Asset Correlation in Structured Finance Portfolios

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Abstract

This paper presents a thorough analysis of rating transitions in structured finance portfolios and investigates the dependence between rating transitions within and between different asset types. Although the number and market share of structured finance products such ABS, CDO, CMBS and RMBS has grown enormously over the past decade, little is known about their behavior in terms of default and rating transitions. Asset correlation within and between portfolios is derived using a two-factor credit risk model. This paper differs from previous empirical studies in that asset correlation estimates are derived from rating transition behavior and not just transitions to default. The results show that ABS, CDO, CMBS and RMBS behave very different in terms of rating transitions. Furthermore, certain asset types such as manufactured housing show very high dependence between rating transitions and are therefore "riskier" assets.

This paper is ongoing work.

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1 Introduction

This paper investigates the dependence of rating migrations for structured finance (SF) assets. Although the number and market share of structured finance products such as asset-backed securities (ABS), commercial mortgage-backed securities (CMBS), collateralized debt obligations (CDOs), and residential mortgage-backed securities (RMBS) has grown enormously over the past decade, little is known about their behavior in terms of rating migrations including defaults.[1] Different structured finance asset types are backed by different assets and are therefore very different products, which is reflected in their rating migration behavior. Credit risk models such as factor models generally rely on the estimation of rating migration and/or default probabilities to model the risk of the individual exposures and asset correlation to model the dependence structure between exposures.[2] Asset correlation significantly affects the portfolio loss distribution and in particular the tails of the distribution. Therefore, the accuracy of its estimate is of vital importance.

The empirical analysis uses Standard & Poor's rating migration data from Jan. 1995 until June 2007. The inputs for the model are six-monthly time-series of default or rating migration probabilities for different asset types. Asset correlation within and between portfolios of SF asset types is obtained using a two-factor credit risk model. The correlation estimates are calibrated using a maximum likelihood approach similar to Gordy and Heitfield (2002).

In this paper, the following topics and questions are discussed:

- Comparison of correlation within ABS, CDOs, CMBS, and RMBS portfolios
- Correlation between ABS, CDOs, CMBS, and RMBS portfolios
- Analysis of rating co-movements of tranches in the same deal. How does this affect the correlation estimates?
- Is rating dependence significantly higher for lower quality assets? Comparison of RMBS prime and subprime portfolios.
- How much are the ABS results in terms of rating migrations and correlation affected by the manufactured housing sector?
- How does rating migration dependence differ between cash and synthetic CDOs?

2 Structured Finance Rating Migrations

2.1 Data Description

The empirical analysis uses Standard & Poor's rating performance data for SF tranches. The sample covers the period January 1985 until August 2007 and consists of 179,236 tranches from 32,755 deals. The average number of tranches per deal has increased from 3.8 to close to 8 over the last decade. The dataset includes US-denominated as well as non-US-denominated assets

[1] The change in rating of an asset is referred to as a transition or migration.

[2] The loss distribution also requires information on the recovery rate. However, the latter is not the focus of this paper.

and only cover assets with a long-term Standard & Poor's rating. First, I analyze the raw data and investigate the codependence between rating changes of tranches in the same deals. I expect the correlation between tranches in the same deal to be significantly higher than the correlation between tranches in different deals. Second, to test the impact of this issue on the overall correlation estimates, similarly rated tranches (often AAA) in the same deal are collapsed into a single tranche. This significantly reduces the number of tranches per deal.

As shown in Table 1, the majority of SF deals are RMBS (41 percent) and issued in North America, especially the US (71 percent). While ABS and CDOs both represent just over 20 percent of the sample, only 5 percent of the sample are CMBS. SYNT is also a relatively small asset types that is a collection of all single-name deals, mainly single-name ABS CDS. Looking at the regional distribution of each of the asset types shows that CDOs are somewhat different from ABS, CMBS, and RMBS. An important percentage of CDOs are issued in Europe. Making a distinction between different types of CDOs, namely cash-flow (CF) or synthetic (Synt), shows that the majority of US CDOs are cash-flow deals, whereas the majority of European CDOs are synthetic deals (see Figure 2). As shown in Figure 1, the most common types of ABS included in the sample are auto loans (23 percent), credit cards (20 percent), student loans (13 percent), and equipment (7 percent).

Table 1: Regional distribition of SF deals in the sample

	ABS	CDOs	CMBS	RMBS	SYNT	Total	
						(No)	(Perc.)
Asia/Japan	563	327	154	273	43	1369	4%
Austr/NZ	142	290	69	554	55	1137	3%
EM Mkts/ LAmerica	207	18	0	9	8	244	1%
Europe	646	3844	294	1017	611	6456	20%
USA/Canada	2388	4064	1193	11652	1197	23549	72%
Total (No)	6946	8543	1710	13505	1914	32755	
Total (Perc.)	21%	26%	5%	41%	6%		

Note: This table presents the number of SF deals with at least one long-term Standard & Poor's rating between Jan. 1985 and May 2007. SF tranches are classified by collateral type.

Over the last decade, the number of rated SF deals has grown enormously. To get an indication of the growth rate, I split the sample into five subperiods and calculate the number of deals which have their first rating in the corresponding periods. Rating migrations are not taken into account, which means that a deal is counted only once. As shown in Panel A of Table 2, every asset type has expanded enormously over the last 20 years, with the most remarkable growth rate for CDOs.

Of the 32755 deals in the sample, 42 percent or 13757 are single-tranche deals. As shown in Table 2 the majority of single-tranche deals are CDOs and single-name transactions. In a single-tranche deal only one tranche of the deal is sold to an investor. Most of them are transacted

Table 2: Average number of deals with first rating in a particular period

	ABS	CDOs Cash	CDOs Synt	CMBS	RMBS	SYNT	Total[(a)]
Panel A: Total sample							
1985 - 1990	263	214	0	54	1052	10	1645
1990 - 1995	966	246	0	243	1598	89	3180
1995 - 2000	1948	346	36	284	1838	543	5042
2000 - 2005	2578	1152	2335	650	4564	896	12175
2005 - 2007	1191	1220	2994	479	4453	376	10713
Total (no.)	6946	3178	5365	1710	13505	1914	32755
Total (perc.)	21%	10%	16%	5%	41%	6%	
Panel B: Single tranche deals							
1985 - 1990	233	197	0	40	714	6	1241
1990 - 1995	681	145	0	140	395	67	1464
1995 - 2000	868	167	27	75	372	447	2002
2000 - 2005	917	330	1986	84	751	715	4783
2005 - 2007	404	160	2670	19	674	340	4267
Single total (no.)	3103	999	4683	358	2906	1575	13757
Single total (perc.)	23%	7%	34%	3%	21%	11%	
$\frac{\text{Single}}{\text{Total}}$ (percent)	45%	31%	87%	21%	22%	82%	

Note: Panel A presents for different subperiods the number of deals that were assigned their first rating during that period. Panel B repeats the same analysis as Panel A but focuses on single-tranche deals. $^{(a)}$ The number of deals in "Total" is the sum of the number deals for the different asset types presented in the table plus a residual group "other", which is a negligible. $^{(b)}$ The ratio is the number of single-tranche deals over the total number of deals in the sample.

privately between collateral managers and a single investor, and have a greater capability to make substitutions in the reference pool. The last row of Table 2 presents the single-tranche deals as a percentage of the total number of deals by asset type. It shows that the majority of synthetic CDOs and single-name transactions have only one tranche, 87 and 82 percent, respectively. The distinction between single-tranche and multi-tranche deals becomes especially important when modeling correlation in SF pools.

2.2 Comovements Between Rating Migrations

Tranches of the same deal could be viewed as corporate bonds issued by the same company. If a firm-specific event happens, it is very likely that the spreads and/or ratings of all bonds issued by that company will be affected. The same holds for tranches of the same deal. As shown in Table 3, the average number of tranches per deal is 5.5 with a standard deviation of 7.3. The average number of tranches per deal has increased over time.

To test the potential impact of the number tranches per deal on the correlation analysis, I investigate the comovements in rating migrations of tranches of the same deal. The analysis is

Table 3: Summary statistics of the number of tranches per deal

	1985-1990	1990-1995	1995-2000	2000-2005	2005-2007	**Total period**
Mean	1.9	4.3	4.2	5.6	6.8	5.5
Stdev	2.1	5.5	5.3	7.6	8.4	7.3
5%	1	1	1	1	1	1
95%	6	16	15	19	22	19
99%	11	23	26	36	36	33
Max	23	59	55	131	151	151

Note: This table presents summary statistics of the number tranches per deal for several subperiods.

done as follows: for each deal, I calculate the total number of rating migration dates (excluding the initial rating date) and the number of rating migrations occurring on the same day, within the same month and within the same year. Deals with no rating migrations or single tranche deals are excluded from the sample. The summary statistics of the three ratios, which are presents in Table 4, show that on average 47 percent of all rating migrations for the same deal happen on the same day.

Table 4: Comovements in rating migrations of the same deal

	Rating migrations	
	Mean	Stdev
Migrations on the same day	47%	25%
Migrations within the same month	50%	25%
Migrations within the same year	61%	22%

Note: This table presents the average number of rating migrations in a particular time frame for a particular deal.

As shown by this analysis, tranches of the same deal are likely to cause an upward bias in any measure of codependence between rating transitions. Therefore, similarly-rated tranches of the same deals are collapsed into a single tranche in what follows. This substantially reduces the average number of tranches per deal from 5.5 to 2.7. The 95th percentile is reduced from 33 to 12 tranches per deal. Alternatively, the sample could be reduced to the single-tranche deals only or multiple tranches could be collapsed into a single tranche. As the majority of the single-tranche deals are synthetic and more single-tranche deals rated at the beginning of the sample period, the first approach would cause a serious selection bias. The second approach would require a set arbitrary rules to determine which tranche (of every deal) should be kept in the sample.

2.3 Comparison between SF and Corporate Rating Migrations

Before discussion asset correlation in SF portfolios, I briefly discuss some of the differences between rating migration behavior of SF deals and corporates. This allows one to better understand the results in the following sections.

A general conclusion that can be drawn is that the rating migration behavior of SF products is much more fat-tailed and shows a different pattern through time than corporates. Panel A and B of Figure 3 present the distribution of notch-level rating migrations for SF tranches and corporates on a semi-annual basis. For both corporates and SF tranches, I analyze the rating at the end of each 6-month period from January 1985 until June 2007 and compare it to the rating at the beginning of the corresponding 6-month period. The maximum notch-level downgrade is -19 (from AAA to D) and the maximum notch-level upgrade is 18 (from CCC- to AAA). Rating migrations to NR are ignored. The following conclusions can be drawn from Figure 3: Firstly, for SF tranches, the number of rating migrations is clearly dominated by upgrades (64 percent), whereas for corporates, it is dominated by downgrades (63 percent).[3] Given that the SF sample is clearly dominated by AAA tranches, the upgrade probability for SF tranches is likely to be even biased downwards. An important different between corporate issuers and SF deals is that the former do not have a maturity, whereas the latter do. When a SF deal approaches maturity, the uncertainty about future cash-flows is significantly reduced. Hence, its rating should improve closer to maturity, given that certain conditions are met. Secondly, for corporates, one or two notch-level rating migrations (up- or downgrades) represent 81 percent of all rating migrations. For SF tranches, however, the number of up-to-two notch-level rating migrations is significantly lower, 58 percent. As a result, the distribution of notch-level rating migrations is concentrated around the mean for corporates and more spread around the mean for SF tranches. Thirdly, the maximum notch-level downgrade is higher for SF tranches than for corporates, -19 and -16 respectively. Furthermore, on average 1.4 percent of the yearly rating migrations for SF tranches is a more than 10 notches (say from AAA to BB+) compared to only 0.6 percent for corporates. In general, there are less rating migrations for SF tranches than for corporates but that the migration jumps are bigger in terms of notches for SF tranches.

As shown in Panel A and B of Figure 4, the semi-annual downgrade probabilities for investment and speculative grade SF tranches and corporates vary substantially over time. The probabilities are calculated as the number of downgrades for investment and speculative grade ratings over a 6-month period divided by the number of investment and speculative grade observations during that period, respectively.[4] For corporates, the probabilities reach a peak at the end of 2001 and remain high for almost a year. This peak moment coincides with a very low growth rate of the OECD US leading indicator. For SF tranches, the peak is reached mid 2003, which is somewhat later than for corporates.

3 Asset Correlation

An important input parameter for credit risk models is the correlation between assets in the underlying portfolio. As suggested by Gordy and Heitfield (2002) and similar to Frey and McNeil (2003), Demey, Jouanin, Roget and Roncalli (2004), Tasche (2005), Jobst and de Servigny (2006),

[3] This is even more pronounced for investment grade ratings (not shown).

[4] Because of a lack of speculative grade SF ratings before 1995, the SF probabilities are only shown from 1995 onwards. The high speculative grade downgrade probability for SF tranches in 1995 is mainly due to a few downgrades from a very small number of speculative grade observations.

and others, I use a two-factor credit risk model and apply the maximum likelihood (ML) method to estimate the factor loadings. The model assumes that correlation between firm asset values is driven by two systematic risk factors, which could be thought of as an economic and an asset-type-specific factor. The approach in this paper differs from the previous empirical studies in that it takes into account all rating migrations instead of only rating migrations to the default state.

In the remainder of this paper, portfolios are generated based on the asset type classification of assets, which implicitly assumes that asset types can be seen as homogeneous risk classes that are driven by similar factors.

3.1 Two-factor Approach without Rating Migrations

In a two-factor model, the asset value V_i is driven by two common, standard normally distributed factors Y and Y_i and an idiosyncratic standard normal noise component ε_n

$$V_n^t = \sqrt{\rho} Y + \sqrt{\rho_i - \rho} Y_i + \sqrt{1-\rho_i} \varepsilon_n \qquad \text{for } n \leq N \tag{1}$$

Y can be seen as a common (or economy wide) factor that affects all assets at the same time and Y_i as a asset–type-specific factor. The asset values are correlated with correlation coefficients ρ and ρ_i. Default occurs when the asset value hits a threshold. An interesting feature of this model is that default events are independent conditional on the two common factors. The conditional default probability of sector i can be written as follows

$$p_D^i(y, y_i) = \Phi\left(\frac{Z_D^i - \sqrt{\rho} y - \sqrt{\rho_i - \rho}\ y_i}{\sqrt{1-\rho_i}}\right)$$

with $Z_D^i = \phi^{-1}(\overline{p}_D^i)$ the default threshold for sector i, $\overline{p}_D^i$ the average (unconditional) default probability for asset type i, and Φ the standard Gaussian CDF. This two-factor model implies the following correlation structure

$$\widehat{\sum}_{MLE} = \begin{pmatrix} \widehat{\rho}_1 & \widehat{\rho} & \dots & \widehat{\rho} \\ \widehat{\rho} & \widehat{\rho}_2 & \dots & \widehat{\rho} \\ \dots & & & \\ \widehat{\rho} & \widehat{\rho} & \dots & \widehat{\rho}_I \end{pmatrix}$$

with $\widehat{\rho}$ the inter asset correlation (or the correlation between I asset types) and $\widehat{\rho}_i$ the intra asset correlation (or the correlation within the ith asset type group). This two-factor model approach differs from a joint default probability approach, which derives joint defaults and default correlation from empirical data, in that the correlation structure $\left(\widehat{\sum}_{MLE}\right)$ is the result of one joint estimation. Default information for all asset type groups is considered at the same time. The factor loadings and asset correlation are obtained using a maximum likelihood (ML) method.

Let D_k^i be a random variable that presents the number of defaults for asset type i and with starting rating class k. Conditional on the common factors Y and Y_i, we assume that the probability of having d_k defaults is binomially distributed

$$\begin{aligned}
& \mathbf{P}\left(D_k^i = d_k^i \left| y, y_i \right.\right) \\
= & \frac{n_k^i!}{d_k^i!}\, p_{k,D}^i(y, y_i)^{d_k^i} \left(1 - p_{k,D}^i\left(y, y_i\right)\right)^{n_K^i} \\
= & \begin{pmatrix} n_k^i \\ d_k^i \end{pmatrix} p_{k,D}^i\left(y, y_i\right)^{d_k^i} \left(1 - p_{k,D}^i\left(y, y_i\right)\right)^{n_K^i}
\end{aligned}$$

The unconditional likelihood is

$$\begin{aligned}
L(\theta) &= \Pi_{k_1=1}^{K-1} \int_{-\infty}^{+\infty} d\Phi(y)\ \Pi_{i=1}^{I} \int_{-\infty}^{+\infty} \begin{pmatrix} n_k^i \\ d_k^i \end{pmatrix} p_{k,D}^i\left(y, y_i\right)^{d_k^i} \left(1 - p_{k,D}^i\left(y, y_i\right)\right)^{n_K^i}\ d\Phi(y_i) \\
LL(\theta) &= \textstyle\sum_t \log(L\left(\theta\right))
\end{aligned}$$

with K the rating states and θ the optimization variables: ρ and ρ_i.

3.2 Two-factor Approach with Rating Migrations

A two-factor approach without rating migrations can easily be extended to a framework which takes into account rating migrations from rating state k_1 to k_2, with k_1 and $k_2 = \{1, 2, ..., K\}$ and K the total number of rating states. The conditional transition probability from k_1 to k_2 of asset type i can be written as follows

$$p_{k_1,k_2}^i(y, y_i) = \Phi\left(\frac{Z_{k_1,k_2}^i - \sqrt{\rho}y - \sqrt{\rho_i - \rho}\ y_i}{\sqrt{1-\rho_i}}\right) - \Phi\left(\frac{Z_{k_1,(k_2-1)}^i - \sqrt{\rho}y - \sqrt{\rho_i - \rho}\ y_i}{\sqrt{1-\rho_i}}\right)$$

with $Z_{k_1,k_2}^i = \phi^{-1}(\overline{p}_{k_1,k_2}^i + \overline{p}_{k_1,k_2-1}^i + ... + \overline{p}_{k_1,D}^i)$ and $\overline{p}_{k_1,k_2}^i$ the average (unconditional) transition probability from rating state k_1 to k_2 for asset type i. If k_1 equals BBB, for example, then $(k_1 - 1)$ equals BBB-. Φ the standard Gaussian CDF.

Let M_{t,k_1,k_2}^i be a random variable that presents the number of rating migrations from k_1 to k_2 in year t. Conditional on the common factors Y and Y_c, the probability of $M_{t,k_1}^i = (M_{t,k_1,1}^i, ..., M_{t,k_1,K}^i)$ rating migrations is multinomially distributed

$$\begin{aligned}
& \mathbf{P}\left(M_{t,k_1,1}^i = m_{k_1,1}^i, ...M_{t,k_1,K}^i = m_{k_1,K}^i \left| y, y_i \right.\right) \\
= & \frac{n_{k_1}^i!}{m_{k_1,1}^i! ...\ m_{k_1,K}^i!}\, p_{k_1}^i(R_t = 1 \left| y, y_i \right.)^{m_0^i} ... p_{k_1}^c(R_t = K \left| y, y_i \right.)^{m_K^i} \\
= & \begin{pmatrix} n_{k_1}^i \\ m_{k_1,1}^i ... m_{k_1,K}^i \end{pmatrix} p_{k_1,1}^i\left(y, y_i\right)^{m_1^i} ... p_{k_1,K}^i\left(y, y_i\right)^{m_K^i}
\end{aligned}$$

where R_t presents the rating of an obligor in a homogeneous group and $n_{k_1}^i = m_{k_1,1}^i + ... + m_{k_1,K}^i$

the total number of observations in rating state k_1. The unconditional likelihood is

$$L(\theta) = \Pi_{k_1=1}^{K-1} \int_{-\infty}^{+\infty} d\Phi(y) \, \Pi_{i=1}^{I} \int_{-\infty}^{+\infty} \binom{n_{k_1}^i}{m_{k_1,1}^i ... m_{k_1,K}^i} p_{k_1,1}^i (y, y_i)^{m_1^i} ... p_{k_1,K}^i (y, y_i)^{m_K^i} \, d\Phi(y_i)$$
$$LL(\theta) = \sum_t \log(L(\theta))$$

with θ the optimization variables: ρ and ρ_i.

4 Empirical Analysis

THE EMPIRICAL ANALYSIS IS STILL ONGOING.

Asset correlation is estimated for different groups defined by collateral type and is obtained using the two-factor model approach. The binomial ML approach uses time series of semi-annual default probabilities for different groups of assets, whereas the multinomial ML approach uses time series of semi-annual transition matrices for groups of assets.[5] As the standard transition matrices have transition probabilities for all possible rating categories, the off-diagonal cells are often zero. To avoid this problem, I calculate a two-by-four matrix with two rating groups, namely investment grade and speculative grade, and four rating actions, namely Upgrades, Same Rating, Downgrades, and Defaults. For each asset type i and every time t, the adjusted transition matrix with transition probabilities can be written as[6]

	$k1 > k2$	$k1 = k2$	$k1 < k1$	$k2 = D$
$1_{(AAA \geq k1 \geq BBB-)}$	$\frac{m_{k_1,k_2}}{n_{k_1}}$	$\frac{m_{k_1,k_2}}{n_{k_1}}$	$\frac{m_{k_1,k_2}}{n_{k_1}}$	$\frac{m_{k_1,D}}{n_{k_1}}$
$1_{(BB+ \geq k1 \geq C)}$	$\frac{m_{k_1,k_2}}{n_{k_1}}$	$\frac{m_{k_1,k_2}}{n_{k_1}}$	$\frac{m_{k_1,k_2}}{n_{k_1}}$	$\frac{m_{k_1,D}}{n_{k_1}}$

.

The averages of the semi-annual default probabilities are used to calculate the thresholds Z_D^i in the model without rating migrations, whereas the averages of the semi-annual transition matrices are used to calculate the thresholds Z_{k_1,k_2}^i in the model with rating migrations.

The analysis covers the period January 1995 until June 2007. Between 1985 and 1995, there are no rating migration observations for CDO and only few transition observations for the other asset types. Therefore, the correlation analysis focuses on rating migration information from 1995 onwards. In what follows, I will focus on ABS, CDO, CMBS and RMBS. SYNT is removed from the sample as it is a very different type of structured product.

At every point in time, the function to be optimized is weighted by the number of rating observations relative to the total number of rating observations during the sample period.

As shown in Table 2, the number of observations for the different asset types has grown enormously and at a different speed. In terms of number of deals, RMBS is the biggest asset type class, whereas CDOs has the highest growth rate. Differences in the number of observations between the

[5] Using quarterly default probabilities and transition probabilities, respectively, does not alter the empirical results.

[6] For simplicity, the notation for asset type (i) and time (t) are ignored.

different asset types might have an impact on asset correlation and its standard deviation. To test this hypothesis, the following analysis is done:

- In the binomial framework: at every time t and every asset type, I rescale the total number of observations and defaults such that the sum of observations is the same for every asset type and equals the maximum of a vector of the total number of observations for every asset type at time t.
- In the multinomial framework: at every time t and every asset type, I rescale the transition matrix such that sum of the observations is the same for every asset type and equals the maximum of a vector of the total number of observations for every asset type at time t. For every asset type i and at time t, the adjusted transition probabilities can be written as follows

	$k1 > k2$	$k1 = k2$	$k1 < k1$	$k2 = D$
$1_{(AAA \geq k1 \geq BBB-)}$	$w.\left(\frac{m_{k_1,k_2}}{n_{k_1}}\right)$	$w.\left(\frac{m_{k_1,k_2}}{n_{k_1}}\right)$	$w.\left(\frac{m_{k_1,k_2}}{n_{k_1}}\right)$	$w.\left(\frac{m_{k_1,D}}{n_{k_1}}\right)$
$1_{(BB+ \geq k1 \geq C)}$	$w.\left(\frac{m_{k_1,k_2}}{n_{k_1}}\right)$	$w.\left(\frac{m_{k_1,k_2}}{n_{k_1}}\right)$	$w.\left(\frac{m_{k_1,k_2}}{n_{k_1}}\right)$	$w.\left(\frac{m_{k_1,D}}{n_{k_1}}\right)$

,

with the weightings $w = \left(\frac{n_{\max}}{n}\right)$, n the total number of observations for asset type i (with $i = 1, 2, ..., I$) at time t and

$$n_{\max} = \max \begin{pmatrix} n_1 \\ n_2 \\ ... \\ n_I \end{pmatrix}.$$

A rescaling of the number of observations and rating migrations does not alter the transition probabilities. Hence, the average transition matrix and threshold matrix to determine rating migrations are not altered. At every point in time, the function to be optimized is weighted by the number of rating observations (not adjusted or scaled) relative to the total number of rating observations during the sample period.

4.1 Structured Finance

The four main structured finance asset types, namely ABS, CDOs, CMBS, and RMBS, have very different characteristics and (rating) behavior. Panel A of Table 5 gives an overview of the average semi-annual default probabilities, which are used to calculate the default thresholds in the modeling framework without rating migrations (binomial approach). Panel B of Table 5 presents the average semi-annual transition matrices, which are used to calculate the thresholds in the framework with rating migrations (multinomial approach). While RMBS and CMBS show very similar downgrade and default probabilities, the average upgrade probability for both investment grade and speculative grade ratings are much higher for CMBS. The latter are backed by commercial mortgage loans. In contrast to residential mortgage loans, most commercial mortgage loans do not allow for unrestricted prepayments by the borrowers. As a result, a CMBS deal embodies little or no prepayment risk and its cash flows are more stable. For ABS, the downgrade and default probabilities are substantially higher then for the other asset types, especially for speculative ratings. This is mainly due to downgrades and default for manufactured housing, synthetic ABS and few small ABS subgroups such as non-performing loans and franchise loans.

Table 5: Average default and transition probabilities for different asset types

Panel A: Two-factor model without rating migrations

	ABS	CDOs	CMBS	RMBS
Avg PD	0.77%	0.03%	0.21%	0.12%

Panel B: Two-factor model with rating migrations

Six-monthly transition matrix

		Upgrade Prob	Same	Downgrade Prob	PD
ABS	IG	1.5%	95.3%	3.1%	0.1%
	SG	0.8%	79.5%	12.7%	7.0%
CDOs	IG	1.6%	95.4%	3.0%	0.0%
	SG	1.9%	94.2%	3.6%	0.2%
CMBS	IG	6.6%	92.8%	0.6%	0.0%
	SG	4.0%	93.2%	2.2%	0.6%
RMBS	IG	2.3%	97.2%	0.4%	0.0%
	SG	2.3%	95.4%	1.6%	0.7%

Note: Panel A of this table presents the average of quarterly and semi-annual probability of default of each asset type, whereas Panel B presents the average of quarterly and semi-annual adjusted transition matrix for the different asset types. The underlying data covers the period Jan 1995 until June 2007.

The results in Table 6 show that ABS, CDO, CMBS and RMBS are very different and not driven by the same common risk factor. Using a modeling framework without rating migrations (Panel A of Table 6) the inter correlation is around 1 percent. Including all rating migrations (Panel B of Table 6) gives a slightly lower result. While inter asset correlation gives an indication of the correlation between the different asset types, intra asset correlation reflects the correlation within asset type groups. Because of a lack of default observations, especially for CDOs, the binomial approach generates intra asset correlation estimates with high standard deviations, which should therefore be interpreted with caution. Furthermore, the results in Panel A show how volatile the results are in case of only few default observations. For CDOs, for example, simply rescaling the number of observations causes the intra asset correlation to jump up from 11 percent to 26 percent. A modeling framework with rating migrations (Table 6) produces more accurate and robust estimates. Intra asset correlation is below 5 percent for CDOs, CMBS, and RMBS, whereas it is around to 20 percent for ABS. Not only has the ABS sector a high dependence between rating migrations, the downgrade and default probabilities are also substantially higher for ABS then for the other asset types. In Section 4.3, I further investigate the dependence between rating actions for the different ABS subgroups. Rescaling the number of observations and rating migration events such that the total number of observations per asset type are the same at every point in time does not alter the results. However, the standard deviations of the correlation estimates are significantly reduced.

To analyze the impact of regional differences on the estimations, all non-US SF tranches are removed from the sample. However, the results (not shown here) are very similar.

Table 6: Asset Correlation for SF Asset Types Using a Two-factor Model Without Transitions (Binomial Approach)

	Inter asset correlation	Intra asset correlation			
		ABS	CDOs	CMBS	RMBS
Panel A: Two-factor model without rating migrations					
With number of events as observed					
Mean	1.3%	5.8%	10.9%	1.6%	4.2%
Stdev	[3.4%]	[7.6%]	[30.0%]	[4.1%]	[6.7%]
With adjusted number of events$^{(a)}$					
Mean	1.2%	6.2%	25.8%	2.1%	4.4%
Stdev	[3.3%]	[7.9%]	[36.2%]	[3.5%]	[6.5%]
Panel A: Two-factor model with rating migrations					
With number of events as observed					
Mean	0.7%	20.4%	1.2%	4.4%	4.4%
Stdev	[0.8%]	[3.6%]	[1.0%]	[2.5%]	[1.5%]
With adjusted number of events$^{(a)}$					
Mean	0.4%	21%	1.0%	3.7%	4.2%
Stdev	[0.4%]	[1.5%]	[0.5%]	[1.0%]	[1.3%]

Note: This table presents asset correlation estimates (ρ and ρ_i) for different SF asset types. The latter are estimated using a two-factor model without rating migrations (Panel A) and a two-factor model with rating migrations (Panel B). The parameters are obtained using a weighted maximum likelihood (ML) approach, with the weights in year t being the number of observations in period t relative to the number of observations over the total sample period (adjusted for NR).

$^{(a)}$The observations are adjusted such that the total number of observations are the same for each asset type. The adjustment does not affect the default probabilities or thresholds.

In what follows, I investigate the dependence between rating migrations for subgroups of ABS, CDOs, and RMBS separately. Because of a lack of rating migration observations for subgroups of CMBS, this asset type is not analyzed separately.

4.2 RMBS

As discussed in Section 2.1, the US takes up most of the issuance and volume of RMBS. The two most important regions after US are Europe and Australia/New Zealand. However, neither of them experienced any defaults in the RMBS sector during the sample period. The European and Australia/New Zealand RMBS sector experienced only 8 and 3 downgrades, respectively, during the sample period. The Asia/Japan RMBS group didn't experience any defaults or downgrades.

Hence, neither the binomial nor the multinomial approach is appropriate to further analyze regional differences in correlation between and within RMBS subgroups. The latter could be investigated using market information such as credit spreads for RMBS indices by regions. However, this is not the focus of this paper.

In a next step, I analyze the correlation within and between different subgroups of RMBS. Deals are split into the following three groups:

- "Prime/Alt" includes Prime and Alt RMBS.
  - Prime RMBS are backed by loans made to borrowers that satisfy financial institutions' standard lending criteria. Nearly all loans made by banks, building societies and credit unions, as well as the majority of those made by traditional mortgage originators, fall into this category.
  - Alta RMBS: RMBS with Alta-A mortgages in the underlying pool. Alt-A loans are originated through an extension of credit to borrowers on a loan package bearing non-standard features. These features can be along the dimension(s) of borrower capacity, collateral, credit. Specifically, Alt-A lending caters to the segment of the borrower population not served by the relatively tight definitions of the lending spectrum occupied by prime and sub-prime mortgages. Alt-A product is positioned in the midst of the MBS/ABS continuum ranging from prime to subprime mortgages.

All European deals, except for 6, are classified as "Prime/Alt" type.

- "Subprime/ HEL" includes
  - Sub-prime RMBS are backed by loans to borrowers who have impaired credit histories or other high-risk characteristics – these loans are typically originated by specialist 'non-conforming' lenders.
  - 1st and 2nd lien high loan-to-value and Closed-end 2nd RMBS
  - conventional Home Improvement RMBS
- 'Other' consists of
  - RMBS NIMs: A net interest margin (NIM) securitization is essentially an interest only strip, with its cash flow derived from a transaction's net interest proceeds as well as from interest rate caps, corridors and swaps, and, for most RMBS NIMs, prepayment penalty charges.
  - Non-performing and Reperforming RMBS
  - FHA-insured Title I Home Improvements RMBS
  - Other RMBS including "Outside the guidelines" and Document Deficiency RMBS

As expected, "subprime/HEL" RMBS are more risky than "prime/Alt" RMBS and "other" RMBS collapsed into one group. As shown in Table 7, this is reflected in higher average downgrade

Table 7: Asset Correlation for RMBS Using a Two-factor Model with Transitions (Multinomial Approach)

Panel A: Average transition matrix

Six-monthly transition matrix		Upgrade	Same	Down	PD
Prime	IG	3.92%	96.0%	0.10%	0.01%
	SG	2.81%	96.2%	0.61%	0.38%
Subprime	IG	0.95%	98.2%	0.79%	0.02%
	SG	0.29%	92.0%	5.22%	2.29%
Other	IG	1.01%	98.5%	0.50%	0.02%
	SG	1.86%	95.9%	1.34%	0.61%

Panel B: Two-factor model with rating migrations

With adjusted number of observations[(a)]

	Inter asset correlation	Intra asset correlation		
		Prime/ Alt	Subprime/ HEL	Other
Mean	3.6%	5.7%	8.2%	4.4%
Stdev	1.7%	3.5%	2.1%	1.9%

Note: This table presents asset correlation estimates (ρ and ρ_i) for different RMBS asset types. The latter are estimated using a two-factor model with rating migrations. The parameters are obtained using a weighted maximum likelihood (ML) approach, with the weights in year t being the number of observations in period t relative to the number of observations over the total sample period (adjusted for NR).

[(a)] The rating migration events are adjusted such that the total number of observations are the same for each asset type. The adjustment does not affect the transition probabilities nor the transition thresholds.

(including defaults) probabilities, especially for speculative grade assets. Panel A of Figure 5 shows that this is mainly due to the high number of downgrades (including defaults) over the last 12 months. From 1995 until beginning of 2006, the downgrade percentage was always below 0.1 percent but in recent months it has gone up to nearly 0.8 percent. Even though the downgrade percentage is low relative to the percentage for other asset types such as ABS, the upward trend significantly affects the intra asset correlation for RMBS (subgroups). For "prime/Alt" RMBS, the downgrade probability has increased somewhat since the beginning of 2006, however it is still below 0.1 percent. As shown in Table 7, its upgrades overwhelm downgrades for both investment and speculative grade ratings.

For "subprime/HEL" RMBS, intra asset correlation derived from rating migrations is around 8 percent, which is higher than for "prime/Alt" RMBS (6 percent) and "other" RMBS (4 percent). However, the difference is relatively small. As expected, different RMBS subgroups are more correlated than ABS, CDOs, CMBS, and RMBS globally. For RMBS, inter asset correlation is 3.6 percent compared to 1 percent between the different asset types.

4.3 ABS

A regional analysis of ABS shows that Europe and US both experienced defaults. However, the default rate for Europe is relatively low. Other regions such as Australia/New Zealand or Japan did not have any defaults and only few rating migrations in the ABS market during the sample period. Some ABS asset types are very regional specific such as, for example, manufactured housing and student loans, which are 99 percent and 100 percent, respectively, US deals. Hence, a regional analysis might not only reflect regional differences but also asset type specific differences. Given that the US covers 76 percent of the ABS market, a split by asset type and region would leave us with only few deals for some of the European asset types. Hence, in what follows I will focus on the asset type only.

For ABS, the sample is split in the following four subgroups:

- Auto Loans, Credit Cards, Student Loans, and Equipment. All of them, except Credit Cards, have never experienced defaults.
- Manufactured Housing (MH): structured finance product backed by a pool of installment sale contracts and/or installment loan agreements. The contracts are secured by liens on the manufactured home (also known as prefab), which is a type of housing unit that is largely assembled in factories and then transported to sites of use. All of the manufactured housing deals in the sample are US deals.
- Other: Aircraft, Autolease, Commercial Paper, Franchise Loans, Future Flows, Rental Cards, Stranded Assets, Traded Receivables, Whole Sale.

For manufactured housing (MH) and "other" ABS the downgrade probabilities are significantly higher than for the ABS subgroup bundling auto loans, credit cards, student loans and equipment, and RMBS, for example. The MH sector has also seen relatively few upgrades and a high number of defaults. Panel A of Figure 5 shows how the time-varying downgrade (including defaults) probability swings from very low levels in 1999, 2000, and 2001 to very high levels in 2003 and 2004. This reflects a high level of dependence between rating migrations for MH. As expected, intra asset correlation is very high for MH (42 percent), which shows that the rating behavior of MH tranches is substantially affected by sector-specific events. The high number downgrades and defaults for MH are mainly due to an increasing trend in the delinquency rate for MH loans and the level of losses in this sector over the last decade. As a result, the majority of MH issuers were affected by high levels of cumulative repossessions and losses.

Inter asset correlation between ABS types is 6 percent, which is quite high.

4.4 CDOs

As the majority of US CDOs are cash-flow CDOs and the majority of European CDOs synthetic, a regional analysis would merely reflect differences between cash and synthetic CDOs. Similar to ABS, a regional analysis in combination with an analysis by asset type is not feasible because of a lack of data for the different subgroups. Therefore, in what follows I focus on the asset type.

Table 8: Asset Correlation for ABS Using a Two-factor Model with Transitions (Multinomial Approach)

Panel A: Average transition matrix					
Six-monthly transition matrix					
		Upgrade	Same	Down	PD
Auto, Equip, CC, Stloans	IG	1.66%	98.2%	0.12%	0.00%
	SG	3.20%	95.3%	1.31%	0.25%
MH	IG	1.10%	86.8%	11.85%	0.25%
	SG	0.61%	73.3%	16.45%	9.65%
Other	IG	1.57%	94.6%	3.72%	0.08%
	SG	0.61%	85.1%	8.73%	5.53%

Panel B: Two-factor model with rating migrations				
With adjusted number of observations				
	Inter asset correlation	Intra asset correlation		
		Auto, Equip, CC, St. Loans	MH	Other
Mean	6.0%	14.6%	41.3%	17.5%
Stdev	4.5%	12.7%	5.1%	5.2%

Note: This table presents asset correlation estimates (ρ and ρ_i) for different RMBS asset types. The latter are estimated using a two-factor model with rating migrations. The parameters are obtained using a weighted maximum likelihood (ML) approach, with the weights in year t being the number of observations in period t relative to the number of observations over the total sample period (adjusted for NR).

[(a)] The rating migration events are adjusted such that the total number of observations are the same for each asset type. The adjustment does not affect the transition probabilities nor the transition thresholds.

The CDO sample is split into the following two subgroups:

- Cash-Flow CDOs, which are more than 80 percent US.
- Synthetic CDOs, which are 65 percent European, and other CDOs such as "hybrid cash-flow/ synthetic" CDOs and "market-value" CDOs.

As shown in Panel A of Table 9, cash-flow CDOs show a stable rating performance. Synthetic CDOs have slightly higher transition probabilities for both investment and speculative grade ratings than cash-flow CDOs. However, as shown in Panel B of Table 9, intra asset correlation is substantially higher for cash-flow CDOs. To get a better idea of the rating migration behavior of both CDO types, Panel B of Figure 5 plots the six-monthly downgrade (including defaults) probability for both CDO types from June 2001. It is clear that the patterns are very different. For synthetic CDOs, the downgrade probability fluctuates around a lower level of around 4 percent, whereas for cash-flow CDOs, the probability peaks between 2002 and 2003 at around 12 percent and then goes to a very low level around 2 percent from 2004 onwards. Correlation between both types of CDOs as indicated by inter asset correlation is close to zero, which is not surprising based on the rating migration behavior presented in Panel B of Figure 5.

Table 9: Asset Correlation for CDO Using a Two-factor Model with Transitions (Multinomial Approach)

Panel A: Average transition matrix				
Six-monthly transition matrix				
	Upgrade	Same	Down	PD
Cash	1.2%	97.1%	1.8%	0.00%
	1.8%	94.0%	4.0%	0.22%
Synt and other	2.3%	93.2%	4.6%	0.00%
	2.7%	93.6%	3.2%	0.42%

Panel B: Two-factor model with rating migrations			
With adjusted number of observations			
	Inter asset correlation	Intra asset correlation	
		Cash-flow	Synt and other
Mean	0.5%	11.0%	0.9%
Stdev	3.2%	4.3%	1.1%

Note: This table presents asset correlation estimates (ρ and ρ_i) for different CDO asset types. The latter are estimated using a two-factor model with rating migrations. The parameters are obtained using a weighted maximum likelihood (ML) approach, with the weights in year t being the number of observations in period t relative to the number of observations over the total sample period (adjusted for NR).
$^{(a)}$The rating migration events are adjusted such that the total number of observations are the same for each asset type. The adjustment does not affect the transition probabilities nor the transition thresholds.

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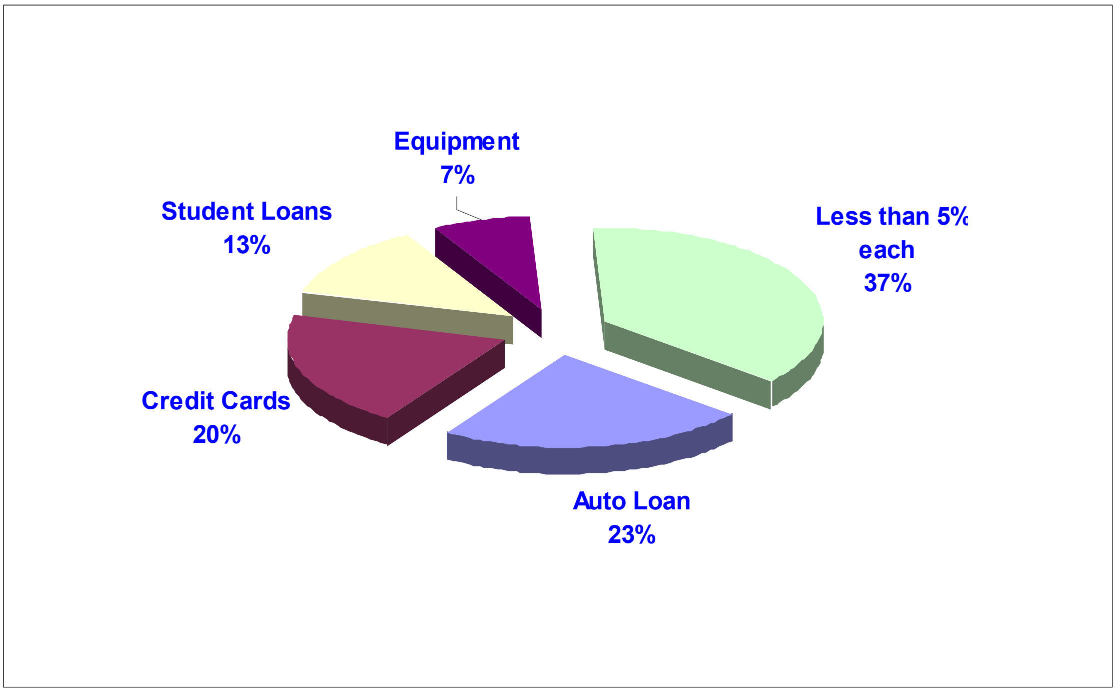
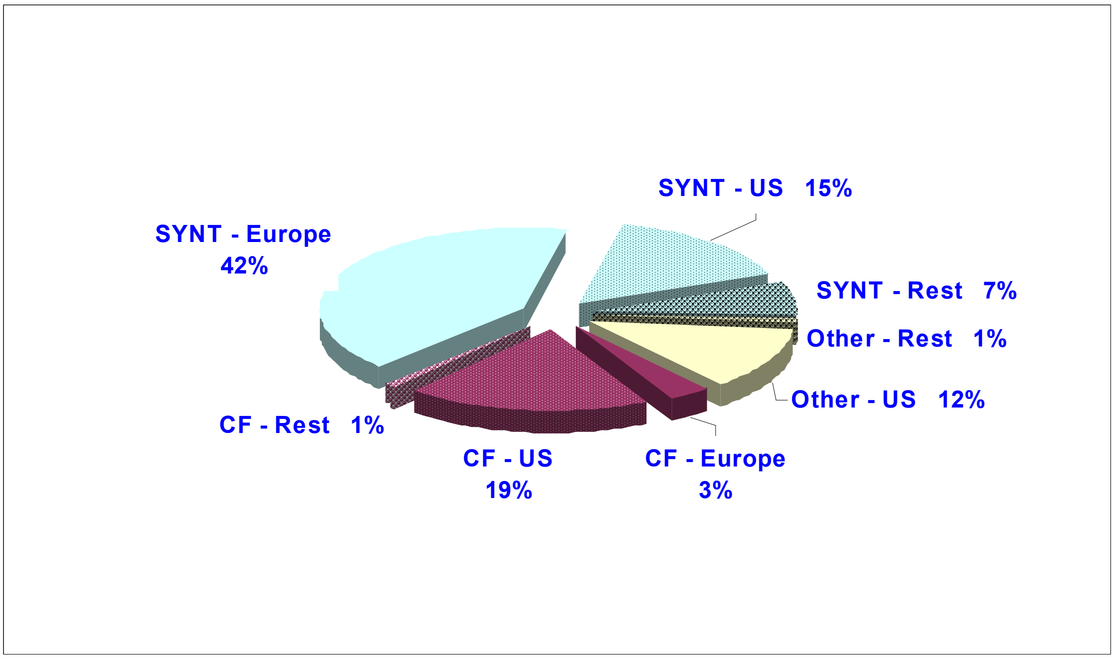
Figure 1: Sample distribution by type of ABS



Note: This graph gives an overview of the main ABS types. The percentages are calculated as the number deals for a specific ABS subgroup divided by the total number of ABS. "Less than 5% each" represents all the other ABS subgroup which individually represent less than 5 percent of the ABS sample. The percentages sum to one.

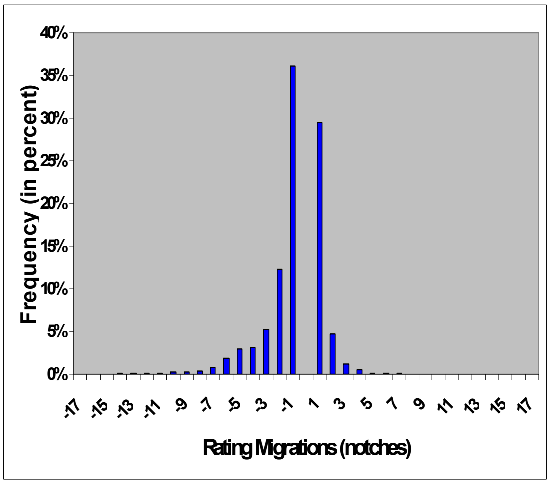
Figure 2: Sample distribution by CDO type



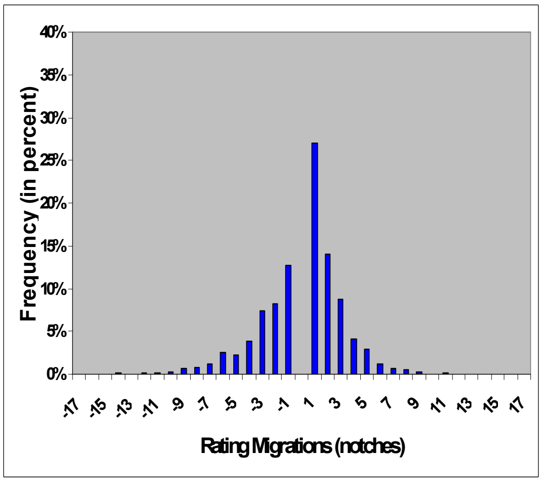
Note: The graph gives an overview of the different types of CDOs: synthetic (SYNT), cash-flow (CF), and other. The latter category covers hybrid, market-value and other CDOs. The percentages are calculated as the number deals for a specific CDO subgroup divided by the total number CDOs in the sample. The percentages sum to one.

Figure 3: 6-Monthly Rating Migrations in Notches

Panel A: Corporates



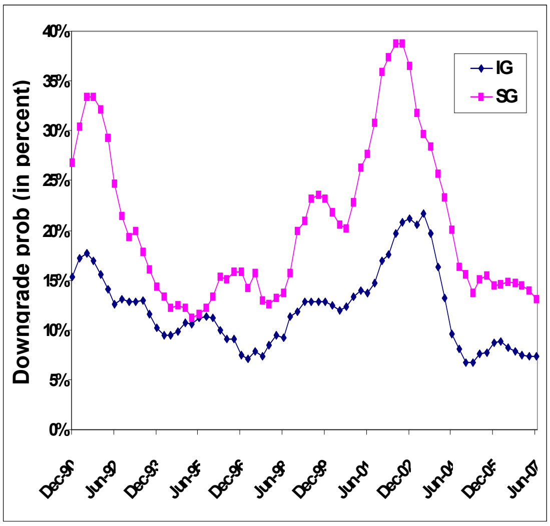
Panel B: SF



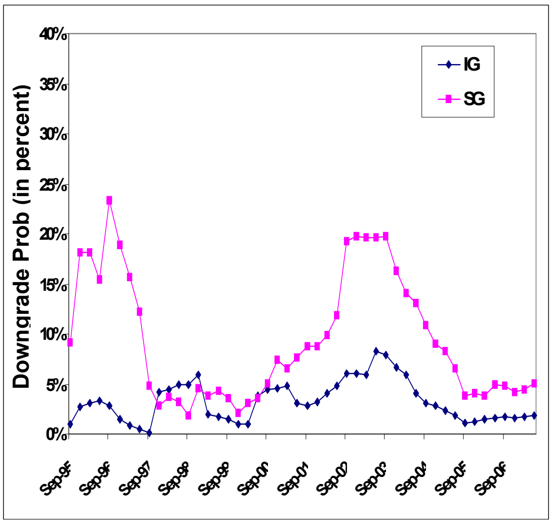
Note: This figure presents the percentage of 6-monthly rating migrations in notches from Jan 1985 until June 2007. The maximum notch-level downgrade is -19 (from AAA to D) and the maximum notch-level upgrade is 18 (from CCC- to AAA). Rating migrations to NR are ignored.

Figure 4: Time-varying rating downgrade probabilities for investment and speculative grade ratings (NR adjusted)

Panel A: Corporates



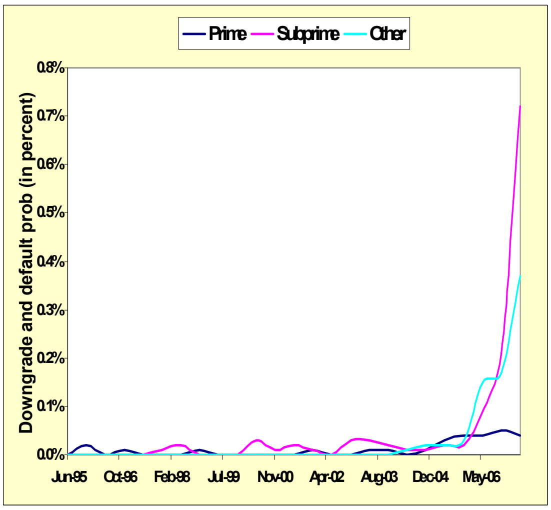
Panel B: SF



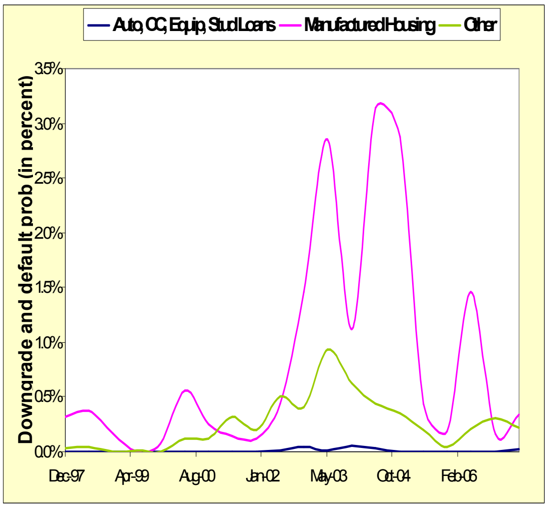
Note: This figure presents the 6-monthly downgrade probability (in percent) for investment grade (pink line) and speculative (blue line) grade ratings from Dec. 1995 until Dec. 2005. The probabilities are calculated as the number downgrades at the end of every 6-month period divided by the total number of investment grade and speculative grade observations at the end of the previous year. Probabilities are adjusted for migrations to NR.

Figure 5: Time-varying rating downgrade probabilities for investment and speculative grade ratings (NR adjusted)

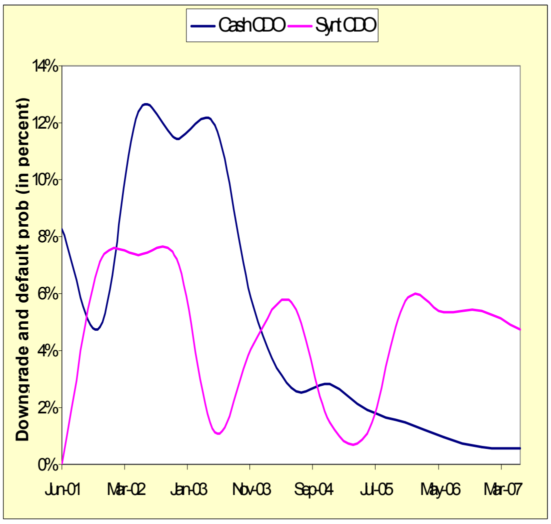
Panel A: RMBS



Panel B: ABS



Panel C: CDOs



Note: Panel A, B and C of this figure present the 6-monthly downgrade probability (in percent) for RMBS, ABS, and CDOs, respectively. The probabilities are calculated as the number downgrades and defaults at the end of every 6-month period divided by the total number observations at the beginning of the corresponding 6-month period. Probabilities are adjusted for migrations to NR.