Estimating EAD for retail exposures for Basel II purposes

Vytautas Valvonis
Faculty of Economics, Vilnius University, Saulėtekio 9, LT-10222 Vilnius, Lithuania; email: vvalvonis@b4net.lt

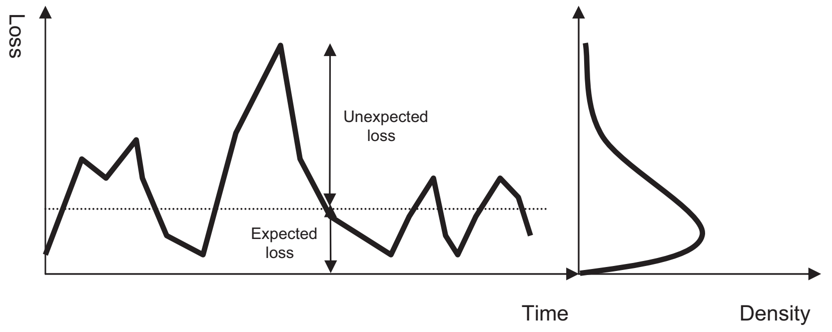
This paper discusses the estimation of exposure at default for Basel II purposes: what is the credit conversion factor (CCF), how it can be estimated for defaulted exposures, what are EAD risk drivers (EADRDs) and how information on CCFs and EADRDs can be used to model EAD for non-defaulted exposures. This paper also provides some empirical CCF estimation and EAD validation results for retail exposures.

1 INTRODUCTION

Having granted a loan to a borrower, the bank accepts the risk that the loan might not be repaid. The bank cannot be sure whether default shall occur or not. The outcome of not receiving the loan back is measured by probability of default (PD). If the borrower defaults, PD is equal to 1, if not PD is equal to 0, and in all other cases, when a borrower is meeting his or her obligations, PD is between 0 and 1. Estimating default probability is not enough. The bank should also estimate the loss that would be incurred if the borrower defaulted on his or her exposure. If the borrower defaults, it is more than likely that the bank shall recover something from the defaulted exposure and shall not lose everything. The loss rate on exposure in case of default is measured by loss given default (LGD). LGD measures what percentage of exposure is outstanding at the moment of default and is expected to be lost. Thus, besides PD and LGD credit risk parameters, one needs to know the exposure amount outstanding at the time of default or EAD risk parameter. Multiplying EAD, LGD and PD gives the expected loss (EL) of exposure. As the bank usually covers EL by the income from the interest margin, risk of loss is realized only in case actual loss exceeds EL (BCBS (2005)).

To cover unexpected losses, banks hold capital. Capital requirement to banks, ie, how much capital to hold against risk, on an international level is issued by the Basel Committee on Banking Supervision (BCBS (2004)); for European banks, this issue is regulated by respective directives (EU (2006)); and locally, capital requirements for banks are set by local supervisors.

In 2004, BCBS introduced the revised capital accord known as Basel II. This allows banks to use internal credit risk models in measuring capital requirements for credit risk or unexpected credit loss. As supervisory capital estimation formulas are based on the abovementioned PD, LGD and EAD risk



parameters,[1] this implies that banks have to model PD, LGD and EAD and input these parameters into supervisory capital calculation formulas to obtain required capital. Much is written about PD modeling and to a lesser extent about LGD modeling but very little research has been done about EAD.

EAD is equal to the amount of money that the borrower owes the bank at the moment of default. Borrowers can borrow money from the bank in very different ways: loans, lines of credit, etc. All of these instruments can be divided into two groups:

1) fixed exposures – exposures having only on-balance part, eg, loans; and
2) variable exposures – exposures having on- and off-balance parts, eg, lines of credit.

For fixed exposures, EAD is equal to the current amount outstanding, so for Basel II purposes no EAD modeling is required. For variable exposures, EAD is equal to the current outstanding amount plus an estimate of additional drawings up to the time of default. As additional drawdowns up to the default day are unknown to banks, the only exposures requiring modeling of EAD are variable exposures.

Although not explicitly stated, the new EU Capital Adequacy Directive (CAD) (EU (2006)) treats the exposure value as consisting of two positions: the amount currently drawn and an estimate of future drawdowns of committed but unutilized credit. The potential future drawdowns are described in terms of the proportion of the undrawn amount and are known as the credit conversion factor (CCF). Thus, EAD modeling is actually about modeling CCF.

The aim of this paper is to discuss up-to-date research and supervisory requirements for EAD modeling and present some empirical estimation results for retail exposures. This paper is structured as follows: Section 2 is devoted to methodological requirements for estimating EAD, like the calculation of CCFs for defaulted exposures, EAD risk drivers (EADRDs), possible EAD modeling methods for non-defaulted exposures and EAD validation methodologies; Section 3 shows some empirical retail CCF estimation outcomes by three methods and retail EAD validation results; and Section 4 concludes with a discussion.

[1] For exposures to corporate, sovereigns and institutions, additional risk parameter (M – maturity) is used.

2 THEORETICAL EAD MODELING ISSUES

For variable exposures, EAD is expressed as follows:

$$\begin{aligned} \text{EAD} = {} & \text{Current\_Outstanding\_Amount} + \text{CCF} \\ & \cdot (\text{Total\_Committed\_Amount} - \text{Current\_Outstanding\_Amount}) \end{aligned}$$

As the current outstanding amount[2] and the total committed amount are known to the bank, the only unknown variable in the equation above is CCF. CCF is defined as the ratio of the currently undrawn amount of a commitment that will be drawn and outstanding at default to the currently undrawn amount of the commitment (EU (2006)). From the definition, some important properties of CCF follow (CEBS (2005)):

- *CCFs are estimated for current commitments:* the bank is required to hold capital for current commitments that it has currently taken on.
- *The CCF must be expressed as a percentage of the undrawn (off-balance) amount of the commitment:* this implies that calculating CCF differently, eg, as the ratio from the whole exposure (the on- and off-balance or the whole credit limit[3]), would violate the requirements of the CAD.
- *The CCF shall be zero or higher:* even though it is not explicitly stated in the EU CAD, it is clear from the definition that CCFs shall be zero or higher. This implies that the EAD of exposure is no less than the current outstanding amount.[4] If additional drawings after the time of default are not reflected in the LGD estimation, they have to be taken into account in the estimation of CCF whatever the method is chosen.

Banks are expected to estimate CCFs on the basis of the average CCFs by facility grade (pool) using all observed defaults within the data sources (EU (2006)). Thus:

- For IRB risk weight estimation purposes, facility grade (pool) average CCFs are used to estimate EADs, ie, one has to use not individual CCFs for every exposure but rather one grade/pool CCF for all exposures in the same grade/pool. On the other hand, for every non-defaulted exposure, individual

[2] The on-balance exposures should be measured not deducting value adjustments (EU (2006)). In accounting (according to IFRS) exposure, the on-balance amount includes accrued but unpaid interest; thus, further in this paper, the on-balance amount should be understood the same way as in accounting, including accrued but unpaid interest.

[3] In this case, CCF is called usage given default (UGD) ratio or loan equivalent (LEQ) factor (Moral (2006)).

[4] The regulatory framework requires capital to cover current outstanding amounts plus the possible additional drawings before default. The interpretation put forward by UK FSA (FSA (2004a)) is that banks should not calculate what EAD would be if default occurred at a specific date in the future. This would imply that the IRB framework should allow for reductions in fixed exposures as well as fluctuations in variable (revolving) exposures. Looking at a future date, one would also see increases in exposures to existing borrowers, new facilities to existing borrowers and new facilities to new borrowers. Correspondingly, capital may have increased over the period because of retentions or new issues.

CCFs could be estimated making use of the fact that where a bank uses direct estimates of risk parameters these may be seen as the output of grades on a continuous rating scale (EU (2006)).

- Banks should define grades or pools for estimating EAD. For this purpose, one needs EADRDs.
- Grade/pool CCF is calculated as a simple average of estimated CCFs for defaulted exposures, ie, default weighted average.[5] Or banks can directly estimate a grade (pool) average CCF without estimating individual CCFs for defaulted exposures.[6]

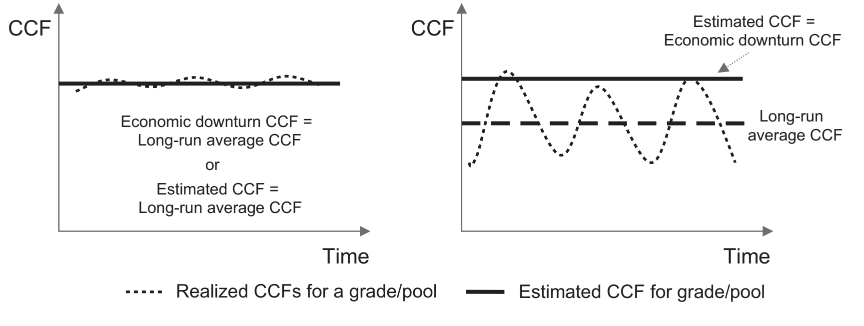
Specifically for Basel II purposes, banks are also required to estimate CCFs that are appropriate for an economic downturn if those are more conservative than the long-run average CCF (see Figure 1).

If CCFs do not fluctuate too much around their long-run average (Figure 1, left), then banks might use average CCF for Basel II purposes. Otherwise, if fluctuations during the economic cycle are material (Figure 1, right), banks must ensure that CCF estimates are appropriate for economic downturn conditions by taking the necessary corrections.

Summarizing it follows that the general CCF and ultimately EAD estimation procedure is as follows:[7]

1) track all defaults and calculate the retrospective (realized) CCF for every defaulted exposure (see Section 2.1);
2) identify EADRDs (see Section 2.2);
3) using information on EADRDs and CCFs of defaulted exposures, estimate CCFs for non-defaulted exposures (see Section 2.3);

FIGURE 1 Economic downturn CCFs.



[5] For a definition of default weighted average, refer to Expert Group (2005).
[6] In practice, eg, the UK's FSA is not expecting to see the latter approach, in the way envisaged for PD estimation, being applied to EAD (FSA (2004b)).
[7] Expert judgment may play some role in Steps 2–4.

4) determine the final CCF estimate by making sure that it is appropriate for economic downturn conditions (see Section 3.1);
5) apply CCF estimates to every non-defaulted exposure to obtain EADs; and
6) validate CCFs and EADs (see Section 2.4 for validation methodology and Section 3.2 for validation results).

Currently, until more detailed empirical evidence is gathered and more experience is gained, supervisors are not ruling out any of the approaches for estimating CCF, consistent with the abovementioned requirements.[8] Regardless of the approach chosen, it is expected from banks to (CEBS (2005)):

- analyze and discuss their reasons for adopting a given approach, justify their choices and assess the impact that the use of a different timeframe would have;
- identify the possible weaknesses of the chosen approach and propose methods to address or compensate for them; and
- evaluate the impact of the chosen approach on final CCF grades and estimates by investigating dynamic effects such as interactions with time to default and credit quality.

2.1 Estimation of CCFs for defaulted exposures

2.1.1 General issues

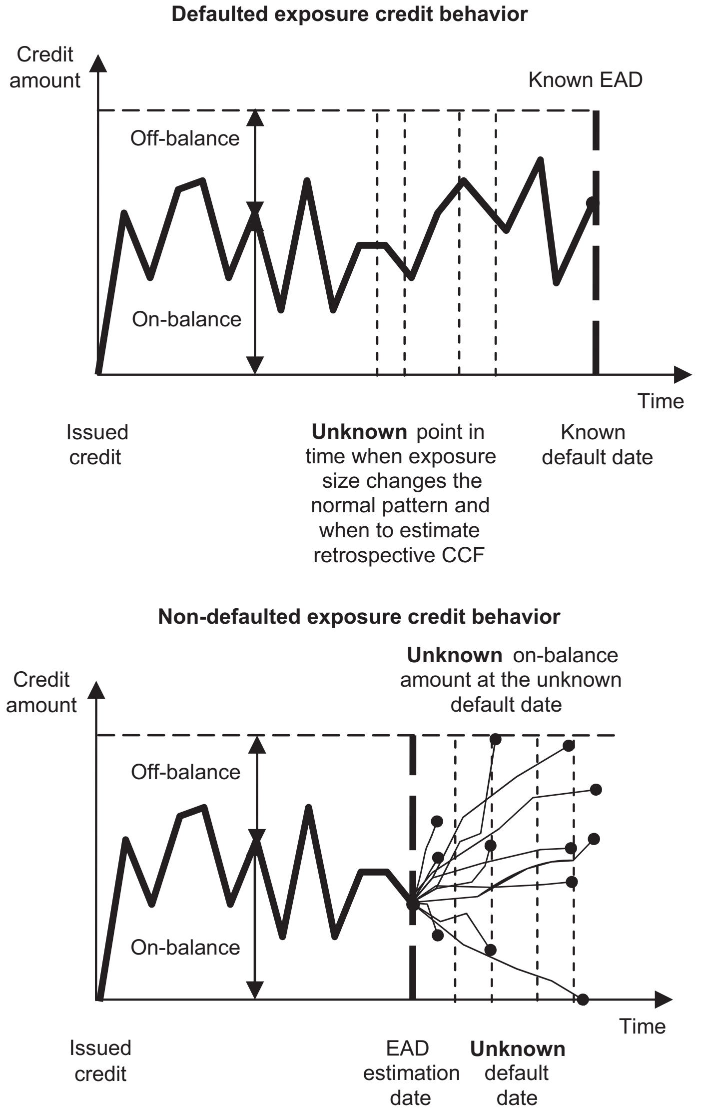
Methods for modeling EAD are the least developed. One of the reasons for this might be that EAD, even more than PD or LGD, depends on how the relationship between banks and clients evolves in adverse circumstances, when the client may decide to draw previously unused exposure. This implies that banks must model EAD using internal data, taking into consideration experience and practice of the bank as well as the external environment in which it operates. Thus, using external data for EAD modeling purposes might be complicated. The other reason might be that there are many unknown parameters that influence EAD. Figure 2 depicts the problem of EAD modeling.

For defaulted exposures (Figure 2, top), the true EAD and the time of default are known. As modeling of EAD is based on CCFs, one has to calculate retrospective (realized) CCF for defaulted exposure (some point in time before default date, because at the time of default CCF equals 0).[9] This possesses the greatest challenge as it is not clear at what point in time before default one should calculate retrospective CCF for defaulted exposure. For non-defaulted exposures, only current (at the time of estimation) exposure is known. But the goal is to estimate what

[8] For EAD estimation, documentation, other requirements and related questions that can be asked by supervisors during onsite inspection, refer to the FSA (2004b). For a discussion of supervisory requirements, comparison of EU CAD and BCBS Basel II paper requirements, refer to the unpublished French implementation proposal "Exposure value/EAD: prudential and accounting issues" by [Commision Bancaire (France)].

[9] Assuming that after default day there were no additional drawdowns or such additional drawdowns were accounted for in the LGD estimate.

FIGURE 2 EAD modeling problem.

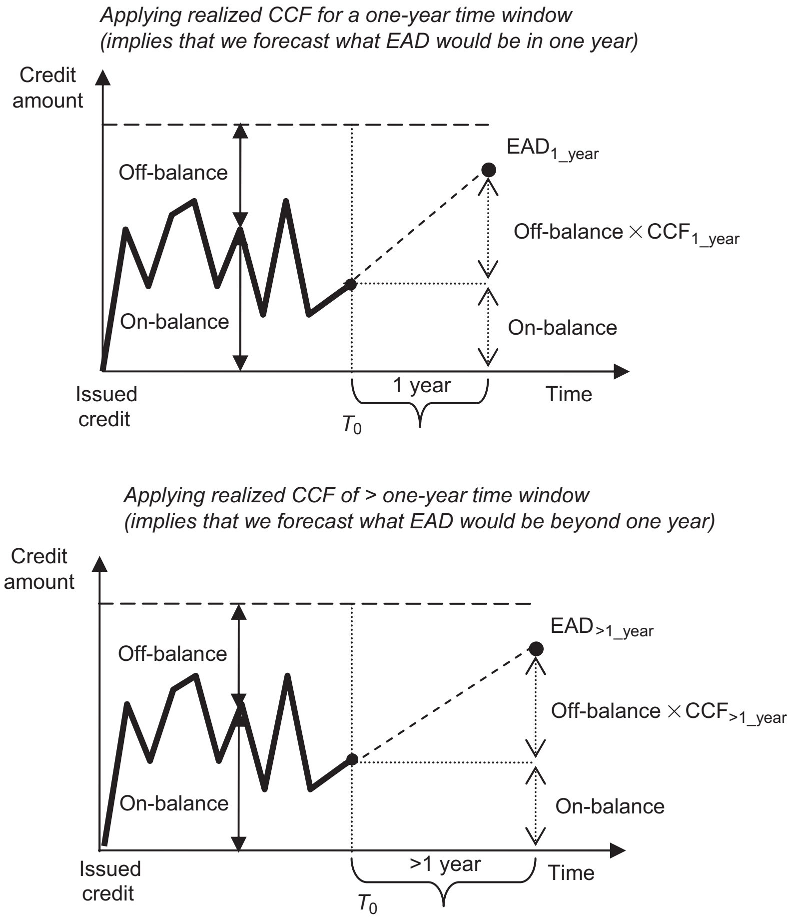


amount of exposure would be outstanding at some point in time in the future when default occurs.

It should be stressed that CCF estimation for defaulted exposures, also EAD estimation and validation for non-defaulted exposures, should be in line with the definition of default probability, ie, that PD is estimated for a one-year time horizon. The definition of PD, showing the likelihood of the borrower defaulting during the next year, for defaulted exposure implies that the maximum time window for estimating realized CCF is one year. Otherwise, if the time window for estimating realized CCF is greater than one year, then applying such realized CCF (with time window greater than one year) to non-defaulted exposure would yield the forecasted EAD that is expected to occur beyond the one-year time threshold. But this would contradict the definition of default probability (see Figure 3).

In Figure 3 (top), a one-year time horizon CCF is used, meaning that default is expected to occur exactly one year from the first day (T_0) and thus estimated EAD using this CCF would forecast the exposure value exactly one-year after the first day. If the CCF time horizon is greater than one year, this implies that default is expected beyond a one-year time period and EAD is forecasted also for the same or longer than one-year time period (Figure 3, bottom). As in Basel II, PD is estimated for a one-year time horizon, and as in Figure 3 (bottom), EAD and PD would be inconsistent with respect to the forecasted time horizon.

FIGURE 3 CCF estimation maximum time window.



2.1.2 Methods for estimating CCFs for defaulted exposures

As it was shown before, EAD is estimated using the following formula:

$$\begin{aligned} EAD = {} & Current\_Outstanding\_Amount + CCF \\ & \cdot (Total\_Committed\_Amount - Current\_Outstanding\_Amount) \end{aligned}$$

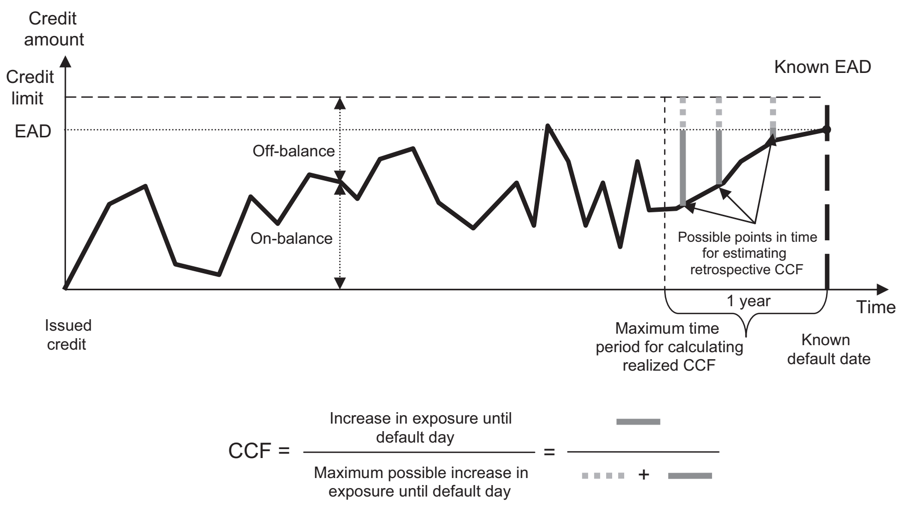
It is clear that CCFs on default day for defaulted exposures must be 0, because at the time of default EAD = Current_Outstanding_Amount. The only thing that can be done retrospectively is to see what the CCF was equal to one day, two days, one week, one month or any other time period before the default day (see Figure 4).

From Figure 4, it is clear that the height of the dashed bar (the difference between total credit limit and EAD) is known and is stable when looking retrospectively. The height of the solid bar (additional utilization of unused credit limit compared to final EAD) depends on the point in time when the CCF is estimated. Variability of the height of the solid bar implies variability of the CCF, ie, CCF for defaulted exposures depends on point in time when it is estimated.

Review of practices in banks shows that CCFs for defaulted exposures are calculated in one of the two ways[10] (CEBS (2005); Department of Treasury (2003)):

1) Fixed-horizon method: the drawn amount at default is related to the drawn/undrawn amount at a fixed time prior to default. This method implies the simplifying assumption that all currently non-defaulted exposures that will

FIGURE 4 Estimation of realized CCF for defaulted exposure.



[10] Both of these are accepted by supervisors. Other methods, like momentum method (CEBS (2005)), are not in line with CAD definition of default and are not considered in this paper. In the latter case, instead of CCF the so-called UGD or LEQ ratios are estimated.

FIGURE 5 Fixed-horizon method.

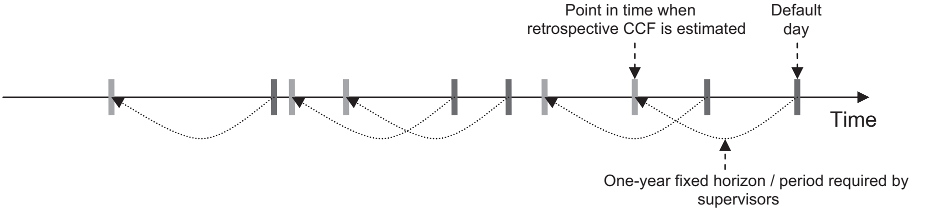
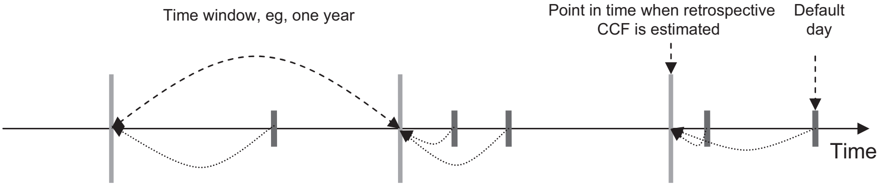


FIGURE 6 Cohort method.



default during the chosen horizon will default at the same point in time: the end of the fixed horizon (see Figure 5).

When using this approach, supervisors require banks to use a time period of one year unless they can prove that a different period would be more conservative and more appropriate (CEBS (2005)).

2) Cohort method: the observation period is subdivided into time windows. For the purpose of realized CCF calculations, the drawn amount at default is related to the drawn/undrawn amount at the beginning of the time window, see Figure 6.

When using this approach, supervisors require banks to use a cohort period of one year unless they can prove that a different period would be more conservative and more appropriate (CEBS (2005)).

The generalization of a fixed-horizon method is called a variable time horizon method. It consists of using several reference points in time within the chosen time horizon rather than one (comparing the drawn amount at default with the drawn amounts at one month, two months, three months, etc, before default).

In this case, many different CCFs are calculated for the same defaulted exposure, see Figure 7. But for EAD estimation purposes for non-defaulted exposures, these CCFs need to be aggregated somehow into a single number. As it was shown before, the maximum time window for estimating a realized CCF for defaulted exposure is one year. This implies that in extreme cases one could estimate the daily CCF in a time window of one year before default (see Figure 8).

FIGURE 7 Variable CCF time window.

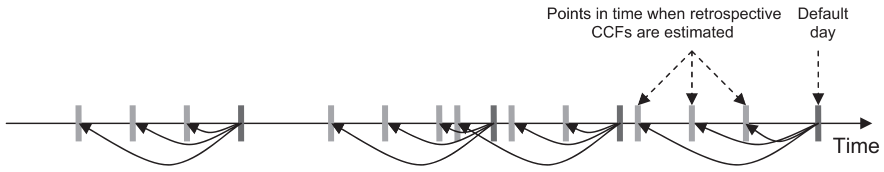
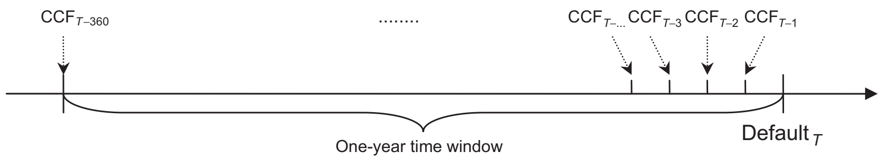


FIGURE 8 Daily CCF.



Making the assumption that default is equally probable on any day in a one-year time window, the expected CCF for defaulted exposure would then equal:[11]

$$\mathrm{CCF}_{\text{expected}} = \frac{\sum_{t=1}^{360} \mathrm{CCF}_t}{360}$$

The expected CCF method is very data intensive, as banks would be required to store data on everyday on-balance values of exposure for one year, ie, this would lead to 360 observation data points for each exposure. If one also tried to collect data on how EADRDs changed during the 360 days before default, this would increase the amount of data collected even further. Having in mind that there might be thousands of credits with credit limits, the expected CCF approach might be impossible to implement in practice. But the expected CCF method is supposed to be superior to the fixed-horizon and cohort methods, as the former method considers all the information in a one-year time window, whereas the latter two approaches take only single point in time information to estimate realized CCF.

[11] For CCF estimation for non-defaulted exposures, one could estimate grade (pool) average CCFs for particular days before default and then obtain daily default probability-weighted average CCF:

$$\mathrm{CCF}_{\text{pool\_expected}} = \frac{\sum_{t=1}^{360} \frac{\sum_{i=1}^{360} \mathrm{CCF}_{t,i}}{n} \cdot p_t}{\sum_{t=1}^{360} p_t}$$

Comparing fixed-horizon and cohort methods, if the assumption that borrowers borrow more and more as default day approaches holds, then the fixed-horizon method should yield higher CCFs and thus be more conservative than the cohort method: a time window in the fixed-horizon method will on average be longer than in the cohort method, thus the utilization of exposure will be lower and thus *ceteris paribus* CCF shall be higher.

Other methods for estimating CCFs for defaulted exposures should also be considered. To perform this task, empirical data is needed on how defaulted exposures behave before default. This kind of information might give some insights on how to model the CCF.

2.1.3 Important issues related to estimating CCFs for defaulted exposures

As it was mentioned before, there are two approaches accepted by supervisors for estimating CCFs for defaulted exposures:

$$\mathrm{CCF}_{\mathrm{fixed\_horizon}} = \frac{\mathrm{EAD} - \mathrm{On\_balance}_{\mathrm{fixed\_horizon}}}{\mathrm{Limit}_{\mathrm{fixed\_horizon}} - \mathrm{On\_balance}_{\mathrm{fixed\_horizon}}}$$

and

$$\mathrm{CCF}_{\mathrm{cohort}} = \frac{\mathrm{EAD} - \mathrm{On\_balance}_{\mathrm{start\_of\_time\_window}}}{\mathrm{Limit}_{\mathrm{start\_of\_time\_window}} - \mathrm{On\_balance}_{\mathrm{start\_of\_time\_window}}}$$

Before starting to calculate CCFs, several issues must be analyzed:

1) How to deal with CCFs > 100%?

If the credit limit changes during a one-year time period before default, this might lead to CCF > 100%, see Figure 9.

FIGURE 9 CCFs greater than 100%

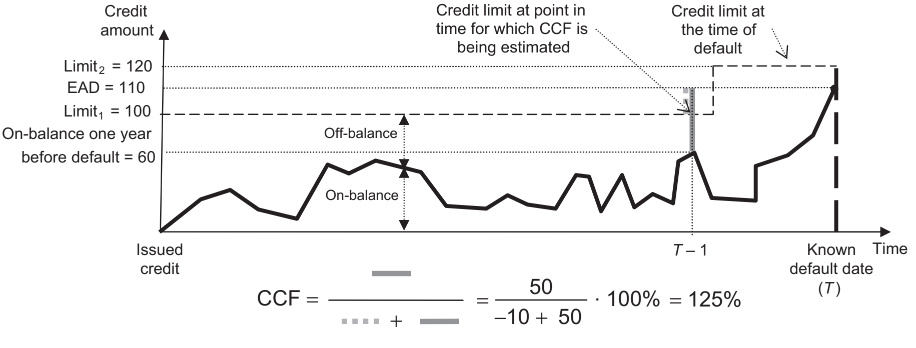
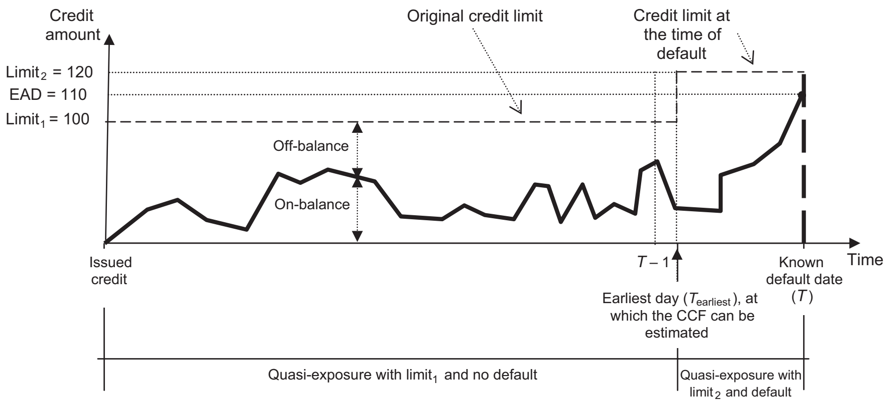


FIGURE 10 Estimation of CCFs for exposures with changing credit limits.



On the other hand, as it was mentioned before, CCFs are estimated for current commitments.[12] This implies that increases in credit limits should be excluded from calculations, ie, increases in credit limit should be treated as a new exposure (see Figure 10).

Figure 10 shows that if for the same contractual exposure the credit limit changes, the change in credit limit should be treated as the end of one exposure and the start of an other exposure with a new credit limit. In Figure 10, default that occurred for the contract is assigned only for the second quasi-exposure and the CCF is estimated using data on this second quasi-exposure. The first quasi-exposure is treated as non-defaulted and thus no realized CCF can be estimated.

2) How to deal with situations when the calculated CCFs for defaulted exposure is negative (as it was mentioned, negative CCFs are not allowed by supervisors)?

If one is estimating the grade (pool) average CCF, there are two possibilities to deal with negative CCFs:[13]

i) To set individual CCF estimates to 0:

$$\mathrm{CCF}_{\mathrm{gradel/pool}} = \frac{\sum_{i=1}^{n} \mathrm{MAX}(0;\mathrm{CCF}_i)}{n}$$

ii) To leave individual CCF estimates negative, but make sure that the grade (pool) average CCF is not negative:

$$\mathrm{CCF}_{\mathrm{gradel/pool}} = \mathrm{MAX}\left(0; \frac{\sum_{i=1}^{n} \mathrm{CCF}_i}{n}\right)$$

[12] For information on how CAD Transposition Group interprets this issue, go to http://www.c-ebs.org/crdtg.htm (Question 84).

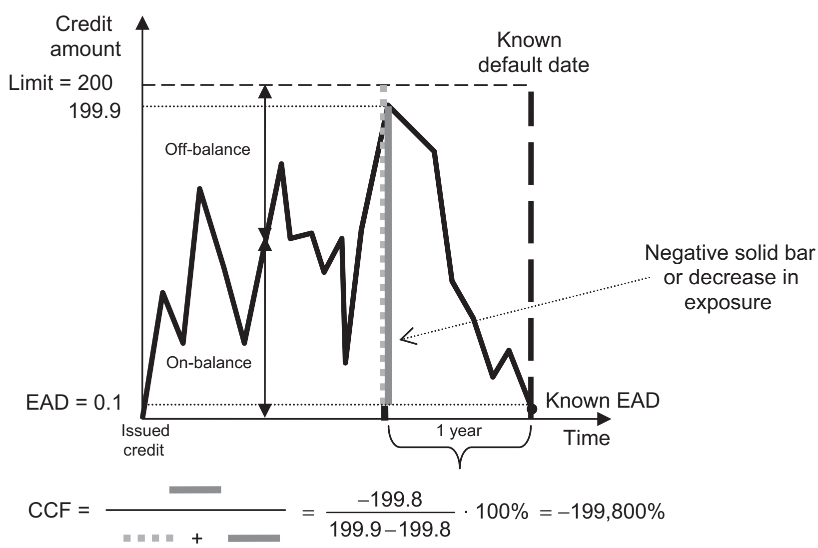
[13] A third possibility is to exclude negative CCFs from the estimation sample. But this possibility is excluded, as negative CCFs also carry some information about pool/grade average CCFs.

Intuitively, it might look like the second approach is better than the first approach as the latter leads to biased average CCFs, ie, as negative individual CCFs are set to 0, we get the overestimated average CCFs. Negative CCFs, if one applies the aforementioned CCF formula, might be “very” negative and bias average grade/pool CCF downward substantially or even it is possible to get negative grade/pool average CCF, see Figure 11.

Having a CCF of –199,800% in the sample, one needs 2,000 CCFs of 100% to get the pool average CCF of 0.1%. Even then, it is clear that this is not a good estimate of an average CCF, as this is a result of one, but very large, negative CCF. The problem is that if one applies the above CCF formula, then it is possible to get very negative CCFs, whereas positive CCFs in most cases will be in the interval 0–100%. Thus, if one wishes to apply the second approach and use negative CCFs in calculating the grade (pool) average CCF, then he or she must make sure that negative CCFs are in interval (–100% to 0%), correspondingly, as positive CCFs are in interval (0–100%). As positive CCFs are estimated as a percentage of the increase in exposure compared to the potential maximum increase in exposure (up to the credit limit), thus for negative CCFs one should compare how much the exposure decreased compared to the maximum possible decrease. This would imply that for negative CCFs one should use the following formula:

$$\mathrm{CCF} = \frac{\qquad}{\qquad + \qquad} = \frac{-\ 199.8}{199.8 + 0.1} \cdot 100\% = -99.95\%$$

FIGURE 11 Negative CCF.



Only by applying this modified CCF formula given above, can the second approach for calculating the average CCF be used and is advised for use instead of the first approach.

3) How to deal with situations when the denominator in CCF formula is equal to 0?
The proposal is to set the CCF to 0 in such circumstances. The reasoning would be as follows: let us take a marginal case when on-balance exposure, at the point of CCF estimation, is not equal to but is approaching exposure limit:

$$\lim_{\text{On\_balance}_t \to \text{Limit}_t} \text{CCF} = \frac{\text{EAD} - \text{On\_balance}_t}{\text{Limit}_t - \text{On\_balance}_t} = -\infty$$

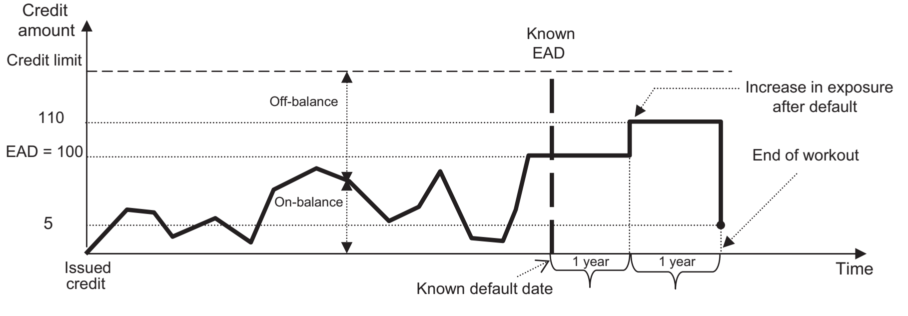
as the numerator in most cases will be negative and the denominator approaches 0.

As supervisors require, estimated EAD cannot be less than current on-balance exposure or equivalently that CCF cannot be negative, the above limit equal to $-\infty$ would imply that for such exposures where the CCF denominator is 0, we should set the whole CCF to 0 (or use the above alternative formula applicable to negative CCFs).

4) Drawdowns after default
Estimates of CCFs should reflect the possibility of additional drawings by the obligor up to, and after the time, of a default event. Notwithstanding this requirement, banks may reflect future drawings either in its CCFs or in its LGD estimates (EU (2006)). The suggestion by UK supervisors is to adjust EAD if additional drawing of funds occurs before default and LGD if it occurs after default (FSA (2004a)).

As it was stated at the beginning of this section, the on-balance part of the EAD is equal to the outstanding on-balance amount at the time of default, gross of value adjustments. It might happen (due to late fees, due to the fact that the bank allows borrower to borrower late payments after 90 days, etc) that after default, the exposure increases compared to the exposure that was outstanding at the time of

FIGURE 12 Drawdowns after default.



default.[14] Figure 12 shows that in terms of EL, it makes no difference whether EAD or LGD is adjusted.

If the exposure after default in Figure 12 increases from 100 to 110, there are two possibilities to account for this increase (yearly discount rate equals 5%):

1) in LGD estimate:

$$\mathrm{EAD} = 100$$

$$\mathrm{LGD} = \frac{\mathrm{EAD} - \mathrm{Recovery}}{\mathrm{EAD}} = \frac{100 + \dfrac{\overset{\text{Increase in exposure or negative recoveries}}{10}}{1.05} - \dfrac{105}{1.05^2}}{100}$$

$$= \frac{100 + 9.52 - 95.24}{100} = 0.1429$$

2) in EAD estimate:

$$\mathrm{EAD} = 100 + \frac{10}{1.05} = 109.52$$

$$\mathrm{LGD} = \frac{\mathrm{EAD} - \mathrm{Recovery}}{\mathrm{EAD}} = \frac{109.52 - \dfrac{105}{1.05^2}}{109.52}$$

$$= \frac{(100 + 9.52) - 95.24}{(100 + 9.52)} = 0.1304$$

The first approach leaves the original EAD unchanged but instead the recovery cash flows change, ie, because of an increase in exposure after default, the negative recoveries appear in the LGD formula. Unchanged original EAD would imply that the CCF estimation will not be affected by additional drawdowns after default.

The second approach includes drawdowns after default and discounts them back to the default date and adds to the exposure outstanding at the time of default.

The final result by both approaches *ceteris paribus*, with respect to EL, is the same:

$$\mathrm{EL} = \mathrm{PD}\cdot\mathrm{LGD}\cdot\mathrm{EAD} = \mathrm{PD}\cdot 0.1429\cdot 100 = \mathrm{PD}\cdot 0.1304\cdot 109.52$$

The only difference between the two approaches is that applying the second approach leads to changing the original EAD and so to changing the CCF. In other words, using the second approach would mean that CCF estimates would incorporate information on additional drawdowns after default. This would imply that while the workout is not finished, there will be no final CCF and EAD and thus LGD, as for LGD estimation purposes EAD is required. Whereas using the first approach would give final EAD and CCF, only the LGD will not be known until

[14] Please note that only the on-balance exposure value, including accrued but unpaid interest, is considered, but provisions and charge-offs are excluded, ie, provisions and charge-offs from exposure on-balance value are not deducted.

the workout process is finished. Thus, as UK supervisors suggest, one should adjust LGD, not the EAD with additional drawdowns after default.

2.2 EADRDs

EADRD can be defined as an attribute or future related to exposure or borrower that impacts EAD. EADRDs, attributable to all kinds of exposures and all kinds of borrowers, not only retail exposures discussed in Section 3, can be classified into four broad categories[15] (FSA (2004a)):

1) *Factors affecting the borrower's demand for funding/facilities*: current risk features of the borrower; risk features of the borrower when the facility was granted; changes in the risk features; seasonality; economic situation or state of the cycle, eg, there is a general opinion that as default day approaches, borrowers need more funding and thus increase the amount borrowed (Department of Treasury (2003)).
2) *Factors affecting a bank's willingness to supply funding/facilities and manage credit risk*: banks should consider its specific policies and strategies adopted in respect to monitoring accounts and processing payments. Banks should also consider its ability and willingness to prevent further drawings in default circumstances, such as covenant violations or other technical default events (EU (2006)).
3) *The nature of the particular facility and its future*: eg, covenant protection; product type; revolving or not revolving; fixed or floating rate and existence of collateral. In the opinion of Araten and Jacobs (2001), since investment-grade borrowers enjoy fewer restrictive covenants, they should have high CCFs. On the other hand, high CCFs should be used for non-investment grade borrowers as there is a greater PD or financial distress, the borrower is more likely to draw down a greater proportion of the unused credit over a given time horizon. As a mitigant to this view, covenants are generally more restrictive for non-investment grade borrowers.
4) *Possibilities to borrow from other sources than banks*: related to this category is the problem of multiple facilities. Banks need to understand how exposures on one may be transferred into another in which the losses are ultimately incurred. This is particularly an issue with the use of overdrafts. There is a tendency for the losses from other facilities to be accounted for through repayments being made through drawing down the overdraft and thus increasing the EAD (and subsequently the losses) on the latter.

Banks need to consider and analyze all material risk drivers. Materiality should be judged on the basis of the specific characteristics of portfolios and bank practices (CEBS (2005)). Since little empirical research has been done on EAD estimation, not too much is known about the exact EADRDs falling into these four broad categories. Because of that, banks need to collect historical data on factors falling into one of the four categories, even if they are not sure whether this is a true

[15] For empirical research on EADRDs, refer to (Araten and Jacobs (2001); Agarwal and Ambrose (2006), also see Moral (2006).

EADRD. As time passes and more experience in modeling EAD is gained, the true EADRDs will show up. Among many possibilities a bank should consider are other risk drivers that do not fall into these four categories (Department of Treasury (2003); FSA (2004b); and Araten and Jacobs (2001)): time from origination, time to expiration, renewal or interest rate adjustment – the longer the time to maturity, the more time available for adverse credit migration, as well as a greater opportunity and need for a borrower to draw down unused lines; size of commitment; current usage; borrower type; industry; country features and economic conditions (this possible EADRD might correlate with borrower/exposure rating/grade).

2.3 Estimating CCFs for non-defaulted exposures[16]

Having estimated CCFs for defaulted exposures, from these one has to infer what CCFs would be for non-defaulted exposures. EADRDs play an important role when estimating CCFs for non-defaulted exposures. For example, for corporate borrowers access (no access) to capital markets might be considered as an EADRD, because corporate borrowers that have access to capital markets have alternative sources of funding so their EAD might be lower than for those corporate borrowers that do not have access to capital markets or alternative sources of funding. Thus, CCFs for non-defaulted corporate borrowers with (no) access to capital markets should be estimated from CCFs of defaulted corporate borrowers with (no) access to capital markets. If there are several EADRDs, CCFs are estimated for every combination of EADRDs.

There are various possible ways to estimate CCFs for non-defaulted exposures, using information on EADRDs:[17]

1) look-up tables or pooling approach (only for estimating grade (pool) CCFs);
2) basic regression;
3) advanced regression; and
4) neural nets and other modern methods.

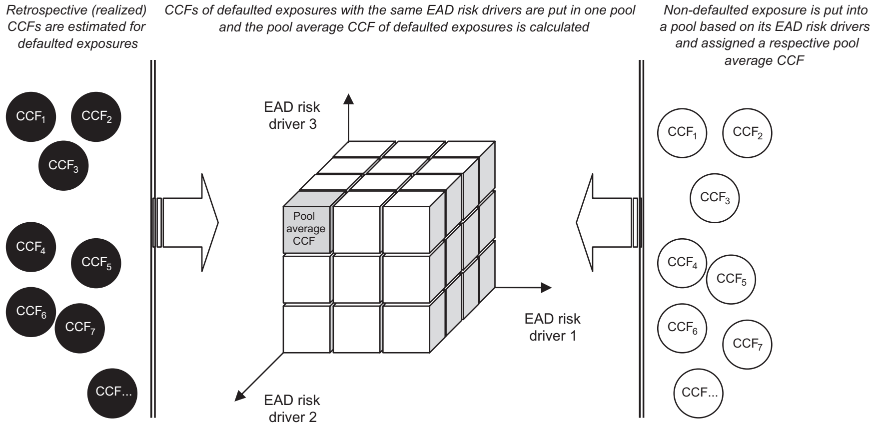
Look-up tables or pooling approach is the most simple to implement and understand. Because EAD estimation methods are not well developed, this might be rather a good method to start with.

The idea behind the look-up tables (pooling) approach is that CCFs of defaulted exposures are grouped based on EADRDs. For every unique combination of EADRDs the average CCF is estimated (Department of Treasury (2003)):

- If the cohort method is used for estimating CCFs for defaulted exposures, to combine results for multiple periods into a single long-run average, the period-by-period means should be weighted by the proportion of defaults occurring in each period.

[16] For information on how EAD is modeled in large US banks, refer to RMA (2004).
[17] The methods presented below are not meant to be exhaustive and do not preclude any other approaches. As EAD is estimated in two stages, similar to that for estimating LGD, the distinguished methods below are taken from (Schuermann (2003)).

FIGURE 13 Look-up tables or pooling CCF estimation approach.



- If the fixed-horizon method is used, the pool average CCF for defaulted exposures is computed from individual CCFs of defaulted exposures.

Non-defaulted exposure is assigned an average CCF that corresponds to a respective combination of EADRDs (Figure 13).

The main drawback of this method is that it is very data intensive. For example, if there are five EADRDs and each can take only two different values, there will be 2^5 or 32 different CCF pools. If the bank has only 1,000 defaulted exposures each CCF pool will contain 31 defaulted exposures on average. This might then raise the problem of reliability for the estimated average CCFs. As exposures will not be distributed evenly between CCF pools, some of the pools might contain no defaulted exposures and no CCFs to calculate the pool average CCF.

In a regression model, CCF is modeled as a function of EADRDs. In its simplest form, one can model CCF as a linear function of EADRDs:

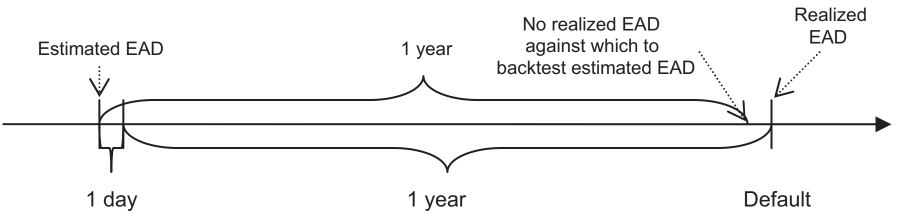
$$\text{CCF} = \alpha_0 + \alpha_1 \cdot \text{EADRD}_1 + \alpha_2 \cdot \text{EADRD}_2 + \cdots + \alpha_n \cdot EADRD_n$$

As the relationship between the CCF and EADRDs might not be linear, a more advanced regression model can be used. The challenge with the regression approach is that one must be very careful when deciding upon the type of the model to choose.

2.4 Validation of CCFs/EADs

As it regards the validation of estimated EADs, from the discussion in previous sections it follows that for validation purposes only estimated EADs one year before default are relevant. In other words, if we take EAD that was estimated for exposure one year and one day before default, this would mean that default has not occurred during the year so there is no realized EAD against which to backtest the EAD estimate (see Figure 14).

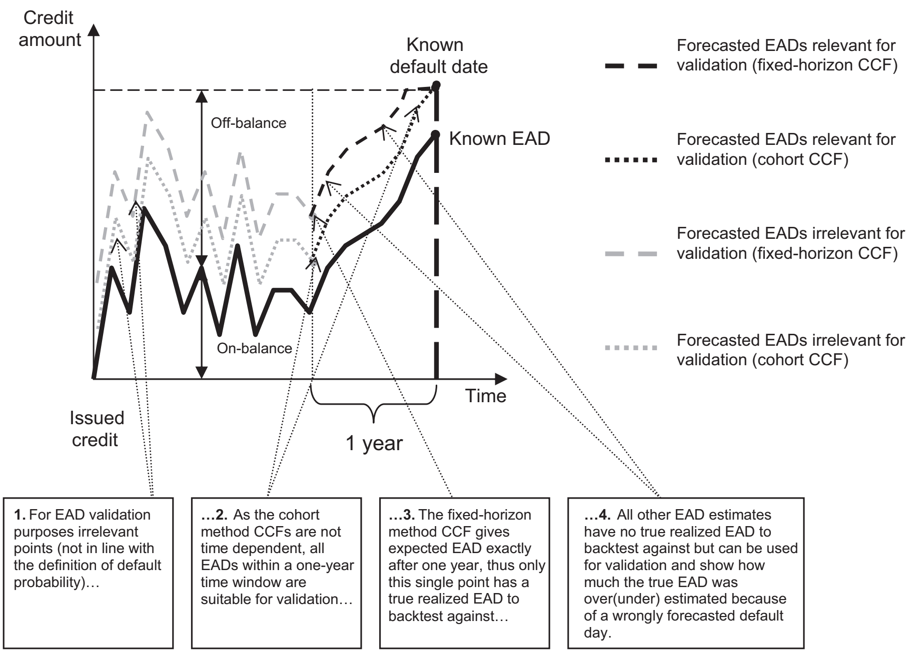
FIGURE 14 Relevant EAD validation time period.



To state it differently, if there was no default in one year after the EAD estimation day, we do not know what would have been the true EAD, should default have occurred in one year after EAD estimation day (see Figure 15).

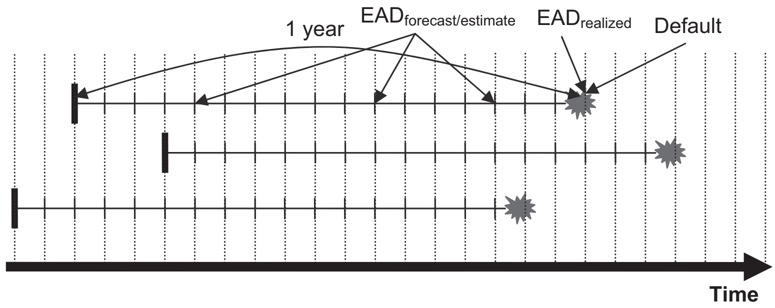
The primary validation tool to check the accuracy of EAD estimates is a backtesting procedure, ie, apply estimated CCFs to defaulted exposures and see whether there was an overestimation or underestimation of EAD on a portfolio basis.[18]

FIGURE 15 Backtesting time period.



[18] Note that the parameter of the final interest is the EAD, not the CCF. Thus, the focus of validation must be the EAD, not the CCF.

FIGURE 16 Backtesting EADs.



For every time point t, eg, every month (see Figure 16):

1) sum estimated (forecasted) EADs for all exposures that existed at that point of time and were no longer than one year prior to default:

$$\mathrm{SUM}(\mathrm{EAD}_t^{\mathrm{estimated}}) = \sum_{i=1}^{N} \mathrm{EAD}_{i,t}^{\mathrm{estimated}} | (t_{\mathrm{default}} - 1\mathrm{y}) \leq t \leq t_{\mathrm{default}}$$

2) sum realized EADs for the same exposures that existed at that point of time and were no longer than one year prior to default:

$$\mathrm{SUM}(\mathrm{EAD}_t^{\mathrm{realized}}) = \sum_{i=1}^{N} \mathrm{EAD}_{i,t}^{\mathrm{realized}} | (t_{\mathrm{default}} - 1\mathrm{y}) \leq t \leq t_{\mathrm{default}}$$

3) compare Points 1 and 2 results for every time point t; make chart, eg, showing how in absolute terms sum of estimated EADs compares to sum of realized EADs; or calculate accuracy ratio, showing the same result in relative terms:

$$\mathrm{Accuracy\_ratio} = \frac{\mathrm{SUM}(\mathrm{EAD}_t^{\mathrm{estimated}}) - \mathrm{SUM}(\mathrm{EAD}_t^{\mathrm{realized}})}{\mathrm{SUM}(\mathrm{EAD}_t^{\mathrm{realized}})} \cdot 100\%$$

3 SOME EMPIRICAL RESULTS

The purpose of this section is to describe some empirical results of CCF estimation and EAD validation, using data from one bank operating in one of the EU countries. In the exercise, CCFs were estimated according to three methods: one-year fixed horizon, cohort (beginning of calendar year) and expected CCF (calculating monthly CCFs).

It should be noted that, eg, if a one-year fixed-horizon CCF estimation method is used, then one-year historical data before default is needed. For this reason, it was not possible to estimate the CCF for every defaulted exposure that defaulted in 2005 (as only historical data for 2005–2006 was available). As it regards expected CCF, this kind of CCF was estimated only for those exposures where historical data, month by month on all 12 months prior to default, was available.

3.1 Realized CCFs

3.1.1 Credit cards to private individuals

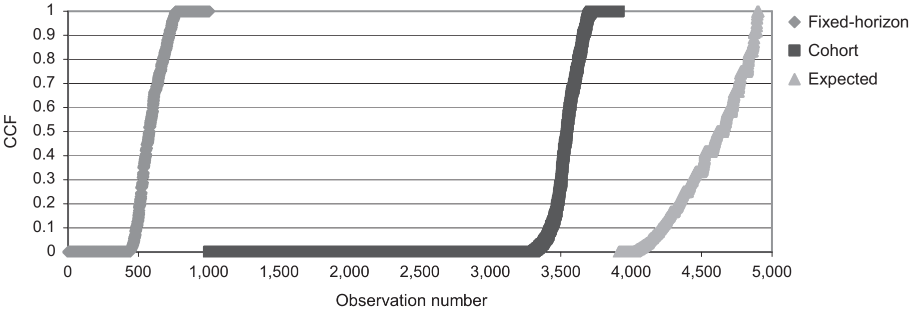
For CCF estimation, in total 3,332 defaults were used, of which 1,877 occurred in 2005, and the rest 1,455 in 2006. Distribution of CCFs calculated by three methods is depicted in Figure 17, and a summary of statistics is provided in Table 1.

As it was expected the greatest number of estimated CCFs according to cohort approach as for many exposures, data at the beginning of the calendar year prior to default was available. From Figure 17, it can be seen that for many exposures realized CCF was equal to 0. Table 1 reveals that in total there were 217 exposures with negative CCFs, which according to assumptions were set to 0, and 2,084 exposures with a directly realized CCF of 0,[19] implying in total 2,301 CCFs equal to 0. At the other end, there were 192 exposures with a CCF greater than 1 (later set to 1). The remaining 417 exposures have a CCF between 0 and 1.

The distribution of fixed-horizon CCFs was slightly different from that of cohort CCFs: the greatest number of observations took negative CCF values, relatively fewer exposures took CCF equal to 0. As it was expected, the fixed-horizon approach yielded the highest average CCF.

For the expected CCF approach, almost all exposures had average (expected) CCF between 0 and 1. This is of no surprise as averaging CCFs for 12 months should, only in exceptional cases, yield CCF equal to 0 (96 cases) or 1 (six

FIGURE 17 Distribution of CCFs according to three approaches (all defaults within observation period).



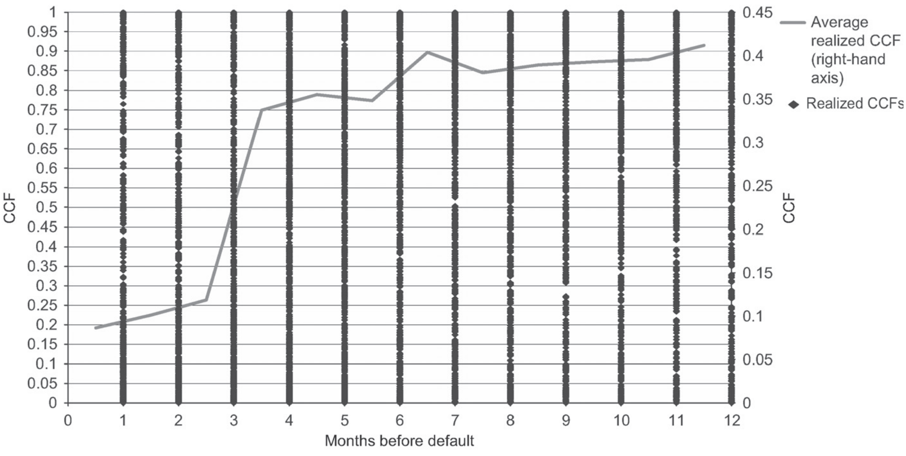
[19] Including all the exposures with CCF formulae, denominator equals to 0.

TABLE 1 CCF estimation statistics for credit cards of private individuals.

	Total number of defaults	Pool average CCF*	Standard deviation of CCF*	Total number of CCFs	Number of CCFs < 0**	Number of CCFs > 1**	Number of CCFs = 0**	Number of CCFs = 1**	Number of 0 < CCFs < 1**	Number of blank CCFs***
Fixed-horizon approach	3,332	0.4117	0.4406	1,001	427	229	10	1	334	2,331
Cohort approach	3,332	0.1257	0.3050	2,910	217	192	2,084	0	417	422
Expected CCF approach	3,332	0.3244	0.2795	992	0	0	96	6	890	2,340

Note: * – after setting CCFs $<$ 0 to 0 and CCFs $>$ 1 to 1; ** – before setting CCFs $<$ 0 to 0 and CCFs $>$ 1 to 1; *** – number of missing CCFs (eg, the CCF is missing because it is outside the observation period as default occurred near the boundary of the observation period or default occurred shortly after the exposure was extended and thus no historical data is available).

FIGURE 18 Distribution of CCFs 1, 2, . . . 12 months before default.



cases). As very often, individual CCFs take a value of either 0 or 1, the average CCF of all 12-month periods prior to default should be close to 0.5, but below this threshold, as more often is the case, CCFs take a value of 0 than 1. Thus, the average CCF for 12 months should be lower than 0.5. The results above confirm this hypothesis.

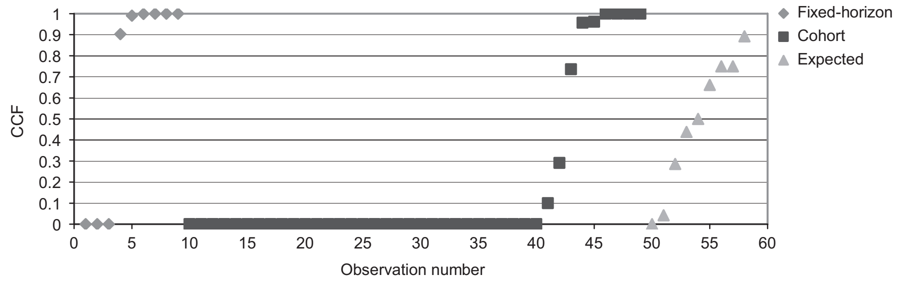
Figure 18 confirms the previous stated hypothesis that it is expected that borrowers borrow more as the default day approaches. If this hypothesis is true, then one should expect to see realized CCFs get smaller and smaller as they are estimated closer to default day: in Figure 18, CCFs are decreasing as one shortens CCFs estimation period prior to default. For example, 12 months before default (the fixed-horizon CCF), the average realized CCF is equal to 41%, whereas one month before default, the realized CCF is equal to 20%. As the fixed-horizon method uses a 12-month time window before default, the cohort approach takes a random time horizon before default (the one outstanding at the beginning of the calendar year), and as the expected CCF method uses information on all 12 realized CCFs, it is not surprising that the fixed-horizon approach is the most conservative.

Generally, it can be concluded that the empirical estimations did not yield any unexpected results from those anticipated in Section 2.

3.1.2 Credit cards for small corporate borrowers

For CCF estimation, in total 44 defaults were used, of which 32 occurred in 2005 and the rest, 12, in 2006. Compared with defaults of private individuals, there was only a very limited number of defaults for credit cards of small corporate

FIGURE 19 Distribution of CCFs according to three approaches (all defaults within observation period).



borrowers. For this reason, if economic downturn CCFs are being estimated, one should add larger margins of conservatism.

The distribution of CCFs, calculated by these three methods, is depicted in Figure 19, and a summary of statistics are provided in Table 2.

Again, from Figure 20, it can be seen that for credit cards of small corporate borrowers, the CCF increases as the CCF estimation period before default increases.

Again, no unexpected results were obtained: the greatest number of observations was for the cohort method, the expected CCF was close to 0.5 and the fixed-horizon CCF was the highest among the three methods.

As it can be seen from Figures 17 and 19, the majority of CCFs take a value of 0 or 1 and only a small part of all defaults take a value between 0 and 1. The shape of CCF distribution implies that the CCF might be better modeled with a logit or probit regression model (see Figure 21).

To model CCF using a logit or probit regression model, one needs to accumulate enough historical data on defaulted exposures, including EADRDs.

3.2 Validation of CCFs and EADs

For EAD validation purposes, the following indicators were calculated:

- absolute accuracy indicator:

$$\text{Absolute\_accuracy\_indicator}_t = \sum_{i=1}^{n} (\text{EAD}_t^{\text{estimated},i} - \text{EAD}_t^{\text{realized},i})$$

- relative accuracy ratio:

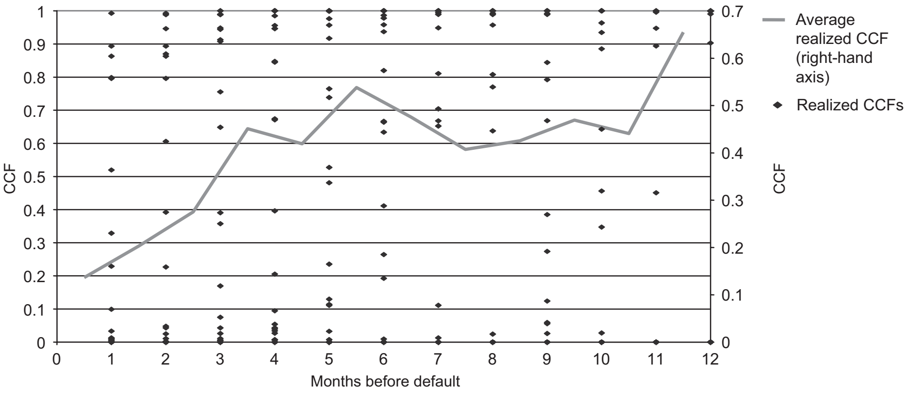
$$\text{Accuracy\_ratio}_t = \frac{\text{SUM}(\text{EAD}_t^{\text{estimated}}) - \text{SUM}(\text{EAD}_t^{\text{realized}})}{\text{SUM}(\text{EAD}_t^{\text{realized}})} \cdot 100\%$$

TABLE 2 CCF estimation statistics for credit cards of small corporate borrowers.

	Total number of defaults	Pool average CCF*	Standard deviation of CCF*	Total number of CCFs	Number of CCFs < 0**	Number of CCFs > 1**	Number of CCFs = 0**	Number of CCFs = 1**	Number of 0 < CCFs < 1**	Number of blank CCFs***
Fixed-horizon approach	44	0.65462	0.49193	9	3	3	0	0	3	35
Cohort approach	44	0.17608	0.36633	40	1	4	30	0	5	4
Expected CCF approach	44	0.48006	0.31837	9	0	0	1	0	8	35

Note: * – after setting CCFs $<$ 0 to 0 and CCFs $>$ 1 to 1; ** – before setting CCFs $<$ 0 to 0 and CCFs $>$ 1 to 1; *** – number of missing CCFs (eg, the CCF is missing because it is outside the observation period as default occurred near the boundary of the observation period or default occurred shortly after the exposure was extended and thus no historical data is available).

FIGURE 20 Distribution of CCFs 1, 2, . . . 12 months before default.

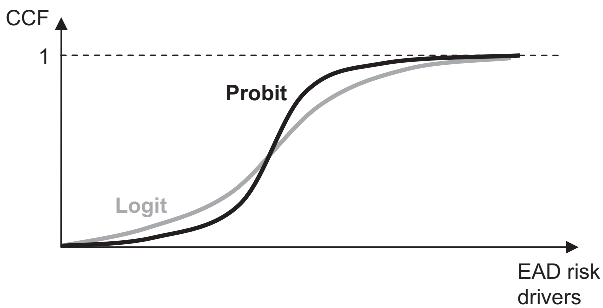


3.2.1 Credit cards of private individuals

Figures 22 and 23 reveal EAD validation results for credit cards of private individuals.

Before going into details of validation results, it should be noted that the last five to six observation points should be interpreted with caution. In the last five to six observation periods, the number of exposures decreases substantially as fewer and fewer new defaults oocur and more and more exposures move out of the sample as the 12-month observation period relevant for validation matures. This means that for the last five to six observation periods the portfolio under validation is unrepresentative, ie, all exposures are close to default and there are very few exposures that are 12, 11, 10 or so months before default. This would never

FIGURE 21 Logit and probit models.



$$\text{CCF} = \frac{1}{1 + e^{-(\alpha_0 + \alpha_1 \text{EADRD}_1 + \alpha_2 \text{EADRD}_2 + \cdots + \alpha_N \text{EADRD}_N)}}$$

FIGURE 22 Absolute accuracy of the methods.

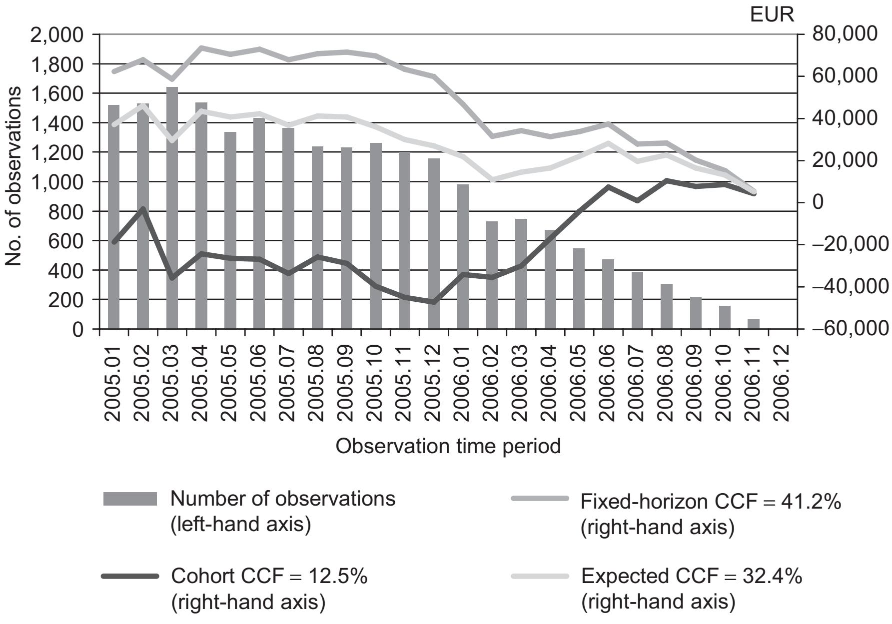
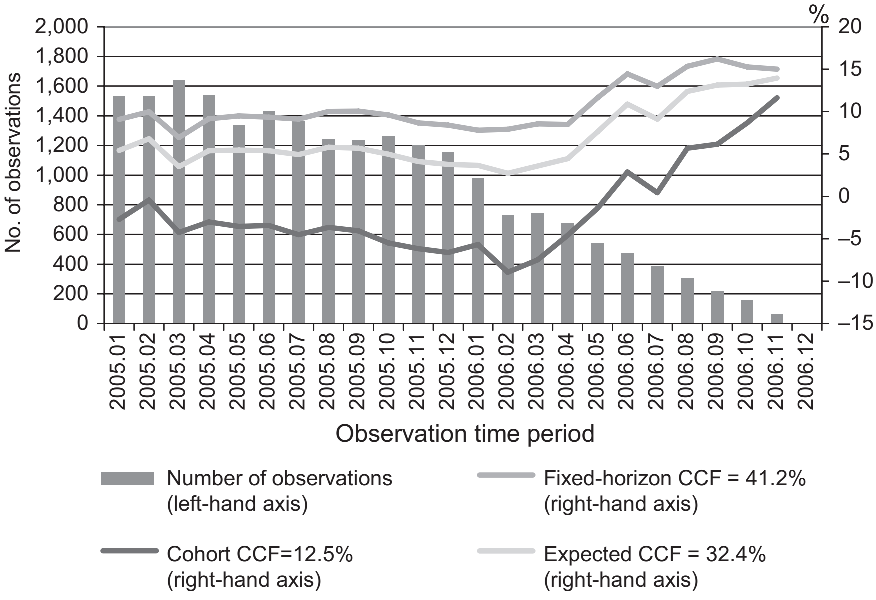


FIGURE 23 Relative accuracy of the methods.



happen in real life, as in reality there will always be new defaults coming into the portfolio. For the same reasons, the first observations should be excluded from the validation results. Summing up, from the whole observation period for validation purposes, roughly, only the period of 2005.02–2006.07 is relevant. As more and more historical data will be collected, the relevant validation period will increase (cut-off periods at the beginning and at the end of the whole observation period should stay pretty much the same).

As the CCF for the fixed-horizon method is the highest, so is the overestimation of true EAD on a portfolio level. Figures 22 and 23 show that on average the true EAD on a portfolio level is overestimated by almost €60,000 or 9%. This allows us to conclude that the CCF estimate is appropriate. The motivation for appropriateness of the fixed-horizon CCF = 41.2%, even for economic downturn conditions, is provided in the next paragraph.

The other two methods with lower average CCFs yield different results: the expected CCF approach shows only slight overestimation of EAD on a portfolio level. This supports the conclusion in previous sections that the expected CCF method should be the most appropriate approach for estimating the CCF as all the information within a one-year time period is included in the calculation, not just one observation point as it is done with the fixed-horizon or the cohort approach. The cohort method for modeled data gives the underestimation of EAD on the portfolio level, ie, the CCF of 12.5% is too low.

From Figure 23, it can be seen that a decrease of CCF by 8.8 percentage points (the fixed-horizon approach CCF compared with the expected CCF) caused on average to decrease surplus of the relative accuracy ratio by 4.3 percentage points. This implies that the true CCF (the one when there is no underestimation or overestimation of EAD on the portfolio level, ie, the relative accuracy ratio is equal to 0) is approximately 18.4% (8.8% · 9%/4.3%). For example, the fixed-horizon approach CCF is set to 41.2 or 22.8 percentage points above the true CCF. Thus, it can be concluded that if banks would choose the fixed-horizon approach, it would be very conservative for setting CCF, even for economic downturn conditions.

3.2.2 Credit cards of small corporate borrowers

Figures 24 and 25 reveal EAD validation results for credit card exposures for small corporate borrowers.

Validation results for credit cards of small corporate borrowers look rather similar to those for credit cards of private individuals. The only significant differences are the following: the greater volatility of accuracy ratios and the greater elasticity of accuracy ratios to changes in CCF. For example, the comparison of cohort and expected CCF approaches shows that a decrease of average CCF from 43.2% to 17.6% or alternatively by 25.6 percentage points has lead to a decrease of relative accuracy ratio by 9.73 percentage points. Thus, in order to reduce 10.9% of the average surplus of the accuracy ratio of the expected CCF method to 0, one needs to reduce the expected CCF by 28.7 percentage points to the level of 14.5%. In other words, having a CCF of 14.5% would lead to an accuracy ratio close to 0.

FIGURE 24 Absolute accuracy of the methods.

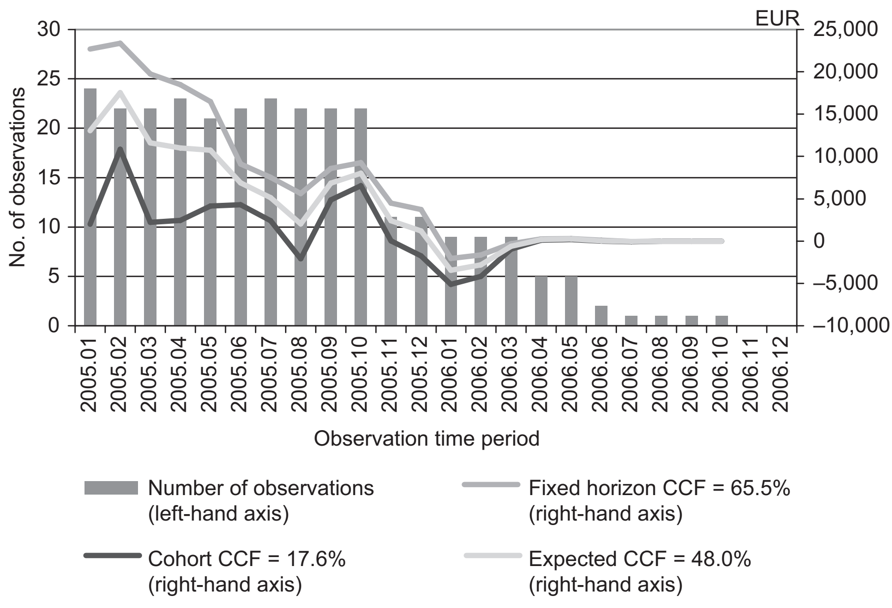
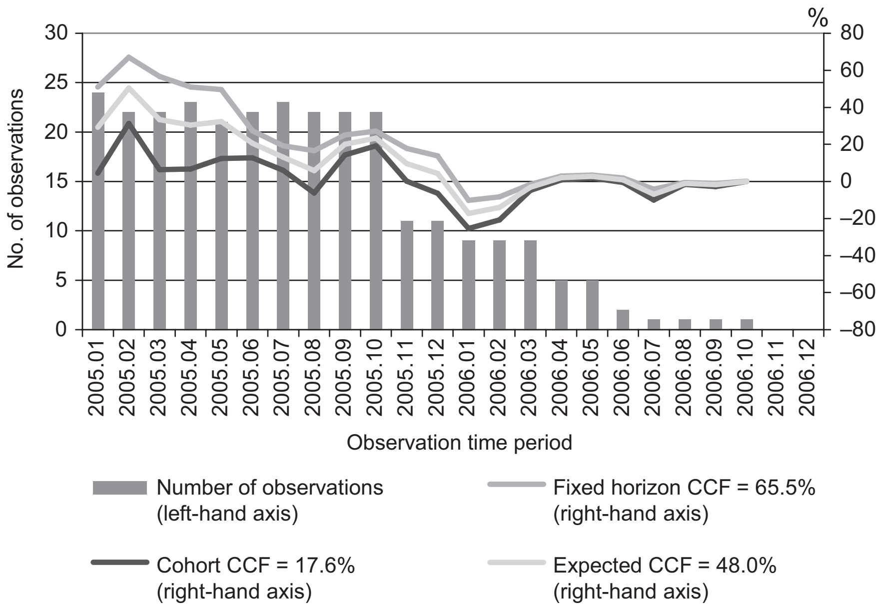


FIGURE 25 Relative accuracy of the methods.



Comparing elasticity or sensitivity of accuracy ratio with changes in the CCF between credit cards for private individuals and small corporate borrowers, it is obvious that validation results of private individuals are much more sensitive to changes in the CCF. This implies that small corporate borrower's credit cards' EAD validation results should be expected to fluctuate relatively less with the economic cycle, despite how much CCF changes. Moreover, empirical results reveal that EAD overestimation on a portfolio level is higher for credit cards of small corporate borrowers.

4 CONCLUSIONS

EAD, being one of the four IRB model parameters, is least analyzed among practitioners and supervisors. This paper shows that many issues on EAD modeling remain open. For example, banks are bound by supervisory requirements to estimate EAD as a function of on-balance, off-balance exposure amounts and the CCF. This precludes any other EAD modeling methods from being used in an IRB framework.

Currently, only two methods are endorsed by supervisors for calculating realized CCFs for defaulted exposures, namely the cohort and the fixed horizon. These two methods take into consideration only information at one point in time while calculating the realized CCF. However, information on how exposure evolved over one year prior to default can have a valuable input. Thus, other methods for expressing the realized CCF for defaulted exposures must be searched. Besides, the calculation of realized CCFs for defaulted exposures should be aligned with a CCF modeling method for non-defaulted exposures.

CCF used for EAD estimation purposes for non-defaulted exposures should be dependent on the utilization ratio of exposure: as EAD at the time of default is fixed, so the EAD model, *ceteris paribus*, should give a rather stable EAD forecast for non-defaulted exposure as the current outstanding amount changes.

Empirical CCF calculation results showed that the majority of realized CCFs take a value of either 0 or 1. This implies that while building an EAD model one should try to model these extreme outcomes, ie, try to model when the exposures shall have a CCF equal to 0 or 1. For these purposes, a logit or probit regression model might work well.

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