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Credit risk in the leasing industry

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Abstract

This paper is devoted to the credit risk modeling issues of retail lease portfolios. Using a resampling method, I estimate the probability density function of losses and VaR measures in a portfolio of 46,732 leases issued between 1990 and 2000 by a major European financial institution. My results show that physical collaterals play a major role in reducing the credit risk associated with lease portfolios. However, because of insufficient recognition of such collaterals under the new regulatory capital framework (Basel II), significant differences are observed between the estimated capital requirements and those calculated in accordance with the various Basel II approaches.
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1. Introduction

In 2002, according to Leaseurope's (2002) estimates, [1] the volume of new business in the lease financing sector rose to more than €199 billion. The penetration rate of equipment lease in comparison with total equipment investments reached 15%.

However, in spite of the importance of lease financing, little is known empirically about its credit risk. Bearing in mind that the final objective of credit risk modeling is to estimate the probability density function (PDF) of potential losses for a given

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[1] Leaseurope is the acronym of the Brussels-based "European Federation of Leasing Company Associations," founded in 1973 to represent the leasing industry. Leaseurope comprises 30 member and correspondent national associations, which in turn represent more than 1300 leasing companies.

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portfolio, this paper highlights the implications of certain key characteristics of retail lease portfolios, i.e., their large size, the legal ownership of the leased assets by the lessors, the low value of individual contracts in comparison with the value of the portfolio, and the limited availability of information about the lessees' financial situation.

Little research has been carried out on the credit risk of private non-traded financial products. The relatively few studies available in this area include those by Carey (1998) on a portfolio of privately invested bonds in the US; Dietsch and Petey (2002) on French SME loan portfolios; and Calem and LaCour-Little (forthcoming) on mortgage loans in the US. Three studies have recently been conducted to assess credit risk in the leasing business. Though based on a relatively small amount of data, De Laurentis and Geranio (2001) provide useful empirical and quantitative information, suggesting, in particular, that the European leasing industry benefits from high recovery rates in the event of default. Working with a much larger sample of 37,259 individual defaulted lease contracts issued between 1976 and 2002 by 12 companies in six different countries, Schmit and Stuyck (2002) extended the investigation to include an analysis of recovery rates relative to the age, term-to-maturity, and default date of each contract. Their study confirmed De Laurentis and Geranio's earlier finding that leasing companies incur relatively low losses when a lease defaults. A later study by Schmit (2003) estimates the PDF of losses and VaR measures in a portfolio of 35,861 vehicle leases issued between 1990 and 2000 by a major European financial institution. The estimates are carried out on a model based on Credit-Risk+™ (Credit Suisse Financial Product, 1997). The results suggest that the capital requirements prescribed under the current Basel capital proposal are excessive for vehicle lease businesses.

This paper focuses on the two major risk components needed for the estimation of loss distribution: probability of default (PD) and loss given default (LGD). Four types of assets are analyzed: vehicles, office equipment/computers, medical equipment, and other kinds of equipment. Sub-portfolio losses for each type of assets are then estimated with a non-parametric simulation, namely, a re-sampling or bootstrap technique similar to the one used by Carey (1998) to estimate credit losses in private debt portfolios.

The next section outlines our methodology to estimate default rates and LGDs in addition to explaining the re-sampling technique used for the calculation of loss distribution tails. Section 3 describes the data while Section 4 provides empirical results. Sections 5 and 6 respectively discuss the results and some regulatory implications. Finally, a conclusion is drawn.

2. Methodology for the estimation of PD, LGD, and loss distributions

2.1. Measuring default probabilities

Given our empirical approach and the degree of detail of the non-public traded data under consideration, we have opted for an actuarial estimation of PDs based on Altman's (1989) life-table methodology [2] and the concept of mortality rate. Focusing on bonds, the author defined a marginal mortality rate and a cumulative mortality rate over a specified time period $(1, 2, \ldots, T$ years). We have transposed these rates into our analysis of leases. With this procedure, calculated mortality rates are adjusted for any change in population size.

A lease contract is defined as defaulted when the lessor has unilaterally cancelled the agreement because the lessee did not pay the scheduled rentals (interests and/or principal). Default does not refer to an interruption of the contract for any other reason. In the event of default, the lessor can repossess the asset, declare the remaining payments due and payable, and claim any losses incurred. As for other unfulfilled obligations, the lessor will be treated like other creditors as far as the economic loss, unpaid rentals, unpaid fees, and the loss of potential earnings on rentals are concerned.

2.2. Measuring loss given default

LGD for a contract is calculated as one minus the recovery rate. The recovery rate is calculated as the discounted amounts recovered in comparison with the outstanding amount on the date of default. The discount rate applied to each cash flow is the ex ante yield to maturity for the lease contract in default. The loss rate for a given sub-portfolio is the sum (in euros) of all LGDs times exposure at default (EADs) divided by the total exposed outstanding belonging to that sub-portfolio.

2.3. Bootstrap calculation of loss distribution

In the present study, the loss rate distribution of a sub-portfolio is estimated by a re-sampling method as used by Carey (1998). The advantage of this method is that it is non-parametric and relies only on observed data. The basic process consists of choosing randomly, with replacement, a portfolio of n lease contracts for a randomly chosen year. The draw of a year can be interpreted as a draw from the best available representation of the possible macroeconomic conditions influencing the risk factor. The assumption is that each year has the same probability of being drawn (e.g., if we have six observation years, each year has a 1/6 probability of being drawn). The process is iterated i times. When a non-default lease is drawn, the associated loss is zero, whereas when the draw is related to a default, LGD is the product of total EAD and (1-recovery rate). LGD on defaulted leases can be either positive or negative. In the latter case, the recovery rate is higher than 100%. A single iteration i of the procedure yields a loss rate for a given state of the economy (or a given year). Using a large number of iterations enables us to obtain a probability distribution of loss rates as a percentage of the total outstanding amount. By performing the draw procedure in two stages (i.e., drawing first a year, then a portfolio of n leases), we avoid the understating of tail loss rates. Otherwise, the combination of default experiences

[2] That is, an actuarial technique for building life tables for human beings.

from different years would lead to a tricky mixture of the underlying systematic factors and hence to over-diversification.

3. The data

Lease is defined "*as an agreement whereby the lessor conveys to the lessee, in return for a payment or series of payments, the right to use an asset for an agreed period of time.*" [3] Lease definition encompasses various types of contracts. In the current research, lease contracts are mainly non-cancellable and lessees are responsible for the selection, acquisition, and maintenance of the asset. The lessee is required to pay the associated taxes and insurance premiums. At maturity, the residual value of the leased asset returns to the lessor but the lessee usually has the right to buy it.

In the vast majority of the studied contracts, the lessee is considered the fiscal owner of the leased asset and must write it off for tax purpose (more than 85% of the lease contracts). Therefore the lessee cannot sell excess tax shields to the lessor, with the consequence that any tax differences between a lessee and a lessor do not influence the lease–buy decision. Since the lessor retains the ownership of the leased asset throughout the contractual term, and given the existence of market imperfections, there currently appears to be a general consensus, backed by empirical findings, [4] that lease financing enables businesses to mitigate agency costs when they are facing problems of information asymmetry (e.g., small companies).

Our database consists of a unique set of 46,732 individual completed lease contracts issued between 1990 and 2000 by a major European leasing company that has more than a 20% share of its national market. All the leases ended before December 31, 2000, and concern commercial activities carried out by lessees.

The database contains all the relevant information concerning the leases throughout their life. The available variables fall into two categories: ex ante and ex post. Ex ante variables are the origination date of the contract, the cost and type of the asset, the maturity of the lease, the periodicity of forecasted payments, the amounts of any up-front payments, the amount of any broker commissions, the estimated residual value, the estimated funding rate, the ex ante internal rate of return (purchase option included), the ex ante internal rate of return (purchase option excluded), the due dates, and the amounts to be paid. As regards ex post variables, we have comprehensive data concerning all effective payments (reimbursement) and the amounts of any prepayments, including the payment dates, the final status of the contract (re-rented, terminated or defaulted), and the date of the declaration of the status.

Descriptive statistics of the sample are shown in Table 1. Panels A–D provide the descriptive statistics and frequency distribution respectively by the issuance date of

[3] See International Accounting Standards Board, 2002, International Accounting Standard, IAS 17 (revised 1997).

[4] For example, Beattie et al. (2000), Deloof and Verschueren (1999), Graham et al. (1998), Lasfer and Levis (1998) and Sharpe and Nguyen (1995).

Table 1
Descriptive statistics of a sample of 46,732 completed lease contracts issued between 1990 and 2000

Date of issuance	Number of leases	Percent of total (%)	Cumulative percent (%)
Panel A: Frequency distribution by issuance date of the lease			
1990	4876	10.4	10.4
1991	5207	11.1	21.6
1992	5976	12.8	34.4
1993	5895	12.6	47.0
1994	5309	11.4	58.3
1995	5876	12.6	70.9
1996	5234	11.2	82.1
1997	4134	8.8	91.0
1998	2014	4.3	95.3
1999	1489	3.2	98.5
2000	722	1.5	100.0
Total	46,732	100.0	100.0
Cost of the asset in €			
Panel B: Frequency distribution by cost of the leased asset			
7300–25,000	32,574	69.7	69.7
25,001–50,000	8561	18.4	88.1
50,001–100,000	4186	9.0	97.0
100,001–200,000	994	2.1	99.2
200,001–300,000	229	0.5	99.7
300,001–400,000	108	0.2	99.9
400,001–500,000	553	0.1	100.0
Minimum = €7346	Maximum = €495,787	Mean = €27,940	Median = €17,972
Term-to-maturity in months			
Panel C: Frequency distribution by the term-to-maturity of the lease			
0–11	5998	12.8	12.8
12–23	1260	2.7	15.5
24–35	2385	5.1	20.6
36–47	11,773	25.2	45.8
48–59	13,668	29.2	75.1
60–71	11,464	24.5	99.6
over 71	184	0.4	100.0
Minimum = 0 months	Maximum = 217 months	Mean = 41 months	Median = 48 months
Type of leased asset			
Panel D: Frequency distribution by the term-to-maturity of the lease			
Automotive	35,861	76.7	
Office equipment–computers	4639	9.9	
Medical equipment	648	1.4	
Other equipment	5549	12.0	

(*continued on next page*)

Table 1 (*continued*)

Date of issuance	Proportion (%)	Date of issuance	Proportion (%)
Panel E: Proportion of leases in the sample in comparison with the number of leases issued by the company			
1990	100.0	1996	75.2
1991	99.9	1997	52.3
1992	99.9	1998	25.3
1993	99.8	1999	15.3
1994	98.8	2000	8.2
1995	97.5		

Term-to-maturity	Number of leases	Percent of total (%)
Panel F: Frequency distribution by status of the lease		
Completed contract	41,887	89.6
Defaulted contract	4263	9.1
Re-rented	547	1.2
Missing value	35	0.1

the lease contract, the cost of the leased asset, the term-to-maturity of the lease, and the type of leased asset. Panel E indicates the number of leases in our sample in comparison with the total number of leases issued between 1990 and 2000 by the company. Fewer data on leases are available for the most recent year, since our database consists only of completed contracts. For the years 1990–1995, our sample covers almost all the contracts issued. Panel F shows the final status of the contract (re-rented, completed, or defaulted). Overall, 9.1% of the contracts in the database are defaulted contracts. The percentage of defaulted contracts in our database is overestimated, since for cohorts after 1995, we have no data concerning contracts still running on December 31, 2000.

4. Results

4.1. Cohorts

Loss distributions for a given sub-portfolio can be calculated only if all the data for a given cohort [5] are available. Therefore, for office equipment and computers, medical equipment, and other equipment categories, the cohorts taken into account are those between 1990 and 1995. Furthermore, since we obtained many data for the automotive category, we split it into three groups, namely, (1) leases with a maturity of less than one year, (2) leases with a maturity between 12 and 47 months, and (3) leases with a maturity over 47 months. This allows us to analyze more data for the automotive segment:

[5] Cohorts are defined on a yearly basis.

- 1990–1999 cohorts for contracts with a maturity up to 11 months,
- 1990–1996 cohorts for contracts with a maturity between 12 and 47 months,
- 1990–1995 cohorts for contracts with a maturity above 47 months.

Table 2 summarizes the years for which observations are available as well as the number of observations for each year, depending on sub-portfolio characteristics. In our study, a sub-portfolio includes all leases with the same underlying type of asset and a given age. Taking these two factors into account is essential, since the recovery rates and the exposures at default (and consequently the risk incurred) vary depending on the asset type and the time elapsed since the issuance of the contract.

4.2. Yearly mortality rate

Table 3 exhibits the yearly weighted average default rate and the standard deviation according to asset types. We obtain a very low default rate on medical equipment, since the lessees are mostly publicly funded institutions. It is also apparent that "Office Equipment–Computers" shows a lower weighted average default rate than the automotive and other equipment lease categories. This is explained by the fact that the residual value of office equipment and computers is generally subject to a high risk factor, and therefore, credit analysts have more stringent requirements when granting a lease.

4.3. Recovery rates

Weighted average recovery rates are calculated in two different ways: (i) when only recoveries from the sale of the leased asset are considered (WRR1); and (ii) when recoveries are also obtained from guaranties, collaterals, and the debtor's net liquidation and late payments (WRR2). Table 4 exhibits the rates for contracts defaulted between 1990 and 2000.

The weighted average of recovery rates is 64% when only the sale of the defaulted lease asset is taken into account and 74% when other kinds of recovered amounts are also considered. In the first case (recoveries from asset sales only), the ratio ranges from 33.9% for office equipment and computer leases to 68.9% for automotive leasing. In the second case (other kinds of recovered amounts taken into account), recovery rates lie between 44.9% and 79.6%. Recoveries from the sale of assets account on average for 86.5% of total recoveries.

Looking at the data as a whole, the volatility of recovery rates appears to be, on average, significantly higher than that observed for other types of financing modes. However, the potential effect of this on the measurement of loss distribution can be expected to be mitigated to some extent because (i) the secondary markets are in most cases very liquid, and (ii) recoveries may exceed 100% (and even reach 200% or 300%), since the proceeds from the resale of the underlying asset can be larger than the book value of the asset concerned.

Looking at the automotive, medical equipment, and other equipment segments, we find that average recovery rates range from 68% to 80%. In other words, they

Table 2
Years of observation for each studied sub-portfolio

Type of asset	Maturity in months	Age in months	Cohorts	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000
Automotive	0–11	0–11	1990–1999	88	355	517	662	861	1357	953	883	631	
	11–47	0–11	1990–1996	952	1149	1198	1343	987	941	859			
		12–23			903	964	992	1227	1026	1080	915		
		24–35				699	891	943	1023	755	830	895	
		Over 35						671	677	755	488	532	665
	Over 48	0–11	1990–1995	1676	2227	2569	2423	2049	2879				
		12–23			1657	2186	2521	2383	1995	2845			
		24–35				1599	2080	2423	2248	1869	2614		
		36–47					1530	1979	2289	2012	1568	2281	
		48–59						1458	1759	1988	1689	1274	2004
		Over 59						635	682	778	608	556	1079
Office equipment	0–72	0–11	1990–1995	642	680	634	600	545	513				
		12–23			639	672	631	589	537	497			
		24–35				626	638	605	556	502	460		
		36–47					607	558	522	482	444	399	
		48–59						290	226	229	229	219	174
		Over 59							114	82	80	74	64
Medical equipment	0–72	0–11	1990–1995	74	115	86	100	101	101				
		12–23			74	115	86	99	101	101			
		24–35				74	115	87	99	101	101		
		36–47					74	107	83	95	98	97	
		48–59						60	71	57	63	71	78
		Over 59							55	59	48	48	69
Other equipment	0–72	0–11	1990–1995	799	831	817	702	693	745				
		12–23			789	813	810	687	680	738			
		24–35				770	781	759	654	645	699		
		36–47					751	706	707	578	596	636	
		48–59						548	470	495	408	415	474
		Over 59							427	364	387	296	298

Table 3
Yearly probability of default by type of asset and by age

Age of lease	0–11 (%)	12–23 (%)	24–35 (%)	36–47 (%)	48–60 (%)	⩾60 (%)
Automotive (0–11 months)						
Weighted average	0.41					
Standard deviation	0.95					
Minimum	0.00					
Maximum	1.41					
Automotive (12–47 months)						
Weighted average	1.99	3.13	2.92	2.09		
Standard deviation	1.15	0.81	0.91	1.28		
Minimum	0.78	1.33	0.95	0.75		
Maximum	3.10	4.16	3.48	3.38		
Automotive (over 48 months)						
Weighted average	1.62	3.93	4.11	3.21	2.61	3.11
Standard deviation	0.47	0.72	0.75	0.99	0.88	0.87
Minimum	1.13	2.95	3.37	2.02	1.05	1.77
Maximum	2.59	4.80	4.71	4.35	3.28	3.78
Medical equipment						
Weighted average	0.17	0.17	0.53	0.42	0.27	0.00
Standard deviation	0.39	0.40	0.77	0.57	0.63	0.00
Minimum	0.00	0.00	0.00	0.00	0.00	0.00
Maximum	0.99	0.98	1.98	1.05	1.75	0.00
Office equipment–computers						
Weighted average	0.78	2.67	2.97	1.62	2.45	1.88
Standard deviation	0.47	0.87	0.90	0.88	1.51	1.74
Minimum	0.47	1.41	2.08	0.57	1.10	0.78
Maximum	1.67	4.46	5.02	2.54	3.95	3.82
Other equipment						
Weighted average	1.56	4.13	3.11	2.47	2.42	3.30
Standard deviation	0.69	1.58	1.10	0.94	1.09	1.63
Minimum	0.73	2.41	1.86	0.53	1.05	1.01
Maximum	2.14	5.68	5.02	3.19	4.08	3.94

Table 4
Recovery rates by type of asset and by age

Age in months	N	WRR1		WRR2		Recovery lag
		AVG (%)	STD (%)	AVG (%)	STD (%)	
Automotive leasing (maturity less than 12 months)						
0–11	15	47	39	48	39	26
Automotive leasing (maturity between 12 and 47 months)						
0–11	175	61	38	69	40	20
12–23	260	78	36	85	34	23
24–35	200	89	67	99	66	16
36–47	66	83	91	99	93	18
Automotive leasing (maturity over 47 months)						
0–11	356	69	28	78	31	25
12–23	785	67	30	78	29	24
24–35	689	67	34	78	30	20
36–47	423	74	43	86	39	19
48–59	204	68	67	88	60	17
⩾60	69	76	75	105	62	12
Automotive leasing (all)						
Total	3242	69	38	80	36	21
Office equipment–computers						
0–11	36	42.5	36.7	53.4	37.5	22
12–23	110	32.1	35.3	47.6	41.4	26
24–35	113	40.7	44.7	48.2	46.7	13
36–47	39	26.1	42.4	38.9	45.8	10
⩾48	26	51.9	45.4	51.9	44.7	11
Total	324	33.9	33.4	44.9	37.3	18
Medical equipment						
All	9	71.9	33.2	77.3	36.7	13
Other equipment						
0–11	80	69.6	40.3	78.1	38.6	27
12–23	199	55.6	37.7	64.2	37.7	23
24–35	151	58.6	34.8	69.0	34.6	13
36–47	80	67.8	58.3	74.4	57.0	10
48–59	55	81.9	43.3	83.8	43.3	11
⩾60	24	22.9	22.9	28.4	37.9	5
Total	589	59.6	41.5	67.9	41.5	21

are quite similar to the recovery rates observed for the best senior secured bank loans (e.g., Hamilton, 2002; Standard and Poor's, 2002).

The observed recovery rates for the automotive leases found in our study are of the same order of magnitude as those observed by Schmit and Stuyck (2002). However, recovery rates in the equipment segment vary considerably from one country to another. This is explained by large differences in portfolio composition among European companies.

4.4. Loss distribution

Table 5 provides summary statistics on loss distributions for each type of asset and according to the age of the portfolios. We show the results obtained by running simulations (50,000 iterations) on sub-portfolios comprising 8000 contracts overall. As discussed later, a sub-portfolio size of 8000 contracts was chosen in order to base our results on a satisfactory estimation of each contract's absolute contribution to the total risk of a portfolio.

In the automotive segment, the loss rates at the 99.9th percentile are between 0.31% and 2.13%. For a given maturity, they tend to decrease with the age of the contract. Furthermore, in sub-portfolios where the age of the contract is relatively near to maturity, the mean and the median of the loss rate distributions are negative.

Concerning the "Other Equipment" and "Office Equipment–Computer" categories, on average total loss rates are higher than those observed for the automotive segment and lie between 0.91% and 7.75% at the 99.9th percentile. On the other hand, the medical equipment segment shows a much lower risk factor, with the 99.9th percentile loss rates ranging from 0% to 1.17%.

However, contrary to the results observed by Carey (1998), an increase in expected losses is not necessarily associated with an increase in the total loss rates for high percentiles.

5. Discussion

5.1. Sample bias

Although a non-parametric technique should provide good estimates of total loss rates, the simulations have been performed on a limited universe of data originating from the years 1990 to 2000. The number of years and the individual years taken into account depend on the sub-portfolio (see Table 2). Furthermore, for each studied portfolio, the draw of any particular year (underlying the realization of the systematic factor) is equiprobable. As a result, loss rates may be overestimated or underestimated when the observed years fall respectively between 1990 and 1996 and between 1997 and 2000. To overcome these problems, we produced one-year results for the first year of each lease. Knowing the number of contracts issued each year by the company, we can include the sample year segments 1991–2000 in all re-sampling exercises for portfolios with an age of up to one year. For these segments, we also compute total loss distribution over the 1992–1994 period, which represents the worst phase of the economic cycle under consideration. However, when looking at the average loss per contract, the worst year is not necessarily included in the 1992–1994 period as shown in Table 6. Therefore, we also perform a simulation for the worst year experienced. 1998, 1996 and 1993 are respectively the worst years

Table 5
Summary statistics on loss rate distributions ($n = 8000$, $i = 50,000$)

Maturity in months	0–11	12–47	12–47	12–47	12–47	Over 47	Over 47	Over 47	Over 47	Over 47	Over 47
Age in months	0–11	0–11	12–23	24–35	Over 35	0–11	12–23	24–35	36–47	48–59	Over 59
Mean	0.21%	0.45%	0.40%	−0.13%	−0.01%	0.36%	0.78%	0.95%	0.37%	0.17%	−0.16%
Standard deviation	0.37%	0.51%	0.32%	0.26%	0.29%	0.34%	0.29%	0.26%	0.22%	0.31%	0.24%
Skewness	0.9	1.8	0.9	0.0	0.2	1.6	1.0	0.0	0.6	0.7	−0.3
Kurtosis	2.4	5.0	3.3	2.0	2.3	4.2	3.0	2.0	2.9	2.5	2.6
99% percentile	1.07%	1.93%	1.27%	0.36%	0.62%	1.27%	1.53%	1.48%	0.96%	0.92%	0.27%
99.9% percentile	1.20%	2.13%	1.48%	0.44%	0.77%	1.39%	1.66%	1.61%	1.14%	1.16%	0.31%
Office equipment–computers											
Age in months	0–11	12–23	24–35	36–47	48–59	Over 59					
Mean	0.39%	1.16%	1.80%	0.98%	0.38%	0.34%					
Standard deviation	0.28%	0.81%	1.81%	0.69%	0.25%	0.56%					
Skewness	0.80	0.13	1.78	0.45	−0.23	1.38					
Kurtosis	2.91	1.40	4.57	2.45	1.81	3.39					
99% percentile	1.11%	2.55%	6.93%	2.57%	0.82%	1.74%					
99.9% percentile	1.27%	2.77%	7.75%	2.84%	0.91%	1.90%					
Medical equipment											
Age in months	0–11	12–23	24–35	36–47	48–59	Over 59					
Mean	0.09%	0.05%	0.06%	0.09%	0.16%	0.00%					
Standard deviation	0.13%	0.10%	0.20%	0.19%	0.36%	0.00%					
Skewness	0.9	1.9	1.5	1.8	1.8	–					
Kurtosis	2.0	4.6	3.9	4.5	4.4	–					
99% percentile	0.36%	0.32%	0.54%	0.60%	1.08%	0.00%					
99.9% percentile	0.39%	0.35%	0.58%	0.65%	1.17%	0.00%					
Other equipment											
Age in months	0–11	12–23	24–35	36–47	48–59	Over 59					
Mean	0.25%	1.24%	1.09%	0.31%	0.41%	1.08%					
Standard deviation	0.20%	0.55%	0.96%	0.28%	0.32%	1.21%					
Skewness	1.2	0.7	1.1	0.8	−0.1	1.0					
Kurtosis	3.0	2.2	2.7	3.3	2.0	3.3					
99% percentile	0.76%	2.50%	3.30%	1.08%	1.00%	4.20%					
99.9% percentile	0.85%	2.79%	3.56%	1.27%	1.12%	4.78%					

Table 6
Average loss per contract (in % of outstanding amount)

	1991 (%)	1992 (%)	1993 (%)	1994 (%)	1995 (%)	1996 (%)	1997 (%)	1998 (%)	1999 (%)	2000 (%)
Automotive (0–11 months)	0.00	−0.20	0.89	0.53	0.67	0.00	0.00	0.00	0.00	0.00
Automotive (12–47 months)	0.09	0.24	0.43	1.63	0.19	0.08	0.10	0.15	0.22	0.07
Automotive (over 47 months)	0.34	0.23	0.18	1.15	0.31	0.09	0.16	0.04	0.27	0.12
Office equipment–computers	0.49	0.07	0.87	0.17	0.49	0.70	0.50	0.91	0.47	0.41
Medical equipment	0.00	0.00	0.01	0.32	0.23	0.05	0.00	0.00	0.00	0.00
Other equipment	0.63	0.10	0.13	0.12	0.35	1.10	1.01	0.49	0.48	0.23

for the office equipment, other equipment, and automotive lease [6] portfolios. 1994 is the worst year experienced for the other portfolios.

The loss rate distributions are shown in Table 7. When looking at a portfolio, the mean loss varies significantly, but the 99.9th loss distribution percentile is rather similar in each period considered. This suggests that the risk associated with retail lease portfolios is more idiosyncratic than systematic in nature. Hence, in estimating the credit risk losses incurred on retail lease portfolios, we can expect little bias resulting from the restriction of sample year coverage to affect the re-sampling estimates, as observed by Carey (1998) in the case of investment-grade portfolios.

5.2. Comparison with parametric modeling

Our findings are compared with those obtained in a previous study (Schmit, 2003) in which modeling based on CreditRisk+™ was applied to the same sample to investigate the automotive segment. In comparison to other credit risk models, CreditRisk+™ presents the advantage of not making any assumptions about the cause of defaults in the analyzed sub-portfolios. Under CreditRisk+™, the number of defaults for a homogeneous sub-portfolio of borrowers follows a binomial distribution. Stochastic default rates are used, since they are assumed to be affected by a Gamma-distributed systematic factor. CreditRisk+™ models the effects of systematic factors by using default rate volatilities rather than by using default correlations as inputs. This can be viewed as a drawback. However, by imposing more restrictive assumptions on the distribution of the systematic factor makes it possible to assess the impact of potential economic disturbances on credit risk. Loss distributions are evaluated by means of Monte-Carlo simulations rather than closed-form solutions. This allows us to use stochastic variables for LGDs, [7] which are considered a constant in

[6] That is, automotive leases with an original maturity of up to 12 months.

[7] For leases belonging to a given sub-portfolio, the values obtained by multiplying LGDs by EADs are assumed to follow a lognormal distribution, given that recoveries are higher or lower than 100%.

Table 7
Loss rate distribution with re-sampling draws originating from different business cycles

Portfolio characteristics					Simulated portfolio loss rates (%) at loss distribution percentiles			
Asset type	Maturity in months	Year used	Mean	Standard deviation	95	99	99.5	99.9
Automotive	0–11	1991–2000	0.21	0.37	0.93	1.06	1.11	1.20
Automotive	0–11	Bad: 1992–1994	0.41	0.46	0.82	1.01	1.11	1.15
Automotive	0–11	Worst case: 1993	0.89	0.11	1.08	1.17	1.20	1.26
Automotive	12–47	1991–2000	0.28	0.48	1.63	1.89	1.97	2.12
Automotive	12–47	Bad: 1992–1994	0.77	0.63	1.84	2.01	2.07	2.21
Automotive	12–47	Worst case: 1994	1.63	0.21	1.97	2.12	2.17	2.26
Automotive	Over 47	1991–2000	0.23	0.34	1.15	1.31	1.36	1.44
Automotive	Over 47	Bad: 1992–1994	0.52	0.45	1.27	1.39	1.43	1.51
Automotive	Over 47	Worst case: 1994	1.15	0.12	1.36	1.45	1.48	1.55
Office equipment	All	1991–2000	0.40	0.31	0.99	1.14	1.19	1.30
Office equipment	All	Bad: 1992–1994	0.44	0.37	1.03	1.17	1.22	1.33
Office equipment	All	Worst case: 1998	0.92	0.13	1.13	1.23	1.27	1.34
Medical equipment	All	1991–2000	0.06	0.11	0.32	0.35	0.36	0.38
Medical equipment	All	Bad: 1992–1994	0.11	0.15	0.35	0.37	0.38	0.39
Medical equipment	All	Worst case: 1994	0.32	0.03	0.36	0.38	0.39	0.40
Other equipment	All	1991–2000	0.46	0.35	1.13	1.24	1.27	1.33
Other equipment	All	Bad: 1992–1994	0.24	0.23	0.70	0.77	0.8	0.85
Other equipment	All	Worst case: 1996	1.10	0.10	1.26	1.33	1.36	1.44

the original presentation of CreditRisk+™. PDs and LGDs are treated as two independent variables. The model estimates loss distribution by combining the distribution of default rates and the exposure (net of recoveries) for each sub-portfolio. Table 8 provides a summary comparison of the methodologies used in the two studies.

Table 9 shows the total loss rates at the 99.9th percentile for well-diversified automotive lease sub-portfolios in the current study in comparison with the previous study by Schmit (2003). Although differences are observed in the valuation of total losses for different sub-portfolios, both methods tested yield consistent results, i.e., the ranking of the risk of sub-portfolios is rather similar in both studies. We also compared the company's portfolio as constituted on June 30, 1995, with Schmit's (2003) results. On that date the portfolio included leases corresponding to all the maturities and times after issuance (ages) studied. The shares of each segment in the studied portfolio, calculated as the outstanding amount of a segment divided by the total value of the portfolio on June 30, 1995, are given in Table 9. The average loss rates are 0.39% and 0.48% when they are estimated respectively with the parametric methodology and the non-parametric simulation. The weighted sum of loss rate estimations at the 99.9th percentile is similar in both studies, i.e., 1.45% when using the bootstrap technique and 1.50% in Schmit (2003). The standard deviations

Table 8
Comparison between the two studies of credit risk for retail lease exposures

	CreditRisk+^{TM} type model	Re-sampling methodology
Type of methodology	Parametric	Non-parametric
Systematic factor	Gamma distributed	Represented by randomly drawn years of observations
Frequency of default	Binomial distributed	No assumption
LGDs × EADs	Lognormally distributed	No assumption
Advantages	• No assumption about the cause of default • No need to measure default correlations (unlike other parametric models)	No assumption about the distribution of key inputs
Drawbacks	• Assumptions about the distribution of the key inputs • PDs and LGDs treated as independent variables	• Simulation performed on limited universe • Drawing any particular year (underlying the realization of the systematic factor) is equiprobable
Sample	35,861 contracts	46,3732 contracts
Timeframe	1990–2000	1990–2000
Type of assets	Automotive	• Automotive • Office equipment • Medical equipment and • Other equipment

are higher with the non-parametric technique, whereas the latest study yields less kurtotic distributions. This can be explained by the fact that robust methodologies were used in Schmit (2003) to estimate key input parameters as well as by the difficulties involved in calibrating the systematic factor. Furthermore, in the current study we have only between 5 and 9 observed years, depending on the sub-portfolios that are assumed to be equally probable. This should lead us to be cautious in comparing the results of the two methods, although they are broadly in line with each other.

5.3. Sub-portfolio size and diversification

Table 10 shows the loss rates at the 99.9th percentile for the various portfolio sizes. When the size of the sub-portfolios increases respectively from 500, 1000, 2000, 4000, 6000, to 8000 contracts, 99.9th percentile loss rates decrease on average by respectively 55%, 42%, 25%, 11%, and 4.5%. The total loss rates shown at a given percentile (e.g., 99.9%) report an absolute value for the risk of a studied sub-portfolio when it is well diversified (e.g., $n = 8000$). However, although from a regulatory point of view a portfolio should be well diversified, this requirement does not apply to each individual sub-portfolio.

Table 9
Comparison of summary statistics on loss rate distributions

Automotive sub-portfolio's characteristics											
Maturity in months	0–11	12–47	12–47	12–47	12–47	Over 47	Over 47	Over 47	Over 47	Over 47	Over 47
Age in months	0–11	0–11	12–23	24–35	Over 35	0–11	12–23	24–35	36–47	48–59	Over 59
Outstanding – June '95	4.1%	9.1%	6.0%	2.4%	2.2%	24.9%	17.9%	15.1%	10.4%	5.6%	2.4%
Bootstrap											
Mean	0.21%	0.45%	0.40%	−0.13%	−0.01%	0.36%	0.78%	0.95%	0.37%	0.17%	−0.16%
Standard deviation	0.37%	0.51%	0.32%	0.26%	0.29%	0.34%	0.29%	0.26%	0.22%	0.31%	0.24%
Kurtosis	2.42	4.96	3.25	2.05	2.28	4.16	3.03	2.00	2.86	2.49	2.64
99.9th percentile	1.20%	2.13%	1.48%	0.44%	0.77%	1.39%	1.66%	1.61%	1.14%	1.16%	0.31%
CreditRisk+™											
Mean	0.17%	0.62%	0.19%	−0.06%	−0.13%	0.27%	0.62%	0.67%	0.25%	0.18%	−0.04%
Standard deviation	0.15%	0.45%	0.11%	0.15%	0.20%	0.11%	0.14%	0.15%	0.11%	0.12%	0.07%
Kurtosis	14.3	24.64	5.97	3.21	7.2	21.29	19.45	18.61	18.42	9.57	4.02
99.9th percentile	1.30%	4.23%	0.67%	0.41%	0.46%	1.07%	1.70%	1.84%	1.09%	0.87%	0.18%

Table 10
99.9th percentile loss rates for different sub-portfolio sizes

Automotive											
Maturity	0–11	12–47	12–47	12–47	12–47	Over 47	Over 47	Over 47	Over 47	Over 47	Over 47
Age in months	0–11	0–11	12–23	24–35	Over 35	0–11	12–23	24–35	36–47	48–59	Over 59
$n = 500$		3.81%	3.23%	1.12%	2.19%	2.43%	2.96%	3.21%	2.89%	3.49%	0.71%
$n = 1000$	2.12%	3.20%	2.49%	0.84%	1.53%	2.03%	2.39%	2.51%	2.14%	2.52%	0.53%
$n = 2000$	1.67%	2.69%	2.01%	0.64%	1.19%	1.75%	2.05%	2.03%	1.68%	1.83%	0.42%
$n = 4000$	1.38%	2.37%	1.71%	0.51%	0.95%	1.54%	1.82%	1.77%	1.35%	1.44%	0.36%
$n = 6000$	1.26%	2.22%	1.55%	0.48%	0.85%	1.44%	1.73%	1.66%	1.21%	1.26%	0.33%
$n = 8000$	1.20%	2.13%	1.48%	0.44%	0.77%	1.39%	1.66%	1.61%	1.14%	1.16%	0.31%
Office equipment–computers											
Age in months	0–11	12–23	24–35	36–47	48–59	Over 59					
$n = 500$	2.81%	4.51%	15.19%	5.50%	1.97%	3.19%					
$n = 1000$	2.18%	3.80%	12.15%	4.47%	1.48%	2.70%					
$n = 2000$	1.73%	3.27%	10.13%	3.68%	1.22%	2.27%					
$n = 4000$	1.47%	2.97%	8.67%	3.25%	1.02%	2.06%					
$n = 6000$	1.34%	2.86%	8.07%	2.97%	0.96%	1.95%					
$n = 8000$	1.27%	2.77%	7.75%	2.84%	0.91%	1.90%					
Medical equipment											
Age in months	0–11	12–23	24–35	36–47	48–59	Over 59					
$n = 500$	0.60%	0.61%	0.91%	1.16%	1.85%	0.00%					
$n = 1000$	0.52%	0.53%	0.76%	0.92%	1.58%	0.00%					
$n = 2000$	0.45%	0.45%	0.68%	0.80%	1.39%	0.00%					
$n = 4000$	0.41%	0.39%	0.62%	0.71%	1.25%	0.00%					
$n = 6000$	0.40%	0.37%	0.60%	0.67%	1.20%	0.00%					
$n = 8000$	0.39%	0.35%	0.58%	0.65%	1.17%	0.00%					
Other equipment											
Age in months	0–11	12–23	24–35	36–47	48–59	Over 59					
$n = 500$	2.33%	5.61%	5.94%	3.13%	2.35%	9.17%					
$n = 1000$	1.74%	4.24%	4.93%	2.25%	1.91%	7.41%					
$n = 2000$	1.27%	3.64%	4.30%	1.81%	1.54%	6.01%					
$n = 4000$	0.99%	3.14%	3.87%	1.49%	1.30%	5.27%					
$n = 6000$	0.90%	2.92%	3.66%	1.37%	1.18%	4.95%					
$n = 8000$	0.85%	2.79%	3.56%	1.27%	1.12%	4.78%					

6. Comparison with the Basel accords. Regulatory implications

The Basel Committee on Banking Supervision, a working group of the BIS, [8] has released a third consultative document (CP3) in April 2003 with a view to establishing a revised capital adequacy accord. The aim is to provide a number of new approaches that are both more comprehensive and more sensitive to risks than the 1988 accord, while maintaining the overall level of regulatory capital. The new accord on regulatory capital is expected to be implemented in the European Union through a directive by 2005, so that all EU financial institutions will be subject to the new provisions.

6.1. Overview of the approaches proposed by the Basel committee

The "standardized" approach relies mainly on external credit ratings to evaluate risk weights in relation to capital adequacy. No reduction is currently provided for in respect to physical collaterals other than real estate.

When using their own rating system, financial institutions have the choice between two options: the internal ratings-based (IRB) "foundation approach" and its "advanced" version. In the IRB foundation approach, only PDs of borrowers have to be reliably estimated (other parameters are set by regulators), whereas in the advanced approach, LGDs and maturity also have to be estimated by financial institutions. Given these parameters, capital requirement is defined through an algebraic formula based on credit risk models. The total capital requirement of a financial institution is then calculated as the sum of requirements for all sub-portfolios.

When claims are classified as retail exposures, both the standardized and the IRB advanced approaches provide for capital requirement deductions. Loans to individuals or to small businesses qualify for such deductions when total exposure does not exceed €1 million. Since the lease contracts in our sample concern private customers or small entities, they should be classified as retail exposures. Indeed, 97% of the leases in our sample have an original value of less than €100,000 and none has an original value in excess of €500,000. Furthermore, no lease value represents more than 0.2% of the total portfolio value.

In the following, we briefly describe the IRB approach in accordance with CP3. The capital requirement K (per euro) is calculated as

$$K = \mathrm{LGD} * N[(1-\rho)^{-0.5} * G(\mathrm{PD}) + (\rho/(1-\rho))^{0.5} * G(0.999)] * M_{\mathrm{adj}}, \tag{1}$$

where

- $N(x)$ denotes the cumulative distribution function for a standard normal random variable and $G(z)$ denotes the inverse cumulative distribution function for a standard normal random variable (the confidence level being set at 99.9%).

[8] The Basel Committee on Banking Supervision is composed of central banks' and supervisory authorities' representatives from Belgium, Canada, France, Germany, Italy, Japan, Luxembourg, the Netherlands, Sweden, Switzerland, the United Kingdom, and the United States.

- LGD is the loss given default. Under the IRB foundation approach, LGD is set at 40% for physical collaterals other than real estate. Under the IRB advanced approach, LGD is estimated on the basis of banks' internal risk assessment data.
- M_{adj} is the adjustment for maturity and is expressed as $[1 - 1.5 * b(\text{PD})]^{-1} * [1 + (M - 2.5) * b(\text{PD})]$ with M being the effective maturity of exposure and b given by $[0.08451 - 0.05898 * \ln(\text{PD})]^2$. In the case of retail exposure, there is no maturity adjustment.
- $$\rho = \rho_{\min} * (1 - \mathrm{e}^{(-x^* \text{PD})})/(1 - \mathrm{e}^{(-x)}) + \rho_{\max} * (1 - (1 - \mathrm{e}^{(-x^* \text{PD})})/(1 - \mathrm{e}^{(-x)})) - S_{\text{adj}}, \quad (2)$$

  where
  - $\rho_{\min}$ is the minimum correlation. It equals 12% for corporate exposures and 2% for retail exposures.
  - $\rho_{\max}$ is the maximum correlation. It equals 24% for corporate exposures and 17% for retail exposures ("other retail exposures" segment).
  - x is a constant. It equals 50 for corporate exposures and 35 for retail exposures.
  - S_{adj} is the firm-size adjustment. It is given by $0.04 * [1 - ((S - 5)/45)]$ where S is the total annual sales in millions of euros. In the case of retail exposures, there is no size adjustment.

The capital required is K times the EAD. The risk weighting-ratio is K divided by 8%.

6.2. Comparison between capital requirements: Internal model vs. CP3

A comparison between capital requirement calculations resulting from our internal model at the 99.9th percentile and those derived from the weighting scheme set forth in CP3 is exhibited in Table 11.

Under the standardized approach, exposures qualifying as belonging to retail portfolios would be assigned a risk weight of 75%. Thus, a 6% (i.e., 75% times 8%) regulatory capital is generally far above the capital requirement we estimated.

Under the IRB foundation approach, LGD for lease contracts is set at 40%. The calculated regulatory capital is much higher that that resulting from the internal model, i.e., approximately 2–10 times higher, as apparent from Table 11. This difference is related to the fact that the IRB foundation approach does not provide for recognition of physical collaterals and for regulatory capital deductions in respect of retail exposures.

The capital requirements calculated with our own internal model are, on average, quite in line with the regulatory capital arising from the IRB advanced approach. The reason for this is that the IRB advanced approach is based on actual LGD, thus allowing physical collateral recognition and capital requirement adjustment for retail exposures.

In the light of our results, banks with portfolios mainly composed of retail exposures are likely to find their choice restricted to the standardized or the IRB

Table 11
Comparison of capital requirements: Internal model vs. Basel Committee's proposals

Maturity (months)	Age (months)	PD (%)	LGD (%)	Standardized approach (%)	IRB foundation approach (%) ($S = 5$; LGD: 40%)	IRB advanced approach (%) (retail exp., actual LGD)	Internal model (%)	Ratio	Ratio	Ratio
				(1)	(2)	(3)	(4)	(1)/(4)	(2)/(4)	(3)/(4)
Automotive leasing										
<12	0–11	0.41	52	6	3.72	3.03	1.20	5.00	3.10	2.52
12–47	0–11	1.99	31	6	7.10	3.81	2.13	2.82	3.33	1.79
	12–23	3.13	15	6	8.30	2.09	1.48	4.05	5.61	1.41
	24–35	2.92	1	6	8.10	0.14	0.44	13.64	18.40	0.31
	36–47	2.09	1	6	7.22	0.12	0.77	7.79	9.37	0.16
>47	0–11	1.62	22	6	6.62	2.52	1.39	4.32	4.76	1.81
	12–23	3.93	22	6	9.06	3.25	1.66	3.61	5.46	1.96
	24–35	4.11	22	6	9.23	3.29	1.61	3.73	5.73	2.04
	36–47	3.21	14	6	8.38	1.97	1.14	5.26	7.35	1.73
	48–59	2.61	12	6	7.78	1.60	1.16	5.17	6.71	1.38
	⩾60	3.11	−5	6	8.28	−0.70	0.31	19.35	26.72	−2.25

Office equipment–computers									
0–11	0.78	47	6	5.01	3.89	1.27	4.72	3.94	3.06
12–23	2.67	52	6	7.85	7.02	2.77	2.17	2.83	2.53
24–35	2.97	52	6	8.15	7.13	7.75	0.77	1.05	0.92
36–47	1.62	61	6	6.62	7.00	2.84	2.11	2.33	2.46
48–59	2.45	48	6	7.62	6.29	0.91	6.59	8.37	6.91
⩾60	1.88	48	6	6.96	5.80	1.90	3.16	3.66	3.05
Medical equipment									
0–11	0.17	23	6	2.31	0.74	0.39	15.38	5.93	1.90
12–23	0.17	23	6	2.31	0.74	0.35	17.14	6.61	2.12
24–35	0.53	23	6	4.21	1.54	0.58	10.34	7.26	2.65
36–47	0.42	23	6	3.76	1.34	0.65	9.23	5.78	2.06
48–59	0.27	23	6	2.99	1.02	1.17	5.13	2.56	0.87
⩾60	0.00	23	6	–	–	0.00	–	–	–
Other equipment									
0–11	1.56	22	6	6.53	2.47	0.85	7.06	7.68	2.91
12–23	4.13	36	6	9.25	5.36	2.79	2.15	3.31	1.92
24–35	3.11	31	6	8.28	4.32	3.56	1.69	2.33	1.21
36–47	2.47	26	6	7.64	3.35	1.27	4.72	6.01	2.64
48–59	2.42	16	6	7.58	2.11	1.12	5.36	6.77	1.88
⩾60	3.30	72	6	8.47	10.13	4.78	1.26	1.77	2.12

advanced approaches. For these institutions, switching from the standardized approach to the IRB foundation approach might not be an economically sound decision since – as apparent from Table 11 – the costs incurred to estimate inputs internally would not necessarily be offset by any benefits in terms of capital charge.

7. Conclusion

This paper presents the first empirical results on the default and loss severity of leases by implementing a non-parametric simulation based on ex ante and ex post data on four types of leased assets.

Results are shown according to the type and age of the leases. The estimated risks for automotive and medical equipment lease portfolios are of the same order of magnitude as for AAA to A private debt rated portfolios (cf. Carey, 1998). The "Office Equipment–Computers" and "Other Equipment" segments show a higher risk factor, comparable to that of A to BB rated portfolios. However, the risk profile of the lease portfolios included in our sample is quite different from that of private debt portfolios. On average, the probabilities of default are higher and loss severity is much lower in our sample.

One of the main objectives of the new framework is to provide banks with reasonable incentives (in the form of capital requirement relief) to switch to the more advanced approaches. However, the foundation IRB approach will lead to higher regulatory capital requirements for a significant proportion of lease portfolios. Furthermore, in spite of potentially substantial differences in regulatory capital requirements, the decisive factor in choosing between the standardized and the IRB advanced approaches is more likely to be the ability of financial institutions to obtain complete data sets on PDs and LGDs than the performance of an in-depth cost–benefit analysis. Most probably, given the structure of leasing businesses in Europe, many financial institutions will not be able to meet the requirements set by national supervisors (cf. IBM Institute for Business Value, 2002). Bearing these observations in mind, the ability to adopt one approach rather than another could result in competitive distortions.

Our study should be helpful in defining a benchmark for adequate capital requirements for leasing businesses. The results are also relevant to issues concerning the insurance and securitization of lease portfolios. We are aware that the data we used in our research to estimate credit risk originate from only one European financial institution. Nevertheless, our study suggests there is a real need to review the capital adequacy proposals in order to allow for better recognition of physical collaterals in view of their contribution to reducing credit risk.

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