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Euro Area banks' sensitivity to changes in carbon price

Abstract

In recent years there has been growing attention on the risks posed by climate change. One relevant question for financial stability is to which extent the materialisation of transition risks emerging from the sudden implementation of climate change mitigation policies would impact the financial system. In this paper we analyze the effects of changes in carbon price on the European banking system. We assess this climate change transition risk through a banking sector contagion model where firms are negatively impacted by an increase in carbon prices. Using a unique granular dataset we evaluate the consequences of a combination of different increases in carbon prices and firm emission reduction strategies. We find that taking early policy action, implying more gradual changes in carbon prices, is not expected to lead to adverse impacts on the banking system, especially if firms reduce their emissions efficiently. Conversely, a disorderly, abrupt transition to a low carbon economy requiring very high sudden changes in carbon prices might have disruptive effects on the financial system, especially if firms fail to reduce their emissions.

Non-technical summary

To meet the goals of the Paris Agreement, policymakers are currently adopting measures to mitigate climate change, aiming to transition to low carbon economies. Also central banks and financial institutions have entered the debate, discussing the effects of climate change, and the effects of climate change mitigation strategies, onto the financial system. In particular, if not well addressed and measured, an abrupt and disorderly transition can have repercussions on the financial system. Some firms might suffer losses due to e.g. increases in energy prices, implementation of carbon taxes or shifts in consumer preferences to less polluting options. Therefore, the transition to a greener economy might put some firms out of business and lead others to the brink of bankruptcy. Banks, as a consequence, can face losses through their exposures to these firms, which can weaken the stability of the financial system.

This paper analyses the risks posed to the financial system stemming from a transition to a low carbon economy, focusing on the impact of changes in carbon prices. We do so in a forward-looking manner, using a banking system contagion model, where banks are connected through loans and securities exposures, and where firms suffer from rises in carbon prices that are absorbed on their balance sheets and therefore may affect their likelihood to default. The impact of the carbon price increase on firms likelihood to default depends on the level of carbon emissions produced by each firm, on their leverage ratio, and on their ability to pass carbon prices onto their customers. We run simulations for different scenarios of carbon price increases and different assumptions on firm emission reductions.

Our results suggest that under more ambitious firm emissions reduction strategies, the losses borne by the financial system would be contained also for large increases in carbon prices. At the same time, our results also suggest that if no action is taken, and firms keep their emissions constant, abrupt and large increases in carbon prices may lead to severe banking system losses which could reach up to 40% more compared to a baseline situation where no policy action is taken.

Therefore, the analysis suggests that in order to hedge themselves from transition risks, banks might have to restrict their lending to less polluting firms, lend to firms with ambitious emissions reduction targets or help firms in transitioning to low carbon business models. In this context, policy measures are pivotal to require firms to disclose the direct and indirect emissions produced, as well as verifiable strategies to reduce them. Policy measures should target banks

too, which should disclose not only their carbon footprint, but especially the climate risks connected to their exposures. Finally, regulators may need to implement further prudential measures to prevent the built-up of banking system losses or pockets of risks through bank exposures to firms not adapting to a greener economy.

1 Introduction

Current global warming has exceeded 1°C above pre-industrial levels, and impacts of human-made climate change have already materialized (IPCC, 2021). The period 2015-2019 has been the warmest five-year-period on record globally (WMO, 2019; ECMWF, 2020), and a number of recent extreme events have been amplified by climate change (see, e.g. Otto et al., 2020). To mitigate the effects of climate change, the Paris Agreement aims at limiting the increase in global temperature in 2100 to well below 2°C above pre-industrial levels, pursuing efforts to limiting it to 1.5°C. The Paris Agreement also promotes low carbon, climate resilient growth and making finance flows consistent with this pathway (UNFCC, 2015; NGFS, 2019). Several countries and regions have committed to reach carbon neutrality or significant emission reductions within the next 30 years[1].

Climate policies are therefore being designed, aimed at limiting emissions through, for example, increasing the price of carbon (e.g. carbon tax, cap and trade schemes for emissions, etc., see e.g. WB, 2020) or setting incentives to implement energy-efficient low-carbon technologies. The assumed necessary carbon price to achieve Paris-compliant emission reductions varies, and depends, amongst others, on assumptions on the parallel implementation of other climate policies. For example, the IMF - assuming parallel implementation of green supply policies - calibrates carbon prices to reach up to 40USD per ton of CO_2 in 2030, and up to 150USD per ton CO_2 in 2050, depending on the country. Conversely, Stern and Stiglitz, discussing alternative approaches to calculating the "Social Cost of Carbon", conclude that "the numbers that are likely to emerge would be more in the region of 100USD per ton by 2030" (Stern and Stiglitz, 2021)[2]. In comparison, prices of EU emission allowances have increased to above 60EUR per ton CO_2 recently[3], with the EU Emissions Trading System (ETS) covering activities that account for ca. 40% of the EU's greenhouse gas emissions[4]. One important aspect of the implementation of carbon pricing schemes is the potential misalignment across countries. This misalignment could lead firms to move their production sites to countries where there are lower carbon pricing

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[1]See e.g. https://news.un.org/en/story/2020/12/1078612

[2]The Social Cost of Carbon (SCC) refers to the "economic cost caused by an additional ton of carbon dioxide emissions or its equivalent"(e.g. Nordhaus, 2017), and "can be used as a carbon tax, acting as a market price" (Stern and Stiglitz, 2021).

[3]See https://ember-climate.org/data/carbon-price-viewer/

[4]The coverage of the EU ETS is currently limited to specific sectors. In addition, a sizeable share of firms/sectors is currently still subject to free allowances, implying that they do not have to purchase allowances on the market.

schemes. However, in order to avoid such problem carbon border adjustment could be designed (see, e.g. Parry, 2021).

Some firms may not be able to adapt their production processes and decrease their emissions in alignment with overall necessary reductions. As a consequence, some non-financial corporations (NFCs) might be at higher risk of default[5]. The risk resulting from such policies, but also from technological or sentiment changes is commonly referred to as climate change transition risk (e.g. NGFS, 2019; BCBS, 2021). Transition risk is argued to increase the longer climate policies are delayed (e.g. NGFS, 2019), as the annual necessary reductions in greenhouse gas emissions increase with each year in which climate action is delayed, and sudden and more stringent policies might need to be implemented. If greenhouse gas emissions were reduced from 2020 onward, reductions of ca. 7.6% per year globally would be necessary to limit global warming to 1.5°C (UNEP, 2019) - a number comparable to the emission reductions estimated in 2020, including the effects of the Covid-19-related lockdown measures (Le Quéré et al., 2020).

Transition risk is a potential threat for the financial system (e.g. NGFS, 2019). Banks that are highly exposed to NFCs that fail to adapt could suffer additional losses, which could exacerbate pre-existing vulnerabilities and lead in the worst case to systemic stress. Such concerns are ever more relevant when considering the financial system is expected to be increasingly also affected by the physical consequences of climate change (physical risks). The monitoring of climate-related financial risks is therefore crucial, both for assessing the resilience of banks, and the banking system as a whole.

Consequently, a number of studies have been published in recent years, attracting the attention of both academics as well as central bank economists. One early example is provided by Battiston et al. (2017) where network analysis is employed to examine the impact of the introduction of climate policies onto the financial system, yielding the conclusion that even though exposure to climate policy relevant sectors are sizeable, climate policies would not have adverse effects if they are implemented timely. Building on this analysis, Roncoroni et al. (2019) showed that for the Mexican financial system (including investment funds), systemic losses are contained (1%-2% of total assets in the Mexican financial system) in mild scenarios while they are found to be more severe (2.5%-4% of total assets) in a scenario where climate policies are more stringent.

Recent work of central banks and supervisors included climate specific features into stress-

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[5]If revenue streams do not grow accordingly.

testing or scenario analysis approaches, in order to measure the impact of climate risk on banks balance sheets. The European Banking Authority has recently published its pilot exercise on climate risk (EBA, 2021), highlighting the need for more disclosure and better data in order to properly assess transition risk. French and Dutch central banks also started preliminary stress-test exercises (see e.g. ACPR, 2019; Allen et al., 2020; DNB, 2018) envisaging the need for further work to deepen the knowledge around the matter.

A report by the European Systemic Risk Board (ECB/ESRB, 2020) presented mixed evidence on banks' decarbonisation. Comparing emission intensities of large firms euro area banks are exposed to between 2014 and 2017 suggests that some banks' portfolios might have seen decreases in their emission intensity, which might however be driven by companies reducing their emissions (as opposed to banks redirecting their financing towards greener corporations). A similar analysis in the report suggests indeed banks seem to not have taken decisive action in this context so far. The same report also presents a preliminary evaluation of the impact of of two transition scenarios, namely an "innovation shock" and "delayed climate mitigating policies", on GDP, estimating that a delayed policy could give rise to loss in GDP as bad as 2% in the short-term. A recent analysis jointly from ECB and ESRB (ECB/ESRB, 2021), moreover, suggests that despite the exposure to firms and sectors highly exposed to transition risk is overall manageable, pocket of vulnerabilities are still present and might exacerbate existing risks especially from the credit portfolio.

Finally, the most recent ECB economy-wide stress climate stress test Alogoskoufis et al. (2021) clearly show the benefits for firms and banks to early adopt green policies. In fact, the study shows how acting early could become a great advantage by outweighing the initial costs due to increased efficiency and decreased energy prices. Not acting (or acting with significant delay) instead , would result in ever increasing risks and losses cause by physical events which will become more frequent in an hot-house-world.

Given its unique and novel features, the importance of forward-looking approaches to measure climate-related financial risks is recognized (e.g. BCBS, 2021). Measurement approaches are needed that are able to reflect the limited ability of historical data to act as a guide for the future, and system interactions characterised by interconnectedness and non-linearity.

In this context, this present study contributes to the growing body of literature targeted at measuring climate change transition risks for the financial system. Using a banking sector contagion model, this study estimates the impact that might stem from abruptly increasing

carbon prices, assessing the sensitivity of banking system losses to different combinations of carbon price changes and firm emission reduction strategies. The paper is structured as follows: Section 2 describes the data used, Section 3 describes the modelling methodology and sensitivity simulations performed for this study, and Section 4 discusses results from the sensitivity analysis. Finally, Section 5 presents the conclusions and discusses policy implications of the findings.

2 Data and methodology

The heterogeneity and wide range of climate related risks, both physical and transition, make apparent the need for refined granular borrower level exposure data. In particular, such heterogeneity speaks against the employment of country-sector level aggregates (Belloni et al., 2020), which might average out significant borrower-level risk exposures. Moreover, borrower-lender information needs to be further enriched with climate data in order to allow for a thorough quantification of climate risks faced by financial institutions.

This work exploits a quarterly granular dataset developed within the ECB which reconciles information from different data sources, including bilateral interbank exposures, exposures to non-credit institutions, both financial, non-financial, and governmental, as well as banks' holdings of securities (Montagna et al., 2020). Table 1 reports the financial network summary statistics.

Sector	Nodes	Edges	Exposures [bn€]	Securities [bn€]	$\langle \text{LGD} \rangle$	$\langle \text{PD} \rangle$
CI	1367	10482	2623.6	685.8	0.321	-
NFC	4125	11569	2062.5	393.0	0.406	0.32
FC	3310	6615	1019.1	844.0	0.423	0.78
HH	217	769	21.8	-	0.292	3.58
All	10354	34787	7457.5	4086.6	0.340	-

Table 1: Summary statistics by institutional sector: nodes are any consolidated entity present in the system; edges refer to any bilateral exposure mapped between any two nodes; exposures, reported in tn €, refer to any direct non-security exposure; the column 'Securities' reports instead all direct security exposures: indirect exposures due to overlapping portfolios are not reported here but are accounted for in the model; $\langle \text{LGD} \rangle$ and $\langle \text{PD} \rangle$ report the mean loss given default and probability of default in each sector. Credit institutions do not receive a probability of default as their dynamics is endogenously modelled. Data refers to reporting period 2019-Q4.

This dataset is further enriched with entity-level balance sheets, credit risk data, as well as information on firm's emissions. In order to quantify climate related risks, firms' emissions are employed to assess climate adjusted probabilities of default.

The analysis presented in this paper takes an entity-level view, requiring granular information on banks' equity and loan-book exposure, and firm-level emissions, as well as firms' probabilities of default, sales and total assets. For the former, supervisory statistics of banks' Large Exposures (LE) as well as Security Holdings Statistics by banking group (SHS-G) are used. Firm-level

emissions are retrieved from Urgentem[6]. Firms' granular information on probabilities of default, sales and total assets are taken from Moody's and Orbis, respectively. Moreover, to compensate for the lack of complete granular exposures (LE and SHS-G can only partially cover the total amount of banks' exposures), country-sectoral credit exposures are filled using FINREP.

2.1 Supervisory data

Though not specifically designed to assess climate-related risks, supervisory data can help assess banks' exposure to specific sectors/firms. Our analysis covers ca. 23.8 EUR trillions. of euro area banks' exposures, from roughly 1900 banks. This includes exposure to non-financial corporations as well as interbank exposures. Overall, exposure to ca. 5.9 EUR trillions to non-financial corporations is covered. As mentioned in the introduction, a share of granular banks' exposures comes from the Large Exposures (LE) reporting. Large Exposures covers exposures for amounts above 300 (see (BCBS, 2014)) millions or exposures that account for more than 10% of bank eligible capital before applying credit risk mitigations and exemptions (EBA, 2013). In our analysis LE accounts for ca. 7.4 EUR tn (or 34.8% of total exposures covered in the analysis) of which more than a quarter of them is towards non-financial corporations.

	Interbank	Real Economy
Nodes	1367	7435
Links	10482	18184
Exposures [bn€]	4309.42	8647.90
Power-law exponent	0.82	0.81
Diameter	3.55	2.92

Table 2: Network summary statistics for interbank and real economy. Data refers to 2019-Q4.

2.1.1 Securities Holdings Statistics

The second main data source of granular exposure used in this study is Securities Holding Statistics by banking group (SHS-G). SHS-G provides granular information on a security-by-security basis for euro-area banks for the following instrument types: debt securities, quoted shares and investment funds shares. Individual securities data include ISIN and MFI codes which allow us to map them with loans exposures first and emissions data then. In the context of this

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[6]Urgentem is an independent provider of carbon emission data; https://www.urgentem.net/

paper, securities are aggregated at holder-borrower level and information about instrument type, maturity, and other instrument's information are disregarded. Exposures through securities amounts to ca. 4.1 EUR trillions of which less than 10% is towards NFCs.

2.2 Probabilities of default and LGDs

In order to assess the risk faced by credit institutions we leverage on firm-bank level data, allowing for a granular estimation of default risks. Borrowers' probabilities of default (henceforth PDs) are retrieved from Moody's Credit Edge[7]. Furthermore, LGDs are estimated at a granular level from *credit risk mitigation reporting*[8] which incorporates information on the extent to which exposures are collateralised, or guaranteed by a third party, or where the risk is hedged away by means of credit derivatives. Probabilities of default refer to 2019 Q4, in order to disentangle the effects arising from the COVID-19 pandemic. Moreover, with the aim of comparing the impact of a carbon tax and the COVID-19 effect, probabilities of default from 2020 Q2 are also used in the analysis.

2.3 Emissions

2.3.1 Emissions data

Official emissions statistics (Eurostat) suggest that the highest contribution to overall direct greenhouse gas emissions in the EU comes from firms in the sectors electricity/gas/steam, manufacturing, agriculture and transportation. Within these sectors, the emissions are concentrated in only a few sub-sectors, including crop and animal production for agriculture, and manufacturing of coke and refined petroleum products, chemicals and chemical products, basic metals and non-metallic mineral products. For transport, land transport has the highest contribution, but emissions of air and water transport are also high. While high sector emissions often also imply high emissions of individual firms, there may be large dispersion between firms within the same sector (see, e.g. ECB/ESRB, 2020), requiring firm-level data as a proxy to assess firms' and banks' exposure to transition risks at entity level.

Firm-level emission reporting is still incomplete, inconsistent and insufficient (ECB/ESRB, 2020). However, reasonable assumptions and methodologies can help filling data gaps[9]. The

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[7]Missing information is filled by country-NACE4 level means.
[8]Credit risk mitigation is also retrieved from COREP.
[9]ECB/ESRB Project Team on climate risk monitoring, "Climate-related risk and financial stability - Data

emission data used in this analysis includes reported data for ca. 1.000 of the total 4.000 firms euro-area banks are exposed to through large exposure. For the remaining ca. 3.000 firms for which data were not available or that could not be matched with emissions data, a country-sectoral averaging was employed to fill data gaps (see Table 3). Given the focus of this study on the impacts of a carbon tax on non-financial corporations, we focused on direct ("scope 1"), and indirect energy-related ("scope 2") emissions. Other indirect ("scope 3) emissions including upstream and downstream emission categories such as transport, business trips or use of sold products are not included.

	n	Exposure amount (bn €)	%
inferred	3023	1011	43.2
reported	939	1330	56.8

Table 3: Emissions coverage of non-financial firms matched with LE and SHS-G

Moreover, one aspect often neglected when assessing firms' emissions concerns firms relative emissions efficiency, which might be largely different across the sample (see Figure 1). Firms might in fact be responsible of large amounts of GHG emissions, but what also matters is how these amounts relate to the relative size and the revenues stream of the firms themselves. Also in this respect there is high heterogeneity across countries and sectors (see, e.g. ECB/ESRB, 2020), which implies that also firms with similar levels of emissions might be able to withstand very differently possible carbon price shocks.

Around 40% of large exposures towards non-financial corporations (or 16% of total exposures towards NFCs) of euro area banks are towards sectors that can be considered as climate policy relevant, depending on the year. Here, sectors considered as climate policy relevant include utilities, energy intensive, fossil fuel, transport and housing. This assessment is based on granular information of firms' economic activity, for which a relatively high coverage of euro area large exposures can be achieved.

Diving into the relationship of exposures and emissions (see Figure 2) suggests that no correlation can be found between the size of the exposure and the level of emissions. The lack of correlation between these two measures highlights the importance of using granular information when evaluating the impact of transition risks on firms and banks. This finding also emphasizes the need to use data that are as granular as possible in order to better understand where pockets
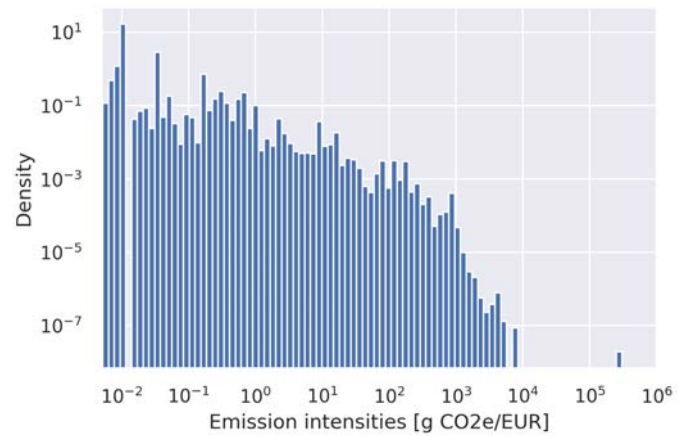
Figure 1: Firms emission intensity; log-distribution. Emissions intensities are defined as grams of CO2e emissions over EUR sales.
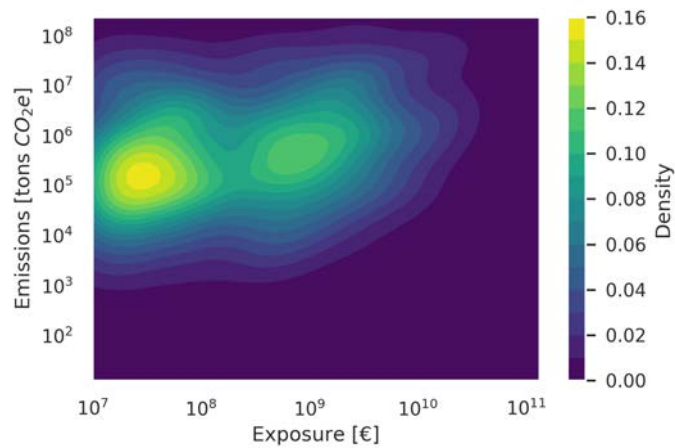

Figure 2: Joint distributions of firms CO2e emissions and banks exposures.

of vulnerability are situated.

3 Modelling framework

A crucial challenge in the assessment of climate related risks comes from their forward-looking non-linear nature (Bolton et al., 2020). Standard risk management practice relies on regression-based approaches attempting to produce out-of-sample forecasts from historical data: while this might be appropriate for small perturbations around an economy's equilibrium, it becomes inadequate and misleading in the face of large scale phase transitions such as those potentially triggered by adverse climate impacts.

Nonetheless, forward-looking assessments are still possible and have started receiving increasing attention in the past years. Here, we perform a sensitivity study, using NGFS scenarios (IIASA, 2020) to obtain reference information about carbon price changes and emission reductions under different climate policy assumptions. Assumptions on changes in carbon price and firm emissions are then used to assess granular firm-level increases in corporates probabilities of default, which are then translated into losses to the banking sector via a stochastic microstructural model of financial contagion, yielding estimates of the loss distribution hitting the banking sector conditional on the realisation of the climate scenarios.

A crucial feature of this approach is its ability to maintain a probabilistic approach while at the same time conditioning on specific potential realisations of climate policy scenarios. This is important as the mean and median behaviour of the system which are often taken as a benchmark, might be by and large unaffected, with tail events becoming instead increasingly likely to materialise and of greater magnitude.

3.1 Simulations

In order to assess the risk associated with abrupt transition shocks that might be transmitted from the corporate sectors to the banking system we employ a micro-structural model of financial contagion built on granular euro area exposure data (see Appendix A for a detailed description of the model). This class of models (Montagna and Kok, 2016; Craig and Von Peter, 2014; Montagna et al., 2020) are characterised by their reliance on real reporting granular networks of interbank exposures and securities portfolios, allowing for entity level disentangling of different sources of risk. In particular, we account for four contagion channels: real economy credit risk, interbank credit risk, liquidity risk, and market risk. The former accounts for credit risk stemming from insolvent real economy counterparties, which can have repercussions on lenders'

balance sheets. Correlated real-economy insolvencies materialise stochastically through Monte Carlo simulations based on counterparty level probabilities of default and are translated into losses for corresponding credit institutions via entity-level exposures and associated losses given default[10]. In addition, an excessive materialisation of losses might also constitute a further source of risk for both direct counterparties in the form of second-round contagion losses as well as indirectly via overlapping-portfolio-mediated contagion (cf. Appendix A).

3.2   Climate adjusted probabilities of default

When assessing banking losses arising from transition risk the firm-level dimension acquires crucial importance, since sector level shocks are known to overestimate overall losses (Belloni et al., 2020). The reason is to be found in the large degree of heterogeneity in emission intensities, whose distribution is characterised by fat tails and strong positive skew. Firm-level emission data suggest a high degree of heterogeneity in emissions not only between sectors but also within, with markedly power-law distributed tails. Consequently, a sectoral approach may fall short of illustrating variability within a sector, making it necessary to take into account a granular firm-level perspective when estimating the impact of transition risk on the financial system.

The high degree of heterogeneity in counterparties' credit risk as well as emission patterns, makes a distributional analysis more desirable. For this reason, it is important to be able to map emission intensities on a granular firm-by-firm level. In order to gauge the short term distress on corporates facing new prices on carbon emissions, each firm's credit risk is reassessed in a Merton framework. More specifically, we assume that each firm would bear a fraction, β, of the carbon tax. The carbon tax is applied on each firm independently of sector and country, solely based on the level of emissions they produce in their production processes.

Adjusted probabilities of default are therefore computed at firm level by modelling each firm's asset value as a stochastic process in a Merton framework (Merton, 1974). In particular, it is assumed that transition scenarios directly impact the value of a firm's assets A_i, bringing its climate adjusted value of assets A_i^* closer to the default point L_i. One can therefore compute climate-adjusted probabilities of default as:

$$PD_i^* = \Phi\left(\frac{\sigma_i}{2} - \frac{1}{\sigma_i}\left(\mu_i + \log\frac{A_i^*}{L_i}\right)\right). \tag{1}$$

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[10]A loss given default is applied which accounts for credit risk mitigation, as per COREP reporting information.

In this setting, firm's i probability of default $PD_i(A_i, L_i, \mu_i, \sigma_i)$ is a decreasing function of its liabilities and asset volatility, and an increasing function of assets. The sudden introduction of a price on carbon T, can be thus thought of as a decline of firm's value of assets, depending on each firm's emissions E_i, through an elasticity $\beta < 1$: the climate-adjusted value of assets is therefore computed as: $A_i^* = A_i - \beta T E_i$. This, in turn, consistently results in increased probability of defaults $PD_i^* \geq PD_i$[11].

3.3 Emission reduction strategies

Different sets of simulations are performed in order to examine the sensitivity of the euro area banking system to carbon price changes, considering different firm emission reduction strategies. The additional carbon cost born by the firms is proxied by the parameters β and T as described in Section 3.2. The combined impact of different levels of carbon price changes and emission reductions can then be evaluated at representative levels of $\alpha = \beta T$. The assumptions underlying developments in carbon price and emissions are based on data obtained through the NGFS scenario explorer hosted by IIASA (IIASA, 2020), using results for the EU (carbon price, emissions) and global (temperature, 1.5°C exceedance probability) from the integrated assessment model REMIND-MAgPIE 1.7-3.0.[12] The following sets of sensitivity simulations are performed for this study:

- Constant emissions at 2018 levels, evaluated at levels of α corresponding to increases in carbon price according to three different policy pathways (1-3 in Fig. 3). These simulations are representative for a situation in which the carbon price increases abruptly, without firms being able to adjust their emissions.

- Reduced emissions according to three different policy pathways (1-3 in Fig. 3), evaluated for levels of α corresponding to an increase in carbon price consistent with the respective policy pathway between different points in time (Table 3.3).

Under the strictest policy assumption (1), the EU carbon price starts increasing sharply from 2020 onward according to NGFS scenarios, reaching ca. 180 US$ (2010)/t CO$_2$ (or ca. 150€/t

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[11]Notice this approach can also be directly applied to the KMV model by computing the adjusted distance to default $DD_i^* = \frac{1}{\sigma_i} \log \frac{A_i^*}{L_i}$. This adjusted distance to default can then be mapped to a climate-adjusted EDF (expected default frequency) in the usual manner.

[12]The carbon price in these scenarios should be understood as a shadow carbon price, essentially reflecting the overall policy stringency.

		$\Delta_{\text{price2025}}$	$\Delta_{\text{price2035}}$	$\Delta_{\text{emissions2025}}$	$\Delta_{\text{emissions2035}}$
(1)	immediate 1.5°C	178	178	30%	81%
(2)	immediate 2°C	46	46	15%	49%
(3)	delayed 2°C	39	162	12%	50%

Table 4: Changes in carbon price in 2010 US$ per t CO_2, under different policy assumptions, for different points in time compared to five years earlier, and changes in emissions compared to 2020, according to NGFS (2020) and obtained through the NGFS scenario explorer hosted by IIASA (IIASA, 2020). All scenarios rely on the REMIND-MAgPIE 1.7-3.0 integrated assessment model.

CO_2) in 2025 and a constant increase of ca. 180 US$ (2010)/t CO_2 thereafter for every 5-year period. It should be noted that these prices correspond to the most stringent scenario with only limited deployment of carbon dioxide removal technologies (also see NGFS, 2020). Steep emission reductions are assumed to kick in as a consequence, down by 30% in 2025 (compared to 2020), reaching net zero emissions in 2050 (see Figure 3). Global mean temperature increase by 2100 would be limited to below 1.5°C with a probability of ca. 75%.

Assuming a timely implementation of policies targeted at 2°C (with limited deployment of carbon dioxide removal technologies) also implies - according to NGFS scenarios - an increase in carbon price and decrease in emissions from 2020 onwards, but less steep trajectories. Under the assumption that the implementation of policies is delayed, the carbon price increases only very little until 2030, with a sharp increase of ca. 160 US$ (2010)/t CO_2 (or ca. 133€/t CO_2) in 2035 compared to 2030. In both cases, the probability of limiting global warming to 1.5°C by the end of the century is only ca. 40%, implying a higher risk from physical consequences of climate change, including the risk to cross dangerous tipping points (IPCC, 2018).
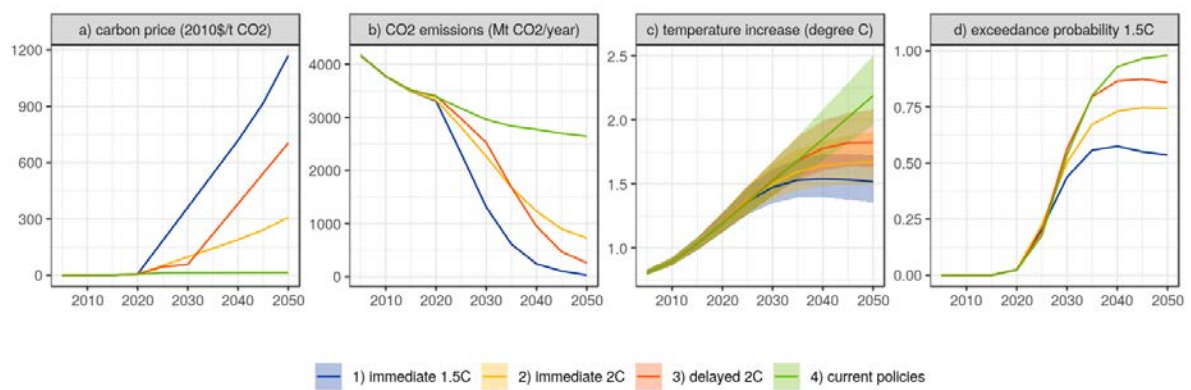
Figure 3: Trajectories of carbon price, CO_2 emissions, global mean temperature increase and exceedance probability of 1.5°C warming under the different policy trajectories (1)-(3) considered in this study, compared to current policies. Temperature increase in (c) is relative to 1850-1900, and shaded areas denote the 25th-75th percentiles. Data source: NGFS (2020), model REMIND-MAgPIE 1.7-3.0.

4 Results

4.1 Shock on PDs

Firms probabilities of default are adjusted to account for changes in carbon prices, as detailed in Section 3. Therefore, for each emission reduction strategy defined in Section 3.3, we derive the associated adjusted probabilities of default. Figure 4 below presents the cumulative distributions of PDs in each scenario.
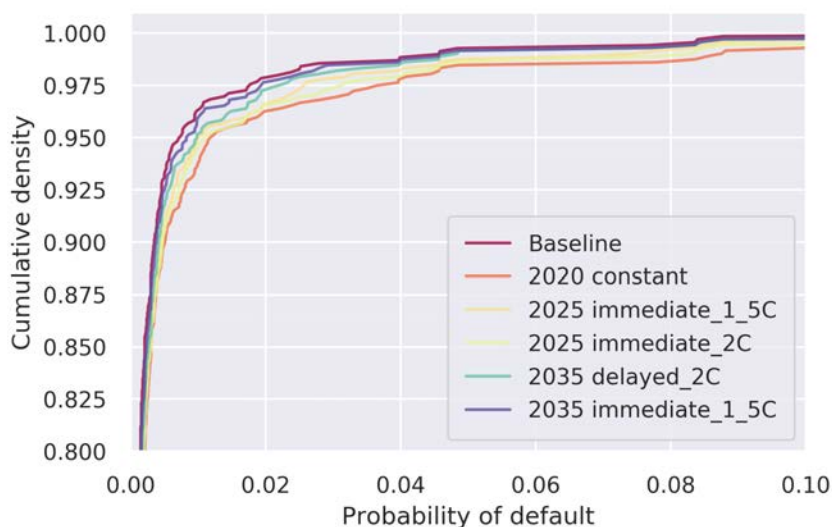
Figure 4: Cumulative density distribution of probabilities of default by emission reduction strategy (for an indicative $\alpha = 70$).

4.2 Constant firm emissions

Under the assumption of firms' emissions staying constant, banking system losses may be sizeable with large changes in carbon price, and considerable tail risks are present in the system. On average (median), an increase in carbon tax of 200€/t would lead to an increase of banking system losses of ca. 10%, compared to the baseline (Fig. 6, Fig. 5 left panel, and Tab. B.2 in the Appendix). While the impact on the center of the distribution would be relatively contained, estimates on the impact on the tails of the loss distribution suggests rare events might acquire more importance with increasing likelihood of large shocks materialising. Tail risks are high with an increase in carbon price of 90€/t or more, with tail losses (expressed through the 99th percentile of the loss distribution) increasing by ca. 10% with an increase in carbon price of 90€/t, and increasing by ca. 33% with an increase in carbon price of 200€/t (also see Tab. B.2
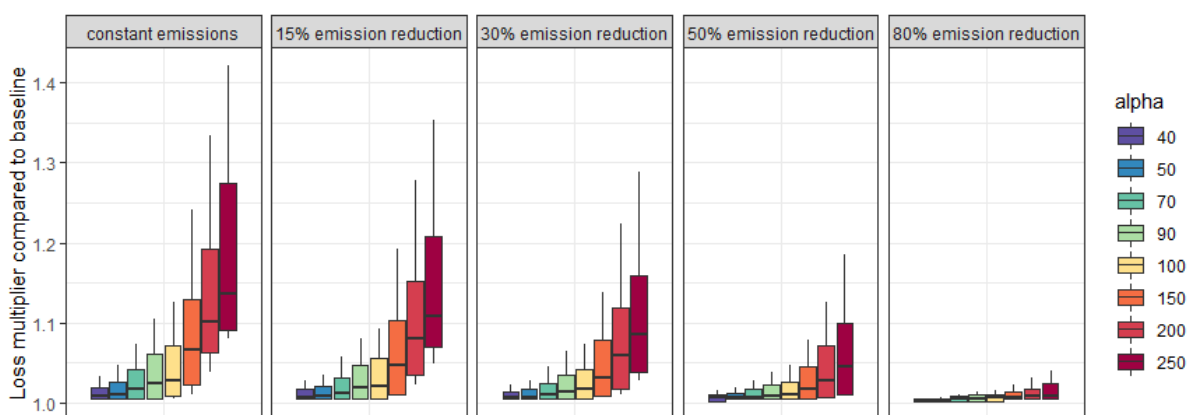
Figure 5: Statistics of banking system loss multipliers compared to a baseline scenario, assuming constant emissions (0% emission reduction), and emission reductions of 15%, 30%, 50% and 80%, depicted in the different panels of the Figure. Colors indicate different levels of α, with carbon cost for firms $\alpha = \beta*$increase in carbon price, and β describing the pass-through of a carbon price to firms.

in the Annex).

These results assume a full pass-through of the carbon price to firms and no further pass-through to firms' selling prices ($\beta = 1$ and $\alpha = \beta*$carbon price increase). With only a fraction of the carbon price absorbed by firms ($\beta < 1$), sensitivity to the carbon price increase would decrease proportionally, e.g. a carbon price of 200€/t and a pass-through of 50% would suggest banking system losses to increase by ca. 2.8% on average, and ca. 12% in a tail scenario. However, given only direct and indirect energy-related emissions (scope 1 and 2) are considered in this calculation, and other upstream and downstream indirect emissions (scope 3) are excluded, a price pass-through to firms of ca. $50\% - 100\%$, depending on the sector, is a reasonable assumption.

Compared to a scenario that reflects the impact of Covid-19 on the banking system in 2020, median losses would be comparable with a carbon price increase of ca. 150€/t, and larger ($4-7\%$) for carbon price increases of 200€/t and 250€/t. This implies that the expected impact of a scenario in which the carbon price increases drastically suddenly, while firms are not able to react, may have an impact that is comparable to the shock induced by Covid-19 in 2020. While carbon price increases of this magnitude seem high compared to currently discussed prices (see Section 1), such increases may be representative of a situation in which effective climate policies are delayed, and then implemented abruptly to limit the consequences of global warming.
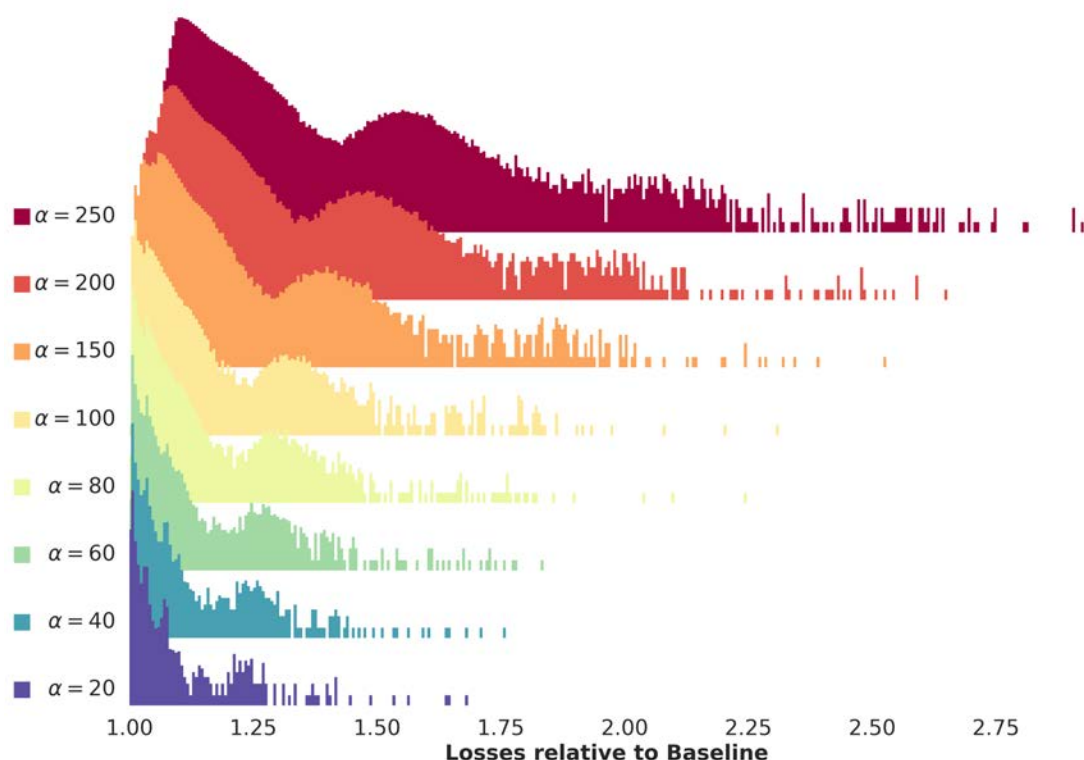
Figure 6: Banking system loss distributions assuming constant emissions for different levels of α, with $\alpha = \beta*$increase in carbon price and β describing the pass-through of a carbon price to firms. Assuming a full pass-through of the carbon price to firms ($\beta = 1$), α can be interpreted as the cost sustained by firms for each tonne of carbon produced. Losses are compared to a baseline situation. Distributions are based on 250 000 Monte Carlo simulations. Heights are log-densities.

4.3 Assuming stylised firm emission reductions

Tail losses remain sizeable for high changes in carbon price and moderately ambitious levels of emission reductions (Fig. 7). For example, with a reduction in firm emissions by 30% and a carbon price increase of 150€/t (and $\beta = 1$), tail losses are estimated to reach ca. 14%, compared to the baseline. This reduction in emissions corresponds to average estimated emission reductions by 2025 compared to 2020 when pursuing policies to limit global warming to 1.5° by 2100 (see Fig. 3, blue line). For firm emission reductions of 50% and a carbon price increase of 150€/t, tail losses are estimated to only increase by ca. 7% compared to the baseline.

Assuming ambitious firm-level emission reductions of 50% or more compared to 2020 levels, our results suggest contained banking system losses on average even for very high changes in carbon price (Appendix B.1 and Fig. 5). With firm emission reductions of 50% and a carbon

price increase of 100€/t, average banking system losses are estimated to increase only by ca. 1% compared to the baseline. This situation corresponds approximately to the estimated change in emissions and necessary 5-year change in carbon price in 2035 compared to 2030, with policies limiting global warming to 2° by 2100 (immediate policies, see Fig. 3, yellow line).

Median and tail banking system losses are sampled for different steps of emission reductions, as pictured in Fig. 8. The results suggest that already small decreases in emission reductions can lead to a sizeable reduction in banking system losses compared to the baseline, implying that already small reductions in firm-level emissions can lead to an important risk reduction. For example, a decrease in firm-level emissions of 15% would, assuming a carbon price change of 200€/t, lead to a banking system loss increase of ca. 6%, compared to 10% with constant emissions. More detailed results and associated statistics can be found in Appendix B.1.

The results presented in this Section assume a uniform emission reduction by all firms in the sample considered here. A further specification of individual firm or sector emission trajectories is beyond the scope of this sensitivity study, as it would require information on firm level emission scenarios, ideally based on information disclosed at firm level (e.g. emissions reduction targets, sustainability linked loans, etc.). However, an extension of this analysis is needed to explore whether different pockets of risk could emerge for the euro area banking system if entire sectors, or groups of firms fail to ambitiously reduce their emissions.
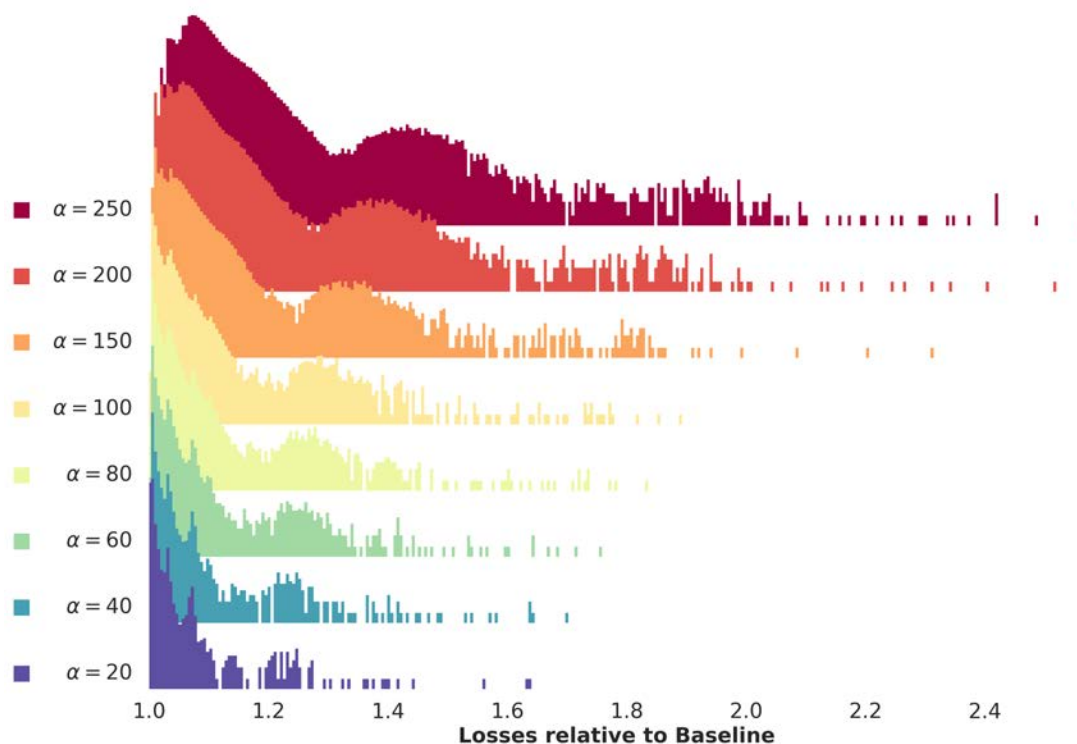
Figure 7: Banking system loss distributions for moderately ambitious emission reductions (-30% compared to 2020) and different levels of α, with $\alpha = \beta \times$ carbon price and β describing the pass-through of a carbon price to firms. Assuming a full pass-through of the carbon price to firms ($\beta = 1$), α can be interpreted as the carbon cost sustained by firms. Losses are compared to a baseline situation. Distributions are based on 250 000 Monte Carlo simulations. Heights are log-densities.
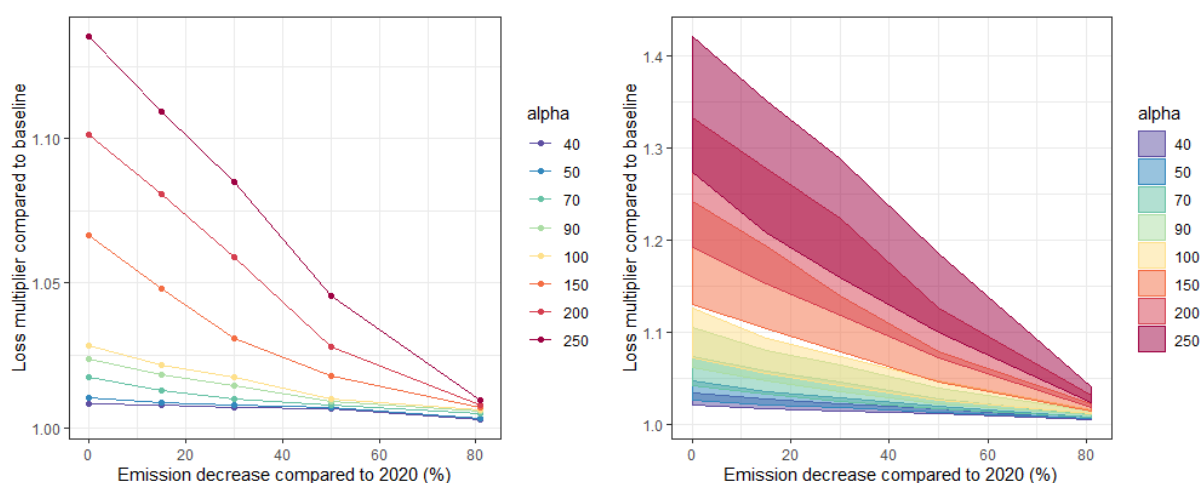

Figure 8: Increase in banking system losses declines with increase in firm emission reductions; median banking system losses (LHS) and tail losses (95th to 99th percentiles, RHS).

5 Conclusions

The study presented here uses a network contagion model to assess the sensitivity of the euro area banking system to changes in carbon price. Changes in carbon price applied for firms' direct (scope 1) and energy-related (scope 2) greenhouse gas emissions are translated into increased real economy probabilities of default which in turn result into additional losses on lenders' balance sheets. This allows to probe the financial stability implications of the introduction of different policies while conditioning on different emission reduction scenarios. The sensitivity of results to different stylised levels of firm emission reductions is also tested.

Results suggest the banking system may be facing substantial risks only with high and abrupt changes in carbon price, if firms do not reduce their emissions accordingly. If delayed policy action makes an abrupt introduction of very high changes in carbon prices (>150 EUR/t) necessary, the banking system may be subject to a shock comparable to that induced by the Covid-19 pandemic in 2020.

This study further finds that high changes in carbon prices might still entail tail risks for the banking system if firms reduce emissions only lightly. In turn, large changes in carbon prices together with ambitious, Paris-consistent emission reductions at firm level across firms are likely to not lead to systemic stress for the banking system.

These results are achieved under the assumption of a full pass-through of a carbon price change to firms[13], and homogeneous emission reductions across all firms, and therefore represent an upper limit of the impact of increases in shadow carbon price. Further research is needed to study what share of carbon price increases would be absorbed by firms and how their balance sheets would be impacted, depending on their emission reduction strategies. Future studies should also investigate how more heterogeneous emission reductions, or a carbon price only applied to specific firms/sectors, may propagate to the banking system, e.g. assuming impacts only in specific industrial sectors or firms. In addition, more comprehensive scenario analyses are needed to consider a broader range of potential transition shocks and transmission channels to the financial system. Furthermore, such studies will benefit from increased efforts to improve firm-level disclosure of their carbon emissions including both direct and indirect emissions, as well as the disclosure of (credible) forward-looking firm strategies to reduce emissions.

Overall, results presented here suggest that in order to shield themselves from losses, banks

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[13]Though the results discussed here are interpreted for a full pass-through of a carbon price change to firms, they can also be interpreted for a limited pass-through.

should assess lending to firms that are not following ambitious emission reduction strategies. Importantly, the results presented here underline the importance of banks' knowledge of their clients' carbon footprints and emission reduction strategies. Consequently, policy measures are needed to foster bank and firm disclosure of both direct and indirect emissions as well as the disclosure of verifiable strategies to reduce emissions. In addition, prudential measures may be necessary to prevent the built-up of banking system losses or pockets of risks through bank exposures to firms that are not able to adapt their business models to a strategy consistent with meeting the goals of the Paris agreement.

Finally, even though the most ambitious policy measures and emission reductions may not completely prevent the materialization of banking system losses, these losses seem to be limited compared to the physical consequences of climate change documented in the literature: global consequences of unmitigated climate change may trigger currently unforeseen consequences, ranging from climate system changes by crossing climate tipping points, to strongly decreasing the area of habitable places on Earth, threatening lives and the economic and political stability of societies.

A   Financial system dynamics

Consider a set of $\mathcal{B}$ banks, characterised by the vectors $\mathbf{K}$ of banks' capitals, and cash holdings $\mathbf{C}$. Moreover consider a set of $\mathcal{E}$ real economy entities (borrowers), and a set $\mathcal{S}$ securities. The financial system is the multilayer network defined by the collection $\mathcal{M} = (\{\mathcal{B}\}, \{\mathcal{S}\}, \{\mathcal{E}\}, \mathbf{L}, \mathbf{S}, \mathbf{E}, \mathbf{F})$, where $\mathbf{L}, \mathbf{S} \in \mathbb{R}^{\mathcal{B} \times \mathcal{B}}$ are the weighted adjacency matrices of unsecured short and long term cross-bank exposures, $\mathbf{E} \in \mathbb{R}^{\mathcal{B} \times \mathcal{E}}$ the weighted adjacency matrix of unsecured banks to real economy exposures, and $\mathbf{F} \in \mathbb{R}^{\mathcal{B} \times \mathcal{S}}$ the banks' portfolios holdings. Banks are subject to both solvency as well as liquidity constraints. A solvency default threshold $\mathcal{D}_j^K$ is defined for each institution as the level of minimum capital requirements plus AT1/T2; in addition, a solvency distress threshold $\mathcal{T}_j^K$ corresponding to the combined buffer requirements is also introduced. Similarly, constraints on liquidity are also accounted for through liquidity default thresholds $\mathcal{D}_j^C = 0$, and liquidity distress thresholds $\mathcal{T}_j^C$ constructed based on individual institutions' *liquidity coverage ratios*. Each bank is therefore further characterised by a trichotomic state encoded in the status vector $\mathbf{s} \in \mathbb{R}^{\mathcal{B}}$: *healthy* ($s_j = 0$ when $K_j > \mathcal{T}_j^K$ and $C_j > \mathcal{T}_j^C$), *distressed* ($s_j = 1$ when either $\mathcal{D}_j^K < K_j < \mathcal{T}_j^K$ or $\mathcal{D}_j^C < C_j < \mathcal{T}_j^C$), or *defaulted* ($s_j = 2$ when either $K_j < \mathcal{D}_j^K$ or $C_j < \mathcal{D}_j^C$).

The system dynamics accounts for three mechanisms of contagion, each modelling a specific class of risk, and each contributing to the amplification and worsening the effects of the others, so that the contagion stemming from each one individually is not simply additive. This is a particularly important feature for a realistic modelling of contagion unfolding. The classes of risk considered, whose modelling is described below, are credit, liquidity, and market risk. While modelling of the first is a mechanical balance sheet contagion mechanism, liquidity and market mechanics involve the search for an equilibrium clearing vector among all market participants in the spirit of (Eisenberg and Noe, 2001). These three mechanisms are iterated until convergence to a steady state in which no more contagion spreads through the system.

Real Economy Credit Risk

The banking system's exposures to real economy entities provide a source of exogenous risk, which can translate, through cascade effects, into amplified losses for banks. In particular, the bipartite topological relation between the banking and real economy sector is crucial in determining how contagion spreads. Yet another crucial role is played by the distribution of probabilities of default PD_j associated with each of the $\mathcal{E}$ firms. In order to capture such

features, the dynamics is initiated via multiple stochastic realisations of defaults.

More specifically, we seek to sample multivariate Bernoulli vector of defaults $\mathbf{d}_{\mathcal{E}} \in \mathbb{R}^{\mathcal{E}}$ with marginal probabilities PD_j and correlation structure defined by a correlation matrix $\mathbf{\Sigma}$ [14]. For each realisation of the Bernoulli vector $\mathbf{d}_{\mathcal{E}}$, one finds a corresponding realisation of losses $\ell_0 = \mathbf{E} \cdot \mathbf{d}_{\mathcal{E}}$ for the banking system. Note that security exposures are also accounted for in $\mathbf{E}$. Such a stochastic approach allows to perform Monte Carlo simulations of different states of the system, hence permitting to study distributional properties of contagion.

One among the possible approaches to sampling correlated multivariate Bernoulli vectors consists in thresholding a multivariate normal distribution with the appropriate correlation structure. Denoting by $z(p)$ the pth quantile of the standard normal distribution, a multivariate Bernoulli vector can be sampled as

$$(\mathbf{d}_{\mathcal{E}})_j = \begin{cases} 0 & \text{if } Z_j > z(PD_j) \\ 1 & \text{if } Z_j \leq z(PD_j) \end{cases} \tag{2}$$

where $Z \sim \mathcal{N}(0, \bar{\mathbf{\Sigma}})$. Crucially, the correlation matrix $\bar{\mathbf{\Sigma}}$ is not the desired correlation matrix, which is instead denoted by $\mathbf{\Sigma}$. In order to infer $\bar{\mathbf{\Sigma}}$, one should consider that

$$\begin{aligned} \Sigma_{jk} = \text{corr}[(\mathbf{d}_{\mathcal{E}})_j, (\mathbf{d}_{\mathcal{E}})_k] = \\ = \frac{\text{cov}[(\mathbf{d}_{\mathcal{E}})_j, (\mathbf{d}_{\mathcal{E}})_k]}{\sqrt{PD_j PD_k (1 - PD_j)(1 - PD_k)}} \\ = \frac{P((\mathbf{d}_{\mathcal{E}})_j = (\mathbf{d}_{\mathcal{E}})_k = 1) - PD_j PD_k}{\sqrt{PD_j PD_k (1 - PD_j)(1 - PD_k)}} \\ = \frac{P(Z_j \leq z(PD_j), Z_k \leq z(PD_k)) - PD_j PD_k}{\sqrt{PD_j PD_k (1 - PD_j)(1 - PD_k)}} \\ = \frac{\Phi[z(PD_j), z(PD_k), \bar{\Sigma}_{jk}] - PD_j PD_k}{\sqrt{PD_j PD_k (1 - PD_j)(1 - PD_k)}} \end{aligned} \tag{3}$$

where $\Phi[x, y, \sigma]$ denotes the standard bivariate normal distribution. This can be solved elementwise for $\bar{\mathbf{\Sigma}}$.

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[14] The correlation matrix $\mathbf{\Sigma}$ is proxied by correlation of CDS spreads at country-sector level.

Interbank Credit Risk

Within the long term layer of interbank credit exposures, described by the weighted adjacency matrix $\mathbf{L}$ of unsecured loans, contagion arises from the insolvency of credit institutions. In particular, the dynamics is initiated by a vector of losses $\ell_0 \in \mathbb{R}^{\mathcal{B}}$ which is transmitted to each individual institution, resulting in a reduction of the vector of capitals. This starts the contagion mechanism by inducing distresses and/or defaults within the system. Upon updating the vector $\mathbf{s}$, the realisation of credit risk coming from banks initially defaulting materialises into a new vector of losses $\ell = \mathbf{L} \cdot \mathbf{d}_{\mathcal{B}}$, where $\mathbf{d}_{\mathcal{B}} \in \mathbb{R}^{\mathcal{B}}$ is the vector of banks in default with elements $(\mathbf{d}_{\mathcal{B}})_j = \theta[s_j - 1]$ (θ being the discrete Heaviside function). Thereby, the capitals are updated as

$$\mathbf{K}_{t+1} = \mathbf{K}_t - \ell, \tag{4}$$

and the vector $\mathbf{s}$ is updated accordingly. Following solvency contagion, the system undergoes further dynamics on the liquidity and market layers, which might lead to further cases of insolvency. As mentioned above, the credit risk mechanics is then reiterated followed once again by the other mechanisms, until the system reaches a steady state.

Liquidity Risk

Following the unfolding of credit contagion, banks might find themselves in a state of distresses, leading to possible further turmoils on the liquidity side (Montagna et al., 2020). In particular, the liquidity contagion mechanism is triggered by preemptive withdrawals from defaulted and distressed banks (Minca and Sulem, 2014), as well as liquidity hoardings from the latters (Covi et al., 2021).

Here we do not account for solvency losses in the short term market, assuming that counterparties of a FOLTF institution have sufficient time to withdraw their positions, given that the time scales of default tend to be longer than the average maturity in this market segment. Instead, we allow banks to satisfy their liquidity needs via pro rata interbank withdrawals – accounted for by the matrix $\mathcal{W} \in \mathbb{R}^{\mathcal{B} \times \mathcal{B}}$ – constrained on their short term assets availability, as well as on the needs of all other market participants. In order to do so, each institution's liquidity shortfall must be a function of the amount of short term funding each other bank is

withdrawing, and can thus be written as

$$L_i^S = \left(\mathcal{T}_i^C - C_i + \sum_j \mathcal{W}_{ji} - \mathcal{W}_{ij} \right)^+ . \tag{5}$$

Consequently, the (residual) short term assets will also be determined in function of such withdrawing as $A_i^R = \sum_j \mathbf{S}_{ij} - \mathcal{W}_{ij}$, and each bank will seek to withdraw a fraction

$$\chi_i = \frac{L_i^S}{A_i^R} \wedge 1 \tag{6}$$

of its short term assets[15]. Searching for the optimal amount of withdrawing is then equivalent to finding a fixed-point for $\mathcal{W}$ and χ, which corresponds to the system's equilibrium (whose existence is guaranteed by the constraints imposed, making χ bounded and monotonic).

Due to the non-linearity of the iterator map, one cannot find a closed form expression for such an equilibrium. Therefore, an explicit computation of the iterator steps is required, leading to an algorithmic procedure which can be loosely interpreted as the unfolding of a liquidity crisis over the course of a short period of time. As mentioned, such an unfolding is triggered by the preemptive withdrawals from defaulted and distressed banks (status $s_j = 1$ or 2), which in turn withdraw their short term holdings as well. Thereby, the initial matrix of withdrawals can be written as

$$\mathcal{W}_{ij} = \begin{cases} \mathbf{S}_{ij}, & \text{if } s_i > 0, \text{ or } s_j > 0, \\ 0, & \text{otherwise.} \end{cases} \tag{7}$$

Through this mechanism, the system might generate liquidity shortages, so that each institution will seek to obtain additional liquidity L_i^S. Here the assumption that each bank will then cover such additional liquidity needs by further withdrawing pro rata, according to its needs and proportionally to the size of each exposure, is made. In particular, a bank in short of liquidity ($L_i^S > 0$) and with positive residual assets A_i^R, will withdraw a fraction L_i^S/A_i^R of its assets from

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[15]Here we employ the by now standard in the field notation (Eisenberg and Noe, 2001) for the element-wise minimum and maximum operators: $(x \wedge y)_i = \min\{x_i, y_i\}$, $(x \vee y)_i = \max\{x_i, y_i\}$ for $x, y \in \mathbb{R}^n$.

the short term market. That is, the extra withdrawal is

$$
\mathcal{W}_{ij}^e = \begin{cases} \frac{L_i^S}{A_i^R}(\mathbf{S}_{ij} - \mathcal{W}_{ij}), & \text{if } A_i^R > L_i^S > 0, \\ \mathbf{S}_{ij} - \mathcal{W}_{ij}, & \text{if } L_i^S > A_i^R > 0, \\ 0, & \text{otherwise.} \end{cases}
\tag{8}
$$

This amount is added to the withdrawal matrix so that $\mathcal{W}_{\tau+1} = \mathcal{W}_\tau + \mathcal{W}_\tau^e$, where τ labels the integer steps of the iterator before convergence. A new value for the extra withdrawals is then computed until convergence of $\mathcal{W}$ to equilibrium, signalled by the convergence of the matrix of additional withdrawals to zero: $\mathcal{W}_{ij}^e = 0$, $\forall i, j$.

Notice that to get to such a fixed point equilibrium state, might not necessarily imply that each bank has fulfilled its liquidity needs. More specifically, this would occur when the entirety of the short term holdings is not sufficient to cover the liquidity needs of one institution. The liquidity positions of all institutions are thus updated, but those in need of additional cash are given the opportunity to raise more through deleveraging: any outstanding liquidity shortage will thus need to be dealt with through the liquidation/decumulation of securities.

Market Risk

Within a network of financial institutions with overlapping portfolios, indirect exposures arising from investments in common assets have the potential to pose significant risk in times of distress, even for institutions with no direct linkages (Cont and Schaanning, 2019). The price-mediated contagion stemming from the depreciation of assets liquidated by deleveraging institutions, leads to strong amplification mechanisms and feedback loops which contribute to aggravate the systemic distress, stimulating further system-wide losses.

While such deleveraging mechanisms can in general be triggered by any kind of portfolios devaluations including exogenous shocks, here we consider only the case of endogenously generated depreciations of the banks' portfolios. In particular, the sale of securities is initiated either by banks in default, or by institutions with residual liquidity shortages $L_i^S > 0$. Because of the depreciation of liquidated assets, each agent in the system must solve an optimisation problem subject to the liquidity needs of all other market participants. Moreover, following portfolios depreciations, more market players might join the sale of assets, giving rise to cascade events.

Denoting by $\mathcal{F} \in \mathbb{R}^{\mathcal{B} \times \mathcal{S}}$ the decumulation matrix, and by $\mathbf{p} \in \mathbb{R}^{\mathcal{S}}$ a normalised vector of

prices, the residual liquidity needs can now be written as

$$L_i^S = \left(\mathcal{T}_i^C - C_i - \sum_j \mathcal{F}_{ij} p_j \right)^+ . \tag{9}$$

The liquidity each institution can raise from liquidation of its marked to market assets $A^M = (\mathbf{F} - \mathcal{F}) \cdot \mathbf{p}$ is clearly constrained by the amount it initially holds, as well as by the equilibrium price vector, determined through the price impact function $\mathcal{P}(\mathbf{p}, \boldsymbol{\Delta})$, where $\Delta = \sum_i \mathcal{F}_{ij}$ is the vector of volumes sold of each individual security. Each bank in need of liquidity will then seek to sell a pro rata fraction $\chi_i = \frac{L_i^S}{A_i^M} \wedge 1$ of its assets. The system equilibrium is here represented by the optimal matrix of decumulation $\mathcal{F}$ and portfolio liquidation vector χ.

Once again, an algorithmic approach must be taken in order to find such an equilibrium. At any point in time, the value of the portfolio of assets each bank disposes of is $\mathbf{F} \cdot \mathbf{p}_\tau$, with $\mathbf{p}_0$ a vector of prices with each element normalised to unity at time zero. Each step of the iterator, consists here in computing a new decumulation matrix according to

$$\mathcal{F}_{ij} = \begin{cases} \mathbf{F}_{ij}, & \text{if } s_i = 2, \text{ or } L_i^S \geq \mathbf{F} \cdot \mathbf{p}, \\ \frac{L_i^S}{\mathbf{F} \cdot \mathbf{p}} \mathbf{F}_{ij}, & \text{otherwise.} \end{cases} \tag{10}$$

The amount of security j sold is thus $\Delta_j = \sum_{i=1}^{\mathcal{B}} \mathcal{F}_{ij}$, and the prices are updated as

$$\mathbf{p}_{\tau+1} = \mathcal{P}(\mathbf{p}_\tau, \Delta). \tag{11}$$

Following the price level reduction in the market layer, the liquidity requirements of some market participants might not be any longer satisfied: this will lead to further liquidation of assets and consequent depreciations. Convergence of the decumulation matrix is here signalled by convergence of the price vector, or equivalently of the vector Δ. Once the equilibrium is achieved, the security holdings are updated to $\mathbf{F} - \mathcal{F}$, as well as the cash holdings as $C_i + \sum_j \mathcal{F}_{ij} p_j$. Most importantly, the risk from indirect exposures materialises in the form of a vector of losses $\mathbf{F} \cdot (\mathbf{p}_0 - \mathbf{p})$ which is then deducted from the banks' capitals. This mechanism leads to further credit risk contagion, possibly leading to further distress in the system, until convergence to steady state.

A final note is in order with regards to the price impact function. One standard approach in

modelling market slippage is to make the assumptions – justifiable under Kyle's model (Kyle, 1985) – that the impact on price of a given transaction is linear in the traded volume, and that its effects are permanent. That is to say $\mathcal{P}_K(p, \Delta) = p \pm \lambda \Delta$, where $1/\lambda$ is a measure of market depth, and the sign of the price impact is determined by whether the transaction is sell or buy initiated. Finally, price impact parameters are calibrated from market data as in (Fukker et al., 2021).

B   Results details

B.1   Loss distributions

The set of figures below shows in a more detailed manner banking system losses distributions across each α and each emissions reduction strategy. More information on emissions reduction strategies and the meaning of α can be found in the main text in Section 3.
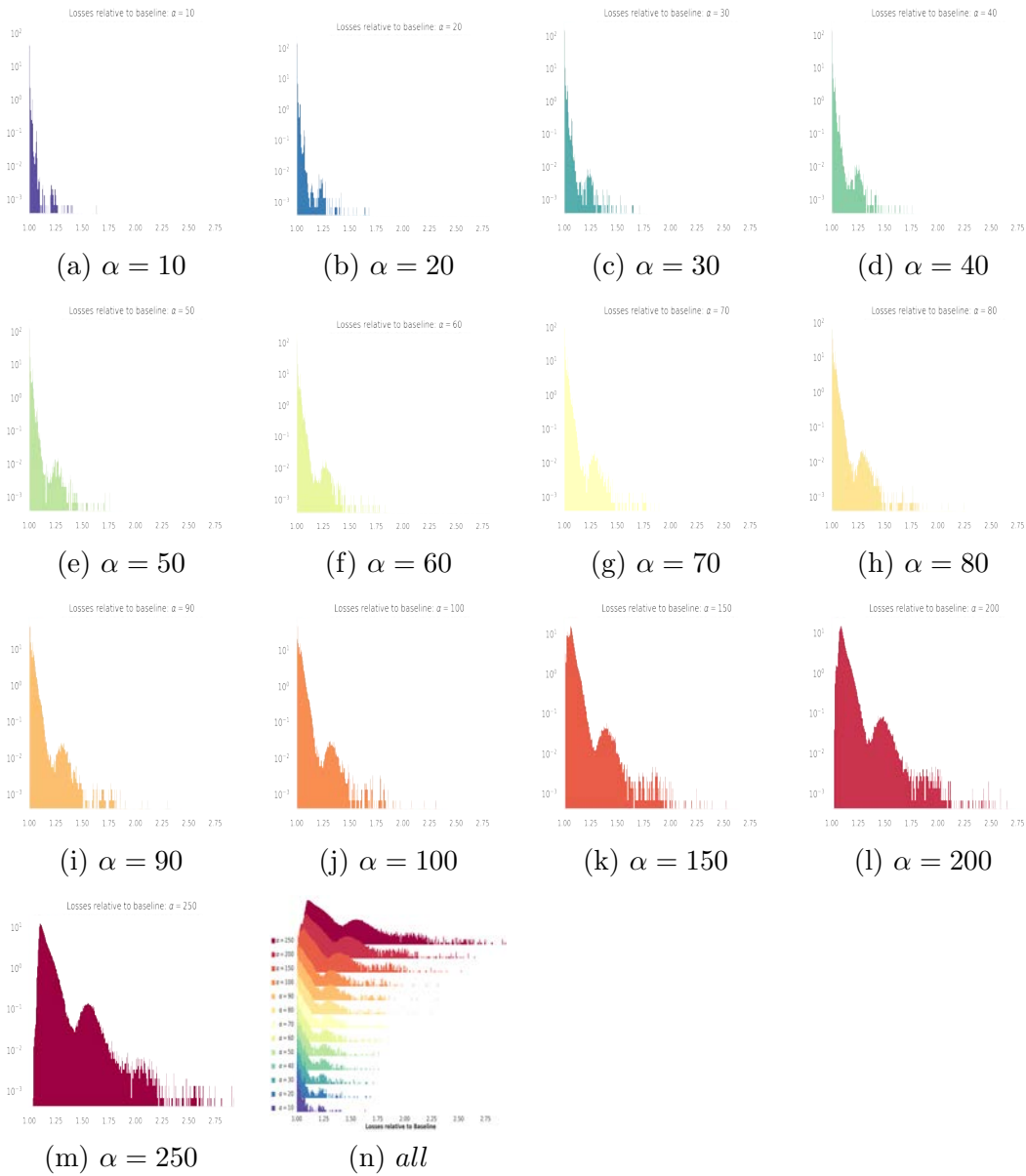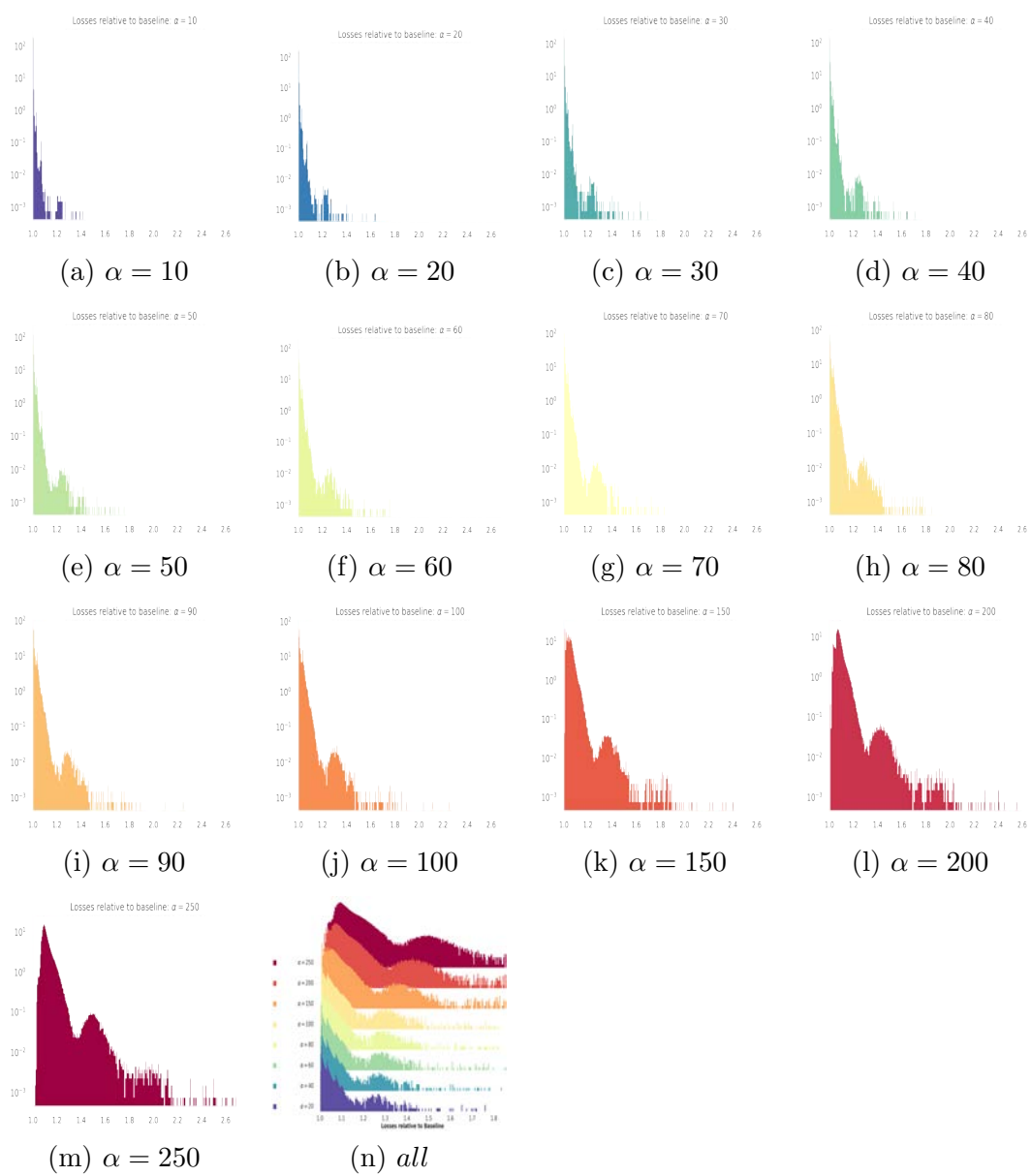
Figure 9: No emissions reduction strategy implemented

(a) $\alpha = 10$ (b) $\alpha = 20$ (c) $\alpha = 30$ (d) $\alpha = 40$

(e) $\alpha = 50$ (f) $\alpha = 60$ (g) $\alpha = 70$ (h) $\alpha = 80$

(i) $\alpha = 90$ (j) $\alpha = 100$ (k) $\alpha = 150$ (l) $\alpha = 200$

(m) $\alpha = 250$ (n) *all*

Figure 10: Emissions reduction strategy of 15%

(a) $\alpha = 10$ (b) $\alpha = 20$ (c) $\alpha = 30$ (d) $\alpha = 40$

(e) $\alpha = 50$ (f) $\alpha = 60$ (g) $\alpha = 70$ (h) $\alpha = 80$

(i) $\alpha = 90$ (j) $\alpha = 100$ (k) $\alpha = 150$ (l) $\alpha = 200$

(m) $\alpha = 250$ (n) *all*
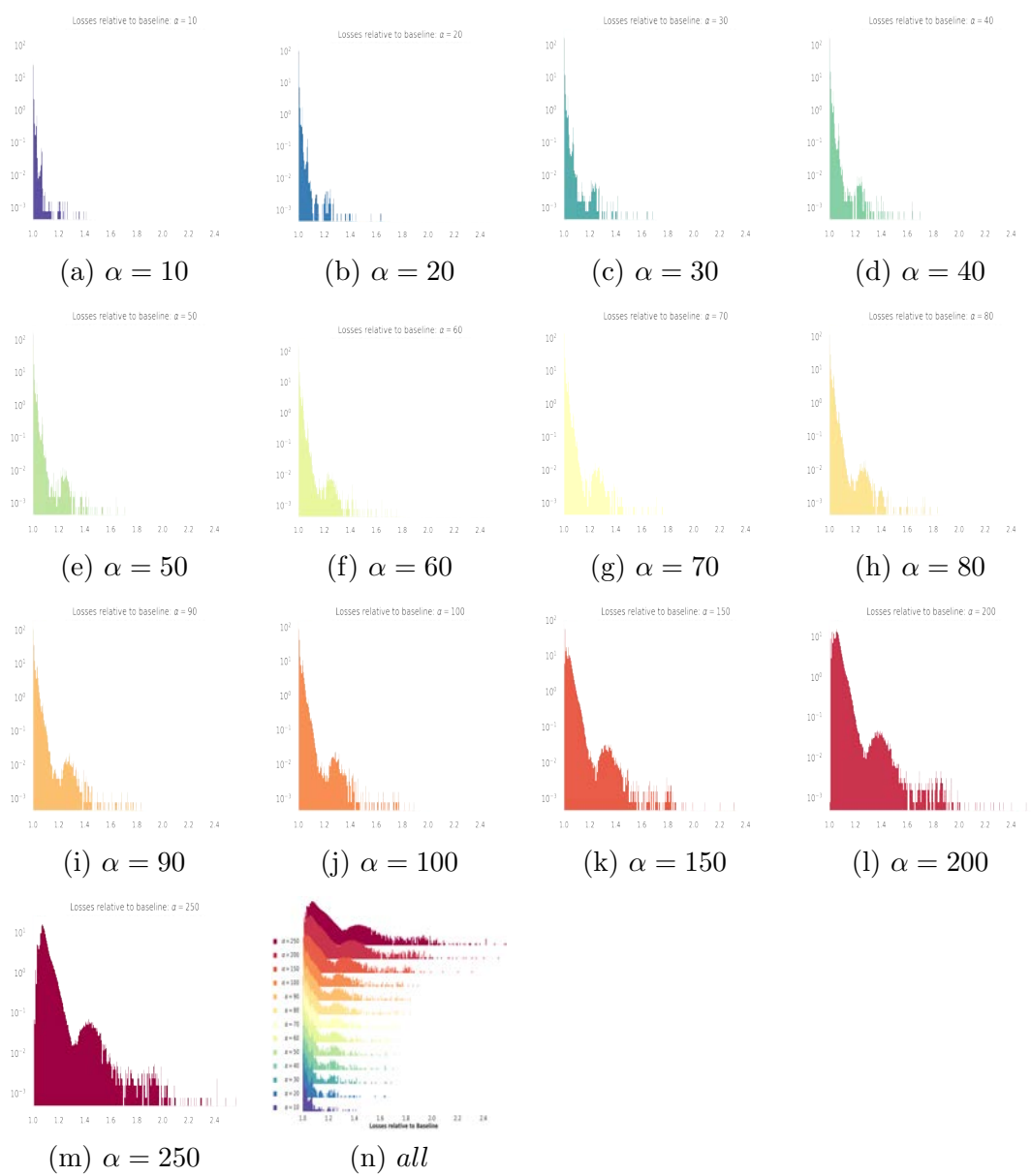
Figure 11: Emissions reduction strategy of 30%

(a) $\alpha = 10$ (b) $\alpha = 20$ (c) $\alpha = 30$ (d) $\alpha = 40$

(e) $\alpha = 50$ (f) $\alpha = 60$ (g) $\alpha = 70$ (h) $\alpha = 80$

(i) $\alpha = 90$ (j) $\alpha = 100$ (k) $\alpha = 150$ (l) $\alpha = 200$

(m) $\alpha = 250$ (n) *all*
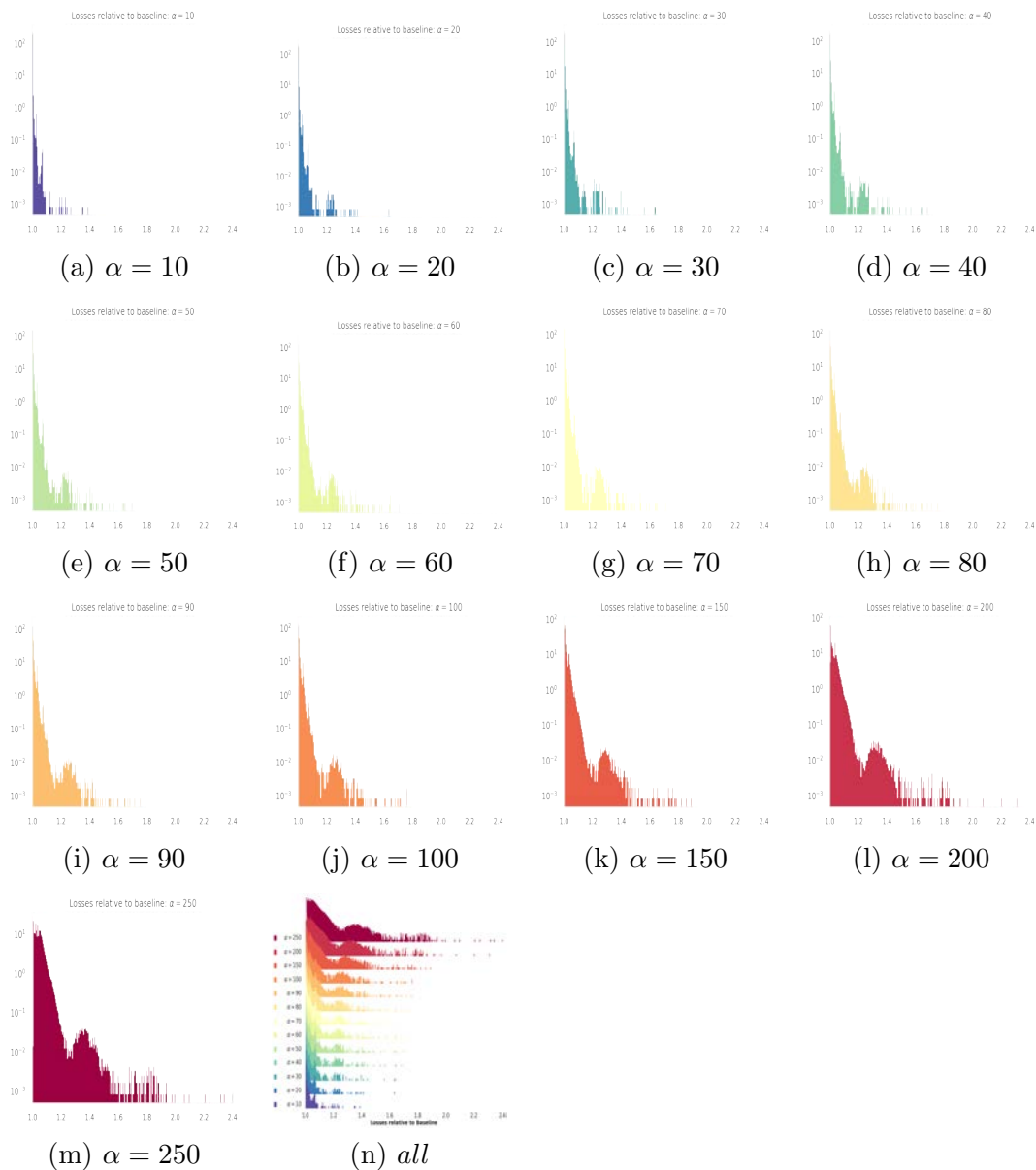
Figure 12: Emissions reduction strategy of 50%

(a) $\alpha = 10$ (b) $\alpha = 20$ (c) $\alpha = 30$ (d) $\alpha = 40$

(e) $\alpha = 50$ (f) $\alpha = 60$ (g) $\alpha = 70$ (h) $\alpha = 80$

(i) $\alpha = 90$ (j) $\alpha = 100$ (k) $\alpha = 150$ (l) $\alpha = 200$
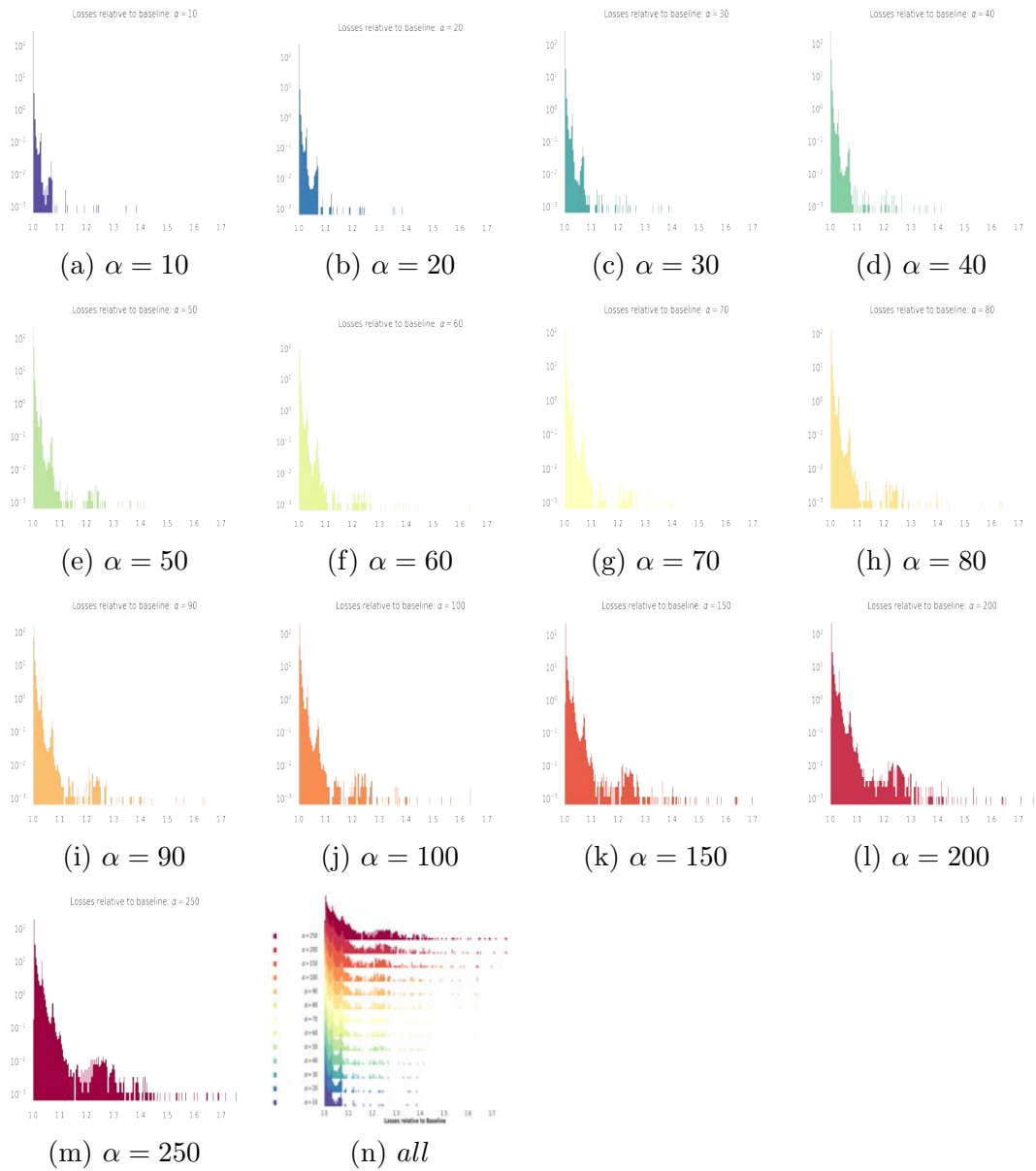
(m) $\alpha = 250$ (n) *all*

Figure 13: Emissions reduction strategy of 81%

B.2 Loss statistics

α	constant emissions	15% reduction	30% reduction	50% reduction	80% reduction
10	0.35	0.26	0.29	0.20	0.23
20	0.64	0.59	0.50	0.34	0.22
30	0.72	0.68	0.65	0.53	0.24
40	0.83	0.76	0.71	0.63	0.27
50	1.01	0.87	0.77	0.68	0.32
60	1.32	1.03	0.87	0.72	0.39
70	1.73	1.29	0.99	0.77	0.46
80	2.02	1.73	1.18	0.83	0.53
90	2.39	1.84	1.47	0.91	0.58
100	2.83	2.18	1.73	1.00	0.62
150	6.66	4.79	3.09	1.79	0.70
200	10.15	8.08	5.90	2.80	0.80
250	13.55	10.92	8.49	4.55	0.94

Table 5: Increase in median losses with different levels of alpha and different assumptions on firm emission reductions, compared to 2020 (in percent).

α	constant emissions	15% reduction	30% reduction	50% reduction	80% reduction
10	0.81	0.63	0.44	0.33	0.21
20	1.61	1.46	1.17	0.78	0.25
30	2.40	2.02	1.70	1.26	0.36
40	3.34	2.75	2.22	1.61	0.46
50	4.70	3.51	2.84	1.99	0.72
60	5.89	4.82	3.50	2.33	0.89
70	7.30	5.79	4.52	2.78	1.07
80	8.54	7.06	5.66	3.28	1.26
90	10.46	8.02	6.41	3.88	1.46
100	12.67	9.34	7.32	4.66	1.50
150	24.20	19.32	13.89	7.81	2.20
200	33.32	27.73	22.40	12.56	3.06
250	42.22	35.24	28.89	18.55	4.09

Table 6: Increase in tail losses (99th percentile) with different levels of alpha and different assumptions on firm emission reductions, compared to 2020 (in percent).

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