Flood risk and financial stability: Evidence from a stress test for the Netherlands*

Francesco Caloia
De Nederlandsche Bank, VU Amsterdam

David-Jan Jansen[a]
De Nederlandsche Bank, VU Amsterdam

November 2, 2021

Abstract

If climate change continues unabated, extreme weather events are expected to occur more frequently. Rising flood incidence will especially affect low-lying countries, both through property damage and macro-financial adversity. Using a stress test framework and geocoded data on real-estate exposures for Dutch banks, we study when floods would start impairing financial stability. We find that the banking sector is capitalised sufficiently to withstand floods in unprotected areas, where there is relatively little real estate. However, capital depletions would increase quickly in case more severe floods hit the densely-populated western part of the Netherlands. These findings have possible implications for various policy areas, including macroprudential policy.

JEL codes: G21, Q54, R30

Keywords: financial stability, flood risk, real estate, stress test

* *Acknowledgements:* We received helpful comments at a DNB research seminar, a Eurosystem workshop on Climate Change Analytics, and during discussions with Maarten Bosker, Wouter Botzen, Ferdinand Diermanse, Hans de Moel, and Kymo Slager. We also thank our colleagues at de Nederlandsche Bank for helpful feedback. We especially thank Merel Vrolijk for contributions during the initial phase of this project. We also thank Jack Bekooij for data support. Naturally, any errors and omissions remain our own responsibility. Views expressed in this paper do not necessarily coincide with those of de Nederlandsche Bank or the Eurosystem.

[a]Corresponding author; E-mail: d.jansen@dnb.nl.

1 INTRODUCTION

This paper studies conditions under which floods become a financial stability concern. Climate change implies slow shifts in the weather distribution (Auffhammer, 2018). Such shifts would mean that extreme weather events occur more frequently. The historical record already indicates that floods can cause economic damage.[1] Examples include the 2005 floods in New Orleans after hurricane Katrina, the U.K. winter floods of 2013-14, and the 2021 floods in several European countries. Should climate change continue unabated, at some point the macrofinancial impact of frequent floods may become so material, that financial stability will be impaired. It is important — for policymakers and practitioners alike — to understand how and when floods could become a systemic-risk concern.

The notion that climate change can imply a financial stability risk is no longer new. In a well-known speech, Mark Carney (2015) was one of the first to argue this point. Likewise, the European Systemic Risk Board (ESRB, 2016) has argued that a delay in the energy transition could affect systemic risk via three main channels, one of which is a rise in the incidence of natural catastrophes. The Network for Greening the Financial System (NGFS, 2019) has emphasized that climate change could have much larger impacts than other sources of structural change affecting the financial system, necessitating the integration of climate-related risks in financial stability monitoring. Bolton et al. (2020) have suggested that climate change could lead to so-called 'green-swan' risks and, therefore, even be the cause of the next systemic financial crisis. These examples are, by no means, exhaustive, with other contributions in this policy debate including ECB (2019), Lane (2019), and Georgieva (2021).

To incorporate climate-change-related concerns in financial stability monitoring, an important step is risk quantification. Quantification is crucial for

[1] See also Dell et al. (2014) for an overview of how weather impacts the economy.

financial firms to manage properly climate-related financial risks, while it also allows supervisors and regulators to assess whether financial firms are in control. To some extent, quantifying how climate change feeds into financial risks is still a challenging task. As summarized by Bolton et al. (2020), climate-financial risks are characterized by deep uncertainty, potential nonlinearities, and most likely fat-tailed distributions.

Still, progress on risk quantification is being made, for instance in the form of climate stress tests. Stress testing is an approach that is often employed to identify tail-risk vulnerabilities. To identify tail risks, stress testing uses macrofinancial assumptions that are severe, but still plausible (Basel Committee on Banking Supervision, 2018). A well-known example of a climate stress test is that by Battiston et al. (2017), who use data on over EUR 1 trillion of equity holdings of the largest 50 European banks. They find that, while direct equity exposures to fossil fuels are small, the overall exposures to climate-policy relevant sectors are both large and heterogeneous. In a stress test for climate transition risks, Vermeulen et al. (2021) find that the CET1-ratio of Dutch banks could decline by several percentage points in case much more stringent carbon pricing would be implemented. A third example is the climate stress test by the French supervisor ACPR for banks and insurers. This stress test found an overall moderate exposure for French financial institutions so far, but also highlighted how the speed and impact of climate change could well increase severity in the next decades (ACPR, 2021).

To quantify flood-related financial stability risks, we start from a standard approach to financial stress testing, which we then modify to incorporate flood-risk considerations. In building on a standard approach, we follow Vermeulen et al. (2021). Our flood stress framework has three distinctive features.

A first feature of our analysis is its focus on real estate. As the global financial crisis of 2007-08 has underlined, shocks to real-estate exposures can have severe implications for the stability of the financial system. It is not unthinkable that a future real estate shock could be due to climate change. In particular, the property damages related to climate physical risks may be an important tail-risk event impacting the soundness of the financial system.

A second distinctive feature is that we provide a perspective for the banking system as a whole. Although individual banks can focus on their individual exposures — and some are doing so — the macroprudential perspective requires a broader approach. Our analysis offers such an approach using data for ten Dutch banks. To begin with, we use granular data on real-estate exposures to determine sensitivity to flood risk. We combine several data sets to gain insights into the location of individual real-estate objects as well as the loan contracts for which these objects serve as collateral. Coupled with official flood risk maps, we then assess the climate-financial-risk implications of floods at the level of 4-digit postal-code areas. In the overall stress test, we use all available exposures from supervisory data sources in order to also assess the sensitivity to broader macrofinancial adversity. By focusing on the overall exposures of these ten banks, we capture more than 95% of the assets of the Dutch banking sector.

A third distinctive feature is that we run, in essence, a reverse stress test. This approach is in line with our aim to understand *when* floods imply systemic risk. Such an aim implies a willingness to consider truly extreme scenarios or calibrations, even if these would, at present, be characterised by very low levels of probability. We assume, in some scenarios, very strong macrofinancial impacts or extreme levels of flood inundation. To be clear, we are not implying that climate physical risks will already be much more likely or severe in the immediate future. Rather, our use of a reverse test follows from the realization that climate change is surrounded by deep uncertainty. Whether we will indeed more often see extreme weather events is going to depend on the nature of the energy transition. In turn, the progress of the energy transition depends on climate policies, energy technology, and consumer preferences. Though it is possible to model these processes, any projection is surrounded by large degrees of uncertainty, in particular as soon as the projection horizon extends beyond the next few decades.[2]

Turning to results, a first conclusion is that the Dutch banking sector has sufficient capital to withstand scenarios with floods in unprotected areas. In those scenarios, the additional capital depletion lies between 110 and 132 basis points. Such magnitudes are still much smaller than commonly reported for bank stress tests. The intuition is that in those parts of the country, there is relatively little real estate and economic activity. However, capital depletions increase quickly once we start assuming flood stress in protected parts of the country. In particular, a flood with an extreme level of inundation in the populated areas of the western half of the Netherlands would put severe stress on the soundness of the banking system. In that most extreme case, the flood event would mean a decline of the CET1-ratio within one year of well over 700 basis points.

This paper proceeds as follows. Section 2 discusses three strands of related literature, while section 3 outlines our stress test framework. Section 4 describes the data, and section 5 presents results for the stress test. Section 6 places the effects on banks' capital positions in context, while section 7 offers concluding comments.

2 RELATED LITERATURE

The literature often classifies the economic damage of a flood, or natural disasters more generally, as either direct or indirect. The direct impact includes everything related to the physical destruction from the disaster

[2]Examples discussing uncertainty in the context of climate change include Barnett, Brock, and Hansen (2020), ESRB (2016), Lane (2019), and Pindyck (2013).

itself. Property damage is one example; other examples include loss of life and damages to infrastructure. Indirect impacts include all follow-up consequences of the initial destruction, for instance additional disruptions to business processes (Kousky, 2014). As Section 3 will discuss, our stress test considers impacts at two levels: property damages and macrofinancial adversity. Of these, the former are direct effects, while the latter combines direct and indirect effects. In Section 3 we will also discuss how we connect our damage estimates to macrofinancial effects using the macroeconometric model NiGEM.

Below, we first discuss the empirical evidence on the economic impacts of floods. Section 2.1 discusses direct impacts on property values and section 2.2 then turns to broader macrofinancial impacts. The purpose of the discussion is to get a sense what 'severe, but plausible' could mean in the context of a flood-risk stress test. In section 2.3, we discuss recent work (academic as well as policy-oriented) that uses stress testing to study climate-change financial stability risks.

2.1 Estimates of property damages

For our stress test, we are interested in estimates of property damage in the wake of actual floods. As highlighted by Beltrán et al. (2019), this question differs from asking to what extent properties located in a floodplain already trade at different prices. In the former case, the actual risk has materialised, which is the relevant perspective for our stress test. In the latter case, which is the approach most papers seem to take, the point is inferring to what extent flood risk is already priced in. One example of such a study in the Dutch context is Bosker et al. (2019), who find that house prices are on average 1% lower in places at risk of flooding. Based on a meta-analysis for studies focusing on the U.S., Beltrán et al. (2018) suggest a price discount for a location within the 100-year floodplain of 4.6%.[3]

Turning to the empirical literature on actual damages, estimates for value effects range from small (around 4%) to substantial (50% or more). For floods along the Meuse river in the Netherlands in the mid-1990s, Daniel et al. (2009) estimate a price decrease of up to 9%. Atreya and Ferreira (2015) combine a hedonic pricing model with geospatial information to study the 1994 flood in Albany, Georgia. Their estimates for price declines range up to 48%, which is the difference between inundated floodplains properties and non-inundated properties outside the floodplain. Pistrika and Jonkman (2010) assess a database of 95,000 damage estimates for buildings in New Orleans due to flooding after hurricane Katrina. They report an average damage rating of 43.3%. Damage rates of more than 50% are reported for 27.6% of the assessed properties. Two further studies focus on floods in the U.K. Beltrán et al. (2019) use a repeat-sales model to analyse the price path of properties affected by floods between 1995 and 2014. Their estimates for price declines in flooded areas range between 21% (in case of coastal flooding) and 25% (in case of inland flooding). Importantly, these price declines are estimated to be short-lived, as differences are no longer significant after a period of 5 years. Garbarino and Guin (2021) focus on one severe flood event flood in England in 2013-14. They find relatively small price effects related to this flood. Compared to unaffected properties in the same district, properties in affected areas shows decreases in sales prices of, at most, 4.2%.

[3] An actual flood event also increases the salience of the associated risk, which can lead to a higher price discount for non-flooded properties that are located in the floodplain. See, for example, Zhang and Leonard (2019).

2.2 Broader macrofinancial adversity

For the purposes of our stress test, the literature on natural disasters suggests two main points with respect to macrofinancial impacts.[4]

First, the negative effects of natural disasters on economic growth are short-lived. Based on a panel VAR, Raddatz (2007) estimates that in developing countries, a climatic natural disaster leads to a decline in real GDP of 2%. This effect on output has disappeared after five years. Cavallo et al. (2011) analyze a sample of 196 countries between 1970 and 2008. Based on synthetic control methods, they find that only extremely large disasters continue to have a negative effect on output in the long run. Even then, this long-run effect is due to radical political revolutions following the disasters.

A second finding is that effects of most natural disasters are mild, especially in developed countries. Based on growth regressions, Noy (2009) finds a negative relationship between property damage and economic growth. In developing countries, this relationship is much stronger. There, a one standard deviation increase in damages leads to an output decline of 9%. In developed countries, this marginal effect is less than 1%. Focusing on the growth impact of hurricanes in the U.S., Strobl (2011) finds evidence of a growth decline at the county level (of 0.45 percentage points) but no effect on national growth rates.

From the perspective of plausibility, the empirical evidence would suggest to focus the stress test on short-term effects, while also not assuming large growth declines. However, especially with respect to the latter point, it is important to keep in mind that the historical record only offers limited guidance in the context of climate change. Even if the impact of climate physical risk has not been large yet, it may well become much more poignant at some point (Bolton et al., 2019). Also, in line with our notion of doing a reverse stress test, we are open to exploring calibrations that may seem

[4]This section draws on Kousky (2014) and Batten (2018), and references therein.

large in light of the impacts of natural disasters so far.

2.3 Work on climate stress testing

Climate stress testing still is a relatively new field, yet attention is growing fast. The best-known example to date is by Battiston et al. (2017). Using data on over EUR 1 trillion of equity holdings of the largest 50 European banks, they find that while direct equity exposures to fossil fuels are small, the overall exposures to climate-policy relevant sectors are large as well as heterogeneous. Another early contribution was a study by the University of Cambridge Institute for Sustainability Leadership (2015), which combined macroeconomic simulations of energy transition scenarios with industry-specific risk factors to gauge the potential losses for investment portfolios. Studying the Netherlands, Vermeulen et al. (2021) construct four tail-event transition scenarios, which incorporate shocks to climate policy and energy technology. Analysing granular data on EUR 2.3 trillion in assets of more than 80 Dutch financial institutions, Vermeulen et al. (2021) find that financial losses due to credit and market risk could be sizeable, suggesting that climate-transition risks warrant close attention from a financial stability perspective. Using a micro-founded stress test, Faiella et al. (2021) conclude that climate risks in Italy are still limited overall and specific to individual households and firms. Lastly, Jung et al. (2021) propose a new measure (CRISK) which is the expected capital shortfall of a financial institution in a climate stress scenario. This measure indicates a strong rise in climate vulnerabilities for banks in the U.S., U.K., Japan and France in recent years.

Important steps are also being taken in the policy domain. The French ACPR (2021) has conducted a pilot exercise for 9 banking groups and 15 insurance groups under its supervision. The exercise focused on both transition and physical risks. For the moment, the exercise revealed an overall moderate exposure and vulnerability to climate risks. The European Central Bank (ECB) has published an economy-wide stress test, which assesses the resilience of both companies and banks in the euro area to a range of climate scenarios. As discussed by De Guindos (2021), it finds that climate change represents a major source of systemic risk, in particular for banks with exposures concentrated in certain economic sectors or regions. Third, the Bank of England's 2021 Climate Biennial Exploratory Scenario (CBES) will explore the resilience of the U.K. financial system to physical and transition risks. For banks, the CBES will focus on credit risk for the banking book, with a particular focus on risks to large counterparties. For insurers, the CBES focuses on invested assets as well as insurance liabilities.

3 METHODOLOGY

3.1 Framework

Figure 1 shows the structure of our flood stress test. As in the transition stress test of Vermeulen et al. (2021), we build on the standard multi-step approach to financial stress testing, which we then modify to incorporate flood-related considerations. We start with a set of six adverse scenarios, each of which has different calibrations with respect to flood events. In the second step, we map these narratives to economic conditions, in this case damages to property as well as macrofinancial adversity in a broader sense. Based on these economic conditions, we turn to stress test models, which we will use to map out implications for the resilience of banks. We now turn to a detailed description of the scenarios, calibration, and stress test modules. Section 4 will give more details on the data sets.

[INSERT FIGURE 1 AROUND HERE]

3.2 Mapping out flood risk

In terms of narrative, the stress test starts with flood maps provided by the Dutch government. These maps constitute the national implementation of the 2007 E.U. Floods Directive. Among other things, this Directive requires Member States to assess flood risk, map the flood extent, and provide information to the public on the results.[5] In the Dutch case, the research institute Deltares makes these flood risk calculations based on various simulation models (Slager, 2019). For the general public, information on flood risk is available via a dedicated website.[6] After entering the postal code of their current residence, people will get an indication of flood risk, for instance the maximum height the water could reach in the vicinity of their residence in case of a flood. In addition, there is also information on possible implications of a flood, such as the unavailability of gas or electricity. For professionals, a wide range of detailed information (including flood risk maps) is available via the National Informationsystem Water and Floods.[7] In addition, there is specific guidance on running a climate stress test at the local level. For instance, provinces or municipalities can use this guidance to assess physical vulnerabilities to factors such as flood, heat, or drought.[8]

Based on the flood maps, we zoom in on geographical areas within the Netherlands that are designated as having a *potentially significant flood risk* (in Dutch: 'Gebieden met een Potentieel Significant OverstromingsRisico' or GPSOR.) The fact that the risk is 'potentially significant' chimes well

---

[5] For details, see `https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=CELEX:32007L0060`. URL last accessed on 17 June 2021.

[6] `www.overstroomik.nl`. URL last accessed on 17 June 2021.

[7] In Dutch: Landelijk Informatiesysteem Water en Overstromingen (LIWO). See also `https://www.helpdeskwater.nl/onderwerpen/applicaties-modellen/applicaties-per/watermanagement/watermanagement/liwo/`. URL last accessed on 17 June 2021.

[8] For information, see `https://klimaatadaptatienederland.nl/stresstest/bijsluiter/`. URL last accessed on 24 July 2021.

with the standard aim of a financial stress test to consider situations that are ‘severe, but plausible’. Importantly, the designation of GPSOR already indicates a potential loss of life or economic damages of more than 40 million euros.

Table 1 shows two relevant dimension of Dutch flood zones. As described in Slager (2019), the Dutch GPSOR areas are distributed across four catchment areas, i.e. the overall area for which all water drains off into a common outlet. These four catchment areas are those of the following rivers: the Rhine, the Meuse, the Scheldt and the Ems.[9] For each of these four catchment areas, a further distinction is made based on two dimensions: whether or not there is formal protection against water, and whether the water system is primary or regional. All four combinations of these two dimensions are designated by the letters A - D.

[INSERT TABLE 1 AROUND HERE]

Next, we use geodata for the GPSOR classes from a dedicated government website. This dataset indicates, at the level of (x,y)-coordinates, the geographical boundaries of the GPSOR areas.[10] Figure 2 indicates the at-risk parts of the Netherlands that we focus on in this paper. The areas shaded in red indicate those areas that are at risk from flood type A, while the gray areas are at risk from flood type B. As can be seen, most of the areas susceptible to those flood types are in the western part of the Netherlands.

[INSERT FIGURE 2 AROUND HERE]

An important consideration for focusing on flood types A and B is insur-

[9] In Dutch, respectively, de Rijn, Maas, Schelde, and Eems.

[10] See Appendix A for links to the geodata.

ability. In the Dutch context, insurance policies cover some, but not necessarily all types of flood risk. Since 2018, effects of local floods are covered by insurance policies under the so-called 'precipitation clause' (in Dutch: neerslagclausule). These local floods correspond to types C and D. Our current stress test does not focus on these two flood types, as financial consequences would be covered by insurers and not banks.[11] However, coverage against flood risk is mostly excluded for properties located outside of areas protected by dikes (i.e. at risk from flood type A). Insurance policies almost always also do not cover damages in case of failure of a primary defense against the water (i.e. flood type B). In case of a major flood the government could, in principle, offer support under the terms of the Calamities Compensation Act (in Dutch: Wet tegemoetkoming schade bij rampen). However, there is no formal obligation to cover part (let alone all) of the property damage. In that case, the property owners would need to bear the costs. To the extent that financial buffers of households would not be sufficient, it becomes increasingly likely that there would be financial implications for banks. There is already some evidence that Dutch floodplain inhabitants underestimate the maximum expected water level of a flood (Mol et al. 2020). In addition, survey evidence suggests that home-owners in flood-prone areas do not have higher financial buffers (Caloia et al, 2021).

To connect the flood maps with the data on banks' real-estate exposures, we map the flood areas to the level of postal codes at the 4-digit level. Table 2 shows the distribution of postal codes across the 8 GPSORs of type A and B. As the table shows, most of the postal codes at risk lie in the catchment area of the Rhine and are of the type B. With this information in hand, we can connect flood risk to our data on the location of real-estate exposures.

[11]In that case, the insurers most likely would turn to reinsurers. This paper does not cover that particular channel. See also section 3.2 of DNB (2017) for further discussion on insurability of flood risk in the Dutch context.

[INSERT TABLE 2 AROUND HERE]

3.3 Scenario calibrations: floods and damages

For flood types A and B, we consider three levels of water stress. Thus, our stress test has six different calibrations. We start from a low level of water stress, then consider an intermediate level, while also considering an extreme level of stress. In choosing these three levels, we broadly follow available guidance on flood incidence and associated inundation depths provided by a Dutch government expert group (Stuurgroep Water, 2018). The top panel of Table 3 has information on the flood characteristics associated with these stress levels. The inundation depth ranges from 1 meter (in scenarios with low severity) to 5 meters (in the extreme scenarios). Broadly speaking, such events could be expected to occur once in 50 years (low), once in 500 years (intermediate) or less than once every 2000 years (extreme).

[INSERT TABLE 3 AROUND HERE]

It is important to note that our paper looks at scenarios where all areas at risk from either flood type A or B are assumed to be affected simultaneously. We realize this is a strong assumption. But, we would argue it is in line with our aim of doing a reverse stress test. By considering such extremes, our stress test shows what could ultimately be at stake. Naturally, in future work, it will also be informative to consider more isolated floods that could affect individual parts of the Netherlands that are at risk from a particular flood type.

To compute the property damage associated with these six scenarios, we use damage functions provided in the so-called National standard method 2017 (Slager and Wagenaar, 2017). These damage functions take inundation depth as input and generate property damage (in euros) as output. There are separate functions for damage to the property itself and damage to household goods and personal effects. We focus on the damage function for the property itself, as it is the property to which the bank would have recourse in case of default. For our stress test, it is important that the standard method also distinguishes between types of real estate. In this paper, we exploit the granularity of our data sources at the level of 4-digit postal-code areas. Further details on how we use the standard method are in Appendix C. Section 3.5 will discuss how we use the damage estimates to calibrate the relevant parameters in the credit-risk modules.[12]

3.4 Scenario calibrations: macrofinancial

As discussed in Section 2.2, the literature so far has found relatively mild effects of natural disasters. In line with this, recent estimates by a Dutch government expert group also suggest that, in most cases, flood damages would be limited. For instance, in a low-stress flood event of type A, the overall economic damages are estimated to be around EUR 1 billion. However, for flood type B, individual floods could have impacts of up to EUR 25 billion. In the worst-case outcome, up to 250.000 people could be affected by a flood of type B. The sum total of economic damages for flood type B in the most extreme scenario could well be EUR 500 billion or more.[13] The intuition is clear: flood type B affects most of the western half of the Netherlands, where the country's industry, commerce, and people are concentrated.

In the stress test, we will use calibrations for economic growth that start at a one-year decline of 0.5 percentage point (in the low-stress scenario for

[12]DNB (2017) also relied on the National standard method in an exploratory estimation of credit losses. That analysis focused on two specific regions in the Netherlands, namely the Rivierenland region and the Kromme Rijn region.

[13]The numbers in this paragraph are taken from Table 4.2 and Figures 4.7 and 4.8 in Stuurgroep Water (2018).

unprotected areas) and that range up to declines of ten percentage points in the extreme scenario for flood type B. For the low-stress scenarios, these calibrations may be somewhat severe, but that would be in line with our aim of doing a reverse stress test. A growth effect of ten percentage points is larger than usually used in stress tests. Such a strong decline would be in line with the concentration of economic activity in those areas vulnerable to floods of type B.

Following Vermeulen et al. (2021) and recent work by the NGFS, we use the macroeconometric model NiGEM to ensure internal consistency between the GDP shocks and other macrofinancial variables.[14] Vermeulen et al. (2021) used NiGEM to create four consistent scenarios with macrofinancial stress for their energy-transition stress test. The NGFS has used NIGEM to generate calibrations for chronic physical climate risks.[15] For acute physical impacts such as floods, standard calibrations at the country level are not yet readily available. However, the climate version of the NiGEM model offers two routes to calibrating macrofinancial shocks. Appendix C outlines the details on this approach. The additional macrofinancial variables that we use as inputs for the stress test modules are unemployment, funding costs, and stock market returns.[16]

[14] For details on this model, see also `https://nimodel.niesr.ac.uk`.

[15] For further information on the NGFS scenarios, see `https://www.ngfs.net/ngfs-scenarios-portal/`

[16] Our calibration does not incorporate shocks to government credit spreads. As noted in Section 3.2, the government is not formally obliged to provide financial assistance in the aftermath of a flood. Following the approach of a reverse stress test, we do not assume government assistance explicitly. If the government were to step in, this would alleviate the impact on banks via the credit risk channel. However, to the extent that the government credit spread would increase, it could still have an impact via losses on government bonds in banks' portfolios.

3.5 Stress test framework

To analyse the financial implications of the various flood scenarios for banks, we use a top-down stress test framework that is used by de Nederlandsche Bank to support its macro- and microprudential responsibilities.[17] As described in Daniëls et al. (2017), the modules in this framework represent different parts of a bank balance sheet and its profit and loss accounts. In previous work on climate stress, Vermeulen et al (2021) also relied on this model to compute implications of energy-transition scenarios.

As indicated in Figure 3, our flood stress test uses modules for credit risk, market risk, and profitability. We use the basic version of these modules, with one important exception concerning the credit risk module.[18] For the credit risk parameters, we use calibrations that are specific to scenarios and banks. The former, naturally, accounts for the differences in flood severity. The latter takes into account that banks may differ in terms of exposure to flood types, as well as in terms of starting point credit risk. To give an example, if a bank has no collateral that is exposed to floods, the increase in the loss-given-default (LGD) parameter only reflects the evolution of the macrofinancial scenario. Instead, banks with a high share of exposures at risk from floods will observe a high increase in the resulting LGD parameter, too, as a result of the property damage. Banks that are more exposed in the case of floods will likely see a higher increase in the probability of default (PD) too, as some debtors (especially non-financials) will no longer be able to meet their obligation.

In our framework, the increase in credit risk as a consequence of the flood is captured by the PD and LGD parameters, which are estimated by means

[17]In a top-down approach, the central bank or supervisor makes an assessment of the stress impact using its own set of models and data. The alternative is a bottom-up approach, where financial institutions themselves are responsible for making the impact calculations. The EBA banking stress test is one example of a bottom-up approach.

[18]See Appendix D for further details on the modules.

of two satellite modules. The PD module returns default projections based on a combination of three sources of shocks: interest rate risk, business risk and collateral repricing risk. Interest rate risk captures the risk associated to changes in the financing conditions of the debtor. An increase in interest rates translates into an increase in the debt service amount of variable interest rate loans and loans subject to interest rate reset. This leads to an increase in the probability of not being able to meet the outstanding obligation. Business risk captures the risk associated to changes in the economic environment, which leads to a change to the earnings and profitability of households and non-financial corporations, and ultimately to their repayment capacity. Eventually, collateral repricing risk captures the strategic default choice associated to a loss in the value of the real estate securing the loan. In the event of a flood, a substantial damage to the property can make debtors also financially go *underwater*, as the outstanding loan amount may become much higher than the current value of the property. This can ultimately affect their decision to continue to service their loans, especially in the case of limited-liability firms that use the commercial real estate for own business use. The LGD module returns the percentage loss that the bank would incur, after that a debtor defaults on a mortgage and the real estate object used as collateral is been liquidated. In this module, the increase in LGD entirely reflects the damage hitting bank real estate collaterals. It does not depend on the macroeconomic context.

4 DATA DESCRIPTION

To assess implications of flood risk, we make use of several proprietary data sources: supervisory data, loan-level data, and administrative microdata. The analysis covers a sample of ten Dutch banks. Together, these ten banks represent more than 95% of total assets of the Dutch banking sector. We now describe the three data sources in more detail.

Starting with the supervisory data, we rely on the Common (COREP) and Financial (FINREP) Reporting frameworks. The COREP and FINREP formats cover the import important aspects of banks business, such as the balance sheet composition, profitability, capital adequacy, asset quality and funding conditions. The information in these templates is reported at quarterly frequency and at the highest level of consolidation. For the stress test, the starting points for exposures are those for the fourth quarter of 2020.

Second, we use loan-level data that is being collected by de Nederlandsche Bank. This loan-level data covers all residential real estate (RRE) and commercial real estate (CRE) properties that serves as collateral for loans provided by Dutch credit institutions. These two datasets contain detailed information on each counterparty (creditor, debtor, servicer), contract, instrument and protection associated to each residential and commercial real estate loan. The information is available at quarterly frequency and covers both the stock and the flow of new loans granted in each reporting period.

Third, we rely on administrative microdata at the level of the residential and commercial real estate objects from Statistics Netherlands. This administrative data covers all objects registered in the basic registry.[19] This basic registry contains several types of information collected for administrative purposes. To begin with, the registry has information on the tax value of each property. In addition, the data set contains a range of property characteristics, such as floor surface (in m^2), location (down to the neighborhood level) and the type of real estate. We use location to determine the level of flood risk, while we use the other characteristics in the computations for the property damage.

[19]In Dutch: 'Basisregistratie Addressen en Gebouwen'.

5 RESULTS

Figure 3 illustrates our key findings. The figure reports the system-wide effect on banks' capital positions in the six stress scenarios. The vertical axis shows the effect on the CET1-ratio (in basis points). We measure this effect as the difference between the level of the capital ratio in the stress scenario and a baseline projection.[20] The horizontal axis denotes two dimensions: flood types and severity. The first three bars indicate effects in case a flood affects unprotected areas. The second set of three bars shows results when a flood affects areas that are, in principle, protected. For both flood types, we show results for the three levels of waters stress, ranging from 1 meter to up to 5 meters.

[INSERT FIGURE 3 AROUND HERE]

Starting with results for unprotected areas, the effects on bank capital remain limited at all three levels of severity. If we assume a water level of 1 meter, the additional decline in the system-wide CET1-ratio is 110 basis points (Figure 3, most-left bar). Such a decline is certainly not negligible, but it appears small compared to recent outcomes of bank stress tests. When we increase the severity of water stress to an inundation depth of 5 meters, the effect on capital comes in at 132 basis points (third bar from the left). The key intuition here is, of course, that only a fraction of Dutch real estate properties are located in the unprotected areas. Naturally then, the property damages will be small. In addition, there is very little macrofinancial adversity associated with floods of unprotected areas.

However, capital depletions would increase quickly when we turn to scenarios that focus on the densely-populated western part of the Netherlands.

[20] For the baseline, we use the macroeconomic outlook in DNB (2020). This baseline projected a gradual recovery from the covid pandemic in the course of 2021.

A flood resulting in one meter inundation depth implies a capital decline of 307 basis points (Figure 3, fourth bar). An additional two meters of water stress results in a system-wide effect on the CET1-ratio of close to 400 basis points. The extreme level of water stress, i.e. five meters inundation, would lead banks' capital to decline by 712 basis points.

As the flood severity increases, the capital depletion is due increasingly to credit losses and increases in risk exposure amounts. To illustrate this, Figure 4 shows contributions of six factors to changes in the CET1-ratio. The top panel has results for a low-impact flood in unprotected areas; the bottom panel has results for an extreme impact flood in protected areas. In the former case, the banks' operational profits are still sizeable. There is some depletion due to credit losses and increased risk exposure amounts. On the whole, the banks are still able to distribute dividends. In contrast, in the extreme flood case (bottom panel), the operational profits are much lower, and they are already taken up by the credit losses. There is also a strong increase in the risk-exposure amounts, which is due to the much higher level of LGD parameters. On the whole, banks no longer distribute dividends in this stress scenario.

[INSERT FIGURE 4 AROUND HERE]

We close by showing how different components of the scenario calibrations contribute to the capital depletion. Figure 5 shows the contribution of three main scenario components: damages to residential real estate (in red), damages to commercial real estate (in blue), and macrofinancial adversity (in green). The y-axis shows the percentage contribution, while the labels in the bars show the contribution in basis points. The left bar focuses on a low-stress event in unprotected areas; the right bar has results for the most extreme flood of type B. In the former case, most of the capital depletion is due to the macrofinancial shocks, which are associated with a capital effect of 59 basis points. In the latter case, most of the effect is due to the damages to residential real estate, which is associated with a capital effect of 402 basis points. The intuition here is that the property damage has a strong LGD-impact, which leads to a marked increase in risk-weighted assets.

[INSERT FIGURE 5 AROUND HERE]

6 DISCUSSION

We now provide further context to the size of the CET1 impact, in particular focusing on how the more extreme flood scenarios link to systemic risk.

A first point is that, at the very least, declines in the CET1-ratio of more than 700 basis points are not common in stress tests for Dutch banks. In the 2021 EU-wide stress test of the European Banking Authority (EBA), the system-wide CET1 depletion for Dutch banks was 520 basis points, while in 2018 the depletion was 530 basis points. Second, the depletion in the EBA exercise is also due to operational risks, which our flood stress test does not consider separately. The reason we do not consider them is that, at least at the moment, the operational challenges of major floods seem difficult to quantify. Nevertheless, in a qualitative sense, it is not difficult to imagine a major impact of severe floods on business operations of financial institutions. For instance, the headquarters of some of the banks are actually located in areas that are at risk from floods. In addition, the impact on infrastructure would most likely inhibit employees commuting to the office. In contrast to the situation during the covid pandemic, working from home may also be far from trivial, if employees themselves also live in flood-prone areas. Third, in interpreting the numbers for the flood scenarios, it is important to remember that they materialize over a relatively short horizon. In the common set-up of the EBA stress test, banks are assumed to be confronted with macroeconomic adversity over a three-year horizon. In the flood scenarios, all of the impact is already concentrated in the first twelve months after the flood event.

An even broader point is that the assets of insurers and pension funds are also vulnerable to flood events. Increasingly, Dutch insurers and pension funds take up a role in mortgage lending. Similar to banks, this means that these institutions would face increased credit risks in the aftermath of severe floods. Second, the non-banks hold relatively large asset positions in real estate. Through these positions, the damage of major floods would lead to severe mark-to-market losses. By combining different data sources, Caloia et al. (2021) give a first indication of the total exposures at risk for Dutch insurers and pension funds. They estimate that around two-thirds of these institutions' real-estate-related exposures are at risk from flood type B. In total, these at-risk exposures for non-banks are close to EUR 90 billion.

7 CONCLUSIONS

This paper finds that, if climate change were to continue unabated, at some point flood events could have implications for systemic risk. The evidence we present uses a stress test framework that incorporates property damage as well as broader macrofinancial adversity. To quantify the effects, we apply the stress test to geocoded real-estate exposures of Dutch banks. In particular if the densely-populated western regions of the Netherlands were hit by an extremely severe flood, the capital impact for Dutch banks would be sizeable. Our calculations suggest capital impacts of more than 700 basis points over a one-year horizon. Such a major financial impact of floods, together with additional adversity for non-banks, suggest that climate-change physical risks have a potential to affect financial stability in a material way.

Taken at face value, our results are important for various policy areas. First, they obviously underline the importance that the Netherlands has traditionally attached to robust flood defenses. Second, the flood scenarios consider tail-risks, which can be mitigated if the transition to a carbon-neutral economy were to take place in a timely and orderly fashion. The potentially detrimental effects of flood events seem relevant to incorporate in thinking about costs and benefits of various transition paths. Third, the notion that several areas of the Netherlands are particularly at risk, combined with our finding that this risk could affect the banking sector, could have implications for discussions on spatial planning. Lastly, there are potential implications for macroprudential policies. Our stress test points out which locations in the Netherlands are possible pockets of risk from the perspective of financial stability. Admittedly, the scenarios we consider are still very much in the tail of the distribution. However, given the complexities that surround both our modeling efforts as well as the broader discussion on climate change, it seems advisable, at the very least, to start a structured discussion on possible policy reactions sooner rather than later.

One aim of this paper is offering a framework to quantify financial implications of climate-change physical risk in a structured manner. We provide first quantifications using the Netherlands as a case study. In closing, we re-emphasize that our estimates are surrounded by a degree of uncertainty. In future research, it will be interesting to incorporate the uncertainties surrounding our stress test approach in a more structured manner. Also, we note again that this paper takes possible consequences of floods to the very extreme. An interesting route for future work would be exploring the financial impacts of flood at higher levels of granularity (i.e. by moving beyond the 4-digit postal codes) or focusing on individual areas particularly at risk from different flood types.

REFERENCES

ACPR (2021). A first assessment of financial risks stemming from climate change: the main results of the 2020 climate pilot exercise.

Atreya, Ajita, and Susana Ferreira (2015). Seeing is believing? Evidence from property prices in inundated areas. *Risk Analysis* 35(5): 828-848.

Auffhammer, Maximilian (2018). Quantifying Economic Damages from Climate Change. *Journal of Economic Perspective* 32(4): 33-52.

Barnett, Michael, William Brock, and Lars Peter Hansen (2020). Pricing Uncertainty Indiced by Climate Change. *Review of Financial Studies* 33(3): 1024-1066.

Basel Committee on Banking Supervision (2018). Stress testing principles. Available at: `http://www.bis.org/bcbs/publ/d450.htm`.

Batten, Sandra (2018). Climate change and the macro-economy: a critical review. Bank of England Working Paper No. 706.

Battiston, Stefano, Antoine Mandel, Irene Monasterolo, Franziska Schtze, and Gabriele Visentin (2017). A climate stress-test of the financial system. *Nature Climate Change* 7: 283-288.

Beltrán, Allan, David Maddison, and Robert Elliott (2018). Is flood risk capitalised into property vales? *Ecological Economics* 146: 668-685.

Beltrán, Allan, David Maddison, and Robert Elliott (2019). The impact of flooding on property prices: A repeat-sales approach. *Journal of Environmental Economics and Management* 95: 62-86.

Bolton, Patrick, Morgan Després, Luiz Awazu Pereira da Silva, Frédérick Samama, and Romain Svartzman (2020). The green swan: Central banking and financial stability in the age of climate change. Bank for International Settlements.

Bosker, Maarten, Harry Garretsen, Gerard Marlet, and Clemens van Woerkens (2019). Nether Lands: Evidence on the price and perception of rare natural disasters. *Journal of the European Economic Association* 17(2):

413-453.

Caloia, Francesco, David-Jan Jansen, Helga Koo, Remco van der Molen, and Lu Zhang (2021). Climate risk and real-estate financial risk. De Nederlandsche Bank, Financial Stability Review, Fall 2021.

Carney, Mark J. (2015). Breaking the tragedy of the horizon — climate change and financial stability. Speech at Lloyds of London, 29 September 2015.

Cavallo, Eduardo, Sebastian Galiani, Ilan Noy, and Juan Pantano (2011). Catastrophic natural disasters and economic growth. *Review of Economics and Statistics* 95(5): 1549-1561.

Claessens, S., N. Coleman, and M. Donnelly, M. (2018). Low-For-Long interest rates and banks interest margins and profitability: Cross-country evidence. *Journal of Financial Intermediation* 35(A): 1-16.

Daniëls, Tijmen, Patty Duijm, Franka Liedorp, and Dimitris Mokas (2017). A top-down stress testing framework for the Dutch banking sector. *DNB Occasional Studies* No. 17-3.

De Guindos, Luis (2021). Shining a light on climate risks: the ECBs economy-wide climate stress test. Available at `https://www.ecb.europa.eu/press/blog/date/2021/html/ecb.blog210318~3bbc68ffc5.en.html`. URL last accessed on 22 June 2021.

Daniel, Vanessa E., Raymond J.G.M. Florax, and Piet Rietveld (2009). Floods and Residential Property Values: A Hedonic Price Analysis for the Netherlands. *Built Environment* 35(4): 563-576.

De Nederlandsche Bank (2017). Waterproof? An exploration of climate-related risks for the Dutch financial sector.

De Nederlandsche Bank (2020). Economic Developments and Outlook. December 2020.

Dell, Melissa, Benjamin F. Jones, and Benjamin A. Oken (2014). What Do We Learn from the Weather? The New Climate-Economy Literature.

Journal of Economic Literature 52(3): 740 - 798.

European Central Bank (2019). Climate change and financial stability. Special feature in the May 2019 Financial Stability Review.

European Systemic Risk Board (2016). Too late, too sudden: Transition to a low-carbon economy and systemic risk, Reports of the Advisory Scientific Committee. No 6 / February 2016.

Faiella, Ivan, Luciano Lavecchia, Valentina Michelangeli, and Alessandro Mistretta (2021). A micro-founded climate stress test on the financial vulnerability of Italian households and firms. Bank of Italy Occasional Papers No. 639.

Garbarino, Nicola, and Benjamin Guin (2021). High water, no marks? Biased lending after extreme weather. *Journal of Financial Stability*.

Georgieva, Kristalina (2021). The IMF is placing climate change at heart of its work. Remarks by IMF Managing Director at the Climate Adaptation Summit. 25 January 2021.

Gross, Marco, Björn Hilberg, and Cosimo Pancaro (2017). Satellite models for bank interest rates and net interest margins. In: S. Dees et al. (Eds). STAMPe: Stress-Test Analytics for Macroprudential Purposes in the euro area.

Jung, Hyeyoon, Robert Engle, and Richard Berner (2021). Climate stress testing. Federal Reserve Bank of New York Staff Reports No. 977.

Kok, Christoffer, Harun Mirza, and Cosimo Pancaro (2019). Macro stress testing euro area banks fee and commissions. *Journal of International Financial Markets, Institutions and Money* 61: 97-119.

Kousky, Carolyn (2014). Informing climate adaptation: A review of the economic costs of natural disasters. *Energy Economics* 46: 576-592.

Lane, Philip R. (2019). Climate Change and the Irish Financial System. *Economic Letter*, Vol. 2019, No. 1.

Mol, Jantsje M., W.J. Wouter Botzen, Julia E. Blasch, and Hans de

Moel (2020). Insights into Flood Risk Misperceptions of Homeowners in the Dutch River Delta. *Risk Analysis* 40(7): 1450-1468.

Pindyck, Robert S. (2013). Climate Change Policy: What do the Models Tell Us? *Journal of Economic Literature* 51(3): 860-872.

Pistraka, Aimilia and S. N. Jonkman (2010). Damage to residential buildings due to flooding of New Orleans after hurricane Katrina. *Natural Hazards* 54: 413-434.

Raddatz, Claudio (2007). Are external shocks responsible for the instability of output in low-income countries? *Journal of Development Economics* 84: 155-187.

Slager, Kymo (2019). Handboek overstromingsrisico's op de kaart: Over de methode van kaartproductie.

Slager, Kymo, and Dennis Wagenaar (2017). Standaardmethode 2017. Schade en slachtoffers als gevolg van overstromingen.

Stuurgroep Water (2018). Overstromingsrisico's in Nederland.

University of Cambridge Institute for Sustainability Leadership (2015). Unhedgeable risk: How climate change sentiment impacts investment. Cambridge, UK: University of Cambridge Institute for Sustainability Leadership.

Vermeulen, Robert, Edo Schets, Melanie Lohuis, Barbara Kölbl, David-Jan Jansen, and Willem Heeringa (2021). The heat is on: A framework for measuring financial stress under disruptive energy transition scenarios. *Ecological Economics* 190(107205).

Zhang, Lei, and Tammy Leonard (2019). Flood Hazards Impact on Neighborhood House Prices. *Journal of Real Estate Finance and Economics* 58: 656-674.

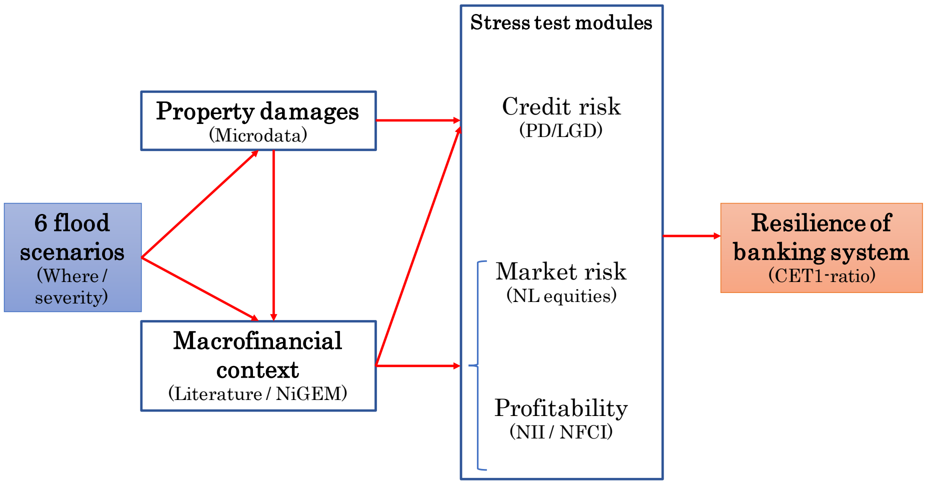


Fig. 1. Studying floods in a top-down stress test framework.

This figure shows the multi-step framework which this paper uses to assess the financial stability implications of floods. We start with a set of 6 flood scenarios that differ in terms of flood types and severity. In the second step, property damages and broader macrofinancial implications are calibrated. The property damages are also input for the calibration of the macrofinancial shocks in NiGEM. In the third step, we use stress test modules to compute implications for credit risk, market risk, and profitability. The overall implications are computed for a sample of ten Dutch banks using a top-down stress test model.

Fig. 2. Flood risk zones in the Netherlands considered in the stress test. This figure shows the areas of the Netherlands which are vulnerable to two main types of flood. The first type would impact unprotected areas (in red), the second flood type would impact protected areas (in light gray) that are mainly located in the western half of the Netherlands.

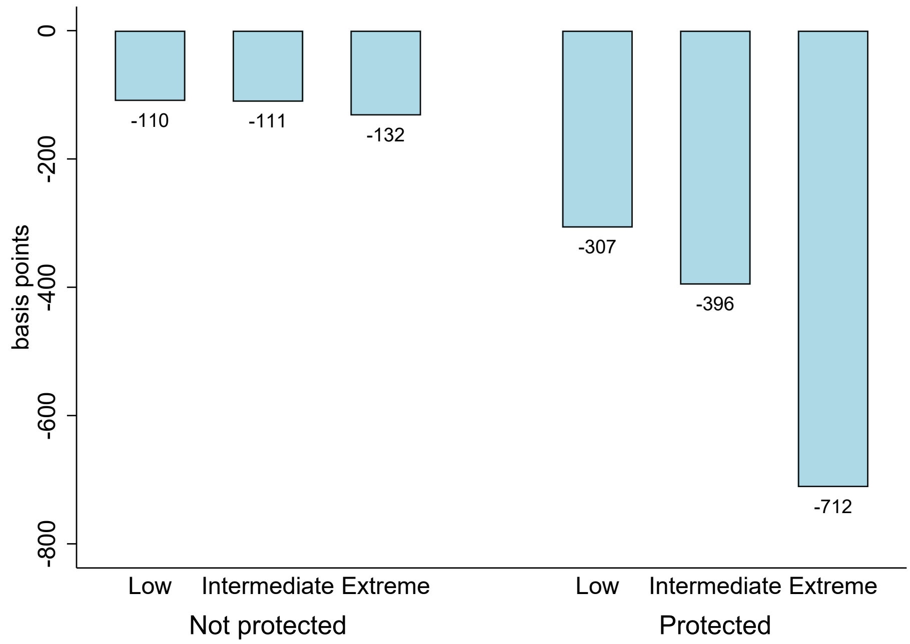
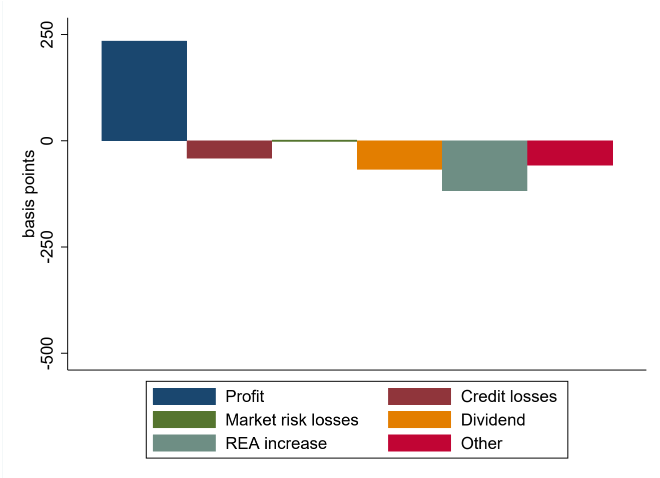


Fig. 3. Capital depletion in six flood scenarios over one-year horizon.
The vertical axis shows the depletion of banks' CET1 capital in basis points. This depletion is defined as the difference between the system-wide capital ratio of banks in the respective stress scenario and the CET1 ratio in a baseline scenario. The stress test horizon is 1 year. The x-axis indicates the level of severity (which ranges from low to extreme) and differentiates between two flood types. The first flood type affects unprotected (yet vulnerable) areas of the Netherlands, the second type affect protected areas. See Table 1 for a taxonomy of flood types. See Table 3 for the shock calibration in these scenarios.

Panel A: Low-impact flood in unprotected areas



Panel B: Extreme impact flood in protected areas

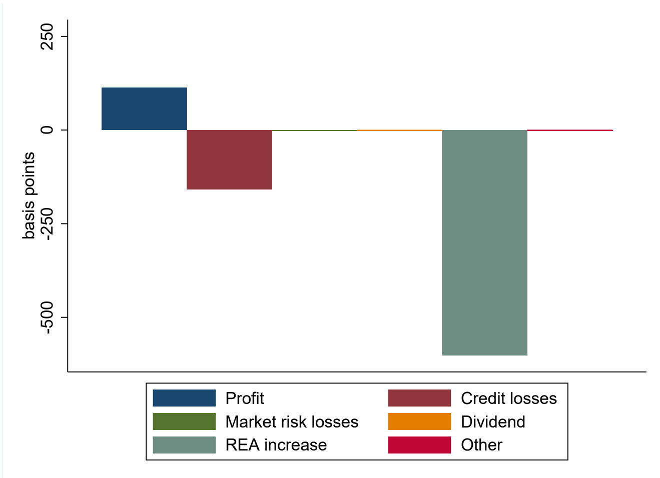


Fig. 4. Contributions to change in capital position in two flood scenarios. The figure shows how six drivers contribute to the change in the CET1-ratio of Dutch banks in two flood stress scenarios. The top panel shows results for a low-impact flood in unprotected areas; the bottom panel has results for an extreme impact flood in protected areas. The six components are bank profits (before credit and market risk losses), credit losses, market risk losses, dividends, the increase in risk exposure amounts, and other factors (including taxes).

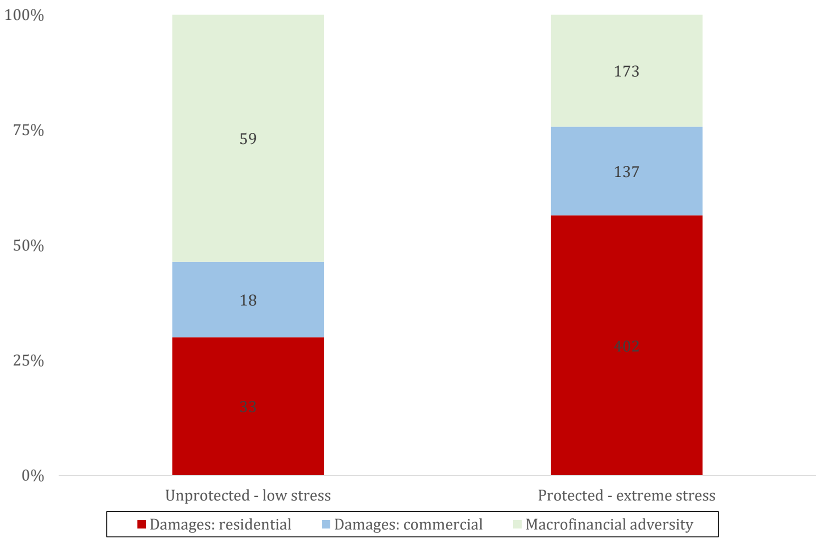


Fig. 5. Decomposition in terms of scenario assumptions.

The figure shows the contributions to the CET1 effect for three components of the flood scenarios. These three elements are damages to residential real estate (in red), damages to commercial real estate (in blue), and macro-financial adversity (in green). The left bar shows a decomposition for a low-impact flood in unprotected areas; the right bar has a decomposition for a high-stress impact in protected areas. The y-axis has the percentage contribution; the labels in the bars indicate the CET1 effect in basis points.

Table 1: Taxonomy of GPSOR classes

This table describes the basic taxonomy for areas with a potentially significant flood risk (in Dutch: GPSOR). The columns indicate whether or not there is protection against water; the rows indicate whether the water system is main or regional. The resulting four classes are indicated by the letters A - D. For details, see Slager (2019).

	Protection against water	
	yes	*no*
Water system		
Main	B	A
Regional	C	D

Table 2: Postal codes and flood types

This table lists the number of postal codes that lie in areas with a 'potentially significant flood risk'. The rows indicate the catchment area (i.e. the main river) and the columns indicate the type of flood (as described in Table 1). The postal codes are at the PC4 level. At this level, the postal codes range from 1000 (Amsterdam region) to 9999 (in the north of the province Groningen). As detailed in Section 3.2, we focus here on floods of type A and B.

	Flood zone type	
	A	*B*
Catchment area		
Rhine	60	2154
Meuse	18	224
Scheldt	3	132
Ems	1	126
Total	82	2636

Table 3: Shock calibrations in stress scenarios

This table reports the calibration for shocks to key variables. These variables cover both flood characteristics (top panel) and the macrofinancial context (bottom panel). We consider three levels of flood severity (low, intermediate, extreme) and differentiate between two flood types (labelled A and B). These two flood types A and B are described in Table 1. Inundation depth is in meters. Incidence is the return frequency in years, i.e. a flood occurs each every x years. All entries for the macrofinancial context are for the Dutch economy. These entries represent deviations from baseline values in percentage points for the year of the flood itself. The range for the GDP shock is based on a literature review. To ensure internal consistency with the other macrofinancial shocks, we use the macroeconometric model NiGEM, as described in Appendix C.

	Flood type					
	A			**B**		
Water stress:	Low	Intermediate	Extreme	Low	Intermediate	Extreme
Flood						
Inundation depth	1	3	5	1	3	5
Incidence (1:x)	50	500	>2000	50	500	>2000
Macrofinancial						
GDP growth	-0.5	-1	-2	-1	-3	-10
Unemployment level	0.2	0.3	0.5	0.25	1	2.5
Funding costs	0.2	0.4	0.5	0.5	1	2
Stock market return	-0.1	-1.25	-2	-1.5	-3.5	-8

Appendix A

URLs for geodata

The underlying geocoded data is available via the following links
(URLs last accessed on 17 June 2021)

Flood types A/B:

`https://geo.rijkswaterstaat.nl/services/ogc/gdr/ror_overstromingsrisico/ows?service=WFS&version=1.1.0&request=GetFeature&typeName=ror_overstromingsrisico_eu2018_v_ab&outputFormat=json`.

Flood types C:

`https://geo.rijkswaterstaat.nl/services/ogc/gdr/ror_overstromingsrisico/ows?service=WFS&version=1.1.0&request=GetFeature&typeName=ror_overstromingsrisico_eu2018_v_c&outputFormat=json`.

Flood types D:

`https://geo.rijkswaterstaat.nl/services/ogc/gdr/ror_overstromingsrisico/ows?service=WFS&version=1.1.0&request=GetFeature&typeName=ror_overstromingsrisico_eu2018_l_d&outputFormat=json`.

Postcal codes:

`https://public.opendatasoft.com/explore/dataset/openpostcodevlakkenpc4/export/`

Appendix B

Estimation of property damage

This appendix describes how we use the National standard method 2017 (Slager and Wagenaar, 2017) to estimate property damage based on the granular data sets for exposures of banks. Table B.1 and B.2 gives an overview of the parameters of the standard method. The first table focuses on residential real estate; the second on commercial real estate.

As the tables indicate, the standard method first specifies the scaling factor that is applied to the damage calculation as a function of inundation depth. Importantly, the damage functions are non-linear: the damage increases non-linearly with the depth of the assumed inundation. Second, the standard method specifies the maximum damage amounts per square meter, for different types of property. For residential real estate, the damage consist of direct damages to the property itself as well as damages to household goods and personal effects. We only focus on the former as, despite the existence of a full recourse system, only the property formally serves as collateral for the mortgage[21]. Once the scaling factors and the maximum damage amounts have been defined, the property damage for the property i of type t in the event of a flooding of depth d is defined as:

$$property\ damage_{i,d,t} = \frac{\theta_{d,t} * maximum\ damage_t * m_i^2}{property\ value_i}$$

Where $\theta_{d,t}$ is the scaling factor associated to a property of type t subject to an inundation of depth d. The property damage is expressed as a percentage

[21]Two further remarks are important. For apartments, damage factors also differ between floor levels. As we cannot distinguish this in our data set, we use the damage factors for the ground floor, which admittedly results in relatively high damage estimates. Also, the damage factors for flood types A are defined for two cases, namely floods occurring every 10 years and floods occurring every 100 years. We use the latter functions in all scenarios.

of the current value of the property.

Table B.1: Details of National standard method 2017 for RRE

This table describes the National standard method 2017 to estimate property damages. This table focuses on residential real estate. The standard method distinguishes between damages to the property itself as well as those of household goods and personal effects. We only focus on the former, as it is the property which serves as collateral for the mortgage. The euro amounts are the maximum damages, either per square meter or property. These amounts are VAT exclusive.

	Flood zone					
		A			**B**	
Inundation depth	1	3	5	1	3	5
Single-family home						
Property damages						
- damage factor	0.05	0.40	1.00	0.05	0.30	1.00
- maximum	EUR 1K per square meter					
Personal effects						
- damage factor	0.50	0.65	1.00	0.50	0.7	1.00
- maximum	EUR 70K per property					
Apartment						
Property damages						
- damage factor	0.50	0.95	1.00	0.50	0.95	1.00
- maximum	EUR 1K per square meter					
Personal effects						
- damage factor	0.00	0.80	1.00	0.50	0.95	1.00
- maximum	EUR 70K per property					

Table B.2: Details of National standard method 2017 for CRE

This table describes the National standard method 2017 to estimate property damages. This table focuses on different types of commercial real estate: meetings, health care, industry, offices, education, sports, and shopping. The maximum amounts are in euro per square meter. These amounts are VAT exclusive.

	Flood zone					
		A			**B**	
Inundation depth	1	3	5	1	3	5
Meeting						
- damage factor	0.60	1.00	1.00	0.60	1.00	1.00
- maximum			EUR 168			
Health care						
- damage factor	0.30	0.55	0.85	0.30	0.55	0.90
- maximum			EUR 1.974			
Industry						
- damage factor	0.40	0.75	1.00	0.40	0.70	1.00
- maximum			EUR 1.497			
Offices						
- damage factor	0.30	0.55	0.85	0.30	0.55	0.90
- maximum			EUR 1.283			
Education						
- damage factor	0.30	0.55	0.85	0.30	0.55	0.90
- maximum			EUR 993			
Sports						
- damage factor	0.40	0.75	1.00	0.40	0.70	1.00
- maximum			EUR 102			
Shopping						
- damage factor	0.60	1.00	1.00	0.60	1.00	1.00
- maximum			EUR 1.508			

Appendix C:
Calibration of macrofinancial context with NiGEM

This appendix discusses how we use NiGEM to calibrate a consistent set of macrofinancial shocks. Vermeulen et al. (2021) already used NiGEM to create four consistent scenarios with macrofinancial stress for their energy-transition stress test. The NGFS has also used NIGEM, in their case to generate calibrations for chronic physical climate risks. For acute physical impacts such as floods, standard calibrations at the country level are not yet readily available. However, the climate version of the NiGEM model offers two routes to calibrating macrofinancial shocks. First, there is an option to shock investment premia. Second, there is an option to assume a broader set of shocks to demand and supply components.

Table C.1 indicates how we calibrate our six flood-stress scenarios. In each case, we take the GDP effects in Table 3 as the starting point, and then calibrate shocks to various input variables to match those GDP effects. In case of the shock to housing wealth, we use additional information from the damage estimates in step 2 of our stress test framework. In terms of economic mechanisms, we build on the discussion in Batten (2018), especially the part related to Table 1 in that paper.

We shock the following variables in NiGEM:

1. Housing wealth (NLHW): The property damage due to the flood decreases household wealth, which will reduce private consumption. We calibrate this shock based on the damage estimates from the Standard method for residential real estate. We compute damage amounts euros per scenario and scale them by total included RRE exposures.
2. Investment premium (NLIPREM): The flood disrupts business decision-making and generates higher levels of uncertainty.
3. Size of export market (NLS): This applies particularly to flood zone B.

The Netherlands is highly dependent on exports; the physical destruction of a flood would severely affect its distribution network and, therefore, shrink its export potential.

4. Imports (NLMVOL): The flood would temporarily increase the dependence of the Netherlands for imports of food and energy.

5. Equity premium (NLIPREM): Investors would require additional compensation to invest in the Netherlands.

Table C.1: Calibrations in NiGEM

This table reports the calibrations in NiGEM that are consistent with GDP shocks in the six flood-stress scenarios. The shocks to housing wealth follow from the damage calculations that use the microdata. The shocks to the other variables are adjusted to match the overall growth effect. The simulations use NiGEM v2.21.

	Flood zone					
	A			**B**		
Water stress:	Low	Intermediate	Extreme	Low	Intermediate	Extreme
Housing wealth	-1	-3	-3.5	-27	-51	-53
Investment premium	0.1	0.15	0.25	0.1	0.4	1.5
Export market	-0.25	-0.5	-0.75	-0.3	-1	-5
Import volume	0.25	0.4	0.75	0.25	0.75	3
Equity risk premium	0.1	0.2	0.25	0.2	0.5	1

Appendix D:
Background on stress-test modules

This appendix contains background information on the stress test framework. As shown in Figure 1, the flood event impacts banks capital adequacy directly (via credit risk) and indirectly (via a change in the macrofinancial context). The direct impact via credit risk reflects the reduction in the valuation of the immovable property used as collateral in RRE and CRE loans. Lower collateral valuations are then associated to increasing defaults and increasing bank losses on defaulted exposures. Since only the direct impact explicitly depends on the damages due to the flooding event, we rely on the existing DNB's top-down stress test model to quantify the indirect impact via market risk, profitability and changes in risk weights. Appendix D1 provides background information on that model. In addition, we develop new PD and LGD modules to quantify the impact on credit risk on exposures secured by residential and commercial immovable properties. Appendix D2 discusses the modules for PD and LGD paths.

D1. Top-down stress-test model

This section contains an broad overview of the stress-test model used in this paper. Daniëls et al. (2017) provides further details. In general, a top-down framework consists of a suite of models focusing on specific parts of balance sheets and profit and loss statements. Each element eventually feeds into the CET1-ratio, where CET stands for Common Equity Tier 1. The CET1-ratio is the ratio between high-quality regulatory capital and risk-weighted assets. It is the main metric used to assess the capital adequacy of banks. The modules in the stress test framework capture changes in the numerator as well as the denominator of the CET1-ratio. In a stress scenario, changes in the numerator can be due to credit losses, losses on financial-asset positions, a decline in net interest income (NII), or a lower level of net fee and commission income (NFCI). Changes in the denominator are due to increases in regulatory risk-weights. We now discuss the main three elements used in the flood-risk computations.

Credit risk

Credit losses and the evolution of risk-weighted assets are projected per specific loan portfolio, such as loans backed by residential mortgages or the corporate loan book. The relevant modules follow the IFRS9 accounting rule for provisions. Given that the flood scenarios cover one year, we maintain the common assumption of a static balance sheet, i.e. banks are not assumed to adjust the size or composition of their positions. Conditional on the flood scenario, we project the path of stage transition matrices and life-time loss rates. Using the projections of IFRS9 credit risk parameters we then project, per flood scenario, transitions of exposures from and to IFRS9 stages and the stock of provisions that each bank needs to hold. Credit losses are calculated as the annual change in the stock of provisions for assets allocated in all three IFRS9 stages.

Concerning risk weights, we model their evolution for two types of portfolios, namely those for which banks follow Internal Ratings (IRB) and those for which they use the so-called Standardised Approach (SA). The difference between IRB and SA is, that for the latter, banks do not model PDs and LGDs themselves. For starting points of regulatory parameters, we rely on supervisory reports. For IRB portfolios, an increase in the default rate will only partially pass-through to the regulatory PD due to the longer length of the financial cycle.

Market risk

In general, Dutch banks have limited trading book exposures. Market risk often has, therefore, a moderate contribution to the overall CET1 impact in a stress test. Moreover, our current flood stress test only calibrates shocks to Dutch equity markets (see Table 3), as it seems unlikely that foreign equity markets would be affected by a flood in the Netherlands. This implies that we only need to consider mark-to-market losses for bank exposures to Dutch listed entities. In the stress test then, we apply the scenario-specific shocks directly to the market value of these Dutch equity positions. The resulting financial losses are scaled by risk-weighted assets to infer the impact on the system-wide CET1-ratio. This approach to market risk is similar to that in Vermeulen et al. (2021). One difference is that Vermeulen et al. (2021) also take into account heterogeneity across NACE sectors under disruptive transition paths in computing shocks to equity returns.

Profitability (NII and NFCI)
Net interest income (NII) is the main component of the profitability of Dutch banks. In addition, for some banks, there is also a sizeable contribution to profitability from fee and commission income. In the flood scenarios, the main effect on NII is the funding cost shock, while NFCI is affected by the equity shock and the decline in economic growth. To assess the implications for NII and NFCI, we rely on panel models estimated on bank-specific supervisory data. For related approaches, see Claessens et al. (2018), Gross et al. (2017), or Kok et al. (2019).

D2. Estimation of credit risk benchmarks

This section discusses the evolution of two main credit risk parameters: the probability of default (PD) and the loss given default (LGD). The first parameter captures the probability that a counterparty defaults on their outstanding obligations. The second parameter reflects the loss that the bank would incur on that exposure, in case that counterparty defaults. The value of both parameter benchmarks are obtained conditional on the parametrisation for flood levels and macrofinancial adversity. Together, they determine the resulting path of IFRS9 transition rates (TR) and loss rates (LR). The scope of both satellite modules is banks' residential and commercial real-estate exposures. These are loans to households (HH) and non-financial corporations (NFC) that are secured by such real-estate loans.

LGD module

The LGD module aligns the value of the immovable property used as collateral to the estimated property damage in each flooding scenario. The resulting values of the loan to value (LTV) and loss given loss (LGL) are obtained accordingly. These parameters reflect the actual loss that the bank would incur in case of default, which mostly depends on the outstanding borrower's obligation and the current and liquidation value of the real estate collateral. The LTV of mortgage i under flood scenario S is given by:

$$LTV_i^S = LTV_i * \frac{1}{1 - property\ damage_i^S} \tag{1}$$

The resulting values of the loss-given-loss (LGL) and loss given default (LGD) are given by:

$$LGD_i^S = ((1 - probability\ of\ cure) * LGL_i^S) + costs \tag{2}$$

Where

$$LGL_i^S = max\left[\left(\frac{LTV_i^S - sales\ ratio}{LTV_i^S}\right)\ ;\ 0\right] \tag{3}$$

When available (CRE data) the reported information on liquidation values (for sales ratios) and administration costs was used. When not available (RRE data), we assume values in line with those reported in the CRE data. The final bank-level LGDs (and the associated multipliers) are obtained by weighting the LGD of each individual exposure by the associated exposure amount. For the calculation of the parameters, we use the 2020Q4 wave of the RRE and CRE data.

PD module

In contrast to the LGD version, for the PD module we require the use of historical data. We estimate the following equation:

$$y_{i,b,t} = c_b + \beta' \mathbf{Z}_{i,b,t} + \delta' \mathbf{X}_{i,b,t} + u_{i,b,t} \tag{4}$$

Here, the dependent variable is the default status of the counterparty i of bank b at time t. The main independent variables $\mathbf{Z}_{i,b,t}$ are the mortgage interest rate, the current loan-to-value, and regional GDP growth. The parameters β then capture the change in the default probability due to changes in interest rate, business and collateral risk.The set of control variables includes the mortgage type (amortizing, deferred-amortization, interest-only), the interest rate type (variable, fix, fix with reset), the residual maturity, the LTV at inception, the type of real estate that serves as collateral, and the presence of a National Mortgage Guarantee (NHG) for RRE loans. The model is estimated via pooled OLS, using DNB's loan level data. The time dimension is annual (where we always use data from the fourth quarter of each year) and the estimation window either covers the period from 2012 to 2018 (RRE loans) or 2015 to 2020 (CRE loans). We obtain the bank-level PD multiplier in each scenario path as:

$$m_i^S = \frac{E(y_{i,b,t} | \mathbf{X}_{i,b,t} \, , \, \mathbf{Z}^S_{i,b,t} \, , \, s = S\,)}{E(y_{i,b,t} | \mathbf{X}_{i,b,t} \, , \, \mathbf{Z}_{i,b,t})} \tag{5}$$

Where the numerator represents the predicted value of eq. (4) conditional on the values of the LTV, GDP growth and interest rates assumed under each scenario. The final bank-level multiplier is obtained by weighting the increased credit risk of each mortgage by the associated exposure amount.