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A top-down stress testing framework

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A top-down stress testing framework for the Dutch banking sector

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Summary

- 6 Stress tests have become an increasingly important tool for macro-prudential policy makers and micro-prudential supervisors. DNB has developed an extensive top-down stress test framework to support its macro- and micro-prudential responsibilities. It is used to quantify financial stability assessments, to challenge calculations that banks provide in supervisory stress tests and to reinforce the link between macro risk assessment and micro-prudential actions. This paper explains DNB's top-down stress test framework with a focus on the characteristics of the Dutch banking sector.

Executive summary

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Since the onset of the global financial crisis in 2007, stress testing has become an increasingly important tool for bank supervisors, as witnessed by the publication of United States (US), European and various national stress testing exercises. In the Netherlands, stress testing has been used by De Nederlandsche Bank (DNB) to assess the solvency of individual financial institutions, and the robustness of the financial system as a whole. Over the past few years, DNB has developed an extensive top-down framework for bank stress testing to improve its risk analysis at both the macro-prudential and the micro-prudential level.

The DNB top-down framework consists of a suite of models that each represent specific parts of bank balance sheets and profit and loss accounts, with the ultimate goal of modelling key drivers of bank capital ratios under stress. The data for the top-down models stems from a variety of sources, predominantly regulatory reports, but also various supporting datasets, such as data on household wealth and taxable income available from Statistics Netherlands (CBS). Specialised models have been developed for the mortgage and the government bond portfolios of Dutch banks, given their large size and specific characteristics. Together, the suite of models in the framework can be used to analyse the impact of a stress scenario on individual portfolios as well as on total capital levels and ratios. An important advantage of a framework consisting of detailed models is that it allows assessment at a holistic as well as a granular level. The suite is also flexible in the sense that it has been used to quantify different supervisory or policy questions over time and is frequently expanded with further models as novel financial stability questions arise.

- 8 DNB uses the top-down framework for quantification of its risk assessments in its Financial Stability Report (FSR), to benchmark stress test calculations of supervised institutions, and to enhance the link between macro-financial risk assessment and micro-prudential action. Future improvements of the framework would be the inclusion of liquidity stress and second round effects, to allow for a more integral macro-prudential risk assessment.

1 Introduction

Since the onset of the global financial crisis in 2007, stress testing has become an increasingly important tool for policy makers and supervisors and has gained significant public attention.¹ During the crisis, stress tests were used as a crisis management tool to increase trust in banks' resilience and to restore market confidence; see for example reports from European Banking Authority (European Banking Authority, 2009), Federal Reserve (Board of Governors of the Federal Reserve System, 2009; Board of Governors of the Federal Reserve System, 2011) and DNB (De Nederlandsche Bank, 2009). The publication of detailed bank-specific results during the financial crisis was a marked policy change and provided unprecedented transparency (European Banking Authority, 2010; European Banking Authority, 2011; Board of Governors of the Federal Reserve System, 2009; Board of Governors of the Federal Reserve System, 2011; Board of Governors of the Federal Reserve System, 2012). Stress tests have thus become a crucial part of the toolkit for macro- and micro-prudential supervision (International Monetary Fund, 2012; Ong, 2014). For an overview of recent stress test exercises see Table 1.

Stress testing exercises can be conducted for macro- or micro-prudential purposes, or both. The purpose of macro-prudential stress tests is to assess the impact of severe macro-economic and financial shocks on the financial system. Such exercises focus on assessing the resilience of the financial system as a whole, and the robustness of systemically relevant institutions. The aim is to ensure that the intermediaries can fulfil their role as credit supplier to the economy, even under stress. The IMF Financial Sector Assessment Program (FSAP) stress test exercises take this macro-prudential perspective, for instance. By contrast, micro-prudential stress test are intended to generate information about the robustness of

¹ See Cavelaars et al. (2013) for a description of the supervisory and policy response to the crisis in the Netherlands.

Table 1 Overview of recent stress test exercises

Banks	Insurance companies	Pension funds
DNB Stress Test 2009 and 2010	DNB Stress Test 2009	DNB Stress Test 2010
CEBS Stress Test 2009 and 2010	CEIOPS Stress Test 2009	EIOPA Stress Test 2015 and 2017
EBA Stress Test 2011, 2014, 2016	EIOPA Stress Test 2011, 2014 and 2016	
IMF FSAP 2011 and 2016	IMF FSAP 2011	
ECB IRRBB sensitivity analysis 2017	DNB Stress Test non-life 2017	
DNB Climate Stress Test	DNB Climate Stress Test	

individual institutions. The tests are then typically tailored to the specific risk profiles of the institutions, focusing on the interaction between the identified vulnerabilities and the business model. Banks may use such exercises to test the viability of their business strategy under different scenarios, or to define mitigating actions for identified vulnerabilities. For supervisors, the stress test results provide a quantitative view on institutions' risk profiles, and are used in the capital adequacy assessment. Moreover, supervisors may require additional capital-strengthening measures to ensure a bank stays sufficiently capitalized in stressed circumstances.

In practice, macro- and micro-stress testing are closely linked, especially in concentrated markets which are dominated by a number of systemically relevant institutions. In such markets, testing the resilience of a few large institutions also provides an indication of the resilience of the sector as a

whole. This holds true for the Netherlands, where the five largest banks represent over 80% of banking sector assets, and are all active in the same markets. Being both a central bank mandated with promoting financial stability, and a supervisor responsible for the solvency and liquidity of the supervised banks, DNB is well-positioned to perform stress test activities that serve both a macro- and micro-prudential aim. The combination of macro- and micro-prudential stress testing has many advantages, but foremost DNB's ability to translate macro-prudential risk assessments into micro-prudential action. The need for close interaction between the macro and micro level has been sharply underlined by the recent financial crisis, during which many banks faced problems that were ultimately rooted in the macro-environment.

The execution of stress tests may differ according to their aim. They may, for instance, be performed from the bottom up. This means that the banks themselves make the impact calculations usually subject to a prescriptive methodology and supervisory quality assurance (e.g. the EBA 2016 stress test can be seen as a constrained bottom-up exercise). Bottom-up exercises have their advantages, most notably the possibility to use an enormous amount of detailed internal bank data, which allows for more precise impact calculations. However, in practice banks find it challenging to collect and stress all required data in a standardised manner. The entire stress test process, from bank calculations to supervisory quality assurance, is quite drawn-out and can easily take several months. This makes it difficult to react promptly to new economic circumstances. Furthermore, bottom-up exercises are resource intensive and require extensive quality controls to check the validity of data, the plausibility of the calculations and to ensure a level playing field between the participating banks.

12 The alternative to bottom-up stress testing is a top-down approach, in which the stress impact is estimated by the central bank or supervisor, using its own models and data readily available in central bank and supervisory data systems. This opens up the possibility of analysing the impact of several scenarios and responding to new developments quickly. However, it also requires sufficiently granular data in order to model risks adequately. DNB has developed a comprehensive top-down stress test approach for macro- and micro-stress testing of banks. Similarly, several other authorities have developed such top-down frameworks, for instance in Austria (Pühr & Schmitz, 2014), the UK (Burrows, Learmonth, & McKeown, 2012), the US (Covas, Rump, & Zakrajsek, 2013), and Canada (Anand, Bédard-Pagé, & Traclet, 2015). The European Central Bank (ECB) conducts top-down stress tests at the European level (Henry & Kok, 2013; European Central Bank, 2013). Results of top-down calculations are regularly published in Financial Stability Reviews, see for instance ECB (2012) and DNB (2014), or are part of supervisory exercises, see Fed (2014) and ECB (2014). The top-down approach also provides supervisors with a tool for challenging bank calculations, as a kind of 'second opinion'.

In line with international practice, DNB's top-down model was used in recent stress test exercises to challenge bank results and initiate a dialogue with banks about their bottom-up calculations. The top-down stress test also served as input for financial stability assessments. For the top-down model, DNB uses various unique datasets, allowing it to overcome an important part of the data issues surrounding top-down stress test modelling. This Occasional Study presents DNB's top-down bank stress test approach for solvency purposes.²

2 Obviously, liquidity stress testing is also important. However, it requires a different framework as risk drivers and risk models differ between the two measures of financial strength. Ideally a top-down stress test combines liquidity and solvency risks as these risks interact with each other (BIS, 2015).

Section 2 explains how DNB uses top-down stress testing. Section 3 discusses the umbrella framework and the top-down building blocks of our model, and Section 4 highlights the modelling of credit risk exposures. In this section we elaborate on the credit risk modelling of the mortgage loans portfolio, which constitutes the largest loan portfolio of Dutch banks. In this section, we also present a separate model for the credit risk parameters of the corporate loans portfolio. Section 5 focuses on market risks, specifically the impact calculation of stress on exposures to government bonds, and Section 6 addresses funding issues. Traditionally, stress tests focus on credit risk, being the largest component of bank balance sheets, but operating income is also a key driver of the stress impact. Section 7 explains how these different components come together in capital calculations. An example of a top-down calculation for large Dutch banks is presented in Section 8. Finally, Section 9 provides directions for future work.

2 Use of top-down modelling

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In the past decade, top-down stress testing has become increasingly important to supervisors. There are three main drivers behind this development. First, since the beginning of the century, regulators have become increasingly aware that stable financial institutions do not guarantee overall financial stability (Crockett, 2000). Hence, several authorities initiated financial stability analyses covering a broad array of banking sector, macroeconomic and financial market developments. The heightened attention for financial stability spurred the wish to be able to detect the impact of negative scenarios on the stability of the financial system. As a key contributor to financial stability, the banking system is under close watch. The corresponding publication wave of Financial Stability Reports by many national and international authorities, called for quantification of the impact of stress scenarios. DNB followed this approach and included stress test calculations in its Financial Stability Report (De Nederlandsche Bank, 2005; De Nederlandsche Bank, 2006; De Nederlandsche Bank, 2007; De Nederlandsche Bank, 2013; De Nederlandsche Bank, 2014; De Nederlandsche Bank, 2015).

Second, the crisis highlighted the lack of credible and mature stress testing approaches at banks. Extreme stress scenarios were hard to conceive when the economy was booming (Basel Committee on Banking Supervision, 2009). In addition, stress tests were in many cases only performed at single business line level rather than taking a group-wide perspective. This led to underestimation of correlations and risk concentrations over and across business lines and portfolios. As a result, the stress tests that were performed did not sufficiently challenge the banks' financial strength nor their business models. Furthermore, these stress tests were not linked to banks' risk appetite, nor were stress test results incorporated into business strategies. In order to obtain their own view of the impact of stress scenarios, supervisors developed supervision-led stress test exercises, which critically assessed banks' own calculations.

Third, stress testing helps to link the macro-risk assessment with micro-prudential supervision, thereby extending the macro-prudential reach. Top-down stress test results which are based on macro risk assessments may help micro-prudential supervisors to highlight macro and bank-specific risks to banks. By incorporating macro risks, micro-prudential supervision becomes more effective, thereby contributing to the stability of the system as a whole. This is known as the macro-micro link. Vice versa, information from micro-prudential supervisors about bank reactions to stress will help to improve the top-down model, notably to model possible second-round effects. Second-round effects could include the impact of a fall in a bank's solvency levels to its counterparties, or the impact of a fall in the system-wide solvency levels to the real economy.

We will discuss these three applications of top-down stress testing below.

2.1 Financial Stability Assessments

In its Financial Stability Report, DNB regularly publishes the results of top-down stress test calculations. Initially, the focus was on quantifying the impact of adverse scenarios on the economy and the financial sector as a whole. For example, the first Financial Stability Reports presented the impact of a base and adverse stress scenario on the overall financial sector, including banks, insurance companies and pension funds. The December 2005 Financial Stability Report, for instance, presented the impact of an overall 'malaise-scenario' and a 'worldwide correction-scenario', these exercises were repeated in June and September 2006. Here, the approach to measuring financial stability was derived from the macro financial risk model designed by Moody's-KMV. This model uses equity prices and debt ratios to determine default risks in various sectors, see DNB (2005). In addition, results are presented for different relevant ratios, such as solvency ratios, interest income at banks, credit losses, etc. Other scenarios presented are a disturbance in

16 the credit risk transfer market (CRT) and operational risk in the payments market (De Nederlandsche Bank, 2007). Liquidity risk was also tested in September 2008.

In more recent years, top-down calculations have been used to investigate specific vulnerabilities identified in the Financial Stability Report, for instance, to assess the impact of increasing risks in the mortgage portfolio or that of possible policy measures. The 2013 spring issue of our Financial Stability Report discusses the impact of an interest rate shock on credit losses, and the 2014 spring Financial Stability Report depicts how the size and distribution of underwater mortgages may develop under different house price scenarios and how this may impact households and banks. Significantly, these reports also suggest some policy measures to counteract any negative results. Here, macro-financial risk analysis and policy making has also pushed the frontier of DNB's modelling efforts.

It is important to combine stress test calculations and suggested policy measures. Not only does this show how stress testing is relevant to informing the need for policy measures, it also underlines how stress testing can help in detailing the format and size of policy measures. To this end, it is important to be able to design and calibrate relevant and tailored stress scenarios. The more granular the stress test model and underlying data, the higher the flexibility of the model to adapt to different policy questions. For instance, top-down calculations may provide information on whether and how new policies in the mortgage loan market (e.g. a limit to LTV-ratios) may impact the financial position of households and banks.

2.2 Challenging bottom-up calculations

Top-down results can be used as a benchmark for the calculations provided by the banks themselves. Usually, in a stress test banks are allowed to use their internal stress test models to calculate the impact of a pre-specified stress scenario. DNB's top-down model provides a useful benchmark for assessing the accuracy of bank calculations. Obviously, bottom-up and top-down approaches do not need to have exactly the same outcome, as they are based on different data sources and rely on different model calibrations. The two approaches are expected to yield a comparable impact however. If differences emerge, this will give rise to thorough further investigation and dialogue with banks, and may lead to either bottom-up calculations or top-down modelling being changed.

In this respect, it is useful if the top-down model is able to calculate the impact of the risk drivers separately. This allows us to follow the banks' calculations as closely as possible and to understand them better. It would also allow for use of the top-down model if only specific parts of the banks' balance sheet or P&L account are included in the stress test. Furthermore, it gives us the opportunity to take any bank-specific issues into account. The DNB top-down framework facilitates this modular use.

This challenger approach was also applied in the stress test performed as part of the 2014 ECB Comprehensive Assessment. As part of this exercise, the banks' calculations were subjected to extensive quality control. First of all, DNB used its top-down model to challenge the banks' own results. Here, DNB compared top-down results with bank calculations for each separate risk module and asked the banks to explain any deviations. Where necessary, banks updated their calculations.

18 Secondly, the ECB top-down model was used to further challenge the figures provided by the banks (European Central Bank, 2014) and to ensure a level European playing field. Similarly, these top-down calculations were used as a benchmark for challenging bank results, rather than as an exact calculation of the 'real' impact of the stress scenario. Hence, the ECB calculations were used as a basis for a dialogue with the banks, which were allowed to explain any deviations. If they were unable to provide a convincing explanation, they were required to restate their calculations.

The use of a top-down model has other merits. Most importantly, it guarantees a level playing field between banks. Where bank models and assumptions may deviate due to differences in conservativeness, the top-down model uses a similar approach across all banks. Hence, both overly conservative and overly optimistic assumptions of banks are subjected to supervisory challenge and dialogue. Comparability between banks is an important issue in nationwide or EU-wide exercises. Indeed, for the 2014 EU-stress test, DNB's approach allowed for comparison between the results for the banking Dutch sector, while the ECB top-down calculations pointed to EU-wide differences. This is all the more relevant if stress test outcomes result in supervisory measures such as capital requirements. In that case, a comparable approach is needed to make sure that banks are treated in the same way.

2.3 Macro-micro link

Key lessons from the crisis call for connecting macro-prudential risk analysis and micro-prudential supervision, and vice versa (International Monetary Fund, Financial Stability Board Secretariat, 2009; Larosière, et al., 2009; De Nederlandsche Bank, 2013). Stress testing is a key tool for linking macro- and micro-risk dynamics. Usually, a stress scenario is based on an informed view of upcoming risks for the macro economy and financial sector, collected in a macro-risk analysis. Obviously, these macro risks will have

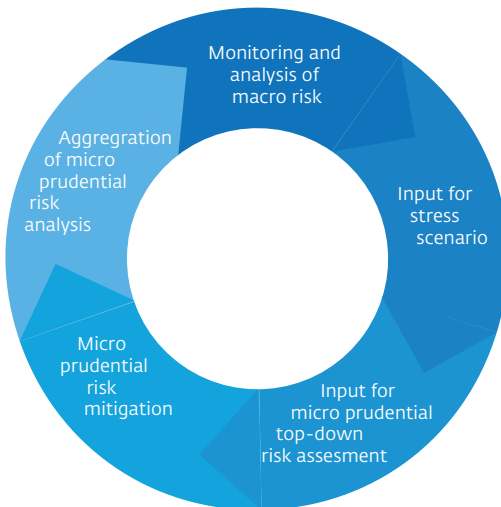
micro-prudential impacts. Results from a top-down model that incorporates these macro risks, thus inform micro-prudential supervisors about the potential impact of a stress scenario on banks and support a meaningful discussion about risks. Hence, by incorporating macro risks, micro-prudential supervision becomes more effective, and thus also contributes to the stability of the system as a whole.

Conversely, financial sector developments also need to feed the macro-risk assessment in order to capture risks in systemic institutions, common exposures or nascent risks stemming from financial innovations. A top-down model can take account of these effects, and these macro-micro and micro-macro interactions can be quantified with the help of a stress test.

DNB, acting both as a central bank and supervisor, is well-positioned to achieve this macro-micro interaction. DNB uses the risks identified in its Financial Stability Report as key input for the development of stress scenarios. In this case, the risks are translated into an anchor scenario, including shocks to the most relevant parameters such as GDP growth, unemployment, long- and short term interest rates, inflation, house prices, real estate prices and equity indices. The top-down stress test then calculates the effects of such macro-economic stress scenarios on individual institutions. The estimated micro-prudential impact is important information for the supervisory evaluation of the capital position of banks. Capitalisation adequacy is formally assessed by the supervisor and communicated to the bank in the annual Supervisory Review and Evaluation Process (SREP). In addition, supervisors of banks, insurance companies and pension funds may use the anchor scenario and the top-down impact to start a dialogue with the supervised entity on stress testing and capitalisation levels. It may, for instance, serve as a benchmark for banks' internal stress scenarios.

20 In addition, micro-risk assessments and impact studies (such as stress tests) together provide relevant information on the exposure to these macro-risks of the financial sector at large. In this way, common risks exposures and similar risk profiles may become visible. This provides relevant information to improve the top-down stress models. Moreover, outcomes from the dialogue on the anchor scenario with banks serve as relevant information for a new macro-risk assessment. The link thus runs from macro to micro, but also from micro to macro (see Figure 1).

Figure 1 Practical implementation of the macro-micro link



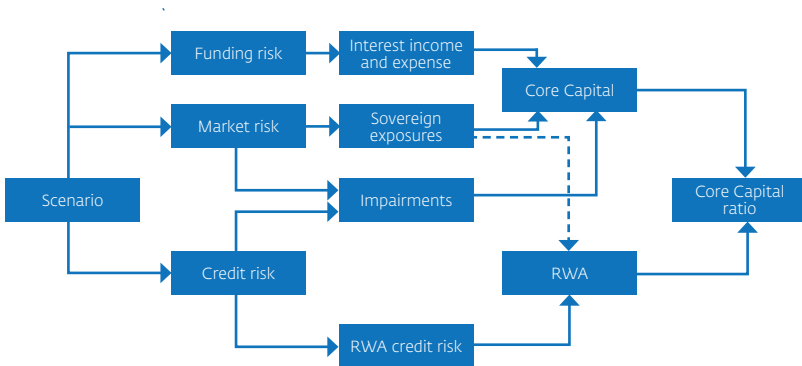
3 Anatomy of a top-down stress test

The key task of a top-down stress test model is to translate the impact of a stress scenario on the capital position of a bank. A breakdown of the impact of a stress scenario on different components of a bank balance sheet allows for a granular calculation. This is especially relevant as the sensitivity to stress of the different risk sources may vary. Moreover, it helps to better understand the drivers underlying the results.

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DNB's top-down framework consists of various sub modules, representing the different building blocks of the ultimate impact of a stress scenario on the capital ratio (Figure 2 presents a schematic overview). We closely follow the approach implicitly employed by the EBA stress test methodologies (European Banking Authority, 2016) and focus on the largest risk components for banks: credit risk, market risk (including securitisations) and funding risk. Operational risk, for simplicity's sake, is not explicitly modelled.

Figure 2 Anatomy of a top-down stress test



22 The top-down approach can be described as follows. The starting point is the hypothetical stress scenario. This scenario includes adverse shocks to key economic variables, such as economic growth, unemployment, long- and short-term interest rates, inflation, housing and commercial real estate prices and equity indices. The scenario is usually based on an assessment of the main risks to the financial system. For the Netherlands, this risk assessment is described in DNB's Financial Stability Report and forms the basis for a detailed narrative indicating which risks may harm the Dutch economy and banking system. This narrative is used to define shocks to the economic forecast models. The resulting output is the stress scenario, which can be viewed as a deviation from expected economic developments. Usually, the scenario has a multi-year horizon. The effect of the scenario will tend to manifest itself gradually on the banks' financial positions. Other elements may also impact bank portfolios slowly over time. For instance, social security provisions will usually limit the impact of unemployment initially. To include this delayed effect, the impact of stress is measured over several years. However, while a multi-year horizon is relevant since banks hold long-term loans, there is a trade-off as forecasting over a longer horizon may require additional assumptions.

The scenario variables will impact the credit risk exposure of banks, which is the risk that a counterparty does not meet its obligations and is mainly related to banks' lending portfolios. For instance, in times of increasing unemployment, some households may no longer be able to meet their mortgage repayments. Banks will incur losses on these exposures. Similarly, in times of declining economic growth, some companies will go bankrupt and fail to repay their loans. Again, banks will suffer losses. So scenario shocks may lead to higher losses or impairments for banks. As more and more debtors run into trouble, the overall credit quality and risk exposure of bank lending portfolios deteriorates. Since regulators require banks to weigh assets by their riskiness, this also implies an increase in risk-weighted assets (RWA).

The scenario variables will also impact market risk exposure. This includes the value of banking sector investments. For instance, if the scenario assumes falling equity indices, equity investments will lose value. In turn, big price adjustments may lead to impairments on exposures. A key point for attention in banks' market risk exposures is their exposure to government bonds. The scenario parameters may include shocks that will impact the value of government bonds (e.g., the market price of bonds may fall). These shocks will also lead to impairments and value adjustments and banks will have to take them into account. The shocks also impact the riskiness of the market portfolio and cause risk-weighted assets to increase.

The scenario usually also covers funding risk as it includes interest rate shocks and assumptions about funding conditions. These shocks will impact the interest rate paid by banks on the funds that they raise, both in wholesale funding markets and on commercial and retail deposits. So it will impact their interest expense. Banks may pass on increases in funding costs wholly or partially to their customers by raising the interest rates on the loans that they provide to their customers. This will influence their interest income. If interest rates paid and interest rates received do not move in tandem, the interest margin may come under pressure.

Credit risk, funding risk and market risk will all have an effect on a bank's capital level. Impairments, declining value of investments and exposure to government bonds, and pressure on interest rate margins will depress net income. As usually net income is at least partially (depending on dividend payments) added to the capital base, negative net income will depress the amount of core capital of a bank. Core capital is the capital that has the highest loss absorbing capacity. Supervisors focus on core capital as it is readily available to cover losses. In addition, increased risk will lead to higher risk-weighted assets. Capital (the numerator) and risk-weighted assets (the denominator) define the overall core capital ratio.

24 To assess whether a bank still has sufficient capital available after stress, the level of the core capital ratio can be measured against a pre-defined threshold value or hurdle rate. For example, the EBA 2014 stress test methodology sets the threshold value at a core capital ratio of 5.5%. Banks falling below this threshold were required to improve their capital position. In addition, the impact or size of the capital ratio reduction itself provides relevant information about the risk-sensitivity of a bank. Analysis of the results at a deeper granular level also gives insight into a bank's risk exposure.

When assessing the impact of a stress test it is therefore important to bear in mind that the outcome strongly depends on both the scenario and the modelling assumptions on which the test is based. A different scenario or different modelling assumptions may have different outcomes. Consequently, stress test results should always be viewed in context rather than in isolation.

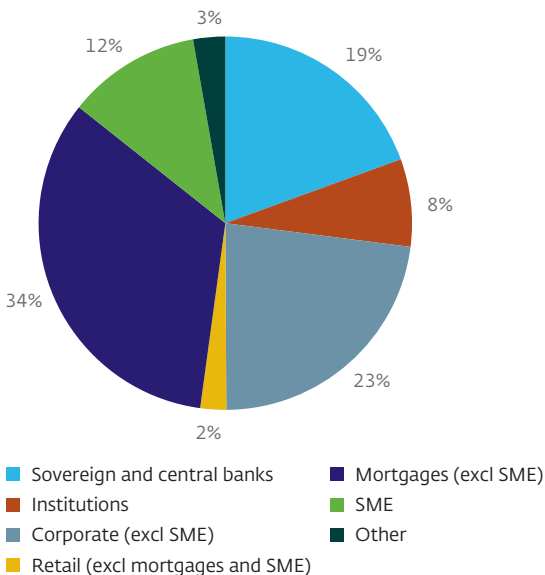
In the next chapters, we will zoom into the components of DNB's top-down stress test model.

4 Modelling credit risk

Credit risk is inherent to the traditional activities of banks, lending, and constitutes the most significant risk exposure for almost all banks. For Dutch banks, the majority of their balance sheet consists of loans and receivables. Of these loans and receivables, the mortgage loan portfolio is the biggest, representing 34% of all loans. Other relevant lending portfolios include corporate and SME loans (23 and 12% respectively). Sovereign exposures and loans to institutions represent 19% and 8% of the loan book respectively (see Chart 1, the numbers of the 2016 EBA stress test exercise shown are based on the data for the four participating Dutch banks, which represent over 80% of the Dutch banking sector).

25

Chart 1 Breakdown of the loan portfolio of Dutch banks (end-2015)



Source: EBA stress test 2016.

26 It is therefore imperative for banks that they are able to make the best possible assessment of the creditworthiness of their counterparties. They should monitor, assess and manage the risk of credit losses. Creditworthiness is expressed as the Probability of Default (PD): the likelihood of the obligor defaulting. Not only is this driven by borrower-specific characteristics, such as the household balance sheet composition and payment behaviour, but also by general macroeconomic conditions, such as unemployment levels and interest rates. In addition, banks can ask for collateral or guarantees to hedge credit risk. If the obligor defaults, the collateral given will dampen the actual loss for the bank. This is reflected in the Loss Given Default (LGD): the amount the bank stands to lose if the obligor defaults.

Given the size of their credit portfolios, banks may use models to calculate the PD and LGD of credit risk exposures. Banks following the Advanced Internal Ratings Based (IRB) approach of the Basel III capital framework are allowed to model both these parameters based on their own data on the credit quality of their portfolio, subject to regulatory approval of the models. Under the Foundation-IRB approach, banks model only the PD based on internal data, and the LGD is prescribed in the regulation. Banks applying the Standardised Approach (SA) use a mapping from assets to risk categories that is prescribed in the regulation and do not model PDs and LGDs themselves.

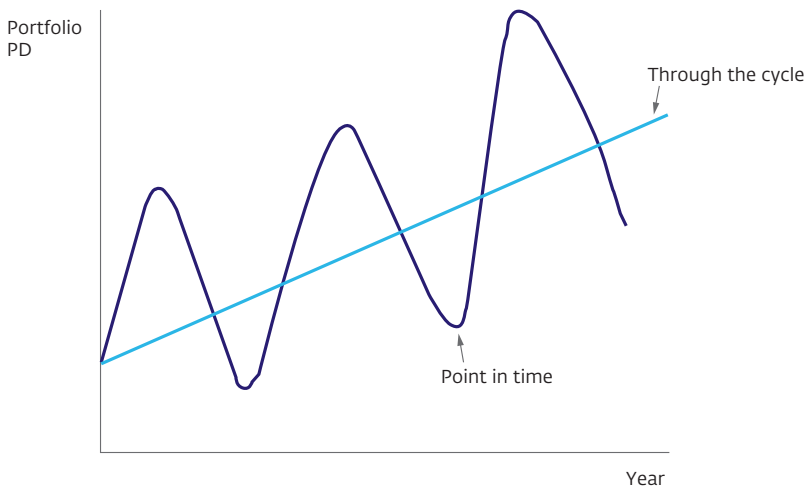
DNB's top-down model builds on the Advanced-IRB approach and uses models to translate scenario shocks into changes in PD and LGD risk parameters. For each portfolio, changes in PD and LGD in response to the relevant macro-economic developments are modelled. For instance, the PD of the mortgage portfolio will be affected by interest rates, unemployment and economic growth trends. The LGD of mortgage loan portfolios will largely be driven by house price movements and fire sale assumptions.

Our calculations of credit risk impact distinguish between credit losses occurring directly as a result of stress, and calculation of capital requirements for credit risk exposure. Although both calculations rely on PD and LGD parameters, there is a notable difference between the two (see Chart 2). Credit losses can be characterised as point-in-time. That is to say, they capture credit risk at a specific moment in time. Usually, we would expect credit losses to decrease during economic upturns and credit losses to increase during economic downturns. This means that the risk parameters PD and LGD needed for the calculation of credit losses, are determined at a specific point during the economic cycle. For regulatory purposes, the risk of credit exposures also needs to be calculated in order to determine capital requirements. However, regulators demand a longer-term perspective on these risks to avoid pro-cyclicality in capital requirements.³ Regulatory PDs are therefore calculated across the entire economic cycle (through-the-cycle). Regulatory PD may consequently come out lower than the point-in-time PD during stress, and vice versa in economic upturns. Similarly, regulatory LGDs are required to be stable over time and at each point in time to reflect an economic down-turn scenario. The resulting LGD may or may not adequately represent stressed conditions.

We base our calculations on the data that banks submit to DNB in what are known as common reporting (COREP) templates. In COREP templates, banks report their regulatory PD and LGD, as well as their credit risk exposure by asset class and by risk bucket according to their own internal classifications. The asset classes, for instance, cover the corporate loan portfolio, the retail portfolio, the real estate portfolio, loans to institutions,

³ It is undesirable that regulatory capital requirements vary significantly with the economic cycle, as tightening bank capital requirements in bad times may deepen the economic cycle.

Chart 2 Through-the-cycle versus point-in-time PD



etc. On average, banks use over ten risk buckets per asset class, each with a corresponding PD and LGD. This implies that the model parameters are available on a relatively granular level. This allows us to better tailor the calculation of credit losses and capital requirements to the specific risk profile of individual banks. Although, in our framework, the applied stress factor is the same for all banks, the actual level of the stressed PD or LGD will depend on the starting value of PD and LGD reported in COREP. This means that we do not impose the same initial risk level of credit exposures on all banks.

4.1 Calculation of credit losses

For the calculation of credit losses under stress, we assume that the concept of expected loss gives a good approximation. The Basel Committee (2005) defines expected losses (EL) as follows

$$EL_t = PD_t \times LGD_t \times EAD_t$$

where EAD_t represents the credit exposure at time of default. This concept of exposure takes debtor behaviour into account which may occur at time of default but may not be visible on a day to day basis, for instance drawing up credit lines to the maximum extent. To calculate losses, we need to model the PD, LGD and EAD under the scenario assumptions. The approach used by the top-down model can be specified as follows:

$$PD_{t, \text{stress}} = PD_{\text{corep}} \times F_{\text{ttc} \rightarrow \text{pit}} \times G_{t, \text{stress}}$$

$$LGD_{t, \text{stress}} = LGD_{\text{corep}} \times H_{\text{ttc} \rightarrow \text{pit}} \times L_{t, \text{stress}}$$

where $PD_{t, \text{stress}}$ and $LGD_{t, \text{stress}}$ refer to the PD and LGD under stress at time t . PD_{corep} and LGD_{corep} refer to the PD and LGD reported by banks in the Common Reporting (COREP) supervisory reports, $F_{\text{ttc} \rightarrow \text{pit}}$ and $H_{\text{ttc} \rightarrow \text{pit}}$ to adjustment factors that translate the reported through-the-cycle parameters (ttc) into point-in-time value (pit) parameters. Finally, $G_{t, \text{stress}}$ and $L_{t, \text{stress}}$ are the stress factors obtained from translating the scenario.

As said, in COREP banks report the regulatory PD, LGD and EAD by asset class and by risk bucket. These parameters serve as input for the calculation of regulatory capital requirements, which are defined as being through-the-cycle (ttc) and hence work with an average over a certain period. By contrast, the stress is supposed to occur at a specific point-in-time (pit).

30 This means that for each asset class, we adjust the reported ttc-value of the PD to a pit-variant. For LGD, COREP requires reporting of the downturn value, which is the LGD experienced during a typical downturn. This value also needs to be adjusted to a pit value. The adjustment factors $F_{\text{ttc} \rightarrow \text{pit}}$ and $H_{\text{ttc} \rightarrow \text{pit}}$ are determined for each portfolio and are based on recent loss data in the market relative to the long-term average. Generally, in weak economic environments we would assume that the PD adjustment factors are larger than one, implying that defaults are higher than the average. For the LGD, the adjustment factor can be either larger or smaller than one, depending on the impact of the scenario relative to a typical downturn.

The stress factors $G_{t,\text{stress}}$ and $L_{t,\text{stress}}$ are determined for each portfolio and are calculated for each time period t . To this end, the stress factors are multiplied by scalars $M_{G,t}$ and $M_{L,t}$ that depend on changes in macroeconomic risk drivers (e.g. GDP, long-term interest rates, unemployment) as defined in the scenario. The sensitivity of the scalar is captured by a vector β of elasticities with respect to the risk drivers, e.g. $M_{G,t} = \beta' \Delta x_t$ where Δx_t represents the macroeconomic shocks specified in the scenario for time t . The stress factor hence becomes $G_{t,\text{stress}} = M_{G,t} \times G_{t-1,\text{stress}}$. To illustrate this for a scenario with shocks on unemployment, economic growth and long-term interest rates, the stress factor G can be simplified as

$$G_{t,\text{stress}} = \left(1 + (\varepsilon_u \times \Delta U) + (\varepsilon_{\text{GDP}} \times \Delta \text{GDP}) + (\varepsilon_{\text{LT interest rate}} \times \Delta i_{\text{LT}}) \right) \times G_{t-1,\text{stress}}$$

Here, ε_u , ε_{GDP} and $\varepsilon_{\text{LT interest rate}}$ are the elasticities of the PD for changes in respectively unemployment, GDP and long-term interest rates. The vector of elasticities differs for each IRB exposure class. Typically, the stressed PD and LGD values are expected to increase during the stress horizon. In addition, the stress factors are determined for the market as a whole, but could also be calculated for individual banks. When we have determined

the stressed PD and LGD values, we can calculate the expected losses under the scenario assumptions.

For assets that are already in default, we include an additional default flow if the stressed LGD at time t exceeds the LGD assumed at the time of default.

$$EL_{t, \text{defaulted}} = (LGD_{t, \text{stress}} - LGD_{t-1}) \times EAD_t$$

4.2 Calculation of stressed capital requirements

Capital requirements for credit risk are needed to cushion the unexpected proportion of credit losses. This means that capital requirements are related to the variability of expected losses. The Basel Committee has defined the formula for determining capital requirements, for which through-the-cycle PD and LGD values serve as key input (Basel Committee on Banking Supervision, 2005). The capital requirement is set such that in 99.9% of the cases the capital is sufficient to cover losses. This formula reads as follows, where the capital requirement (K) also depends on the average maturity (M) of the portfolio and the typical correlation (R) between the assets of the portfolio (which is a parameter prescribed in the Basel framework). Additionally, $b(\text{PD})$ is a smoothed over PDs maturity adjustment factor. Both terms differ depending on the asset class.

$$K = \left[LGD \times \underbrace{\Phi\left(\frac{\Phi^{-1}(\text{PD})}{\sqrt{1-R}} + \sqrt{\frac{R}{1-R}} \times \Phi^{-1}(0.999)\right)}_{\text{calculate PD at 99.9\%}} - PD \times LGD \right] \times \underbrace{\left(\frac{1}{1-1.5 \times b(\text{PD})}\right)}_{\text{correct for maturity}} \times \left(1 + (M - 2.5) \times b(\text{PD})\right)$$

We use the stressed pit PD and LGD values derived from the calculated expected losses to re-calculate the regulatory PDs and LGDs. The regulatory PD is defined to be ttc, hence it is usually calculated as an average of PDs over the last few years. For stress calculations, the PD in COREP represents

32 a default history of a given duration, say five years. We then add the stressed PD to the calculation of the average PD. For each risk bucket, this gives a longer time series which (typically) increases the regulatory PD. For LGD, we compare the downturn value of LGD reported in COREP with the stressed LGD. Only if the stressed LGD is higher, the regulatory LGD is replaced by the stressed parameter.

$$LGD_{reg,t,stress} = \max(LGD_{t,stress}, LGD_{corep})$$

The stressed regulatory PD and LGD values are then used as input for the calculation of the stressed capital requirements using the Basel formula per asset class (Basel Committee on Banking Supervision, 2005). Banks are subject to a number of different capital requirements for different types of quality of capital.⁴ For non-defaulted assets, most of these capital requirements are expressed as a percentage of Risk-weighted assets and total capital must not be lower than 8%. For this reason, risk-weighted assets are derived by multiplying the capital requirement K by 12.5 (equivalently, dividing by 8%). For defaulted assets, capital requirements are based on the difference between the regulatory LGD and the LGD at the time of default.

To illustrate our approach, the next section explains how we model mortgage lending risk

4.3 Mortgage lending portfolio

The mortgage lending portfolio constitutes the largest credit risk portfolio of the Dutch banking sector, representing 34% of all loans (see Chart 1). Mortgage debt in the Netherlands is large, accounting for over 100% of GDP

4 E.g., the requirements for core capital are the lowest; on top of that banks will need to hold additional capital which is less loss-absorbing but can nevertheless be put to use in times of extreme losses. See section 7.

in 2012 (see Table 2). The mortgage lending portfolio is characterised by high loan-to-value (LTV) ratios: the average LTV ratio on new mortgage loans peaked at around 100% in the past. These high LTV ratios are largely driven by tax incentives, as interest payments on mortgage loans are tax-deductible. Currently, LTV ratios of new mortgage loans are curbed by regulations and they are below 95% on average. Yet they remain high by international standards (Verbruggen, Molen, Jonk, Kakes, & Heeringa, 2015). Interestingly enough, despite a 21% fall in nominal house prices from peak to trough, mortgage loan losses remained low at an average of 20 basis points in 2015.

Table 2 International comparison of mortgage lending portfolios

	NL	DK	IE	ES	UK	US
Total outstanding mortgage debt (% gdp), maximum 2004-2015	101.2	94.1	87.3	62.9	78.7	86.2
Nominal house prices, relative fall peak-to-trough (%) 2007-2016*	-21.5	-19.6	-54.4	-36.9	-20.9	-19.7
Unemployment, absolute increase trough-to-peak (%-point) 2007-2016	5.0	5.0	11.5	19.3	4.0	6.5
Payment arrears, 2016H1**	1.4	0.2	8.0	4.5	0.9	4.6
Underwater mortgages (%), 2016H1***	22	n.b.	43	n.b.	n.b.	8

Source: EMF, BIS, IMF.

* The selected period depends on the country and concerns the fall from the moment that the property bubble burst in the relevant country.

** Source: DNB (NL), Association of Danisk mortgage banks (DK), Central Bank of Ireland (IE), Banco de Espana (ES), FRB (US)

*** Source: DNB (NL), Central Bank of Ireland (IE), Corelogic (US)

34 These elements require a tailored model for the mortgage market which is able to take these loan specifics into account. As household balance sheet characteristics are a key factor for PD and LGD developments, we based our model directly on the sensitivity of household balance sheet characteristics to the scenario assumptions. In other words, we use a micro-simulation of household balance sheets to calculate mortgage credit losses. One advantage of this method is that it requires virtually no information in the time series dimension. This is important given the large number of changes to market regulations, the varying market structure and the limited occurrence of severe crashes. To model the impact of a stress scenario, we consider how it would impact household income and mortgage characteristics. We can then infer how our proxies of PD and LGD would change under the scenario. Other techniques typically rely on linking the dynamics of PD and LGD directly to aggregate macro-economic variables in the time series dimension. However, long time series for loan loss parameters of sufficient quality are hardly ever readily available.

Data

We use a unique dataset obtained from Statistics Netherlands (CBS), known as the Inkomenspanelonderzoek (IPO) dataset. This dataset includes a representative sample of the Dutch population ($n > 100,000$) and builds on the tax returns households are required to submit. Hence, it covers a rich dataset on family size, income, interest payments, property value and mortgage loan, savings, debts, etc. Although data are collected annually, we only use the most recent wave for our top-down model. This represents the latest information about the financial strength of households.

In addition, we can cross-check the data from the IPO dataset against very detailed loan level data that banks report to DNB. The loan level data include information on loan size and type, property value and location, income at

origination, the default status of the borrower, interest rates, next reset date, etc. Where possible these data are also used in the calibration of the micro model.

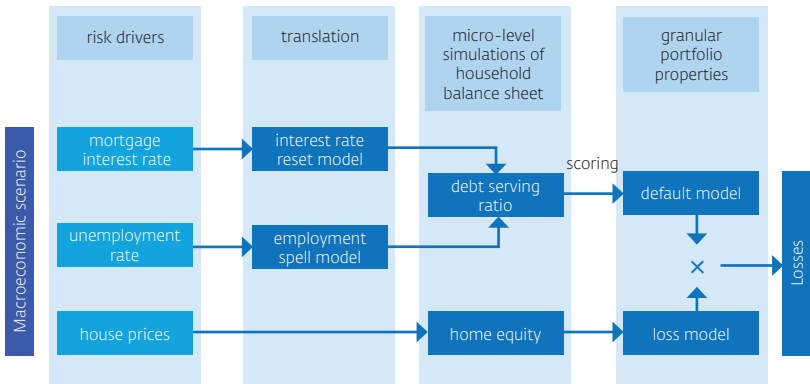
Model

We take a direct approach. First, we identify the “risky” households in the dataset. Risky households are defined as households whose mortgage interest rate payments exceed the standards specified by the code of conduct that banks have agreed upon. We assume that these households are representative of the proportion of households in default. The proportion of households in distress determines the initial PD for the sample. For each risky household, we determine the potential loss in case the house is sold. We assume this to be the initial LGD. We then shock the balance sheet positions of the sample based on the scenario assumptions. These shocks will change the group of risky households and hence the PD. In addition, the LGD will change following scenario assumptions on the housing market. It should be noted that it is not so much the starting level of PD and LGD that is important, but rather the change in PD and LGD levels that provide relevant information about the stress impact.

Our model uses three specific scenario shocks (see Figure 3):

- The unemployment rate: the trend in unemployment affects household income and therefore is a key determinant of the PD.
- Interest rates: the trend of interest rates affects the debt servicing ratio and hence impacts the capacity of households to continue paying their mortgage instalments. This is another key determinant of the PD.
- Real estate prices: real estate price trends affect the value of residential property and impact the value of the collateral, and therefore LGD.

Figure 3 Outline of top-down mortgage model



Indeed, the pool of risky households will change as a result of simulation of the change in interest payments and in unemployed households and the impact on income (differentiating between unemployment rates for different age groups). Both components are relevant for our definition of risky households, which compares interest payment obligations with available income, and hence for the PD. For both PD drivers (unemployment and interest rate payments), we developed satellite models to assess the PD impact.

The *satellite interest rate reset* model combines the scenario developments with information on households with fixed or floating interest rates on their mortgage loans and the expected interest rate reset date to provide the impact of the stress scenario on households' interest rate payments. Generally, and under the assumption of increasing interest rates, this will lead to a gradual increase of the average mortgage interest rate of the population. Based on a large number of simulations, we determine the average impact of the stress scenario on interest rate payments.

Similarly, based on a large number of simulations, the satellite unemployment model provides the likelihood of a household becoming unemployed within the scenario horizon, the income it receives during unemployment, and the probability of becoming employed again, using a micro-econometric hazard model. We assume that loss of employment results in a 30% income drop, in line with unemployment benefits in The Netherlands. If households remain unemployed for longer periods of time, their income will fall even further to social assistance levels. If a household becomes employed again, we assume a recovery to previously observed income levels, adjusted for a human capital loss which grows together with the period of unemployment. In this way, we can also model the impact of longer-term unemployment and the resulting fall in income. From these simulations, we then determine the average impact on the debt-servicing ratio. Combining both satellite models, we can define the impact on PD.

Finally, we model LGD as a function of the collateral and the recourse possibilities for the bank. Thus, if a household defaults, the LGD value determines how much the bank stands to lose if it sells the property. We impose the house price shocks from the scenario on the collateral provided by the pool of risky households, including fire sale costs, to determine the stressed LGD.

After obtaining the stressed PD and LGD values, we can project the change in expected losses and stressed capital requirements, similar to the approach described in Sections 4.1 and 4.2. Since we have the stress impact of the scenario at the household level, we can tailor it to the original risk profile of the bank, e.g. considering the LTV distribution of the portfolio and the households' financial situation. Generally, we find that LGD responds stronger to the scenario assumptions than PD. This is not surprising, as house prices and LTV levels affect losses directly, whereas unemployment

38 and interest rates also depend on other aspects such as the use of floating or fixed interest rate contracts, reset date, unemployment benefits and other social assistance mechanisms. Hence, unemployment and interest rate trends have a gradual impact on the quality of the mortgage loan book and losses may occur with a time lag.

An important benefit of the IPO dataset is that it allows us to use a truly independent and audited data set for comparison against figures provided by the banks. Another advantage of this approach for the mortgage portfolio is that the model is flexible and can be adjusted to different scenario assumptions through the simulation of household balance sheets. This greatly improves the quality of the top-down projections. For instance, it allows us to project long-run scenarios and sensitivities (see the spring 2014 issue of our Financial Stability Report). This is especially relevant given the long-term nature of mortgage loans. We can also model the impact of changes in tax deductibility or social assistance, which is useful in informing policymakers. In addition, the PD- and LGD-dynamics can be combined with other characteristics such as age, LTV- or LTI-ratios.

4.4 Corporate lending portfolio⁵

The corporate lending portfolio consists of loans to large corporates and small to medium sized enterprises (SMEs). Loans to large corporates account for around 23% of total loans while loans to SMEs comprise 12% of the Dutch banking sector's loan book (Chart 1). In general, lending to corporates is riskier compared to mortgage lending, which implies that required capital for corporate loans is also larger.

5 We thank Robert Vermeulen for his contribution to this part.

Model

The development of a bank's corporate loan book under stress is modelled using a ratings migration approach. For this, we use a transition matrix, which indicates which part of the loan book will migrate to a lower rating or will move into default. Standard rating transition matrices are available from rating agencies and contain: 1) information on the probability of default for loans with a certain riskiness (i.e. rating), and 2) probabilities of loans becoming of better or worse quality during a year. For our model, we have to estimate how the transition matrix changes due to the stress scenario. We use the following model:

$$Matrix_{t, stress} = Matrix_{ttc} \times \sigma_{Matrix(ttc)} \times \varphi$$

where $Matrix_{ttc}$ is a through the cycle (ttc) transition matrix, $\sigma_{Matrix(ttc)}$ is the standard deviation of each cell in the ttc matrix, and φ is a stress factor which is determined by the economic cycle.

Table 3 Rating migration matrix 1981-2014

From/To	AAA	AA+	AA	AA-	A+	A	A-	BBB+	BBB
AAA	87.03	5.76	2.57	0.70	0.16	0.24	0.13	0.00	0.05
AA+	2.50	76.73	12.01	3.83	0.80	0.43	0.21	0.05	0.11
AA	0.45	1.28	80.01	8.72	2.93	1.25	0.40	0.42	0.14
AA-	0.05	0.13	4.11	77.39	10.19	2.50	0.64	0.30	0.17
A+	0.00	0.07	0.52	4.62	77.21	9.11	2.40	0.70	0.38
A	0.04	0.05	0.25	0.49	5.21	77.88	6.94	2.58	1.00
A-	0.05	0.01	0.08	0.16	0.52	6.83	76.37	7.56	2.34
BBB+	0.00	0.01	0.07	0.08	0.25	0.90	7.30	73.86	8.58
BBB	0.01	0.01	0.05	0.03	0.12	0.38	1.11	7.56	74.75
BBB-	0.01	0.01	0.01	0.06	0.07	0.18	0.31	1.31	9.37
BB+	0.06	0.00	0.00	0.04	0.02	0.11	0.10	0.53	2.02
BB	0.00	0.00	0.05	0.02	0.00	0.08	0.06	0.21	0.61
BB-	0.00	0.00	0.00	0.01	0.01	0.01	0.06	0.12	0.26
B+	0.00	0.01	0.00	0.04	0.00	0.04	0.07	0.05	0.05
B	0.00	0.00	0.01	0.01	0.00	0.05	0.06	0.02	0.08
B-	0.00	0.00	0.00	0.00	0.02	0.05	0.00	0.10	0.07
CCC/C	0.00	0.00	0.00	0.00	0.04	0.00	0.11	0.07	0.07
D	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

We employ a ttc transition matrix developed by S&P (Table 3).⁶ It contains the average probability during 1981-2014 of a corporate retaining its rating, moving from one rating class to another, or moving into default. In the modelling set-up the non-rated category is ignored, which implies that no loans can migrate from or to this category.

⁶ Table 23 in the 2014 Annual Global Corporate Default Study And Rating Transitions van S&P Ratingdirect, April 30, 2015. (<https://www.globalcreditportal.com>)

BBB-	BB+	BB	BB-	B+	B	B-	CCC/C	D	NR
0.00	0.03	0.05	0.00	0.00	0.03	0.00	0.05	0.00	3.19
0.05	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	3.29
0.09	0.05	0.03	0.02	0.02	0.00	0.02	0.05	0.02	4.11
0.08	0.03	0.00	0.00	0.03	0.09	0.00	0.00	0.03	4.27
0.09	0.07	0.10	0.01	0.08	0.03	0.00	0.00	0.06	4.54
0.31	0.13	0.12	0.09	0.11	0.02	0.00	0.02	0.07	4.69
0.67	0.17	0.17	0.14	0.13	0.03	0.01	0.04	0.08	4.65
1.85	0.43	0.37	0.15	0.20	0.13	0.03	0.08	0.13	5.60
6.42	1.50	0.71	0.32	0.28	0.14	0.04	0.07	0.19	6.30
71.76	5.41	2.29	0.88	0.44	0.29	0.18	0.25	0.30	6.86
12.01	63.72	6.62	3.01	1.07	0.67	0.23	0.48	0.40	8.92
2.38	9.81	64.41	7.78	2.31	1.16	0.40	0.65	0.64	9.44
0.43	1.97	9.45	63.02	8.51	3.16	0.86	0.78	1.09	10.26
0.12	0.31	1.57	7.88	63.63	8.46	2.62	1.76	2.23	11.17
0.04	0.17	0.32	1.42	8.58	60.39	8.26	4.35	4.29	11.95
0.15	0.12	0.20	0.49	2.59	11.04	52.59	11.40	7.50	13.70
0.07	0.04	0.18	0.43	1.22	2.95	9.09	43.85	26.38	15.49
0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	100.00	0.00

Source: (Standard&Poor's, 2015)

The modelled time-varying rating transition matrix will change with the state of the economy. So, the aim is to transform the ttc transition matrix to a point in time (pit) transition matrix. To accomplish this we shock the matrix using the stress factor. This stress factor is a multiplication factor for off-diagonal cells. In case of a stress scenario, we add the stress factor

42 multiplied by the cell's standard deviation to a cell's value in the cells to the right of the diagonal. This increases the probability of migrating from a relatively good rating to a worse rating. The procedure ensures that all row sums remain equal to 100% and that all values in the matrix are larger or equal to zero.

In order to determine the value of the stress factor we estimate a bankruptcy equation for the Dutch economy. That is, the equation models the average bankruptcy probability of Dutch companies given the state of the economic cycle. Here the bankruptcy probability is calculated by dividing the number of bankruptcies in a specific quarter by the total number of companies (excluding sole proprietors) in the economy. To keep the model parsimonious we only include GDP growth and stock price changes as explanatory variables (which are both significant at the 1% level in all of our regressions). In order to make the model suitable for stress tests both a 'median' (for baseline estimations) and a 'stress' equation are estimated using quantile regression. For the median the 50th percentile is estimated and for the stress equation the 75th percentile. This leads to the following equations:

$$P(\text{bankruptcy})_{\text{median},t} = 0.018 + 0.892 \times \text{default}_{\text{median},t-1} - 0.453 \times \Delta \log(\text{GDP}_{t-1}) - 0.027 \times \left(\frac{1}{2} (\Delta \log(\text{AEX}_{t-1}) + \Delta \log(\text{AEX}_{t-2})) \right)$$

$$P(\text{bankruptcy})_{\text{stress},t} = 0.024 + 0.894 \times \text{default}_{\text{stress},t-1} - 0.580 \times \Delta \log(\text{GDP}_{t-1}) - 0.050 \times \left(\frac{1}{2} (\Delta \log(\text{AEX}_{t-1}) + \Delta \log(\text{AEX}_{t-2})) \right)$$

There are two important differences to point out between the median and the stress equation. First, the constant is higher in the stress equation. Assuming no GDP growth and no change in equity prices, the equilibrium bankruptcy probability is about 30% larger in the stress equation. Second, the coefficients on the economic variables are larger in absolute terms in the stress equation. In fact, the coefficient on equity price changes is about twice as large in the stress equation, suggesting that the bankruptcy rate reacts more strongly to equity prices during a downturn.

We link changes in the macroeconomic bankruptcy probability to changes in the default probability of the transition matrix. We calibrate the stress factor in such a way that the deviation of the loan default probability from its through the cycle mean (as calculated by the transition matrix and appropriate loan weights) equals the percentage difference in the bankruptcy probability from the historical average mean bankruptcy probability in the economy. As a concrete example, suppose the bankruptcy probability is 0.18% and the average bankruptcy probability is 0.15%, then the current bankruptcy probability is 20% higher than its mean. We calibrate the stress factor to ensure that the default probability is also 20% higher than the mean. As another example, if the current bankruptcy probability equals the long-term average, the stress factor equals one. It turns out that we can estimate a linear function to calculate the stress factor for the economically relevant range of values:

$$\varphi = 1.31 \times \text{deviation of the economy's bankruptcy probability from its mean}$$

Finally, to run the model for individual banks it is necessary to map the loan book of individual banks in S&P ratings classes. Banks report their corporate loan book in COREP risk classes. Each of these risk classes contains a through the cycle PD of the loans in this specific risk class. In order to

44 translate the COREP risk classes to S&P rating classes, ranging from the highest rating (AAA) to the lowest rating (CCC/C), for each S&P risk class a lower and upper PD-bound has to be defined. In order to determine these bounds the average probability of default per risk class from 1981-2014 is used. We estimate a model to obtain a mapping between PD and S&P rating to determine lower and upper bounds. So, a loan falls in a certain rating class if its PD is equal to or larger than the lower bound and strictly smaller than the upper bound.

From these calculations, we can define the impact on the pit PD and ttc PD. An important advantage of this approach is that the stress is tailored to the credit quality of the corporate loan book of a bank. The granular approach allows to apply different stress levels on loans with different quality and also to model the migration from good to bad quality loans.

5 Modelling market risk

45

The second relevant risk exposure for banks is market risk. Market risk constitutes the risk of losses due to changes in market prices. This, for instance, includes a fall in equity prices, a change in exchange rates or a move in interest rates which impacts the value of financial instruments and increases their volatility. Banks usually hold financial instruments on their trading books for a short period of time, aiming at selling the instruments at a profit. The trading book consequently includes a variety of instruments, which may include all kinds of options-related products as well as more exotic and complex products. Unexpected value changes imply losses as these trading book securities are valued at market prices. The banking book includes loans and other long-term investments of banks which they intend to keep for a longer period of time. Market risk shocks will also impact the value of the instruments in the banking book. However, the capital impact depends on the accounting treatment of these positions. Assets classified as Available-for-Sale (AFS) are usually valued at market prices. Changes in the value of these assets will be incorporated in capital, possibly subject to regulatory filters. Assets classified as Hold-to-Maturity (HTM) are valued at book prices and will not respond to market price changes.

Most Dutch banks have limited trading book exposures, meaning that market risk is fairly small compared to credit risk. By way of illustration, per end 2015, risk-weighted assets for market risk comprise less than 5% of total risk-weighted assets, whereas credit risk exposures account for 83% of total risk-weighted assets (the remaining 13% are risk weighted assets for operational risk).

For stress testing purposes, a set of specific market risk shocks is specified for market risk exposures. The market risk shocks include shocks on equity prices, interest rates, foreign exchange prices, commodities, etc., and they are directly applied to the market values of the exposures. Losses are accounted for in the P&L, or where applicable in equity.

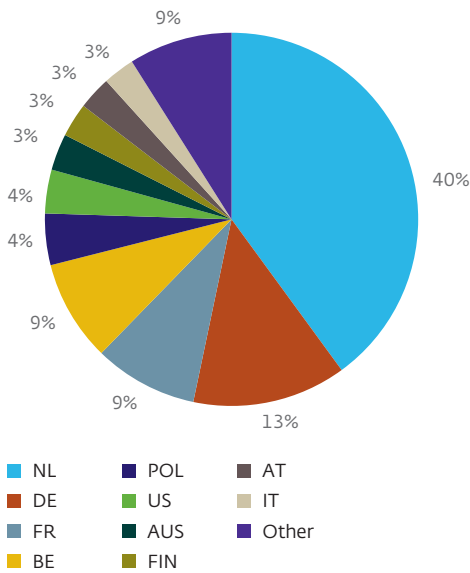
5.1 Government bond haircuts

In the market risk module, exposure to government bonds has been a special focus point due to its size. Like most financial institutions, Dutch banks have considerable government bond portfolios. The sovereign exposures of the banks that participated in the 2016 EBA Stress test exercise totalled EUR 194 billion in end-2015, or 9% of total assets. The largest part of the exposure is accounted for by domestic bonds (40%), government bonds from key countries such as Germany (13%), Belgium (9%) and France (9%) account for the majority of the remainder (see Chart 3).

Sovereign risk weights are generally low, and these exposures account for just 2% of risk-weighted assets. However, Dutch banks have classified a considerable proportion of these exposures classified as Available-for-Sale (AFS) or held for trading purposes, meaning that their value on the bank balance sheet will be impacted directly by market shocks due to accounting regulations. Some other sovereign exposures are classified as Hold-to-Maturity (HTM) and hence valued at book prices due to accounting regulations. These are still exposed to developments in the creditworthiness of the counterparty (i.e. to PD and LGD developments). This means that these sovereign exposures are also subject to the stress scenarios.

For sovereign exposure carried at market prices (those in the trading book and in the AFS portfolio), we shock the current value of sovereign bonds held by banks based on the scenario. This entails a two-step procedure. First, we calculate the haircuts applicable to each possible type of exposure based on the scenario. In the second step, we apply the haircuts based on the scenario shocks to these exposures.

Chart 3 Top 10 sovereign exposures of Dutch banks per end-2015



Source: EBA stress test 2016.

To determine the size of the haircut, we make a satellite calculation in which we value all issued government bonds at a given reference date, using yields of benchmark bonds combined with information from Dealogic on all outstanding bonds.⁷ We then apply the interest rate and prescribed credit risk shocks of the scenario to re-price the government bonds, using a discounted cash flow model. Comparison of the pre-shock and post-shock value of the bonds gives a country- and maturity-specific haircut.

⁷ Dealogic is a database containing information on bonds issued by various parties, including sovereigns

48 To disentangle the impact of credit risk shocks on government bond portfolios, we determine the haircut both excluding and including the credit risk shock. The haircuts as a result of credit spread shocks are applied to the bank's holding of government bonds. The haircuts as a result of the (risk free) interest rate shocks are also applied to the bank's government bond holdings, but the impact is adjusted for the bank's interest rate risk hedging behaviour. We follow standard accounting practices and supervisory rules to reflect the impact of the sovereign haircuts on the profit and loss accounts and capital positions of the banks. That means losses on sovereign exposures in the trading book are deducted from P&L. Losses on sovereign exposures in the AFS portfolio are deducted from capital, subject to regulatory filters. The use of these filters means that any gains or losses on the revaluation of these assets are only partially included in capital. In the coming years, these filters will be phased out gradually.

5.2 Securitisations

Securitisations have become a relevant part of bank balance sheets, which is why they are also included in the stress test framework. Given that securitised exposures are held in the trading book and are generally valued at market prices, market risk shocks are applied to them. This means that we calculate mark-to-market losses given the scenario shocks. For the calculation of risk-weighted assets of securitised exposures, we employ a rating migration approach similar to the EBA stress test methodology. Here, we assume that ratings deteriorate depending on the asset class and initial rating. The stressed risk-weighted assets are then determined based on the new ratings.

6 Modelling interest income and funding risk

The previous sections outlined the approach to estimate credit losses for banks. In general, banks receive operating income that can compensate the incurred losses. However, in a stressed environment, income will generally also be under pressure. For many banks, interest income and interest expenses are the main determinants of operating income. Indeed, for Dutch banks, interest net income (the sum of net interest income and interest expenses) represents over 95% of gross operating income. Not surprisingly, shocks to net interest income are usually a key driver of the final stress test results. This is why we focus our approach on these elements and keep other income elements, such as fee income, stable for simplicity reasons.

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Modelling interest income and expense is a complex exercise. Apart from interest rate trends, net interest income depends on various factors, such as the portfolio composition, the maturity profile, funding sources, pricing policies, hedging, etc. Such price, volume, quality and strategic elements will have different effects on interest income and expense, which in some cases may even counteract each other. Banks predominantly receive interest income from loans or from bond investments. Loans generally have a multi-year maturity. Interest rate trends will only filter through gradually as maturing loans are replaced by new loans against the new interest rates. Interest expense stems from the interest that banks have to pay on their funding, mostly deposits and wholesale funding, which have a shorter maturity than the loan book. Hence, interest rate movements will be quickly reflected in funding costs. As a result, a flattening yield curve will reduce interest rate margins, normally implying lower net interest income. A parallel shift of the curve will usually affect interest rates on short-term liabilities whereas those on the relatively large bucket of existing long-term assets may remain relatively unchanged, also resulting in lower net interest income. Under a static balance sheet assumption, funding risk is also captured by changes in interest expenses. Funding stress may emerge

50 as a sudden change in the interest rates demanded by a bank's creditors to compensate for risk, pushing up expenses and reducing operating income.

For stress testing purposes, we have two separate models available to model net interest income. The first is an econometric model, which projects total net interest income at the level of an individual bank, based on historical relations, mainly with the long- and short-term interest rates. The main advantages of this model are the relatively parsimonious input requirements and its calibration on historical bank microdata.

The second model is a very granular tool that allows us to stress the income and expenses associated with individual asset and liability categories on the banks' balance sheet. For many stress tests, in addition to broad macro-economic scenario assumptions on long term and short-term rates, important additional assumptions are imposed on bank funding costs and its consequences for loan price setting behaviour. The EBA stress test (European Banking Authority, 2016), for instance, assumed that banks would face increased funding costs on liabilities due to a rating downgrade and could only pass on part of the increase in funding costs to their customers. The second interest income model, which is called the funding shock tool, allows for very detailed projections of net interest income to capture the effects of these assumptions, but requires a lot of input information on the exact composition of banks' balance sheets, as well as projections of interest rates for individual asset and liability items. This type of data is not readily available and must be constructed from supervisory data sources, bottom up stress test reporting, and requires a more elaborate scenario with respect to interest rates for different asset and liability categories. Fortunately, especially bottom up stress test reports often contain granular information about the maturity and run-off of different portfolios and segments, as is needed for the funding shock tool.

In practice, we often combine the output of the two models. For instance, we may use the econometric model to project the impact of the baseline scenario on net interest income. After all, under the baseline scenario, income may be expected to move in line with historical patterns. We then use the funding shock tool to calculate the additional impact of funding shocks and pass through constraints under the adverse scenario.

6.1 Econometric estimates of net interest income

Interest income

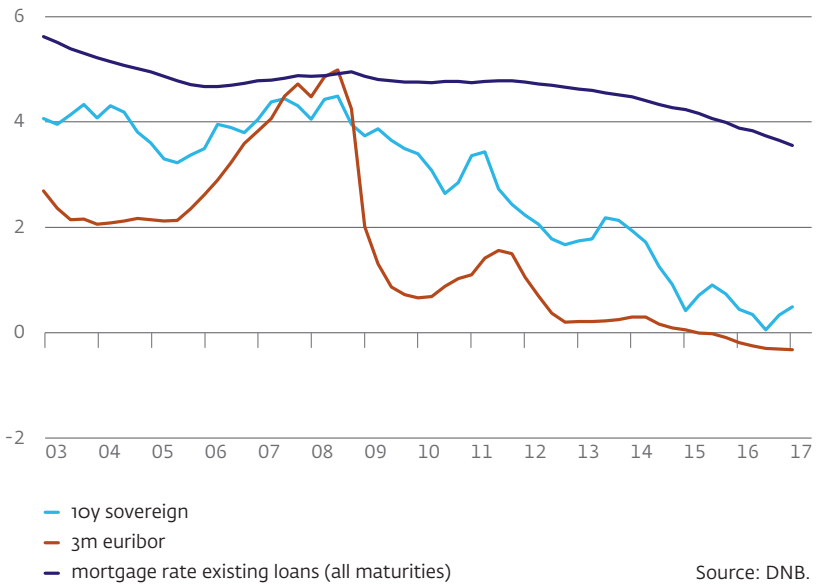
Interest income depends on the level of interest rates as well as on the portfolio composition of a bank. Bank lending portfolios can be broken down into loans to households (mainly mortgage loans), corporate and SME loans, and loans to other financial institutions. All of these loans have different characteristics. Loans to financials and non-financial institutions generally have short-term horizons. As loans to non-financials consist mainly of corporate and SME loans, we have assumed that interest income on these loans is affected only by short-term interest rates. For mortgage loans, we assume that banks can additionally earn an additional premium due to the longer-term nature of these loans. This is reflected in mortgage interest rates, which are usually related to long-term interest rates, although banks may not follow long-term rate exactly due to pricing policies (see Chart 4).

Interest income can be modelled as a function of these elements

$$\frac{II_t}{Assets_{t-1}} = a_1 + \gamma_1^I \left(\frac{LNCl_{t-1} + LCl_{t-1} + LMor_{t-1}}{Assets_{t-1}} \times r_{ST,t-1} \right) + \gamma_2^I \left(\frac{LMor_{t-1}}{Assets_{t-1}} \times (r_{mor,NL,t-1} - r_{ST,t-1}) \right) + \varepsilon_{I,t}$$

where II_t refers to interest income, $LNCl_{t-1}$ are loans to non-credit institutions (i.e. corporates, SMEs), LCl_{t-1} are loans to credit institutions, $LMor_{t-1}$ are

Chart 4 Interest rates in selected markets



mortgage loans, $r_{ST,t-1}$ is the three month-Euribor as a proxy of short-term interest rates, $r_{mor_NL,t-1}$ is the average interest rate on existing Dutch mortgage loans, t represents the time factor and $\varepsilon_{i,t}$ the bank-specific error term. Both interest income and the loan portfolio are scaled with total assets to account for size differences between banks. Finally, α_i represents the individual fixed effect to account for bank-specific characteristics.

The model is calibrated based on data stemming from supervisory reporting (2003Q1-2013Q1) of the largest Dutch banks and public data on interest rates. Model results show a high explanatory power and the explanatory variables are all highly significant (see Table 4).

Table 4 Modelling results for interest income

Variables	Interest income (t)/ Assets (t-1)	
$(LMor_{t-1} / Assets_{t-1}) \times (r_{Mor_NL,t-1} - r_{ST,t-1})$	0.125***	(0.031)
$((LNCl_{t-1} + LCl_{t-1} + LMor_{t-1}) / Assets_{t-1}) \times r_{ST,t-1}$	0.221***	(0.017)
Number of obs	160	
R-squared (adj.)	0.821	

Note: *** significant at 1% level.

Interest expense

Bank interest expenses are defined by the costs of their funding sources. Banks' funding sources mainly consist of deposits from retail and corporate clients and of wholesale loans mostly from other banks. The interest rates that banks pay on both sources will typically follow the short-term interest rates, although the level of the respective rates will differ. For instance, competition considerations may determine the rates banks that pay on their client deposits. Wholesale rates depend on the bargaining power that banks have on the interbank market, which depends on various aspects including solvency and liquidity ratios as well as relationship considerations. Our model takes account of these differences.

$$\frac{IE_t}{Assets_{t-1}} = a_i + \beta_1^{IE} \left(\frac{Cl_{t-1}}{Assets_{t-1}} \times r_{ST,t-1} \right) + \beta_2^{IE} \left(\frac{NCl_{t-1}}{Assets_{t-1}} \times r_{ST,t-1} \right) + \varepsilon_{it}$$

54 IE_t refers to interest expense, CI_{t-1} to funding obtained from credit institutions, NCI_{t-1} are the deposits from non-credit institutions (i.e. retail clients and corporates and SME), $r_{ST,t-1}$ is the three month-Euribor as a proxy of short-term interest rates, t represents the time factor and ε_{it} the bank-specific error term. Both interest expenses and the loan portfolio are scaled by the total assets to account for size differences between banks. This models shows high explanatory power, see Table 5.

Table 5 Modelling results for interest expense

Variables	Interest expense (t)/ Assets (t-1)	
$(CI_{t-1} / Assets_{t-1}) \times r_{ST,t-1}$	0.519***	(0.058)
$(NCI_{t-1} / Assets_{t-1}) \times r_{ST,t-1}$	0.143***	(0.023)
Number of obs	160(4)	
R-squared (adj.)	0.79	

Obviously, the level of interest rates that banks set and pay on their assets and liabilities does not automatically follow from interest rate developments in financial markets. Rather, banks will set lending and deposit interest rates according to their long- and short-term strategy. Hence, they may decide to raise deposit rates above market rates in order to attract liquidity, or to keep loan rates stable even though market rates have risen in order to gain market share. The econometric model focuses on price and quantity effects and leaves strategic or pricing considerations out of scope. The model results show that, historically, market trends are by and large the main drivers of banks' interest income and expense. However, to capture more detailed assumptions on liquidity stress and price setting, as may emerge under adverse scenario, we have developed the second model; the funding shock tool.

6.2 Funding shock tool

The funding shock tool has been developed for the projections of interest income and interest expenses of Dutch banks under detailed stress assumptions for funding costs and price setting. The projections are performed at the portfolio level for every portfolio of assets and liabilities. The model exploits very granular information about the maturity profile and the effective interest rate of every portfolio. In a nutshell, the model projects the interest income (or expenses) by adjusting the effective interest rate of the portfolio according to a prescribed scenario path of the portfolio interest rate series, in line with imposed assumptions on funding costs and their consequences for price setting behaviour.

The projections are based on the following idea. Assume that the bank reports $p=1,2,\dots,P$ portfolios of assets and liabilities. Each portfolio contains $i=1,2,\dots,N$ individual items (these can be loans, deposits, securities etc.) with volumes $V_{i,p}$ and each individual item is priced at an interest rate $r_{i,p,t}$. By definition, the effective interest rate of each portfolio would be the total income (expenses) earned (spent) on the portfolio over the total volume of the portfolio. Therefore,

$$EIR_{p,t} = \frac{\sum_{i=1}^N r_{i,p,t} \times V_{i,p}}{\sum_{i=1}^N V_{i,p}}, \text{ for } p=1,2,\dots,P.$$

According to the static balance sheet assumption, the volumes of the individual portfolio items remain constant over the scenario horizon, since the maturing items are replaced with instruments with the same contractual and risk characteristics. However, the interest rate at which individual items are priced changes according to the scenario. The new interest rate will be lower or higher from the interest rate at which the individual portfolio items were previously priced. This creates a 'price effect' which is reflected in the effective interest rate of the portfolio and ultimately in the interest income (expenses) of the portfolio.

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The idea behind the model is simple and rather mechanical. If we assume that $M \leq N$ items of the portfolio mature, we can use the following formula to adjust the effective interest rate,

$$EIR_{p,t+1} = EIR_{p,t} + \frac{1}{\sum_{i=1}^N V_{i,p}} (s_{1,p,t} s_{2,p,t} \dots s_{M,p,t}) (V_{1,p,t} V_{2,p,t} \dots V_{M,p,t})', \quad p=1, \dots, P$$

where $s_{i,t+1} = r_{i,p,t+1} - r_{i,p,t}$ are the 'repricing shocks' of the individual portfolio items. These shocks are the difference between the new rate of the portfolio item and the rate at which the item was originally priced.

Finally, the interest income $II_{p,t+1}$ (or expense) of a portfolio is calculated by the formula:

$$II_{p,t+1} = EIR_{p,t+1} \times \sum_{i=1}^N V_{i,p}, \quad p=1, 2, \dots, P.$$

According to the above, the income (expenses) of the portfolio will increase (decrease) if the maturing items are priced at a higher (lower) interest rate.

We use figures at the level of portfolios of certain classes of assets and liabilities to determine the maturing volumes and the repricing shocks. The vector of maturing volumes is obtained from a reported maturity profile of the portfolio. The original interest rate of each maturing volume is obtained as the historical value for the rate of new business of the portfolio as many years back as the original maturity of the maturing volume. To make the calculations more granular, we calculate the repricing shocks by using the appropriate point on the interest rate yield curve. Furthermore, no interest income is calculated on defaulted assets.

This approach is extremely granular and has several advantages compared with the econometric model to model stress scenarios that differ clearly from historical patterns. For instance, the funding shock tool is able to capture the effect of a persistently low interest rate regime, or the effect of a sudden spike in the underlying short-term funding rates.⁸ To capture the effect of low interest rates, zero lower bounds may be imposed to deposit items. In general, the model is sensitive to shifts in the slope of the yield curve which are priced in through the calculation of the repricing shocks. Moreover, the approach is sensitive to maturity mismatches between assets and funding sources, while it can also explicitly take into account the hedging behaviour of the bank, provided the volumes and maturity schedule of hedges are available. The latter is achieved by adding the net cash flow from hedges to the net interest income generated by assets and liabilities. The main drawback of the funding shock tool is that it is very data-intensive.

⁸ For the impact of persistently low interest rates on Dutch banks profitability see Chaudron (2016)

7 Modelling the capital ratio

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Capital is the most important balance sheet item available for loss absorption. Within the capital available to a bank, shareholder capital and reserves are the highest quality buffers. These are also known as Common Equity Tier 1 Capital (CET1-capital) or Core Capital. Other capital items include various forms of hybrid debt, which can most likely only be partially used to absorb losses. For this reason, supervisors focus on CET1-capital levels.

The nominal level of capital provides little information about a bank's resilience. Rather, the relative level of capital should be put into perspective. One way of doing this is to compare it against risk-weighted assets. A bank with higher risk-weighted assets runs higher risks, and would therefore need more capital to be able to withstand adverse shocks. The comparison of CET1-capital with risk-weighted assets is the CET1-capital ratio (CET1-capital divided by RWA). Supervisors set strict thresholds to the level of this ratio. For instance, in the recent SSM Comprehensive Assessments, banks were required to hold a CET1-ratio of at least 8% of risk-weighted assets in normal circumstances and 5,5% in stressed circumstances.

Another measure for banks' resilience is the ratio of total capital to the balance sheet total. A bank with a larger balance sheet relative to capital would be more debt-financed, posing larger risks for debtholders. The comparison of capital with the total balance sheet is called the leverage ratio, as it measures how leveraged (financed with debt) an institution is. Regulators have recently added the leverage ratio as a regulatory requirement.

The capital impact of the stress scenario is determined as the sum of income and expenses. The top-down net interest income calculations will define the revenues a bank may expect under the scenario assumptions. In addition,

the calculated credit and market losses will increase costs. The total impact on net income will then be the combination of both effects. We assume that the remaining net income will be added (or subtracted in case of negative net income) to the capital level in the form of retained earnings, subject to dividend policies and tax rates.

This means that our top-down model combines all calculations from the different risk modules (credit risk, market risk, funding risk). We aggregate the losses and subtract them from the stressed operating income. After adjusting for tax and dividends (based on past dividend pay-out ratios), we add the stressed net income to the capital base. As net income usually becomes negative under stress, this implies a reduction of capital. In addition, we include the impact from direct capital deductions from the AFS sovereign exposures, adjusted for any applicable regulatory prudential filters.

For the risk base, we add the changes in risk-weighted assets from the different risk modules. For the portfolios and risk types not included in the top-down model, we extrapolate the results from the top-down model to the entire balance sheet. This extrapolation could over or underestimate the total impact as the rest of the portfolios are not modelled due to their limited size and risk level. Combination of the stressed capital and stressed risk-weighted assets results in a stressed capital ratio:

$$\begin{aligned}
 & CET1ratio_t = \\
 & = \frac{CET1capital_{t-1} + (income_{stress,t} - credit\ and\ market\ losses_{stress,t}) - sovereign\ losses_t + tax\ effects_t - dividends_t}{RWA_{t-1} + \Delta(RWA)_t}
 \end{aligned}$$

8 Example

60 To illustrate the functioning of our top-down model, we will present a full calculation. We use the same hypothetical stress scenario as in the 2016 EBA stress test, which covers three years from 2016Q1 to 2018Q4. The stress scenario assumes a sudden reversal of global risk premia, weak bank profitability in a low interest rate environment, increasing concerns on debt sustainability of public and non-public sectors and rising stress in the shadow banking sector. These shocks lead to decline in economic growth, rising unemployment, increasing interest rates and falling asset prices (see Table 6). The baseline scenario assumes 'normal' economic conditions.

Table 6 Hypothetical stress scenario for the Netherlands (selected indicators)

	Baseline scenario			Stress scenario		
	2016	2017	2018	2016	2017	2018
Annual GDP growth	1.0	1.3	1.7	-0.5	-1.5	0.5
Unemployment (ILO-definition)	7.4	7.2	6.8	7.5	8.5	9.6
1-yr Euro swap rates	0.4	0.6	0.7	1.4	1.4	1.4
Long-term interest rates (%)	2.0	2.3	2.4	3.3	3.3	3.4
House prices (%)	-2.1	2.1	5.0	-9.3	-5.9	-2.4
Commercial real estate prices (%)	-2.5	0.5	2.7	-7.1	-5.9	-2.7

Source: EBA 2016 stress test.

The impact of the scenario is calculated for the largest Dutch banks. They represent over 80% of the banking sector. The scenario is applied on end-of-year 2015 data. In addition, we assumed that banks cannot respond to stress by, for example, changing their balance sheet composition (static balance sheet assumption). We did not differentiate between country-

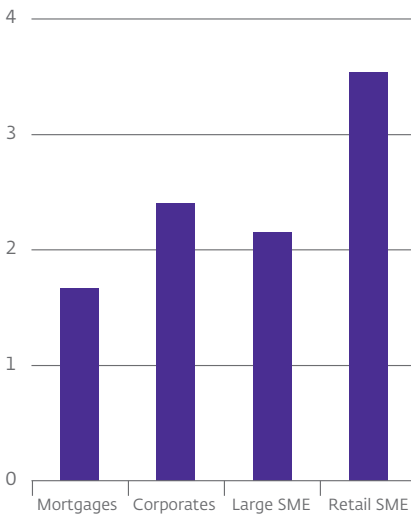
specific shocks, and as the lion's share of Dutch banks' exposures concerns the domestic market, we consider this to be sufficiently representative. Furthermore, banks will be confronted with higher funding costs due to the increased interest rates, but we assume that only part of this increase can be passed on to customers, as prescribed by the EBA Methodology for the 2016 stress test (European Banking Authority, 2016).

Conceptually, the stress scenario will cause the quality of credit portfolios to deteriorate. As corporate and private clients are confronted with increased unemployment rates and subdued economic activity exacerbated by rising interest rates, an increasing number of customers will not be able to repay their loans. In addition, falling house prices will also depress loan quality as properties will be sold below their anticipated selling price. Therefore, PD and LGD parameters are expected to increase during the scenario.

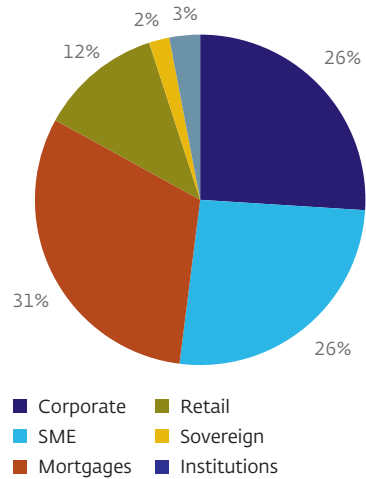
Our top-down model shows that this is indeed the case. As a result of the higher PDs and LGDs, loss rates will rise (see Chart 5a). While for mortgage loans the loss rate becomes 1.5 times larger, for retail SME loans the loss rate more than triples. Overall, credit losses will double compared to the baseline expectations during the scenario horizon (not shown). Most of the losses stem from the mortgage portfolio triggered by rising unemployment, closely followed by losses on the corporate and SME portfolios (see Chart 5b). The impact of the increase in government bond yields is rather limited due to relatively limited open positions, i.e. positions that are not hedged, and thereby banks are less vulnerable for the change in government bond yields.

Chart 5a and b Impact of stress scenario on loss rates (left) and breakdown of credit losses over the scenario horizon (right)

a. Increase in loss rates (wrt end-2015 position)



b. Credit losses over the scenario horizon

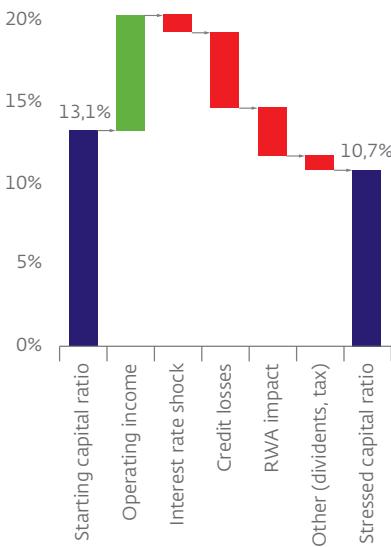


Source: DNB top-down calculations.

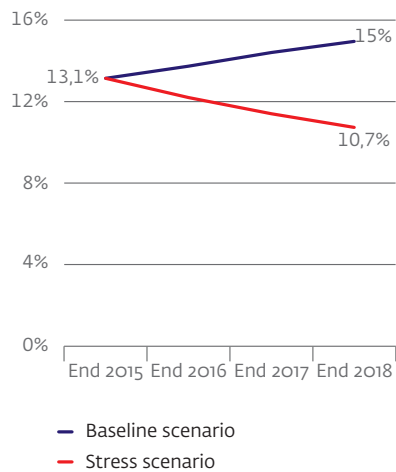
Chart 6a shows the total effects of the baseline and the stress scenario on the different components of a top-down stress test. For each component, the impact of the scenario shocks on the capital ratio is presented, where green bars represent positive effects and red bars negative effects. In addition, the first three red/green bars represent impacts on the level of capital (i.e. the numerator of the capital ratio), whereas the fourth red bar represents the impact on the risk-weighted assets (i.e. the denominator of the capital ratio). The last bar shows the impact of other elements, which

Chart 6a and b Results of the top-down stress test

a. Drivers of the capital ratio in the stress-over the scenario horizon



b. Capital ratio of Dutch banks in top-down stress test



Source: DNB top-down calculations.

are not directly related to the scenario. These items, for instance, represent the impact of taxes (which partially offset losses) and dividend pay-outs.

So starting with a weighted average capital ratio of 13.1%, positive capital impacts stem from operating income before the interest rate shock. This will raise the capital ratio by approximately 7%-points in the stress scenario. The interest rate shock will decrease capital. Also credit losses will depress capital, with a large negative impact on the capital ratio of 4.5%-points.

64 The increase in RWA pushes the capital ratio further down. Other effects have only a minor effect on the capital ratio. The breakdown underlines the sensitivity of the Dutch banks for funding and credit risks, and also points to relatively low RWA-density. In the end, the stress scenario has a substantial impact on the capital ratio. At the end of the three-year stress scenario horizon, the weighted average capital ratio of the banking sector has fallen by 2.4%-points to 10.7%. By contrast, in the baseline scenario, the weighted average capital ratio would increase by 1.9%-points to 15% (Chart 6b).

9 The way forward

Top-down stress testing has become increasingly important in recent years, and further opportunities to use this approach are emerging on the horizon. Since 2014, DNB has been formally mandated to safeguard financial stability. It has also been provided with macro-prudential tools to achieve this goal. These tools include the possibility to set systemic buffer requirements, introduce countercyclical buffers, and to raise risk weights for specific asset classes. Top-down stress testing is a crucial instrument for informing macro-prudential supervisors about the usefulness and impact of the use of these tools.

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Obviously, the introduction of the Banking Union and the Single Supervisory Mechanism (SSM) in Europe, has a direct impact on the way stress testing will be employed at the national level. While bottom-up stress tests for larger banks under SSM supervision will be organised at a European level, financial and economic imbalances and shocks will manifest themselves still predominantly at the national level. National macro-prudential authorities are best positioned to identify such country-specific risks. Hence, national macro-prudential stress testing exercises will remain relevant.

For future development of the Dutch stress test framework, there are two important routes. First of all, the top-down framework can be extended to include liquidity effects, as has been done in some other countries, see for instance Anand, Gauthier, & Souissi (2015) for Canada, Pühr and Schmitz (2014) for Austria, and Bank of England (2013) for the UK. In this way, it will become possible to assess the impact of a stress scenario on both solvency and liquidity standards, providing supervisors with a comprehensive view of the financial position of a bank. A second extension, work on which is currently underway, is to include second-round effects. Second-round effects could occur, for instance, if the stress test results trigger behavioural reactions from stressed banks. For example, banks may decide to reduce

66 lending, change their business model, shift their portfolio mix, or raise additional capital. This will have an impact on the real economy, inducing a new round of effects on banks. Other second-round effects could include the impact of a fall in a bank's solvency levels on its counterparties. Research on this such interlinkages assumes, for instance, that in response to stress, banks may be cut short on the interbank market and have to sell liquid assets to cover funding needs. This may start a fire-sale spiral in which asset prices keep falling, triggering losses at other banks. These interconnectedness risks can be substantial (Alves, et al., 2013).

All in all, top-down stress testing lends itself to many purposes and analyses. It is a valuable tool to inform supervisors and policy makers about the resilience of individual banks and the financial system as a whole.

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Abbreviations

AFS	Available for Sale
AT	Austria
AUS	Australia
BCBS	Basel Committee on Banking Supervision
BE	Belgium
CBS	Centraal Bureau voor de Statistiek
CEBS	Committee of European Banking Supervisors
CEIOPS	Committee of European Insurance and Occupational Pensions Supervisors
CET1	Core Equity Tier 1
COREP	Common Reporting
CRT	Credit Risk Transfer
DE	Germany
DK	Denmark
DNB	De Nederlandsche Bank
EAD	Exposure at Default
EBA	European Banking Authority
ECB	European Central Bank
EIOPA	European Insurance and Occupational Pensions Authority
EL	Expected Losses
ES	Spain
ESRB	European Systemic Risk Board
EU	European Union
EUR	Euro
Fed	Federal Reserve
FIN	Finland
F-IRB	Foundation Internal Ratings Based
FR	France
FSAP	Financial Sector Assessment Program
FSB	Financial Stability Board
FSR	Financial Stability Report

74	GDP	Gross Domestic Product
	HTM	Hold to Maturity
	IE	Ireland
	ILO	International Labor Organization
	IMF	International Monetary Fund
	IPO	Inkomenspanelonderzoek
	IRB	Internal Ratings Based
	IRRBB	Interest Rate Risk in the Banking Book
	IT	Italy
	KMV	Kealhofer, McQuown and Vasicek
	LGD	Loss Given Default
	LTI	Loan to Income
	LTV	Loan to Value
	NL	Netherlands
	P&L	Profit and Loss accounts
	PD	Probability of Default
	pit	Point in Time
	POL	Poland
	RWA	Risk Weighted Assets
	S&P	Standard & Poor's
	SA	Standardized Approach
	SME	Small to Medium Enterprise
	SREP	Supervisory Review and Evaluation Process
	SSM	Single Supervisory Mechanism
	ttc	Through the Cycle
	UK	United Kingdom
	US	United States of America

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