial \sigma}{\partial \ln \pi} = -\frac{1}{2\sigma}\frac{1}{1 + \pi(DS - 1)} < 0 \tag{1.22}$$

$$\frac{\partial \sigma}{\partial \ln DS} = -\frac{1}{2\sigma}\frac{1 - \pi}{1 + \pi(DS - 1)} < 0 \tag{1.23}$$

Proof of Lemma 1c)

We show that given a lognormal loss rate distribution, the share of the expected loss borne by the FLP declines with a first order stochastic dominance deterioration. The expected loss of the FLP equals $(FLP - EP)$ with $E(P)$ being the expected loss of a put on the loss rate with strike price FLP. Applying the Black-Scholes model, the expected loss of the put equals

$$EP = -\lambda WADPN(h) + FLPN(h + \sigma)$$

with $h = \ln(FLP/\lambda WADP)/\sigma - \sigma/2$. Hence the share of the expected loss borne by the FLP is

$$s = FLP/\lambda WADP - EP/\lambda WADP = N(h) + (FLP/\lambda WADP)(1 - N(h + \sigma)) \tag{1.24}$$

Differentiating s with respect to $\ln WADP$ yields

$$\begin{aligned}\frac{\partial s}{\partial \ln WADP} &= \frac{FLP}{\lambda WADP}\left(-[1-N(h+\sigma)]-n(h+\sigma)\frac{\partial\sigma}{\partial \ln WADP}\right)\\ &= -\frac{FLP}{\lambda WADP}\left(1-N(h+\sigma)-n(h+\sigma)\frac{1}{2\sigma}\frac{1}{1+WADP(DS-1)}\right).\end{aligned}$$

Hence $\partial s/\partial \ln WADP < 0$ if the term in the second bracket is positive.

Next we show that the second bracket is positive whenever $FLP \geq \lambda WADP$ and $\sigma(1+WADP(DS-1)) > 0.1$.

$1-N(h+\sigma)-n(h+\sigma)\frac{1}{2\sigma}\frac{1}{1+WADP(DS-1)} > 0$ if

$\sigma(1+WADP(DS-1)) > \frac{1}{2}\frac{n(h+\sigma)}{1-N(h+\sigma)}$.

$FLP \geq \lambda WADP$ implies $h+\sigma > 0$. For $h+\sigma \geq 0$ the right hand side of the previous inequality attains its maximum at $h+\sigma = 0$ which then yields about 0.1 for the right hand side. Hence $FLP \geq \lambda WADP$ and $\sigma(1+WADP(DS-1)) > 0.1$ are sufficient for $\partial s/\partial \ln WADP < 0$.

It remains to be shown that $\sigma(1+WADP(DS-1)) > 0.1$. This is always true. Taking the square of this inequality and substituting for σ yields

$\ln\left(1+\frac{\frac{1}{WADP}-1}{DS}\right) > \left(\frac{0.1}{1+WADP(DS-1)}\right)^2$.

Taking exponentials yields approximately

$1+\frac{\frac{1}{WADP}-1}{DS} > 1+\left(\frac{0.1}{1+WADP(DS-1)}\right)^2$ or

$100\left(\frac{1}{WADP}-1\right) > \frac{DS}{(1+WADP(DS-1))^2}$.

The right hand side attains its maximum at $DS = (1/WADP-1)$. Therefore the last inequality holds if

$100 > \frac{1}{(1+WADP(DS-1))^2}$.

This is always true. q.e.d.

Proof of Lemma 2a)

We need to show that, given a lognormal loss rate distribution, a mean preserving spread of this distribution implies a lower (higher) support-probability of the FLP if and only if the condition in Lemma 2a) holds.

Consider the probability distribution $N\left(\frac{\ln l-\mu}{\sigma}\right)$. Differentiate with respect to $\ln DS$.

$\frac{\partial N(.)}{\partial \ln DS} = n\left(\frac{\ln l - \mu}{\sigma}\right)\left(-\frac{\ln l - \mu}{\sigma^2}\frac{\partial \sigma}{\partial \ln DS} - \frac{1}{\sigma}\frac{\partial \mu}{\partial \ln DS}\right).$

$\partial N(.)/\partial \ln DS = 0$ at $l = \hat{l}$ if

$-\frac{\ln \hat{l} - \mu}{\sigma}\frac{\partial \sigma}{\partial \ln DS} = \frac{\partial \mu}{\partial \ln DS}.$

Substituting from (1.10) and (1.12) yields $\ln \hat{l} = \mu + \sigma^2$. Hence $\partial N(.)/\partial \ln DS = 0$ at $l = FLP$ if $\ln FLP = \mu + \sigma^2$. $\partial N(.)/\partial \ln DS > 0$ at $l = FLP$ if $\ln FLP > \mu + \sigma^2$ for a mean preserving contraction. Since $\mu = \ln E(l) - \sigma^2/2$, $FLP \geq E(l)exp(\sigma^2/2)$ is necessary and sufficient for $\partial N((\ln FLP - \mu)/\sigma)/\partial \ln DS > 0$. Substituting for σ yields the condition in Lemma 2a).

1.8.3 Proof of Lemma 3

We need to show for a lognormal loss rate distribution that an adjustment of the FLP to a change in portfolio quality which preserves the loss share leads to a specific adjustment of the support-probability of the FLP if and only if $h < n(h+\sigma)/(1 - N(h+\sigma))$. The loss share is given by equation (A.10). Differentiating with respect to $\ln \pi$ yields

$$\frac{\partial s}{\partial \ln \pi} = \frac{\partial FLP}{\partial \ln \pi}\frac{1 - N(h+\sigma)}{\lambda \pi} - \frac{FLP}{\lambda \pi}(1 - N(h+\sigma)) - \frac{FLP}{\lambda \pi}n(h+\sigma)\frac{\partial \sigma}{\partial \ln \pi} \quad (1.25)$$

Hence $\partial s/\partial \ln \pi = 0$ implies

$$\frac{\partial FLP}{\partial \ln \pi} = 1 + \frac{n(h+\sigma)}{1 - N(h+\sigma)}\frac{\partial \sigma}{\partial \ln \pi} \quad (1.26)$$

The support-probability of the FLP is $\gamma(FLP) = N(h+\sigma)$. Hence

$\frac{\partial \gamma}{\partial \ln \pi} = n(h+\sigma)\left[\frac{1}{\sigma}\left(\frac{\partial \ln FLP}{\partial \ln \pi} - 1\right) - \left(\frac{\ln \frac{FLP}{\lambda \pi}}{\sigma^2} - \frac{1}{2}\right)\frac{\partial \sigma}{\partial \ln \pi}\right]$

$= \frac{n(h+\sigma)}{\sigma}\left[\frac{\partial \ln FLP}{\partial \ln \pi} - 1 - h\frac{\partial \sigma}{\partial \ln \pi}\right]$

Hence $\partial \gamma/\partial \ln \pi < 0$ if the bracketed term is negative. Substitute $\partial \ln FLP/\partial \ln \pi$ from (A.12). Then the bracketed term yields

$$\frac{\partial \sigma}{\partial \ln \pi}\left[\frac{n(h+\sigma)}{1 - N(h+\sigma)} - h\right]. \quad (1.27)$$

Since $\partial \sigma/\partial \ln \pi < 0$ by (A.8), the term in (A.13) is negative if $h < n(h+\sigma)/(1 - N(h+\sigma))$. This proves Lemma 3 with respect to $WADP = \pi$. The proof for DS is analogous.

To prove the last statement in Lemma 3, note that $\partial \sigma/\partial \ln \pi < 0$ and (A.12) imply $\partial \ln FLP/\partial \ln \pi < 1$. Hence $\partial FLP/\partial \pi < 1$ if $FLP \leq \pi$.

Chapter 2

Default Risk Premia in Synthetic European CDOs

2.1 Introduction

The market for securitizations of assets has grown substantially up to the onset of the subprime crisis in 2007. The global issuance volume of Asset Backed Securities increased from \$ 271 bn in 1997 to \$ 2000 bn in 2006 (HSBC, 2007) with European transactions accounting for approx. \$ 30 bn (39 bn €) in 1997 and \$ 560 bn (370 bn €) in 2006. In the first half of 2007 this trend continued but the subprime crisis led to mistrust and investors all but abandoned the market. In total, global issuances went down 17% in 2007 to 2006 and further decrease in 2008 is anticipated.[1]

Collateralized debt obligations (CDOs) are one class of Asset Backed Securities. In CDO transactions investors earn premia for bearing potential default losses of a loan or bond portfolio, usually paid as credit spread on top of the risk-free interest rate. Since summer 2007, sophisticated risk assessment of CDOs appears to be ever more necessary, as well as understanding the pricing mechanisms.

This paper addresses the pricing mechanisms as it analyzes the default risk premia of the CDO-tranches, i.e. the credit spreads of these tranches. The credit spread compensates investors for the expected annualized default loss and for the risk of default losses. We focus on the second component, the pure risk aversion premium. Thus, the paper attempts to estimate the relative risk aversion implied by the credit spread of a tranche and its loss rate distribution. More specifically, does the implied relative risk aversion vary across tranches? How does it depend on the quality of the securitized portfolio? What role do information asymmetries play? These questions are empirically examined on a dataset of 59 synthetic European transactions consisting of 215 differently rated tranches.

In order to determine the default risk premia, we use a pricing kernel approach. In general, the pricing kernel is defined to be the transition function that describes the relation between the physical and the risk-neutral density functions. Jackwerth (2000), Ait-Sahalia and Lo (2000), Rosenberg and Engle (2002) and others studied the pricing kernel in stock markets. Thus, this paper extends their studies to the market for default risks. Ait-Sahalia and Lo (2000) provide a survey of relative risk aversion estimates that is updated by Bliss and Panigirtzoglou (2004). The range of results is vast, between 0 and 55, yet most studies yield relative risk aversions between 0 and 13. The mean relative risk aversion implied by the 215 CDO tranches investigated in our study is 4.4, the results vary between 2.6 and 10.

[1] See HSBC, 2007.

Tranche losses that predominantly occur in a crisis situation like the one seen in 2008 should earn a higher premium than losses more evenly distributed over possible future states. Our pricing methodology accounts for this by using the aggregate loss rate as the systematic risk factor. The realization of this loss rate defines a state of nature which, in turn, determines the stochastic discount factor as given by the pricing kernel. The risk-return profile of a given tranche and in particular its correlation structure with the systematic risk factor imply a risk aversion parameter. For each tranche this parameter is estimated.

In a simulation model, the repayment distribution of the underlying portfolio conditional on the realization of the aggregate loss rate is derived. Next, the loss allocation rules of the respective CDO are applied to generate the time series of expected tranche repayments conditional on the aggregate loss rate. We insert this information into a classical pricing equation, combined with the promised credit spread. This allows to solve for the parameter of relative risk aversion implied by the CDO tranche. Since originators as well as most investors in the CDO market are financial intermediaries[2], the aggregate wealth in this sector is assumed to depend on the aggregate loss rate ignoring other systematic components of wealth. This is in line with the limits of arbitrage hypothesis. Market participants are significantly exposed to credit risk but not to other risks. For Mortgage Backed Securities that have a similar structure as CDOs, yet differ with respect to the underlying, Gabaix et al (2007) find evidence for this hypothesis.

In our methodology, the full credit spread is interpreted as compensation for bearing default risks. Consequently, market frictions that may motivate higher spreads will show in higher values for the estimated relative risk aversion. These frictions include information asymmetries between originator and investors and costs to diversify idiosyncratic credit risks. Additionally, the market may be segmented due to clientele effects, motivating the originator to issue differently risky tranches. Our paper examines market segmentation and market frictions by identifying features of CDO transactions or of single tranches that systematically result in higher estimated risk aversion parameters which are indicative of additional premia.

The issued tranches of the analyzed CDOs differ strongly with respect to the amount of credit risk transferred. Do investors who buy different tranches also exhibit different risk attitudes? We hypothesize that the risk aversion of an investor is lower the riskier the tranche he buys. The data confirm this *risk effect*. However, the lowest rated tranche deviates. It earns an additional premium. This may be due to a higher

[2]For evidence for the German market see Deutsche Bundesbank (2004).

importance of information asymmetries with respect to the underlying portfolio or the structure of the CDO itself ('complexity premium').

In view of this result we investigate how the quality of the securitized portfolio affects the implied risk aversion. Two dimensions of portfolio quality are distinguished: i) the average quality of the securitized loans or bonds measured by the weighted average default probability (WADP) and ii) the degree of diversification in the portfolio, as measured by the diversity score (DS). When analyzing the influence of portfolio quality on the risk premia of issued tranches, also the originator's adjustments in the tranche structure have to be taken into account, in particular changes in the loss protection of the tranches. This holds for both WADP and DS.

For portfolios with lower average debt quality the loss protection of the issued tranches is higher. However, tranches referring to such a portfolio are on average still more risky. This, in turn, leads to the somewhat counter-intuitive result that *lower* risk aversion parameters are associated with tranches that refer to portfolios with high WADP. On the other hand, higher expected portfolio losses due to high WADPs also leave more room for asymmetric information. This should increase the spread to be paid on tranches and thus, ceteris paribus, the measured risk aversion parameter. Testing this counteracting effect on the data shows that it is only relevant for the lowest two of all rated tranches, probably because their loss protection is not considered high enough to shield against information problems.

Information problems are also important for the impact of portfolio diversification on the implied risk aversion of single tranches. Given tranche risk, poor diversification should thus raise risk premia. The data confirm this information hypothesis, but again only for the lowest two of all rated tranches. Surprisingly, the average implied risk aversion of a CDO transaction shows a significantly stronger reaction to changes in portfolio diversification than any tranche specific implied risk aversion. The additional effect is driven by changes in the tranche structure. CDOs referring to poorly diversified portfolios tend to have a larger first loss piece and issue fewer tranches that on average are better rated. These better rated and less risky tranches correspond to higher levels of implied risk aversion *due to the risk effect*. Turned around this means that good diversification is beneficial for originators since it allows them to transfer more risk to investors at relatively low additional costs.

In addition to tranche risk and portfolio quality, several variables are added as controls. The implied relative risk aversion tends to be higher for CDOs issued at times when corporate bond spreads were high and for CDOs with longer maturity. This indicates a co-movement of the corporate bond and the CDO market as well as an additional premium compensating for the higher uncertainty of longer transactions. Bond transactions imply higher relative risk aversions than loan transactions, but this is mainly due to higher loss protection of the rated tranches and to the lower number of rated tranches issued. Characteristics of the originating bank such as its rating have basically no effect.

The paper proceeds as follows. The next section reviews the relevant literature. In section 3 the pricing model is explained and the hypotheses are derived. Section 4 presents the dataset, the variables characterizing the CDO transactions and the simulation procedure. In section 5 the derived relative risk aversion parameters of the different tranches are used to empirically test the hypotheses. Section 6 describes some robustness checks and section 7 concludes.

2.2 Literature Review

We examine the risk premia in the market for corporate default risks by analyzing pricing kernel functions. Several papers have investigated pricing kernel functions in the stock market. Often option prices on stock indices are used to estimate risk-neutral densities which are then compared to physical densities derived from time series data of the underlying indices. The approaches differ in the choice of the state defining variable. For example, Jackwerth (2000), Ait-Sahalia and Lo (2000), Rosenberg and Engle (2002) use approximations of total wealth in an economy such as the value or the return of the S&P 500 index as a state defining variable. Ait-Sahalia and Lo (2000) report an average value for relative risk aversion of 12.7. Bliss and Panigirtzoglou (2004) differentiate power and exponential utilities. For the power utility case as investigated in this paper they derive values between two and seven. Further, they update Ait-Sahalia and Lo's overview on other studies most of which yield results between 0 and 13. Rosenberg and Engle (2002) estimate empirical pricing kernels on a monthly basis and show that the corresponding risk aversion is mean reverting and ranges from 2.3 to 12.6 with a mean of 7.4.[3]

Jackwerth (2000) non- parametrically estimates pricing kernels and shows that after the stock market crash in 1987 the risk-aversion functions are negative, equivalently pricing kernels are increasing in wealth, for index levels close to the forward price. This empirical finding is called the pricing kernel puzzle. One possible way of explaining

[3]Rosenberg and Engle (2002) further show that specifying the pricing kernel as an orthogonal polynomial fits the S&P option prices better. However this approach needs more parameters and lacks a straightforward interpretation in terms of implied risk aversion.

this puzzle is modifying the state variable. Some studies consequently include further variables when defining a state of nature. Buraschi and Jackwerth (2001) and Coval and Shumway (2001), among others, add volatility and find evidence for a negative volatility risk premium. Brennan, Liu and Xia (2005) add further state variables and find that the lack of these variables in part resolves some empirical problems of classical asset pricing models. Chabi-Yo, Garcia and Renault (2008) claim that adding latent state variables explains the pricing kernel puzzle.

This paper also studies the pricing kernel, but in the market for corporate default risks. We follow the limits of arbitrage theory[4] and assume the wealth of market participants to be driven by the aggregate default losses in the economy as the only systematic risk factor. Gabaix et al (2007) find support for this hypothesis in the market for Mortgage Backed Securities (MBS). They show that in the MBS market the risk of homeowners prepaying their mortgages is priced. This contradicts the assumption of a diversified representative investor in this market as prepayment risk is 'a wash in the aggregate'.

The pricing of index CDOs was recently studied by Longstaff and Rajan (2008). They analyze the market prices of tranches on the CDX credit index and derive market expectations about clustering of corporate defaults. They find that the combination of three Poisson processes explains the spread variations very well. They account roughly two third of the CDX spread to firm specific risk. One fourth of the spread is found to be due to market expectations of all firms in one industry sector defaulting simultaneously. The remaining 8 percent are explained by systemic default risk. As a consequence, Longstaff and Rajan argue that a significant portion of credit risk in corporate debt may not be diversifiable.

The question how single name corporate debt is priced and what impact systematic and unsystematic risk factors have on the credit spread has been widely studied in the literature with different approaches. Elton, Gruber, Agrawal and Mann (2001) analyze the spreads of US corporate bonds over US treasury bills using market data from 1987 to 1996. They first subtract expected losses and a tax premium from these spreads and then regress the remainder on Fama-French risk factors finding evidence that the return on corporate bonds contains a significant premium for these factors. Huang and Huang (2003) calibrate several structural credit risk models to historical default rates and historical equity premia and find that for investment grade bonds (rated Baa or better) credit risk accounts for only 20 to 30% of the observed credit spread. Chen, Lesmond and Wei (2007) suggest an illiquidity premium as a further component of corporate bond spreads. Driessen (2005) uses six components to explain the credit

[4] See Shleifer and Vishny (1997).

spreads of bonds in an intensity based model. He explicitly distinguishes the risk of the default event from the risk of credit spread changes if no default occurs. When excluding the default jump risk he finds that the model underestimates expected excess returns on corporate bonds and overestimates observed default rates. He, and others, refer to this and similar findings as the 'credit spread puzzle'. Driessen shows that the default event risk earns a premium that explains an economically significant part of Baa rated corporate bond returns. Thus he argues that 'default jump risk may not be diversifiable'. In general this would motivate a risk premium on idiosyncratic risks - a question addressed in this paper on a CDO level.

Amato and Remolona (2003 and 2005) also analyze the credit spread puzzle. Both papers argue that, due to the strong skewness of the default loss distribution, idiosyncratic default risk can not be fully diversified in realistically sized portfolios - and therefore has to earn a premium. They define the *spread ratio* of a corporate bond as the ratio of the promised spread and the annualized expected loss of this bond. For European Aaa, Aa, A and Baa rated bonds they find the average spread ratio to be 210, 35, 6.7 and 1.6, respectively. They reckon that the large size of these ratios provides evidence for significant risk premia associated with idiosyncratic default risk. The spread ratio defined by Amato and Remolona can be seen as an approximation of the relation between the risk-neutral and the physical default probability for a two state setting. The pricing kernel to be estimated in this paper is a generalization of the spread ratio from the two-state setup to a model with a continuous state space. Usually CDO transactions refer to relatively large portfolios of bonds or loans. Since each bond or loan can default, there is a range of possible terminal values for the portfolio. Consequently the total repayment of the issued tranches will take almost continuous values from this range.

If a bank securitizes a portfolio of debt by issuing a collateralized debt obligation (CDO) it has an information advantage over most investors who may take default risks. This resembles one of the settings modeled by DeMarzo (2005). Pooling the claims now on the one hand destroys information since else separate signals about debtor quality would have been possible. On the other hand pooling has a positive diversification effect allowing the originator to issue low-risk tranches that are less sensitive to private information. DeMarzo (2005) shows that for large portfolios the positive diversification effect outweighs the disadvantages of information destruction.

In an empirical study on tranching, Cuchra and Jenkinson (2005) find support for market segmentation in the securitization market as well as for asymmetric information. Cuchra (2005) investigates the launch spreads of a broad class of structured bonds. He finds the credit rating to be the key pricing factor, yet not the only determinant of the price. For example, longer maturities tend to increase the spread. Further, Cuchra provides evidence for different degrees of diversification in the reference portfolio driving spread differences. For given ratings he finds higher spreads for CDO tranches compared to tranches of securitizations referring to other asset classes like auto or credit card loans. He argues that this is due to the relatively poorer diversification in CDO portfolios and to stronger asymmetric information.

2.3 Model and Hypotheses

In a perfect capital market securitization design and banks are irrelevant. Given an imperfect market for corporate debt, securitizations may be beneficial for both originator and investors. As argued by DeMarzo (2005) tranching is profitable given asymmetric information. Investor heterogeneity may also motivate the issuance of differently risky tranches. Due to their heterogeneous risk profile we investigate the tranches separately. We thereby argue that the market for CDO tranches is separated. Each tranche is a note credit linked to a particular portfolio of loans or bonds and is difficult to replicate for an investor. Further, as the market for CDO tranches is highly illiquid, investors looking to exploit pricing differences between tranches can hardly do so directly, e.g. by short-selling some tranches.

In this section we first show how the implied parameter of relative risk aversion is estimated for each tranche. While we have to assume a parametric form for the pricing kernel this method has the advantage of not only accounting for the repayment profile of each tranche but also for the state dependence of repayments. The states of nature are defined by the aggregate loss rate in the economy. In this approach only systematic default risk earns a premium. If higher spreads are paid for the same amount of systematic risk this will show in higher estimated parameters. Thus a high parameter is a fingerprint of an additional premium. In the sections' second part we investigate the reasons for additional premia and derive hypothesis referring to market imperfections.

2.3.1 Pricing Model

For the pricing of the CDO tranches we use a classical pricing kernel approach. Suppose that tranche i of some CDO transaction is purchased by a group of investors with a similar risk attitude. This is reflected by a tranche-specific pricing kernel function

$\phi_i = \phi_i(s)$. s defines a state of nature. Then the forward pricing equation for this tranche can be written as

$$F_i = E^{Q_i}(P_i) = \int_{s\in\mathcal{S}} E(P_i|s)\cdot q_i(s)\,ds = \int_{s\in\mathcal{S}} E(P_i|s)\cdot f(s)\cdot \phi_i(s)\,ds\ , \tag{2.1}$$

where F_i denotes the forward price of tranche i, P_i denotes the payoff of the tranche that depends on the state s and $f(s)$ denotes the physical density function of the state variable. The risk neutral measure that has to be applied here depends on the investor group/market segment. For investor group i the risk neutral measure is labelled Q_i, and the corresponding density function q_i is computed as $q_i(s) = f(s)\cdot\phi_i(s)$. The expected value under this risk neutral measure is labelled E^{Q_i}, and $E(P_i|s)$ denotes the expected payoff of tranche i conditional on state s.[5]
For illustration, $\phi_i(s)$ can be interpreted as the standardized marginal utility of an investor representative for investor group i: $\phi_i(s) = \frac{u_i'(s)}{E(u_i'(\cdot))}$.[6]
In defining the relevant state variable for CDO-transactions we assume that banks and investors are strongly exposed to credit risks, but not to other risks. Hence their wealth is concentrated in debt claims. The terminal wealth of a bank or an investor is defined by

$$\textit{terminal wealth} = \textit{initial wealth endowment} + \textit{interest earned} - \textit{default losses}\ .$$

Excluding other macro risk factors from terminal wealth is consistent with 'limits of arbitrage'[7] claiming that many agents concentrate in certain types of assets ignoring potential arbitrage opportunities between different asset markets.
E_0 (equity), borrows the amount L_0 and invests $(E_0 + L_0)$ in debt claims with initial market value $D_0 = E_0 + L_0$. Then terminal wealth W_1 after one period equals

$$W_1 = D_0(1 + i_D - \text{loss rate}) - L_0(1 + i_L),\ \text{with}$$
$$i_D: \ \text{interest rate to be paid by debtors} \quad i_L: \ \text{refinancing interest rate.}$$

The credit spread $(i_D - i_L)$ covers the expected default loss rate and the pure risk premium. The latter can be estimated from bond market data. We assume that the

5 Note that the law of iterated expectations has been used to obtain the last equation.
Further note that the state conditional expected payoff $E(P_i|s)$ is the same under the statistical measure and the risk adjusted measure Q_i.

6 See, e.g., Poon and Stapleton, 2005 for the general formula. u_i denotes the utility function for investor group i.

7 See Shleifer and Vishny (1997). For empirical evidence from the MBS market see Gabaix et al (2007).

risk premium equals five times the expected loss rate.[8]

We assume each investor's wealth to depend on the same aggregate loss rate.[9] Further, we can not distinguish investors with respect to their initial wealth or leverage. We assume that investors are homogeneous in this respect. The problem of homogeneity restrictions we have in common with many asset pricing models.[10] However, we allow investors to differ with respect to their risk attitude. Measuring different degrees of risk aversion associated with CDO tranches and explaining the variations is the focus of this paper.

The economy-wide loss rate l thus is the systematic risk factor of our model as it determines the terminal wealth of all investors. In above equation the one year loss rate $l = l_1$ is used. The terminal wealth after t periods, W_t, depends on the economy-wide loss rate cumulated over t years, l_t, and the credit spread that is earned t times on the non-defaulted loans. The terminal wealth at date t is used to price a t year transaction. Besides the credit spread $(i_D - i_L)$ the distribution of terminal wealth depends on the cumulative loss rate distribution and the initial leverage D_0/E_0. The estimation of the loss rate distribution is described in the next chapter and in Appendix 2.9.1. As initial leverage we assume 10, i.e. a representative bank or investor with an equity ratio of 10%. Robustness checks relaxing the assumptions are conducted in chapter 2.6.

Given a realization of the aggregate loss rate the simulation procedure[11] yields a *time series* of payments for each tranche. All these payments are considered in the pricing model. We compound all intermediate payments until maturity of the tranche at the risk free rate. Thus we assume an investor who reinvests all payments risk-free. This reduces the model to a one period setting. We further standardize the face value of each tranche to one. For a tranche issued at par this means an investor pays one Euro in exchange for a risky payment at date t. For a given tranche i the stochastic repayment at maturity P_i^t depends on l_t as does investor wealth W_t. Thus we can modify equation

[8]Between January 2000 and December 2005 the average spread of a five year BBB bond over the risk free rate - measured by the average difference in yield to maturity of the IBOXX BBB corporate bond index over the IBOXX sovereign index for maturities 3-5 and 5-7 years - was 127 basis points (bp). The average of Moody's and S&P prediction for the probability of default for a five year BBB bond is 1.95%. For an average loss given default of 55% this implies an expected loss of 1.07% over five years or roughly 21 bp annually. So 21 bp of the 127 bp spread compensate for expected loss and roughly 5·21 bp are paid as risk premium.

[9]This can be seen as an element of market integration.

[10]See, e.g. Ross (1977) for a discussion on the CAPM.

[11]See the next chapter and Appendix 2.9.2 for details.

(2.1):

$$
\begin{aligned}
F_i^t &= \int_{l_t=0}^{1} E(P_i^t|l_t) \cdot f(l_t) \cdot \phi_k(W_t(l_t)) dl_t \\
\Leftrightarrow \quad 1 = P_0(i) = \frac{F_i^t}{(1+r)^t} &= \int_{l_t=0}^{1} \frac{E(P_i^t|l_t)}{(1+r)^t} \cdot f(W_t(l_t)) \cdot (W_t(l_t))^{-\gamma_i} d\, l_t. \qquad (2.2)
\end{aligned}
$$

In the latter equation, we assume constant relative risk aversion in the pricing of each tranche. This corresponds to a pricing kernel $\phi(W_t) = W_t^{\gamma_i}$. Given the monotonously negative dependance of tranche repayments on the aggregate loss rate, an increase in γ_i always depreciates the right hand side of equation (2.2). Consequently, the γ_i solving (2.2) is uniquely defined. Ceteris paribus more losses allocated to a tranche will decrease γ_i, a higher credit spread will increase γ_i. For each tranche separately, the implied risk aversion coefficient γ_i is estimated.

2.3.2 Hypotheses

We now theoretically investigate reasons for variations in the estimated γ_i. Tranches differ with respect to their risk profile. They refer to underlying portfolios of various size, industry structure and average debtor quality. They are issued at different times and vary in maturity. All these differences may motivate variations in implied risk aversion.

Tranche risk

The issued tranches of a given transaction differ strongly with respect to the transferred risk. This is due to *strict subordination*, a strict ranking between tranches in the priority of interest and principal payments. Default losses first reduce the size of the first loss piece (FLP). Exceeding losses reduce the principal of the lowest rated tranche and proportionately the interest claims of this tranche for the remaining maturity. If the principal of this most junior tranche has been wiped out, the next tranche is assigned the exceeding losses, etc. For given tranche sizes, this way of assigning the payments maximizes the loss protection for the senior tranches. Further it minimizes their exposure to idiosyncratic risks and thereby also their vulnerability with respect to information asymmetries. Tranche risk can be measured by the rating or by the seniority of the tranche, i.e. the position of the tranche in the loss allocation rules of a transaction.

Strictly subordinated tranches of a single CDO vary in their exposure to information asymmetries as well as in the transferred credit risk. This may induce clientele effects.

Investors buying different tranches may vary with respect to their ability to resolve information asymmetries and/or with respect to their risk attitude. First we hypothesize on the *risk effect*. Since most information problems refer to the underlying portfolio, we address them below when discussing the role of average portfolio quality and portfolio diversification.

More senior and better rated tranches carry a smaller spread due to the fewer risks transferred. These relatively safe tranches may attract investors that are more risk averse. Less risk averse investors may prefer junior tranches with a weaker rating that pay higher spreads. Thus, risk appetite may segment the market for CDO tranches.

Hypothesis 1 (risk effect): The measured relative risk aversion should be lower for junior tranches respectively for tranches with a weaker rating.

Average Portfolio Quality

How does the average loan or bond quality of the portfolio underlying a transaction influence the risk aversion parameter for the issued tranches? It is problematic to answer this question only with respect to single tranches since for CDOs referring to portfolios of different quality originators may choose different CDO *designs*. In particular, the size and loss protection of a given tranche may be adapted to the quality of the underlying portfolio making an ad-hoc prediction on the above question difficult.

Therefore we first investigate how the average loan/bond quality may influence the *average* risk aversion parameter of a CDO transaction. This average can either be defined as the weighted average of all tranche parameters. Or it can be defined as the coefficient γ_{CDO} that, instead of equation (2.2), solves

$$\sum_{i=1}^{\#\text{of tr.}} w_i \cdot P_0(i) = \sum_{i=1}^{\#\text{of tr.}} w_i \cdot \int_{d_t=0}^{1} \frac{E(P_i^t|d_t)}{(1+r)^t} \cdot f(W_t(d_t)) \cdot (W_t(d_t))^{-\gamma_{CDO}} d\, d_t \ . \quad (2.3)$$

In both cases the weight of tranche i, w_i, is defined as $\frac{\text{size}_i}{\sum_{i=1}^{\#\text{of tr.}} \text{size}_i}$. We refer to γ_{CDO} that solves this equation for a given CDO transaction the *transaction-*γ.

To isolate the effect of loan/bond quality we idealize and analyze two CDOs, CDO_A and CDO_B, each referring to a perfectly diversified portfolio. Then the loss rates of portfolio A and B are:[12] $l_A = l \cdot a$, $l_B = l \cdot b$, where l is the aggregate loss rate and a, b are positive constants. Without loss of generality we assume the loans in portfolio A to be of better quality: $a < b$. Further, we normalize the portfolio volume to one and let

[12]Perfect diversification means that portfolio losses are deterministically driven by the macro factors because all idiosyncratic risk is diversified away. For simplicity I assume a maturity of one year and drop the respective index. The results are easily generalized to multi-year transactions.

at_{A_i} (at_{B_i}) and de_{A_i} (de_{B_i}) denote the attachment[13] and detachment point of tranche i of the respective CDO. Crucial for the tranches of the transaction is how these points are chosen given the quality of the portfolio. As a benchmark case we first assume that both CDOs have the same S&P rating structure of the tranches.[14] This corresponds to:

Assumption 1. The corresponding tranches of the two CDOs display equal probability of default. Consequently, for both transactions the respective tranches cover *the same quantiles of the loss distribution.* I.e. for each transaction tranche number i is characterized by

$$\begin{aligned} Prob(\text{loss}PF_A < at_{A_i}) = \quad & Prob(\text{loss}PF_B < at_{B_i}) = \quad p_i \\ Prob(\text{loss}PF_A > de_{A_i}) = \quad & Prob(\text{loss}PF_B > de_{B_i}) = \quad p_{i-1} \ , \end{aligned}$$

where $i-1$ denotes the next higher tranche.

Given this assumption there exist uniquely defined values l^i and l^{i-1} of the loss rate such that $p_i = F^{-1}(l^i)$ and $p_{i-1} = F^{-1}(l^{i-1})$, where F denotes the cumulative distribution function of the loss rate. Given l^i and l^{i-1} the attachment and detachment points are $at_{A_i} = l^i \cdot a$, $de_{A_i} = l^{i-1} \cdot a$ and $at_{B_i} = l^i \cdot b$, $de_{B_i} = l^{i-1} \cdot b$. Let spr_{A_i} (spr_{B_i}) denote the promised spread for tranche i of CDO$_A$ (CDO$_B$), A_i (B_i). Then the repayments per € invested in tranche i of CDO$_A$ conditional on l are:

$$\text{repayment per € invested} = \begin{cases} 1 + r + spr_{A_i} & \text{if} \quad l < l^i \\ \frac{l^{i-1}-l}{l^{i-1}-l^i}(1 + r + spr_{A_i}) & \text{if} \quad l^i < l < l^{i-1} \\ 0 & \text{if} \quad l > l^{i-1} \end{cases}$$

and the analogous equation for tranche B_i where spr_{A_i} is replaced by spr_{B_i}.

Due to the equal repayment structure, both tranches A_i and B_i are in the same market segment and the same γ_i should be applied in the respective pricing equations (2.2). Accordingly $spr_{A_i} = spr_{B_i}$, else at least one of the equations does not hold. This yields

Hypothesis 2a: The γ_i's of the issued tranches and therefore also the weighted average γ, and the transaction-γ are not influenced by differences in the average quality of the underlying portfolio.

[13]The attachment point is defined as the percentage of portfolio losses starting from which the tranche repayments will be decreased if additional losses occur. If the portfolio losses reach the detachment point, no (further) payments are made to the tranche.

[14]The rating agencies differ with respect to the repayment characteristics defining their respective assessment. Moody's put the emphasis on the expected loss of the tranches whereas S&P uses the probability of default. In the idealized setting discussed here, these two characterizations are equivalent.

Empirically however, assumption 1 is questionable. Franke, Herrmann and Weber (2007) find that the loss probability of the lowest rated tranche increases for lower average loan/bond quality of the reference portfolio. More risk transferred in a transaction should lower the implied risk aversion:

Hypothesis 2b: Lower average portfolio quality corresponds to a lower weighted average γ, respectively to a lower transaction-γ.

These two hypotheses address the amount of risk transferred in combination with the risk effect of hypothesis one. They do not take into account the interplay of portfolio quality and information problems. Yet, information asymmetries may be relevant in some CDO transactions and only partially resolved by the rating agencies. The rating agencies' signal on the portfolio quality may be the more accurate the better the quality of the underlying portfolio because there is usually more ambiguity with respect to lower rated loans. For instance, the differences in predicted default probability between neighboring rating classes increase for lower ratings. Consequently, information problems should show in additional premia for reference portfolios of low average quality.

For more senior and better rated tranches however, this effect should be smaller. On the one hand, their higher loss protection shields these tranches against idiosyncratic risks. On the other hand is the better rating of these tranches a more precise signal on the tranche quality than for lower tranches with weak rating. Taking information problems into account thus adds a third hypothesis:

Hypothesis 2c: Lower average portfolio quality increases the weighted average γ, respectively the transaction-γ due to stronger information asymmetries. For the tranche-γ_i's this increase is stronger for lower tranches.

Portfolio Diversification

The effect of portfolio diversification on the risk premium of a given tranche also depends on the extent of frictions in the credit risk market. If there are little or no market frictions, all market participants can easily diversify their credit risks and information problems are small. Further, there is no need for the originator to change the transaction design for different degrees of portfolio diversification. This leads to:

Hypothesis 3a (no market frictions): The implied relative risk aversion of a tranche does not depend on the degree of diversification of the securitized portfolio.

If market frictions do play a role, the situation is different. Amato and Remolona (2003 and 2005) argue that sufficient diversification is harder to achieve in bond markets than

in stock markets. Due to the asymmetric payoff distribution a lot of bonds are needed leading to non-negligible transaction costs when building a well diversified portfolio. Given that diversification is costly there may be a premium on idiosyncratic risks, too. The findings of Longstaff and Rajan (2008) and Amato and Remolona (2005) support this. As the pricing model only rewards premia on systematic credit risk, a higher spread compensating for idiosyncratic risk of a tranche would, ceteris paribus, show in a higher estimated γ_i. For highly rated tranches though, the idiosyncratic risks should have less influence due to the stronger loss protection.
Additionally, more idiosyncratic risks in a poorly diversified portfolio leave more room for information asymmetries which may also result in a higher γ_i. As was the case with the information problems caused by lower average portfolio quality, this effect should be stronger for lower tranches. This motivates

Hypothesis 3b (market frictions): For tranches referring to a well diversified portfolio the implied relative risk aversion should be lower. This effect should be stronger for lower rated tranches with less loss protection.

The originator may react to information problems by increasing the loss protection of these tranches. Note however that this will result in less risky tranches that presumably correspond to higher risk aversion (hypothesis 1) and therefore rather reinforce than counteract hypothesis 3b.

Maturity, CBOs vs. CLOs

Longer maturities may increase uncertainty with respect to the loss rate distribution of the portfolio and accordingly also to the repayment structure of the tranches. This uncertainty may allow for stronger information asymmetries and make itself felt in additional premia.

Hypothesis 4: The implied relative risk aversion of a tranche is higher, the longer the maturity.

In loan transactions, investors may see a larger potential for adverse selection and moral hazard since often the collateralized loans refer to obligors that are less well known than the obligors in a CBO.

Hypothesis 5: Tranches of loan transactions imply higher relative risk aversion parameters than tranches of bond transactions.

Issuance Date

Market sentiment as well as the attitude towards risk is subject to changes. This may

cause the risk premium for credit risk transferred in CDO tranches to vary over time. On the other hand, learning effects may also play a role. Cuchra and Jenkinson (2005) analyze a broad set of securitizations over a time horizon similar to the one investigated here and find that investor sophistication increases over time. This suggests that market participants improve their understanding of the CDO structures leaving less uncertainty for example concerning the loss allocation or the general properties of the portfolio loss distribution. This should result in a decreasing 'mistrust' premium over time since information asymmetries diminish. Given that the mistrust premia are included in the computed risk premia the latter should decrease over time.
Alternatively, if the reduction over time in the perceived information asymmetries is small we would rather see risk premia that vary along other measures of how the market values risk, for example the spreads of corporate bonds within a given rating class. This leads to two hypotheses:

Hypothesis 6a: Variations in the risk aversion parameter include a time trend due to learning effects and changes in perceived information asymmetries.

Hypothesis 6b: Variations in the risk aversion parameter over time are better explained by changes in corporate bond spreads than by changes in issuance dates.

2.4 Data and Simulation

2.4.1 Data

The data set contains 59 multi-tranche synthetic CDOs issued by European originators, including 19 collateralized bond obligation- transactions (CBOs) and 40 collateralized loan obligation- transactions (CLOs). These CDOs comprise 236 *differently ranked* tranches, i.e. tranches that differ in their position in the loss allocation rules. For 21 highest ranked tranches, with 20 rated Aaa and one rated Aa2, belonging to 19 different transactions the simulations yield no losses and therefore no value of γ_k would solve equation (2.2), since they pay positive credit spreads. They are removed from the data set leaving 215 tranches.

For each CDO up to five differently rated tranches exist:[15] six CDOs have two tranches, 20 have three, 22 have four and 11 have five. The tranches are characterized by:

[15]If several tranches are ranked pari passu in the loss allocation rules and only differ with respect to the currency or the type of interest payment - i.e. fixed or floating - I count this as only one tranche

- *Rating*: The Rating of a tranche, measured as an integer. A Aaa rating corresponds to -1, Aa1 corresponds to -2 etc. The frequency of tranche ratings is reported in the following table:

Rating	Aaa	Aa	A	Baa	Ba	B
Tranches	37	44	45	52	36	1

- *E(an.loss)*: The annualized expected loss of a given tranche.[16]

- *Rank*: The position of a tranche in the hierarchy of the transaction. The tranche with the highest loss protection and accordingly with the highest rating carries number 1. The next tranche number 2, etc.

- *Highest*: A dummy variable equal to one if the tranche has rank 1.

- *Lowest*: A dummy variable equal to one if the tranche is the lowest in the hierarchy of the transaction, i.e. if the only loss protection comes from the first loss piece.

- *FLP*: Size of the first loss piece in percent of the portfolio volume. It ranges between 0.7% and 14% with a mean of 3.3%.

- *Credsup*: Credit Support of a tranche. For the lowest rated tranche this is equal to *FLP*. For the other tranches it is the sum of *FLP* and the combined size of all lower ranked tranches.

Issuance Date

The transactions were issued between 1999 and 2005:

Year	1999	2000	2001	2002	2003	2004	2005
Transactions	4	12	14	19	5	3	2

49 transactions were arranged between 1999 and 2002. This accounts for more than half of the market for European synthetic CDOs in this period. Between 2003 and 2005 there are 10 transactions in the data set representing a smaller portion of the market. To account for potential changes over time we use

- *Date*: The date of issuance, measured by an integer for each quarter (e.g. 1.Q 1999 $\hat{=}$ 1, 1.Q 2000 $\hat{=}$ 5).

[16]This variable is strongly correlated (nearly 75%) to the variable *rating*. In order to avoid endogeneity problems the expected loss is computed using the approximation described in Franke, Herrmann and Weber (2007), i.e. assuming a lognormal loss distribution whose parameters are fitted to the WADP and diversity score of the portfolio.

- *IBOXX-spread*: The spread of the IBOXX BBB-corporate bond index over the IBOXX sovereign index, both taken for maturities of five to seven years. Over the analyzed time period it varies between 58 and 250 basis points.

Average Portfolio Quality

Each obligor is either assigned an external rating by Moody's or an equivalent rating derived by mapping the internal rating system of the originator onto the external (Moody's) rating scale. For each transaction, the average loan rating is known, for some deals the frequency of single loan ratings is also known. The average rating is converted into

- *WADP*: Weighted average default probability of the securitized portfolio. It ranges between 0.7% and 8% with a mean of 2.3%.

Portfolio Diversification

The rating reports from Moody's provide a diversity score (DS) for the portfolio. It can be interpreted as the diversity-equivalent number of equally sized independent loans.

- *DS*: Moody's diversity score. It ranges between 12 and 135 with a mean of 77.

Other Variables

Further CDO-specific variables included in the regressions are

- *Maturity*: The total maturity of the transaction measured in whole-numbered years. It ranges between 2 and 8 years. Nearly half the transactions (27 out of 59) have a maturity of 5 years.

- *Dyn*: A dummy variable equal to 1 (0) in dynamic (static) transactions. 44 CDOs are dynamic, 15 are static.

- *CBO*: A dummy variable equal to 1 (0) in bond (loan) transactions. 19 transactions are CBOs, 40 are loan transactions.

Systematic Risk Factor: The Aggregate Loss Rate

The aggregate loss rate is the single systematic risk factor of the pricing model. It is defined as the percentage loss rate of all outstanding debt in the economy. It has a direct impact on the aggregate wealth of the agents in the debt market and it also influences the payments of the CDO tranches. The t-year loss rate of loan n, $l_{t,n}$, is defined as zero, if loan n does not default until year t and as the (stochastic) loss given default (LGD) of loan n (LGD_n) in case of default. The t-year aggregate loss rate in the economy, l_t, is the weighted average loss rate of all loans:

$$l_t = l_t(d_t) = d_t \cdot E(LGD|d_t) \ . \tag{2.4}$$

Here, d_t is the t-year default rate in the economy, i.e. the face value-weighted fraction of all outstanding loans defaulting over t years. Note that d_t and l_t are not annualized but cumulated figures.[17]

When estimating the distribution of d_t, we use data provided by Moody's (2007). This cohort study includes aggregate default and loss data on all corporate borrowers rated by Moody' starting from 1970. For each year and for each of seven rating classes (Aaa to Caa) the cumulative default rates are given for all maturities between one and 20 years. We take the weighted average of the seven rating specific cumulated default rates as a proxy for the economy-wide default rate. For each maturity this yields a sample of cumulated default rates.[18] For most maturities up to eight years this sample is explained best by a lognormal distribution.[19] The parameter estimates for d_t and features of the resulting terminal wealth are given in Appendix 2.9.1.
Moody's (2007) further provides an annual average of the LGD. The LGD is assumed to be normally distributed (truncated between zero and one). The mean is 60% and the standard deviation is 10%. The LGD and the default rate are positively correlated with $\rho = 0.5$. This is accounted for in the simulation.[20]

2.4.2 Simulation Procedure

In our simulation we implement a simple credit risk model. The default probability of each loan or bond[21] is directly linked to the default rate in the economy d. d, in turn, is connected by equation (2.4) to our systematic risk factor, the aggregate loss rate.

[17]It is assumed that at least at the beginning of a period face value and market value of the loans coincide. E.g. if $d_3 = 10\%$ and $E(LGD|d_3 = 10\%) = 60\%$, then 10% of all loans defaulted over three years causing a loss of $l_3 = 6\%$ of the aggregate face value.

[18]Strictly speaking, it is a time series of cumulated default rates. The time series properties, in particular autocorrelation are accounted for when modeling dynamic transactions. See Appendix 2.9.3 for details.

[19]Compared to gamma- and negative binomial distributions that we also fitted.

[20]Since $E(LGD|d_t)$ increases with d_t the distribution of l_t is *more skewed* than the distribution of d_t, i.e. more skewed than lognormal.

[21]In the remainder of this chapter we will refer to portfolios of loans only. All results hold for bond portfolios as well with the same derivation.

For a t year loan with rating j the (cumulative) probability of default *conditional on the default rate in the economy* d_t, $PD_{j,t}(d_t)$ is given by

$$PD_{j,t}(d_t) = \overline{PD_{j,t}} \cdot \frac{d_t}{E(d_t)} \quad . \tag{2.5}$$

$\overline{PD_{j,t}}$ denotes the unconditional default probability of the loan.[22] In this setting the default events are independent conditional on the macro factor. This means that given, for example, a scenario with twice as many defaults in the economy as expected, $d_t = 2 \cdot E(d_t)$, the default probability of every loan is modeled to be twice as high as its unconditional default probability. Note that high (low) realizations of the default rate in the economy lead to high (low) default probabilities of all the loans. Thus, this procedure induces an implicit correlation of default events. This correlation structure is similar to the one generated in a migration model.[23]

For a given realization d_t of the default rate the Monte Carlo simulation proceeds as follows. First, the conditional (cumulative) default probability of each loan is determined using equation (2.5). Then independent loan-specific random variables determine which loans default. Subsequently, for each defaulting loan the loss given default (LGD) and the default time are determined. This yields a time series of losses induced by the underlying portfolio. Next, given this information, the repayments to the tranches are computed. Finally, discounting these repayments to the issuance date of the transaction yields $\frac{P_i}{(1+r)^t}|d_t$. The average value of this term, taken from repeated runs of the simulation for the same d_t converges to $E\Big(\frac{P_i}{(1+r)^t}|d_t\Big)$. For a detailed description of the simulation procedure see Appendix 2.9.2.

Figure 2.1 exemplifies the relationship between the aggregate loss rate in the economy and discounted tranche repayments per Euro invested for a sample transaction. It can be interpreted in the following way: investors buying one of the tranches pay one (risk-free) Euro in exchange for the respective risky payoff that depends on the six year aggregate loss rate as depicted.[24] For each tranche separately, the risk aversion parameter is computed from this distribution according to equation (2.2).

[22]Of course, $PD_{j,t}(d_t)$ has to be truncated at one, but this would only become necessary for extremely high values of $\overline{PD_{j,t}}$. Equation (2.5) follows the CreditRisk+ framework. In general, CreditRisk+ defines the (cumulative) probability of default of a loan or bond conditional on the realization $x = (x_1, \ldots, x_K)$ of a vector of macro variables as $PD_{j,t}(x) = \overline{PD_{j,t}}\Big(\sum_{k=1}^{K} \omega_{jk}(x_k)\Big)$. Here, ω_{jk} denote the factor loadings. For a detailed description see either Gordy (2000) or Credit Suisse Financial Products (1997).

[23]Appendix 2.9.4 presents a migration model and compares the implied default correlations.

[24]See Appendix 2.9.2 for a detailed interpretation of Figure 2.1.

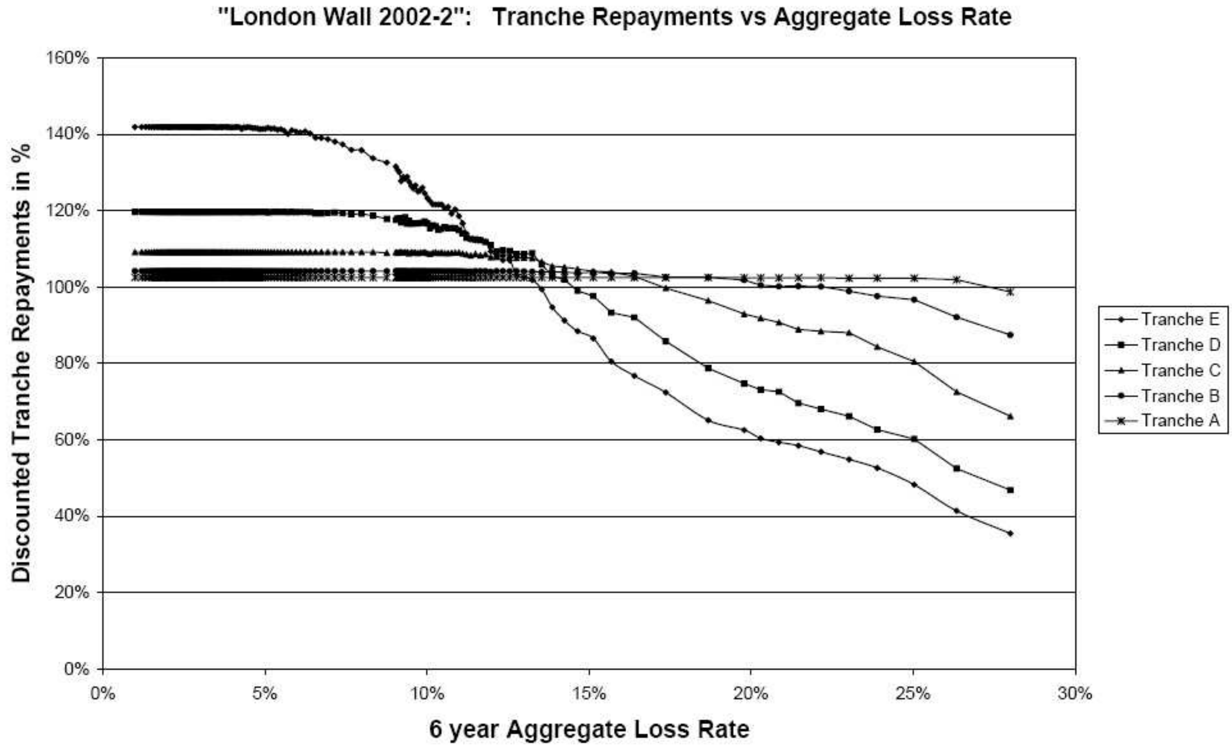

Figure 2.1: Simulation results for the discounted expected repayments of five differently rated tranches from the CDO transaction 'London Wall 2002-2', maturity six years, conditional on the six year aggregate loss rate l_6. For high loss rates we use finer data point grids in order to better focus on the relevant cases.

2.5 Results and Discussion

For each of the 215 tranches, the implied relative risk aversion parameter γ_i is derived. The estimated γ_i vary between 2.6 and 10.2 with a mean of 4.37:

Further, for each of the 59 transactions the weighted average of the γ_i's ($\bar{\gamma}$) for the issued tranches is computed as is the respective transaction-γ (γ_{CDO}) solving equation (2.3). The histograms for γ_{CDO} and $\bar{\gamma}$ are depicted in Figure 2.3. The average value for γ_{CDO} is 4.05 and the standard deviation is 0.6. $\bar{\gamma}$ is more prone to outliers. Its average value is 4.75 and the standard deviation is 1.1.

Tranche Risk

The results for γ_i vary systematically for tranches of different risk. Table 2.1 shows that irrespective of whether the risk is measured by the rating of the tranche or by the expected annual loss per € invested, hypothesis 1 is confirmed. There is a *risk effect*,

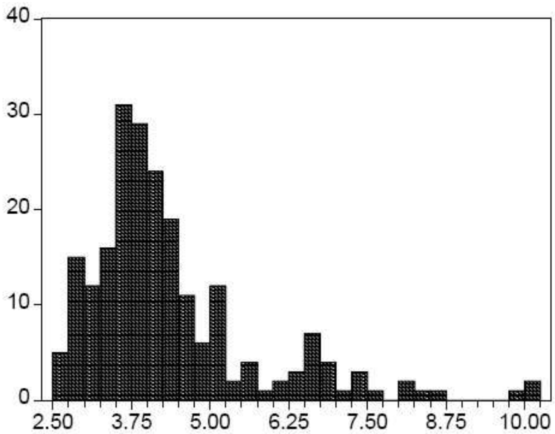

Figure 2.2: Histogram for the tranche specific relative risk aversion coefficient γ_i.

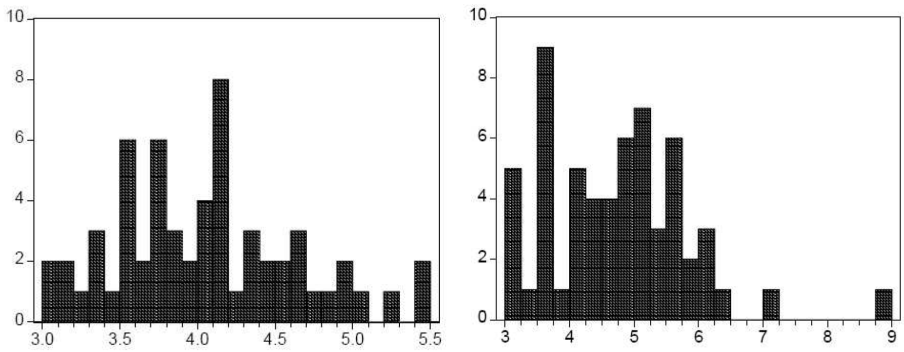

Figure 2.3: Left hand side: histogram for the transaction-γ (γ_{CDO}). Right hand side: histogram for the weighted average γ of the transactions, $\bar{\gamma}$.

as the risk aversion is lower for riskier tranches.

More risk averse investors seem to restrict themselves to Aaa and Aa rated tranches, similarly to tranches with low expected loss per € invested. When looking at the rank of a tranche within a CDO as a proxy for its risk, the results are similar. Figure 2.4 plots γ_i against the variable *rank*.

The average γ_i is highest for the tranches with the highest loss protection within a given CDO (rank 1) and decreases for tranches with rank two and three. Surprisingly, the average γ_i for tranches with rank four or five - 3.88 and 3.89, respectively - is *higher* than that of tranches with rank three, 3.74. To further analyze the impact of the variables *rating, log(E(an.loss))* and *rank* on γ_i several regressions are run. The results are displayed in Table 2.2. The first three columns show the univariate effects.

ratings	all	Aaa	Aa1 to Aa3	A1 to A3	Baa1 to Baa3	Ba1 to B1
γ_k- mean	4.37	6.00	4.44	3.93	3.89	3.90
γ_k- stdev	1.38	3.12	1.34	0.89	0.67	0.53
observations	215	37	44	45	52	37
E(an.loss in %)		≤ 0.1	$0.1 < x \leq 0.2$	$0.2 < x \leq 0.5$	$0.5 < x \leq 1$	> 1
γ_k- mean		5.47	4.70	3.98	3.73	3.68
γ_k- stdev		0.82	1.45	0.95	0.59	0.56
observations		54	35	49	41	36

Table 2.1: Upper part: Results for the tranche specific risk aversion parameter γ_i given different tranche ratings. Lower part: Results for γ_i given different ranges of annualized expected loss per € invested.

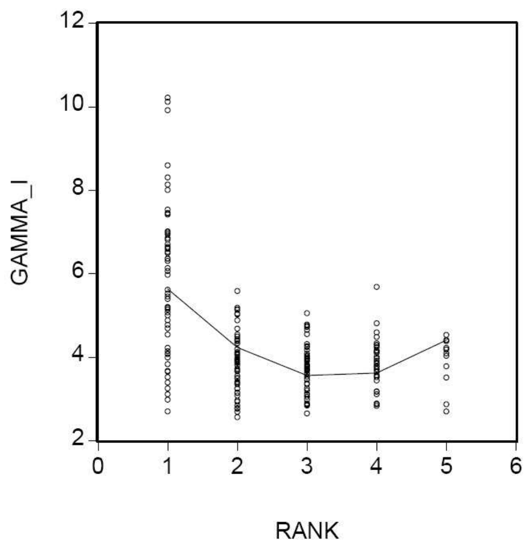

Figure 2.4: Risk aversion parameter vs. rank of the tranche. The line depicts the fitted values of a regression of γ_k on a second order polynomial of *rank*. The respective number of observations for positions one to five are: 59, 59, 53, 33, 11.

Regressing the tranche specific risk aversion γ_i						
rating	0.15 (0.000)	-	-	-	0.06 (0.044)	-
log(E(an.loss))	-	-0.50 (0.000)	-	-	-	-0.30 (0.000)
rank	-	-	-0.55 (0.000)	-2.50 (0.000)	-	-
$(rank)^2$	-	-	-	0.36 (0.000)	-	-
highest	-	-	-	-	1.82 (0.000)	1.69 (0.000)
lowest	-	-	-	-	0.60 (0.000)	0.61 (0.000)
adj. R^2	0.18	0.24	0.22	0.36	0.41	0.46

Table 2.2: This table displays the coefficients (Newey-West heteroscedasticity adjusted p-values in brackets) of OLS-regressions explaining the tranche-γ_i with tranche specific variables.

In order to capture nonlinear effects in *rank* I add $(rank)^2$. As shown in column 4, this increases the explanatory power. There seems to be a convex relationship, Figure 2.4 also suggests this. Replacing *rank* and $(rank)^2$ by the variables *highest* and *lowest* and combining these with either *rating* or *log(E(an.loss))* yields the highest adjusted R^2. These results shown in the last two columns provide evidence that there is an additional premium for the lowest issued tranche.[25] The positive and significant coefficient of *lowest* suggests an influence of market frictions on tranche pricing. Even though hypothesis 1 is confirmed in general, the lowest tranche deviates. Investors buying this tranche are the first to be hit by losses. They have to be concerned most about idiosyncratic risks and information asymmetries regarding the underlying portfolio. They further have to scrutinize the exact loss allocation rules within the CDO. This is costly and may motivate a 'complexity premium'. The potential influence of these market imperfections will reviewed when addressing hypotheses 2c and 3b.

[25]It is difficult to translate a higher γ_i into additional spread since this relation strongly depends on the loss distribution. Lowering γ_i by 0.6 for example for the lowest issued tranche of the transaction "Promise G" ("Promise K") corresponds to a decrease in promised credit spreads by roughly 70 (120) basis points.

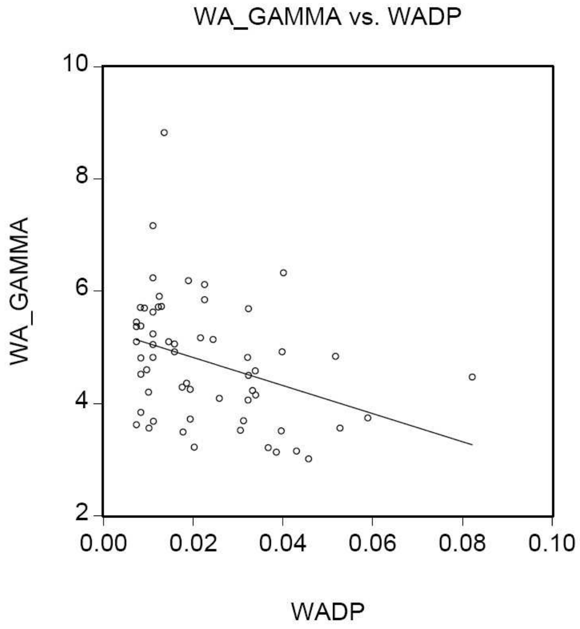

Figure 2.5: The weighted average γ of the CDOs plotted against the weighted average default probability (WADP) of the reference portfolio. The line depicts the fitted values of a linear regression.

Average Portfolio Quality

Given variations in the average portfolio quality, hypothesis 2a predicts no systematic effect on the risk aversion coefficient whereas hypothesis 2b predicts γ to be lower for lower quality portfolios. The hypotheses differ with respect to the assumed relationship of tranche loss protection and weighted average default probability (*WADP*) of the reference portfolio. They both do not take information problems into account. The plot of the weighted average γ, $\bar{\gamma}$, of the transactions against the *WADP* depicted in Figure 2.5 shows that higher *WADP* correspond to lower values of $\bar{\gamma}$. This rejects hypothesis 2a and supports hypothesis 2b.

Regressions of either $\bar{\gamma}$ or the transaction-γ, γ_{CDO}, on WADP confirm hypothesis 2b, too. In both cases the coefficient is significantly negative and the R^2 is close to 11 %, as shown for γ_{CDO} in the first column of Table 2.3. We have seen that higher tranche risk appears to imply lower risk aversion. The reasoning in hypothesis 2b is based on the assumption that for lower quality portfolios with higher *WADP* the loss protection is higher, but not high enough to offset the additional risk. Therefore the issued tranches are on average more risky leading to lower γ_{CDO}, $\bar{\gamma}$. Figure 2.6 plots the loss protection of the Aaa- and Aa rated tranches against the *WADP*, respectively the loss protection

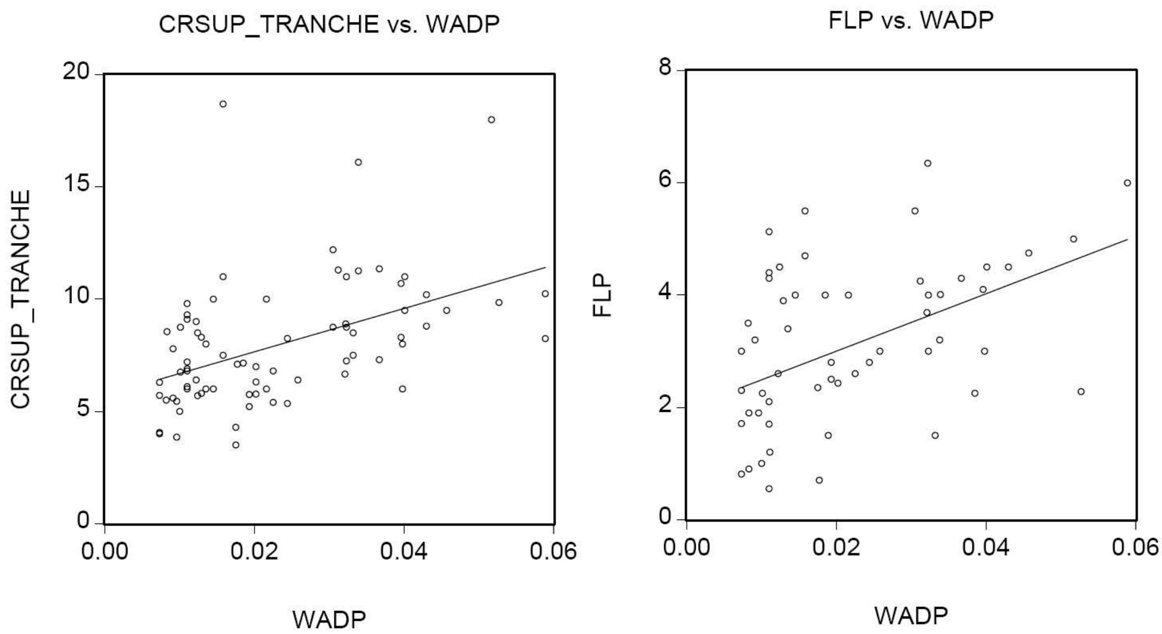

Figure 2.6: Figure 6. The credit support is plotted against the *WADP* of the reference portfolio. On the left hand side this is done for all tranches rated Aa or better. On the right hand side for all lowest tranches of the respective transactions. The credit support of the lowest rated tranche equals the size of the first loss piece (FLP). In both plots the data point with the highest *WADP*, *WADP*= 8.2% is omitted. Including it does not alter the results.

of the lowest rated tranche - which equals the (*FLP*) - against the *WADP*. Linear regressions of the tranche credit support *credsup* on *WADP* show significantly positive constants. This means that credit support increases less than proportionally given an increase in *WADP*. as can also be seen from the corresponding fitted value lines in Figure 2.6. Consequently the default probabilities of the tranches increase given an increase in *WADP* backing the assumption made for hypothesis 2b.

Thus, $WADP$ should influence single tranches' risk aversion coefficients, too. The net impact of a higher *WADP* should be a more risky tranche and a lower γ_i. This impact can be decomposed when multivariately regressing the tranche γ_i on the *WADP* of the portfolio and the credit support (*credsup*) of the tranches. The regression results are shown in columns three and four of Table 2.3. A higher *WADP* decreases γ_i whereas a higher credit support lowers the tranche risk and thereby increases γ_i. Put differently, both a higher *WADP* and a lower credit support increase tranche risk and thereby decrease γ_i. The same reasoning applies on the transaction level, the respective results are given in the second column of Table 2.3. The first four columns of Table 2.3 again confirm the risk effect of hypothesis 1.

subsets	transactions		all tranches		upper tranches		mid tr.	lowest
Observations	59		215		103		53	59
WADP in %	-0.13	-0.27	-0.22	-0.50	-0.40	-0.76	-0.26	-0.14
	(0.028)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.024)
FLP/credsup	-	0.15	-	0.20	-	0.22	0.10	0.11
		(0.000)		(0.000)		(0.000)	(0.012)	(0.017)
adj. R^2	0.11	0.27	0.06	0.27	0.12	0.29	0.22	0.08

Table 2.3: The first two columns display the coefficients (Newey-West heteroscedasticity adjusted p-values in brackets) of OLS-regressions explaining the transaction-γ. The other columns show the respective coefficients when explaining the tranche-γ_i. The upper tranches are defined as all tranches that have at least two lower ranked tranches 'beneath' with respect to the loss allocation rules. The mid tranches are of rank two or lower and there exists exactly one lower ranked tranche. The lowest tranches are the first rated tranches to be hit by losses. The adjusted R^2 is shown in the last row. When accounting for loss protection, the size of the first loss position *FLP* is used on the transaction level and the tranche specific credit support *credsup* is used on the tranche level.

Hypothesis 2c states that a higher *WADP* should aggravate information problems leading to higher γ's. Further, this increase should be stronger for lower tranches. On a transaction level, this hypothesis is rejected as seen in columns one and two of Table 2.3. Columns three and four show that for all tranches combined the hypothesis is also rejected. Looking at different subsets of tranches, however, gives a more differentiated picture. Columns five and six show the results when regressing γ_i on *WADP* and *credsup* only for "upper" tranches where at least two lower ranked tranches were issued in the CDO. The coefficients show that if more risk is transferred to the tranches, indicated by higher *WADP* and lower *credsup*, this leads to a stronger decrease in γ_i than for the average of all tranches. Column seven shows the result for the mid tranches, tranches of rank two or lower, where exactly one lower ranked tranche was issued. Here, the respective coefficients are smaller. Finally, the last column shows the result for the 59 lowest tranches of the transactions. For these tranches the coefficients are smaller and less significant and the explanatory power is weaker.

For all tranche groups a higher risk is associated with a lower γ_i, probably by attracting less risk averse investors. The smaller regression coefficients for mid and lower tranches indicate that this influence is counteracted by the rising information asymmetry given higher tranche risk leading to additional premia. A further effect may be that even for low *WADPs* and correspondingly little risk in the highest tranches a *minimum spread*

subsets	all tranches		upper tranches		mid tranches		lowest tranches	
Observations	215		103		53		59	
log(E(an.loss))	- 0.50 (0.000)	-0.45 (0.000)	-0.60 (0.002)	-0.50 (0.019)	-0.33 (0.000)	-0.20 (0.046)	-0.23 (0.000)	-0.13 (0.063)
log(DS)		-0.31 (0.17)		-0.54 (0.18)	-	-0.38 (0.097)	-	-0.35 (0.030)
adj. R^2	0.24	0.25	0.19	0.19	0.28	0.32	0.16	0.22

Table 2.4: This table displays the coefficients (Newey-West heteroscedasticity adjusted p-values in brackets) of OLS-regressions explaining the tranche-γ_i. The upper tranches are defined as all tranches for which at least two tranches exist that are ranked lower with respect to the loss allocation rules. For the mid tranches there is exactly one lower ranked tranche. The lowest tranches are the first rated tranches to be hit by losses. The adjusted R^2 is shown in the last row.

has to be paid. This would also increase the γ_k of the highest tranche when *WADP* is (very) low.

Portfolio Diversification

The effect of portfolio diversification is first discussed on a single tranche level, subsequently on the transaction level. When analyzing the effect on a tranche level we control for the pure risk effect by adding the logarithm of the expected annualized loss *log(E(an.loss))* as an additional variable in the regressions. The first two columns of Table 2.4 display the results when regressing all tranche γ_i's on *log(DS)* and *log(E(an.loss))*. Here, *log(DS)* is insignificant and does not add explanatory power compared to the univariate regressions on *log(E(an. loss))*. This backs hypothesis 3a, that premia associated with market frictions are small. Again this picture changes somewhat when differentiating upper, mid and lowest tranches. The results are shown in columns three through eight of Table 2.4. For the upper tranches, the diversification of the underlying portfolio does not seem to be relevant. Columns five and six reveal that *log(DS)* is weakly significant when regressing only the mid tranches and that it adds some explanatory power. When regressing only the lowest issued tranches, *log(DS)* is significant and it adds more explanatory power. For these tranches *log(DS)* is more significant than *log(E(an.loss))*.[26] These results are displayed in the final two columns. tranche risk, better portfolio diversification lowers the risk premium only for

[26]The adjusted R^2 of the univariate regression on *log(DS)* is higher (19%) than when regressing on *log(E(an.loss))*.

correlation of	no. of differently rated tranches	rating of lowest tranche	weighted average tranche rating	size of FLP
with *log(DS)*	0.37	-0.29	-0.21	-0.17

Table 2.5: This table displays the correlation coefficients of *log(DS)* with the number of differently rated tranches, the rating of the lowest tranche, the weighted average rating of the tranches and the size of the first loss position.

Regressing the transaction-γ, γ_{CDO}					
no. of differently rated tranches	-0.23 (0.004)	-	-0.15 (0.059)	-	-
rating of lowest tranche	-	0.13 (0.000)	0.10 (0.001)	-	0.08 (0.004)
log(DS)	-	-	-	-0.72 (0.000)	-0.63 (0.000)
adj. R^2	0.14	0.18	0.22	0.39	0.45

Table 2.6: This table displays the coefficients (Newey-West heteroscedasticity adjusted p-values in brackets) of OLS-regressions explaining the transaction-γ, γ_{CDO}. The adjusted R^2 is shown in the last row.

mid and lower tranches. For these tranches this provides evidence for the pricing of idiosyncratic risk and/or additional spreads paid due to information problems, partially confirming hypothesis 3b. For mid tranches the effect is only weakly significant. The higher the tranche within the structure of a CDO the smaller is this effect.[27]

When looking at the impact of portfolio diversification on a transaction level, the adjustments in CDO design are crucial. Table 2.5 shows the correlation coefficients of *log(DS)* with some transaction characteristics. The better diversified the portfolio, the higher the tendency to issue more tranches, the lower the rating of the lowest tranche and the weighted average of all tranche ratings, the smaller the FLP. Put differently, better diversification allows the originator to transfer more risk to investors. This should decrease the implied risk aversion parameter of the CDO, γ_{CDO}, because the portion of tranches bought by less risk averse investors is probably higher. The results shown in Table 2.6 confirm this. A higher number of differently rated tranches corresponds to a lower γ_{CDO}, as does a weaker rating of the lowest tranche. This is seen in columns one through three. The impact of the weighted average rating and of the

[27]Using the tranche rating as proxy for tranche risks yields similar results. They are not shown.

size of the first loss position[28] is less pronounced, these results are not shown. Columns four and five show the strong impact of portfolio diversification on the implied risk aversion of a transaction. Better diversification, showing in a higher diversity score, significantly lowers γ_{CDO}. This is due to a twofold effect. On the one hand, a higher *DS* reduces γ_i for lower and mid tranches, given tranche risk as seen in Table 2.4. Further, in transactions referring to a well diversified portfolio, more tranches tend to be issued and the lowest tranche tends to have a weaker rating, which adds to the effect. This combined impact shows in a highly significant coefficient of *log(DS)*. Further, it may explain why this coefficient is higher in magnitude than any single tranche *log(DS)*-coefficient in Table 2.4.

Put differently, strong diversification allows originators to issue more and on average more risky tranches paying relatively moderate risk premia on the additional tranches. This can be seen as a benefit of diversification.

Maturity

The estimated risk aversion parameter tends to be higher the longer the maturity of the transaction supporting hypothesis 4. This holds true for transaction averages as well as tranche specific numbers. Of course, default probabilities rise with longer maturities, but the simulation procedure takes that into account. The higher estimated γ therefore hint at *additional* premia paid for longer transactions. Due to the highly illiquid market for CDO tranches most investors pursue buy and hold strategies. The additional premia may be demanded as compensation for higher uncertainty associated with longer transactions.[29]

When regressing all tranche γ_i on several explanatory variables, the coefficient for maturity always is significant and adds explanatory power. It varies around 0.3 depending on the other variables included. The results are shown in Table 2.7. In columns three to eight again higher, mid and lower tranches are differentiated. The value of the coefficient is higher for higher tranches but the added explanatory power is larger for lower tranches. The additional premium for longer maturity itself, as well as the fact that it is more pronounced for upper tranches is in line with the findings of Cuchra (2005).

Issuance Date

Two hypotheses were stated with respect to the effect of the issuance date. Here, clearly the *IBOXX-spread* plays a stronger role. When univariately regressing the transaction-

[28]The size of the FLP alone has no explanatory power. However if combined with WADP, it is important. This will be re-addressed in Table 2.7.

[29]The estimates for the weighted average default probability tend to be less accurate for longer time periods.

subsets	transactions				all	upper	mid	lowest
Observations	59				215	103	53	59
WADP in %	-0.17 (0.000)	-0.09 (0.004)	-0.06 (0.026)	-0.09 (0.004)	-0.57 (0.000)	-0.89 (0.000)	-0.11 (0.005)	-
FLP/*credsup*	0.08 (0.008)	-	-	-	0.20 (0.000)	0.24 (0.000)	-	-
log(DS)	-0.58 (0.000)	-0.60 (0.000)	-0.50 (0.000)	-0.45 (0.000)	-	-	-0.28 (0.090)	-0.26 (0.026)
rating of lowest tranche	-	0.08 (0.006)	-	-	-	-	-	-
CBO-dummy	-	-	0.58 (0.001)	0.37 (0.008)	-	-	0.60 (0.002)	0.29 (0.037)
maturity	-	-	-	0.11 (0.009)	0.30 (0.000)	0.41 (0.000)	0.11 (0.007)	0.15 (0.000)
IBOXX-spread	-	-	-	0.23 (0.032)	0.40 (0.008)	0.50 (0.055)	-	0.29 (0.026)
adj. R^2	0.48	0.50	0.55	0.61	0.35	0.37	0.56	0.41

Table 2.7: This table displays the coefficients (Newey-West heteroscedasticity adjusted p-values in brackets) of OLS-regressions explaining the tranche-γ_i. The upper tranches are defined as all tranches for which at least two tranches exist that are ranked lower with respect to the loss allocation rules. For the mid tranches there is exactly one lower ranked tranche. The lowest tranches are the first rated tranches to be hit by losses. The adjusted R^2 is shown in the last row. The second row, the coefficients for *FLP* are shown in the first four columns referring to regressions on γ_{CDO}. Columns five through eight in this row show the coefficients for the tranche credit support *credsup* when regressing γ_i.

γ on the *IBOXX-spread*, the variable is significant at the 1 % level and the adjusted R^2 is 11%, supporting hypothesis 6a. The variables *date* and $(date)^2$ are insignificant and the adjusted R^2 of regressing the transaction-γ on either one of them or the two combined is almost zero rejecting hypothesis 6b. Further, the results displayed in Table 2.7 show that in multivariate regressions of γ_{CDO} as well as γ_i including several other variables *IBOXX-spread* adds explanatory power. A higher *IBOXX-spread* increases the implied risk aversion. This is intuitive, since higher spreads paid in the corporate bond should correspond to higher spreads in the CDO market that in turn show in higher γ's. In contrast, *date* and $(date)^2$ do not add explanatory power, these results are not shown.

CLOs vs. CBOs

On average, bond transactions display higher estimates for γ_{CDO} contradicting hypothesis 5. The average transaction-γ is 4.58 for the 19 CBO transactions compared to 3.80 for the 40 CLOs. This would correspond to a coefficient of 0.78 when univariately regressing γ_{CDO} on the CBO-dummy. However, bond- and loan-transactions differ systematically in the portfolio characteristics as measured by *WADP* and *DS* and in the size of the first loss piece *FLP*. Further, bond transactions tend to be issued when the *IBOXX-spread* is higher what may indicate market timing of the originators. The results of multivariate regressions of γ_{CDO} on these variables are shown in columns one to four of Table 2.7. Including the *IBOXX-spread* reduces size and significance of the CBO-dummy. The correlation between the CBO-dummy and the *IBOXX-spread* is 28%. CLO originators may tend to issue in times of low spreads in the bond market. This reduces the spread they have to pay for securitizing loans they already had on their balance sheet. CBO originators also have to pay more to investors in times of higher IBOXX-spreads. Yet this may be overcompensated by higher spreads on the securitized bonds that are bought simultaneously.

The coefficients when regressing the single tranche γ_i are shown in columns five to eight of Table 2.7. For the set of all 215 tranches as well as for the upper tranches the CBO-dummy is insignificant and close to zero when accounting for the afore mentioned variables. For mid and lower tranches, however, the coefficient is significantly positive.

Thus the CBO-dummy displays a relatively high and significant coefficient with respect to the transaction-γ and lower and partially insignificant coefficients when regressing single tranche γ_k's. This result can be explained in a similar way as the influence of portfolio diversification: bond transactions tend to have fewer tranches, three on average, than loan transactions (average: 3.95). Further, their mid (lowest) tranche is on average rated A (BBB) compared to a BBB+ (BB/BB+) rating for respective tranche of the average CLO. These better ratings correspond to higher γ_i and lead to higher transaction-γ's in CBOs.

2.6 Robustness Checks

Our model is based on several assumptions. In particular the leverage of the representative bank was assumed to be ten. Changing this to, say, 12.5, equivalent to an equity ratio of eight percent alters the results. However, as can be seen from Figure 2.7, the results are mainly shifted downwards, for shorter maturities more than for longer maturities. In the regressions this shows in a larger coefficient for maturity, all other coefficients basically remain unchanged as do the interpretations of the previous section.

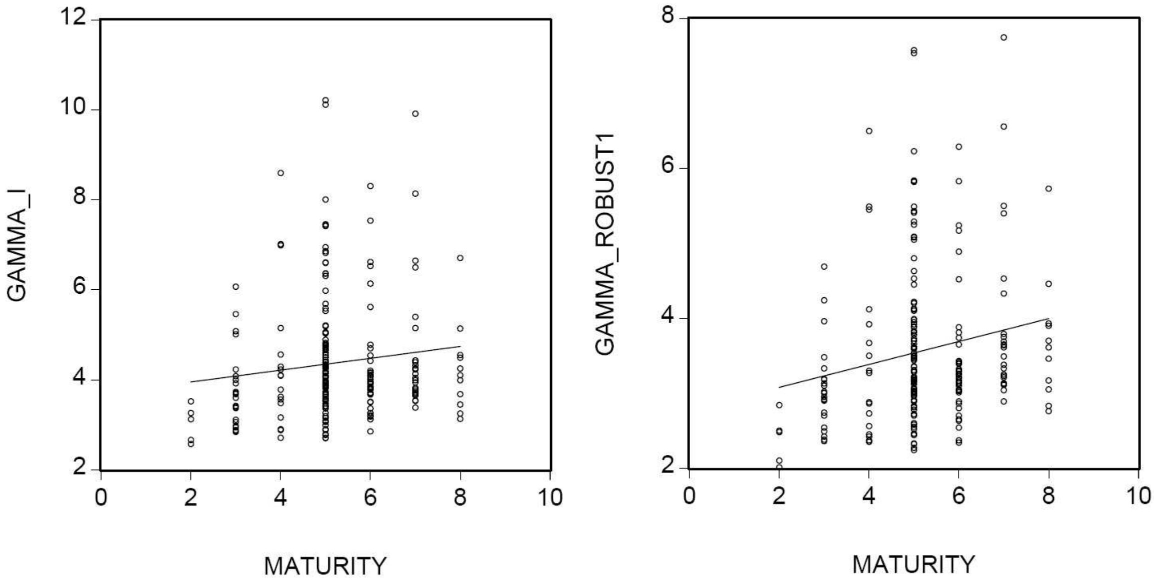

Figure 2.7: Figure 7. On the left hand side the tranche γ_i is plotted against the maturity of the transaction based on an equity ratio of 10, on the right hand side based on 12.5.

In the previous section, sometimes several variables measure similar properties. For example, tranche rating as well as the expected annual loss proxy for tranche risk. Substituting these variables in the previously described regressions somewhat alters the p-values and explanatory power, but not the qualitative results. Including originator specific variables like rating, capital ratio or previous returns does not add explanatory power.

2.7 Conclusion

Our analysis the risk-return profile of 215 CDO tranches from 59 different CDOs shows that the implied coefficient of relative risk aversion varies strongly. This coefficient is derived from the repayment structure of the tranches. A substantial portion of the variation can be ascribed to tranche and portfolio characteristics. This holds both on a tranche and a transaction level. Most significantly, the measured relative risk aversion is *lower* for tranches with higher risk (*risk effect*). This indicates market segmentation, i.e. riskier tranches paying higher spreads attracting less risk averse investors. The CDO market as an aggregate therefore displays decreasing relative risk aversion. Given this finding and ignoring other market frictions for a moment, any change in the underlying portfolio structure or the tranching of the CDO that increases the average tranche risk lowers the risk aversion implied by the overall transaction. For example this effect may be caused by a lower average portfolio quality combined with a less than proportionate increase in tranche credit support. Vice versa, due to relatively larger first loss pieces bond transactions exhibit higher average tranche quality in accordance with higher implied risk aversion.

Information asymmetries and risk premia for idiosyncratic risks add to the picture. Accounting for the amount of risk transferred, there is a significant additional premium on the lowest tranche. Investors in this tranche are hit by losses first. They, more than others, have to examine the details of the loss allocation rules as well as of the underlying portfolio and are compensated by a higher spread.

Lower average portfolio quality and poor diversification probably aggravate information problems. This should show in additional premia. However, tranches that are protected against losses by the first loss piece and least two further rated tranches seem to be shielded well against these problems. Here the respective proxy variables have no significant effect on the implied risk aversion.

For lower tranches the situation is different. Here, higher tranche risk aggravates the information problems and this counteracts the risk effect above. Lowering portfolio diversification leads to *higher* premia in these tranches when holding the ratings constant. This indicates additional premia for unsystematic risks and information asymmetries that in turn make the transfer of credit risk less attractive. Originators react by transferring fewer risks. They choose a higher first loss piece and fewer rated tranches. Thus, good diversification is beneficial for the originator as the lower tranches require less credit spread and more credit risk can be transferred.

To quantify the premia for unsystematic risk more precisely and to specify the effects of information asymmetry on the tranche spreads is a task for future research.

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2.9 Appendix

2.9.1 Loss Rate and Aggregate Wealth

We use Moody's (2007) to estimate the distribution of the cumulative default rate d_t. For each maturity t we take the weighted average of the rating specific cumulated t year default rates as a proxy for the economy-wide default rate. As weight for a rating class we want to use the portion of debtors in this class with respect to all debtors rated by Moody's provided in Moody's (2007). These portions vary slightly over time. In order to avoid a potential bias we use the average portions between 1970 and 2006:

rating class	Aaa	Aa	A	Baa	Ba	B	Caa
proportion	4.64%	13.04%	28.67%	24.66%	17.27%	10.02%	1.61%

For a given maturity and for each year starting 1970 we use these weights to derive the default rate proxy. This yields one time series of cumulative default rates for each maturity. The results show that the lognormal distribution fits this sample of cumulative default rates for the maturities needed reasonably well, i.e. for $t = 1, \ldots, 8$. So, we assume $ln(d_t) \sim N(\mu_t, \sigma_t)$ for all t and estimate the parameters by maximum likelihood. The estimates for the mean and the standard deviation of $ln(d_t)$ and d_t, respectively, are:

t	1	2	3	4	5	6	7	8
μ_t	-4.66	-3.90	-3.48	-3.18	-2.97	-2.80	-2.67	-2.55
σ_t	0.81	0.56	0.51	0.49	0.48	0.48	0.46	0.44
$E(d_t)$	1.24%	2.36%	3.51%	4.66%	5.73%	6.75%	7.65%	8.52%
$Stdev(d_t)$	0.86%	1.29%	1.77%	2.19%	2.63%	3.01%	3.27%	3.49%

Table 2.8: Estimates of the parameters μ_t and σ_t of the lognormal default rate distribution as well as the corresponding mean and standard deviation for maturities t of one to eight years.

Table 2.8 shows two things. The expected default rate increases with time, but at a decreasing rate. Further, the relative width of the distribution, measured either by σ_t or by the ratio $Stdev(d_t)/E(d_t)$, decreases over time.

Given the distribution of losses, how does the distribution of total wealth look like and how does it evolve over time? We normalize the initial total volume of outstanding debt to 100%. In the following we provide an overview of all assumptions made in chapter 2.3 and 2.4.

- A representative bank or investor with leverage of 10, equivalently starting wealth of 10%.
- A credit spread that covers the expected default losses plus five time the expected loss rate as a risk premium.
- A loss given default (LGD) that is normally distributed, truncated between zero and one, with mean of 60% and standard deviation of 10%.
- A correlation of $\rho = 0.5$ between LGD and the default rate.

The latter two are estimation results from Moody's 2007. Additionally we assume a bank refinancing rate of 4%. Given these assumptions and the d_t estimates the expected value of W_t and its respective 95% and 99.9% quantile develop over time according to Table 2.9.

t	1	2	3	4	5	6	7	8
W_t^{max}	14.46%	19.02%	23.35%	27.63%	31.68%	35.14%	38.82%	41.75%
$E(W_t)$	13.71%	17.51%	21.13%	24.69%	28.07%	30.95%	34.02%	36.45%
95% Quantile	12.37%	15.49%	18.32%	21.18%	23.84%	26.02%	28.71%	30.70%
99.9% Quantile	7.56%	9.08%	9.94%	11.34%	12.22%	12.93%	14.99%	16.42%

Table 2.9: Description of the distribution of aggregate wealth given an economy with total outstanding debt volume normalized to 1 = 100% and assuming a starting leverage of 10. Maximum possible wealth W_t^{max}, expected wealth $E(W_t)$ and the 95% and 99.9% quantiles, respectively, are stated for maturities t of one to eight years. W_t^{max} is the wealth when there are no losses at all.

The longer the time horizon, the more dispersed is the wealth distribution. This is obviously true in absolute terms since over a longer time horizon more credit spread accrues in good scenarios and higher losses accumulate in bad scenarios. Table 2.9 shows that in *relative terms* the wealth distribution is stable for maturities of three years and longer. For example the 99.9% (95%) quantile of the wealth distribution equals roughly 45 (85) percent of the expected wealth for any maturity between three and eight years.

2.9.2 Simulation procedure

Starting from a given value of the economy-wide default rate d_t the simulation draws loan specific random variables to determine which loans default until maturity t. Since conditional on d_t loan defaults are independent these variables are constructed independent. For each loan defaulting, the loss given default (LGD), is determined subsequently by drawing a normally distributed LGD-variable (truncated between zero and one). The expected LGD given the default rate d_t is computed as

$$E(LGD|d_t) = E(LGD) + Stdev(LGD) \cdot \left[\sqrt{\rho} \; \frac{ln(d_t) - \mu_t}{\sigma_t} \right] .$$

The standard deviation of the LGD conditional on d_t is given by $stdev(LGG|d_t) = stdev(LGD) \cdot \sqrt{1-\rho}$. The (unconditional) expected value of the LGD for the underlying portfolio, $E(LGD)$, is often explicitly stated in the rating reports of CDO transactions. Sometimes also the (unconditional) standard deviation of the LGD is provided. If this is the case, we use these values from the reports, otherwise we use the estimates from Moody's, i.e. a mean of 60% and a standard deviation of 10%.
Besides of the LGD of a defaulting loan also the time of default is relevant for the transaction, since the premium payments referring to this loan stop at this date.[30] Given a loan defaults during the t years of a transaction, we assume the time of the default to be a discrete random variable with t possible realizations that is independent of all other stochastic factors in the model. The distribution of this random variable depends on the rating and the maturity of the respective loan. For example a loan with a very good rating (Aaa or Aa) is very unlikely to default in its first year. But due to potential subsequent negative rating changes the default probability is disproportionately higher in the following years. For loans with ratings close to the default state, the converse is true: the default probability for the second year given the loan 'survived' the first year will be lower than the default probability of the first year. This finding translates to cumulative default probabilities rising in a convex manner for high rating classes and in a concave manner for low rating classes. We capture this effect with the following procedure:
given rating class j and maturity t years as provided by a rating agency. Then given that loan k with initial rating $j(k)$ defaults until year t, the conditional probability

[30]Recall that this paper deals with synthetic transactions only. If a loan defaults, the SPV covers the losses by selling a part of the (risk free) collateral that was purchased from the issuance proceeds of the tranches. This decreases future interest income. Further, the credit default swap between originating bank and SPV no longer involves this loan. This decreases the premium payments starting from the time of loan default.

$p_{k,\tau|def}$ of default in year $\tau \in \{1, \ldots, t\}$ is

$$p_{k,\tau|def} = \frac{CP_{j(k),\tau} - CP_{j(k),\tau-1}}{CP_{j(k),t}} \quad , \quad \sum_{\tau=1}^{t} p_{k,\tau|def} = 1$$

This equation transforms cumulative default probabilities rising in a convex (concave) manner with rising maturity, into conditional default probabilities that increase (decrease) in t.

After determining the default dates and LGDs for all defaulting loans the subsequent aggregation of all payments and losses yields - for this run of the simulation - the time series of cash flows generated by the portfolio of loans and the time series of losses induced by the same portfolio. In a next step we convert these portfolio cash flows and losses into payments to the various issued tranches using the strict subordination between tranches:

In the year τ in which the cumulated principal losses[31] for the first time exceed the first loss piece, the face value of the tranche ranked lowest is reduced by this exceedance. Consequently the interest payment to this tranche is reduced proportionately to face value at dates $(\tau+1), \ldots, t$. All losses occurring in subsequent years further reduce the face value of the tranche, potentially down to zero - in this case all losses not covered by this tranche are allocated to the next higher tranche, and so on.

In this manner we generate a time series of cash flows for all issued tranches of the transaction for each simulation run. By compounding all interest payments to maturity using the risk free rate and adding the remaining face value that is repaid at maturity we compute the total payoff $P_i^t|d_t$ given d_t for each tranche.[32] The average value of $P_i^t|d_t$ taken from repeated runs of the simulation for the same d_t converges to $E(P_i^t|d_t)$. Subsequently varying d_t yields $E(P_i^t|d_t)$ for every d_t. In order to have a better comparability between transactions of different maturities the tranche repayments are discounted at the risk free rate to the date of issuance.

[31]Recall that synthetic transactions cover losses on principal only and no interest losses.

[32]I.e. we mimic an investor who reinvests all the proceeds earned over the lifetime of the transaction risk free. At maturity of the transaction he receives the final payment and the sum of all compounded coupons. This procedure reduces the model to a one period setting which facilitates the estimations. Note that we assumed a flat risk free interest rate curve at 4% that is constant over time when compounding the coupon payments.

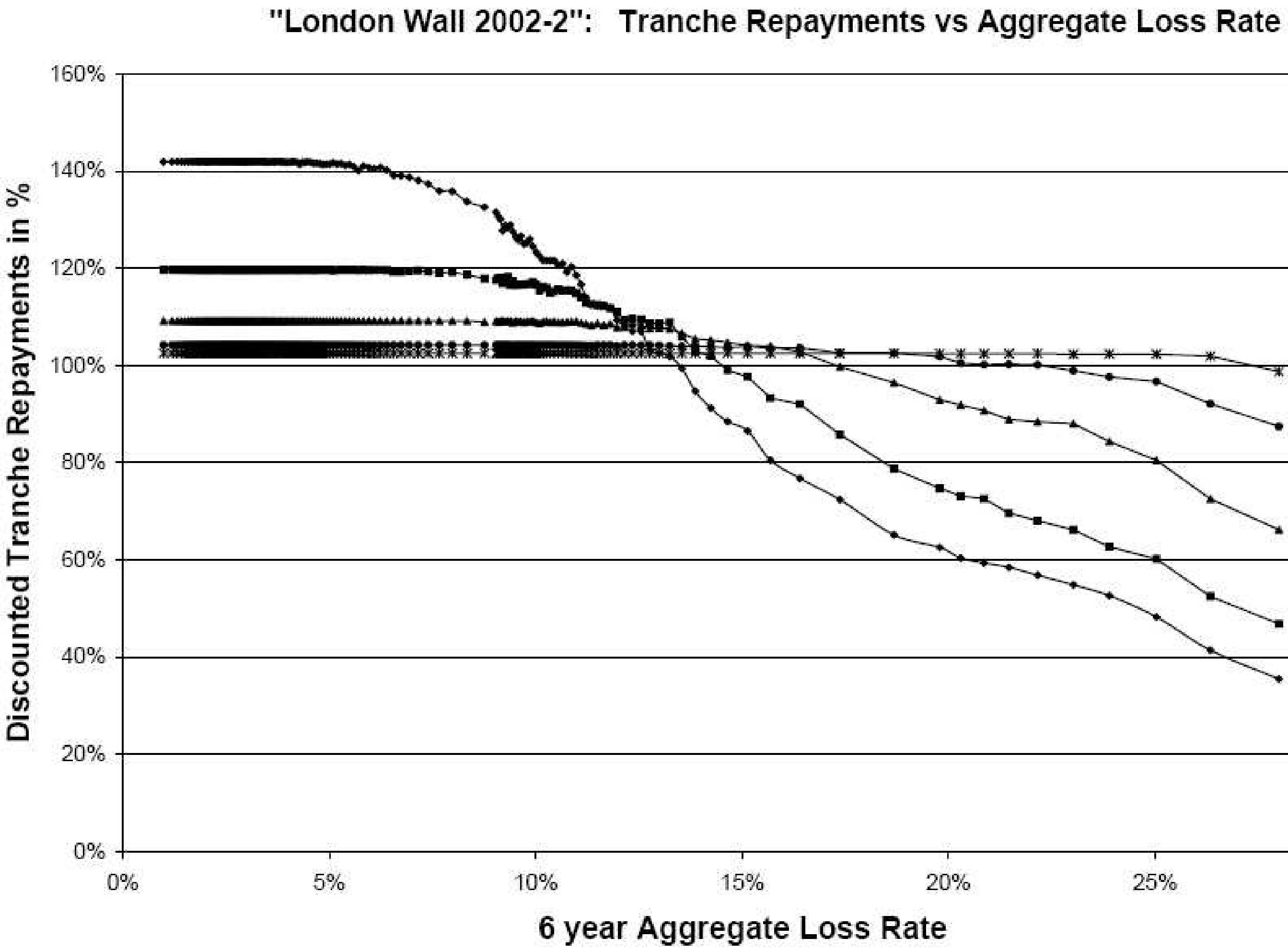

Figure 2.1 (reprint). Simulation results for the discounted expected repayments of five differently rated tranches from the CDO transaction 'London Wall 2002-2', maturity six years, conditional on the six year aggregate loss rate l_6. For high loss rates we use finer data point grids in order to better focus on the relevant cases.

Figure 2.1 depicts the six year cumulative default rate d_6 and the corresponding discounted expected tranche repayments $E(P_i^6|d_6)/(1+r)^6$ for the five tranches of the CLO transaction 'London Wall 2002-2' issued by Deutsche Bank, a six year deal. If the tranche bears no losses, investors will receive the full promised credit spread spr_i in addition to the risk free interest rate r each year $\tau \in \{1, \dots, t\}$ up to maturity. The face value (of 1 €) of the tranche is paid back in year t. The maximum value for P_i^t (at time t) therefore is $P_{i,max} = \sum_{\tau=1}^{t}(r + spr_i)(1+r)^{t-\tau} + 1$. For example, tranche E of 'London Wall 2002-2' is rated Ba1 and pays an annual spread of 8% over the three months Euribor if portfolio losses are sufficiently low. Discounted to issuance this yields close to 1.42 € per € invested. With roughly 4% probability this tranche suffers losses, this predominantly in 'bad' states with high default rates and corresponding low wealth. A risk neutral agent would not be influenced by this fact, her price for the tranche would be the expected value under the statistical measure, in this case 1.39 €. Risk averse investors will take the state dependence of tranche repayments into account. Relatively low repayments in 'bad' states are weighted higher by the pricing kernel function than in the risk neutral case, repayments in states with higher wealth are weighted relatively lower. In case of tranche E of 'London Wall 2002-2', a risk aversion coefficient of $\gamma_k = 4.54$ solves equation (2.2). The parameters of relative risk aversion computed for the tranches D to A are 4.16, 4.01, 4.07 and 7.54. The respective tranche ratings are Baa2 for tranche D, A2 for tranche C, Aa2 for tranche B and Aaa for tranche A. Note that the impact of the aggregate loss rate on the tranche repayments is higher the 'worse' the states are, i.e. when the default rate is high. In the better than average states[33] the default rate has no impact on tranche repayments at all, since the first loss piece provides enough loss protection. This holds for all deals. Of course, the size of the region where changes in the default rate do not matter differs between transactions. Within the same transaction this region is larger the higher the loss protection of a tranche, i.e. the higher the position of the tranche within the transaction.

For each value of d_t, one hundred simulations are run. The value of d_t is varied along its distribution to mimic 100 representative cases, the first being the 0.5% quantile of the loss rate distribution as a proxy for the distribution between zero and the 1% quantile the second being the 1.5% quantile etc. Since for high d_t the impact on repayments is stronger, a finer grid of quantiles is used with each quantile correspondingly carrying a lower weight. For the highest five percent of the d_t distribution, the 'worst' 5 percent of cases, one grid point is used for every 0.1% of the distribution. For the highest 0.2 percent of the loss rate distribution one grid point is used for every 0.02% of the distribution. This way, 10+48+95=153 different values of d_t are used resulting in 15,300 simulation runs per transaction.

2.9.3 Modelling dynamic transactions

When analyzing a dynamic CDO transaction with maturity of t years, we have to proceed in several steps. We assume all loans of the *initial* portfolio to have the same rating j_1 and the same maturity $\tau_1 < t$. Consequently the loans will be paid back at time τ_1. At time τ_1 we have to check whether any replenishment criteria are breached. If so, we assume the transaction ends at τ_1. If no replenishment criteria are breached,

[33] States in which the default rate d_t is below its average $E(d_t)$.

we assume the originator replenishes and replaces the loans by new ones with average rating of j_2 and maturity τ_2. We assume j_2 and τ_2 to comply with the minimum criteria described in the offering circular.[34] At time $\tau_1 + \tau_2$ we again assume loans are replaced by new loans with the respective minimum characteristics - given no violation of the replenishment criteria - and so on, until the maturity $t = \sum_j \tau_j$ of the CDO transaction is reached. For each of these steps we take the expected default probability from the rating tables like in the static case.

In a static t-year-deal the t-year-default rate determines the portfolio default probability. In a dynamic transaction the final repayment will - due to the replenishments made in the portfolio - depend on a sequence of realizations of the sub-period default rates $S_{\tau_1}, \dots S_{\tau_J}$. These realizations cannot be drawn independently since, especially for shorter time periods, e.g. one or two years, the successive default rate is highly positively correlated to the preceding ones. We take these autocorrelations into account by drawing the subsequent default rate from a distribution conditional on the realization of the preceding ones.[35] Finally, from this sequence we compute the the overall t year cumulative default rate as $1 - (1 - s_{\tau_1}) \cdot \ldots \cdot (1 - s_{\tau_J})$.

2.9.4 Comparing Credit Risk Models

In contrast to the model implemented in this paper where the macro factor influence on single name default probabilities is modelled directly, Franke and Krahnen (2005), Krahnen and Wilde (2006) and Hein (2006) use an approach that depends on latent variables. In a Monte Carlo simulation these latent variables drive yearly rating-migrations of the underlying loans. This method approximately corresponds to the simulations implemented in valuation tools of Moody's and S&P.[36] In every run of the simulation and for each year of the transaction a stochastic migration variable is drawn for each loan in the portfolio. Depending on the quantile of the migration variable either the rating class of the loan remains unchanged or the loan is up- or downgraded by one or more rating notches. A downgrade to rating class 'D' means that the loan defaults. The limits of these quantiles are calibrated to the historic rating migration matrices of the respective rating agency.[37] The migration variables are

[34] Note that 'minimum criterium' with respect to the maturity of the securitized loans means the *longest* maturity allowed.

[35] Using a logarithmic transformation allows us to use the standard formula for conditional normal distributions. See, e.g. Greene, 2003, p.871f.

[36] These approaches are, in turn, based on the CreditMetrics framework, see Gupton et al (1997).

[37] See, e.g., www.sandp.com for a description of the S&P evaluator.

assumed to be independent over time but correlated between firms within the same year. This correlation structure is modeled by drawing the loan specific migration variables from the marginal distribution of a multivariate normal distribution whose covariance matrix possesses a certain structure reflecting the composition of the loan portfolio. In Franke/Krahnen and Hein this multivariate normal distribution is generated by a Cholesky transformation of previously independent migration variables. Krahnen/Wilde decompose each migration variable into several systematic factors and one idiosyncratic factor. By varying the factor loadings for the different systematic factors they can implement any correlation structure. In the easiest case - with one macro factor M - the latent migration variable y_k of obligor k is defined as

$$y_k = M \cdot \sqrt{\rho} + \epsilon_k \cdot \sqrt{1-\rho} \quad . \tag{2.6}$$

All ϵ_k are independent. M and ϵ_k and thus also y_k are standard normal. Obligor k defaults, if y_k falls beneath a certain threshold ζ_k. In this setting the macro factor M can best be interpreted as the average rate of return on corporate assets in an economy. Consequently, ρ is called *asset correlation*. Conditional on M rating migrations and defaults are independent.

Default Event Correlations

In the model used in this paper high (low) realizations of the default rate in the economy lead to high (low) default probabilities of all the loans leading to correlated default events. Default correlation drives the width of the loss distribution of a loan portfolio. In a latent variable model default correlation is induced by plugging some asset correlation into equation (2.6).
Generally, the correlation between the default events of two loans i, j with (unconditional) probabilities of default $\overline{PD_i}$ and $\overline{PD_j}$ is given by

$$Corr_{i,j} = \frac{\overline{PD_{i,j}} - \overline{PD_i} \cdot \overline{PD_j}}{\sqrt{\overline{PD_i} - \overline{PD_i}^2} \cdot \sqrt{\overline{PD_j} - \overline{PD_j}^2}}$$

where $\overline{PD_{i,j}}$ denotes the (unconditional) joint default probability of both loans. In this equation only $\overline{PD_{i,j}}$ depends on the modelling assumptions. In the credit risk model used here the default probability of a given loan i is seen as a random variable - yet conditional on the realizations of the default rate in the economy d_t it is constant:

$$PD_i(d_t) = \overline{PD_i} \cdot \frac{d_t}{E(d_t)} \quad .$$

The joint default probability *conditional on* d_t therefore also is constant:

$$PD_{i,j}(d_t) = \overline{PD_i} \cdot \frac{d_t}{E(d_t)} \; \overline{PD_j} \cdot \frac{d_t}{E(d_t)} \quad .$$

To get the unconditional joint default probability $\overline{PD_{i,j}}$ we have to compute the expected value over all possible realizations d_t:

$$\begin{aligned}\overline{PD_{i,j}} = E(PD_{i,j}(d_t)) &= E\Big(\overline{PD_i} \cdot \frac{d_t}{E(d_t)} \overline{PD_j} \cdot \frac{d_t}{E(d_t)}\Big) \\ &= \overline{PD_i} \cdot \overline{PD_j} \cdot E(\frac{d_t^2}{(E(d_t))^2}) \quad .\end{aligned}$$

In comparison, from equation (2.6) the joint the joint default probability can be written as

$$\overline{PD_{i,j}} = PD_{i,j} = \mathcal{N}_\rho(N^{-1}(PD_i), N^{-1}(PD_j)) \quad ,$$

where $\mathcal{N}_\rho(.,.)$ denotes the cumulative distribution function of the bivariate normal distribution with correlation coefficient ρ and $N^{-1}(.)$ denotes the inverse cumulative distribution function of the univariate normal distribution.

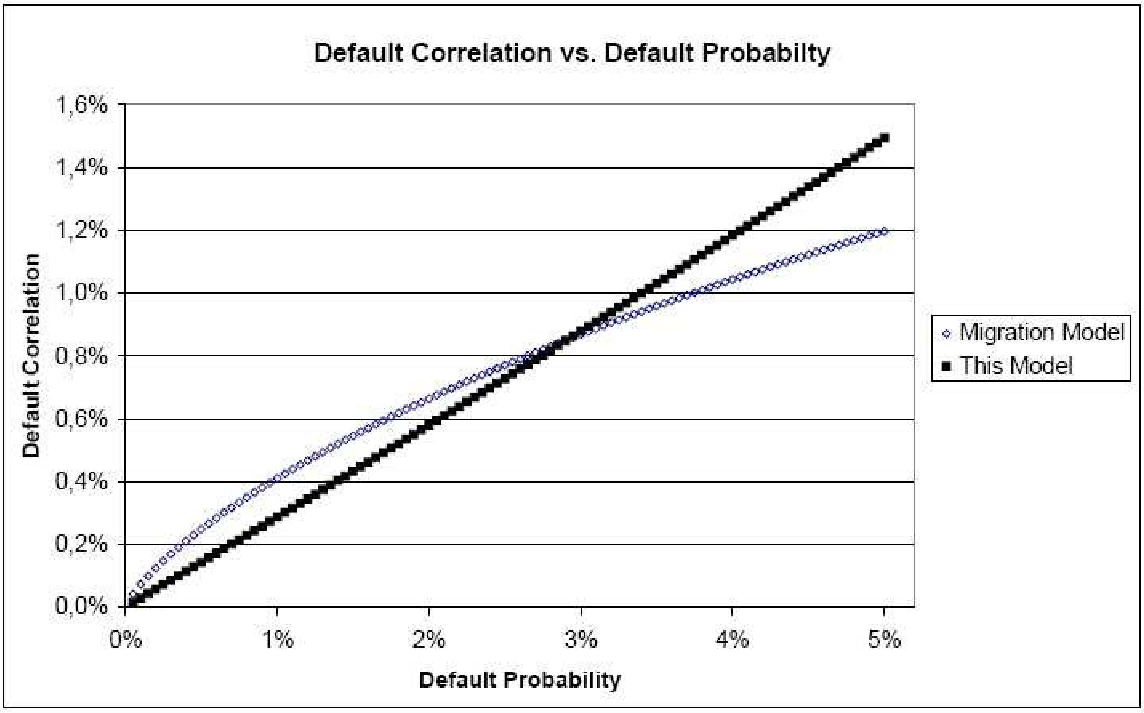

Figure 2.8: Default event correlations of two identical loans for different default probabilities. Diamonds: values for a one factor migration model with uniform asset correlation of $\rho = 6\%$. Squares: values for one factor CreditRisk+ type model used in this paper.

For both models this yields default correlations that increase with rising $\overline{PD_i}$, $\overline{PD_j}$.

This is in line with empirical observations.[38] For equally rated loans (i.e. $\overline{PD_i} = \overline{PD_j}$) Figure 2.8 shows the relationship between default probabilities and default event correlations for the two models. Empirical results for the asset correlation to be plugged into the migration model vary. Akhavein et al (2005) use data from Fitch ratings on US corporates and retrieve five year inter- and intra-industry asset correlations of 4.56% and 7.85%, respectively. Five years is the average maturity of the CDOs analyzed in this paper. Since equation (2.6) only considers one macro factor and therefore a uniform pairwise asset correlation, we fix ρ at 6%.

90% of the investigated CDO transaction display an average default probability of their loans below five percent, only one portfolio exceeds six percent. Figure 2.8 shows that within this range the model used here generates default event correlations similar to those of a migration model with a uniform asset correlation of six percent.

[38] See, e.g. Schwarz (2005) for evidence from Austria for small and medium sized companies.

Chapter 3

How to react to the Subprime Crisis? - The Impact of an Interest Rate Freeze on Residential Mortgage Backed Securities

3.1 Introduction

Starting in mid 2007, rising delinquency and foreclosure rates in the US subprime mortgage market triggered a severe financial crisis which spread around the world. Although subprime mortgages, that were granted to borrowers with weak credit record and often require less documentation, only account for about 15 percent of all outstanding US mortgages, they were responsible for more than 50 percent of all mortgage loan losses in 2007.[1] Most of the subprime losses were caused by high foreclosure rates on hybrid adjustable rate mortgages (ARM). These loans offer fixed initial interest rates at a fairly low level, which are replaced by higher rates linked to an interest rate index after two or three years.[2] Thus, borrowers face a significant payment shock after the interest reset which increases the probability of delinquencies. In previous years, rising real estate prices and, thus, increasing home owner equity enabled mortgage associations to waive part of delinquent interest payments in exchange for an increase in nominal value of the mortgage or to renegotiate the mortgage. But during the last year the trend in real estate prices has reversed in many regions of the United States leading to "negative equity" of many borrowers, i.e. to real estate values that are lower than their outstanding debt. Consequently, default rates increased.[3]

Several policy options have been discussed to tackle this crisis. The primary concern of policy makers was to lower the financial burden of subprime borrowers and, thus, to avoid further delinquencies and foreclosures which in turn may stabilize house prices. The first policy option is to provide direct financial support by disbursing money to borrowers. In fact, this has been done in February 2008 by means of the *Economic Stimulus Act 2008*, which included tax rebates amounting from $300 to $600 per person. Whereas this policy action benefited every tax payer and was not directly linked to the mortgage loans, the *Housing Bill* of July 2008 was especially targeted to subprime borrowers. Here a second policy option was taken by providing state guarantees for mortgage loans. Thus, borrowers, who are close to foreclosure, can refinance their loans at lower interest rates. Although both policy actions certainly help to improve the situation of borrowers, the big drawback of these instruments is that they are mainly financed by the tax payer who cannot be blamed for the crisis. In contrast, mortgage banks, who have been criticized for lax lending standards[4], benefit from less defaults without accepting a responsibility.

[1] See *International Monetary Fund* (2008).

[2] According to the *IMF* (2008), $ 250 billion subprime mortgages are due to reset in 2008.

[3] Mortgage loan contracts in the United States often exclude personal liability such that borrowers do not face any further financial burden when they default.

[4] See, for example Keys et al. (2008).

A third policy option, which takes the banks' failure into account and which was proposed by the US government on December 6th, 2007, is an interest rate freeze. This means that banks agree to waive (part of) the interest rate step up on their ARMs. Although this proposal did not become effective it raises the question whether such an instrument may be better suited to mitigate the current crisis. The aim of this paper is therefore to investigate the implications of an interest rate freeze.

Of course, subprime debtors will benefit from this measure through reduced interest obligations. In contrast, the effect on the lenders is not a priori clear. On the one hand, they receive lower interest on a significant portion of mortgage loans. On the other hand, they might benefit in a twofold way. First, the number of defaults potentially declines. Second, the average loss given default (LGD) might be lower when house prices stabilize. Consequently, there will be a shift in the repayment distribution of the mortgage loan portfolio, which will be examined in the paper.

But the impact of an interest-rate freeze is not limited to borrowers and lenders. More than half of all subprime mortgages that were granted in recent years were sold in residential mortgage backed securities (RMBS). In these RMBS transactions cash flows from the underlying mortgage pool are allocated to tranches with different seniority: several rated tranches and an equity tranche. Due to a priority of payments scheme the equity tranche absorbs most of the losses whereas the senior tranche exhibits only low risk. Part of the RMBS tranches were purchased by outside investors, i.e. foreign banks, non-mortgage banks, insurance companies. As (part of) the mortgage interest payments is used to cover losses that otherwise might hit the rated tranches, RMBS investors lose part of their loss protection following an interest rate freeze. However, they also benefit from potentially lower default losses. The combined effects lead to a reallocation of cash flows and losses among investors which will also be analyzed in this paper.

Throughout the paper we look at three sample portfolios: two subprime RMBS portfolios, from which one is well diversified across regions and the other is geographically concentrated in regions that are later hit hardest by the crisis, and one portfolio representing the US mortgage market as a whole. First, we simulate the stochastic repayments of each single mortgage loan using Monte Carlo simulation. In particular, we use the regional house price index as the systematic factor driving the default rate as well as the loss given default. Additionally, we assume that each increase in the payment obligations of a debtor, e.g. through an interest rate step up, raises the default probability. Taking regional diversification into account, we aggregate the single payments to get the repayment distributions of the mortgage loan portfolios underlying the different RMBS transactions.

For all three portfolios we further assume a true-sale RMBS transaction with four differently rated tranches and an equity piece. We use a benchmark scenario without crisis elements to calibrate the sizes and loss protection of the tranches to the respective rating. This scenario includes an interest rate step-up after year two for non-prime mortgage loans.

Subsequently, we derive the portfolio repayment distributions and the resulting tranche characteristics in a crisis scenario that reflects the current situation in the United States. In particular, the average house prices are assumed to have decreased by six percent in the second year of the RMBS transaction. As we show, the crisis leads to a significant reduction of the expected discounted cash flows of the respective portfolios ranging from five percent for the US market portfolio to more than 15 percent for the non-diversified subprime portfolio. Hence, the equity piece often does not suffice to cover the losses which means that the rated tranches need to absorb a significant share of the portfolio loss. Consequently, the risk characteristics of all tranches worsen as compared to the benchmark case which makes severe downgrades necessary as observed in the markets.

Starting from this crisis scenario we investigate the impact of an interest rate freeze. We assume all scheduled interest rate step-ups to be waived which decreases the claims on the RMBS portfolio. As subprime borrowers evade this payment shock, foreclosure rates decrease. First, we study only this direct effect of an interest rate freeze. Our simulation results show that the net change in expected portfolio payments is negative as is the effect on most tranches. The consequences are not uniform for all tranches however: the better the tranche, the less its characteristics deteriorate. The senior tranches of the two subprime RMBS even improve.

In the second case, we additionally include a positive 'second round' effect on house prices. In particular, the lower number of foreclosures takes pressure off the housing market resulting such that the negative downward trend is stopped. Given this combined impact, our results indicate that the positive effects are able to (over-)compensate for the loss due to the interest rate freeze. In particular. all rated tranches benefit in this scenario as compared to the crisis scenario. Therefore we conclude that an interest rate freeze on mortgage loans does not only improve the debtor situation, but might also render investors in RMBS tranches better off at the expense of the equity tranche which takes most of the crisis losses.

The remainder of this paper is structured as follows. First we comment on related literature. Section 3 describes the set-up and calibration of our simulation model. In section 4, we analyze the effects of a mortgage crisis on our sample mortgage portfolios and also on RMBS-tranches backed by these portfolios. Furthermore, we investigate the consequences of an interest rate freeze on portfolio and tranche characteristics. Section 5 concludes.

3.2 Literature Review

Our paper is closely related to the empirical study by *Cagan* (2007) analyzing the impact of an interest rate reset in adjustable rate mortgages (ARM). Based on a dataset of ARMs originated between 2004 and 2006, he estimates that 59% of these mortgages face a payment increase of more than 25% after the initial period with low rates. He anticipates that in total approximately 13% of adjustable-rate mortgages will default due to the interest rate reset, which corresponds to 1.1 million foreclosures over a total period of six to seven years. This increase in default rates is not equally distributed across all mortgages but depends on the size of the interest rate step-up and the loan-to-value ratio. Additionally, the author estimates that each one-percent fall in national house prices causes an additional 70,000 loans to enter reset-driven foreclosure. Given a house price drop of 10% he projects that more than 22% of ARMs will default due to the interest rate reset. This underlines the impact of a policy reaction to scheduled interest rate step-ups in the present market environment.

Ashcraft and Schuermann (2008) discuss the securitization of subprime mortgages. First they provide a detailed analysis of the key informational frictions that arise during the securitization process and how these frictions contributed to the current subprime crisis. They also document the rating process of subprime mortgage backed securities and comment on the ratings monitoring process. They conclude that credit ratings were assigned to subprime RMBS with significant error which has led to a large downgrade wave of RMBS tranches in July 2007.[5]

Several further research articles provide general information about subprime loans and the current mortgage crisis. *Chomsisengphet/Pennington-Cross* (2006) comment on the evolution of the subprime market segment. In particular, some legal changes in the beginning of the 1980s, which allowed to charge higher interest rates and higher fees on more risky borrowers and which permitted to offer adjustable rate mortgages,

[5] In fact there was a second downgrade wave in the beginning of 2008 on which the authors do not comment.

enabled the emergence of subprime loans. The Tax Reform Act in 1986 allowing interest deductions on mortgage loans made high loan-to-value (LTV) ratios financially more rewarding and, thereby, subprime mortgages more attractive. In the beginning of the 1990s the increasing use of securitizations as funding vehicles triggered rapid growth in the subprime mortgage market. Between 1995 and 2006 the volume in this market segment increased from $65 billion to more than $600 billion and also the share on the total mortgage market significantly increased.[6] At the same time the percentage of the outstanding subprime loan volume being securitized went up from about 30% to around 80%.[7] *Dell' Ariccia et al.* (2008) show that the rapid expansion of the subprime market was associated with a decline in lending standards. Additionally, they find that especially in areas with higher mortgage securitization rates and with more pronounced housing booms lending standards were eased. Lower lending standards can thus be identified as one reason for the subprime mortgage crisis.

According to the *IMF* (2008), subprime borrowers typically exhibit one or more of the following characteristics at the time of loan origination: weakened credit histories as indicated by former delinquencies or bankruptcies, reduced repayment capacities as indicated by low credit scores or high debt-to-income ratios and incomplete credit histories. Given this very broad definition subprime borrowers are not a homogeneous group. For example, Countrywide Home Loans, Inc. distinguishes four different risk categories of subprime borrowers.[8] These subcategories may depend on the borrower's FICO (Fair Isaac Corporation) credit score, which is an indicator of the borrowers credit history, the Loan-To-Value (LTV) ratio of the mortgage loan.and the debt-to-income ratio.[9] Analyzing a data set of securitized loans from 1995 to 2004, *Chomisengphet/Pennington-Cross* (2006) find strong evidence for risk-based pricing in the subprime market. In particular, interest rates differ according to credit scores, loan grades and loan-to-value ratios.

Using a dataset of securitized subprime mortgages from 2001 to 2006, *Demyanyk/Hemert* (2007) compare the characteristics of different loan vintages in order to identify reasons for the bad performance of mortgages originated in 2006, which triggered the subprime mortgage crisis. Their sample statistics show that the average FICO credit score increased from 620 in 2001 to 655 in the 2006 vintage, which corresponds to the observation that the market expanded in the less risky segment. During the same

[6]See also *Kiff/Mills* 2007.

[7]See also *Keys et al.* (2008).

[8]See www.cwbc.com or *Chomsisengphet/Pennington-Cross* (2006).

[9]*Kiff/Mills* (2007) classify a mortgage as subprime if the LTV is above 85% and/or the debt-to-income ratio exceeds 55%.

period average loan size increased from \$151,000 to \$259,000 whereas the average loan-to-value (LTV) ratio at origin stayed approximately the same at 80%. Applying a logit regression model to explain delinquencies and foreclosure rates for the vintage 2006 mortgages, *Demyanyk/Hemert* (2007) identify the low house price appreciation as the main determinant for the bad performance. Also *Kiff/Mills* (2007), who comment on the current crisis, see the slow down in house prices as the main driver for the deterioration in 2006 vintage mortgage loans. Furthermore they emphasize that although the average subprime borrower credit score increased during the last years, also LTV and debt-to-income ratios increased, which made the mortgages more risky.

Gerardi et al. (2007) analyze a dataset of homeownership experience in Massachusetts. They find that the 30 day delinquency rate shows rather limited variance as it fluctuates between 2 % and 2.8 % of borrowers. Further, there is no significant correlation to the change in house prices. In contrast, they find a strong negative correlation between foreclosure rates and the house price index over the whole sample period from 1989 to 2007. In particular, *Gerardi et al.* point out that the house price decline starting in summer 2005 was the driver of rising foreclosure rates in 2006 and 2007. These findings show that the house price index drives the portion of delinquent mortgages that are foreclosed rather than the number of delinquencies themselves.

Estimating cumulative default probabilities they further find that subprime borrowers default six times as often as prime borrowers. This corresponds to *Pennington-Cross* (2003) who also compares the performance of subprime to prime mortgage loans and finds that the latter are six times more likely to default and 1.3 times more likely to prepay. Analyzing the determinants of default he concludes that for both - prime and non-prime loans - decreasing house prices as well as increasing unemployment rates increase credit losses.

All these empirical studies indicate a strong relationship between mortgage loan defaults and house price appreciation in the subprime market. This corresponds to the theoretical literature on mortgage loan default. According to option pricing theory a borrower, who is not personally liable, should default when the associated put option is in the money, e.g. when the mortgage debt exceeds the house value. Therefore we will use the house price index as the main determinant of default in our simulation model.

3.3 Model Set-Up

Our analysis is based on a cashflow simulation model. Mortgage loans are more likely to default when they are in "negative equity", i.e. when the current real estate value is lower than the outstanding debt. This event is usually triggered by a downturn in the house price. Therefore we use a macro factor representing the regional house price index as the systematic determinant of default. We assume the regional house price index to have a nationwide and a regional component. The house price at default further determines the loss incurred in a distressed sale following a foreclosure.

Payment shocks due to interest rate resets can cause additional foreclosures, especially when house prices have already declined. We account for this by adding a function depending on changes in payment obligations to the idiosyncratic debtor component of our model.

3.3.1 Simulation Model

RMBS are usually backed by mortgage loans from different regions. This regional diversification reduces the variance of the repayment distribution of the mortgage portfolio and thereby helps to make the rated tranches less risky. For each region we assume the regional house price index (HPI) to be the main driver of the foreclosure rate. Further, for each region k we decompose the percentage change of the HPI in year t into an overall positive long-term trend c and a deviation from this trend driven by a nationwide factor M_t and an orthogonal regional factor $B_{k,t}$:

$$\Delta HPI_{k,t} = c + a \cdot (\sqrt{\rho_M} M_t + \sqrt{\rho_k} B_{k,t}) = f(M_t, M_{t-1}, B_{k,t}, B_{k,t-1}) \tag{3.1}$$

Unconditionally, M_t and $B_{k,t}$ are assumed to be standard normally distributed. Empirical evidence suggests, however, that house price changes display a strong positive autocorrelation.[10] Therefore we incorporate a first-order autocorrelation of 0.5 for each factor. Thus, conditional on M_{t-1}, M_t has a mean of $0.5 \cdot M_{t-1}$ and a standard deviation of $\sqrt{0.75}$. The same holds for the regional factors.

ρ_M and ρ_k account for correlations of house price changes across and within regions. We calibrated the nationwide and regional correlations to $\rho_M = 0.1$ and $\rho_k = 0.2$ and the scaling factor to $a = 0.1$. This implies unconditional standard deviations of 5.5% (3.7%) for annual regional (nationwide) house price changes which is in line with

[10] In an empirical study based on 15 OECD countries *Englund and Ioannidis* (1997) estimate an average first-order autocorrelation coefficient of 0.45.

empirical evidence.[11] The unconditional mean annual change of the HPI equals the long-term trend c on both, the regional as well as the national level.

For the loans in the underlying mortgage pool we distinguish five debtor groups by credit quality: Prime, Alt-A, Subprime 1, Subprime 2 and Subprime 3. These groups can be interpreted as representing different ranges of the FICO score and further borrower characteristics like payment history and bankruptcies.[12] The assumed expected default probabilities for the different debtor groups and maturities are shown in the credit curves in Table 3.2 in Appendix 3.7. The numbers correspond to empirical evidence (see e.g. *Gerardi et al.* 2007).

In each simulation run a path of annual group migrations is computed for each loan in the portfolio. For debtor i located in region k this path depends on a series of latent migration variables $L_{i,k,t}$, $t = 1, \ldots, 7$. In this respect our simulation model resembles a migration model for the assessment of collateralized loan obligations where debtors can "migrate" between different rating groups.[13]

At each annual payment date t, we derive the latent variable

$$L_{i,k,t} = \frac{1}{a}(\Delta HPI_{k,t} - c) + \sqrt{1 - \rho_M - \rho_k} \cdot \varepsilon_{i,t} \quad \text{with } \varepsilon_{i,t} \text{ iid } \mathcal{N}(0,1) \; . \tag{3.2}$$

If the value of the latent variable $L_{i,k,t}$ lies above (below) a certain threshold, which corresponds to the quantile of the standard normal distribution associated with the migration probabilities in the so-called migration matrix, the mortgage is upgraded (downgraded) to the respective debtor category. Panel A of Table 3.2 shows the unconditional expected annual migration probabilities for years without changes in interest obligations as well as the corresponding multi-year cumulative default probabilities. The numbers are chosen to match the empirical findings on prime and subprime default rates of *Geradi et al.* (2007). Since these numbers are estimated from a time series between 1987 and 2007, they already incorporate the positive long-term trend in house prices. Consequently we subtract the long-term trend c from our house price

[11]There exist different house price indices for the US. For example, Freddie Mac's Conventional Mortgage Home Price Index (CMHPI-Purchase Only) shows a standard deviation of 3.8% (nationwide) and 5.2% regionally, since 1975.

[12]There exist no general classification scheme of mortgage loans except for the distinction between Prime, Alt-A and Subprime. Nevertheless it is common to further subdivide the subprime category into several grades (see *Chomsisengphet/Pennington-Cross* 2006).

[13]In general, either migration models or factor models are used to model loan defaults. E.g. in the literature on securitization, *Franke/Krahnen* (2006) simulate rating transitions whereas *Hull/White* (2004) use a one-factor model and *Duffie/Garleanu* (2001) as well as *Longstaff/Rajan* (2008) apply multi-factor models in their analysis. We use a mixture of these two approaches.

changes such that only the deviation from the expected (positive) long-term growth during the last years enters the latent variable.

Due to our assumption of positive autocorrelation in house price changes, our latent variable is not necessarily standard normally distributed, but only normally distributed and the mean depends on the previous realizations. As the thresholds for $L_{i,k,t}$ stay unchanged this yields higher (lower) downward migration and default probabilities in years where negative (positive) house price changes are expected.[14]

As can be seen in equations (3.2), ρ_M and ρ_k also account for correlation of loan defaults across and within regions. Given our calibrated numbers, 30% (= 0.1 + 0.2) of the default risk is due to systematic risk in house price changes and 70% is due to idiosyncratic risks. The idiosyncratic component is given by $\varepsilon_{i,t}$, which includes borrower specific shocks like unemployment, illness or divorce. A payment shock resulting from an increase in interest obligations of a debtor adds to the idiosyncratic risk. We capture this by subtracting a deterministic term from the latent variable in the year of an interest rate step-up. In total,

$$L_{i,k,t} = \frac{1}{a}(\Delta HPI_{k,t} - c) + \sqrt{1 - \rho_M - \rho_k} \cdot \varepsilon_{i,t} - b_i(r_{i,t} - r_{i,t-1}) \quad , \tag{3.3}$$

where $r_{i,t}$ denotes the contractual interest rate of loan i in year t. The impact factor b_i determines the magnitude of the payment shock and is calibrated for each debtor group separately: We chose b_i such that the number of additional defaults due to an interest rate reset matches the forecast made in Cagan (2008) for the corresponding percentage interest rate step-up and loan-to-value ratio.

In our simulations we assume an interest step-up in year three by 1% for all Alt-A loans and by 2% for all Subprime loans. Together with the impact factors (see Table 3.3) this implies higher downgrade and also higher default probabilities in year 3 as shown in the stressed one-year migration matrix given in Panel B of Table 3.2. Applying this stressed migration matrix in the year of the interest rate freeze, significantly increases multi-year default probabilities even though migration probabilities are assumed to return to the 'normal' case in the following years.

For simplicity we consider interest only mortgages, i.e. in each year, in which the mortgage stays in one of the five debtor categories, only interest payments are made

[14]Hence, our migration model implicitly accounts for endogenous migration thresholds which is an extension to classical migration models where always standard normally distributed migration variables are drawn.

whereas the total nominal value is due at final maturity.[15] The interest rate consists of a variable base rate and a spread component. The amount of the spread is determined by the debtor category of the mortgage at the beginning of the transaction. In case of default we assume the real estate to be sold in a distress sale with a discount of q percent of the current market value. Given the HPI of date t defined as:

$$\begin{aligned} HPI_{k,0} &= 1 \\ HPI_{k,t} &= \prod_{\tau=1}^{t}(1+\Delta HPI_{k,\tau}) \end{aligned} \tag{3.4}$$

the percentage loss given default of a mortgage in region k at date t is then derived as

$$LGD_{i,k,t} = 1 - \underbrace{(1-q)}_{\text{percentage proceed in distressed sale}} \cdot \underbrace{\frac{1}{LTV}HPI_{k,t}}_{\text{1/LTV at date } t} \tag{3.5}$$

Thus, we implicitly account for a positive correlation between foreclosure rates and loss given defaults. Due to the definition of our latent variable, a decline in HPI triggers higher default rates and at the same time implies higher loss given defaults.

Having derived the annual portfolio cash flows we calculate the sum of discounted cash flows net of transaction costs (DC_n) for each simulation run n:

$$DC_n = \sum_{t=1}^{T} \frac{CF_{n,t}}{(1+r_f)^t} - PV(TC) \tag{3.6}$$

where $CF_{n,t}$ denotes the portfolio cash flow at date t and $PV(TC)$ the present value of annual transaction costs. Dividing this figure by the initial portfolio volume we get a proxy for the relative value of the underlying portfolio. We perform 10,000 simulation runs and determine the distribution of this portfolio value as well as several statistics like mean, standard deviation and 99%-quantile.

Given the simulated portfolio cash flows at each annual payment date we subsequently derive tranche payments. We assume that all losses (interest and principal) are first covered by the excess spread of the transaction, i.e. the difference between the interest income from the underlying portfolio and the interest payments to the rated tranches net of transaction costs, and then by reducing the nominal value of the equity tranche. Further, we assume the existence of a reserve account which means that if the excess

[15] According to *Ashcraft/Schuermann*(2008) only about 20 percent of mortgage loans in MBS pools are interest only. Other loans mostly pay annuities, which mainly comprise interest payments in the first years, and may even contain a grace period of two to five years in which only interest is paid. Since we only consider a seven year RMBS transaction, our assumption seems to be reasonable.

spread of one period is not wiped out by period losses, the excess cash flow is collected in this account earning the risk-free rate and providing a cushion for future losses.[16] The holder of the equity tranche does not receive any payments until maturity when he receives the remaining cash flow of the transaction. If the equity tranche has been reduced to zero due to previous losses, the face value and subsequently the interest claim of the lowest rated tranche is reduced to cover the losses. If this tranche claim has already been reduced to zero, the next tranche is used to cover the losses, etc.

3.3.2 Sample Transactions

Throughout our analysis we consider three illustrative sample portfolios: two subprime mortgage portfolios and one representing the US mortgage market as a whole. The former only include Alt-A and subprime mortgage loans and differ with respect to their regional diversification. The latter predominantly consist of prime (60%) and Alt-A loans (25%). Five percent each fall in the three subprime classes giving a total subprime share of 15% for the portfolio which roughly resembles the subprime portion in the US mortgage market. The explicit portfolio compositions are given in Table 3.3 in Appendix 3.7.

Each mortgage is assumed to pay the risk-free rate, which is assumed to be constant at 4%, plus a spread ranging between 150 and 400 basis points differentiated by debtor category as shown in Table 3.3. Further we assume that mortgage loans with an initial subprime (Alt-A) rating include an interest rate step-up of 2% (1%) after two years, i.e. all spreads are increased by 200 bps (100 bps) after this initial period.[17] The long-term trend is house prices is assumed to be $c = 3\%$, the loan-to-value ratio at origin is 90% for each mortgage[18] and the discount in case of a distressed sale is $q = 30\%$.[19] Geographically we differentiate five regions[20]: Pacific, North Central

[16]According to *Ashcraft/Schuermann* (2008) excess spread is at least captured for the first three to five years of a RMBS deal, which justifies the assumption of a reserve account.

[17]This step-up is assumed to be fixed at loan origination and is independent of possible downward migrations until the reset date.

[18]*Gerardi et al.* (2007) report a mean LTV ratio of 83% and a median of 90% in the last three years.

[19]*Pennington-Cross* (2004) provides a survey study on the discount in case of a distressed sale and finds that foreclosed property appreciates on average 22% less than the area average appreciation rate. Given that foreclosures also lead to additional costs, we will assume a discount of 30% on the current market value in our simulation analysis. *Cagan* (2007) also states that foreclosure discounts of 30% are quite usual.

[20]We followed the regions defined in Freddie Mac's Conventional Mortgage Home Price Index but pooled some neighbouring regions.

(including Mountain), South Central, Atlantic (middle and south) and New England. The first subprime portfolio is concentrated in Pacific (40%) and New England (40%), the regions to perform worst in the crisis, the remaining 20% are North Ventral and Mountain. The other two portfolios are well diversified across all regions.

First we simulate payments for the portfolios in the benchmark case, i.e. without any crisis. In year 3 the latent variable $L_{i,k,t}$ for each loan is stressed by the impact factor of the current debtor category times the scheduled interest rate step-up which causes an increase in expected cumulative default rates as shown in Panel B of Table 3.2. Since there is no step-up for prime loans, the expected default rates of these loans stay the same.

Columns 3 in Tables 3.4, 3.5 and 3.6 present some statistics describing the portfolios' repayment distribution. In the benchmark case the expected value of discounted cash flows (net of transaction costs) clearly exceeds the nominal value for all three portfolios. The exceedance equals more than two times the standard deviation of discounted cash flows. For the subprime portfolios the average value of the discounted portfolio payment stream after deducting all fees is 113.4% of the initial face value. Since we use the risk-free rate for discounting, this number corresponds to a yearly average premium of 1.9% on top of the risk-free rate. The standard deviations over seven years are 5% for the well diversified portfolio and 5.6% for the concentrated one. In case of the representative portfolio the expected discounted value in the benchmark case is 105.5%, yielding an average premium of 0.8% p.a., with a standard deviation of 2.4% over seven years.

Subsequently, we simulate payments of three residential mortgage backed security (RMBS) transactions which are backed by the sample portfolios and have a maturity of seven years. We assume that four rated tranches AAA, AA, A and BBB are issued that earn the usual market spreads as shown in Table 3.3. Additionally, we assume annual transaction costs of 1%, which are paid before any interest payment to the tranches.

We calibrate tranche sizes such that their default probabilities in the benchmark scenario are roughly in line with the historical averages given by Standard & Poor's for the respective rating classes and a seven year maturity. The resulting tranche sizes are also shown in Tables 3.4, 3.5 and 3.6.[21] The calibrated tranche structures correspond to typical RMBS structures observed in the market.[22] As can be seen the AAA tranches

[21] A slightly different tranche structure would arise when using the expected loss rating from Moody's. But it should be noted that tranches with the same rating have nearly the same expected losses in our benchmark case.

[22] see *Ashcraft/Schuermann* 2008

Table 3.1: *Definition of the Crisis Scenario*
Columns 3 and 4 depict the assumed nationwide and regional factor realizations in year 1 and 2. Columns 5 and 6 give the corresponding regional HPI after one and two years. The last three columns show the mean of the distribution for the third year, the corresponding expected change in regional house prices and the corresponding expected HPI after three years according to our modelling assumptions.

Region		Year 1	Year 2	HPI_1	HPI_2	μ_3	$E(\Delta HPI_3)$	$E[HPI_3]$
US-Average	M	-0.19	-2.80	*1.03*	*0.96*	-1.4	*-1.2%*	*0.95*
Pacific	B_1	0.13	-2.60	1.03	0.85	-1.3	-7.2%	0.79
New England	B_2	-0.76	0.18	0.99	0.94	0.09	-1.0%	0.93
N. Central	B_3	-0.09	0.43	1.02	0.98	0.22	-0.5%	0.98
Atlantic	B_4	0.13	0.44	1.03	0.99	0.22	-0.4%	0.99
S. Central	B_5	0.58	1.52	1.05	1.06	0.76	2.0%	1.08

is smallest and the equity tranche is highest for the 'Pacific' subprime portfolio, which is due to a worse regional diversification.

3.4 Analysis of Mortgage Crisis

3.4.1 Crisis Scenario

Having calibrated our model to the benchmark case we now turn to modelling the crisis scenario. In particular we assume that the sample transaction was set-up two years ago (e.g. second quarter of 2006) with tranche sizes as derived before. The nationwide and regional house price index changes are set to match Freddie Mac's Conventional Mortgage Home Price Index[23]. In the first year of the transaction, the increase in national house prices slowed down to 2.6%, in the second year there was a downturn of 6%. Regionally, Pacific developed worst with a cumulated two year decrease of 15% in house prices, whereas South Central saw an appreciation of 6%. Table 3.1 shows all regional trends and the corresponding nationwide and regional macro factors. Figure 3.1 shows the expected average house price development over seven years that is implied by the realizations of the first two years and our modelling assumptions.

Given these macro-factor values in the first two years, we again simulate portfolio cash flows and tranche payments. Due to the positive autocorrelation, the negative trend

[23]Our reference index is the 'purchase only' index.

(as well as the positive trend) in regional house price indices affect the realizations of the latent variable in the following years. For illustration the mean of the macro factors for the third year as well as the corresponding expected cumulative HPI up to year 3 are shown in Table 3.1.

For the three portfolio settings the resulting portfolio and tranche characteristics given this crisis scenario are depicted in Tables 3.4 to 3.6. The crisis leads to a sharp drop in the expected level of the national house price index after seven years from 1.23 to 1.03 (appr. 16%) which translates into significantly lower discounted cash flows. In fact, our simulation results show that the house price index and the portfolio cash flows are positively correlated with 0.8. Whereas the expected discounted cash flow of the diversified subprime portfolios stays above the nominal issuance volume, the expected discounted cash flow of the US mortgage market portfolio drops roughly to $ 100 million indicating that there is no premium left for originator. The 'Pacific' subprime portfolio concentrated in the Pacific, New England and North Central region shows a drop to less than $ 96 million, a severe loss. Obviously, the crisis causes a severe first order stochastic dominance deterioration in the distributions of discounted cash flows of all three portfolios as depicted in Figure 3.2.

The shift in the distribution of discounted cash flows causes all tranches to exhibit much higher default probabilities and expected losses such that it would be necessary to downgrade them several rating notches. For example the AAA tranche of the diversified subprime portfolio would now receive an (A-) rating and the most junior tranches would only get a (B-) rating. The effect of the crisis on the tranches' risk characteristics is even slightly stronger for the US mortgage market portfolio. Here the default probabilities and expected losses are roughly ten times higher than before whereas for the diversified subprime portfolio the numbers only increase by a factor of about eight. Of course, the effect is largest for the Pacific subprime portfolio with default probabilities increasing by 30 times and the most junior tranche being certain to default.

The main part of the decrease in expected payments is allocated to the equity tranche. Looking at the diversified subprime portfolio the expected present value of equity tranche payments decreases by $ 9.2 million, 92% of the total portfolio decrease of $ 10 million. For the US portfolio the situation is similar. The expected discounted cashflow to the equity tranche decreases by $ 4.2 million - about 80% of the total portfolio decrease. Nevertheless the decline in expected discounted portfolio cashflows is rather moderate, only 10% for the subprime portfolio and 5% for the US mortgage market portfolio. This is due to the fact that both portfolios are assumed to be well diversified concerning the regional allocation with some regions still displaying a positive house price trend. In contrast, the Pacific subprime portfolio concentrated in regions performing poorly decreases by nearly 18% in expected discounted cash flow. Here, the equity tranche bears only 71% of this decline as the rated tranches are hit more heavily. Curiously, the equity tranche still has a positive expected cash flow of $ 1.3 million, even though the lowest rated tranche is always hit by losses. This is due to excess spread collected in later years. Fewer excess spread would accrue in case of an interest rate freeze.

3.4.2 The Impact of an Interest Rate Freeze

Starting from the crisis scenario described in the previous subsection we now analyze the effects of an interest rate freeze on the sample RMBS. In particular, we assume that the interest step-up after two years is cancelled such that all mortgage loans continue to pay the low initial rates. The direct effect of this freeze will be twofold. On the one hand, lower interest rates reduce the portfolio payment claims and, thus, negatively affect payments to the issued tranches. On the other hand, an interest rate freeze takes pressure from borrowers such that there will be less foreclosures which in turn lowers the foreclosure costs. We study this trade-off of direct effects first.

In the second part of this section we investigate different scenarios of house price reactions following the freeze. In fact, the lower number of foreclosures may have a positive feedback effect on house prices. We find that a relatively moderate stabilization of house prices renders the net effect on most tranches positive.

Pure Interest Rate Freeze

As noted before, the interest rate freeze does not only lead to less interest payments from the portfolio, but has also a positive effect on the portfolio default rate. In particular, there are less downward migrations and also less defaults in year three because the stress component of all Alt-A and subprime debtors disappears (see equation 3.2) due to unchanged payment obligations. In effect, by avoiding downgrades the interest rate freeze does not only decrease default rates after three years but also results in lower cumulative default probabilities in subsequent years.

We simulate portfolio repayments and tranche characteristics for this scenario. The results are shown in Figure 3.2 and Tables 3.4 to 3.6. Although the interest rate freeze lowers the default rate of the underlying portfolio, this does not compensate for the decline in interest payments from years three to seven. Thus, the freeze leads to a deterioration in the distributions of discounted cashflows. For the US mortgage market portfolio we see a first order stochastic dominance deterioration with the expected discounted portfolio cashflow being further reduced by $ 1 million. Also all RMBS tranches deteriorate as compared to the crisis scenario. The former AAA tranche which would have to be downgraded to BBB+ due to the crisis would now only receive a BBB rating. Again a substantial share of the additional loss is allocated to the equity tranche (appr. 87%).

For the diversified subprime portfolio we see an additional loss of $ 2.2 million due to the interest rate freeze and a second-order stochastic dominance deterioration in the distribution. In fact, lower quantiles slightly improve as compared to the crisis scenario. Consequently, the senior tranche benefits from the interest rate freeze whereas all other RMBS tranches suffer additional losses. Here the equity tranche takes 69% of the additional expected loss. Concerning the 'Pacific' subprime portfolio the additional expected loss is only $ 0.8 million. As the regions represented in this portfolio saw the steepest downturn in house prices bringing many debtors close to default, waiving interest claims will avoid most foreclosures such that the positive effect of a rate-freeze is strongest in this case as compare to the other portfolios. Again we see a second-order stochastic dominance shift in the expected discounted cashflow distribution leaving the senior tranche better off at the expense of lower rated tranches and the equity piece.

Interest Rate Freeze and Positive Feedback Effect

As shown in the previous subsection, the first round effects of an interest rate freeze are not sufficient to attenuate the crisis. Yet a decrease in foreclosure rates may take pressure off the housing market such that the negative trend in the regional house prices is mitigated.[24] This in turn will lead to a positive effect on subsequent foreclosure rates.

In the previous scenarios, persistent trends in the house price index are implemented by positive autocorrelation in the house price index. Therefore the downturn in years one and two leads to an expected downturn in year three, i.e. the conditional mean of the variable describing changes in the house price index is negative. Combined with the regional components, this yields expected house price changes of between -7.2% and 2.0% for the respective regions, nationwide -1.2% (see Table 3.1) which is substantially below the long-term mean of 3%. We now assume these negative trends to be stopped

[24] Cagan (2007) finds significant additional foreclosure discounts in regions with high foreclosure rates. This indicates limited buyer capacities unable to absorb the excess supply without additional discounts.

by the interest intervention. In effect, expected house price appreciations rise to the long-term trend of 3% for region 1 (Pacific) and up to 6.4% for region 5 (South Central) in year 3. We implement this by excluding the autocorrelation effects from year two to year three in the nationwide factor as well as in all regions with negative factor realization in year 2. In total, the average HPI stabilizes by four percent in year three. Feedback effects in subsequent years result in an average HPI that by the end of year seven is appr. 11 percent higher than in the crisis scenario, as shown in Figure 3.1. The results for the portfolios are displayed in Figure 3.2 and Tables 3.4 to 3.6.

For both subprime portfolios the expected discounted cashflow exceeds the value in the crisis scenario without an interest rate freeze. Comparing the cumulative expected discounted cash flow distributions this positive feedback scenario second-order stochastically dominates the crisis scenario with all lower quantiles being substantially improved. Consequently, all rated RMBS tranches benefit concerning their default probabilities and also their expected losses. Given the diversified subprime portfolio the AAA and the AA tranche perform as well as in the benchmark scenario without crisis meaning that no downgrade would be necessary. The costs of the interest rate freeze are completely borne by the owner of the equity tranche.

The US mortgage market portfolio loses less interest payments due to the interest rate freeze as prime mortgage loans representing 60% of the portfolio do not incorporate an interest step-up. Here, the positive effect of stopping the house price decline overcompensates the foregone interest resulting in higher expected discounted cash flow compared to the crisis scenario. All tranches including the equity tranche profit with higher tranches benefiting most. This is due to a more narrow distribution of losses. Compared to the crisis we again observe a second order stochastic dominance shift in cumulative repayments.

Summarizing, our results indicate that an interest rate freeze may help to alleviate the current crisis. Even though RMBS tranche investors lose a significant portion of their loss protection, this deterioration may be overcompensated by improvements in mortgage payments due to lower foreclosure rates and a positive feedback effect in the housing market. For all three portfolios we derive positive net effects on all rated RMBS tranches as compared to the crisis scenario. The higher the tranche, the more it improves. Especially, the AAA tranche benefits from the rate freeze. Thus, the RMBS market will benefit from an interest rate freeze which can induce positive spill over effects on other markets. In particular, markets for other structured instruments containing RMBS tranches may stabilize. Especially, special investment vehicles backing their commercial paper funding with senior RMBS tranches may recover.

3.4.3 Robustness Checks

(i) Assumptions concerning House Price Developments

Our previous results depend on several assumptions concerning house price developments which are motivated by empirical findings. We set the *crisis scenario* to match house price developments in the main US regions during the last two years. When discussing the positive feedback effect of an interest rate freeze we had to make a specific assumption concerning house price stabilization. Naturally, other house price reactions are also possible.

As robustness checks we derive portfolio and tranche repayments for less favorable assumptions concerning house price stabilization. In particular we assume the negative house price trend only to be partially offset by the interest rate freeze. Instead of zero autocorrelation in year three increasing the average house price index by four percent compared to the crisis situation, we now assume that only half (one fourth) of this effect is realized. Figure 3.1 shows the expected average house price development for these two scenarios. Tables 3.4 to 3.6 display the tranche and portfolio characteristics for these additional scenarios.

As can be seen, a more moderate stabilization of two percent in year three (translating into 5.5 percentage points until year seven) is sufficient to substantially improve all rated RMBS tranches (see *Robustness 1*). Even a stabilization of only one percent in year three (incresing to 2.7 percent in year seven) leaves the rated tranches slightly better off than in the crisis scenario (see *Robustness 2*).

Given these results we conclude that the qualitative results are quite stable towards changes in the assumption of house price stabilization: Due to lower excess spread, the payments to the equity tranche will be reduced the most and due to lower probabilities of high losses the highest rated tranche will profit most from an interest rate freeze. Even for modest house price reactions the net effect of the freeze is positive.

(ii) Assumptions concerning RMBS-Structure

A further assumption which needs to be critically reviewed is our assumption concerning the payment waterfall for our RMBS tranches. In the previous simulations we always assumed the existence of an unlimited reserve account, which means that the holder of the equity tranche only receives payments at final maturity and that at each annual payment dates all excess cash flows are placed in an extra account which can be used to cover future losses. In fact other reserve account specifications are possible, e.g. a capped reserve account, where all excess cash flows above this cap are paid out to the holder of the equity piece periodically, or even a structure without any reserve account, in which the holder of the equity tranche receives all excess cash flow at each payment date.

This assumption mainly influences the calibration of tranche sizes in the benchmark case. In particular, a structure without a reserve account will lead to a much smaller AAA tranche a bigger equity tranche. In this case the effect of the interest rate freeze is less pronounced since the tranche sizes are already calibrated to provide a better protection against interest losses. Nevertheless, the qualitative effects stay the same with the difference that now an even more moderate house price stabilization is sufficient to make all rated tranches better off than in the pure crisis scenario.

3.4.4 Other Policy Options

(i) Interest Rate Cuts

Throughout the paper we assumed that the risk-free interest rate on top of which credit spreads are paid stays the same over seven years. In fact the crisis might lead to a cut in this reference rate. Looking at the repayments of the mortgage loans analyzed in this paper lowering the reference rate would have a positive effect. Thus, interest rate cuts are an additional policy option worth examining. However, discussing the macroeconomic consequences of interest rate cuts is beyond the scope of this paper.

(ii) Housing Bill

For mortgage debtors the effects of the proposed interest rate freeze are comparable to the sought impact of the Housing Bill of July 2008. Here, state guarantees help troubled borrowers to refinance at lower rates. The key difference between the two policy options is on the lender side. With the interest rate freeze, mortgage banks and equity tranche holders bear the potential costs. Looking at a portfolio of mortgage loans the state guarantee included in the Housing Bill adds a large state owned first loss position, irrespective of the portfolio being securitized. Compared to our simulation results above, lenders, all rated tranches and especially the equity tranche would profit at the tax payers expense.

3.5 Conclusion

The discussed interest rate moratorium for subprime mortgages is one option to tackle the current crisis. It is an agreement between two parties - the U.S. government and the originating banks - that affects two different third parties: the mortgage debtors and investors in RMBS tranches. The first group will unambiguously profit from an interest rate freeze. Some of their payment obligations are waived, thus they might avoid default. Additionally, they benefit from a stabilizing housing market.

The effect on RMBS-tranches is more ambiguous. First, we show that the pure interest rate freeze decreases the portfolio payment stream's expected value by one to 2.2 percent, depending on portfolio composition. The vast majority of this decrease is borne by the equity tranche. Default probability and expected loss of rated tranches only slightly deteriorate as compared to the crisis scenario with senior tranches even being better off. Second, we take into account that the interest rate freeze may have a positive second round effect as a reduction in foreclosures takes pressure off the housing market. In this case we find that already a very moderate mitigation of the house price downturn yields a positive net effect on all rated tranches. A stabilization of one percent in year three leaves all tranches in each of our three sample transactions better off (compared to the crisis scenario without policy reaction). For the holder of the equity tranche, the situation is different. Looking at the average of the three sample RMBS a four percent stabilization in house prices is needed for him to slightly benefit from the interest rate freeze. Thus, should the US government and loan and savings associations decide on an interest moratorium on adjustable rate subprime mortgages, this would probably not come at the expense of the RMBS investors as a third party. If additional losses occur they are borne by originators and equity tranche investors. As these parties are the ones in charge of the criticized lending standards we argue that reconsidering this policy option is worth wile.

3.6 References

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3.7 Appendix: Tables and Figures

Panel A (Standard Case): Credit Curve

t	1	2	3	4	5	6	7
Prime	0.20%	0.52%	0.94%	1.47%	2.07%	2.75%	3.50%
Alt-A	0.50%	1.11%	1.80%	2.57%	3.41%	4.30%	5.23%
Sub1	1.50%	2.98%	4.44%	5.87%	7.29%	8.69%	10.06%
Sub2	2.50%	4.88%	7.15%	9.31%	11.36%	13.32%	15.19%
Sub3	3.50%	6.71%	9.67%	12.41%	14.94%	17.30%	19.51%

Panel A (Standard Case): Derived One-Year Migration Matrix

Debtor	Prime	Alt-A	Sub1	Sub2	Sub3	D
Prime	88.0%	6.5%	3.0%	1.5%	0.8%	0.2%
Alt-A	9.0%	82.0%	5.0%	2.0%	1.5%	0.5%
Sub1	3.0%	6.0%	82.0%	5.0%	2.5%	1.5%
Sub2	0.5%	2.5%	6.0%	82.0%	6.5%	2.5%
Sub3	0.2%	0.8%	3.0%	7.5%	85.0%	3.5%
D	0.0%	0.0%	0.0%	0.0%	0.0%	100.0%

Panel B (Stressed Migration): Stressed One-Year Migration Matrix in $t = 3$

Rating	Prime	Alt-A	Sub1	Sub2	Sub3	D
Prime	88.00%	6.50%	3.00%	1.50%	0.80%	0.20%
Alt-A	6.80%	81.51%	6.22%	2.63%	2.08%	0.76%
Sub1	0.66%	1.96%	74.44%	10.45%	6.67%	5.82%
Sub2	0.07%	0.58%	1.96%	84.44%	14.25%	8.69%
Sub3	0.03%	0.15%	0.77%	2.65%	85.13%	11.28%
D	0.00%	0.00%	0.00%	0.00%	0.00%	100.00%

Panel B (Stressed Migration): Resulting Credit Curve

t	1	2	3	4	5	6	7
Prime	0.20%	0.52%	0.94%	1.47%	2.07%	2.75%	3.50%
Alt-A	0.50%	1.11%	2.81%	3.62%	4.49%	5.41%	6.36%
Sub1	1.50%	2.98%	8.29%	9.82%	11.32%	12.78%	14.2%
Sub2	2.50%	4.88%	12.67%	14.84%	16.89%	18.83%	20.68%
Sub3	3.50%	6.71%	16.36%	19.00%	21.43%	23.69%	25.80%

Table 3.2: Assumed Credit Curve and One-Year Migration Matrix
Panel A gives the *credit curve*. Each entry describes the probability of default for a given initial debtor group and maturity t. The numbers are chosen in accordance with empirical results (see e.g. *Gerardi et al.* 2007). The one-year migration matrix is fitted to this credit curve. Panel B displays the stressed migration matrix for year 3. The payment shock due to the interest rate step-up increases the downgrade probabilities of all non-prime loans in year 3. Even though the migration probabilities in the following years return to the normal level, the expected cumulative default probabilities in every subsequent year are increased as shown in the resulting credit curve in Panel B.

	('Pacific') Subprime Portfolio	US Mortgage Market Portfolio	
Portfolio:			
Initial Volume	$ 100,000,000	$ 100,000,000	
Number of Mortgages	500	500	
initial LTV	90%	90%	
Share in Region			
Pacific	20% (40%)	20%	
New England	20% (40%)	20%	
North Central	20% (20%)	20%	
Atlantic	20% (-)	20%	
South Central	20% (-)	20%	
Share of			*Spreads (bps)*
Prime	-	60%	150
Alt-A	20%	25%	225
Subprime 1	30%	5%	300
Subprime 2	30%	5%	350
Subprime 3	20%	5%	400
⊘ Interest Rate ($t = 0$)	7.2%	6.0%	
Interest Rate Step-Up *(after 2 Years)*			Impact Factor (b)
Prime	0%	0%	0
Alt-A	1%	1%	15
Subprime 1-3	2%	2%	30
RMBS-Structure:			*Spreads (bps)*
Tranches	AAA	AAA	30
	AA	AA	50
	A	A	80
	BBB	BBB	150
	Equity	Equity	-
Transaction Costs	1% p.a.	1% p.a.	
Maturity	7 years	7 years	

Table 3.3: Portfolio Characteristics and Model Assumptions
This table present the assumed portfolio compositions of our three sample portfolios as well as the assumed tranche structure. The two subprime portfolios only differ in their regional diversification. The regional composition of the 'Pacific' Subprime portfolio is given in brackets. The depicted spreads are paid in addition to the risk-free rate of 4%.

		Benchmark	Crisis	Crisis & Freeze	Crisis & Freeze Positive Feedback	Crisis & Freeze Robustness 1	Crisis & Freeze Robustness 2
Portfolio Characteristics							
Exp. Discounted CF (in $)		113,417,751	95,678,380	94,870,489	98,466,841	96,323,606	95,954,193
% of initial Volume		113.42%	95.68%	94.87%	98.47%	96.32%	95.95%
Standard Deviation		5.60%	5.32%	3.94%	2.58%	4.01%	3.77%
1%-Quantil		94.27%	80.79%	82.75%	89.58%	84.05%	83.89%
Tranche Characteristics							
Rating	Size	*Default Probabilities*					
AAA	84.50%	0.29%	10.09%	8.07%	0.80%	4.97%	5.34%
AA	4.70%	0.71%	24.54%	24.69%	3.53%	16.15%	17.37%
A	3.90%	1.37%	46.12%	53.09%	13.26%	37.72%	40.10%
BBB	4.40%	4.49%	99.99%	99.99%	99.97%	99.98%	99.99%
		Expected Loss					
AAA		0.01%	0.37%	0.26%	0.02%	0.15%	0.16%
AA		0.36%	12.86%	11.61%	1.42%	7.45%	7.94%
A		0.81%	27.87%	28.80%	5.66%	20.10%	20.91%
BBB		2.03%	66.48%	67.03%	48.39%	60.72%	61.46%
Equity Tranche	2.50%						
Exp. Discounted CF (in $)		13,829,942	1,200,436	297,281	1,358,743	800,465	536,498

Table 3.4: 'Pacific' Subprime Portfolio - Simulation Results

Each column of this table shows the simulation results for a different simulation scenario: The benchmark scenario (without any crisis) the crisis scenario, the crisis scenario together with an interest rate freeze as well as the crisis scenario with an interest rate freeze and an additional positive feedback effect which resets house price trends after 2 years to zero, or lowers positive autocorrelation by a half (robustness 1) and one fourth (robustness 2), respectively. The first lines show some portfolio characteristics - the expected discounted cash flow net of transaction costs, the standard deviation and the 99%-quantile of the discounted cashflows distribution. The following lines show the default probabilities and expected losses of the rated tranches. Finally the expected discounted cash flow to the equity tranche is depicted.

		Benchmark	Crisis	Crisis & Freeze	Crisis & Freeze Positive Feedback	Crisis & Freeze Robustness 1	Crisis & Freeze Robustness 2
Portfolio Characteristics							
Exp. Discounted CF (in $)		113,409,975	103,433,389	101,204,384	103,870,437	102,743,287	101,984,251
% of initial Volume		113.41%	103.43%	101.20%	103.87%	102.74%	101.98%
Standard Deviation		4.97%	4.43%	3.15%	2.15%	2.70%	3.03%
1%-Quantil		96.94%	90.74%	91.53%	96.49%	94.03%	92.39%
Tranche Characteristics							
Rating	Size	*Default Probabilities*					
AAA	88.10%	0.27%	1.58%	1.41%	0.10%	0.51%	0.93%
AA	4.60%	0.68%	5.61%	6.67%	0.78%	2.66%	4.71%
A	2.80%	1.35%	12.31%	15.72%	2.40%	6.59%	11.15%
BBB	2.90%	4.34%	36.99%	39.99%	16.95%	25.26%	32.61%
		Expected Loss					
AAA		0.01%	0.04%	0.03%	0.002%	0.01%	0.02%
AA		0.37%	2.49%	2.72%	0.25%	0.97%	1.85%
A		0.81%	6.82%	8.12%	1.06%	3.29%	5.64%
BBB		2.01%	17.05%	18.20%	3.99%	8.88%	13.45%
Equity Tranche	1.60%						
Exp. Discounted CF (in $)		13,003,043	3,804,631	1,656,349	3,521,528	2,655,818	2,163,384

Table 3.5: Subprime Portfolio - Simulation Results

This table present the same simulation results as in Table 3.4 but now for a regionally well diversified Subprime Portfolio.

		Benchmark	Crisis	Crisis & Freeze	Crisis & Freeze Positive Feedback	Crisis & Freeze Robustness 1	Crisis & Freeze Robustness 2
Portfolio Characteristics							
Exp. Discounted CF (in $)		105,506,354	100,249,781	99,273,594	101,411,345	100,540,460	99,921,438
% of initial Volume		105.51%	100.25%	99.27%	101.41%	100.54%	99.92%
Standard Deviation		2.41%	2.79%	2.50%	1.54%	2.05%	2.36%
1%-Quantil		96.50%	91.50%	91.26%	95.95%	93.55%	92.08%
Tranche Characteristics							
Rating	Size	*Default Probabilities*					
AAA	89.40%	0.28%	2.24%	2.90%	0.24%	0.84%	1.90%
AA	3.10%	0.73%	6.86%	9.19%	0.89%	3.44%	6.10%
A	1.90%	1.35%	13.53%	18.32%	2.60%	7.49%	12.53%
BBB	3.90%	4.50%	45.55%	62.42%	19.42%	36.92%	49.38%
		Expected Loss					
AAA		0.01%	0.05%	0.06%	0.004%	0.02%	0.04%
AA		0.37%	3.20%	4.16%	0.37%	1.48%	2.81%
A		0.77%	7.61%	10.10%	1.23%	3.92%	6.81%
BBB		2.00%	20.53%	27.54%	5.95%	13.72%	20.31%
Equity Tranche	1.70%						
Exp. Discounted CF (in $)		5,178,193	972,104	118,113	1,258,858	818,838	598,038

Table 3.6: US Mortgage Market Portfolio - Simulation Results

This table present the same simulation results as in Table 3.4 but now for the US Mortgage Market portfolio.

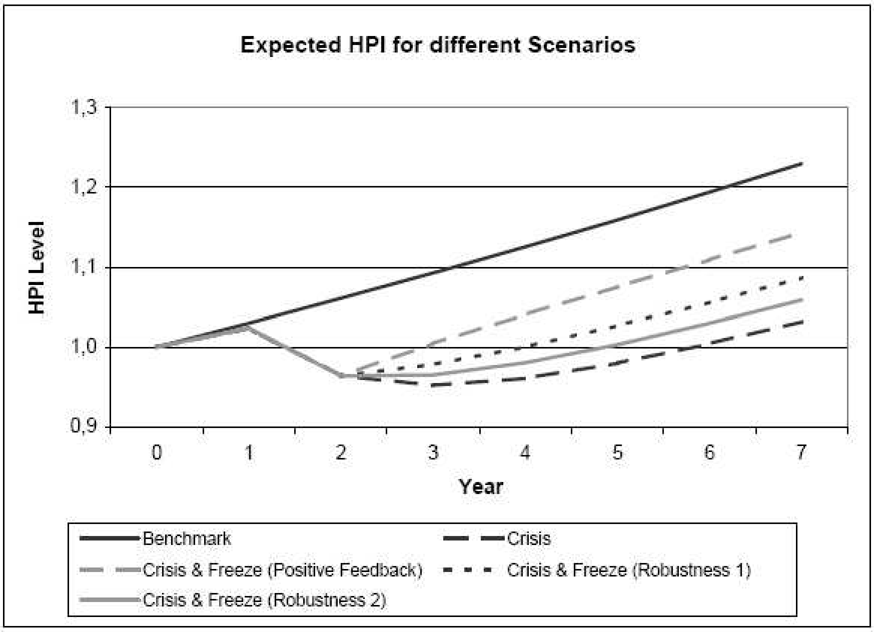

Figure 3.1: Expected House Price Index Developments
This figure shows the expected development of the House Price Index (HPI) averaged over our five regions for different simulation scenarios: In the benchmark case a long-term house price growth of 3% p.a. is assumed. The crisis scenario is set by fixing macrofactor realisations in the first two years (see Table 3.1) which cause a severe decline in house prices. Departing from this crisis scenario the positive feedback scenario assumes that there is no autocorrelation between years 2 and 3, such that house prices recover faster from the crisis. The scenarios Robustness 1 and 2 assume a weaker house price stabilization as the autocorrelation is only reduced by a half or one fourth, respectively.

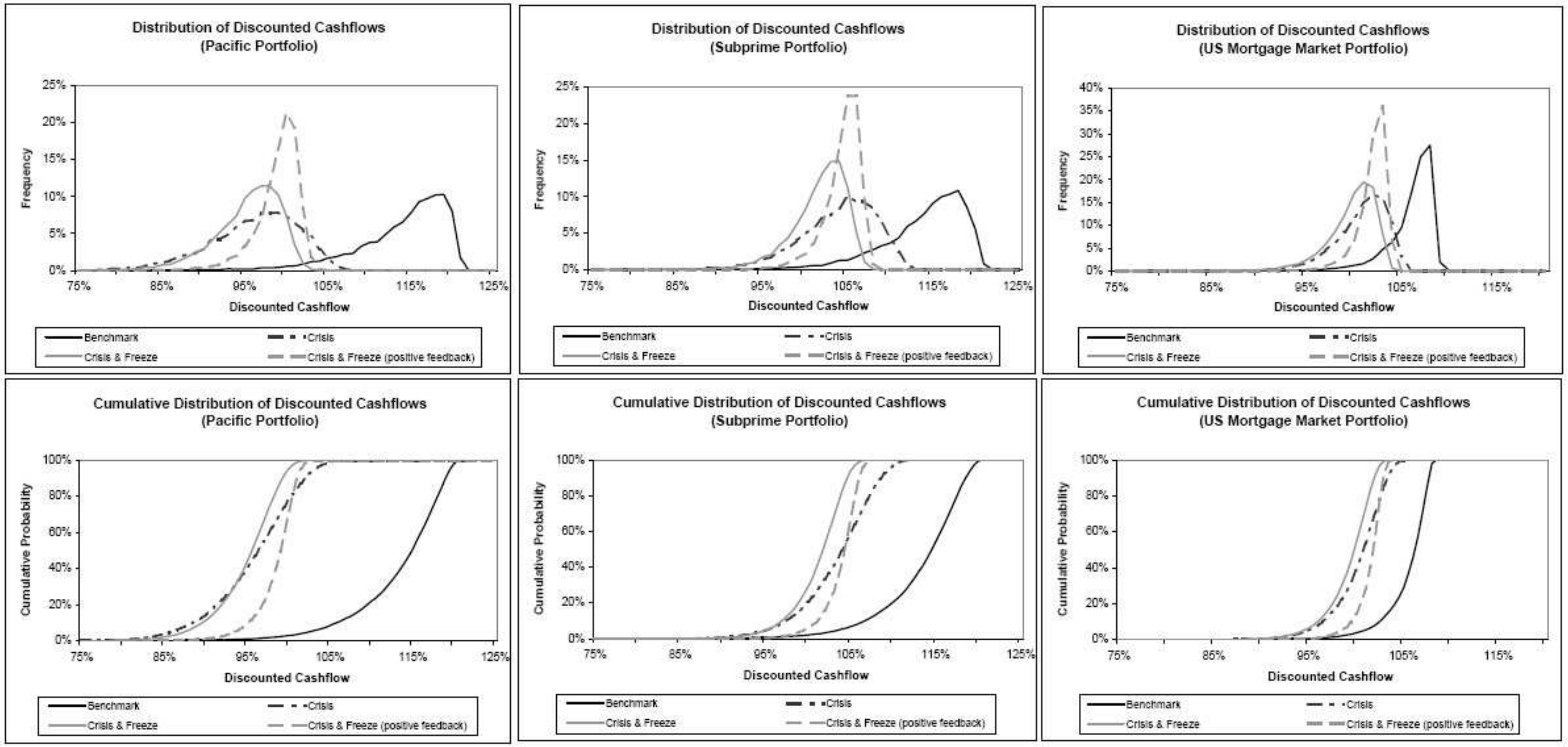

Figure 3.2: Mortgage Portfolios Repayment Distributions
This figure shows the distributions of discounted cash flows (in percent of initial portfolio volume) for all three portfolios ('Pacific' Subprime Portfolio, Subprime Portfolio, US mortgage market Portfolio) and four different simulation scenarios.

Chapter 4

Matching Ability-Elites in Partnerships: The Economics of Organizing Entrepreneurial Activity

4.1 Introduction

We investigate the effects of fostering firm foundations by establishing an "incubator"-organization. Individual ability mirrors the probability to cause the failure of a team project. Within the "incubator" risk-averse individuals are rationally matched to found entrepreneurial partnerships. The alternative to joining a partnership always consists of receiving a certain wage in industrial employment. As expected, rational matching induces more entrepreneurial activity compared to the situation where teams of randomly matched individuals can decide to spin-off partnerships. Specifically, more high-ability individuals found entrepreneurial firms and, on average, investments in such firms increase.

However, partnerships of risk-averse individuals always entail inefficient underinvestment. In contrast, industrial firms choose the efficient capital input conditional on the expected quality of their teams. Yet, in presence of an "incubator", the expected quality of these still randomly matched project teams decreases. Consequently, the respective investment level in industrial firms also decreases. Further, our simulations show that the relationship between industry-wide investments and individual risk-aversion is non-monotonic - i.e. "u-shaped." Also, welfare gains from improved matching only arise in societies whose members exhibit relatively low degrees of risk-aversion. Finally, rational matching becomes dominant with higher interest rates - i.e. when capital is not readily available.

There currently exist two rivaling views concerning the benefits of entrepreneurship: on the one hand, De Meza and Webb (1999) and Boadway and Keen (2006) show that, due to asymmetric information in the labor market, the welfare contribution of the marginal entrepreneur is negative. Coelho et al. (2004) add that individuals who become entrepreneurs are generally over-optimistic. Thus, these studies propose to tax self-employment. On the other hand, Baumol et al. (2007, ch. 1) emphasize that entrepreneurship transforms scientific-technological progress into a driver of economic growth. According to Djankov et al. (2002), Boadway and Tremblay (2005), and Kanniainen and Poutvaara (2007) excessive regulation and taxation then obstructs this important link and should be removed.

Empirically however, Van Stel et al. (2005) and Wong et al. (2005) find that there is no effect of total entrepreneurial activity on growth. Only the numbers of nascent and fast-growing entrepreneurial firms exhibit a positive impact. According to Baumol et al. (2007, p. 104), such "*productive entrepreneurship* [is] *innovative and replicative.* [We] *are interested in the former, for it is only by commercializing new products and* *services or by adopting new and better ways of making or delivering existing ones that the economic frontier moves out.*" The knowledge spillover theory of entrepreneurship then further motivates the dominance of new firm foundations over other forms of commercializing innovations.

This theory specifically applies to and has been tested for science-driven innovations.[1] Since the knowledge to generate such innovations is embodied in the economic agent and is both non-exhaustable and non-excludable, it implies two distinguishing features: first, the agent can only appropriate the returns to her knowledge by becoming an entrepreneur herself.[2] Second, as shown by Löfsten and Lindelöf (2002), Audretsch et al. (2005), and Link and Scott (2005), the inclusion of or even simply the geographic proximity to a research university as a training facility enhances the frequency and success of such innovative start-ups.

The United States have been early to recognize the increasing importance of scientific innovations: the Bayh-Dole and Stevenson-Wydler Acts of 1980 and the Federal Technology Transfer Act of 1985 empower universities to actively engage in technology transfer. However, only recently the European Union has also taken steps to align its member states respective efforts.[3] Responding to such incentives, universities and research institutes world-wide have begun to operate technology transfer units.[4] Moreover, these units leave the traditional paths of industry cooperation and licensing their patents.[5] According to Chukumba and Jensen (2005) and Markman et al. (2005), direct support of academic spin-offs increasingly substitutes licensing-for-cash activities.

Lacetera (2005) and Aghion et al. (2005) then explain performance differentials between academic and industrial spin-offs due to the different objectives of founders that belong to the scientific community. Demougin and Fabel (2007) and Macho-Stadler et al. (2008) confirm the importance of incentives set by ownership for both the inventor and the mediator, e. g. a transfer office. Generally, Druilhe and Garnsey (2004), Markman et al. (2004), and Powers and McDougall (2005) show that the success of incubating new ventures depends on both the research environment and the availability of human, financial, and organizational capital.

All of the above agree that the success of incubator activities should be measured in terms of revenues generated by the start-ups.[6] In contrast, Baumol et al. (2007, p. 234)

[1]E. g. Audretsch and Stephan (1999).
[2]Audretsch (1995, p. 179-180).
[3]EU Commisssion (2006) and CORDIS (2006).
[4]Colyvas et al. (2002).
[5]Siegel et al. (2003).
[6]Thursby et al. (2001) discuss the goals and objectives in technolgy transfer.

emphasize that wealth creation requires the "*right blend of entrepreneurial capitalism and big firm capitalism*." Hence, our model and simulations address the "*blend*" that is induced by the representative agent's risk-aversion, the distribution of abilities, and the availability of capital. Specifically, we investigate the changes in entrepreneurial activity, investments, and welfare that result when incubating new ventures implies a switch from random to rational matching of entrepreneurial partnerships.

The paper is organized as follows: the next section introduces the model framework. We add an appendix to show that partnerships constitute the dominant organizational form for spin-offs. Sections 3 and 4 derive the characteristics of the "random matching" and "incubator" equilibria. Section 5 compares the two institutional regimes. The final section contains a summary of our results.

4.2 The model

4.2.1 Basic assumptions and notations

Output is defined as the successful completion of a development process. Each firm produces a single unit of this output good. Higher-quality variants of the good - e.g. more timely completion of the process - require higher capital input K. The market price of capital is ρ. Revenue resulting from a successful process is $r = K^{\gamma}$, with $0 < \gamma < 1$. This process also combines two necessary human tasks, indexed $t = 1, 2$ in the following. Imperfect performance of either of these two tasks renders the process incomplete. An incomplete process generates no market value. Hence, a firm's revenue equals zero if one of the two tasks is not performed perfectly.

There exists a pool of professionals; e.g. individuals who have received training as students or junior researchers at a specific university or research institute. Professional i's ability in performing task t is denoted a^{ti}. These abilities constitute realizations of two random variables $\tilde{a}^{ti}$ which are each drawn from the interval $A = [a_L, 1]$. Let $S = \{(a^{1i}, a^{2i}) \mid a^{ti} \in A\,,\, t = 1, 2\}$ then denote the set of possible ability profiles of industry professionals. The joint density function $f(a^1, a^2) > 0$, for individual profiles $(a^1, a^2) \in S$, and $f(a^1, a^2) = 0$, for $(a^1, a^2) \notin S$, constitutes common knowledge of all economic agents. The corresponding joint distribution function is denoted $F(a^1, a^2)$. For mere technical reasons, the lower bound on ability realizations a_L is positive. Yet, a_L can be arbitrarily small and in the limit approach zero.

Individual task ability is measured by the respective probability of perfect task performance. In particular, suppose that two professionals are teamed up such that individual i performs task 1 and individual j carries out task 2. Then, the team realizes revenue r with probability $a^{1i}a^{2j}$. The revenue equals zero with probability $(1- a^{1i}a^{2j})$. According to this so-called "*O-Ring*" production technology, differences in individual task abilities thus imply differences in team success probabilities.[7] This property appears characteristic for project teams consisting of researchers with different profiles of necessary disciplinary knowledge.[8]

Individual preferences are characterized by the identical utility function $u(y)$ where $y \geqq 0$ denotes income. As usual, $u'(y) > 0$, $u''(y) \leqq 0$, for $y > 0$, and $\lim_{y\to 0} u'(y) = \infty$. It is assumed that all individuals possess an identical initial wealth income $Y > 0$. Finally, our welfare analysis compares the expected utilities and certainty equivalent incomes of individuals who do not know the realization of their ability profiles yet. Thus, welfare effects emerge from the *ex-ante* risk-type uncertainty as well as the realized *ex-post* project success risk.

4.2.2 Entrepreneurial firms

Suppose two individuals i and j have decided to become entrepreneurs and subsequently form a production team. Specifically, they found a partnership of equals.[9] Due to their professional expertise, they can observe each other's task abilities. Let $\bar{a}^{ij} = \{(a^{1i}, a^{2i}), (a^{1j}, a^{2j})\}$ denote the corresponding set of ability profiles within such a team. Clearly, the partners will allocate tasks to economize on their respective comparative advantages. Hence, the project success probability is given by $q^E(\bar{a}^{ij}) = \max\{a^{1i}a^{2j}, a^{1j}a^{2i}\}$.

It follows that the partnership promises identical expected utility

$$U^E(q^E(\bar{a}^{ij}); \rho) = q^E(\bar{a}^{ij})u(Y + \frac{1}{2}[\big(K^E(q^E(\bar{a}^{ij}); \rho)\big)^\gamma - \rho K^E(q^E(\bar{a}^{ij}); \rho)]) + (1 - q^E(\bar{a}^{ij}))u(Y - \frac{1}{2}\rho K^E(q^E(\bar{a}^{ij}); \rho)) \tag{4.1}$$

for each of the two partners where the capital input $K^E(q^E(\bar{a}^{ij}), \rho)$ is implicitly deter-

[7]Kremer (1993).

[8]Fabel (2004).

[9]Lemma 3 proved in Appendix 4.8.1 shows that, within a Nash-bargaining framework, the partnership of equals actually constitutes the dominant organizational form for entrepreneurial firms.

mined by the first-order condition

$$q^E(\bar{a}^{ij})u'(Y+\frac{1}{2}[(K^E)^\gamma-\rho K^E])[\gamma(K^E)^{(\gamma-1)}-\rho]= \tag{4.2}$$
$$(1-q^E(\bar{a}^{ij}))u'(Y-\frac{1}{2}\rho K^E)\rho \; .$$

4.2.3 Industrial firms and competition

Industrial firms are organized on behalf of outside investors who supply the capital K and claim the residual income. Outside investors are assumed to be risk-neutral. However, they cannot verify their employees' abilities. Such investors are therefore indifferent with regard to the task allocation over their two employees. Competition for task assignments among the employees then implies that the (certain) wages associated with each task must be identically equal.

Assumption 1 *Before occupational choices are made, all economic agents - professionals as well as outside investors -* a priori *believe that the expected success probability in industrial firms is given by* $q^I \in [(a_L)^2, 1]$.

The opportunity costs of becoming an entrepreneur are given by the foregone certain utility of employment in an industrial firm. Hence, professionals must know the wage offers of industrial firms in order to make rational occupational choices. These offers are taken to constitute binding commitments by outside investors.

Definition 1 *A competitive equilibrium in the labor pool for professionals is characterized by the following properties:*

(a) Before production commences all members of the pool are either employed by outside investors or have become entrepreneurs.

(b) The occupational choices maximize the professionals' expected utilities.

(c) The a priori *beliefs concerning the expected success probability* q^I *in industrial firms are confirmed by the induced occupational choices of the professionals.*

(d) Outside investors can freely enter and leave at no costs.

The free-entry condition (d) ensures that competition for profitable investment opportunities within the industry will increase wage-offers until outside investors believe to earn only the market rate of return on their investment. Thus, let w^* denote the unique wage offer by outside investors in such competitive equilibrium. Given Assumption 1, all such investors maximize their expected profit

$$\pi = q^I K^\gamma - \rho K - 2w^*. \tag{4.3}$$

which yields the first-order condition

$$\gamma q^I (K)^{(\gamma-1)} - \rho = 0, \tag{4.4}$$

Let $K^I = K^I(q^I;\rho)$ then denote the optimal capital input that satisfies (4.4).

Thus, the reservation wage for potential entrepreneurs is given by

$$\begin{aligned} w^* &= w^*(q^I;\rho) \\ &= \frac{1}{2}\left[q^I \left(K^I(q^I;\rho)\right)^\gamma - \rho K^I(q^I;\rho)\right] \\ &= \frac{(1-\gamma)\, q^I}{2} \left(K^I(q^I;\rho)\right)^\gamma \end{aligned} \tag{4.5}$$

upon insertion from (4.4) into (4.3) above and setting $\pi = 0$. Let $U^I(q^I;\rho) = u(Y + w^*(q^I;\rho))$ denote the corresponding certain utility of an employee in competitive equilibrium. Figure 4.1 in section 4.8.2 then illustrates the professionals' occupational choice.

4.3 Self-selection in "random matching"-equilibria

Even without an incubator organization professionals learn about each others' ability profiles. However, such learning takes place while individuals are already cooperating in production teams within university institutes or industrial research departments. Thus, the benchmark case for our analysis assumes that these teams are randomly matched - i.e. they are not intentionally combined to maximize the success of entrepreneurial spin-offs. This argument implies the following information and decision structure:

Assumption 2 *All professionals are randomly matched to form production teams. Each team member then observes her colleague's ability profile. Subsequently, the members of such teams can decide to found an entrepreneurial firm.*

Thus, the option to spin-off an entrepreneurial firm merely constitutes a means to align the interests of two randomly matched team members in making their occupational choices. All teams of professionals i and j for which

$$U^E(q^E(\bar{a}^{ij});\rho) \geqq U^I(q^I;\rho) \tag{4.6}$$

will choose to found an entrepreneurial firm. From (4.6) define $\bar{q}$ such that

$$U^E(\bar{q}(q^I);\rho) = U^I(q^I;\rho)\ . \tag{4.7}$$

Given every *a priori* belief $q^I \in [(a_L)^2, 1]$, (4.7) implicitly defines a continuous, monotonically increasing function $\bar{q}(q^I) \geqq q^I$. Clearly, $\bar{q}(q^I) > q^I$ if professionals are risk-averse and $q^I \in (0,1)$.

Let $q^I(\bar{q}) = \bar{q}^{-1}(q^I)$. Since task assignments in industrial firms constitute independent drawings, equilibrium occupational choices must confirm that

$$q^I(\bar{q}) = \begin{cases} \frac{1}{\int_{a_L}^1 f_{\tilde{a}^2}(a^2) F_{\tilde{a}^1}(\frac{\bar{q}}{a^2}) da^2} \times \int_{a_L}^1 \int_{a_L}^{\frac{\bar{q}}{a^2}} a^1 f_{\tilde{a}^1}(a^1) da^1 a^2 f_{\tilde{a}^2}(a^2) da^2 & , \quad \bar{q} \geq a_L \\ \frac{1}{\int_{a_L}^1 f_{\tilde{a}^2}(a^2) F_{\tilde{a}^1}(\frac{\bar{q}}{a^2}) da^2} \times \int_{a_L}^{\frac{\bar{q}}{a_L}} \int_{a_L}^{\frac{\bar{q}}{a^2}} a^1 f_{\tilde{a}^1}(a^1) da^1 a^2 f_{\tilde{a}^2}(a^2) da^2 & , \quad \bar{q} < a_L \end{cases} \tag{4.8}$$

where $F_{\tilde{a}^t}(a^t)$ and $f_{\tilde{a}^t}(a^t)$, $t = 1, 2$, denote the unconditional marginal distribution and density functions, respectively. From (4.7), all teams realizing $q^E(\bar{a}^{ij}) \geqq \bar{q}(q^I)$ will found entrepreneurial firms.

Proposition 3 *(a) If professionals are risk-averse, Assumption 2 implies that both firm types coexist in every competitive equilibrium. (b) There exists at least one such equilibrium.*

Proof. (a) If beliefs were such that all randomly matched teams of professionals should remain employed in industrial firms $q^I(1) = \int_{a_L}^1 a^1 dF_{\tilde{a}^1}(a^1) \int_{a_L}^1 a^2 dF_{\tilde{a}^2}(a^2) < 1$. However,

$$\begin{aligned} &\lim_{a^1 \to 1, a^2 \to 1} [U^E(a^1 a^2;\rho) - U^I(q^I(\bar{q});\rho)] \qquad (4.9) \\ &= u\left(Y + \frac{1}{2}\left[\left(K^I(1;\rho)\right)^\gamma - \rho K^I(1;\rho)\right]\right) \\ &-u\left(Y + \frac{1}{2}\left[q^I(1)\left(K^I(q^I(1);\rho)\right)^\gamma - \rho K^I(q^I(1);\rho)\right]\right) > 0 \end{aligned}$$

since $\lim_{a^1 \to 1, a^2 \to 1} K^E(a^1, a^1;\rho) = K^I(1;\rho)$ and, according to (4.4), $\partial K^I(q;\rho)/\partial q > 0$.

In contrast, suppose that all randomly matched teams of professionals would spin off entrepreneurial firms in equilibrium. Then, for $0 < (a_L)^2 < 1$,

$$\begin{aligned}
&\lim_{a^1 \to a_L, a^1 \to a_L} [U^E(a^1 a^2; \rho) - U^I(q^I(\bar{q}); \rho)] \qquad (4.10)\\
&= (a_L)^2 \, u \left(Y + \frac{1}{2}[\left(K^E((a_L)^2; \rho)\right)^\gamma - \rho K^E((a_L)^2; \rho)] \right) \\
&\quad + (1 - (a_L)^2) u(Y - \frac{1}{2}\rho K^E((a_L)^2; \rho)) \\
&\quad - u \left(Y + \frac{(a_L)^2}{2} \left[\left(K^I((a_L)^2; \rho)\right)^\gamma - \rho K^I((a_L)^2; \rho) \right] \right) < 0.
\end{aligned}$$

since, according to (4.4) and (4.2), $K^E((a_L)^2; \rho) < K^I((a_L)^2; \rho)$ if professionals are risk-averse. An industrial firm offering $w^*((a_L)^2)$ would therefore attract some employees and earn positive expected profits. Thus, (4.9) and (4.10) rule out competitive equilibria in which the entire industry consists of only one firm-type.

(b) Notice that $U^E(\bar{q}; \rho)$ and $U^I(q^I(\bar{q}); \rho)$ are both monotonically increasing in $\bar{q}$ and $q^I(\bar{q})$, respectively. Also, (4.8) yields $\partial q^I(\bar{q})/\partial \bar{q} > 0$. Given part (a) above, there must exist at least one $\bar{q}$ that satisfies (4.7) and (4.8). ■

Inequality (4.9) shows that, even if the self-selection criterion for entrepreneurial teams $\bar{q}$ approaches unity, top ability professionals still found partnerships. Since the probability of project failure converges to zero for such teams, they choose the first-best capital input and receive the corresponding certain utility. In contrast, industrial firms can only expect to realize average ability in their teams. Although the capital input would also be chosen according to the first-best rule, the respective capital level and the corresponding certain utility of their employees would still be lower than in entrepreneurial firms founded by top-ability professionals.

As the self-selection criterion $\bar{q}$ approaches its positive lower bound, the risk-pooling effect of industrial firms vanishes. Hence, inequality (4.10) reflects that outside investors would then only employ a single - e. g. the lowest - ability-type in both tasks. Outside investors would therefore choose the first-best capital input level conditional on the highest project risk which can possibly be realized. Exactly this project risk would also be realized in the respective marginal entrepreneurial firms. However, the partners in such firms are risk-averse and would, thus, choose a lower capital input.

Since both the expected utility of marginal entrepreneurs and the certain utility of employees monotonically increase if the self-selection of entrepreneurs becomes more restrictive, these arguments suffice to establish a crossing property. Moreover,

$$\frac{\partial^2 U^E(\bar{q};\rho)}{(\partial\bar{q})^2} = \frac{1}{2}\Big[u'(Y+\frac{1}{2}[(K^E(\bar{q};\rho))^\gamma - \rho K^E(\bar{q};\rho)])\left((K^E(\bar{q};\rho))^{(\gamma-1)} - \rho\right) \qquad (4.11)$$
$$+u'(Y-\frac{\rho}{2}K^E(\bar{q};\rho)])\rho\Big]\frac{\partial K^E(\bar{q};\rho)}{\partial\bar{q}} > 0$$

due to (4.2). However, from (4.5) and the definition of $U^I(q^I(\bar{q});\rho)$,

$$\frac{\partial^2 U^I(q^I(\bar{q});\rho)}{(\partial q^I(\bar{q}))^2} = u''(Y+w^*(q^I;\rho))\left[\frac{\left(K^I(q^I;\rho)\right)^\gamma}{2}\frac{\partial q^I(\bar{q})}{\partial\bar{q}}\right]^2 \qquad (4.12)$$
$$+u'(Y+w^*(q^I;\rho)\frac{\gamma\left(K^I(q^I;\rho)\right)^{(\gamma-1)}}{2}\left[\frac{\partial q^I(\bar{q})}{\partial\bar{q}}\right]^2$$
$$+u'(Y+w^*(q^I;\rho))\frac{\left(K^I(q^I;\rho)\right)^\gamma}{2}\frac{\partial^2 q^I(\bar{q})}{(\partial\bar{q})^2}.$$

From (4.8) $\partial q^I(\bar{q})/\partial\bar{q} > 0$. Yet, the sign of $\partial^2 q^I(\bar{q})/(\partial\bar{q})^2$ depends on the specific distributional assumptions. Hence, a single-crossing property cannot be taken for granted. The competitive equilibrium is therefore not necessarily unique.

Proposition 4 *There exists a unique efficient competitive equilibrium. Given Assumption 2, the respective self-selection criterion $\bar{q}^*$ satisfies*

$$\bar{q}^* = \arg\max_{\bar{q}\in((a_L)^2,1)} q^I(\bar{q}) \qquad (4.13)$$
subject to (4.7) and (4.8).

Proof. An efficient self-selection equilibrium must solve the above optimization problem since $U^I(q^I(\bar{q});\rho)$ is increasing in $q^I(\bar{q})$ and all entrepreneurs' expected utilities satisfy (4.6). Let $h^i = h(a^{1i},a^{2i};\bar{q})$ denote the probability that a professional with ability profile (a^{1i},a^{2i}) will found an entrepreneurial firm. Then $\bar{q}^*$ maximizes

$$V^i = h(a^{1i},a^{2i};\bar{q})E_{(\tilde{a}^1,\tilde{a}^2|a^1\geqq\frac{\bar{q}}{a^{2i}}\vee a^2\geqq\frac{\bar{q}}{a^{1i}})}\left\{U^E(q^E(\bar{a}^i;\rho))\right\} \qquad (4.14)$$
$$+\left(1-h(a^{1i},a^{2i};\bar{q})\right)U^I(q^I(\bar{q});\rho)$$

for all professionals i. According to Proposition 1, $\bar{q}\in((a_L)^2,1)$ and the constraint (4.7) must be binding. Uniqueness immediately follows from $\partial U^E(\bar{q};\rho)/\partial\bar{q} > 0$, $\partial q^I(\bar{q})/\partial\bar{q} > 0$, and (4.9). These conditions imply the existence of a value $\bar{q}^*$ such that $U^E(\bar{q};\rho) > U^I(q^I(\bar{q});\rho)$ for all $\bar{q}\in(\bar{q}^*,1]$. Hence, $\bar{q} > \bar{q}^*$ cannot characterize a competitive equilibrium and all possible competitive equilibria with $\bar{q} < \bar{q}^*$ are Pareto-dominated. ■

Risk-aversion induces an endogenous separation of professionals into two groups providing industrial and entrepreneurial labor. Hence, the efficient competitive equilibrium maximizes the team-quality in industrial firms. This equilibrium implements a second-best trade-off. Risk-shifting by joining industrial firms can only be achieved at the expense of foregoing some of the allocative benefits associated with rational task-assignments in entrepreneurial firms.

4.4 Self-selection in "incubator"-equilibria

4.4.1 Rational ability-matching by choosing partners

In the "random matching"-setting above, professionals cannot choose partners. In contrast, formal incubator organizations seek to coordinate entrepreneurial activities. Specifically, they allow to observe abilities and to search for partners prior to contracting. In fact, they aim at reducing the respective information and search costs. In this section, Assumption 2 is therefore replaced by:

Assumption 3 *All professionals observe each others' ability profiles before making occupational choices.*

Given such perfectly informed professionals, part (b) of Definition 1 implies that, in competitive equilibrium, potential entrepreneurs maximize their expected utility by choosing partners.

Lemma 4 *Given Assumption 3, superior realizations of the success probabilities in entrepreneurial firms reflect that both tasks are performed perfectly with higher probabilities.*

Proof. Suppose four professionals denoted k, ℓ, m, and n decide to become entrepreneurs. Without loss of generality, they are taken to team up in two partnerships between k and ℓ, respectively m and n and realize $q^E(\bar{a}^{k\ell}) \leqq q^E(\bar{a}^{mn})$. Given that these individuals have maximized their expected utilities,

$$\begin{aligned}
&\text{(a) } q^E(\bar{a}^{k\ell}) = a^{1k}a^{2\ell} \text{ and } q^E(\bar{a}^{mn}) = a^{1m}a^{2n} \Longrightarrow a^{1k} \leqq a^{1m} \wedge a^{2\ell} \leqq a^{2n},\\
&\text{(b) } q^E(\bar{a}^{k\ell}) = a^{1\ell}a^{2k} \text{ and } q^E(\bar{a}^{mn}) = a^{1m}a^{2n} \Longrightarrow a^{1\ell} \leqq a^{1m} \wedge a^{2k} \leqq a^{2n},\\
&\text{(c) } q^E(\bar{a}^{k\ell}) = a^{1\ell}a^{2k} \text{ and } q^E(\bar{a}^{nm}) = a^{1n}a^{2m} \Longrightarrow a^{1\ell} \leqq a^{1n} \wedge a^{2k} \leqq a^{2m},\\
&\text{(d) } q^E(\bar{a}^{k\ell}) = a^{1k}a^{2\ell} \text{ and } q^E(\bar{a}^{nm}) = a^{1n}a^{2m} \Longrightarrow a^{1k} \leqq a^{1n} \wedge a^{2\ell} \leqq a^{2m}.
\end{aligned} \tag{4.15}$$

If $q^E(\bar{a}^{k\ell}) < q^E(\bar{a}^{mn})$, at least one inequality must be strict in cases (a) - (d). Further, $q^E(\bar{a}^{k\ell}) = q^E(\bar{a}^{mn})$ implies equalities everywhere. Otherwise, $a^{ti} > a^{tj}$ for one $t = 1, 2$, with $i = k, \ell$ and $j = m, n$, in (a) - (d) would imply that either k or ℓ could team up with m or n to found a partnership which would yield higher expected utility for both individuals. ■

The expected utility maximizing behavior of potential entrepreneurs in choosing partners induces a ranking of abilities across the respective production teams. The professional with highest ability in task 1 teams up with the professional who is characterized by the highest ability in task 2. Then, the professional with next to top ability in task 1 founds an entrepreneurial firm with the professional whose ability in task 2 is second-ranked as well. Generally, individuals are ranked by their ability in the task that they perform relatively better.

4.4.2 Self-selection in "incubator" -equilibrium

In equilibrium, all individuals with ability profiles that allow them to become part of a production team of quality $q \geq \bar{Q}$ where

$$U^E(\bar{Q};\rho) = U^I(q^I(\bar{Q});\rho) \tag{4.16}$$

cofound entrepreneurial firms.

Lemma 5 *Competitive equilibria only support* a priori *beliefs of the type*

$$S^I = S^I(\bar{Q}) = S^I(z_1, z_2) = \{(a_1, a_2) \in S \mid a_1 < z_1 \leqq 1 \vee a_2 < z_2 \leqq 1\} \tag{4.17}$$

where S^I denotes the set of ability profiles characterizing industrial employees. In equilibrium, the expected quality of a randomly matched team in industrial firms is therefore given by

$$q^I(\bar{Q}) = q^I(z^1, z^2) = \frac{\int_{a_L}^{z^2}\int_{a_L}^{z^1} a^1 f(a^1,a^2)da^1da^2}{\int_{a_L}^{z^2}\int_{a_L}^{z^1} f(a^1,a^2)da^1da^2} \frac{\int_{a_L}^{z^1}\int_{a_L}^{z^2} a^2 f(a^1,a^2)da^2da^1}{\int_{a_L}^{z^1}\int_{a_L}^{z^2} f(a^1,a^2)da^2da^1}\ . \tag{4.18}$$

Proof. According to Lemma 1, $z_1, z_2 \in [a_L, 1]$ are uniquely defined by $z_1 z_2 = \bar{Q}$ such that z_t, $t = 1, 2$, constitutes the ability level all professionals performing task t in marginal entrepreneurial firms. Hence, every professional k with either $a^{1k} \geq z_1$ or $q^{2k} \geq z_2$ will become an entrepreneur. She can find a partner to realize a team quality $q^E \geq \bar{Q}$. Professionals l where both $a^{1l} < z_1$ and $a^{2l} < z_2$ will opt for industrial employment, i.e. all professionals with ability profile $(a^1, a^2) \in S^I$ as defined above. Such *a priori* beliefs then imply (4.18). ■

With rational matching, equilibrium beliefs must anticipate that high-ability specialists will always found entrepreneurial firms. Again, it can then be shown:

Proposition 5 *(a) Given Assumption 3, there exists at least one competitive equilibrium. (b) Both firm-types coexist in all such equilibria.*

Proof. (a) To begin with, assume $a_L < z^t < 1$ for $t = 1, 2$. Recall that $\partial U^E(q^E)/\partial q^E > 0$. Thus, $\partial U^E(q^E(\bar{a}^{ij}))/\partial a^{pt} = \frac{\partial U^E(q^E)}{\partial q^E} \frac{\partial q^E}{\partial a^{pt}} \geqq 0$, for each of the two partners $p = i, j$ and both tasks t. Strict inequality follows if partner p actually carries out task t in the entrepreneurial firm. By Lemma 2, equilibrium occupational choices support *a priori* beliefs of type (4.17). Then, $U^E(\bar{Q}; \rho)$ defined in (4.16) above constitutes an upper bound on the expected utilities of all professionals i characterized by abilities $a^{it} = z^t$ and $a^{i\tau} < z^\tau$ where $t, \tau = 1, 2$ and $t \neq \tau$.

(b) It is easily verified that $\lim_{z^1 \to 1, z^2 \to 1}[U^{Ez}(z^1, z^2; \rho) - U^I(q^I(z^1, z^2); \rho)]$ yields inequality (4.9) derived in part (a) of the proof of Proposition 1 already.
Also, $\lim_{z^1 \to a_L, z^1 \to a_L}[U^{Ez}(z^1,\ z^2; \rho) - U^I(q^I(z^1, z^2); \rho)]$ only restates (4.10) from above. Consequently, due to $\partial U^E(q^E)/\partial q^E > 0$ and Lemma 2, there must exist a combination (z^1, z^2), with $a_L < z^t < 1$ for at least one task $t = 1, 2$ such that (4.16) is satisfied. Hence, competitive equilibria with either only entrepreneurial or only industrial firms are ruled out. ■

Given Assumption 2 as well as Assumption 3, professionals first observe each others' ability profiles and then decide whether to found an entrepreneurial firm. As discussed in the preceding section, this argument alone suffices to establish a competitive equilibrium in which both firm-types coexist. To a considerable extent the proof of Proposition 3 therefore only restates results from the proof of Proposition 1. The important difference is that the probability to found an entrepreneurial firm is now either equal to unity or zero contingent only on the professional's own ability profile. In particular, top-ability task-specialists will always cofound an entrepreneurial firm.

Although Proposition 3 establishes a crossing property for the expected utilities associated with occupational choice, a single-crossing property again does not necessarily follow.

Proposition 6 *Given Assumption 3, an efficient competitive equilibrium is characterized by selection criteria* (ζ^1, ζ^2) *such that*

$$(\zeta^1, \zeta^2) = \arg \max_{z^1 \in (a_L,1), z^2 \in (a_L,1)} q^I(z^1, z^2) \ , \tag{4.19}$$

subject to (4.16) and (4.18)

Efficient competitive equilibrium uniquely determines the success probability $\overline{Q}^* = \zeta^1\zeta^2$ *in the marginal entrepreneurial firm.*

Proof. From Proposition 3, a competitive equilibrium only supports belief structures of type (4.17) with $z^t \in (a_L, 1)$, for $t = 1, 2$. The arguments pursued in part (b) of the proof of this proposition imply that (4.16) constitutes a binding constraint if $q^I(z^1, z^2)$ is given by (4.18). Then, assume that there exist two competitive equilibria characterized by self-selection criteria $(\hat{\zeta}^1, \hat{\zeta}^2)$ and (ζ^1, ζ^2) and $q^I(\hat{\zeta}^1, \hat{\zeta}^2) < q^I(\zeta^1, \zeta^2)$.

Due to $\partial U^I(q^I, \rho)/\partial q^I > 0$, it follows that $U^I(q^I(\hat{\zeta}^1, \hat{\zeta}^2); \rho) < U^I(q^I(\zeta^1, \zeta^2); \rho)$. Further, $U^E(q^E(\bar{a}^{ij}); \rho) > U^{Ez}(z^1, z^2; \rho)$ for all professionals i and j who found a non-marginal entrepreneurial firm implying that $a^{pt} \geqq z^t$, with $p = i, j$ and $t = 1, 2$, with strict inequality for one of the two tasks t. Hence, all industry professionals realize higher expected utility in the equilibrium characterized by (ζ^1, ζ^2) than given the equilibrium with selection criteria $(\hat{\zeta}^1, \hat{\zeta}^2)$. Consequently, an efficient equilibrium must satisfy (4.19).

Part (b) of the proof of Proposition 3 also implies that $U^{Ez}(z^1, z^2; \rho) > U^I(q^I(z^1, z^2); \rho)$ for all combinations (z^1, z^2) which yield $z^1 z^2 \in (\bar{Q}^*, 1]$, where $\bar{Q}^* \equiv \zeta^1\zeta^2$. As shown above, all possible competitive equilibria with $z^1 z^2 \in \left[(a_L)^2, \bar{Q}^*\right)$ are not efficient. Hence, $\bar{Q}^*$ is uniquely determined in efficient competitive equilibrium. ■

Again, efficiency requires to implement a second-best trade-off between risk-shifting in industrial firms and economizing on comparative advantages. However, as illustrated by Figures 4.2 and 4.3 in section 4.8.2, the efficient "incubator"-equilibrium clearly implies a different mix of professionals remaining in the pool for industrial employment compared to the efficient "random matching"-equilibrium.

4.5 Comparing "random matching" and "incubator"-equilibria

4.5.1 General industry structure effects

We now compare the respective efficient equilibria with respect to the degree of entrepreneurial activity generated in the industry. Thus, recall from above that the two regimes induce qualitatively different self-selections of individuals. This qualitative difference then implies the following quantitative equilibrium effect:

Proposition 7 *The entrepreneurial sector of the industry is smaller in efficient "random matching"-equilibrium than in efficient "incubator"-equilibrium:* $\bar{Q}^* < \bar{q}^*$.

Proof. Take any (z_1^*, z_2^*)-combination that satisfies $z_1^* z_2^* = \bar{q}^*$. Comparing (4.8) with $\bar{q} = \bar{q}^*$ and (4.18) with $(z_1, z_2) = (z_1^*, z_2^*)$, it is immediately clear that $q^I_{(4.8)}(\bar{q}^*) > q^I_{(4.18)}(z_1^*, z_2^*)$. It follows that

$$\begin{aligned} & U^I(q^I_{(4.8)}(\bar{q}^*); \rho) = U^E(\bar{q}^*; \rho) \\ = \; & U^{Ez}(z_1^*, z_2^*; \rho) > U^I(q^I_{(4.18)}(z_1^*, z_2^*); \rho) \; . \end{aligned} \tag{4.20}$$

Focussing on efficient equilibria only, Propositions 2 and 4 therefore imply $\zeta^1 \zeta^2 = \overline{Q}^* < \bar{q}^*$. ■

Ceteris paribus - i.e. holding the team quality of the marginal entrepreneurial firm constant - consider two professionals with high abilities in the same one of the two tasks and very low abilities in the other task. If such individuals happen to be matched in "random matching"-equilibrium, they would decide not to become entrepreneurs and rather enter the industrial workforce. However, these professionals would become entrepreneurs in "incubator"-equilibrium because they could search for and then team up with individuals characterized by a compensating ability profile.

Hence, moving from "random matching" to "incubator"-equilibrium more high ability individuals decide not to seek industrial employment. Consequently, the expected team quality in such firms decreases. Further, recall that efficient equilibria are unique and in both cases maximize this expected team quality. Thus, the team quality of the marginal entrepreneurial firm must also be lower in efficient "incubator"-equilibrium. Clearly, this conclusion implies that more individuals found partnerships.

4.5.2 Evaluating industry structure and welfare effects

The assumptions for simulating the model

General analysis cannot assess the size of the structural effect reported in Proposition 5 above. Obviously, the increase in entrepreneurial activity by moving from a "random matching" to an "incubator"-equilibrium depends on risk-preferences and the properties of the ability profile distribution. Moreover, the corresponding welfare effects are generally ambiguous. On the one hand, the certain utility of professionals employed in industrial firms is lower in efficient "incubator"-equilibrium. On the other hand, high ability professionals do not face the risk of an "unlucky" match.

Simple simulations may, however, provide some insights into the relative importance of risk-aversion and the cost of capital for the size of the structural effects and the welfare dominance of the two regimes. Reasonably, such simulations again only compare the efficient outcomes under both regimes. For parsimony, the analysis above has already assumed a simple Cobb-Douglas type production function. Now, we set $\gamma = 0.3$ to match current estimates of the share of labor income in GDP.[10]

Positive initial wealth Y has actually only been introduced to the model to ensure positive optimal investments of entrepreneurs. In our simulations, $Y = 0.5$ then. This value has proved to induce well-scalable effects of varying the degree of risk aversion and the interest rate over broad ranges. Risk-preferences are expressed by a CRRA utility function. Hence, $u(y) = \frac{y^{1-c}}{(1-c)}$, for $c \neq 1$, and $u(y) = ln(y)$, for $c = 1$.[11] According to Kaplow (2005), the degree of relative risk-aversion c can plausibly take on even very high values - i.e. greater than 10.

Further, we assume that individual task abilities are identically and independently distributed. In the remaining, let therefore $f(a^1, a^2) = g(a^1)g(a^2)$. Further, we specify g as the uniform density on $[a_L, 1]$ with a_L itself set equal to 0.1.

Changes in industry structure and capital usage

Given the assumptions above, the simulations reported in Tables 4.8.2 a) and b) in section 4.8.2 confirm Proposition 5. The entrepreneurial sector is always larger in the "incubator"-equilibrium.

Interestingly, lower interest rates decrease the size of the entrepreneurial sector in both

[10]Gollin (2002).
[11]Since $Y > 0$, risk preferences can also be seen to reflect HARA rather than CRRA-utility.

scenarios. This somewhat counter-intuitive effect can be explained by recalling the occupational options depicted in Figure 4.1, section 4.8.2. An increase in the interest rate "harms" successful as well as unsuccessful entrepreneurs. *Ex-ante* entrepreneurial partnerships respond by reducing the optimal capital input. Obviously, the same adjustment is carried out in industrial firms. Yet, entrepreneurial partnerships also increase their self-insurance by shifting payoff from the success to the failure state.

In contrast, more industrial employment implies better risk-sharing. Hence, higher degrees of risk-aversion decrease the size of the entrepreneurial sector. However, the respective effect on industry-wide capital-usage - i.e. calculated by taking the average over industrial and entrepreneurial firms - is generally ambiguous:

- Higher risk-aversion induces an increase in the number of high-ability individuals employed in the industrial sector. This effect tends to increase average team quality in this sector and, consequently, investments by outside investors.

- Some low quality teams that, with lower risk-aversion, would have become entrepreneurs now opt for industrial employment. This effect tends to increase average team quality in the entrepreneurial sector. Yet, although capital-usage is an increasing function of team quality, the respective investment effect is only of second-order. It is more than offset by the direct negative impact of increasing in risk-aversion on capital choices by entrepreneurial partnerships.

- Finally, there is an effect of relative sector sizes. For low degrees of risk-aversion the average capital input in industrial firms is small compared to that in entrepreneurial firms. Thus, the increased size of the industrial sector tends to lower industry-wide investments. For high degrees of risk aversion the average capital input is higher in industrial firms. Hence, a larger industrial sector results in a higher overall capital input.

In all our simulations, this third effect implies that the capital usage in the industry constitutes a non-monotonic function of the degree of risk-aversion: it decreases with higher risk-aversion at low degrees of risk-aversion, then reaches a minimum, and increases for higher degrees of risk-aversion. Further, minimum investment levels are always realized at lower degrees of risk-aversion in the efficient "random matching"-equilibrium.

Clearly, higher interest rates decrease the capital usage in industrial as well as entrepreneurial firms. Moreover, the entrepreneurial sector increases because lower-quality teams found entrepreneurial partnerships. Comparing efficient “random matching” and “incubator”-equilibria again, the marginal entrepreneurial firm therefore always uses less capital in the latter case.

Figures 4.4 a) - c) in section 4.8.2 illustrate these structural effects. The light and the dark columns display the average capital input of entrepreneurial firms and the capital input of industrial firms, respectively. The line then indicates the average capital input in the industry taken over all firms. Qualitatively, all figures depict the same functional relationship between risk-aversion and capital inputs as regimes are compared. Yet, the levels of these capital inputs decrease with higher interest rates.

Welfare effects

If risk aversion c approaches 0 - i.e. if we assume risk-neutrality - no individual seeks industrial employment since $q^E \geq q^I$. In this case, the expected team quality is therefore given by $E(q) = E(\tilde{a}^1) \cdot E(\tilde{a}^2)$ under the “random matching”-setting and $E(q) = E((\tilde{a}^1)^2)$ in the “incubator”-regime. The latter expression always exceeds the former then.[12] In contrast, for extremely risk averse professionals - hence, if c approaches infinity - the welfare difference between the two regimes approaches zero. Both regimes converge to the same all-employee borderline case.

Hence, a trade-off emerges only if individuals are moderately risk averse: on the one hand, entrepreneurs can choose their partners in the “incubator”-setting. Consequently, the entrepreneurial sector realizes higher average team quality compared to the “random matching”-case. On the other hand, however, the average quality of industrial teams and the industrial wage is lower in the “incubator”-setting. Then, recall that higher risk aversion implies a larger share of industrial employees in both settings. This structural effect therefore tends to render the “random matching”-setting dominant.

These conclusions are confirmed by the simulations reported in Table 4.2 in section 4.8.2. For low degrees of risk aversion, the “incubator”-equilibrium is welfare dominant. As c increases, the “random matching”-regime *ceteris paribus* becomes dominant. Moreover, for very high degrees of risk aversion the welfare differences expressed in certainty equivalents or in terms of relative difference in expected utilities decreases.

As noted above, increasing the interest rate yields more entrepreneurial activity under

[12]This general difference in calculating expected team qualities between the two regimes also implies that the conclusions derived below can be transferred to the case of positively correlated task abilities.

both regimes due to enhanced self-insurance in the entrepreneurial partnerships. Thus, higher interest rates should tend to support the welfare-dominance of the “incubator”-equilibrium. The results reported in Tables 4.3 a) and b), section 4.8.2, confirm this conclusion. Yet, given our specific simulation model and realistic movements of interest rates, the capital-cost effect appears to be weak: comparing welfare differentials between the two regimes, the effect of increasing the interest rate by 4% can (on average) be offset by lowering the degree of risk aversion by only one unit.[13]

4.6 Concluding discussion

Competitive equilibria in which industrial firms and entrepreneurial partnerships coexist are supported by institutions to match complementary individual task abilities prior to making occupational choices. Two such institutions have been analyzed in detail: (corporate) spin-offs of randomly matched production teams and incubator organizations in which individuals are rationally matched. Aligning with the goals of technology transfer policies, efficient “incubator”-equilibria always entail more entrepreneurial activity.

However, other consequences of such policies are not as easily appreciated: first, improved matching implies that the capital inputs of marginal entrepreneurial firms decrease. Moreover, the “incubator”-equilibrium yields less industry-wide risk-sharing. Consequently, higher degrees of risk aversion render the “random matching”-equilibrium dominant. In this respect, it has been noticed that US households are willing to bear more risk than their European counterparts.[14] This difference in risk-aversion could then explain why incubator organizations, such as the *Silicon Valley* network, emerge as efficient institutions in the US while they require persistent public support in Europe.

Second, higher interest rates obviously reduce the capital usage in both entrepreneurial and industrial firms. However, they also imply better self-insurance in partnerships. Contrasting with studies on the success of transfer or entrepreneurship centers, the “incubator”-equilibrium therefore dominates when capital is scarce rather than readily available. Third, industry-wide capital usage follows a “u-shaped” function of risk-aversion given both matching regimes. The respective minima of the two functions

[13]Hence, suppose a situation in which the efficient “spin-off”-equilibrium welfare dominates. Starting from this situation, a 4% increase in the interest rate would then (on average) render the “incubator”-equilibrium dominant. However, assuming an increase of the risk-aversion parameter c by one would again restore the original dominance of the “spin-off”-equilibrium.

[14]Allen and Santonomero (1999) are among the first to report this conclusion.

generally occur at different degrees of risk-aversion. Hence, improved ability-matching may increase or decrease industry-wide investments. Moreover, even if investments increase, welfare may still decrease.

4.7 References

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4.8 Appendix

4.8.1 The partnership of equals as the dominant organizational form for entrepreneurial firms

Generally, define the expected utilities of two professionals i and j, founding a new firm as

$$\begin{aligned} U^{ij} = T(\bar{a}^{ij}) & \left[a^{1i}a^{2j}u(Y-\phi(\bar{a}^{ij})+(1-\beta(\bar{a}^{ij}))[(K(\bar{a}^{ij}))^{\gamma}-\rho K(\bar{a}^{ij})])\right. \\ & \left. +(1-a^{1i}a^{2})u(Y-\phi(\bar{a}^{ij})-(1-\beta(\bar{a}^{ij}))\rho K(\tilde{a}^{i}))\right] \\ +\left(1-T(\bar{a}^{ij})\right) & \left[a^{1j}a^{2i}u(Y-\phi(\bar{a}^{ij})+(1-\beta(\bar{a}^{ij}))\left[(K(\bar{a}^{ij}))^{\gamma}-\rho K(\bar{a}^{ij})\right])\right. \\ & \left. +(1-a^{1j}a^{2i})u(Y-\phi(\bar{a}^{ij})-(1-\beta(\bar{a}^{ij}))\rho K(\bar{a}^{ij}))\right] \end{aligned} \tag{4.21}$$

and

$$\begin{aligned} U^{ji} = T(\bar{a}^{ij}) & \left[a^{1i}a^{2j}u(Y+\phi(\bar{a}^{ij})+\beta(\bar{a}^{ij})[(K(\bar{a}^{ij}))^{\gamma}-\rho K(\bar{a}^{ij})])\right. \\ & \left. +(1-a^{1i}a^{2})u(Y+\phi(\bar{a}^{ij})-\beta(\bar{a}^{ij})\rho K(\bar{a}^{ij}))\right] \\ +\left(1-T(\bar{a}^{ij})\right) & \left[a^{1j}a^{2i}u(Y+\phi(\bar{a}^{ij})+\beta(\bar{a}^{ij})\left[(K(\bar{a}^{ij}))^{\gamma}-\rho K(\bar{a}^{ij})\right])\right. \\ & \left. +(1-a^{1j}a^{2i})u(Y+\phi(\bar{a}^{ij})-\beta(\bar{a}^{ij})\rho K(\bar{a}^{ij}))\right] \ , \end{aligned} \tag{4.22}$$

where $T(\bar{a}^{ij}) = \{0,1\}$ indicates the two possible task allocations within the team.

In (4.21) and (4.22) $\phi(\bar{a}^{ij})$ constitutes a transfer of fixed income between the two partners. Partner j additionally receives the share $\beta(\bar{a}^{ij})$ in the firm. Thus, if $\beta(\bar{a}^{ij}) = 0$ ($\beta(\bar{a}^{ij}) = 1$) professional i (professional j) becomes a single entrepreneur paying the wage $\phi(\bar{a}^{ij})$ to her employee j (employee i). It is assumed that the ownership structure, the capital input, and the task allocation within this new entrepreneurial firm are simultaneously determined as the solution of the symmetric Nash-bargaining problem

$$\max_{K(\bar{a}^{ij}),T(\bar{a}^{ij}),\phi(\bar{a}^{ij}),\beta(\bar{a}^{ij})} \left[U^{ij}-v^{i}\right]^{\frac{1}{2}} \left[U^{ji}-v^{j}\right]^{\frac{1}{2}} \tag{4.23}$$

subject to

$$T(\bar{a}^{ij}) \in \{0,1\} \ , \tag{4.24}$$

$$0 \leqq \beta(\bar{a}^{ij}) \leqq 1 \ , \tag{4.25}$$

$$K(\bar{a}^{ij}) \geqq 0, \tag{4.26}$$

$$U^{ij} - v^{i} \geqq 0 \text{ and } U^{ji} - v^{j} \geqq 0 \tag{4.27}$$

where v^i and v^j denote reservation utility levels for the two professionals. Let the superscript "E" denote the bargaining outcomes.

Lemma 6 *Within the current model framework, the symmetric Nash-bargaining solution implies* $\phi^E(\bar{a}^{ij}) = 0$ *and* $\beta^E(\bar{a}^{ij}) = \frac{1}{2}$*. The capital input* $K^E = K^E(q^E(\bar{a}^{ij}); \rho)$ *in such entrepreneurial firms satisfies (4.2)*

Proof. Consider the optimization problem (4.23) to (4.27). Obviously, for every $K(\bar{a}^{ij})$, $\phi(\bar{a}^{ij})$, and $\beta(\bar{a}^{ij})$ (4.23) is always maximized by choosing the task allocation according to the rule of comparative advantage. Hence, the optimal task allocation implies $T^E(\tilde{a}^i) = 1$ (0) if $a^{1i}a^{2j} \geqq (<) \, a^{1j}a^{2i}$ which yields the definition of $q^E(\bar{a}^{ij}) = \max \{a^{1i}a^{2j}, \, a^{1j}a^{2i}\}$ in the lemma. Further, let

$$y_s^{ij} \equiv Y - \phi(\bar{a}^{ij}) \; + (1 - \beta(\bar{a}^{ij}))[(K(\bar{a}^{ij}))^\gamma - \rho K(\bar{a}^{ij})] \tag{4.28}$$

$$y_{ns}^{ij} \equiv Y - \phi(\bar{a}^{ij}) \; - (1 - \beta(\bar{a}^{ij}))\rho K(\bar{a}^{ij}) \tag{4.29}$$

$$y_s^{ji} \equiv Y + \phi(\bar{a}^{ij}) \; + \beta(\bar{a}^{ij})[(K(\bar{a}^{ij}))^\gamma - \rho K(\bar{a}^{ij})] \tag{4.30}$$

$$y_{ns}^{ji} \equiv Y + \phi(\bar{a}^{ij}) \; - \beta(\bar{a}^{ij})\rho K(\bar{a}^{ij}) \tag{4.31}$$

For interior solutions, the first-order conditions with respect to $\beta(\bar{a}^{ij})$, $K(\bar{a}^{ij})$, and $\phi(\bar{a}^{ij})$, can then be rearranged to yield

$$\left[q^E(\bar{a}^{ij})u'(y_s^{ij})[(K(\bar{a}^{ij}))^\gamma - \rho K(\bar{a}^{ij})] - (1 - q^E(\bar{a}^{ij}))u'(y_{ns}^{ij})\rho K(\bar{a}^{ij})\right] \left[U^{ij} - v^i\right]^{-\frac{1}{2}} \tag{4.32}$$

$$\left\{ \begin{array}{c} \geqq \\ = \\ \leqq \end{array} \right\} \left[q^E(\bar{a}^{ij})u'(y_s^{ji})[(K(\bar{a}^{ij}))^\gamma - \rho K(\bar{a}^{ij})] - (1 - q^E(\bar{a}^{ij}))u'(y_{ns}^{ji})\rho K(\bar{a}^{ij})\right] \left[U^{ji} - v^j\right]^{-\frac{1}{2}}$$

$$\text{if } \beta(\bar{a}^{ij}) \left\{ \begin{array}{c} = 0 \\ \in (0,1) \\ = 1 \end{array} \right. ,$$

$$\left[q^E(\bar{a}^{ij})u'(y_s^{ij})[\gamma(K(\bar{a}^{ij}))^{\gamma-1} - \rho] - (1 - q^E(\bar{a}^{ij}))u'(y_{ns}^{ij})\rho\right] \left[U^{ij} - v^i\right]^{-\frac{1}{2}} (1 - \beta(\bar{a}^{ij})) \tag{4.33}$$

$$= - \left[q^E(\bar{a}^{ij})u'(y_s^{ji})[\gamma(K(\bar{a}^{ij}))^{\gamma-1} - \rho] - (1 - q^E(\bar{a}^{ij}))u'(y_{ns}^{ji})\rho\right] \left[U^{ji} - v^j\right]^{-\frac{1}{2}} \beta(\bar{a}^{ij}) \, ,$$

and

$$\left[q^E(\bar{a}^{ij})u'(y_s^{ij}) + (1 - q^E(\bar{a}^{ij}))u'(y_{ns}^{ij})\right] \left[U^{ij} - v^i\right]^{-\frac{1}{2}} \tag{4.34}$$

$$= \left[q^E(\bar{a}^{ij})u'(y_s^{ji}) + (1 - q^E(\bar{a}^{ij}))u'(y_{ns}^{ji})\right] \left[U^{ji} - v^j\right]^{-\frac{1}{2}} \; ,$$

respectively. In the following, assume that $U^{ij} - v^i > 0$ and $U^{ji} - v^j > 0$. (i) Suppose that $\beta(\bar{a}^{ij}) = 0$ in the optimum. Then, (4.34) implies

$$q^E(\bar{a}^{ij}) + (1 - q^E(\bar{a}^{ij}))\frac{u'/Y + F(\bar{a}^{ij})\ )}{u'(Y - F(\bar{a}^{ij})\ \ - \rho K(\bar{a}^{ij}))} = \frac{[U^{ji} - v^j]^{-\frac{1}{2}}}{[U^{ij} - v^i]^{-\frac{1}{2}}}\frac{u'(Y + F(\bar{a}^{ij})\ )}{u'(Y - F(\bar{a}^{ij})\ \ + (K(\bar{a}^{ij}))^{\gamma} - \rho K(\bar{a}^{ij}))}\ . \tag{4.35}$$

The expected surplus $q^E(\bar{a}^{ij})(K(\bar{a}^{ij}))^{\gamma} - \rho K(\bar{a}^{ij})$ must be positive if $K(\bar{a}^{ij}) > 0$ and, hence, production will take place. Then, (4.35) contradicts that the LHS of (4.32) can be greater or equal than the RHS. (ii) Assuming that $\beta(\bar{a}^{ij}) = 1$ yields a very similar argument as in (i) above. Hence, this case can also be excluded. (iii) Consequently, let $0 < \beta(\bar{a}^{ij}) < 1$. Conditions (4.34) and (4.32) then imply

$$\begin{aligned}&\left[q^E(\bar{a}^{ij})(K(\bar{a}^{ij}))^{\gamma} - \rho K(\bar{a}^{ij})\frac{(1 - q^E(\bar{a}^{ij}))u'(y_{ns}^{ij})}{u'(y_s^{ij})}\right] \times \\ &\left[q^E(\bar{a}^{ij}) + \frac{(1 - q^E(\bar{a}^{ij}))u'(y_{ns}^{ji})}{u'(y_s^{ji})}\right] \\ = &\left[q^E(\bar{a}^{ij})(K(\bar{a}^{ij}))^{\gamma} - \rho K(\bar{a}^{ij})\frac{(1 - q^E(\bar{a}^{ij}))u'(y_{ns}^{ji})}{u'(y_s^{ji})}\right] \times \\ &\left[q^E(\bar{a}^{ij}) + \frac{(1 - q^E(\bar{a}^{ij}))u'(y_{ns}^{ij})}{u'(y_s^{ij})}\right]\ .\end{aligned} \tag{4.36}$$

The second terms on each side of (4.36) are clearly positive. Thus, suppose the two terms in the first quantities on both sides of the equation are also positive. In this case, (4.36) is easily verified to imply

$$\frac{u'(y_s^{ij})}{u'(y_{ns}^{ij})} = \frac{u'(y_s^{ji})}{u'(y_{ns}^{ji})}\ . \tag{4.37}$$

This conclusion may not hold if, and only if, both first terms on each side of (4.36) are negative. Yet, in this case (4.36) and (4.33) contradict. Hence, (4.37) must hold true in the optimum. Either (4.34) or (4.32) then further yield

$$\frac{[U^{ji} - v^j]^{-\frac{1}{2}}}{[U^{ij} - v^i]^{-\frac{1}{2}}}\frac{u'(y_s^{ij})}{u'(y_s^{jj})} = 1\ . \tag{4.38}$$

Notice that, for both institutional regimes, $v^i = v^j = \bar{v}$ since each partner's alternative is to seek industrial employment and, thus, to receive the same wage-income. Further, $U^{ij} = U^{ji} \geq \bar{v}$ with equality only for the marginal entrepreneurial firm. Hence, (4.38) and (4.37) then necessarily imply $\phi(\bar{a}^{ij}) = 0$ and $\beta(\bar{a}^{ij}) = \frac{1}{2}$. Insertion into (4.33) finally yields the capital input rule (4.2). ■

Also, the above assumption that each partner can observe her colleague's ability profile before production commences can now be supported. The expected utility of each partner of an entrepreneurial firm only depends on team quality. This team quality is maximized by choosing an optimal task allocation. Thus, potential partners possess effective incentives to communicate their abilities in both tasks truthfully.

4.8.2 Tables and Figures

Table 4.1: a) Cut-off team qualities in the "random matching"-case ($\bar{q}^*$) and in the "incubator"-case ($\overline{Q}^*$)

risk aversion c		3	4	5		3	4	5
$\rho = 1\%$	$\bar{\mathbf{Q}}^*$	0.19	0.62	0.79	$\bar{\mathbf{q}}^*$	0.65	0.78	0.86
$\rho = 2\%$		0.05	0.28	0.61		0.53	0.68	0.78
$\rho = 3\%$		0.03	0.08	0.43		0.44	0.61	0.72
$\rho = 4\%$		0.02	0.05	0.21		0.38	0.56	0.68
$\rho = 5\%$		0.02	0.04	0.1		0.32	0.51	0.64
$\rho = 6\%$		0.02	0.03	0.06		0.28	0.47	0.61
$\rho = 7\%$		0.02	0.03	0.05		0.25	0.44	0.58
$\rho = 8\%$		0.02	0.03	0.04		0.22	0.4	0.55
$\rho = 9\%$		0.02	0.02	0.04		0.19	0.38	0.52
$\rho = 10\%$		0.02	0.02	0.03		0.19	0.35	0.50

b) Percentage of entrepreneurs in the economy

risk aversion c		3	4	5		3	4	5
$\rho = 1\%$	Incubator	86	42	23	Random	9	3	1
$\rho = 2\%$		98	77	43	Matching	17	7	3
$\rho = 3\%$		99	96	62		25	11	5
$\rho = 4\%$		> 99	98	84		31	14	7
$\rho = 5\%$		> 99	99	94		39	18	9
$\rho = 6\%$		> 99	99	97		45	22	11
$\rho = 7\%$		> 99	99	98		50	25	13
$\rho = 8\%$		> 99	> 99	99		55	29	15
$\rho = 9\%$		> 99	> 99	99		61	31	17
$\rho = 10\%$		> 99	> 99	99		61	35	19

Table 4.2: Welfare dominance of regimes under varying degrees of risk-aversion

risk aversion c	1	2	3	4	5	6	7	8	9	10
$E(u\|incubator)$	-0.28	-1.47	-1.25	-1.53	-2.12	-2.62	-3.20	-4.04	-5.19	-6.82
$E(u\|rand.match.)$	-0.50	-1.73	-1.43	-1.45	-1.61	-1.91	-2.38	-3.07	-4.07	-5.47
$CE(incubator)$	0.76	0.68	0.63	0.60	0.59	0.60	0.61	0.62	0.63	0.63
$CE(rand.match.)$	0.61	0.58	0.59	0.61	0.63	0.64	0.64	0.65	0.65	0.65

Definitions: $E(u|incubator)$ [$E(u|\ rand.match.)$] and $CE(incubator)$ [$CE(rand.match.)$] denote the *ex-ante* expected utility and the certainty equivalent income associated with the efficient "incubator" ["random matching"] equilibrium.

Note: The interest rate ρ has been set equal to 4% in this simulation.

Table 4.3: Welfare effects of varying interest rates and relative risk aversion

a) Expected utilities [$E(u|incubator)$, respectively $E(u|rand.match.)$]:

risk aversion c		3	4	5		3	4	5
$\rho = 1\%$	**Incubator**	-1.137	-1.013	-0.935	**Random**	-0.951	-0.787	-0.737
$\rho = 2\%$		-1.199	-1.409	-1.498	**Matching**	-1.195	-1.099	-1.126
$\rho = 3\%$		-1.229	-1.499	-1.878		-1.343	-1.305	-1.404
$\rho = 4\%$		-1.252	-1.527	-2.124		-1.433	-1.450	-1.611
$\rho = 5\%$		-1.270	-1.546	-2.189		-1.504	-1.572	-1.788
$\rho = 6\%$		-1.286	-1.564	-2.220		-1.549	-1.667	-1.928
$\rho = 7\%$		-1.299	-1.579	-2.235		-1.580	-1.739	-2.055
$\rho = 8\%$		-1.310	-1.593	-2.253		-1.606	-1.813	-2.169
$\rho = 9\%$		-1.322	-1.605	-2.269		-1.628	-1.859	-2.275
$\rho = 10\%$		-1.332	-1.617	-2.284		-1.636	-1.910	-2.356

b) Certainty equivalent incomes [$CE(incubator)$, respectively $CE(rand.match.)$]:

risk aversion c		3	4	5		3	4	5
$\rho = 1\%$	**Incubator**	0.663	0.690	0.719	**Random**	0.725	0.751	0.763
$\rho = 2\%$		0.646	0.618	0.639	**Matching**	0.647	0.672	0.686
$\rho = 3\%$		0.638	0.606	0.604		0.610	0.634	0.650
$\rho = 4\%$		0.632	0.602	0.586		0.591	0.613	0.628
$\rho = 5\%$		0.627	0.600	0.581		0.577	0.596	0.612
$\rho = 6\%$		0.624	0.597	0.579		0.568	0.585	0.600
$\rho = 7\%$		0.620	0.595	0.578		0.563	0.577	0.591
$\rho = 8\%$		0.618	0.594	0.577		0.558	0.569	0.583
$\rho = 9\%$		0.615	0.592	0.576		0.554	0.564	0.576
$\rho = 10\%$		0.613	0.591	0.575		0.553	0.559	0.571

Figure 4.1: The payoff (lottery) associated with occupational choices

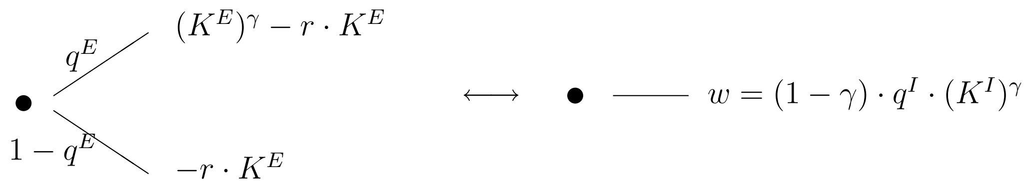


Figure 4.2: Professionals seeking industrial employment in "random matching" equilibrium

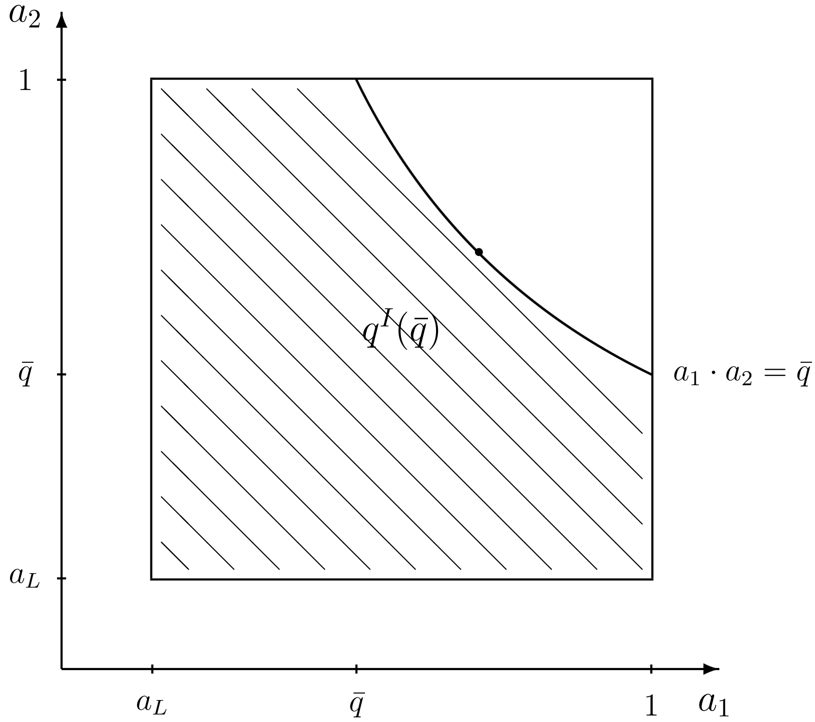


Figure 4.3: Professionals seeking industrial employment in "incubator" equilibrium

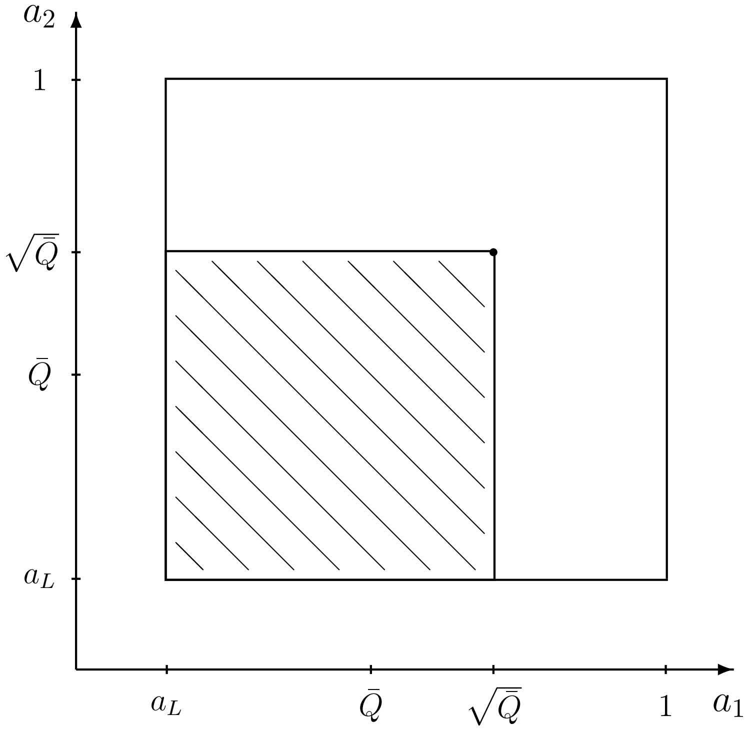
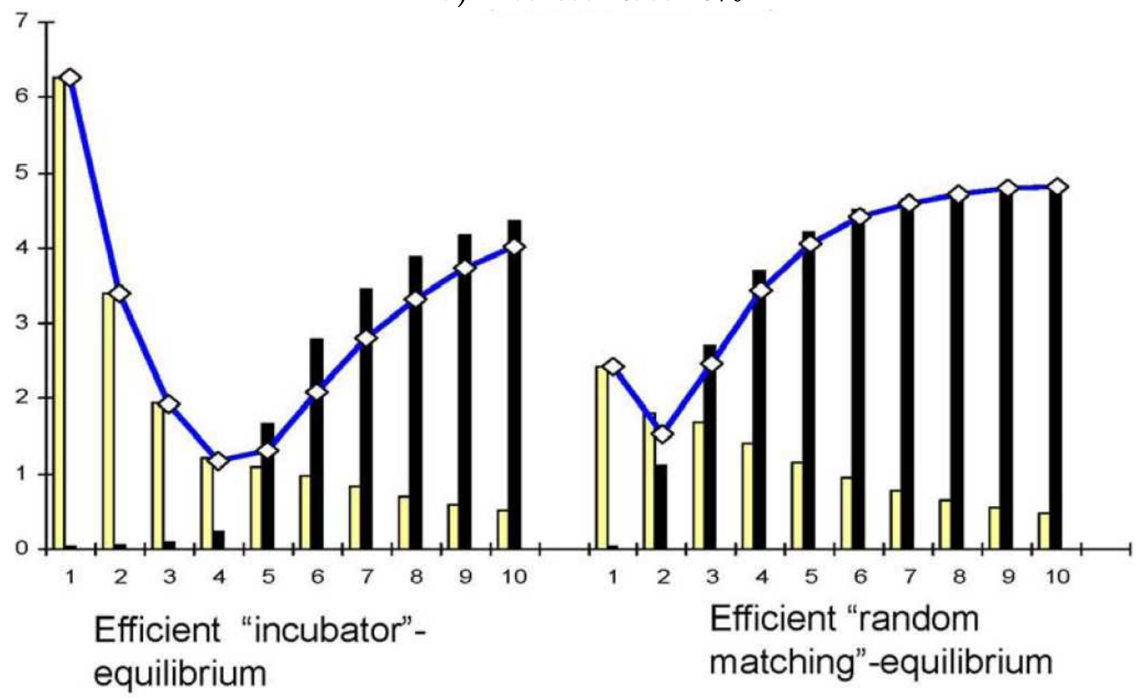


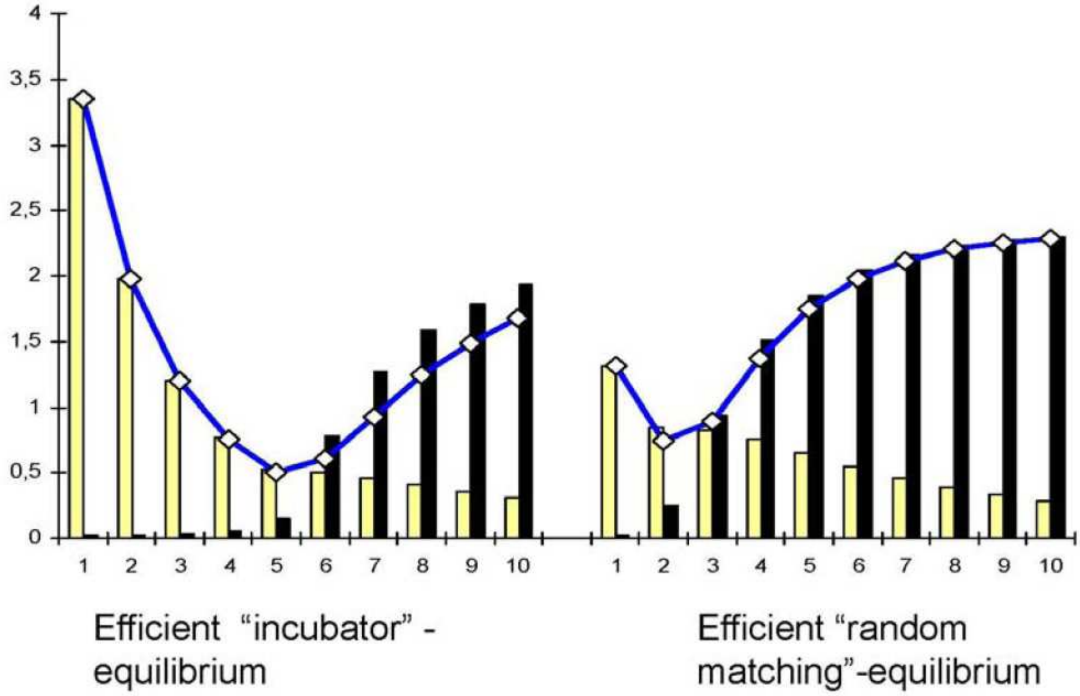
Figure 4.4: Capital input as a function of risk-aversion

a) Interest Rate: 3%

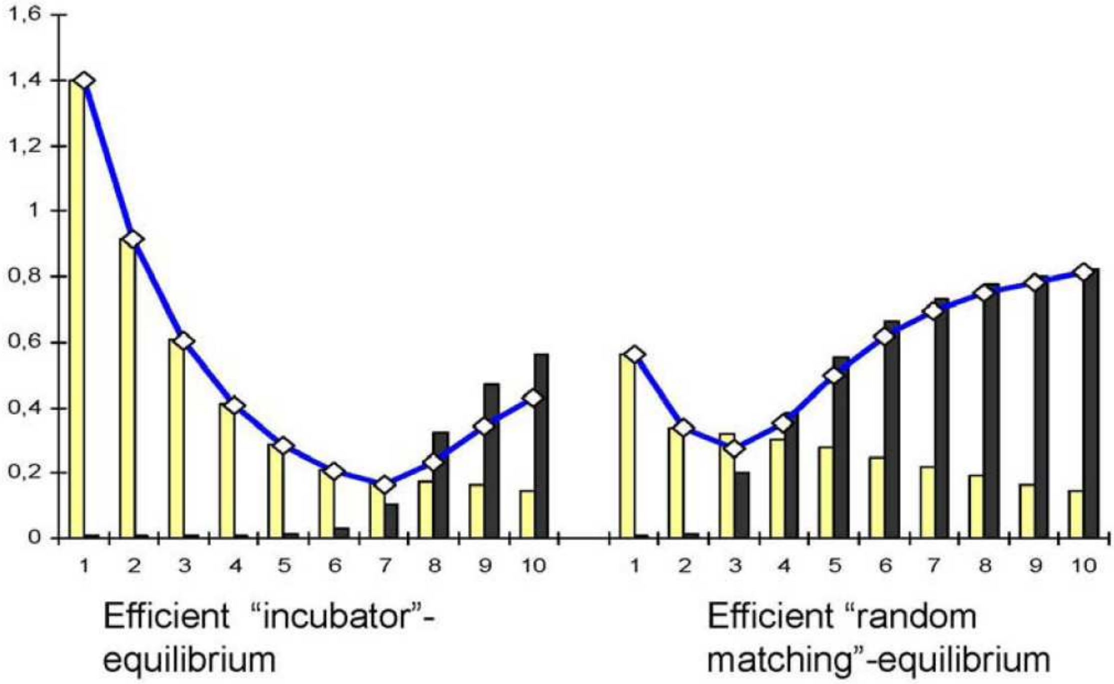


Remarks: dark columns: capital input of the industrial firm; light columns: average capital input of the entrepreneurial firms; line with diamonds: average capital input in the industry.

b) Interest Rate: 5%



c) Interest Rate: 10%



Remarks: dark columns: capital input of the industrial firm; light columns: average capital input of the entrepreneurial firms; line with diamonds: average capital input in the industry.

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Erklärung

Ich versichere hiermit, dass ich die vorliegende Arbeit mit dem Thema

Four Essays on Debt Securitization and Entrepreneurial Finance

ohne unzulässige Hilfe Dritter und ohne Benutzung anderer als der angegebenen Hilfsmittel angefertigt habe. Die aus anderen Quellen direkt oder indirekt übernommenen Daten und Konzepte sind unter Angabe der Quelle gekennzeichnet. Weitere Personen, insbesondere Promotionsberater, waren an der inhaltlich materiellen Erstellung dieser Arbeit nicht beteiligt.[15] Die Arbeit wurde bisher weder im In- noch im Ausland in gleicher oder ähnlicher Form einer anderen Prüfungsbehörde vorgelegt.

Konstanz, den 26. September 2008

(Thomas Weber)

[15] Siehe hierzu die Erklärung zur Abgrenzung auf der folgenden Seite.

Abgrenzung

Das erste Kapitel dieser Dissertation entstammt einer gemeinsamen Arbeit mit Prof. Franke (Universität Konstanz) und Dr. Markus Herrmann (HSBC London). Die Idee für das theoretische Modell stammt von Prof. Franke. Die Hypothesen wurden gemeinsam von Prof. Franke, Dr. Herrmann und mir ausgearbeitet. Das Sammeln und Aufbereiten der Daten sowie die empirische Analyse gehen auf mich zurück. Die empirischen Ergebnisse wurden von Prof. Franke und mir gemeinsam interpretiert.

Das zweite Kapitel habe ich ohne die Mitwirkung Dritter angefertigt.

Das dritte Kapitel entstammt einer gemeinsamen Arbeit mit Julia Hein, Universität Konstanz. Meine individuelle Leistung bei Erstellung dieser Arbeit beläuft sich auf 50%.

Das vierte Kapitel entsammt einer gemeinsamen Arbeit mit Prof. Fabel (Universität Wien). Der theoretische Teil der Arbeit ist hälftig Prof. Fabel und mir zuzurechnen. Die für den Vergleich der Gleichgewichte notwendigen Simulationen stammen von mir. Die Ergebnisse wurden gemeinsam interpretiert.