Web-appendix: Modelling the energy transition risk stress test

DeNederlandscheBank

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1 Data

This section provides an overview of the data used in the stress test. Sections 1.1 through 1.3 explain the various ways in which we enriched our dataset to make it fit for our purposes.

Table 1.1 Overview of data sources

Bond and equity holdings	DNB's security holdings statistics for banks, insurers and pension funds. For banks we use the consolidated holdings of ABN AMRO, ING Bank and Rabobank. For insurers and pension funds we perform a one-step "look-through" for holdings in investment funds when the bond and equity allocation of the investment is available.
Corporate loan exposures	Corporate loan exposures of ABN AMRO, ING Bank and Rabobank, acquired through a targeted survey. The exposures in both the internal risk based (IRB) and standardized approach (SA) portfolios are disaggregated by industry. For IRB loans the exposures are further disaggregated by internal risk bucket, probability of default, loss given default and maturity.
Industry classification of bonds	Centralized Securities Database, Thomson Datastream (for details, see Section 1.1.).
Bond ratings	Thomson Datastream, Bloomberg and OpenDataSoft (for details, see Section 1.2)

1.1 Industry classification of stocks and bonds

Our dataset contains information on the bond and equity holdings of banks, insurers and pension funds at the level of individual stocks and bonds. For our stress test, we primarily need the International Security Identifier Number (ISIN) and the NACE code that indicates the economic sector in which the issuing party of a stock or bond is active. Using ISINs, we were able to retrieve NACE codes from the Centralized Securities Database (CSDB) for the majority of the securities in our sample.

The initial assignment of NACE codes to the bond and equity holdings in our sample presented two issues. First, a large amount of securities was classified with NACE code K.64 (finance). Upon closer inspection, however, many of these K.64-classified securities were issued by financing vehicles of firms that are active outside of the financial sector. For example, a bond issued by BMW Finance is marked as K.64 (finance), while for our purposes it would be more appropriate to assign it to C.29 (manufacturing of motor vehicles), i.e. the industry of the parent company. The second issue was that there was still a share of the data for which no NACE code had been identified.

To address these issues we cross-checked the stock and bond holdings against Thomson Datastream ratings database. Industry classifications in NACE, NAICS, GICS, TRBC and SP format were collected for all stocks and bonds in the banks', insurers' and pension funds' portfolios. We used mappings to translate the alternative classification formats to the NACE format at the two-digit level. We then cross-checked our initial NACE classifications against these alternative classifications, adding NACE codes that were initially missing and replacing the NACE codes of securities with code K.64 if one of the five databases had a different industry classification. Overall, the NACE classifications from Thomson Datastream were the most useful for the (re-)classification of stocks, while for bonds both the NACE and SP classifications were fruitful.

By cross-checking the industry classifications we were able to (re-)assign a NACE code to about 8 percent of the total equity holdings and 24 percent of the total bond holdings. Despite the re-/ new assignments, the number of missing industry classifications remains at about a quarter of the total equity portfolio and less than five percent for the bond portfolio measured in terms of market value. Inspection revealed that stocks and

bonds without a NACE code are primarily exposures to investment funds for
which we do not have information on the investment portfolio.

1.2 Obtaining bond ratings

**The bond ratings for the 23,383 unique bonds in our sample were
obtained through a four-step process.** Taken together, these steps allowed
us to assign a rating to about 81 percent of all the unique bonds, which
corresponded to 95 percent of the market value of the bond holdings in our
sample. The process was as follows:

1. First, we obtained rating information from S&P, Moody's, Fitch and
    Dominion using Thomson Datastream, where we used the bond ISINs
    to match each bond with the corresponding rating. As we use the S&P
    rating scale for all bonds, ratings from other rating agencies were mapped
    to this scale. Whenever the rating for a bond varied between rating
    agencies, we used the lowest rating. This approach is in line with the
    purpose of the stress test, which is to consider worst-case scenarios, and
    partially hedges against the potential incentive of rating agencies to bias
    ratings upwards. With this first step, 69 percent of the total number of
    bonds could be assigned a rating.
2. For the bonds that could not be assigned a rating in the first step, we
    collected rating information from S&P, Moody's, Fitch and Dominion using
    Bloomberg. We then assigned ratings in the same way as in the first step.
    This step allowed us to assign a rating to an additional 9 percent of bonds.
3. For the bonds that could not be assigned a rating in steps one and two,
    we consulted the freely available online database OpenDataSoft. This
    database acquires rating information on the basis of the U.S. regulation
    that obligates rating agencies to publish their rating assignments (SEC
    Regulation 17g-7). As only Fitch, Dominion, Japan Credit Agency LTD and
    A.M. Best use an ISIN code as identifier in this database, we could only
    collect information from these rating agencies. This step allowed us to
    assign a rating to an additional 2 percent of bonds.

4. As a final step, we performed an issuer name matching for sovereigns. When the database contains no rating for a specific bond, but when the issuing sovereign is known, we assign the rating of the issuing sovereign to this bond. We obtained issuer information from the ESCB's Centralized Securities Database. This step allowed us to assign a rating to an additional 1 percent of bonds.

In order to assign a risk class to the remaining bonds we took a closer look at the characteristics of these bonds. It turned out that the majority of bonds without a rating consisted of junior tranches from Mortgage Backed Securities (MBS) for which no rating is available. We made the simplifying assumption that all bonds to which no rating could be assigned, have rating B. This assumption reflects that, on the one hand, junior tranches of MBSs are relatively risky, while on the other hand, Dutch mortgages are overall (historically) relatively safe investments.

1.3 Obtaining bond durations

The duration of a bond captures the bond's sensitivity to interest rate changes. To calculate the price impact due to changes in interest rates, we simply multiply the change in the interest rate by the duration of the bond. Our measure for duration is the widely used Macaulay duration.[1] In order to calculate the Macaulay duration we first calculate the present value of a future cash flow i of a bond (PV_i):

$$PV_i = \frac{CF_{i,t}}{(1+r)^t}$$

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[1] See e.g. Ross, S.A., Westerfield, R.A. and Jaffe, J. (2002). *Corporate Finance* (Sixth Edition). New York: McGraw-Hill, pp. 716-718.

where $CF_{i,t}$ is the cash flow (coupon or principal) at time t and r is the relevant discount rate for the specific bond. Given a certain maturity date of the bond (N), we can then calculate the Macaulay duration as:

$$Duration = \frac{\sum_{i=1}^{N} t_i * PV_i}{\sum_{i=1}^{N} PV_i}$$

where PV_i is the present value of cash flow i that occurs at time period t. We define the duration of a zero coupon bond to be equal to its residual maturity. We further assume that the duration of a floating rate bond is equal to zero, as the floating rate coupon is generally based on the interest rate that prevails at the moment that the coupon needs to be paid. Lastly, we make the simplifying assumption that all bonds are bullet bonds, with the exception of perpetuals. While the vast majority of bonds in the sample are indeed bullet bonds, this assumption may lead to a slight overestimation of the duration of bonds that have a prepayment option.

To calculate the duration of bonds with a very long term, or bonds for which information on coupon payments was missing, we made some additional assumptions. In order to calculate the duration of perpetuals we project cash flows up to sixty years in the future (more distant payments will only have a minor impact on the duration). Bonds for which information on coupon payments is missing are treated as zero-coupon bonds, such that the calculated duration is an upper bound.

2 Macroeconomic modelling approach

The macroeconomic simulation of the stress test scenarios was conducted using NiGEM version V1.18-b. Section 2.1 describes which model changes were made to make the model suited to our particular scenarios. Section 2.2 discusses which shocks were applied to the variables in NiGEM.

2.1 Adjustments to the model

Since NiGEM does not include a renewable energy sector, we had to make several model changes to accommodate the technological breakthrough in the technology shock and double shock scenarios. Specifically, we changed the role of fossil fuel energy in the production function and the energy intensity functions. Below we describe the changes for the Dutch economy, but we apply the same changes to all other countries.

As a first step, we adjusted the production function to reflect that in the technology shock scenario, energy is increasingly produced from renewable sources. Consider the production function in NiGEM, which is based on capital (DNLCAP), labor (DNLLAB) and energy (NLOIVOL*NLY):

NLYCAP = nlgamma*((((DNLCAP+DNLLAB)**(1./(-nlrho)))**(1.-nlalpha))* ((wdgreen*NLOIVOL*NLY)**nlalpha)),

where NLYCAP represents trend output for capacity utilization, NLOIVOL represents the volume of fossil fuels used in production and NLY is real output. Nlgamma, nlrho and nlalpha are parameters. The parameter wdgreen is not normally part of the production function, but was introduced by us to capture the energy efficiency gains that result from the technological breakthrough in the technology shock and double shock scenarios. When wdgreen is equal to one, the production function corresponds to the baseline case. The technology shock can then be

modeled by increasing wdgreen to a value larger than one, which implies that agents need less fossil fuels to achieve the same level of output. For example, if wdgreen is 1.25, NLOIVOL can be reduced by 20 percent to achieve the same production level. Note that, depending on the elasticity of substitution nlalpha, an adjustment in wdgreen could lead agents to substitute the capital-labor complement for energy.

To be consistent with the scenario storyline, the adjustment in the production function needs to be complemented by an adjustment in the fossil fuel intensities of output. In the default calibration of NiGEM, a value of wdgreen larger than one makes fossil fuels appear more efficient, which leads to an increase in fossil fuel use. In the scenario storyline, however, fossil fuel use should decrease because fossil fuels are replaced by renewables. To achieve this result, we adjust the fossil fuel intensities of output. First note that, in the expanded energy model, NiGEM contains three fossil fuels (coal, oil and gas), which have the following equations:

Coal: log(NLOIF) = log(NLOIF (-1)) - 0.025*(log(NLOIF (-1)) + 0.0025 + log(WDPF(-1)*NLRX(-1)/ NLCED(-1))) - 0.171057093 - log(wdgreen) + log(wdgreen(-1))

Gas: log(NLOIG) = log(NLOIG(-1)) - 0.025*(log(NLOIG(-1)) + 0.0025 + log(WDPG(-1)*NLRX(-1)/ NLCED(-1))) - 0.09464 - log(wdgreen) + log(wdgreen(-1))

Oil: log(NLOIO) = log(NLOIO(-1)) - 0.025*(log(NLOIO(-1)) + 0.0025 + log(WDPO(-1)*NLRX(-1)/ NLCED(-1))) - 0.07200 - log(wdgreen) + log(wdgreen(-1))

The equations show that the demand for fossil fuels is determined by the consumer price level (NLCED), the real exchange rate (NLRX) and the prices of the fossil fuels (WDPF, WDPG and WDPO). We then added the parameter wdgreen such that the demand for fossil fuels also depends on the efficiency of renewable energy.[2] Together these variables determine total energy use NLOIVOL (fossil energy use proportion of GDP, 2011 prices):

NLOIVOL = DNLOIo / (1000. * dpppnlwd / delrxwd),

d DNLOIo = dwdpobd * (dnloils * dwdpowd * 100. * NLOIO + dnlgass * dwdpgwd * 100. * NLOIG + dnlcols * dwdpfwd * 100. * NLOIF),

where dpppnlwd, delrxwd, dwdpobd, dnloils, dwdpowd, dnlgass, dwdpgwd, dnlcls and dwdpfwd are parameters.

2.2 Shocks by scenario

Policy shock scenario

In the policy shock scenario, the carbon price increases globally by USD 100 per ton of CO_2 emitted, which we translate into price shocks in NiGEM. First, consider that an oil barrel contains 42 gallons of oil. Burning a gallon of crude oil emits 10.3 kg CO_2. Hence, burning a barrel of crude oil emits 432 kg CO_2. A CO_2 price increase of USD 100 per ton would therefore raise the oil price by USD 100*0.432 = USD 43.20. To calculate the price increase for coal and natural gas, we need some additional steps. For coal, we know that 0.21 tons of coal are equivalent to one barrel of oil in terms of energy. Burning a ton of coal coke emits 3,107 kg CO_2 (one short ton emits 2,819 kg and one short ton is about 0.9 metric tons).

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2 Since the equation is dynamic only changes in the log-level of wdgreen are taken into account. Otherwise the equation will become explosive.

Hence, burning a "barrel" of coal emits 653 kg CO_2, which implies a price increase of USD 65.30. Natural gas emits 0.054 kg CO_2 per standard cubic foot (scf). Since 5801 scf are equivalent to one barrel of oil, we can now compute that burning a "barrel equivalent" of gas emits 316 kg CO_2. The price increase for natural gas due to the carbon tax would then be USD 31.60. Thus, we can model this scenario by increasing the NiGEM baseline prices of coal (WDPF), gas (WDPG) and oil (WDPO) by USD 65.20, USD 31.60 and USD 43.20, respectively.

Technology shock scenario

We model the technology shock scenario by applying two shocks in NiGEM: (i) adjusting the production function such that fewer fossil fuels are used to produce a given amount of output, and (ii) increasing the speed of depreciation of fossil fuel intensive fixed capital. Shock (i) is modelled by gradually increasing the parameter wdgreen from 1 to 1.25 during the five year scenario horizon. As a result of this shock, the share of fossil fuels required to produce a given amount of energy falls by 20 percent at the end of the five year horizon. Shock (ii) is modelled by imposing an additional 6 percent of depreciation of the capital stock in the first year, and an additional 4 percent of depreciation of the capital stock in the second year. In total, 10 percent of the current capital stock is written off because of the technological breakthrough.

Double shock scenario

The double shock scenario contains all of the shocks from the policy shock and technology shock scenarios. No additional shocks are applied and no additional assumptions are made about the interaction between the shocks.

Confidence shock scenario

We model the confidence shock scenario by applying three shocks in NiGEM: (i) an increase in the investment premium (IPREM), (ii) an increase in the equity risk premium (PREM), and (iii) confidence shocks which reduce private consumption (C). The investment and equity risk premiums each receive a one percentage point permanent increase. For private consumption, we shock the residual by subtracting -0.25 percentage points from the residual in each quarter. The shocks are applied to all economies globally.

3 Calculation of transition vulnerability factors (TVFs)

We calculate transition vulnerability factors for all scenarios to capture each industry's sensitivity to the scenario developments. We assume that an industry's vulnerability to the energy transition mainly arises from its reliance on fossil fuels and the resulting CO_2 emissions. Therefore, we use industry specific risk factors that capture an industry's reliance on CO_2 emissions, relative to the economy as a whole. These risk factors, or TVFs, should be interpreted as capturing the relative riskiness of an industry to the shocks in a particular energy transition scenario. The transport industry, for example, depends relatively heavily on the use of fossil fuels and therefore emits a lot of CO_2 relative to its value added. As a result, the transport industry has a high TVF. To make the calculations we used emissions and value added data from EXIOBASE 2015 and followed NACE 2.2 industry classifications.

The TVFs are calculated taking the policy shock scenario as a starting point. In the policy shock scenario, government policies jointly lead to an increase of the effective carbon price by USD 100 per ton of CO_2 emitted. To construct the corresponding TVFs, we make the simplifying assumption that the costs of the carbon price are fully passed on by intermediate good producers to final good producers. Hence, the carbon price affects an industry proportionally to the amount of CO_2 emitted in the total supply chain for its final goods and services.

Illustrative example

To illustrate our approach, we provide the example of a stylized input-output table for the production of apple syrup (Table 3.1, numbers are fictional). The table contains an agricultural sector ("Agri") and a food production sector ("Food"). The column "Total production" displays the total value of the production of each industry. The column Agri shows that the agricultural sector does not buy any inputs from other industries, while

the column Food shows that the food production sector buys inputs from the agricultural sector and from firms within the food production sector.[3] The column Consumption shows the value of the final goods and services delivered to consumers. The row Value added displays each industry's total value added (total production value minus the value of inputs used). The two rows below the input-output table display the amount of CO_2 emitted (in tons) and the resulting TVF for both industries.

Table 3.1 Stylized input-output table for apple syrup and CO_2 emissions

	Agri	Food	Consumption	Total production
Agri	0	50	50	100
Food	0	50	100	150
Value added	100	50		
CO_2 (tons)	80	40		
TVF	0.67	2.67		

Using the input-output table and the emissions data, the TVFs are calculated as follows. Consider the food production sector: first, we determine how many of each industry's emissions should be attributed to the food production sector's final goods. Thus, we assign a share of the total emissions of the agricultural sector (80 tons) to the final goods of the food production sector:

$$\frac{CO2_{Agri} \times VA_{Food}}{VA_{Agri}} = \frac{80 \times 50}{100} = 40 \; tons$$

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3   This can arise if one company in the food industry supplies inputs to another company in the food industry.

Similarly, we assign a share of the total emissions of the food production sector (40 tons) to that industry's final goods: (40 x 50) / 50 = 40 tons. The total amount of emissions associated with the production of final goods for the food production sector is therefore 40 + 40 = 80 tons of CO_2. This is because the Agricultural sector needs to emit 40 tons of CO_2 to produce the inputs of the Food industry. The amount of embodied emissions per unit of value added then equals:

$$\frac{CO2_{Total\ assigned\ to\ Food}}{VA_{Food}} = \frac{80}{50} = 1.6$$

To calculate the TVF, we scale the embodied emissions per unit of value added by dividing it by the total embodied emissions of the economy, i.e.:

$$TVF_{Food} = \frac{CO2_{Total\ assigned\ to\ Food}/VA_{Food}}{CO2_{Total}/VA_{Total}} = \frac{1.6}{120/200} \approx 2.67$$

The above example is simplified and only considers a closed economy. In the actual calculations we also take the CO_2 emissions from foreign suppliers into account when calculating the TVFs, and all deliveries to foreign industries and consumers are taken into account as well.

Implication of chosen approach

Note that this methodology ensures that the weighted average TVF for the global economy is equal to 1. The weights are here given by the relative share of the value added of each industry.

We assume that the industry-specific TVFs are identical across countries. While this is a simplifying assumption, calculating TVFs at the country level could also lead to noisier estimates when industries are relatively small within certain countries. Country-specific TVFs may furthermore be less reliable for multinational companies, which typically dominate the portfolios of institutional investors.

Our approach to calculating TVFs has several advantages. First, this approach effectively punishes final goods and services which require a lot of CO_2 emissions to be produced. Not only direct emissions are taken into account, but also emissions by firms upstream in the value chain. Second, calculations with the input-output table and CO_2 emissions to obtain embodied CO_2 emissions in final products are well established in the literature.[4] Third, the calculation of the TVFs is straightforward and transparent.

One consequence of the suggested approach is that industries that do not emit a lot of CO_2 directly, but use inputs from industries with many emissions appear more carbon intensive. This is a conscious choice because we want to take emissions in the entire production process into account. A possible disadvantage of this approach is that it considers only the amount of CO_2 emitted in the production of final goods and services and not the CO_2 emitted when consumers use the final good. Put differently, this methodology takes all emissions from producing a car into account, but not the emissions from using the car. This latter shortcoming can potentially

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4   For an overview of methodologies for calculating embodied CO_2 emissions, see e.g., Wiebe, K. and Yamano, N. (2016), Estimating CO_2 Emissions Embodied in Final Demand and Trade Using the OECD ICIO 2015: Methodology and Results, OECD Science, Technology and Industry Working Papers, 2016/05, OECD Publishing, Paris, as well as Owen, A. (2017), *Techniques for Evaluating the Differences in Multiregional Input-Output Databases, A Comparative Evaluation of CO_2 Consumption-Based Accounts, Calculated Using Eora, GTAP and WIOD*, Springer International Publishing AG.

be addressed by extending the TVF calculation to include data on CO_2
emissions during the use phase of products. At this stage such data is not at
our disposal.

### TVFs for the technology shock scenario

**We adapt the TVFs for the technology shock scenario which assumes
a technological breakthrough in electricity production, storage and
smart grids.** The technology shock leads to a scenario in which the
transition risks are more concentrated in a select group of industries.
As electricity can in this scenario be produced to a larger extent by more
climate friendly technologies, we assume that firms that use electricity
benefit, while those relying on fossil fuels cannot switch easily and end up
with stranded assets. To model this, we remove all CO_2 emissions from the
electricity producing industry and redistribute them across the industries
that are expected to be hit particularly hard as a result of the reduced
demand for fossil fuels. These industries are Mining and quarrying, Utilities
(i.e. electricity, gas, steam and air conditioning supply) and Manufacture
of coke and refined petroleum products. The distribution of the additional
CO_2 emissions across these industries is ½, ¼, and ¼, respectively. After the
redistribution of CO_2 emission the TVFs are calculated in the same way as
before.

**Figure 3.1 illustrates how the technology shock scenario TVFs differ from
the policy shock scenario TVFs.** The additional emissions that we assign
to the Mining and quarrying industry and Manufacture of coke and refined
petroleum products industry have a significant impact on the TVFs for these
sectors. The TVFs for the other industries, on the other hand, are highly
correlated between the two scenarios (dashed line in Figure 3.1).
The solid line in Figure 3.1 reflects the 45 degree and makes it easier to
see how the TVFs per scenario differ from each other. As the Mining

and quarrying industry and Manufacture of coke and refined petroleum products industry have larger TVFs in this scenario, all other TVFs are pushed downward somewhat to ensure that the TVFs average out to 1.

Figure 3.1 TVFs policy shock and technology shock
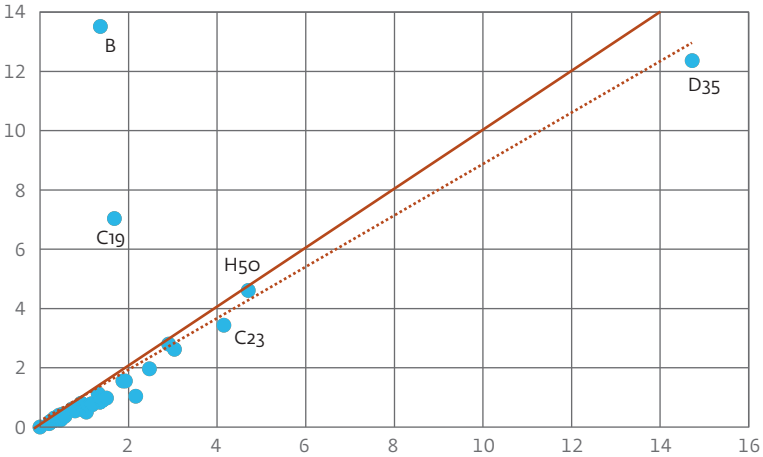
Notes: B = Mining and quarrying, C19= Manufacture of coke and refined petroleum products, C23 = Manufacture of other non-metallic mineral products, D35 = Electricity, gas, steam and air conditioning supply and H50 = Water transport.

TVFs for the double shock scenario

The double shock scenario used the same TVFs as the technology shock scenario. In the double shock scenario, the technological breakthrough will again concentrate losses to the industries that have difficulty switching to electricity.

TVFs for the confidence shock scenario

In the confidence shock scenario firms are not affected by their exposure to CO_2 emissions. Therefore, we assume that in this scenario, all assets follow the aggregate returns that follow from the macroeconomic simulation.

4 Calculating changes in the credit risk spread for bonds

To calculate changes in the credit risk spread of bonds we build on the corporate credit risk module in DNB's top down stress test model for the banking sector, with some modifications. To explain the approach, we first provide a brief overview of the corporate credit module in Cassandra.[5]

4.1 Cassandra's corporate credit module

In a nutshell, the corporate credit module in Cassandra exploits credit rating information to estimate the probability of default of a loan under stressed conditions. When applying the module to bank loans, the first step is to assign credit ratings to the banks' loan portfolio. As we already obtained credit ratings for the bonds in our sample (see Section 1.2), however, we can skip this step.

Once credit ratings are known, the Cassandra corporate credit module can estimate how the probability of default of a bond would change under stressed conditions. As a starting point, the module uses a rating transition matrix (available from rating agencies), which contains the probability that a bond will transition to a higher/ lower rating during the course of a year, including the probability that a bond will transition into default. In a stress scenario, the probability of default increases. To calculate the probability of default in times of stress the module uses a stress factor, which is calculated on the basis of macroeconomic inputs (GDP and aggregate stock prices). The calculation is calibrated on the basis of historical data for the Netherlands.

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5 Details on the top-down model are given in Daniëls, T., Duijm, P., Liedorp, F. and Mokas, D. (2017), A top-down stress testing framework for the Dutch banking sector, DNB Occasional Studies 2017 No. 3.

4.2 Adapting the module for corporate bond exposures

Using scenario- and industry-specific stress factors, Cassandra's corporate credit module calculates a new probability of default for each bond. As NiGEM provides us with GDP growth and aggregate stock prices, it is possible to calculate a stress factor for each scenario. Moreover, stock prices can be multiplied with the transition vulnerability factors for each industry, such that we get an industry-specific stress factor.

By calculating a new probability of default for each bond, we can calculate the change in credit spread as the difference between the new and old probability of default. The credit spread of a zero coupon bond with a residual maturity of one year is equal to the probability of default for that year, assuming 100 percent loss given default.[6] The change in credit spread is therefore given by the difference between the new and old probability of default.[7] When the residual maturity is longer than one year, the cumulative change in the probability of default can be calculated according to the following formula:

$$Cumulative\ \Delta PD \ = \ \sum_{t=1}^{T}(1 - \Delta PD_{t-1})^{t-1} \times \Delta PD_t,$$

where ΔPD_t stands for the difference between the new and old probability of default in year t, and T is the residual maturity (rounded up to whole years). As we consider a five-year period for the stress test, we assume that default probabilities return to normal after five years, i.e. $\Delta PD_t = 0$ for $t > 5$.

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6 Note that, for bank loans, we are able to use loss given default rates at the industry level, as reported to us through the targeted survey to banks. When applying the corporate credit module in the top down module to bank loans, we shock the loss given default with the TVFs to create scenario-specific loss given defaults at the industry level. This reflects that changes in collateral values will differ across industries.

7 For example, if PD_{old} = 3.00 percent and PD_{new} = 5.50 percent, the credit spread increases with 550 – 300 = 250 bp.

As a final step, we translate the change in credit spread to a change in the value of each bond:

$$V_{New} = V_{Old} \times (1 - Cumulative\ \Delta PD)$$

Note that, in order to not overcomplicate the calculation, we ignore the coupon payments of the bonds.

To reflect that industries which suffer very large equity losses also suffer a large deterioration in credit quality, we make the additional step of linking industry specific stock returns to credit rating downgrades. Specifically, a bond whose issuer is in industry i receives a one notch downgrade (e.g. from A- to BBB+) if industry i's stock price decreases by more than 20 percent. In case the stock price decreases by more than 30 percent the rating downgrade is two notches, by more than 40 percent three notches, etc. Consequently, a rating downgrade will further increase the change in the credit risk spread in the corporate credit module.