Did we open the floodgates?
Flood Damage and Infrastructure Loan Defaults

Working Paper

January 22, 2023

Abstract

We provide a novel approach to estimating asset-level expected damage from flooding for 52 airports, ports, and power plants globally. We find that expected damage from flood increases the probability of default on infrastructure loans. We estimate expected damage from flooding using multiple damage functions to highlight the lenders' attention to adaptation as a physical climate risk hedging strategy. We also estimate expected damage from flooding using multiple climate scenarios to highlight lenders' attention to the uncertainty introduced by climate change. We find limited evidence for the integration of adaptation and future climate scenarios in infrastructure loans probability of default.

Keywords: Physical climate risk, loan probability of default, infrastructure finance, climate scenarios analysis, climate finance.

JEL Codes: F21, F34, G12, G15, G21, G23.

1 Introduction

Infrastructure assets are by nature exposed to physical climate risks such coastal and riverine flooding (Panagoulia and Dimou 1997; Wilby and Keenan 2012; Hirabayashi et al. 2013; Kundzewicz et al. 2014; Wasko et al. 2021). Floods can cause interruptions in the services provided by infrastructure assets and damages to that requires repairs; hence generating potential losses in revenues and increases in costs that affect the cashflows of the infrastructure operator or project (Burbidge 2016; Garcia-Alonso, Moura, and Roibas 2020; Vogiatzis et al. 2021).

The cashflow generation ability of an infrastructure project is crucial to the success of its financing. Over the last two decades, a large proportion of infrastructure projects were financed through special purpose vehicle (SPV) structures whereby the repayments of principal and interest to lenders, as well as return to equity investors, is solely based on project's cashflows. Physical climate risks such as floods can therefore have direct implications for infrastructure project lenders and investors.

In this paper, we examine whether the damage that could be expected from floods is factored into the pricing of loans to infrastructure. Lenders can price flood damage through different channels. We focus on the probability of default as a channel for the pricing of flood damage.

We begin by exploring the universe of infrastructure financing transactions between 2000 and 2020. We extract a sample of 952 electricity generation plants, ports, and airports from the database. Based on the geolocation of each infrastructure, we estimate the expected damage from flooding based on the Global Flood Riks modelling framework (GLOFRIS) (Winsemius et al. 2016) and a set of damage functions we collected based on literature review (Huizinga, De Moel, Szewczyk, et al. 2017).

Finally, we match our assets and financing transactions with infrastructure probability of default and recovery rates from Moody's Investor Services. We find that there is a positive and statistically significant relationship between expected damage from flood and the probability of default on infrastructure loans. Our findings are robust to multiple alternative specifications and to placebo tests.

Our findings are consistent with the climate finance literature and add to it in many ways. First, our findings are consistent with the broader literature linking physical climate risk to the pricing of debt instruments such as bonds (Kling et al. 2021; Cevik and Jalles 2020; Cevik and Jalles 2022). By broader, we refer to studies that did not focus on flood as a physical climate risk but rather used composite indexes such as the ND-GAIN.

Our findings are also consistent Allman 2021, Painter 2020, and Goldsmith-Pinkham et al. 2021 that studies sea-level rise impact on various types of bonds, as well as the literature exploring the impact of floods and sea-level rise on house prices and mortgage loans (Barrage and Furst 2019; Bernstein, Gustafson, and Lewis 2019; Baldauf, Garlappi, and Yannelis 2020; Filippova et al. 2020; Bajaj and Kaur 2022; Pagliari 2021; Garbarino and Guin 2021).

We add to this literature as we are, in our best knowledge, the first to estimate not only the exposure of assets to floods but also the expected damage from floods. Painter uses sea-level rise damage figures for his enquiry on municipal and corporate bonds, however; however, the damages are estimated at the level of an entire country and not a specific asset.

Our paper shows the importance of asset-specific estimations when it comes to physical climate risks. These risks cannot simply be mitigated by relocating the infrastructure assets as these infrastructures are often built to serve a specific community or industry and are constrained by the choice of location. The remaining mitigation option is the investment in adaptation measures that would reduce the damages from floods (Becker et al. 2013). Being able to estimate the damages at the level of an asset is the only way for lenders and investors to reward such adaptation measures by reducing the cost of capital for infrastructure.

We discuss the importance and relevance of adaptation as a determinant of infrastructure probability of default through the lens of damage functions. We identify in the literature 15 functions that link the level of flooding with physical damage to assets. Of these 15 we select three: the two boundary damage functions that reflect the highest damages and the lowest, and a median damage function. Each one of these damage functions reflects a different degree of adaptation to flooding.

We estimate our expected damage from flood for each one of these damage functions and find that it is always positively related to the probability of default with coefficients of the same magnitude and statistical significance. This likely indicates that infrastructure lenders are not yet considering the differentiations between assets in terms of adaptation but rather still in terms of potential damage only. To our best knowledge, Jiang, C. W. Li, and Qian 2019 is the only study that estimated damage from sea-level rise for corporate syndicated loans. Our method refines Jiang, C. W. Li, and Qian 2019's approach greatly and introduced the discussion on adaptation. The development of accurate and granular damage functions is a key research area for climate finance (Hong, F. W. Li, and Xu 2019).

In essence, the discussion about adaptation and damage functions reflects the uncertainty over the path of the economy in response to climate change as outlined by Barnett, Brock, and Hansen 2020. Based on our study, using variations in damage functions reflection uncertainty over adaptation response to the risk of flooding does not lead to major differentiation in the assessment of the probability of default on infrastructure loans. Climate change also introduced uncertainty in terms the development of flooding as a physical climate risk (Giglio et al. 2021). This uncertainty is related to investors' and lenders' ability to estimate current flood risk as opposed to future flood risk (Baldauf, Garlappi, and Yannelis 2020). Baldauf, Garlappi, and Yannelis 2020 make this distinction and goldsmith introduces a discussion on the path of climate change by estimating exposures to sea-level rise for different climate change scenarios.

We follow the same approach and estimate our expected flood damage for high climate change scenarios (RCP8.5) and low climate change scenarios (RCP4.5). Here again, the expected damage from a flood is positively related to the probability of default, in consistence with our baseline results, with coefficients of larger magnitude for the high climate change scenario. Our findings however indicate that infrastructure lenders factor in expected damage from flooding based on historical flood data and not necessarily on future climate scenarios.

Our findings add to the broader literature on climate change pricing in loans (Capasso, Gianfrate, and Spinelli 2020; Benincasa 2021) and open a new area of research focusing on infrastructure as an asset class and the underlying major gaps in the measurement and understanding of physical climate risk and adaptation.

2 Should flood risk matter to infrastructure lenders?

2.1 Flood Damage and Adaptation

Climate change is leading to an increase in the frequency of extreme events such as floods (Panagoulia and Dimou 1997; Wilby and Keenan 2012; Hirabayashi et al. 2013; Kundzewicz et al. 2014; Wasko et al. 2021).

According to the World Resource Institute (WRI), the number of people impacted by floods will double worldwide by 2030 from 65 million to 132 million and the amount of property damaged by riverine floods will increase three times from USD 157 billion to USD 535 billion over the same period (WRI 2020). Ward, Jongman, et al. 2013 estimate that the global flood damage could amount to USD 1.3 trillion. Similarly, Hallegatte et al. 2013 estimate that global losses from coastal flooding in 2005 already amounted for USD 6 billion per year and will increase to USD 53 billion per year in 2050. Limiting such damages requires significant investment in adaptation measures. Hinkel et al. 2014 estimate that for coastal flooding "annual investment and maintenance cost with dikes are significant with annual investment and maintenance costs of USD 12 to 71 billion in 2100, but much smaller than the global cost of avoided damage" (Hinkel et al. 2014).

A large portion of damages caused by floods affect infrastructure assets (R. Dawson and J. Hall 2006; R. J. Dawson et al. 2018), and the interdependencies between different types of infrastructure can amplify the impact of such events. The cost of flooding to infrastructure is large and will increase over time; and billions in flood protection investment are needed

(Hallegatte et al. 2013).

The estimations of damage due to flood are highly sensitive to the different flood protection standards (Ward, Jongman, et al. 2013) in place. Flood protection infrastructure can significantly reduce this damage (Ward, Jongman, et al. 2013). Jongman, Winsemius, Aerts, et al. 2015; Jongman, Winsemius, Fraser, et al. 2018; Jongman 2018 emphasis the benefits of reducing vulnerability to flood. They estimate the vulnerability of different countries between 1980 and 2010 and conclude that if the most vulnerable countries reach the average vulnerability level, through adaptation, the global losses would be reduced by an estimated US 233 billion (Jongman, Winsemius, Aerts, et al. 2015).

The International Panel on Climate Change (IPCC) defines adaptation as "the process of adjustment to actual or expected climate and its effects" (Pörtner et al. 2022). It sets the objective of adaptation as "moderate or avoid harm or exploit beneficial opportunities" (Pörtner et al. 2022). Adaptation is further classified into "incremental adaptation" and "transformational adaptation".

In the rest of the paper, we define "adaptive capacity" or "adaptation" in the same way it is defined by the IPCC "the ability of systems, institutions, humans, and other organisms to adjust to potential damage to take advantage of opportunities, or to respond to consequences" (Pörtner et al. 2022). In our context, the infrastructure is the system we consider.

Floods impacts all types of infrastructure asset. However, the way the different types of infrastructure are damaged, as well as the measures that are aimed at reducing these damages, can be different. This warrants a study of flood impact that takes into account these differences.

2.2 Flood Damage to Infrastructure Assets

M.-P. Poo et al. 2018 perform a comprehensive literature review of 105 papers relevant for the adaptation of climate change to seaports and airports and conclude that "comparing all climate threats, sea level rise (SLR) and storming and flooding currently present, according to the literature, the most severe impact in ports and airports".

Burbidge 2016 studies climate change risks to European airports and identifies five main risk areas, of which one is related to precipitations and floods. Changes in precipitation can require the increase of separation distance between aircrafts, increase the airport surface that needs to be equipped for heavy winter weather, drainage infrastructure might not be sufficient to cope with the level of rainfall, and ground transport equipment and electrical equipment can be inundated.

In terms of adaptation strategies to address climate change at the level of airports Vogiatzis et al. 2021 perform an adaptation study on the Athens International Airport (A.I.A.). They project the usual temperature, rainfall and wind speed parameters up to 2040 and 2070 using various climate models. They conclude with identifying three main risks (1) the increase in energy demand for cooling and therefore energy bill, (2) localized flooding in the drainage infrastructure during heavy rain events, and (3) the safety and health risks for airport staff. They show that stressing drainage infrastructure to ensure robustness to extreme flooding events is the most effective physical adaptation strategy for airports(Vogiatzis et al. 2021).

The United Nations Conference on Trade and Development (UNTCAD) mentions that port operations can be affected by climate change through various climatic factors: sea level rise, temperature, precipitations, and wind.

The study of Izaguirre et al. 2021 indicates that climate change impact such as sea-level rise of heat stress can "compromise port operations, resulting in an increase in operational shutdowns and subsequent economic losses" with the Pacific Islands, Caribbean Sea and Indian Ocean being the most exposed.

There is a broad consensus on the climate variables that are affecting seaports from rising sea level, increasing extreme temperatures, precipitation, and wind, and increase storm surge Becker et al. 2013; Scott et al. 2013 (UNTCAD, 2020; PIANC, 2020; British Ports Association, 2021). These can cause changes in maintenance practices, reduction in productivity, increase in days of operation, or delays in ship discharging (Becker et al. 2013). High waves can damage port facilities, infrastructure can be flooded, the port can experience coastal erosion, deposition and sedimentation or downtime in the port operations (Yang et al. 2018). Impact can go beyond the operations and extend to the services provided to communities through ports such as energy, transport, or consumables (PIANC - The World Association for Waterborne Transport Infrastructure, 2020). The degree of connectedness of the port will compound the disruption of port operations.

The impact can be at the loading and unloading of goods, damage to the port infrastructure and reduction of port lifespan, or through directly damaging cargo (UNCTAD, 2020). Garcia-Alonso, Moura, and Roibas 2020 show that coastal flooding can disrupt port operations due to demand variability.

The adaptation measures to climate change for ports can be classified in hard and soft strategies (Becker et al. 2013). Soft strategies can be enhanced emergency evacuations plans, increased standards of port construction, increased access to finance for port adaptation; and hard strategies can range from raising port elevation, building coastal defenses, expanding dredging and nourishment programs or to handle sedimentation (Becker et al. 2013; Yang et al. 2018; Lin et al. 2020).

2.3 Infrastructure Finance

Damage to infrastructure can generate additional capital and operational costs. Interruptions of service can impact the revenue generation capacity of airports, ports, and power plants. Given the unique financing model of infrastructure projects, such disruption of cash-flows can translate into solvency issues.

Infrastructure projects are mostly financed through project finance structures. Project finance is defined as "the method of funding in which the lender looks primarily to the revenues generated by a single project, both as the source of repayment and as security for the loan. This type of financing is usually for large, complex and expensive installations such as power plants, chemical processing plants, mines, transportation infrastructure, environment, media, and telecoms. Project finance may take the form of financing the construction of a new capital installation, or refinancing of an existing installation, with or without improvements" (BIS, 2013).

Infrastructure project finance is a subset of the syndicated loan universe where syndicated loans are defined as loans "extended by a group of financial institutions to a single borrower". Project finance loans exhibit a different credit risk profile from the rest of the syndicated loans universe.

Adopting a project finance structure implies that a special-purpose vehicle (SPV) is set with the only objective of financing the infrastructure project. The SPV then raises equity financing and subscribes debt to finance the construction and operation of the infrastructure asset. The major differences between project finance and corporate finance are that project finance has "separate incorporation, comprehensive contractual agreements, and high leverage" (Brealey, Cooper, and Habib 1996; Blanc-Brude and Yim 2019).

For lenders to infrastructure projects, such an SPV structure means that the repayment of the debt is relying only on the project's cash-flows as opposed to a corporate type of financing where the sources of cash-flows can support the project development (Yescombe and Farquharson 2018).

Contractual arrangements specific to project finance are regarded as more transparent as they reduce information and agency issues typically found in corporate finance (Frédéric Blanc-Brude, Hasan, and O. R. Ismail 2014; Blanc-Brude and Yim 2019). Evidence from private-public partnerships suggest that project finance structures are so effective in risk management that "technical risks are diversified away" and "factors like loan size, maturity, and leverage do not show up as significant determinants of the cost of debt" (Frederic Blanc-Brude and Strange 2007).

Most infrastructure has a useful lifetime of more than 20 years and the loans used to finance these projects have long tenors of more than 10 years. This means that both the operators of the infrastructure and the lenders to the project could be exposed to mid- and long-term extreme climate event. Infrastructure might be, with real estate, one of the only asset class with such an exposure. The question for us is then whether the project finance unique “network of contracts” (Blanc-Brude and Yim 2019) is also able to “diversify away” physical climate risk as it does for other “technical risks” (Frederic Blanc-Brude and Strange 2007).

2.4 Flood risk and asset pricing

Climate finance papers have extensively explored the linkage between physical climate risks and asset pricing. However, to our best knowledge a gap remains when it comes to infrastructure finance.

The impact of physical climate risk on sovereign debt was studied extensively (Kling et al. 2021; Cevik and Jalles 2020; Cevik and Jalles 2022). Although most of the studies did not focus on a specific climate risk, but rather relied on composite indexes such the ND-GAIN as a measure of physical climate risk. ND-GAIN has more than 40 sub-indicators covering various non-climate issues, as well as aspects such as economic development, social development, and governance.

Kling et al. 2021 find using the ND-GAIN index as a measure of climate vulnerability that climate vulnerability lead to an average increase of cost of debt by 0.63 percent between 1991 and 2017. Cevik and Jalles 2020; Cevik and Jalles 2022, also using the ND-GAIN, find that climate vulnerability has adverse effects on sovereign credit ratings.

More specific analysis, focusing on floods and sea-level rise, was conducted on corporate (Allman 2021) and municipal bonds (Painter 2020; Goldsmith-Pinkham et al. 2021).

Painter 2020 uses the estimations of Hallegatte et al. 2013, we previously mentioned, to study the impact of sea-level rise on corporate bond yields and underwriting fees for municipal bonds. He finds that counties affected by sea-level rise face higher issuance costs.

However, this is only true for long-term bonds and is exacerbated for counties with low credit rating. These results are supported by the findings of Goldsmith-Pinkham et al. 2021. Goldsmith-Pinkham et al. 2021 do not use a quantification of the damage from sea-level rise, but rather the exposure of an asset to the risk. They find that sea-level rise affects long-maturity municipal bonds and that it is not only driven by short-term floods. They estimate that a one standard deviation increase in the fraction of exposure to sea level rise is accompanied by a 5.3 basis point increase in municipal bond credit spreads.

Allman 2021 conducts a similar exercise focusing on corporate bonds issued by firms located in areas exposed to sea-level rise. He finds that a standard deviation increase in firms' sea-level rise exposure is associated with a 3 percent increase in average yield spread.

However, it is the housing prices and mortgage loans markets where the impact of sea-level rise and floods was studied the most (Barrage and Furst 2019; Bernstein, Gustafson, and Lewis 2019; Baldauf, Garlappi, and Yannelis 2020; Filippova et al. 2020; Javadi and Masum 2021; Bernstein, Billings, et al. 2022).

Bernstein, Gustafson, and Lewis 2019 find that homes exposed to sea level rise sell for approximately 7 percent less than observable unexposed properties. They find that buyer sophistication and communities belief in climate change also generate discount in property prices. They confirm that concerns over sea level rise are of long-term nature as they find no relationship between the risk and rental rates and find only a 4 percent discount among properties not projected to be flooded for almost a century.

Baldauf, Garlappi, and Yannelis 2020 find that houses located in areas with higher inundation projections, and neighborhoods with higher believer in climate change, sell at a discounted price. The study's findings suggest that when it comes to the housing prices, the investor attention dimension might be critical in the pricing of climate risks.

Barrage and Furst 2019 look at the impact of sea-level rising on new house construction. The find that sea level rise exposure is associated with significant reduction in new construction in areas of higher belief in climate change.

However, such results should be nuanced as evidence from outside the US-market show different results. In New Zealand, Filippova et al. 2020 show that the disclosure of information on sea-level rise and coastal erosion did not lead to a significant impact on housing prices.

Evidence from the UK housing market suggest that mortgage lenders underestimate climate risks related to flood. Garbarino and Guin 2021 compare property transactions before and after a major flood event as well the subsequent refinancing condition. They find that property valuations are biased upward and do not integrate the new information from the flood event.

Both Jiang, C. W. Li, and Qian 2019 and Garbarino and Guin 2021 look at how the exposure to floods affect the terms at which lenders provide loans.

Jiang, C. W. Li, and Qian 2019 the impact of sea-level rise on the pricing of corporate loans. They measure the sea-level rise exposure of a corporate as the expected loss from sea-level rise in the country where the corporate is based. The figures use by Jiang, C. W. Li, and Qian 2019 are also based on the estimations of Hallegatte et al. 2013. They find that the long-term cost of the loans to a firm go up when it relocates to a country with higher sea-level rise risk. They also find evidence that the contractual arrangements, such as covenants and fees, within a syndicated loan structure are more stringent for firms located in countries with higher sea-level rise. A particularly interesting finding of Jiang, C. W. Li, and Qian 2019 is that the change in terms is only valid for long-term loans, consistent with the findings of Painter 2020 for municipal bonds.

Some additional evidence is provided by Pagliari 2021 that averse flood events Europe lead to a drop in loans to households and non-financial corporations.

However, Garbarino and Guin 2021 also find that mortgage lenders do not offset this bias by adjusting interest rates or loan amounts. One explanation is that lenders do not track the impact of extreme weather events ex-post.

This suggests again, that there are differences in the factoring of sea-level rise and flood in loan pricing based on the nature of the asset class, syndicated loans vs. mortgages, as well the geography. The level of investor attention might be a channel explaining such differences, in addition to the idiosyncratic characteristics of the asset classes.

Jiang, C. W. Li, and Qian 2019; Baldauf, Garlappi, and Yannelis 2020; Painter 2020; Allman 2021 explore the impact of investor attention on the pricing of sea-level rise. Jiang, C. W. Li, and Qian 2019 provide evidence that the loans spreads for syndicated loans when the lead bank has more experience with sea-level rise risk and in times of heightened media attention. Painter 2020 finds that there is a difference in issuance cost for municipal bonds issued before and after the publication of 2006 Stern Review on climate change. Allman 2021 finds that the effect of sea-level rise on corporate bond spreads is more pronounced after the Paris Agreement. Finally, as mentioned previously, Baldauf, Garlappi, and Yannelis 2020 finds that the price discount linked to inundation risk for houses is only relevant in neighborhoods with higher belief in climate change; and Barrage and Furst 2019 that high climate change belief leads to lower new construction in area exposed to sea-level rise.

2.5 Hypothesis construction

Evidence from the infrastructure finance, climate finance and asset pricing literature suggest that there could be a premium attached to the exposure to flood risk in the infrastructure lending. Although the impact of the exposure to flooding was investigated for asset classes with long lifespans such as mortgages, it was not for infrastructure loans. The investigation is also worthwhile given the unique nature of the project finance model adopted to finance infrastructure. In addition, hedging options are limited as the choice of a location of an infrastructure asset depends not only on the exposure to climate risk but also on the service the infrastructure is aimed at providing. Our first hypothesis is:

H1-a: Higher expected damage from flood leads to higher probability of default on infrastructure loans.

Hong, Karolyi, and Scheinkman 2020 identify that one of the key areas of contribution in the climate finance research agenda is around damage functions. We, therefore, estimate the expected damage from flood using various depht-damage function in order to add to the literature that mostly focuses on exposure and did not discuss adaptation components. Our second hypothesis is:

H1-b: estimations of expected flood damage using different damage functions leads to significant differences in the effect on the probability of default.

Barnett, Brock, and Hansen 2020, Giglio et al. 2021 and Goldsmith-Pinkham et al. 2021 identify the uncertainty over the path of climate change a key uncertainty that might investors attention. Our third hypothesis is:

H1-c: estimations of expected flood damage using different climate change scenarios functions leads to significant differences in the effect on the probability of default.

3 Methodology

3.1 Damage from flood at infrastructure asset-level

Our objective is to estimate the percentage of a port, airport, or power plant's structure that would have been damaged by floods based on its location.

The assessment of physical climate risks such as flood is well documented in the engineering literature. Risk is expressed in terms of expected loss or damage. Yesudian and R. J. Dawson 2021 in the "Global analysis of sea level rise risk to airports" express the risk of flooding at an airport as the "expected risk of disruption of aircraft routes for a given sea level scenario". The risk r is expressed as:

$$r = \int_{\max(EFP,EA)} \rho(l) D_R dl \tag{1}$$

Where EA is the airport elevation, EFP is the elevation of the flood protection, (l) is the probability density function of the extreme water level. D_R is the damage function in terms of number of airport routes that can be disconnected. D_R is the function that tells us about vulnerability and impact in dollar terms (Yesudian and R. J. Dawson 2021).

The expression of risk used by Yesudian and R. J. Dawson 2021 draws from the seminal work of R. Dawson and J. Hall 2006 on "Adaptive importance sampling for risk analysis of complex infrastructure systems", J. W. Hall, Sayers, et al. 2006 estimation of the "Impact of climate change on coastal flood risk in England and Wales", and in J. W. Hall, R. J. Dawson, and Wu 2015 "Analysing flood and erosion risks and coastal management strategies on the Norfolk coast".

In all these studies, expected damage is expressed as a function of probability density function (l) of the climate hazard or variable (flood in the case of these studies) (J. W. Hall, Sayers, et al. 2006), $D(l)$ is a spatially variable damage function constructed from market values (J. W. Hall, R. J. Dawson, and Wu 2015), and c is the climate variable under consideration.

$$r = \int_{\max(c)} \rho(l)D(l)dl \tag{2}$$

This formulation of climate risk has been developed for general assessment of risk in infrastructure (R. Dawson and J. Hall 2006), then used for the assessment of flood risk (J. W. Hall, Sayers, et al. 2006) and later for erosion risk (J. W. Hall, R. J. Dawson, and Wu 2015). We therefore adopt this approach as the basis of our estimation of flood expected damage for ports, airports, and power plants.

3.1.1 Estimation of expected flood damage for individual infrastructure

Our approach to estimating the damage from floods can be summarise in three steps: (1) we determine the location of each infrastructure, (2) we estimate the level of flooding for each flood return period at the location of each infrastructure, (3) we use damage functions to estimate the damage to infrastructure resulting from floods.

Location of the infrastructure assets

We select all the ports, airports, and power plants financing transactions that reached a financial close among the 8,039 deals identified in the Inframation database. Out of these transactions, 2,113 transactions are loans. We are able to identify the locations, expressed in latitude and longitude, of 951 ports, airports, and power plants (See figure 1).

[**Insert figure 1 about here**]

Exposure of each asset to flood

We then assess the exposure to flood using the flood depth expressed in meters. Flood depth is in turn the input to our damage function that then provides a dollar estimation of the damage to infrastructure. In this section we will describe the flood depth data we use as well as the damage functions.

We use data from the World Resources Institute (WRI) Aqueduct Floods Tool. WRI is a leading nonprofit in the climate change science and policy space and the Aqueduct Floods Tool is widely seen as reference tool for flood risk assessment. The WRI flood methodology (Ward, Winsemius, et al. 2020) is based on the modelling framework developed by the Global Flood Risk with IMAGE Scenarios (GLOFRIS) (Winsemius et al. 2016). The flood hazard is "represented by inundation maps showing the flood extent and depth for floods of several return period (2, 5, 10, 25, 50, 100, 250, 500, and 1,000 years) at a resolution of 5x5 arc minutes" (Ward, Winsemius, et al. 2020). The WRI flood hazard maps provide flood depth modelling based on historical data since 1950 for various return period. The return period in flood risk management is a measure of the probability of occurrence of a flood event. A return period is "the inverse of probability, it gives the estimated time interval between events of a similar size or intensity" (NIWA, 2021). A return period of 100 years for instance means a flood occurring with a probability of 1 percent.

Using latitude and longitude geospatial data, we place our 951 infrastructure assets on WRI flood maps corresponding to flood depth for 2, 5, 10, 25, 50, 100, 250, 500, and 1,000 years returns periods.

[**Insert figure 2 about here**]

We extract the corresponding flood depth for various return periods, or flood probability of occurrence. Figure 2 provides an example for the Brussels Airport.

[Insert figure 3 about here]

This geospatial analysis provides us with an estimation of the level of flooding, expressed in meters, that would occur at the location of each port, airport, and power plant in our sample. In fact, for each infrastructure asset we obtain eight measures of the level of flooding, each measure represents flood in meters for a magnitude of flood expressed in return periods or probability of occurrence.

The next step is to determine the level of damage that each of these levels of flood would cause to each infrastructure.

Estimating damage

A damage function expresses the evolution of financial damage as a function of climate variable such temperature or precipitation.

There is no database that tracks damages at asset level. Damage functions modelling the performance on infrastructure assets under extreme events are scattered in the literature. Habermann and Hedel 2018 compiled damage functions for transport infrastructure focusing on wildfires and flood events. They review 327 papers and emerged with the conclusion that there is a large consensus on the definition of damage well as damage categories.

Damages are classified as "direct damages resulting from direct contact with the hazard [...], and indirect damages resulting from the event but not its direct impacts"(Habermann and Hedel 2018). Each category can further be sub-divided into "Tangible damages specifiable in monetary terms [...], and intangible damages difficult to assess in monetary terms" (Habermann and Hedel 2018). In our study we focus on direct and tangible damage which refers to the structural damage to the infrastructure (Habermann and Hedel 2018).

We then use the damage functions developed by Huizinga, De Moel, Szewczyk, et al. 2017 to estimate the damage, for each flood return period, to the infrastructure asset. This damage is expressed in terms of percentage of the total size of the asset. The damage functions were computed by Huizinga, De Moel, Szewczyk, et al. 2017 for regions and sectors - see Table 1. This measure lacks precision in the sense that it does not consider the exact physical characteristics of an asset. However, Huizinga, De Moel, Szewczyk, et al. 2017 are widely referred to and were for instance used by Prahl et al. 2018 to estimate damage from coastal flooding within the 600 largest European cities.

We estimate the expected damage from flood as the average of the expected damage for each flood return period weighted by inverse return period as described in equation 3:

$$\text{ExpectedFloodDamage}_{\ j} = \left(\sum_{\text{return period } i} \frac{1}{\text{return period } i} D\left(i, j\right) \right) \times \left(\text{ Maximum Damage }_{j} \right) \tag{3}$$

Where j is the specific infrastructure loans transactions, i is the return period we are calculating the flood depth for, and d is the flood depth at a specific return period for a specific asset based on WRI and GLOFRIS.

D is the flood damage function for the region where the asset is located based on Huizinga, De Moel, Szewczyk, et al. 2017.

[**Insert table 1 about here**]

Using Huizinga, De Moel, Szewczyk, et al. 2017 damage global function, we calculate the damage in percentage that would occur for each flood return period (probability of occurrence) using the flood depth data estimated at the previous step.

Studying the uncertainties introduced by climate change

As noted by Giglio et al. 2021, the uncertainty over the path of climate change and the uncertainty over the path of the economy has implications for asset pricing. We would like to understand if such uncertainty matters in the effect of flood damage on infrastructure loans probability of default.

For our baseline estimation of expected damage, we use the global depth-damage function developed by Huizinga, De Moel, Szewczyk, et al. 2017. This damage function is referred to as “global” because it does not take any asset specific consideration such as the country, the type, or the exact characteristics.

Although these characteristics are crucial in the assessment of flood risk, the data necessary to factor these in our models is not available. However, we can still use the 15 other depth-damage functions developed by Huizinga, De Moel, Szewczyk, et al. 2017 in to estimate the sensitivity our results to the change in damage function.

We therefore try to estimate the expected damage from flood for various damage functions.

Figure 4 shows the flood depth-damage functions we identified through our literature review. We select three damage functions in addition to our baseline global function: the damage function developed for the infrastructure sector, the function that results in the highest damage corresponding to the industry sector in North America, and the damage function resulting in the lowest damages developed for the industry sector in Africa.

[**Insert figure 4 about here**]

When it comes to uncertainty over the trajectory of climate change, we factor it in our analysis by calculating the values of expected flood risk under two climate scenarios RCP4.5 and RCP8.5.

RCP stands for Representative Concentration Pathways and the methods to capture the economic, social, and physical assumptions influencing climate change in each scenario. The number 4.5 and 8.5 represent watts per square meter of radiative forcing targeted in each of the climate scenarios. Radiative forcing is the difference between incoming and outgoing radiation at the top of the atmosphere. Radiative forcing target scenarios are five 2.6, 4.5, 6.0, and 8.5 – 2.6 is the “no radiative forcing” or no climate change scenario. We chose to consider the impact of flood on infrastructure loan pricing in the case where climate change would follow a RCP4.5, low emissions scenario, pathways as well as the RCP8.5 high emissions scenario. That will allow us to examine investors understanding of climate risk and the scenarios they are considering.

In summary we estimate the expected damage from flood for four damage functions, the baseline flood exposure, and flood exposure in two climate change scenarios. This results in 12 values of expected flood damage.

3.2 Sample and Summary Statistics

3.2.1 Sample

The sample we use to study the impact of flood risk on infrastructure loan defaults is a dataset of 8,039 infrastructure deals that took place between 2000 and 2020 accessed through the Inframation infrastructure deals database. Out of the 8,039 deals, we select 2,113 transactions based on the following criteria: (1) we include only loans (loans account for 4,888 transaction in the total dataset); (2) only deals that reached a financial close as the database also includes transaction that were cancelled or are still being closed; (3) deals that financed power generation, airports, and ports assets; (4) we include loans across the capital structure: secured, unsecured, mezzanine, and subordinated loans. Table 2 reports statistics relative to our sample of infrastructure loans.

Out of the 2,113 transactions, we can identify the geographic location, longitude and latitude, of 952 electricity generation plants, airports and ports. We focus on electricity generation plants, airports and ports as these assets have a small geographic footprint that allows us to estimate the expected loss from flood more accurately. We exclude infrastructure with large footprints such as roads, railways, or internet connectivity infrastructure than can span hundreds of kilometres.

Annual infrastructure total loan financing increased from 2.8 USD billion in 2000 to 83.5 USD Billion in 2020, with a significant inflexion point in 2010. Before 2010, the average annual infrastructure loan financing was 14 USD billion, while it was 65 USD billion on average after 2010. For our three-sector sample, the dynamic is similar with loan financing increasing from 244 USD million in 2001 to 28 USD billion in 2020. The average financing before 2010 in our sample was 3.8 USD billion, and 28.5 USD billion after 2010. Our three sectors represent 43 percent of the total loan financing.

Infrastructure loan default probability will depend on multiple factors (Yescombe and Farquharson 2018; Blanc-Brude and Yim 2019).

First it will depend on whether the infrastructure is yet to be build "greenfield", or already existing (Frédéric Blanc-Brude and O. Ismail 2013). Greenfield projects represent 57 percent of the total loan financing in our sample and 43 percent are refinancing deals.

Macroeconomic and political risks are major determinants of infrastructure finance (Sachs, Tiong, and Wagner 2008; Crăciun 2011). In terms of geographic distribution, 50 percent of the deals in our sample are loans for projects in Europe. Asia comes second with 29 percent of the deals and 8 percent for North America. Latin America and the Caribbean, Africa, the Middle East, and Australia and New Zealand all have a respective share below 5 percent of the total deal volume.

Each type of infrastructure has a unique economic role that determines its ability to generate revenues and the nature of its costs (Dutra and Barbalho 2017). Sector considerations are therefore important in loan default probability. Renewable energy transactions represent 47 percent of the total sample, non-renewable energy power 22 percent, and ports and airports represent 31 percent of the sample.

Infrastructure projects can generate revenue through different models (Kumar 2022). Revenues can be guaranteed through contractual arrangements with parties that commit to buy the service of the infrastructure. For instance, for electricity generation infrastructure, the government can commit to buying the electricity from the power plant through what is called a power purchase agreement (PPA) or the electricity can be sold in the electricity market and subject to supply and demand fluctuations.

Similarly, some infrastructure such as rail or roads can receive payments from a government based on the "availability" of the service and pre-agreed availability and quality of service KPIs regardless of the traffic. Finally, projects can generate revenues based on a demand-based model totally based on the volume of traffic, this is often the case for airports or ports. We know the revenue model for 958 transactions, 45 percent of our sample. 72 percent of the loan deals in our sample are for projects with high reliability of revenues as they are financed through PPAs. The rest of the sample has some form of uncertainty as they are financed through availability-based models or demand-based models.

Another determinant of a project's probability of default is the availability of government guarantees to cover some of the project's risks and increase the reliability of cashflows. 27 percent of the loan transactions in our sample are backed by some form of government guarantee. All the loans in our sample are senior loans. 98 percent are senior secured loans and 2 percent senior unsecured. This means that in 98 percent of the cases in our sample, lenders have the maximum claim over a project's cashflows and assets in the case of a default.

For lenders, another financial risk factor is the exposure to a project in terms of total size of a loan. It is referred to in the language of the Basel regulation as "Exposure at Default". The average size of a loan in our sample is 237 USD million and 49 percent of the loans have a size larger than 500 USD million. This adds to the important of studying climate risk for infrastructure loans a default of a single transaction can lead to large losses for the lender.

Finally, the long tenors of infrastructure loans is also a risk factor (Thierie and De Moor 2018). 63 percent of the loans in our sample have a tenor of at least seven years, and 33 percent have a tenor of more than 20 years. This unique feature means that risks linked to climate change that might materialize over many decades are directly relevant for infrastructure (Ho and Wong 2021; Allman 2021).

3.2.2 Summary Statistics

We match every transaction in our sample with the damage and adaptation values we estimated. We also match every transaction with probability of default and recovery rate data from the Moody's Infrastructure Defaults and Recovery database. Tables 2,3,**??**,and 4, report summary statistics on the transactions in our sample.

[**Insert table 2 about here**]

[**Insert table 3 about here**]

[**Insert table 4 about here**]

Table 2 shows that the renewable electricity generation sector attracted the largest amount of loan financing with a total of 168 USD billion over the period. The conventional electricity generation sector comes second with 77 USD billion in total. In terms of regions, Europe attracted the largest amount of loan finance with 155 USD billion in total. Asia is second with 90 USD billion in finance.

The largest transaction is a 12 USD billion loan for an airport project in Asia. The average size of projects is the largest for non-renewable energy electricity generation with 468 USD million average, followed by airports with 400 USD million average loan size. Renewable electricity generation projects have the smallest size with an average of 172 USD million per loan although the sector attracted the largest amount of financing.

Looking at probabilities of default, Table 3 shows that airports, non-renewable generation, and ports have higher probability of default than renewable energy projects. This could be explained by the policy support to the renewable energy sector through PPA agreement and government guarantees. Airports, ports, and non-renewable electricity generation are more exposed to demand fluctuations. However, it is worth noting that recovery rates are higher for airport projects. This means that the expected loss from the default of an airport project might still be less than other assets if the recovery rate is also considered. In line with the economic rational, loans to greenfield projects that hold a construction risk have a higher average probability of default than loans provided for refinancing purposes to already operation infrastructure projects.

Similarly, recovery rates are higher for already operating projects.

Average probabilities of defaults are lower for projects in Europe, north America, Australia, and New Zealand. They are higher for projects in developing economies in Latin America and the Caribbean, Asia, and Africa. This is consistent with the expected country risk premium associated with investment in developing economies Sachs, Tiong, and Wagner

2008; Crăciun 2011. Average probabilities of default are also higher for loans with a tenor of more than 20 years and of a size of more than 500 USD Million suggesting that the larger the exposure and the longer the duration of the loan the higher the risk to the lender (Thierie and De Moor 2018; Kumar 2022). This confirmed by the recovery rate data as recovery rates are also lower for loans with more than 20 years tenor and a size larger than 500 USD Million.

Table **??** report summary statistics on our constructed damage and adaptation variables. On average, our calculated expected damage from flood is largest in North America, Latin America, and Asia. Our adaptation factor is largest of Europe, North America, Asia, Australia and New Zealand.

3.3 Expected Flood Damage as a Determinants of Infrastructure Loans Probability of Default

We use the following model specification to test for the validity of our hypothesis H1-a including our measure of floods damage and adaptive capacity to flood, while controlling for known factors determining loan default probability:

$$PD_{i,t} = \beta_0 \text{ ExpectedDamage }_{i,t} + \sum_{j=1}^{n} \beta_j X_{j,i,t} + \gamma_c + \delta_c + \varepsilon_{i,t} \quad i = 1 \dots N \tag{4}$$

Where PD is the probability of default of a loan to a port, airport, or power plant in our sample on the year t. $ExpectedDamage$ is the damage from flood we estimate based on the location of the infrastructures, flood maps and the Huisinga et al (2017). X represents variables informing on the characteristics that are known to determine the probability of default and pricing of infrastructure loans. The variables in X include categorical variables about the country and region of the infrastructure; the natural algorithm of the size of the loan in USD; the natural algorithm of the tenor of the loan transaction in years; a dummy variable equal to 1 if the loan is guaranteed by the government. All the variables are defined in Table 5.

[Insert table 5 about here]

We then estimate 4 using values of $ExpectedDamage$ calculated using the three damage functions mentioned previously.

We use the following model specification to test for the validity of our hypothesis H-b in the case of future RCP4.5 and RCP8.5 climate scenarios following equations 5 and 6:

$$PD_{i,t} = \beta_0 \text{ ExpectedDamageRCP45 }_{i,t} + \sum_{j=1}^{n} \beta_j X_{j,i,t} + \gamma_c + \delta_c + \varepsilon_{i,t} \quad i = 1 \dots N \tag{5}$$

$$PD_{i,t} = \beta_0 \text{ ExpectedDamageRCP85 }_{i,t} + \sum_{j=1}^{n} \beta_j X_{j,i,t} + \gamma_c + \delta_c + \varepsilon_{i,t} \quad i = 1 \dots N \tag{6}$$

Again, we then estimate 5 and 6 using values of $ExpectedDamage45$ and $ExpectedDamageRCP85$ calculated using the three damage functions mentioned previously.

Table **??** is reporting correlations between the various variables used in our analysis. The correlation factors are low and suggest that multicollinearity is of limited concern for our multivariate analysis.

4 Results

4.1 Baseline Model results

To evaluate our hypothesis (H1), we start by estimating a simple univariate model based on equation 7.

$$PD_{i,t} = \beta_0 \text{ ExpectedDamage }_{i,t} + \varepsilon_{i,t} \quad i = 1 \dots N \tag{7}$$

Results from our univariate analysis are reported in model 1 of 6.

Model 1 shows that $ExpectedDamageHist$ increases the probability of default PD with high statistical significance (p<0.01) in support of our hypothesis (H1-a). A marginal 1 percent increase in $ExpectedDamage$ results in 0.004 percent increase in probability of default PD.

Table 6 report the results of our multivariate analysis under different model specifications following equation 8. Models from 2 to 5 include controle variables, as well as country and sector fixed effects.

$$PD_{i,t} = \beta_0 \text{ ExpectedDamage }_{i,t} + \sum_{j=2}^{n} \beta_j X_{j,i,t} + \gamma_c + \delta_c + \varepsilon_{i,t} \quad i = 1 \ldots N \tag{8}$$

Across models 1 to 5, increases in damage also increase probability of default in a statistically significant way (p<0.01) and coefficient around 0.005 in support of hypothesis (H1-a). Model 5 implements the specification described in 8 including all control variables, country, and sector fixed effects.

The estimation of $ExpectedDamage$ used in models 1 to 5 is based on the same damage function. The damage function we use here is the global flood damage, common to all types of sectors and assets, developed by Huizinga, De Moel, Szewczyk, et al. 2017.

Such a method to estimate damage from flood would in theory not account for differences between the individual infrastructure in our sample. The lack of granular damage functions is one of the main gaps that hinder the estimation of physical climate risks in infrastructure and hence the pricing of such risks.

In absence of such granular damage functions, we estimate $ExpectedDamage$ using a set of different damage functions, based on each asset's flood exposure. The analysis results are shown in Models 1 to 4 summarised in table 7.

[Insert table 6 about here]

Model 1 is our baseline model that uses a global damage function describing the relationship between flood depth damage as a percentage of maximum damage for all types of physical assets global. This damage function, is not specific to infrastructure and is not specific to a region. As was mentioned previously, we find a positive and statistically significant relationship between $ExpectedDamage$ and PD.

4.2 Damage Functions and Adaptation

In model 2, we estimate $ExpectedDamage$ using a different damage function. This time, the damage function is specific to infrastructure (Huizinga, De Moel, Szewczyk, et al. 2017). Here again, expected damage from flood increases probability of default ($p<0.01$); however, the coefficient is marginally larger at 0.00517 in this case compared to model 1 where the coefficient was 0.00516. The use of a damage function specific to infrastructure resulted in an marginal increase of the effect of flood damage on probability of default.

The damage function used in model 2 already accounts for some differences in vulnerability to flood specific to infrastructure. However, it will not account for the specifics to each type of infrastructure assets, and the adaptation measures in place to reduce the damage from flood in place within the same family of infrastructure assets.

In other words, at best, the Huizinga, De Moel, Szewczyk, et al. 2017 infrastructure damage function would account for potential differences in damage between infrastructure and other types of buildings, but for instance, would not account for differences between two airports in two different countries or two airports within the same country.

In the absence of the asset-specific damage functions, we collect 15 damage functions linking flood depth to damage based on Huizinga, De Moel, Szewczyk, et al. 2017 and Habermann and Hedel 2018. Of these 15 damage functions, we select the lowest and the highest damage function. The lowest damage function refers to the damage function where the increase in flood depth results in the least increase in damage. The highest damage function refers to the damage function where increases in flood depth result in the fastest increase in damage.

We estimate $ExpectedDamage$ again using the two boundary damage functions. The results are summarized in table 7 under models 3 and 4.

The results of the estimation of models 3 and 4 are consistent with previous results in that there is a positive and statistically significant relationship between $ExpectedDamage$ and PD ($p<0.01$). However, the results in terms of size of the coefficient do not add much to our understanding. If anything, the fact that coefficients are different means that the choice of the damage function can help refine the pricing of flood risk and its effect on the probability of default.

The fact that all the coefficients, regardless of the choice of damage function, are of similar magnitude is indicating that much more refining of the damage function is needed if we are to better factor adaptive capacity in the analysis of flood damage.

[**Insert table 7 about here**]

These findings are consistent with the portion of the climate finance literature that provides evidence of the impact of flood risk exposure on debt pricing. First, it is consistent with the findings of Allman 2021 on corporate bonds, and the findings of Painter 2020 and Goldsmith-Pinkham et al. 2021 on the effect of flood exposure on municipal bonds. The findings of Painter 2020 and Jiang, C. W. Li, and Qian 2019 are particularly relevant as they both use damage from flood as an explanatory variable. However, our findings add to the understanding built by Painter 2020 and Jiang, C. W. Li, and Qian 2019 as our measure of $ExpectedDamage$ is more granular.

Our findings are consistent with the literature studying the effect of physical climate risk on loan pricing. Javadi and Masum 2021 find that loans to companies exposed to drought risk have higher spreads. Our findings are also consistent with the findings of the broader literature on climate risk, beyond physical climate risk. Capasso, Gianfrate, and Spinelli 2020 finds that high carbon intensity increase firms probability of default. Ehlers, Packer, and Greiff 2022 find that loans to high carbon intensity borrowers come with a significant carbon premium. Benincasa 2021 finds that home climate policies have an impact on cross-border bank lending. Infrastructure loan lending is mainly cross-border and higher probability of default induced by flood might lead to similar results.

To our best knowledge, it is the first time that flood damage is estimated at an asset level for infrastructure and adaptation is discussed as a factor explaining probability of default and assets pricing in general. In that sense, our findings open new avenue of research that could focus on refining the measure and the impact of adaptation on asset prices.

4.3 Control Variables

Blanc-Brude and Yim 2019 perform an extensive analysis on private infrastructure debt looking at the risk factors explaining spreads and study how these factors evolve over time. They identify four combinations of factors that drive spreads: market trends, credit risk (size of the transaction, demand risk exposure, and transaction sector), liquidity risk (maturity of the loan, size, and refinancing), and cost of funding (measure as base interest rate benchmark such libor) (Blanc-Brude and Yim 2019). We use these factors as control variables.

Table 6 model 5 reports the multivariate regression models where we look at each control variables individually. We use one control variable for each model in addition to our country and sector fixed effects.

We use the size of the loan as a control variable consistent with Berk 1995 asset pricing model that argues that size explains part of the cross-section of expected returns. Ho and Wong 2021 and Ehlers, Packer, and Greiff 2022 looking at carbon transition risk impact on syndicated loan spreads further demonstrate that loan size is negatively associated with credit spreads for the universe of syndicated loans. Sorge and Gadanecz 2008 and Blanc-Brude and Yim 2019 finds similar results for project finance loans. Since size is negatively associated with credit spreads, one might expect it to be also negatively associated with probability of default.

As reported in Model 6 of Table 6, the effect of size on probability of default is statistically significant ($p<0.01$). Therefore our findings are consistent with the literature.

The maturity of loans is another important determinant of credit spreads. Blanc-Brude and Yim 2019 argue that in the contrary to the corporate debt universe, project finance loans have lower spreads for longer maturities (Frédéric Blanc-Brude and O. Ismail 2013; Kleimeier and Megginson 2000; Sorge and Gadanecz 2008). The attribute such dynamic to both the greater lender confidence that a longer-term loan suggests (Esty 2003) in addition to the very nature of the cashflows of infrastructure assets that suggests that more time goes, the more certainty over the cashflows as the construction risk dissipates (Frédéric Blanc-Brude and O. Ismail 2013). However, as noted by Blanc-Brude and Yim 2019, the maturity was not always demonstrated to be a strong driver of the credit spread for infrastructure loans. For instance, Gatti 2007; Stefano Gatti et al. 2022 find that maturity is not a statistically significant determinant of spreads.

In our sample, as reported in Table 6 model 5, maturity or tenor has a statistically significant negative relationship with the probability of default ($p<0.01$) in consistence with the literature on project finance loans.

The discussion on loan maturity ties in with the role of the financing stage. During the construction stage, infrastructure assets do not generate cashflows. This means an increased uncertainty over the cashflows for the greenfield projects and improved certainty at the refinancing stage. Frederic Blanc-Brude and Strange 2007 find that refinancing loans for infrastructure have 20 to 50 basis point lower credit spread. During the construction phase, the cashflows of projects are more volatile. Francis et al. 2004 and Chen and Silva Gao 2012 provide evidence that cashflow volatility should be negatively correlated associated with the cost of capital. As reported in Table 6 model 4, we find that loans provided to projects for refinancing purposes, are associated with lower probability of default. This relationship is statistically significant (p-value ¡0.05).

As mentioned previously, Blanc-Brude and Yim 2019 find that cost of funding, measured through base interest rates benchmark such libor, is a determinant of infrastructure loan spreads.

We control for the cost of funding using the yield of 10 years US treasury and not Libor.

We consider that it is preferable to use a long-term funding benchmark for loans with average maturity of more than 10 years. Libor is a short-term benchmark that doesn't reflect the dynamics of the long end of the yield curve. In addition, the Libor is currently in the process of being phased out as an inter-bank lending market benchmark.

The results reported in Model 5 Table 6 show that there is a positive and statistically significant ($p<0.01$) association between the ten years US treasury yield and infrastructure loans probability of default. An increase is the treasury yield reflects an increase in the overall medium to long-term funding conditions that in turn translate into increase probability of defaults. Here again, our findings are consistent with the literature.

4.4 The pricing of climate change scenarios

Barnett, Brock, and Hansen 2020 discuss in the details the pricing uncertainty induced by the modelling of the relationship between climate change and the economy. They identify three areas of uncertainty: risk that refers to uncertainties within a model, ambiguity referring to uncertainties across models, and misspecification, referring to uncertainty about models.

Giglio et al. 2021 note that the uncertainty over the path of climate change and the uncertainty over the path of the economy have implications for asset pricing. The IPCC introduced the concept of Representative Concentration Pathway (RCP) as a way to capture such uncertainty by creating a set of scenarios, or narratives, corresponding to assumptions on both the path of climate change and the economy.

The implication of such uncertainties for our study is that we cannot draw findings on the effect of flood damage on probability of default based only on the historical flood exposure and a damage function based on historical damage only. We first need to stress-test our findings with exposures to flood in different future climate change scenarios. Second, we need to consider different damage functions that reflect different degrees of adaptation, i.e. different degrees of response of the economy to climate damage.

Goldsmith-Pinkham et al. 2021, taking into account the uncertainty considerations mentioned by Barnett, Brock, and Hansen 2020, discussed the impact of Sea-Level Rise on bonds for the RCP8.5 and RCP4.5. Yet almost none of the studies exploring the effect of physical climate risk on asset pricing provided a discussion of the results under different climate scenarios; specifically in IPCC terms of RCPs (Bernstein, Gustafson, and Lewis 2019; Barrage and Furst 2019; Painter 2020; Baldauf, Garlappi, and Yannelis 2020).

[**Insert table 5 about here**]

The quadrant in figure 5 summarises the design of our scenario analysis. We estimate models 1 to 4, in summarized in Table 8, for four combinations of climate scenarios and damage functions. We analyse the effect of flood damage calculated using: a high climate scenario RCP8.5 and low-adaptation damage function; a high climate scenario RCP8.5 and high-adaptation damage function; a high climate scenario RCP4.5 and low-adaptation damage function; and finally, a low climate scenario RCP8.5 and high-adaptation damage function.

Although the effect of $ExpectedDamage$ on PD is positive and statistically significant for all models 1 to 4 (p<0.01). The coefficients for the $ExpectedDamage$ calculated using flood exposure values based on RCP8.5 are larger that those based on RCP4.5. Similarly, both for $ExpectedDamage$ estimated using RCP8.5 and RCP4.5, the coefficients are larger when using a high damage function (low adaptation) than when using a low-damage damage function (high adaptation).

A possible interpretation is that infrastructure investors see higher climate change scenario happening in the future, and that there will be little response in terms of adaptive capacity to this increase in climate risk. The work of Goldsmith-Pinkham et al. 2021 and Barnett, Brock, and Hansen 2020 indicate that investors might more concerned with the worst climate scenarios. Therefore, this finding is consistent with the literature.

More broadly, the sizes of the coefficients of $ExpectedDamage$ estimated in the context of climate change are lower than those estimated previously using exposure figures based on historical flood exposure. A possible interpretation here again is that infrastructure investors mainly rely on historical flood exposures and damage to draw the probability of defaults on infrastructure loans.

[**Insert table 8 about here**]

5 Robustness Checks

In this section we assess the robustness of our main findings by estimating different variations of our main specification. We start by modifying the specification of our explanatory variable $ExpectedDamage$. We then perform a placebo test by estimating the effect of $ExpectedDamage$ on infrastructure loan recovery rates.

5.1 Alternative Specifications of Expected Damage

We check if our results are robust to alternative specifications of our key variable $ExpectedDamage$.

As highlighted in equation 3, our estimation of expected damage function requires (i) the selection of flood depth maps and values based on the location of assets, (ii) a choice of the damage function to use and (iii) a choice of method to calculate damage values based on damages from floods of different return periods.

As reported in table 1, when estimating $ExpectedDamage$ using different damage function of medium, high, and low, damage profiles, there is always a positive and statistically significant (p<0.01) relationship between expected damage from flood and probability of default.

In table 9, we use, in addition to alternative damage functions, alternative flood maps reflecting flood risks in the locations of our infrastructure assets for different future climate change scenarios. In our four alternative specifications, there is a statistically significant (p<0.01) positive relationship between $ExpectedDamage$ and the probability of default.

Finally, we estimate the model described in equation 4 using different choices and combinations of flood exposures for different return periods (flood probability of occurrence). The results are reported in table 1.

In our baseline specification, we estimated the expected damage from flood as the average damage of all the return periods included weighted by the probability of occurrence of the flood, i.e. the inverse of the return period, following equation 3.

First, we estimate a model where expected damage is a simple average of all the damage for all the return periods as described in equation 9. We find a positive and statistically significant ($p<0.01$) relationship between *ExpectedDamage* and the probability of default. The coefficient of *ExpectedDamage* is of similar magnitude to our baseline estimation.

We then estimate two additional models using the damage for a single return period each time. We estimate our model using the damage in the case of a 100-year flood and find that there is a still positive and statistically significant ($p<0.01$) relationship between *ExpectedDamage* and probability of default, with a coefficient of similar magnitude as in the baseline case. We also find the same when estimating our model using only the damage for a low probability, high impact, flood of a 1000-year return period.

$$\text{ExpectedFloodDamage}_j = \sum_{i=1}^{N} \frac{D\left(d_{i,j}\right)}{N}, N \text{is the number of return period} \tag{9}$$

Our results are robust to changes in the specification of our key explanatory variable *ExpectedDamage*.

[**Insert table 9 about here**]

5.2 Placebo Tests

Along with the probability of default, the recovery rate key measure of credit risk for infrastructure project loans (Blanc-Brude and Yim 2019). In a case where an infrastructure project would default on a loan because of damages resulting from floods, the lenders would have a claim over the assets in order to recover full or part of their capital. The damage from the flood would lead to a reduced value of the asset, and therefore, a reduced value of the lender's recovery rate. The intuition is that expected flood damage should be negatively associated with the project's recovery rates.

We use the recovery rate as a placebo outcome for our inquiry on the probability of default. Contrary to our findings for the probability of default, we do not find a negative association between recovery rate and expected flood damage, and the effect of expected flood damage on recovery rates is not statically significant. The results are summarized in table 10.

[**Insert table 10 about here**]

6 Discussion

6.1 Flood damage and adaptation and probability of default

Infrastructure assets are exposed to large losses due to flooding events (Hallegatte et al. 2013; Hinkel et al. 2014). We find that a one percent increase in the expected damage from floods leads to 0.5 percent increase in an infrastructure project probability of default. This is consistent with the findings of Painter 2020 and Goldsmith-Pinkham et al. 2021 that find that exposure to seal level rise leads to an increase in municipal bonds spreads. Our findings are also consistent with Allman 2021 findings that an increase in sea-level rise exposure is associate with an increase in corporate bonds yields.

Infrastructure loans have similar characteristics to municipal bonds in the sense that they are two forms of long-term debt. It is also worthwhile, to compare the two assets classes since many infrastructure projects are financed though the proceeds of municipal bonds (LY, Peng-Peng, and Huan-Huan 2007; Platz 2009; Inderst 2013; Chung 2019). However, the comparison could stop there. An investor buying a municipal bond is exposed to the risk of the municipality itself. Although floods might affect facilities in the municipality and disrupt economic activity, the level of damage and interruptions might no lead to a deterioration of the municipalities finance to the level that it cannot pay back its debt. In addition, municipalities can often rely on the central government's support in the case of default (Mochida 2008; De Mello Jr 2001).

Mortgage loans have the same long-term characteristics as infrastructure loans and municipal bonds. They are a step closer in terms of risk to infrastructure finance than municipal bonds. The proceeds of a municipal bonds can finance a multitude of projects, whereas a mortgage is destined to finance a single asset, in the same way as an infrastructure loan. Garbarino and Guin 2021 find that interest rates and loans amount for mortgages to houses in the UK are not affected by the exposure to flood. Our findings are not necessarily opposite to Garbarino and Guin 2021 for two reasons. First, the value of the house is important as a collateral for the mortgage, but when providing a mortgage, a lender is ultimately exposed to the risk of the borrower and not necessarily to the asset itself. This is not the case for infrastructure assets where the cashflows of the projects themselves are a determinant of the loan characteristics (Yescombe and Farquharson 2018; Blanc-Brude and Yim 2019). The second reason is that we study the effect of flood risk on the probability of default and not the loan terms. The loan terms might or might not reflect the actual probability of default because of investor attention and commercial considerations (Stroebel and Wurgler 2021; Giglio et al. 2021).

In that regard our findings unbundle the impact of flood of infrastructure debt and provide evidence on the channels through which this physical climate risk is affecting infrastructure finance (Hernández-Trillo 1995; Turnbull 2003).

Our findings are also consistent with Jiang, C. W. Li, and Qian 2019 who explore the impact of floods on syndicated loans and find that the long-term cost of the loans to firms go up when they are located in countries with high sea-level rise risk. We expend the findings Jiang, C. W. Li, and Qian 2019 in a couple of ways. First, we construct a more granular measure of flood damage as we concentrate only on infrastructure, and not the entire damage to the economy, and we estimate the damage for each individual infrastructure asset in our sample. Second, infrastructure loans are a subset of the syndicated loans universe. Therefore, Jiang, C. W. Li, and Qian 2019 findings should also relevant to our syndicated loans in our sample. Finally, we put focus on the channels through which the pricing of loans is affected, namely the probability of default.

From the perspective of a lender to an infrastructure project, infrastructure loans are illiquid assets (Hagströmer, Hansson, and Nilsson 2013). Risks, such as flood, might not be easy to hedge (Girardone and Snaith 2011; Cepni, Demirer, and Rognone 2022; Giglio et al. 2021) for lenders and strategies such divestment or exclusion that can be considered to manage transition risks linked to carbon emissions (Gianfrate 2018; Plantinga and Scholtens 2021), cannot be considered for infrastructure assets. The spacial distribution of ports, airports, or power plants, has economic implications as evidence by the economic geography literature (Rietveld 1994; Ottaviano 2008; Thoung et al. 2016). The implication of this is that the assessment of the adaptation measures designed reduce the physical impact of floods on ports, airports, and power plants should be part of an infrastructure investors climate risk hedging strategy, specifically for lenders.

All global studies on the impact of floods emphasis the importance of adaptive capacity in limiting the damage from floods (Hallegatte et al. 2013; Hinkel et al. 2014; Ward, Jongman, et al. 2013; Jongman, Winsemius, Fraser, et al. 2018). However, the enquiries on the impact of flooding on assets prices did not include a discussion on adaptation. The reason for that is likely the lack of databases and methods on the observation of the exact adaptation measure in place at the level of a house, a city, a corporate, or an infrastructure.

It is likely that infrastructure projects already extensively include adaptation measures to flood. Important literature defined adaptation interventions for ports and airports at a global scale (Griggs 2020; Mark Ching-Pong Poo et al. 2021; Yesudian and R. J. Dawson 2021), and individual examples are available for US airports (Sarah Lindbergh et al. 2022; Lindbergh et al. 2022), the Mediterranean (De Vivo et al. 2022), Singapore (Dolman and Vorage 2020), or the Netherlands (Dolman and Sindhamani n.d.). Similar detailed studies are available for ports (Becker et al. 2013; Portillo Juan, Negro Valdecantos, and Campo 2022;

Vellinga and Jong 2012; Yang et al. 2018) and power plants (Espinoza et al. 2016; Nguyen et al. 2017; Zimmerman and Faris 2010; In et al. 2022). However, it is not easy to observe these adaptation measures. This is particularly difficult for soft adaptation measures aiming to foster stakeholder collaboration, better governance, and increase institutional capacity to deal with flooding (Morris 2020; Punt et al. 2022; Lindbergh et al. 2022).

We consider that the ultimate result of implementing adaptation measures is that the flood depth-damage functions would be altered. If we imagine two airports with the exact same exposure to flooding, one with advanced adaptation measures and one without. The airport with the advanced adaptation measures included in the design will have flood depth-damage function the feature lower damages for a similar level of flooding.

Following this logic, we collected damage functions from the literature (Huizinga, De Moel, Szewczyk, et al. 2017) that reflect different levels of damage and therefore adaptation. We estimated the expected damage from flooding for each infrastructure using different damage functions. We find that the effect of expected damage on probability of default does not vary significantly even if the damage functions themselves vary greatly.

This result suggests that infrastructure lenders might not have the tools to accurately evaluate the adaptation measures in place and reward them through a lower cost of capital.

This finding had important policy implications. The objective of climate disclosure principles such as the Task Force for Climate-Financial Disclosures (TCFD) is to encourage investment in adaptation to climate change by requiring financial institutions to disclose exposure to climate risks (Carney 2019). Although a lot of progress has been made, the results of the latest climate scenario analysis pilot exercise by central banks around the world did not include physical climate risks such as flooding (Robins, Dikau, and Volz 2021; Kyriakopoulou et al. 2022). One of the reasons is the lack of climate information to assess these risks (Bruin et al. 2020). Even when such information is available, it mostly allows the assessment of exposure to climate risks and perhaps sensitivity to these risks but doesn't allow the assessment of adaptive capacity (Thomas et al. 2019). Yet, investors need to be able to assess and reward adaptation, especially in infrastructure. If not, climate disclosure could result in perverse incentives whereby lenders simply avoid lending to projects exposed to flooding, or other physical climate risks, whereas the risk might not be material (Gostlow 2020; Krueger, Sautner, and Starks 2020; Gourdel et al. 2021).

7 Conclusion

This paper studies the effect of the expected damage from flooding on the probability of default of loans to these assets based on the location of infrastructure assets. We construct a comprehensive data-set of infrastructure loan probability of defaults and estimate the expected damage from flood to these infrastructures based on historical flood data, future projections for high and low climate change, and flood depth-damage functions.

We find that there is a statistically significant and positive relationship between expected damage from flood and loan probability of default. This result is robust to multiple alternative specifications and tests and suggests that infrastructure lenders understand flood risk and price it in infrastructure loans through the channel of probability of default. The relevance of the probability of default as a primary channel for the pricing of flood risk is supported by our robustness checks that do not show any relationship between expected damage from flood and infrastructure loan recovery rates, the other key parameter for infrastructure loan pricing.

We estimate flood risk expected damage using multiple damage functions to highlight the importance of the relationship between exposure to physical climate risk and adaptation to flooding. This has been a gap in the literature since most studies so far focused on exposure only and the ones including damage did not estimate it at asset-level. We find little difference in the magnitude of the coefficients for flood expected damage when using damage functions that reflect low level and high levels of adaptation to flood. We find similar results when using flood exposures based on climate change scenarios. This suggests that although infrastructure lenders might factor in expected damages from floods in probability of default estimations, they take a backwards looking approach based on historical damage with perhaps little regard to the future direction of the risk due to climate change and the adaptation investment needed to mitigate the future impacts.

Our findings support the literature on the pricing of climate risk in loans and debt financing instruments in general. It also offers financial regulators and investors a framework to assess flood risk and climate risk in general in lending operations. This framework is based on the principles of including forward-looking climate scenarios and stress-testing potential damages by using multiple damage functions that reflect multiple levels of adaptation. Such an approach could better highlight the benefits of adaptation investment and reward such investment through a reduced cost of capital.

The study also highlighted the research gaps that need to be bridged to effectively deploy such a framework. A lot of work remains to be done on developing damage functions specific to types of infrastructures and regions with similar climate characteristics. Damage functions also need to be better linked to specific adaptation measures, both soft and hard adaptation. In fact, the adaptation principles are yet to be clearly developed for infrastructure and other physical assets. But the biggest challenge ahead of the climate finance community is to be able to measure adaptation for infrastructure in a way that enables it to be better priced in financing operations.

Tables

Table 1: European Commission JRC Global flood depth-damage functions. Huizinga et al. 2017

	Damage function					
Flood depth, [m]	EUROPE	North AMERICA	Central &South AMERICA	ASIA	AFRICA	GLOBAL
0	0	0.03	0	0	0	0
0.5	0.15	0.32	0.67	0.28	0.06	0.3
1	0.27	0.51	0.89	0.48	0.25	0.48
1.5	0.4	0.64	0.95	0.63	0.4	0.6
2	0.52	0.74	1	0.72	0.49	0.69
3	0.7	0.86	1	0.86	0.68	0.82
4	0.85	0.94	1	0.91	0.92	0.92
5	1	0.98	1	0.96	1	0.99
6	1	1	1	1	1	1

This table describes damage functions developed by (Huizinga, De Moel, Szewczyk, et al. 2017) for the industrial sector linking flood depth in meters to the damage expressed in percentage of the assets value.

Table 2: Infrastructure Summary - Transactions size and number

		Number of Transactions	Total Transaction USD Million	Min Transaction USD Million	Max Transaction USD Million	Average Transaction USD Million
1	Renewables	1316	168711.05	0.00	2454.99	172.15
2	Power	204	77213.97	0.00	3323.00	467.96
3	Ports	286	41184.56	0.00	1514.00	228.80
4	Airports	307	68585.21	0.00	12000.00	401.08
5	Greenfield	1346	201976.03	0.00	12000.00	222.93
6	Refinancing	767	153718.76	0.00	6457.88	260.54
7	Europe	1060	155907.21	0.00	6457.88	203.53
8	Latin America and Caribbean	222	22674.50	0.00	925.00	160.81
9	Middle East	12	3355.46	21.20	720.00	305.04
10	North America	173	41112.54	0.00	4100.00	328.90
11	Asia	334	90767.35	0.00	12000.00	399.86
12	Australasia	245	29733.22	0.00	1428.39	171.87
13	Africa	67	12144.51	0.00	1175.00	229.14
14	Senior Secured					
15	less than 7					
16	More than 7					
17	More than 20					
18	Below 100					
19	More than 100 Mn - 500 Mn					
20	More than 500 Mn					
21	Grantor					

This table summarises infrastructure loan transactions with private sector participation between 2000 and 2020 reported in the Inframation database. For each category or type of infrastructure, the table shows the number of transactions, the total amount of transactions, the maximum, the minimum, and the average amount.

Table 3: Infrastructure Summary - Probability of Default and Recovery Rate

		Min.PD	Max.PD	Average.PD	Min.RR	Max.RR	Median.RR
1	Renewables	0.04	0.10	0.05	0.44	0.74	0.70
2	Power	0.04	0.10	0.06	0.44	0.74	0.70
3	Ports	0.04	0.10	0.06	0.44	0.75	0.70
4	Airports	0.04	0.11	0.06	0.43	0.75	0.71
5	Greenfield	0.04	0.11	0.06	0.43	0.72	0.69
6	Refinancing	0.04	0.10	0.05	0.67	0.75	0.72
7	Europe	0.04	0.10	0.05	0.44	0.74	0.70
8	Latin America and Caribbean	0.06	0.11	0.07	0.43	0.74	0.70
9	Middle East	0.04	0.06	0.05	0.69	0.72	0.70
10	North America	0.05	0.07	0.05	0.67	0.73	0.71
11	Asia	0.05	0.10	0.06	0.44	0.73	0.68
12	Australasia	0.05	0.08	0.05	0.68	0.75	0.71
13	Africa	0.05	0.07	0.06	0.65	0.68	0.66
14	Senior Secured	0.04	0.10	0.05	0.44	0.75	0.70
15	less than 7	0.04	0.10	0.05	0.44	0.75	0.70
16	More than 7	0.04	0.10	0.05	0.44	0.74	0.70
17	More than 20	0.04	0.11	0.06	0.43	0.75	0.70
18	Below 100	0.04	0.10	0.05	0.44	0.75	0.70
19	More than 100 Mn - 500 Mn	0.04	0.10	0.05	0.65	0.74	0.70
20	More than 500 Mn	0.04	0.11	0.06	0.43	0.75	0.70
21	Grantor	0.04	0.11	0.06	0.43	0.72	0.69

This table summarises probability of default and recovery rates estimations for each type of infrastructure, region, and size category based on Moody's Investor Services infrastructure default and recovery database.

Table 4: Summary statistics: variables for multivariate analysis

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Probability of Default	2,113	0.053	0.011	0.039	0.044	0.058	0.112
Log_PD	2,113	−1.282	0.084	−1.409	−1.356	−1.234	−0.951
Recovery Rate	2,105	0.700	0.026	0.434	0.687	0.713	0.746
Log_RR	2,105	−0.155	0.018	−0.362	−0.163	−0.147	−0.128
Damage	2,113	0.024	0.050	0.000	0.00000	0.028	0.524
Log_Damage	2,113	−0.414	1.448	−5.573	−1.428	0.609	3.112
Adaptation	2,113	0.096	0.093	0.035	0.035	0.104	1.000
Log_Adaptation	2,113	−0.047	0.055	−0.464	−0.048	−0.015	0.000
Year	2,113	2,015.007	4.816	1,946	2,013	2,018	2,021
Size	1,421	250.313	488.059	1.070	53.330	290.570	12,000.000
Tenor	976	11.583	6.054	0.500	5.015	16.000	30.000

This table provides summary statistics for the variables used in our multivariate analysis.

Table 5: Key variable description

Variable	Description	Source
Dependent variables		
Log (Probability of Default)	Log of the probability of default of the infrastructure project based on sector, country, year, and maturity and expressed in percentage value.	Moody's Investor Services.
Explanatory variables: Expected Loss from flood		
Log (Damage)	Log of the expected loss from flood calculated for the transactions based on the methodology described in this study.	WRI/GLOFRIS 10-years to 1000-years flood maps and Huiginza et al. (2018) damage functions.
Explanatory variables: Infrastructure project characteristics		
Log(size)	Log of the loan tranche size expressed in USD dollars.	Inframation infrastructure database.
Log(maturity)	Log of the loan tranche maturity expressed in number of years	Inframation infrastructure database.
Financing stage	Categorical variable describing if the project is in the refinancing or primary financing stage.	Inframation infrastructure database.
Sector	Dummy variable describing the transaction's sector.	Inframation infrastructure database.
Country	Dummy variable describing the transaction's Country.	Inframation infrastructure database.
Explanatory variables: Interest rate environment		
Log (Treasury)	Log of the interest rate on 10 years treasury bill for the year of the issuance of the infrastructure loan.	Bloomberg.

Table 6: Multivariate analysis results

	Dependent variable:				
	Log_PD				
	(1)	(2)	(3)	(4)	(5)
Log_FloodDamage	0.004***	0.004***	0.004***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log_Size		−0.030***	−0.017**	−0.023***	−0.024***
		(0.006)	(0.008)	(0.007)	(0.007)
Log_Tenor			−0.020	−0.017	−0.026**
			(0.012)	(0.010)	(0.011)
Log_Treasury				0.225***	0.228***
				(0.024)	(0.024)
TypeRefinancing					−0.020**
					(0.008)
Constant	−1.230***	−1.154***	−1.167***	−1.243***	−1.222***
	(0.006)	(0.017)	(0.025)	(0.023)	(0.024)
Observations	951	951	563	551	551
Adjusted R^2	0.017	0.040	0.035	0.184	0.191
Note:					*p<0.1; **p<0.05; ***p<0.01

Models (1) to (5) provide the results of OLS regression for our sample of 952 infrastructure projects. The dependent variable is the probability of default and the independent variables are our estimated flood damage metric and control variables. The sample of projects covers airports, ports, and power plants from all world regions.

Table 7: Multivariate analysis using different damage functions

	Dependent variable:			
	Log_PD			
	(1)	(2)	(3)	(4)
Log_FloodDamage	0.00516***			
	(0.001)			
Log_FloodDamage_Infra		0.00517***		
		(0.001)		
Log_FloodDamage_LowDamage			0.00508***	
			(0.001)	
Log_FloodDamage_HighDamage				0.00501***
				(0.001)
Log_Size	−0.024***	−0.024***	−0.024***	−0.024***
	(0.007)	(0.007)	(0.007)	(0.007)
Log_Tenor	−0.026**	−0.026**	−0.026**	−0.026**
	(0.011)	(0.011)	(0.011)	(0.011)
Log_Treasury	0.228***	0.228***	0.228***	0.228***
	(0.024)	(0.024)	(0.024)	(0.024)
TypeRefinancing	−0.020**	−0.020**	−0.020**	−0.020**
	(0.008)	(0.008)	(0.008)	(0.008)
Constant	−1.222***	−1.222***	−1.224***	−1.225***
	(0.024)	(0.024)	(0.024)	(0.024)
Observations	551	551	551	551
Adjusted R^2	0.191	0.191	0.190	0.191
Note:	*p<0.1; **p<0.05; ***p<0.01			

Models (1) to (5) provide the results of OLS regression for our sample of 952 infrastructure project. The dependent variable is the probability of default and independent variables are our estimated flood damage metric and control variables. Each model includes an estimation of flood damage that uses a different damage function. Model (1) includes flood damage estimated using a global damage function constructed using damages from across regions and assets. Model (2) includes flood damage estimated using a damage function constructed using damages to infrastructure assets. Model (3) includes flood damage estimated using a damage function constructed using low damages. Model (4) includes flood damage estimated using a damage function constructed using large damages.

Table 8: Flood risk pricing under different climate change and adaptation scenarios

	Dependent variable:			
	Log_PD			
	(1)	(2)	(3)	(4)
Log_FloodDamage_RCP85_LowDamage	0.00489***			
	(0.001)			
Log_FloodDamage_RCP45_LowDamage		0.00469***		
		(0.001)		
Log_FloodDamage_RCP85_HighDamage			0.00496***	
			(0.001)	
Log_FloodDamage_RCP45_HighDamage				0.00475***
				(0.001)
Log_Size	−0.024***	−0.024***	−0.024***	−0.024***
	(0.007)	(0.007)	(0.007)	(0.007)
Log_Tenor	−0.024**	−0.025**	−0.024**	−0.025**
	(0.011)	(0.011)	(0.011)	(0.011)
Log_Treasury	0.226***	0.225***	0.226***	0.225***
	(0.024)	(0.024)	(0.024)	(0.024)
TypeMA	−0.007	−0.007	−0.007	−0.007
	(0.017)	(0.017)	(0.017)	(0.017)
TypeRefinancing	−0.020**	−0.020**	−0.020**	−0.020**
	(0.008)	(0.008)	(0.008)	(0.008)
Constant	−1.224***	−1.226***	−1.223***	−1.226***
	(0.024)	(0.024)	(0.024)	(0.024)
Observations	551	551	551	551
Adjusted R^2	0.189	0.188	0.189	0.188
Note:				*p<0.1; **p<0.05; ***p<0.01

Each model (1) to (4) includes an estimation of flood damage that uses a different damage function and two climate scenarios. Models (1) and (2) includes flood damage estimated using a damage function constructed using low damages for the high climate change scenario RCP8.5 and low climate change scenarios RCP4.5. Models (3) and (4) includes flood damage estimated using a damage function constructed using large damages for the high climate change scenario RCP8.5 and low climate change scenarios RCP4.5.

Table 9: Damage Estimation using Alternative Specifications

	Dependent variable:		
	Log_PD		
	(1)	(2)	(3)
Log_FloodDamage_Average	0.00480***		
	(0.001)		
Log_FloodDamage_100yr		0.00388***	
		(0.001)	
Log_FloodDamage_1000yr			0.00455***
			(0.001)
Log_Size	−0.024***	−0.023***	−0.024***
	(0.007)	(0.007)	(0.007)
Log_Tenor	−0.025**	−0.027**	−0.025**
	(0.011)	(0.011)	(0.011)
Log_Treasury	0.228***	0.227***	0.228***
	(0.024)	(0.024)	(0.024)
TypeMA	−0.006	−0.007	−0.006
	(0.017)	(0.017)	(0.017)
TypeRefinancing	−0.020**	−0.021**	−0.020**
	(0.008)	(0.008)	(0.008)
Constant	−1.229***	−1.233***	−1.232***
	(0.024)	(0.024)	(0.024)
Observations	551	551	551
Adjusted R^2	0.194	0.181	0.195
Note:	*p<0.1; **p<0.05; ***p<0.01		

Each model (1) to (3) includes an estimation of flood damage that different calculation methods for a based on historical flood modelling and the global damage function. Models (1) includes expected flood damage computed as a simple of average of the damages estimated for each return period. On the contrary to our baseline estimation of damage, the average is not weighted using the inverse return periods. Model (2) includes expected flood damage for 100 years return period only. Model (3) includes expected flood damage for 1000 years return period only.

Table 10: Flood expected damage, probability of default, and recovery rates

	Dependent variable:	
	Log_PD	Log_RR
	(1)	(2)
Log_FloodDamage	0.005***	0.0002
	(0.001)	(0.0004)
Log_Size	−0.024***	0.004
	(0.007)	(0.003)
Log_Tenor	−0.026**	−0.002
	(0.011)	(0.004)
Log_Treasury	0.228***	0.014
	(0.024)	(0.009)
TypeRefinancing	−0.020**	0.011***
	(0.008)	(0.003)
Constant	−1.222***	−0.148***
	(0.024)	(0.009)
Observations	551	550
Adjusted R^2	0.191	0.031
F Statistic	22.608*** (df = 6; 544)	3.884*** (df = 6; 543)
Note:		*p<0.1; **p<0.05; ***p<0.01

Model (1) shows the results of OLS regression analysis where the probability of default is the dependent variable and model (2) reports the results of OLS regression analysis where the dependent variable is the loan recovery rates.

Figures

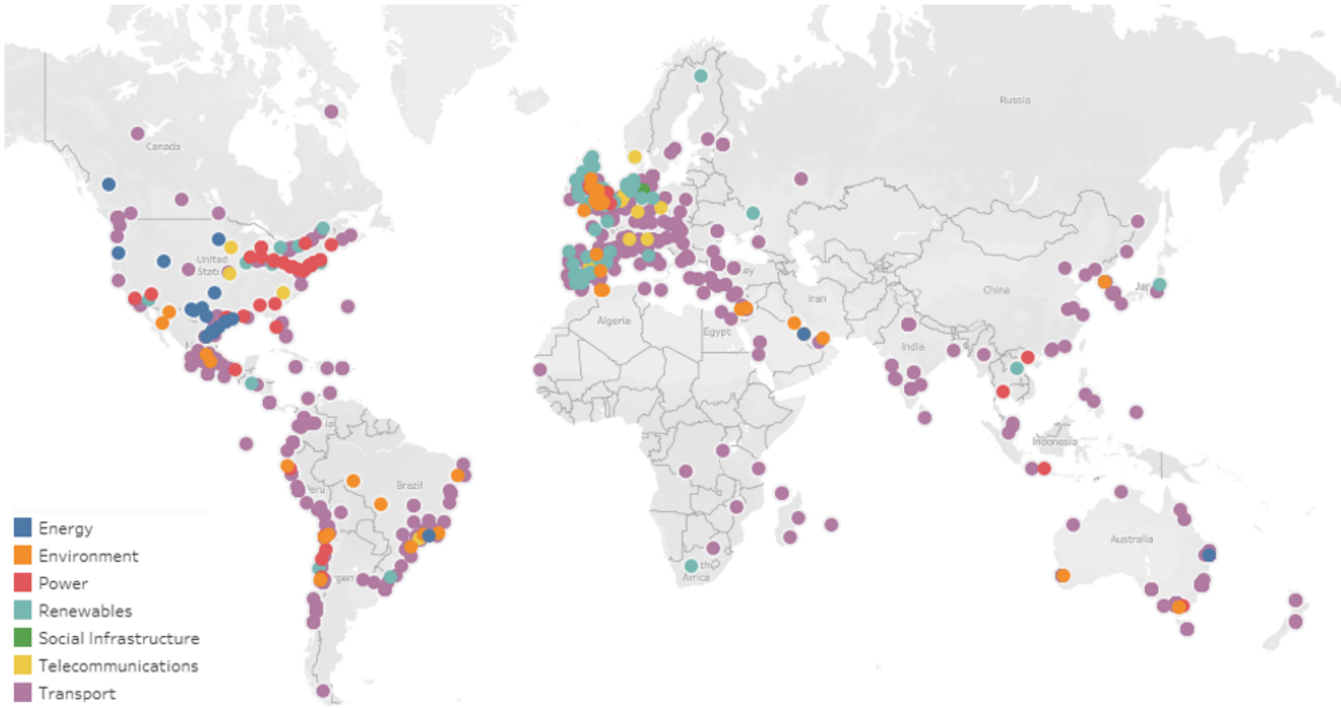

Figure 1: 950 infrastructure assets included in the analysis

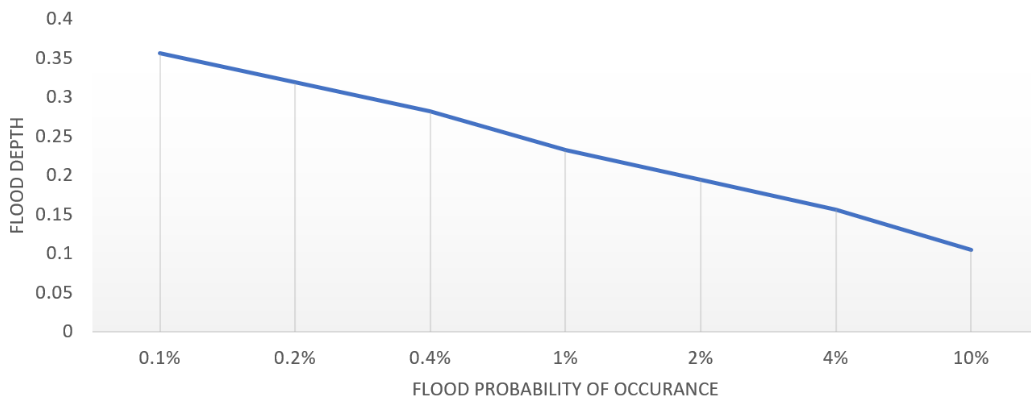

Figure 2: Example: Brussels Airport. Flood depth and flood probability of occurance

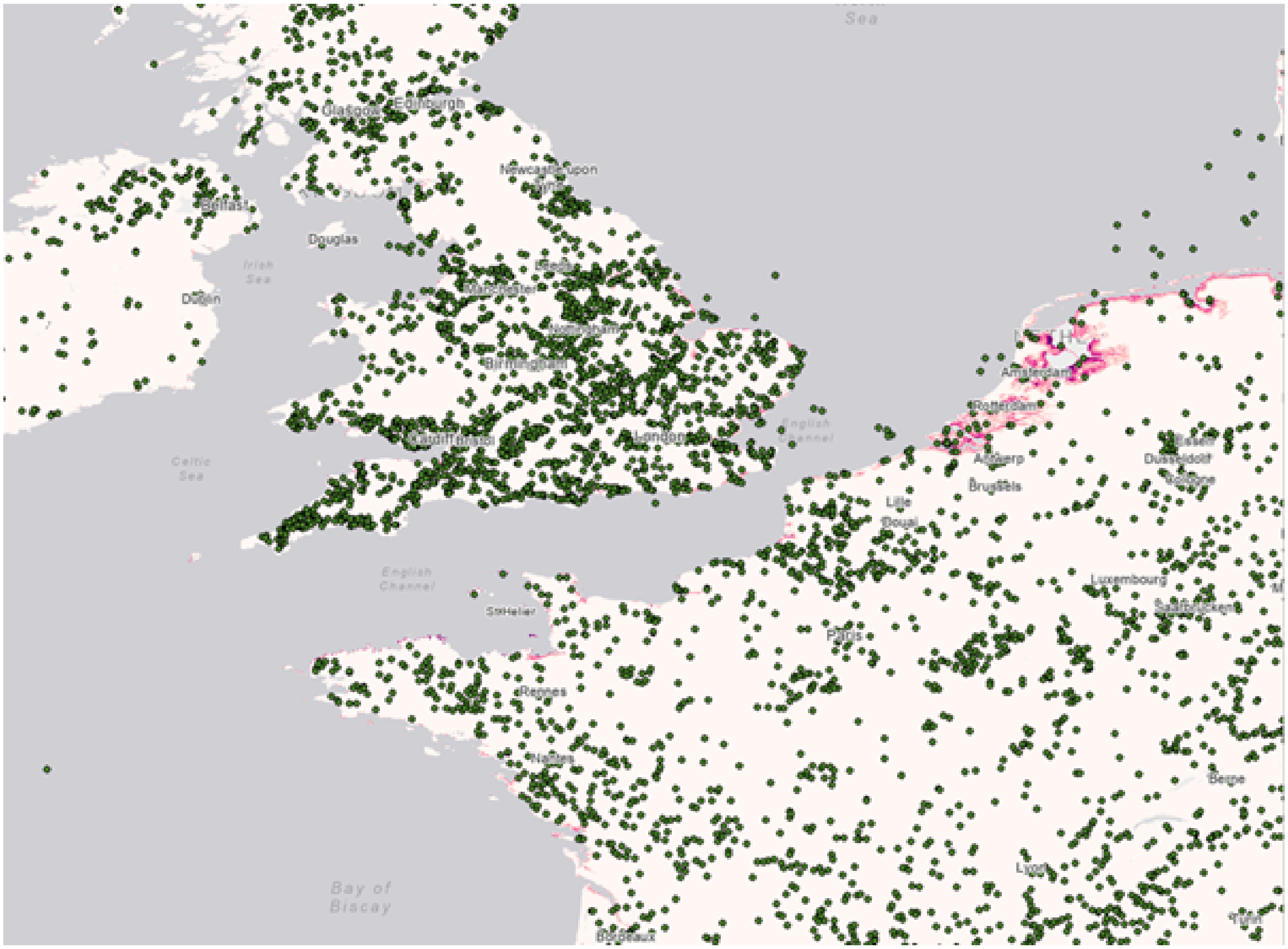

Figure 3: Example of Infrastructure Exposed to 100 year flood

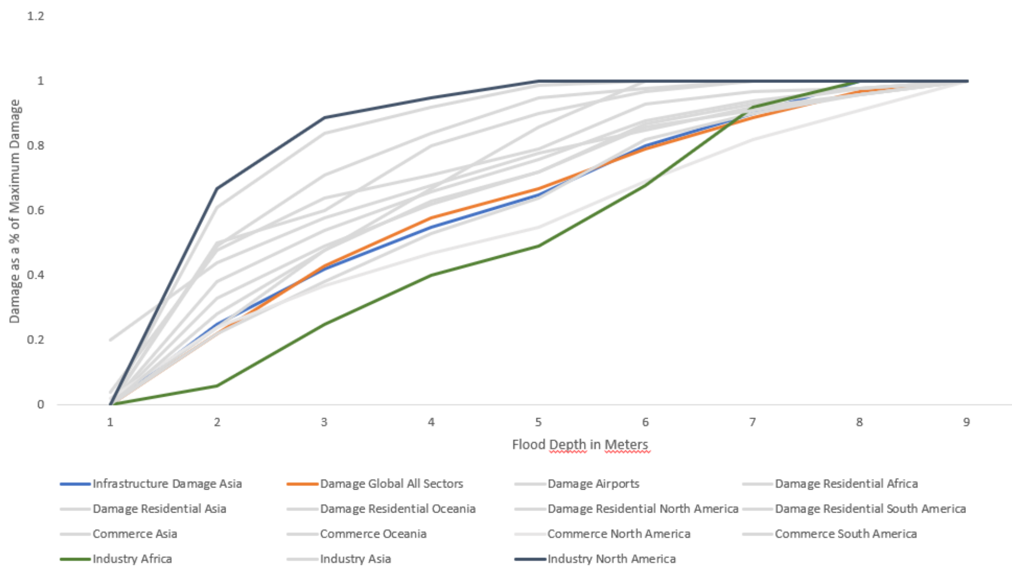

Figure 4: Flood depth-damage functions for sectors and regions

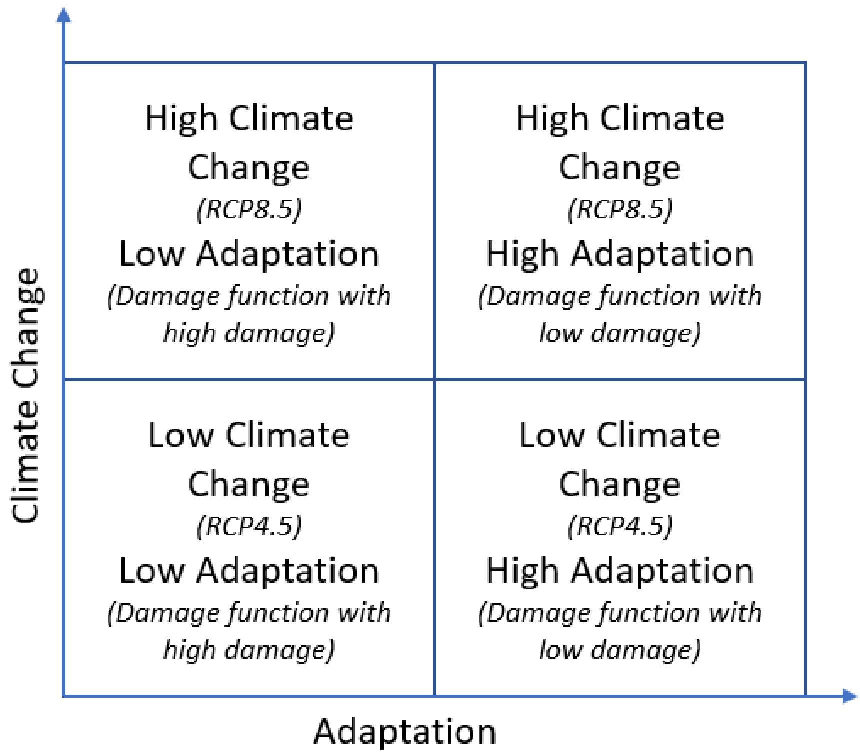

Figure 5: Climate Scenario Stress Testing

References

Allman, Elsa (2021). "Pricing Climate Change Risk in Corporate Bonds". In: *Available at SSRN 3821018*.

Bajaj, Isha and Mandeep Kaur (2022). "Validating multi-dimensional model of financial literacy using confirmatory factor analysis". In: *Managerial Finance* ahead-of-print.

Baldauf, Markus, Lorenzo Garlappi, and Constantine Yannelis (2020). "Does climate change affect real estate prices? Only if you believe in it". In: *The Review of Financial Studies* 33.3, pp. 1256–1295.

Barnett, Michael, William Brock, and Lars Peter Hansen (2020). "Pricing uncertainty induced by climate change". In: *The Review of Financial Studies* 33.3, pp. 1024–1066.

Barrage, Lint and Jacob Furst (2019). "Housing investment, sea level rise, and climate change beliefs". In: *Economics letters* 177, pp. 105–108.

Becker, Austin H et al. (2013). "A note on climate change adaptation for seaports: a challenge for global ports, a challenge for global society". In: *Climatic change* 120.4, pp. 683–695.

Benincasa, Emanuela (2021). "Climate policy and cross-border lending: evidence from the syndicated loan market". In: *Economic and Political Studies* 9.4, pp. 463–476.

Berk, Jonathan B (1995). "A critique of size-related anomalies". In: *The Review of Financial Studies* 8.2, pp. 275–286.

Bernstein, Asaf, Stephen B Billings, et al. (2022). "Partisan residential sorting on climate change risk". In: *Journal of Financial Economics*.

Bernstein, Asaf, Matthew T Gustafson, and Ryan Lewis (2019). "Disaster on the horizon: The price effect of sea level rise". In: *Journal of financial economics* 134.2, pp. 253–272.

Blanc-Brude, F and JL Yim (2019). "ThePricingofPrivateInfrastructureDebt-ADynamicApproach". In: *EDHEC Infrastructure Institute Publication*.

Blanc-Brude, Frederic and Roger Strange (2007). "How banks price loans to public-private partnerships: Evidence from the European markets". In: *Journal of Applied Corporate Finance* 19.4, pp. 94–106.

Blanc-Brude, Frédéric, Majid Hasan, and Omneia RH Ismail (2014). "Unlisted infrastructure debt performance measurement". In: *EDHEC-Risk Institute, Singapore*.

Blanc-Brude, Frédéric and ORH Ismail (2013). "Who is afraid of construction risk". In: *Economics* 33.1, pp. 3–56.

Brealey, Richard A, Ian A Cooper, and Michel A Habib (1996). "Using project finance to fund infrastructure investments". In: *Journal of applied corporate finance* 9.3, pp. 25–39.

Bruin, Karianne de et al. (2020). "Physical climate risks and the financial sector—synthesis of investors' climate information needs". In: *Handbook of Climate Services*. Springer, pp. 135–156.

Burbidge, Rachel (2016). "Adapting European airports to a changing climate". In: *Transportation Research Procedia* 14, pp. 14–23.

Capasso, Giusy, Gianfranco Gianfrate, and Marco Spinelli (2020). "Climate change and credit risk". In: *Journal of Cleaner Production* 266, p. 121634.

Carney, Mark (2019). "TCFD: strengthening the foundations of sustainable finance". In: *Proceedings of the TCFD Summit*.

Cepni, Oguzhan, Riza Demirer, and Lavinia Rognone (2022). "Hedging climate risks with green assets". In: *Economics Letters* 212, p. 110312.

Cevik, Serhan and João Tovar Jalles (2020). "Feeling the heat: Climate shocks and credit ratings". In: *Available at SSRN 3772492*.

— (2022). "An Apocalypse Foretold: Climate Shocks and Sovereign Defaults". In: *Open Economies Review* 33.1, pp. 89–108.

Chen, Linda H and Lucia Silva Gao (2012). "The pricing of climate risk". In: *Journal of Financial and Economic Practice, Vol12 (2), Spring*, pp. 115–131.

Chung, Christine Sgarlata (2019). "Rising tides and rearranging deckchairs: How climate change is reshaping infrastructure finance and threatening to sink municipal budgets". In: *Geo. Envtl. L. Rev.* 32, p. 165.

Crăciun, Mihnea (2011). "Macroeconomic and Political Risk Management in Infrastructure Projects." In: *Petroleum-Gas University of Ploiesti Bulletin, Economic Sciences Series* 63.3.

Dawson, Richard and Jim Hall (2006). "Adaptive importance sampling for risk analysis of complex infrastructure systems". In: *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences* 462.2075, pp. 3343–3362.

Dawson, Richard J et al. (2018). "A systems framework for national assessment of climate risks to infrastructure". In: *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 376.2121, p. 20170298.

De Mello Jr, Luiz R (2001). "Fiscal decentralization and borrowing costs: the case of local governments". In: *Public Finance Review* 29.2, pp. 108–138.

De Vivo, Carmela et al. (2022). "Risk assessment framework for Mediterranean airports: A focus on extreme temperatures and precipitations and sea level rise". In: *Natural Hazards* 111.1, pp. 547–566.

Dolman, Nanco and Vivekanandhan Sindhamani (n.d.). "Climate change impacts on airports and measures–case of Schiphol Airport". In: ().

Dolman, Nanco and Peter Vorage (2020). "Preparing Singapore Changi Airport for the effects of climate change". In: *Journal of Airport Management* 14.1, pp. 54–66.

Dutra, Joisa and Antonio Barbalho (2017). "The convergence of business models and long-term financing in the energy transition". In: *Competition and Regulation in Network Industries* 18.3-4, pp. 256–270.

Ehlers, Torsten, Frank Packer, and Kathrin de Greiff (2022). "The pricing of carbon risk in syndicated loans: which risks are priced and why?" In: *Journal of Banking & Finance* 136, p. 106180.

Espinoza, Sebastián et al. (2016). "Multi-phase assessment and adaptation of power systems resilience to natural hazards". In: *Electric Power Systems Research* 136, pp. 352–361.

Esty, Benjamin C (2003). *Modern project finance: A casebook*. John Wiley & Sons.

Filippova, Olga et al. (2020). "Who cares? Future sea level rise and house prices". In: *Land Economics* 96.2, pp. 207–224.

Francis, Jennifer et al. (2004). "Costs of equity and earnings attributes". In: *The accounting review* 79.4, pp. 967–1010.

Garbarino, Nicola and Benjamin Guin (2021). "High water, no marks? Biased lending after extreme weather". In: *Journal of Financial Stability* 54, p. 100874.

Garcia-Alonso, Lorena, Ticiana Grecco Zanon Moura, and David Roibas (2020). "The effect of weather conditions on port technical efficiency". In: *Marine Policy* 113, p. 103816.

Gatti, S (2007). "Project characteristics, risk analysis, and risk management". In: *Project Finance in Theory and Practice: Designing, Structuring, and Financing Private and Public Projects*, pp. 31–62.

Gatti, Stefano et al. (2022). "Government and market-based instruments and incentives to stimulate long-term investment finance in infrastructure". In: *OECD long-term investment project*. OECD Eco Working Paper.

Gianfrate, Gianfranco (2018). "Designing carbon-neutral investment portfolios". In: *Designing a Sustainable Financial System*. Springer, pp. 151–171.

Giglio, Stefano et al. (2021). "Climate change and long-run discount rates: Evidence from real estate". In: *The Review of Financial Studies* 34.8, pp. 3527–3571.

Girardone, Claudia and Stuart Snaith (2011). "Project finance loan spreads and disaggregated political risk". In: *Applied Financial Economics* 21.23, pp. 1725–1734.

Goldsmith-Pinkham, Paul S et al. (2021). "Sea level rise exposure and municipal bond yields". In: *Jacobs Levy Equity Management Center for Quantitative Financial Research Paper*.

Gostlow, Glen (2020). "The materiality and measurement of physical climate risk: evidence from form 8-K". In.

Gourdel, Régis et al. (2021). "Assessing the double materiality of climate risks in the EU economy and banking sector". In: *Available at SSRN 3939895*.

Griggs, Gary (2020). "Coastal airports and rising sea levels". In: *Journal of Coastal Research* 36.5, pp. 1079–1092.

Habermann, Nadine and Ralf Hedel (2018). "Damage functions for transport infrastructure". In: *International journal of disaster resilience in the built environment* 9.4/5, pp. 420–434.

Hagströmer, Björn, Björn Hansson, and Birger Nilsson (2013). "The components of the illiquidity premium: An empirical analysis of US stocks 1927–2010". In: *Journal of Banking & Finance* 37.11, pp. 4476–4487.

Hall, Jim W, Richard J Dawson, and Xing Zheng Wu (2015). "Analysing flood and erosion risks and coastal management strategies on the Norfolk coast". In: *Broad Scale Coastal Simulation*. Springer, pp. 233–254.

Hall, Jim W, Paul B Sayers, et al. (2006). "Impacts of climate change on coastal flood risk in England and Wales: 2030–2100". In: *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences* 364.1841, pp. 1027–1049.

Hallegatte, Stephane et al. (2013). "Future flood losses in major coastal cities". In: *Nature climate change* 3.9, pp. 802–806.

Hernández-Trillo, Fausto (1995). "A model-based estimation of the probability of default in sovereign credit markets". In: *Journal of Development Economics* 46.1, pp. 163–179.

Hinkel, Jochen et al. (2014). "Coastal flood damage and adaptation costs under 21st century sea-level rise". In: *Proceedings of the National Academy of Sciences* 111.9, pp. 3292–3297.

Hirabayashi, Yukiko et al. (2013). "Global flood risk under climate change". In: *Nature climate change* 3.9, pp. 816–821.

Ho, Kelvin and Andrew Wong (2021). "Effect of Climate-Related Risk on the Pricing of Bank Loans: Evidence from Syndicated Loan Markets in Asia Pacific". In.

Hong, Harrison, G Andrew Karolyi, and José A Scheinkman (2020). "Climate finance". In: *The Review of Financial Studies* 33.3, pp. 1011–1023.

Hong, Harrison, Frank Weikai Li, and Jiangmin Xu (2019). "Climate risks and market efficiency". In: *Journal of econometrics* 208.1, pp. 265–281.

Huizinga, Jan, Hans De Moel, Wojciech Szewczyk, et al. (2017). *Global flood depth-damage functions: Methodology and the database with guidelines*. Tech. rep. Joint Research Centre (Seville site).

In, Soh Young et al. (2022). "Climate-related financial risk assessment on energy infrastructure investments". In: *Renewable and Sustainable Energy Reviews* 167, p. 112689.

Inderst, Georg (2013). "Private infrastructure finance and investment in Europe". In.

Izaguirre, C et al. (2021). “Climate change risk to global port operations”. In: *Nature Climate Change* 11.1, pp. 14–20.

Javadi, Siamak and Abdullah-Al Masum (2021). “The impact of climate change on the cost of bank loans”. In: *Journal of Corporate Finance* 69, p. 102019.

Jiang, Feng, C Wei Li, and Yiming Qian (2019). “Can firms run away from climate-change risk? Evidence from the pricing of bank loans”. In: *Unpublished manuscript*.

Jongman, Brenden (2018). “Effective adaptation to rising flood risk”. In: *Nature communications* 9.1, pp. 1–3.

Jongman, Brenden, Hessel C Winsemius, Jeroen CJH Aerts, et al. (2015). “Declining vulnerability to river floods and the global benefits of adaptation”. In: *Proceedings of the National Academy of Sciences* 112.18, E2271–E2280.

Jongman, Brenden, Hessel C Winsemius, Stuart A Fraser, et al. (2018). “Assessment and adaptation to climate change-related flood risks”. In: *Oxford Research Encyclopedia of Natural Hazard Science*.

Kleimeier, Stefanie and William L Megginson (2000). “Are project finance loans different from other syndicated credits?” In: *Journal of Applied Corporate Finance* 13.1, pp. 75–87.

Kling, Gerhard et al. (2021). “The impact of climate vulnerability on firms’ cost of capital and access to finance”. In: *World Development* 137, p. 105131.

Krueger, Philipp, Zacharias Sautner, and Laura T Starks (2020). “The importance of climate risks for institutional investors”. In: *The Review of Financial Studies* 33.3, pp. 1067–1111.

Kumar, B Rajesh (2022). “Infrastructure Financing Instruments”. In: *Project Finance*. Springer, pp. 31–54.

Kundzewicz, Zbigniew W et al. (2014). “Flood risk and climate change: global and regional perspectives”. In: *Hydrological Sciences Journal* 59.1, pp. 1–28.

Kyriakopoulou, Danae et al. (2022). “Central banks and climate-related disclosures: applying the TCFD’s recommendations”. In.

Lin, Yufeng et al. (2020). “Climate change adaptation by ports: the attitude of Chinese port organizations”. In: *Maritime Policy & Management* 47.7, pp. 873–884.

Lindbergh, S et al. (2022). “Decoding climate adaptation governance: A sociotechnical perspective of US airports”. In: *Journal of Cleaner Production* 334, p. 130118.

Lindbergh, Sarah et al. (2022). “Cross-sectoral and multiscalar exposure assessment to advance climate adaptation policy: the case of future coastal flooding of California’s airports”. In: *Climate Risk Management*, p. 100462.

LY, Wang Joni, Zang Peng-Peng, and Wang Huan-Huan (2007). “Theoretic review: municipal bonds and infrastructure Finance”. In: - 3, pp. 80–83.

Mochida, Nobuki (2008). *Fiscal decentralization and local public finance in Japan*. Routledge.
Morris, Lauren L (2020). "Stakeholder collaboration as a pathway to climate adaptation at coastal ports". In: *Maritime Policy & Management* 47.7, pp. 953–967.
Nguyen, Thanh Tuu et al. (2017). "Flood Risk for Power Plant using the Hydraulic Model and Adaptation Strategy". In: 8.4, pp. 287–295.
Ottaviano, Gianmarco IP (2008). "Infrastructure and economic geography: An overview of theory and evidence". In: *EIB papers* 13.2, pp. 8–35.
Pagliari, Maria Sole (2021). "LSIs' exposures to climate change related risks: an approach to assess physical risks". In.
Painter, Marcus (2020). "An inconvenient cost: The effects of climate change on municipal bonds". In: *Journal of Financial Economics* 135.2, pp. 468–482.
Panagoulia, Dionysia and George Dimou (1997). "Sensitivity of flood events to global climate change". In: *Journal of hydrology* 191.1-4, pp. 208–222.
Plantinga, Auke and Bert Scholtens (2021). "The financial impact of fossil fuel divestment". In: *Climate Policy* 21.1, pp. 107–119.
Platz, Daniel (2009). "Infrastructure finance in developing countries: The potential of subsovereign bonds". In.
Poo, Mark Ching-Pong et al. (2021). "Climate Change Risk Indicators (CCRI) for seaports in the United Kingdom". In: *Ocean & Coastal Management* 205, p. 105580.
Poo, MC-P et al. (2018). "Review on seaport and airport adaptation to climate change: a case on sea level rise and flooding". In: *Marine Technology Society Journal* 52.2, pp. 23–33.
Portillo Juan, Nerea, Vicente Negro Valdecantos, and Jose Marıa del Campo (2022). "Review of the Impacts of Climate Change on Ports and Harbours and Their Adaptation in Spain". In: *Sustainability* 14.12, p. 7507.
Pörtner, Hans-Otto et al. (2022). "Climate change 2022: Impacts, adaptation and vulnerability". In: *IPCC Sixth Assessment Report*.
Prahl, Boris F et al. (2018). "Damage and protection cost curves for coastal floods within the 600 largest European cities". In: *Scientific data* 5.1, pp. 1–18.
Punt, Eline et al. (2022). "Beyond the dikes: an institutional perspective on governing flood resilience at the Port of Rotterdam". In: *Maritime Economics & Logistics*, pp. 1–19.
Rietveld, Piet (1994). "Spatial economic impacts of transport infrastructure supply". In: *Transportation Research Part A: Policy and Practice* 28.4, pp. 329–341.
Robins, Nick, Simon Dikau, and Ulrich Volz (2021). "Net-zero central banking: A new phase in greening the financial system". In.

Sachs, Tillmann, Robert LK Tiong, and Daniel Wagner (2008). “The quantification and financial impact of political risk perceptions on infrastructure projects in Asia”. In: *The Journal of Structured Finance* 13.4, pp. 80–104.

Scott, Helen et al. (2013). “Climate change adaptation guidelines for ports”. In: *Enhancing the resilience of seaports to a changing climate report series, National Climate Change Adaptation Research Facility, Gold Coast*, p. 26.

Sorge, Marco and Blaise Gadanecz (2008). “The term structure of credit spreads in project finance”. In: *International Journal of Finance & Economics* 13.1, pp. 68–81.

Stroebel, Johannes and Jeffrey Wurgler (2021). *What do you think about climate finance?*

Thierie, Wouter and Lieven De Moor (2018). “Loan tenor in project finance”. In: *International journal of managing projects in business.*

Thomas, Kimberley et al. (2019). “Explaining differential vulnerability to climate change: A social science review”. In: *Wiley Interdisciplinary Reviews: Climate Change* 10.2, e565.

Thoung, CHRIS et al. (2016). *Future demand for infrastructure services.* Cambridge University Press, Cambridge.

Turnbull, Stuart M (2003). “Pricing loans using default probabilities”. In: *Economic Notes* 32.2, pp. 197–217.

Vellinga, Tiedo and Michiel de Jong (2012). “Approach to climate change adaptation in the port of Rotterdam”. In: *Maritime transport and the climate change challenge.* Routledge, pp. 333–347.

Vogiatzis, Konstantinos et al. (2021). “Climate Change Adaptation Studies as a tool to ensure airport’s sustainability: The case of Athens International Airport (AIA)”. In: *Science of The Total Environment* 754, p. 142153.

Ward, Philip J, Brenden Jongman, et al. (2013). “Assessing flood risk at the global scale: model setup, results, and sensitivity”. In: *Environmental research letters* 8.4, p. 044019.

Ward, Philip J, Hessel C Winsemius, et al. (2020). “Aqueduct floods methodology”. In: *World Resources Institute*, pp. 1–28.

Wasko, Conrad et al. (2021). “Incorporating climate change in flood estimation guidance”. In: *Philosophical Transactions of the Royal Society A* 379.2195, p. 20190548.

Wilby, Robert L and Rod Keenan (2012). “Adapting to flood risk under climate change”. In: *Progress in physical geography* 36.3, pp. 348–378.

Winsemius, Hessel C et al. (2016). “Global drivers of future river flood risk”. In: *Nature Climate Change* 6.4, pp. 381–385.

Yang, Zaili et al. (2018). “Risk and cost evaluation of port adaptation measures to climate change impacts”. In: *Transportation Research Part D: Transport and Environment* 61, pp. 444–458.

Yescombe, Edward R and Edward Farquharson (2018). *Public-Private Partnerships for infrastructure: Principles of policy and finance*. Butterworth-Heinemann.

Yesudian, Aaron N and Richard J Dawson (2021). “Global analysis of sea level rise risk to airports”. In: *Climate Risk Management* 31, p. 100266.

Zimmerman, Rae and Craig Faris (2010). “Infrastructure impacts and adaptation challenges”. In: *Annals of the New York Academy of Sciences* 1196.1, pp. 63–86.