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## A cash-flow analysis of VCL\_9

*02/2010 as of 01/2007*

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### Part 1: A brief description of the major structural features

The analysis is based on information taken from the originator's website:

[http://www.vwfsag.de/fsag/ucus/vwfsag/en/investor\\_relations/refinancing/asset\\_back\\_ed\\_securities/vcl\\_9.html](http://www.vwfsag.de/fsag/ucus/vwfsag/en/investor_relations/refinancing/asset_back_ed_securities/vcl_9.html)

<b>Notes</b>	VCL_9 is an auto leasing transaction that was closed in 2007 (cut-off date: 31 January) with a legal maturity date in April 2012. It has two tranches: tranche A initially had a notional of EUR 940.2 million, a AAA or equivalent rating from the major rating agencies and a margin of 5 basis points over one month Euribor; tranche B had an initial notional of 30.35 EUR million, a rating of A+ and a margin of 13 basis points.
<b>Collateral</b>	The initial discounted balance of the total collateral pool was Eur 1,011 million, consisting of the amortising portion of the lease transactions – the residual value was not securitised. The discount rate was 5.136%.
<b>Interest rate hedging</b>	The transaction benefits from two swaps, both balance guaranteed. One has a notional equal to the actually outstanding notional of the class A notes where the counterparty pays 5 basis points over one-month Euribor and receives a fixed rate of 4.0895%. The notional of the other swap equals that of the class B notes with a floating payment of 13 basis points and a fixed rate of 4.1795%.

<b>Credit enhancement</b>	<p>A subordinated loan of EUR 28.3 million supported the transaction at inception. It was used to fund the cash collateral account of size EUR 17.862 million of which EUR 12.132 million is a ‘general amount’ and EUR 5.73 million is a tax risk reserve.</p> <p>Furthermore, the deal was initially overcollateralised by EUR 12.168 million (the difference between the aggregated discounted loan balance and the sum of the total notional of the notes and the subordinated loan – in fact, taking only the notes into account the overcollateralisation was much more significant).</p>
<b>Waterfall</b>	<p>The simplified payment structure (prior to enforcement) looks as follows:</p> <ol style="list-style-type: none"> <li>1. Fees (trustee, servicer, etc.)</li> <li>2. Net swap payment to the counterparty</li> <li>3. Class A interest</li> <li>4. Class B interest</li> <li>5. Cash collateral account replenishment</li> <li>6. Class A principal</li> <li>7. Class B principal</li> </ol> <p>In each period on the class A and class B principal payment there’s an upper limit: the outstanding balances should decrease to such an extent that they are exceeded by the outstanding collateral pool balance by a certain percentage. This percentage can change over time as a function of the losses in the pool.</p>

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## Part 2: Cash-flow modelling

### Section 2.1: Assumptions

- *Composition of the collateral pool.* We built our collateral file from the table on page 57 of the offering circular: this aggregates the individual lease level data into 31 maturity buckets and assigns a discounted balance to each bucket. The interest rate we used was the discount rate of 5.136%.  
As there were a total of more than 77,000 loans in the initial pool using a model pool with 31 elements (corresponding to the 31 maturity buckets) could have distorted the results substantially. Therefore, to increase the granularity of the pool we divided each bucket into 10 equally sized sub-buckets and used these as the model loans (so the number of loans in the simulations was 310).  
The model we used for the collateral enables us to reflect the strength of the relationship among the individual loans. As we shall see below we had two

scenarios: one with a lack of connectedness (asset-correlation of 0) and one with higher connectedness (asset-correlation of 0.8).

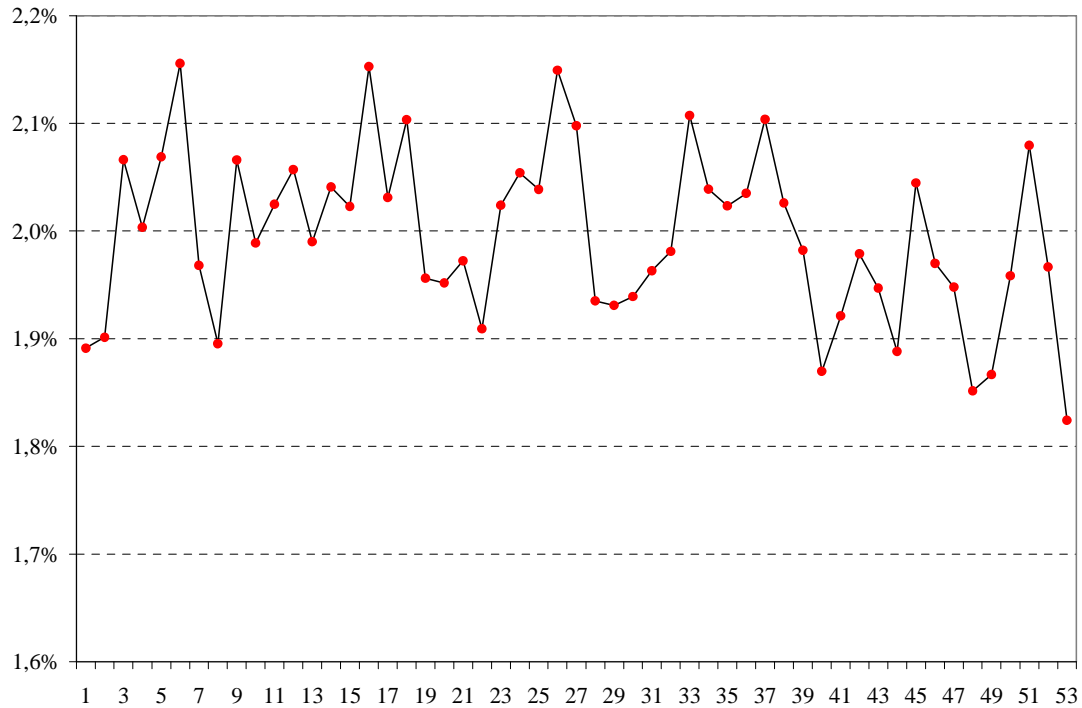
- *Swaps*. We modelled only one swap – we took the discount rate of 5.136 percent as the fix leg (paid by the SPV) and a margin of 7 basis points on the floating leg (received by the SPV). We assumed that the swap counterparty will always fulfil its payment obligation towards the SPV.
- *Cumulative net loss ratio in the overcollateralisation calculation*. Instead of net losses we used defaults. This is less conservative an assumption with regards to the class A notes as the trigger is hit sooner and therefore class A is paid down sooner.
- *Class A and B Targeted Overcollateralisation Amount*. We didn't take the minimum amounts set in the offering circular, we simply used the amount resulting from the overcollateralisation percentage requirement.
- *Level 1 and Level 2 Credit Enhancement Increase Conditions*. We excluded the sub-condition referring to the number of months that have passed since closing.
- *Specified General Cash Collateral Account Balance*. We modelled the reserve fund as non-amortising at its initial level of EUR 12,132,220.
- *Waterfall*. We didn't model the fees at the top of the waterfall and didn't model items below class B principal payment.
- *Tax*. We didn't deal with any tax issues (neither in the waterfall, nor in relation to the tax reserve).
- *Clean-up call*. We assumed no clean-up call occurring.
- *Insolvency*. We didn't model set-off and commingling risk, or any other risks stemming from the insolvency of any of the parties.
- *Enforcement Event*. We didn't model the waterfall after such an event.

## Section 2.2: Simulation set-up

We ran 4 times 1000 simulations plus two “base case” scenarios. The below table shows the settings for the base cases (both under “pd0”) and each of the sets of 1000 runs:

scenario name	probability of default	asset correlation	interest rate
pd0	0	0	stochastic
pd2_w0	2%	0	stochastic
pd2_w80	2%	0.8	stochastic
pd6_w0	6%	0	stochastic
pd6_w80	6%	0.8	stochastic

The pd0 scenario was run at a prepayment rate (CPR) of zero as well as a yearly 5%. The rest of the scenarios were run at a CPR of 5%. Probability of default refers to yearly default rate or – as the rate is always applied to ‘surviving’ loans – yearly default intensity. The rate applied was the same for all loans in the pool. The interest rate was generated by the CIR model with an initial and long term rate of 2%, an adjustment parameter of 0.5 and a volatility of 0.005. A pattern from this process is shown in the following figure:



\* x-axis: months

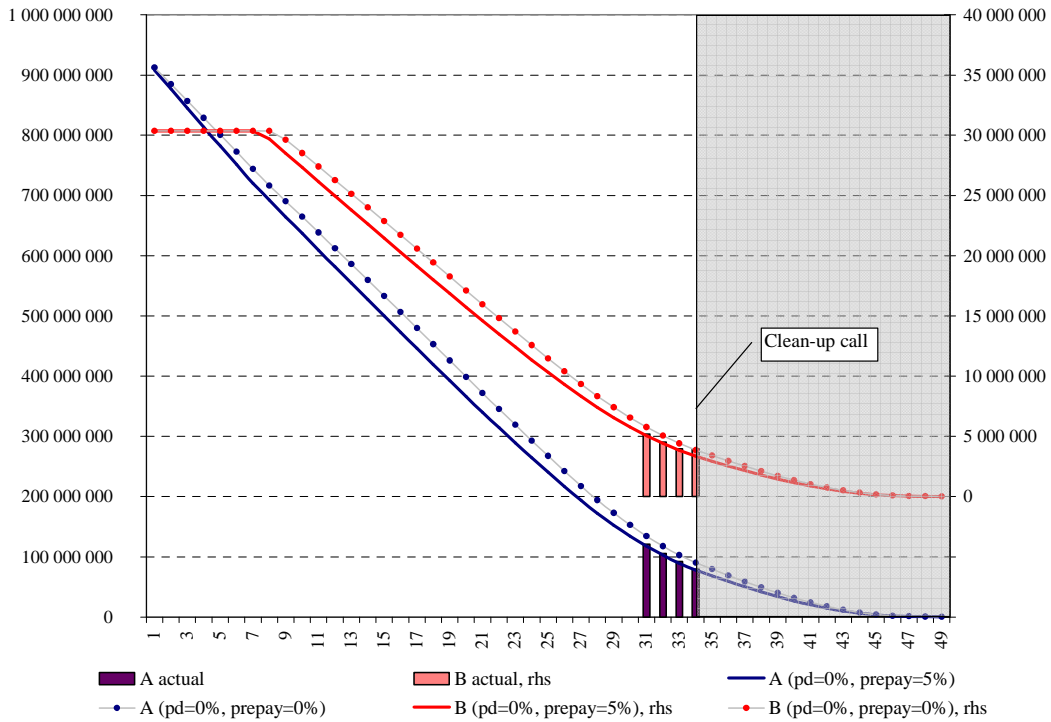
Recovery rate was modelled at 50% and we assumed that the full recovery amount is received 4 months after default.

### Section 2.3: Results

We examined the following 5 quantities:

- the number of defaults in the collateral pool
- the amount of defaults in the collateral pool
- the predicted balance of the class A notes in month 35 (December 2009)
- the maturity of the class A notes
- the present value of the class A notes (by discounting back all the cash flows received by class A during the whole life of the deal to the closing date)

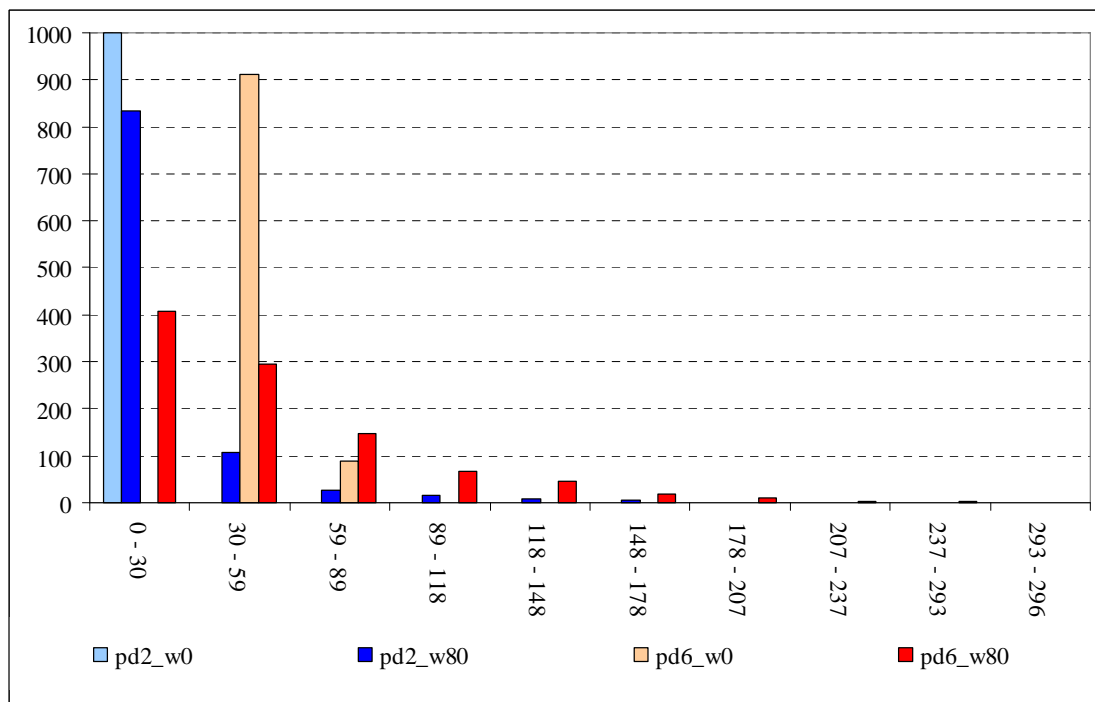
Before turning to these results, however, we found it interesting to compare our pd0 scenario results to how the deal actually developed (two scenarios, one with and the other without prepayment/early settlement). The basis of this comparison is the fact that the default rate in the actual deal turned out to be very low, close to 0%. At the same time, there were early settlements; based on the last investor reports the rate of these was around 5% per annum. The chart below shows the month end outstanding balances of the class A and class B notes from our two pd0 scenarios and for the last four months also from the investor reports (we only have this latter data starting from month 32).



The chart shows a very good fit of the model's prediction to the actual outcome (this is remarkable even if we made use of the information about the true default and prepayment rates).

Now turning back to the scenario analysis, charts CHART 1 to CHART 5 explore the distribution of the above quantities under these 5 scenarios.

CHART 1: The distribution of the number of defaults



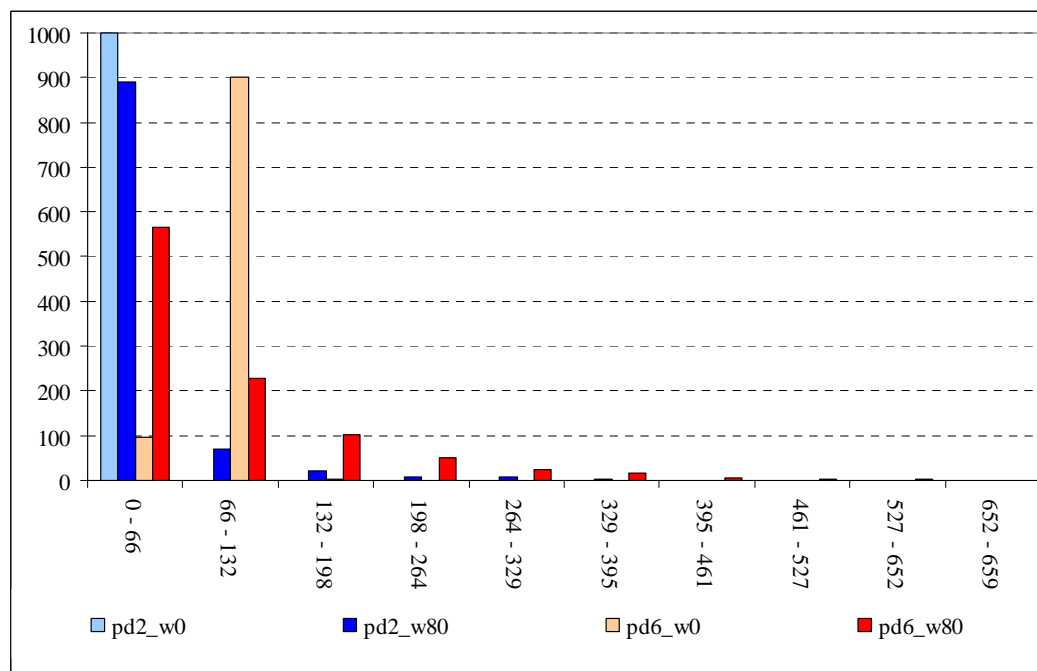
\* x-axis: No. of total defaults

Chart 1 confirms the well known feature of the asset-value model we applied: as the magnitude of correlation decreases down towards zero the distribution of defaults collapses to the expected value of the default probability. As correlation increases towards +1, the probability of the extreme default rate outcomes of 0 and 100 percent respectively increases (while the expected rate is unchanged).

In the pd2\_w0 scenario we can only see defaults in the 0-30 category. This corresponds to a default rate of roughly between 0 and 10 percent (this makes sense as we have a yearly average default probability of 2 percent and the maximum life of the pool is somewhat more than 4 years). As we increase correlation (pd4\_w80) we can see such number of defaults that are farther away from the average: we can observe more runs falling into the 30-59 category and some even in the 148-178 category, for example.

The same can be observed in the pd6 scenarios where the theoretical average number of defaults over the 4 years of the life of the pool is around 68. In fact, as the average maturity of the pool is much smaller it is reasonable to see the peak in the 30-59 category in the pd6\_w0 scenario. Again, as correlation increases the probability of the occurrence of default rates much larger or smaller than this average increases.

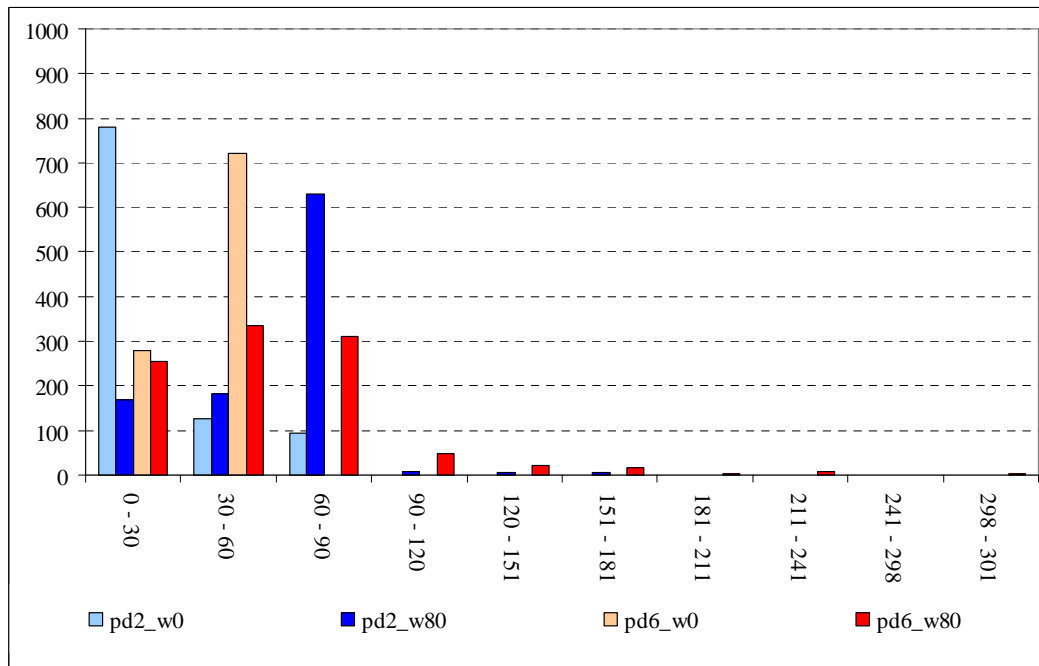
CHART 2: The distribution of the amount of defaults



\* x-axis: EUR million

This chart resembles the previous one and the similarity between the two is due to the granularity of the pool; if the pool were less granular than for any level of the default rate we would see very different total default amounts in the different runs.

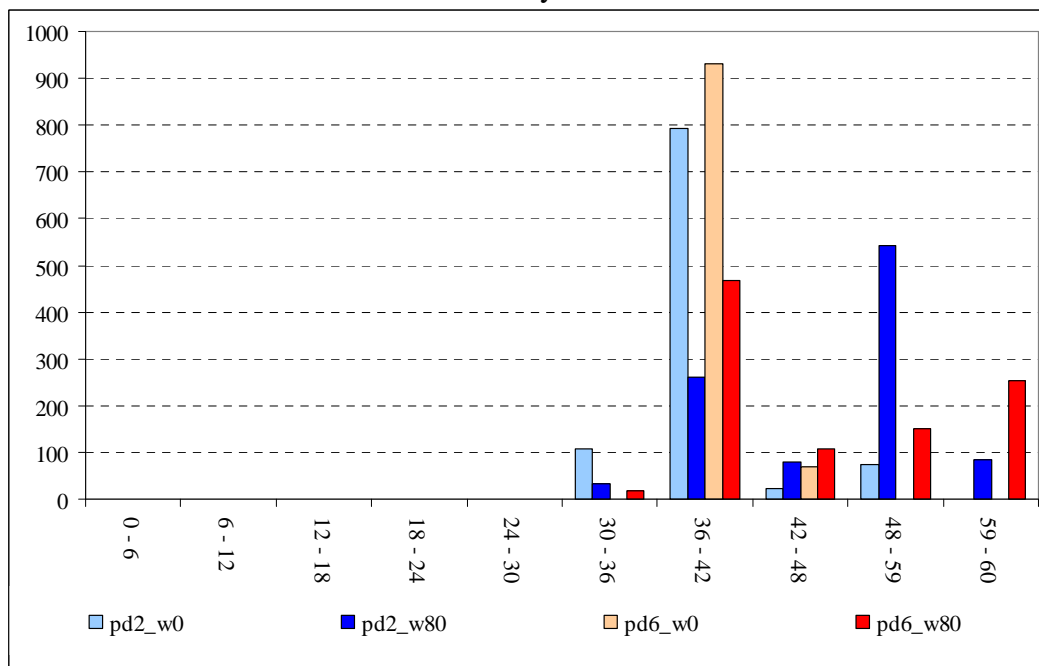
CHART 3: The distribution of class A notional at the beginning of month 35 (December 2009)



\* x-axis: EUR million

With zero default the model's prediction is an outstanding balance of around EUR 78 million at the beginning of month 35. In general, defaults can speed up the paydown as is evidenced by this figure: recoveries (these were modelled at 50 percent with 4 months time to recovery) are larger than amortisation payments and, additionally, defaults will switch on triggers to speed up the paydown of the class A notes. However, as default rates (and default correlations) increase further there is an increasing chance of a higher outstanding amount in a given month.

CHART 4: The distribution of the maturity of the class A notes

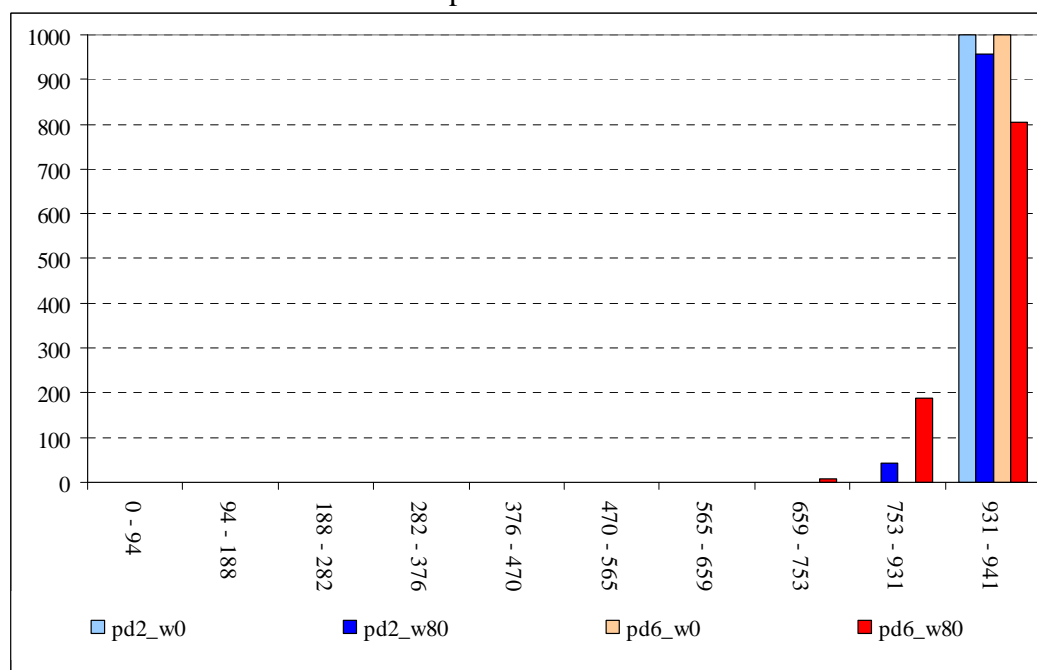


\* x-axis: months

Chart 4 reinforces the conclusion of Chart 3 that a small rate of default can speed up the paydown of the A class, but increasing default rates will eventually lead to losses: observations in the 59-60 category correspond to such simulation runs where the class A balance was not paid back in full to investors.

Another conclusion from the chart can be that the final paydown can't really be expected in any case until 3 years have passed after closing (without a clean-up call).

CHART 5: The distribution of the present value of the class A notes



\* x-axis: EUR million

Finally, Chart 5 shows an interesting relationship between losses on the one hand and default rates and default correlation on the other: a steady 6 percent default in the pool is better than a more volatile default rate with an average of 2 percent as in some scenarios in the latter situation the actual default rate might turn out to be higher than 6 percent. So the highest default rate that class A can withstand at a high significance level (say, 99 percent) is below 2 percent.