Climate risk and financial stability in the network of banks and investment funds*

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Abstract

We analyze the effects on financial stability of the interplay between climate policy shocks and market conditions. To this end, first we combine the frameworks of the Climate Stress-test with the framework of the network valuation of financial assets, in which the valuation of interbank claims accounts for market volatility as well as for endogenous recovery rates consistent with the network of obligations. Moreover, we also consider the dynamics of indirect contagion through common asset exposures between banks and funds, which are key players in the low carbon transition. Second, we derive some analytical results on the relation between financial stability and key drivers of climate transition risk. We then apply the model to a unique supervisory data-set of banks and investment funds to assess the level of climate transition risk in an emerging economy in a range of climate policy scenarios. While under mild shock scenarios systemic losses are contained, we identify the climate policy scenarios and market conditions under which systemic losses can pose a threat to financial stability.

Keywords: financial stability, climate risk, sustainable finance, climate stress-test, low-carbon transition risk, 2°C opportunities, JEL Codes: D85, D86, E58, G01, Q54

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1 Introduction

In the view of many academic scholars and experts from the private sector, there is a growing gap between climate objectives and the allocation of financial capital: 2-degrees Investing Initiative (2012), Batten et al. (2016) and Clark et al. (2018). Narrowing this gap requires to enhance standard financial risk metrics (e.g. value-at-risk) to encompass climate risk. Moreover, given the interconnectedness of today's business, these enhanced metrics of risk and impact need to be based on network models of both investment chains and supply chains, Nuss et al. (2016) and Carvalho et al. (2016).

In the aftermath of the Paris Agreement, the relationship between climate risk and financial stability has taken center stage in the policy debate (Carney, 2015; Bank of England, 2018). Financial supervisors such as the European Central Bank (ECB) and the European Insurance and Occupational Pensions Authority (EIOPA) have started to conduct preliminary assessments of climate-related financial risk in their financial stability reviews (ECB, 2019; EIOPA, 2018) Very recently, an assessment of climate transition risk was carried out as a collaboration between financial supervisors (EIOPA), researcher in climate economics and researchers in climate finance (Battiston et al., 2019).

On the one hand, there is evidence from several economic sectors of the growing opportunities for green sectors[1] along 2-degree compatible trajectories. On the other hand, in other countries, risk can build up from the increasing misalignment between the current trajectories of some sectors of the economy and the trajectories required by the 2° C targets, as set out in the context of the 2015 Paris Agreement. The later is the alignment of these sectors to these 2-degree trajectories, the more abrupt the adjustment must be and the larger the losses these sector would have to bear.

Forward-looking scenarios have been identified as a key element in the assessment of related financial risk for policy applications (Battiston, 2019).

While the importance of the topic is now widely recognised and a stream of work on financial stability builds on the recent concept of climate stress-test of the financial systemBattiston et al. (2017), several crucial issues remain unaddressed.

[1]Green sectors in our context are sectors which favour the green economy like renewable energy, waste management, green construction, among other. These sectors are compatible with 2-degree trajectories given that these economic activities do not generate, or reduce, greenhouse emissions, in comparison with their brown sectors equivalents.

In particular, the impact on financial stability of the interplay between climate policy shocks and market conditions has not been analysed so far and there is no existing framework to do so.

So the first contribution of this paper is to fill this gap in the literature by providing an analytical understanding of such interplay. To this end, we combine in a novel way and for the first time the Climate Stress-test framework with the framework of **Ne**twork **Va**luation of Financial Assets (NEVA) for banks and funds at the same time. Further, we have included a common asset contagion component building on (Greenwood et al., 2015; Battiston et al., 2016). The investigation is carried out with a set of analytical results on the relation between financial losses and climate transition risk.

The second contribution is the application of the developed Climate Stress-test methodology to the supervisory data of Banco de México, including exposures of banks and funds on climate policy relevant sectors.

Mexico is an interesting case study because, on the one hand it is a large emerging economy, heavily exposed to climate change risks and, on the other hand, its Central Bank has collected high-granularity financial data which can be used to perform stress-tests. Our empirical results provide an assessment of climate transition risk in Mexico, conditional to a wide range of climate policy shock scenarios. The results allow to draw some policy implications. Notice that, while some of the numerical results are specific to the economy of Mexico and, possibly, to some other Latin American countries, the analytical results and thus most of the policy implications hold more in general.

The rest of the paper is structured as follows. Section 1.1 describes the different streams of literature that are relevant for the paper. In Section 2 we describe the methodology we have developed to carry out the extended climate stress-test analysis. In Section 4 we discuss our data set. In Section 5 we analyze our empirical results, and Section 6 concludes.

1.1 Related work

Indeed, existing stress-testing frameworks have focused so far on the banking system. However, the banking sector is little exposed, in a direct way, to the economic sectors that are most relevant for the low-carbon transition. In contrast, investment funds have been found by previous empirical analyses Battiston et al. (2017) to be at the same time largely exposed to climate relevant sectors, as well as to be a crucial actor for scaling up the investments needed to finance the low-carbon transition. To the best of our knowledge, the combined effect of banks and investment funds has not been studied so far.[2] Additionally, in some countries like Mexico, development banks could also play a relevant role in the low carbon transition. At the same time they can have an impact on financial stability (Monasterolo et al., 2018). In this paper, we address this issue by developing a stress-test model that

[2]Normally, investment funds are not included in stress tests, mostly because of the lack of information. This paper leverages on the access to supervisory data set for investment funds.

encompasses at the same time commercial banks, development banks and investment funds.

In general, our work builds on the stream of literature focusing on pecuniary externalities arising from common exposures of financial institutions Kiyotaki and Moore (2002); Greenwood et al. (2015); Caccioli et al. (2014).

In particular we build on the stream of literature following the DebtRank paper (Battiston et al., 2012b) focusing on distress contagion in financial networks (Bardoscia et al., 2015; Barucca et al., 2016; Battiston et al., 2017; Roncoroni et al., 2018; Monasterolo et al., 2018) to study the effects of shocks arising from the misalignment of energy and utility sectors in a wide range of climate policy scenarios. Further, we extend the current NEVA methodology Barucca et al. (2016) to include both banks and funds.

So far, most of the models to estimate losses arising from financial contagion have focused on distress contagion and common exposures contagion separately. In this paper we show that the combination of the two effects gives rise to losses that are larger than the sum of the individual contributions. This result implies that not considering the interplay between the two channels of financial contagion underestimates systemic risk. We address this issue by extending the NEVA framework by (Barucca et al., 2016) to include the liquidation of common assets mechanism, also known as asset fire sales. The inclusion of both types of contagion proved to be very important in this context. More precisely, direct exposures to energy intensive sectors by the banking system are rather small; nevertheless, these two channels worked as powerful amplification mechanisms.

The climate stress test methodology has been only based on the DebtRank model so far, without including more recent extensions of financial contagion models. In this paper, we address this issue by extending the concept of climate stress test to the NEVA framework in order to account for the ex-ante valuation of financial assets and market volatility in a set of climate policy scenarios.

For the first time, we develop an extended stress-test framework that encompasses banks, brokerage houses, development banks and investment funds, by building on previous work of the authors on stress-test frameworks in bank networks (i.e. DebtRank Battiston et al. (2012a), and NEVA Barucca et al. (2016)). In the model, we study the effect of the contagion channel between investment funds and banks. Additionally, investment funds are subject to a balance-sheet contagion mechanism (i.e. building on the insights of Kiyotaki and Moore (2002); Greenwood et al. (2015)) leading to a spiral of deleveraging and fire sales.

The NEVA model is used for the valuation of claims for banks which are connected through their balance sheets. For some parameter choices, NEVA is equivalent to some of the best known contagion algorithms like the Eisenberg and Noe 2001, the default cascades Furfine 2003, Rogers and Veraart 2013 and Bardoscia et al. 2015. The method basically performs the ex-ante valuation (à la Merton) of the institutions' cross-holding claims in a decentralized fashion.

Finally, we discuss the policy implications of our finding and the avenues for future research. Some of the insights from our analyses are valid in general for all countries, although the magnitude of the effect is country specific. In particular, this is of interest for EU countries, where the debate on climate transition risk is most advanced but such an exercise has not yet been carried out, at least at this level of granularity. Other insights are relevant more specifically for countries of the region Latin America.

2 The model structure

In this section we provide a short description of the assumptions we made, the methods we built on and the necessary extensions that we used in this work. Then, we describe the set of operative steps used to carry out the computation.

2.1 Climate stress-test

There are two channels through which climate change can result in risks for public and private financial institutions: physical risk and transition risk. On the one hand, physical risk (e.g. damages to physical assets, natural capital, and/or human lives) can result from climate-induced extreme weather events (IPCC WGII, 2014; IPCC, 2018). On the other hand, climate risks could also result from the transition to a low-carbon economy, referred to as transition risk (ESRB, 2016; Batten et al., 2016). In this paper we focus on the impact on financial stability of the latter.

Transition risk refers to the risk that some sectors of the economy might face when humans move to a greener economy. This transition could translate into important losses for those sectors which are considered to be less environmentally friendly. The financial system in general and the banking system in particular are more or less subject to transition risk depending on their investment decisions and on their willingness (and speed) to move their investments towards greener activities.

It is useful to think of transition risk in terms of an event tree, as described in figure 1. There are two main possibilities. Either the transition to a low carbon economy occurs or it does not. Furthermore, if the transition occurs, there are two further possibilities: transition to a low-carbon economy in an *orderly* fashion or in a *disorderly* fashion. A disorderly transition means that investments are shifted suddenly to be in line with climate targets and market players are only partially able to anticipate price adjustments. An orderly transition implies that market players are able to fully anticipate those price adjustments. Those dynamics are closely related to the concept of *climate sentiments* that has been formalized in Dunz et al. (2018, 2019).

In this paper we consider shocks arising from the inability of market players to fully anticipate the price adjustments of carbon intensive asset. As described in (Monasterolo et al., 2017) there are three important sources of shocks that could limit the ability of market participants to fully anticipate price adjustments of carbon-intense assets. These sources include: i) technological developments (e.g. renewable energy production costs); ii) scientific discovery (e.g. new evidence on likelihood to miss the 2°C target Rogelj et al. (2016); iii) introduction/implementation of climate-relevant policies (e.g., the achievement of COP21 agreement in 2015, or the US withdrawal from the Paris Agreement in 2016). Climate relevant policy shocks (positive and negative) are important because of carbon stranded assets and resources, Bos and Gupta (2019).

The first methodology to account for climate-related transition risk in the computation of financial risk metrics for individual financial institutions has been introduced in (Battiston et al., 2017). In particular, the method allows to compute a Climate Value at Risk and to conduct a Climate Stress-Test of both individual institutions and of the whole banking system in a given region. The methodology aims to quantify risk of a disorderly price adjustment in the economic sectors related to energy. It estimates distributions of shocks on a portfolio of investments in non-financial firms in economic sectors that can be affected positively or negatively by late and sudden alignments to climate policies. For instance, within a country that delays its alignment to 2°C targets in terms of composition of its energy production sources (energy mix), the firms in the energy sector that have not adapted to the targets face unanticipated costs associated with the transition. In contrast, firms that have invested in green technologies would profit. Accordingly, financial investments in energy firms reflect positive and negative shocks. Under a set of mild assumptions, the magnitude of these shocks can be related to the characteristics of forward-looking trajectories of output of the various economic sectors. These trajectories are obtained from the LIMITS database which provides the scenarios consistent with a range of climate targets, according to a set of well-established Integrated Assessment Models. More details on the selection of climate policy scenarios used in this paper is reported in Appendix B.[3]

There are two ways to estimate distributions of shocks in sectors' market share from the LIMITS trajectories. The first way uses the longitudinal variation along each trajectory Battiston et al. (2017). The second way uses the variation in market share across trajectories. In this paper, we follow the latter approach, in which each shock is interpreted as the variation in market share of a sector resulting from the country moving from a business-as-usual scenario into one of the possible standard climate policy scenarios (according to IPCC and IEA) in a disorderly way.

2.1.1 Policy scenarios analysis

[3] A more complete description of the LIMITS database can be found on the website maintained by IIASA at `https://tntcat.iiasa.ac.at/LIMITSDB/dsd?Action=htmlpage&page=about`. The corresponding scientific reference is (Kriegler et al., 2013).

In this section we discuss, in a simplified way, the possible chain of events in the face of climate physical and transition risk. Figure 1 illustrates such possible scenarios.

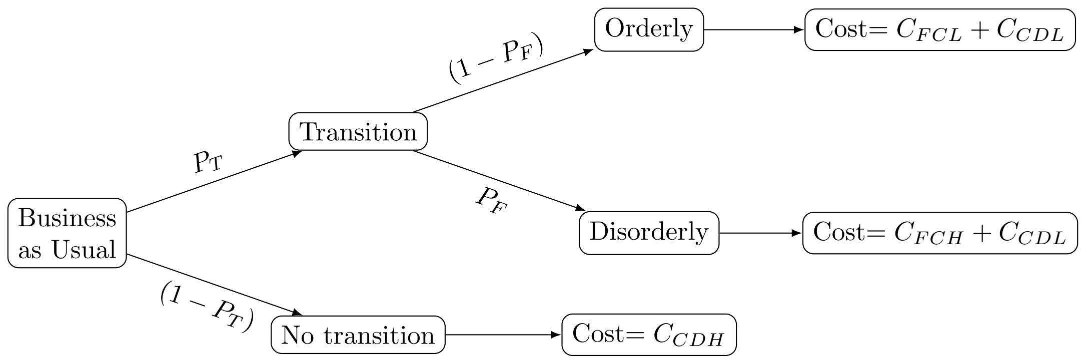


Figure 1: Illustration of the event tree of the transition to a low-carbon economy.

Where the indices indicate the type of cost in each branch of the event tree, namely

- CDH: Climate Damage High,
- CDL: Climate Damage Low,
- FCL: Financial Cost Low,
- FCH: Financial Cost High.

We refer as P_T the probability of the transition to happen. It follows that $(1-P_T)$ is the probability of no transition. In case of no transition, the cost of extreme climate events is large and we define it as C_{CDH}. The goal of the transition is to mitigate climate risk and reduce the cost of extreme climate events to a lower value C_{CDL}, where $C_{CDL} < C_{CDH}$ (Carney, 2015). The transition to a low carbon economy can either occur orderly, with probability $(1-P_F)$, or disorderly with probability P_F. In the first case the cost would be low C_{FCL}, in the second case it would be high C_{FCH}. The expected cost of climate risk is

$$\mathbb{E}(\text{Cost of Climate Risk}) = P_T P_F (C_{FCH} + C_{CDL}) + P_T(1-P_F)(C_{FCL} + C_{CDL}) + (1-P_T)C_{CDH}. \quad (1)$$

However, the probability for the transition to occur is endogenous, as it depends on how the various actors involved (e.g., policy makers, non-financial corporations , financial institutions, and society) perceive the costs in equation 1 (Bretschger and Pattakou, 2018). Since $P_T < 1$, if follows that risk neutral agents have an incentive to support the transition if the cost of climate change C_{CDH} is large enough, i.e.

$$C_{CDH} > (1-P_F)\, C_{FCL} + P_F\, C_{CFH} + C_{CDL} \quad (2)$$

Notice that, risk averse investors would have an incentive for the transition to occur even for lower expected financial losses. In fact, estimating the threshold for risk neutral agents corresponds to an upper bound of the threshold. As shown in equation 2, the probability of the transition to happen depends on climate damage cost and the expected cost of the transition. Notice that Equation 2 also depend on the probability of whether the transition happens in an orderly or disorderly way. One could also derive a more general upper bound for transition losses below which it is always better to shift to a low carbon economy. In fact, if the sum of the cost of the transition and the low climate cost in case of mitigation is lower than the large cost of climate damage in case of no transition, i.e.,

$$C_{CDH} > C_{FCH} + C_{CDL}, \tag{3}$$

market players always have an incentive to support the shift.

In this paper we do not aim to estimate the probabilities P_F or P_T, in contrast we focus on estimating the cost for the financial system of a disorderly transition. In particular, we contribute to the policy discussion on climate risk by showing that this cost depends on the interplay between climate policy shocks and market conditions.

2.2 Extended bank-fund climate stress-test

In this paper we mainly extend three models of financial contagion (Barucca et al., 2016; Roncoroni et al., 2018; Greenwood et al., 2015) to derive the first climate stress-test methodology that combines an ex-ante valuation of financial assets, an endogenous recovery rate and a fire-sales reaction that consider several types of financial institutions at the same time. The term ex-ante valuation refers to the fact that the valuation of interbank claims take place before maturity and accounts for possible uncertainty on the value of external assets in the meantime. In this paper we refer to external assets to indicate all assets that are not investments into other financial institutions. On the contrary, interbank assets are banks' and funds' investments into other banks. The term endogenous recovery rate indicates that banks use what remain in their balance sheet to honor their obligations towards other financial institutions. The dynamics of contagion are summarized in Table 1.

In this paper we refer to a *shock scenario* as the combination of: i) a *market conditions scenario* i.e., a range of values for the parameters recovery rate R, market volatility σ, market elasticity α, and the funds' VaR;[4] and ii) a *climate policy shock scenario*, i.e., a set of shock arising from the late and disorderly alignment from BAU trajectory to a set of climate target trajectories. Therefore the output of the extended climate stress test framework, is a database of trajectories for the systemic losses (see

[4]These variables are known as financial variables or market variables in the stress testing literature; see for example Borio et al. (2014)

Climate stress-test module	Features
Climate policy shocks (Battiston et al., 2016)	We estimate the impact of a late and disorderly alignment to a climate policy building on forward looking economic trajectories provided in the **LIMITS database**(Kriegler et al., 2013). The database provides scenarios of the output of relevant sectors of the real economy across selected climate policy scenarios. We define the climate shock as the difference between the Business as Usual (BAU) scenario and each climate policy scenarios and we translate it into a shock on the value of bonds and loans, following standard finance assumptions as shown in Equation 5.
First round (Battiston et al., 2016)	**First round losses** are those suffered by banks and funds due to **direct exposures** i.e. via bonds and loans to firms in selected Climate Policy Relevant Sectors (CPRS, see main text. Losses amount to the product of financial institutions' exposures towards CPRS and the Climate Policy Shocks. This implies that financial institutions suffer a **set of correlated shocks** from multiple asset classes.
Second round (Barucca et al., 2016)	We carry out **an ex-ante valuation of intra-financial assets** due to the first round shock using a generalized model of financial contagion which includes an endogenous recovery rate. Second we estimate the devaluation of funds assets due to banks' increased probability of default. In this context, we use the world generalized because, with the right choice of parameters, the contagion framework encompasses well established models of contagion such as (Eisenberg and Noe, 2001; Battiston et al., 2012b).
Third round (Kiyotaki and Moore, 2002; Greenwood et al., 2015; Cifuentes et al., 2005)	Banks' and funds' **reaction** to the shock to get to their **initial risk management strategies** (leverage for banks, VaR for funds). The liquidation suddenly increases the supply on the market further causing losses on banks and funds balance sheets. Value at Risk (Var) is the estimated loss with a given probability.
Fourth round (Roncoroni et al., 2018)	Losses too large to be absorbed by banks' capital and are transmitted to **external creditors**.

Table 1: Description of the stages of the contagion dynamics.

Table 4) in each stage of the contagion process.

2.2.1 Model features

In the following, *direct contagion* refers to the transmission of financial losses from a financial institution i to another institution j via a bilateral contract stipulating a financial obligation of j to i.

In contrast, *indirect contagion* refers to the transmission of financial losses from a financial institution i to another institution j via holdings of the same financial asset (also called *common asset exposure*, issued by a third party k (non-financial firm). The transmission channel works as follows Kiyotaki and Moore (2002): a negative shock on institution i induces it to sell some quantity of asset k. If the sale volume has a market impact, i.e. it makes a downward pressure on the asset price, institution j suffer from a negative shock on its own balance sheet. The effect is also referred as a *pecuniary externality*.

The novelties of our model with respect to prior models to study financial contagion are illustrated in Table 2 along the following dimensions.

- **Endogenous Recovery Rate.** The term refers to the fact that the recovery rate is computed as the ratio between the face value of an interbank obligation and its value at the equilibrium of the clearing process. (Eisenberg and Noe, 2001) were the first to prove the existence and to determine the conditions for uniqueness of the endogenous recovery rate in a financial network. In the model based on DebtRank the recovery rate is exogenous. Barucca et al. (2016) have shown how to endogenize the recovery rate in the DebtRank framework. This approach has been applied to supervisory data in Roncoroni et al. (2018).

- **Ex-Ante Valuation.** The term refers to a network coherent valuation, i.e. coherent with the structure of financial contracts, of financial assets which is carried out before the maturity of contracts. The concept has been introduced by Battiston et al. (2012b) and extended in Barucca et al. (2016) to encompass the case of à la Merton valuation of external assets, i.e. which consider uncertainty on the value of external assets at the maturity of financial contracts.

- **Firesales Contagion.** The term refers to losses arising from the sudden liquidation of the exposures to common assets. To encompass firesales contagion in our contagion framework, we build on the models discussed in Kiyotaki and Moore (2002); Greenwood et al. (2015); Caccioli et al. (2014); Cifuentes et al. (2005); Caballero and Simsek (2013).

- **Investment Funds.** The term refers to the fact that our model also considers investment funds when computing the exposure of the financial system towards climate relevant scenarios and when computing losses arising from financial contagion.

- **Climate Module.** The terms refers to the fact that the initial shocks are triggered by a late and disorderly alignment to climate targets. To estimate the climate policy shocks we build on a long stream of literature that includes Battiston et al. (2017); Monasterolo et al. (2017, 2018); Dietz et al. (2016).

Notice that combining banks and investment funds in the same dynamics of contagion poses some challenges. First, ignoring the exposures of funds towards banks would underestimate the losses that trigger liquidation. Second, by the nature of the asset fire-sales dynamics when including the sudden reaction of a larger set of financial institutions the losses due to price drop spirals are larger.

	Model features				
Literature reference	Endogenous Recovery Rate	Ex-Ante Valuation	Firesales Contagion	Investment Funds	Climate Module
Systemic Risk Eisenberg and Noe, 2001					
DebtRank Battiston ea., 2012					
Leveraging the Network Battiston ea., 2016					
Pathways Bardoscia ea., 2017					
NEtwork VAluation Barucca ea., 2016					
Interconnected Banks Roncoroni ea., 2018					
Climate Stress Test Battiston ea., 2017					
Our work **Roncoroni ea., 2019**					

Table 2: Overview of literature on financial contagion summarizing the novelty of the methodology introduced in this paper. The color of cells show whether each of the cited papers includes or not each model feature: the shade of green means that it includes the feature, white means that it does not include the feature.

3 The financial contagion model

In this section we illustrate each stage of the financial contagion model. First, we define here the concept of *market conditions*.

Definition 1. **Market conditions**

We define as *market conditions* the set of parameters $\{\sigma, R, -\alpha\}$, where σ is the asset price volatility, R is the interbank recovery rate and $-\alpha$ is the market liquidity. In particular, we define as *strong* market conditions the scenario where R and $-\alpha$ are large, and σ is small. Conversely, we define as *weak* market conditions the scenario where R and $-\alpha$ are small, and σ is large.

3.1 First round: losses due to direct exposure

While Battiston et al. (2017) focuses on the valuation, under climate policy shocks, of equity holdings of banks in firms in the energy and utility sectors, (Monasterolo et al., 2018) focuses on the valuation, under climate policy shocks, of loans to firms in the energy and utility sectors. In our dataset, the majority of exposures of banks to climate relevant sectors are on the form of loans and corporate bonds. For the investment funds, they are corporate bonds. Therefore, we follow the valuation formula in (Monasterolo et al., 2018).

The valuation works under the following set of assumptions. There are two type of shocks affecting the value of the firms. The first is the policy shock which is deterministic and correlated across firms in a given sector, as it affects the whole sector. The second is an idiosyncratic shock that affects each firm independently (due to management capabilities[5] and productivity shocks specific to the firms). At this stage of the model, we assume that the idiosyncratic shocks on the borrower asset side are drawn from the same distribution, which is assumed to be a non-negative random variable with a continuous, differentiable distribution function. While it is possible to handle computationally any empirical distribution of shocks, we do not have the data at a firm level to do so. For the sake of simplicity, at the current stage of the model, we approximate the distribution of idiosyncratic shocks with a uniform distribution, for a justification of this assumption see also Section 3.2.

We treat loans and bonds in the same way, based on the valuation approach of expected value. Under our mild assumptions, it is shown in Monasterolo et al. (2018) that, conditional to the policy shock, the change in the expected value of a loan reads:

$$\Delta A_{ij}(m,p,c,s,t) = F_{ij}(1-r_j)\frac{E_j}{\delta}\chi u_{mpcst} \tag{4}$$

where A is the expected value of the bond issued by j and held by i, F is the face value of the bond, r is the recovery rate, E is the equity of the firm, δ is the support of the distribution of idiosyncratic shocks, χ is the elasticity of profitability in respect to the market share of the sector, and u is the market share shock, m labels the model chosen to estimate the trajectory in the climate policy scenario p introduced at time t, in years, on sector s of country c. We thus define the multi-dimensional matrix of LIMITS shocks L as

$$L_{mpcst} = \frac{\Delta A_{ij}(m,p,c,s,t)}{F_{ij}}, \tag{5}$$

[5]The terms management capabilities here refers to the fact that there might be heterogeneity in the distribution of shocks affecting individual firms. In this project we focus on the aggregate result.

and, as in Monasterolo et al. (2018), setting $r_j = 0 \,\forall\, j$, $\frac{E_j}{\delta} = 1$, and $\chi = 1$. Notice that this corresponds to an upper bound of losses.

To estimate the impact of the shocks on the value of firms in each sector on banks' and investment funds' exposures we build on (Battiston et al., 2016) and on the multi-dimensional matrix notation from (Roncoroni et al., 2018). The shock absorbed via direct exposure is called first round shock and is expressed as

$$\Xi_{it}^{1st} = \min\left\{0\,,\, \sum_c \sum_s \min\left\{0\,,\, L_{mpcst}\right\} \cdot A_{icst}^{\text{loans, bonds}} + \sum_c \sum_s L_{mpcst} \cdot A_{icst}^{\text{equity}}\right\}, \tag{6}$$

where the index i labels the financial institution, c labels the country of the exposure, s labels the sector of the exposure, t labels the year of introduction of the policy aimed at mitigating climate change, and A is the multi-dimensional matrix of exposures of financial institutions. While the methodology is able to capture the impact of positive shocks on equity holdings as well, we empirically observe that the majority of banks' and investment funds' exposures towards energy sectors are on the form of loans and corporate bonds. Further, since only banks are subject to limited liabilities, the shock suffered by banks is bounded by their initial equity. Notice that, to solve the taxonomy issue, to estimate the shock on market share of each CPRS sector we did as follows. For the "Fossil-Fuel" sector we used the trajectories (BAU and those corresponding to the introduction of climate policies) of the "Primary Energy|Fossil" LIMITS sector. For the "Utilities" sector we used the trajectories (BAU and those corresponding to the introduction of climate policies) of the "Secondary Energy|Electricity|Gas" LIMITS sector. Since only a fraction of the Mexican electricity is produced using gas, we applied a factor to the amount of assets invested in the utility sector. Using data from International Energy Agency, we set this factor to 83.16%.[6]

3.2 Second round: network valuation of financial assets

To compute the network coherent devaluation of banks' bilateral claims we build on several previous papers[7]. In particular, we assume that a portion of the non-shocked external assets is subject to market volatility which generates stochastic shocks that follow a uniform distribution, as shown in Roncoroni et al. (2018). In order to account for financial friction, an exogenous recovery rate R is applied to banks' payments in order to simulate market imperfections such as legal costs. Figure 2 illustrates with more detail the time dimension of the contagion dynamics. We assume that banks

[6] https://www.iea.org/statistics/monthly/#electricity

[7] (Barucca et al., 2016; Allen and Gale, 2001; Gai and Kapadia, 2010; Roukny et al., 2013; Di Iasio et al., 2013; Tabak et al., 2013; Thurner and Poledna, 2013; Poledna and Thurner, 2016; Fink et al., 2016; Puliga et al., 2014; Bardoscia et al., 2015, 2017; Roncoroni et al., 2018)

allocate their exposures towards other banks at time t_0. At time t_1 the climate policy shock, which we call *deterministic shock* observable shock and we compute using the LIMITS trajectories, modifies the value of the external asset classes reducing the banks' capitalization. At time t banks carry out a coherent network valuation of interbank claims that mature at time T. Between t and T a stochastic shock induced by market volatility modifies the value of banks' external assets further reducing the mark-to-market value of banks' capital. The probability of banks' default thus depends on the initial network structure, the *deterministic climate policy shock* as well as on the distribution of the *future stochastic shock*.

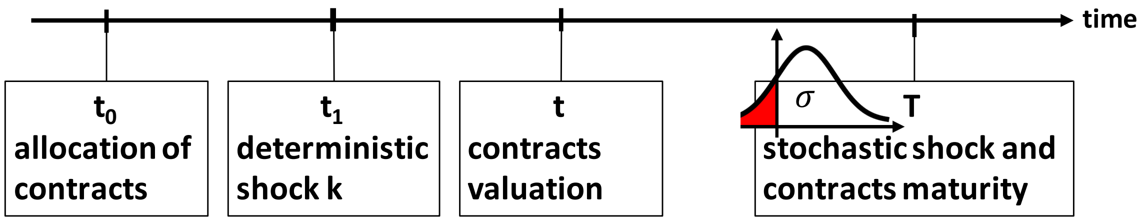


Figure 2: Illustration of the time dimension of the contagion model. At t_0 contracts are written, at time t_1 a known shock reduces the value of banks' external assets, at time t the valuation is carried out, at time T the value of banks' external assets is further reduced due to market volatility thus reducing mark-to-market banks' capital.

The methodology developed in Barucca et al. (2016) can be solved numerically for any distribution of stochastic shocks. However, it can be solved analytically only for a small set of distributions. In this paper we model a uniform distribution for the following reasons. Assuming that the market value of bonds held by banks corresponds to their face value, the stochastic shock is by definition bounded between zero and negative one. Thus, one can not model it using a Gaussian distribution. We decided to model the stochastic shocks using a beta distribution (Bolt and Tieman, 2004). Additionally, we assume that banks' have a risk management strategy such that the shocks on their total asset follow a non-convex distribution, i.e. the probability is larger for intermediate shocks and lower for very large shocks (Ruszczyński and Shapiro, 2006). This means that they aim to contain the left-hand side tail of the distribution. However, since we still want to model extreme events, among all the non-convex beta distribution functions we chose the one that has the heaviest tail (which in the limit of $\beta(1, 1)$ coincides with the uniform distribution). A uniform distribution can be uniquely defined by the size of its support. In fact, a uniform distribution is defined by the boundaries. In our model, one of the boundaries is set to 0 so the second one uniquely defines the distribution of stochastic shocks, as well as its support. Notice that this is not what it is usually done in the classical finance, where log-normal distributions of stochastic shocks are usually assumes (Merton, 1974). However, since the probability of extreme events is by construction higher when modeled with a uniform distribution instead of a log-normal one, the results we obtain from direct contagion when market volatility is large can be considered as an upper bound of losses. In this project we assume that banks are exposed to risk proportionally to their initial capital. Notice that, one of the caveats of using uniform distribution in the negative regime is that we are not considering positive shocks on the value of loans and bonds. This is still reasonable if the market value of loans and bonds is assume to coincide with the face value and thus the price can not increase due to a positive shock. However, it is worth mentioning that the methodology allows also to consider positive shocks and to account for an increase expected value of bonds and loans. Because the stochastic shock is induced by market volatility of external assets, and because the volatility of a stochastic variable following a uniform distribution is proportional to the size of its support[8], we call "market volatility" the proportionality factor between initial equity and the support of the stochastic shock and we label it by σ. The stochastic shock is thus uniformly distributed between 0 and M_i, where

$$M_i = \max\{0, \min\{A_i^e\,,\ \sigma E_{0i}\}\}. \tag{7}$$

It is important to notice that the model could still be solved numerically under any empirical distribution. However, for the sake of simplicity and also because of the lack of data, we made the choice that allowed us to solve the problem analytically. While this is a limitation of the current stage of the model, this choice is particularly useful because it allows us to identically recover the (Eisenberg and Noe, 2001) model (setting $\sigma = 0$ and $R = 1$) and the (Battiston et al., 2012b) model (setting $\sigma = 1$).

Building on (Barucca et al., 2016) we assume that banks' equity is a function of the probability of default of their counterparties

$$E_i(t) = A_i^e - L_i^e + \sum_{j=1}^{N} A_{i,j}^b \mathbb{V}_{ij}(\mathbf{E}(t)) - \sum_{j=1}^{N} L_{i,j} \qquad \forall i, \tag{8}$$

where the valuation of interbank claims $\mathbb{V}$ corresponds to the mark-to-market valuation of financial assets. More precisely

$$\mathbb{V}_{ij}(\mathbf{E}(t)) = 1 - p_j^D(E_j) + R\rho_j(E_j), \tag{9}$$

where p_j^D is the probability of default of bank j, R is the exogenous recovery rate, and ρ_j is bank's j endogenous recovery rate. The endogenous recovery rate accounts for how many assets remain on banks' balance sheets, the exogenous recovery rate accounts for financial frictions such as bankruptcy costs. The literature focusing on assessing the value of R is very scarce. Furfine (2003) show that banks in the US typically recover 40-95% of their losses. Evidence from some defaults of small Danish

[8] The volatility of a stochastic variable following a uniform distribution between zero and x is $\frac{x}{2\sqrt{3}}$.

banks suggest that 30-87% of losses are recovered (Amundsen and Arnt, 2005). Banks' j probability of default is computed as

$$
\begin{aligned}
p_j^D(E_j) = \mathbb{E}\left[\mathbb{1}_{E_j(T)<0}\right] = \int_0^{M_j} dx \frac{1}{M_j} \mathbb{1}_{x>E_j} = \\
= \left(1 - \frac{\max\{0, E_j\}}{M_j}\right) \mathbb{1}_{M_j>E_j},
\end{aligned} \tag{10}
$$

where x is the value of the future stochastic shock induced by market volatility and $\mathbb{1}$ is the indicator function and is equal to 1 if the condition is satisfied and 0 otherwise. Similarly, banks endogenous recovery rate is expressed as

$$
\begin{aligned}
\rho_j(E_j) = \mathbb{E}\left[\left(\frac{E_j(T) + \bar{p}_j}{\bar{p}_j}\right)^+ \mathbb{1}_{E_j(T)<0}\right] = \\
= \int_0^{M_j} dx \frac{1}{M_j} \left(\frac{E_j - x + \bar{p}_j}{\bar{p}_j}\right) \mathbb{1}_{x>E_j} \mathbb{1}_{E_j - x + \bar{p}_j > 0},
\end{aligned} \tag{11}
$$

where $\bar{p}$ is the vector of total interbank liabilities and the "+" symbol indicates that only the positive part is considered in order to avoid negative payments. For a more exhaustive derivation of the valuation function, including the case when $\sigma = 0$, refer to (Roncoroni et al., 2018). Notice that this definition of valuation function is said to be *feasible*, as in (Barucca et al., 2016).

Definition 2. **Feasible valuation function**

Given an integer $q \leq n$, a function $\mathbb{V} : \mathbb{R}^q \to [0, 1]$ is called a feasible valuation function if and only if:

1. it is non-decreasing: $\mathbf{E} \leq \mathbf{E'} \Rightarrow \mathbb{V}(\mathbf{E}) \leq \mathbb{V}(\mathbf{E'}), \forall \mathbf{E}, \mathbf{E'} \in \mathbb{R}^q$,
2. it is continuous from above.

Inserting the valuation vector in equation (8) one obtains the dynamics to compute the fixed point of the algorithm that identifies the ex-ante valuation of interbank claims which is network coherent and considers future stochastic shocks. Each element of the vector of valuation $\mathbb{V}$ is bounded between 0 and 1, where 1 means that the loan is paid with probability 100% and 0 means that the counterparty j will not honor its obligation towards bank i.

To include other financial institutions, such as investment funds, into the stress test dynamics we assume that their exposure towards banks is mark-to-market. Since we observe empirically funds' exposures towards banks via securities but not the opposite side exposures; and the default of funds is more difficult to model, we compute the losses induced by the increased probability of banks after interbank contagion. Losses due to indirect exposures are thus written as

$$\Xi_{it}^{2nd} = \sum_j A_{ij}^b \cdot (1 - \mathbb{V}_{ij}(T)), \tag{12}$$

where losses that exceeds banks equity are capped for the same reason as before.

3.3 Third round: fire-sales contagion among financial institutions

After absorbing losses due to direct and indirect exposures, the balance sheet of financial institutions is substantially modified. On the one hand banks used their capital to absorb the shock, on the other hand funds are exposed to a new profile of risk. In the spirit of Kiyotaki and Moore (2002); Caballero and Simsek (2013); Diamond and Rajan (2011); Adrian and Shin (2008); Allen et al. (2012); Caccioli et al. (2014); Georg (2013); Tasca and Battiston (2016), we assume that banks react by liquidating part of their portfolio to quickly restore their initial level of leverage. Notice that, we assume that banks and funds liquidate their assets in a proportionate way and do not have any preference on which asset class to suddenly sell. This is because we do not assume for any coordination between financial institutions nor heterogeneous risk management strategy.

There is growing interest in the policy community in understanding the role of investment funds in financial stability and in works that model investment bank funds' behaviour in the context of fire sales. To our knowledge, there is little academic work on this question so far.

There is however, anecdotal evidence that motivates us to model funds decision making based on Value at Risk. Indeed, in Mexico, investment funds are required to disclosure their Value at Risk[9]. Moreover, using Value at Risk for risk management purposes is a common practice also among funds operating in international financial markets.[10]

Therefore, we model funds' decision making by assuming that, conditional upon the shock, they aim to restore their initial level of Value at Risk (VaR). When determining the amount that has to be liquidated in order to restore the initial balance sheet constraints, we assume that each asset class is sold proportionally. Notice that as in Greenwood et al. (2015), we do not allow for a coordinated liquidation among financial institutions.

[9]See for instance https://www.cnbv.gob.mx/SECTORES-SUPERVISADOS/SOCIEDADES-DE-INVERSION/Buscador-de-Sociedades-de-Inversión/Paginas/Comparador.aspx

[10]For example, a prospectus from one of Blackrock funds states: "Accordingly the Manager will employ a risk-management process which enables the Manager to monitor and measure at any time the risk of the derivative positions and their contribution to the overall risk profile of a Fund. In these circumstances, the Manager applies a "Value at Risk" approach to calculate a Fund's global exposure and to ensure it complies with the investment restrictions set out in Appendix 3". (from `https://www.blackrock.com/uk/individual/literature/prospectus/blackrock-investment-funds-prospectus.pdf?locale=en_GB&switchLocale=y&siteEntryPassthrough=true`)

3.3.1 Fire-sales contagion among banks

After second round shocks, we assume that banks liquidate a portion of their assets in order to recover their initial leverage value. The new value of banks' leverage is

$$\Lambda_{it}^{2nd} = \frac{A_{it}^{2nd}}{E_{it}^{2nd}} = \frac{A_{it} + \Xi_{it}^{1st} + \Xi_{it}^{2nd}}{E_i(0) + \Xi_{it}^{1st} + \Xi_{it}^{2nd}}. \tag{13}$$

When banks liquidate part of their assets, they decrease their leverage for two reasons: (1) they have less exposure, and (2) they increase their capital. By defining k the portion of total assets that is liquidated, the new level of leverage can be rewritten as

$$\Lambda_{it} = \frac{(1-k_i)\left(A_{it} + \Xi_{it}^{1st} + \Xi_{it}^{2nd}\right)}{E_i(0) + \Xi_{it}^{1st} + \Xi_{it}^{2nd} + k_i\left(A_{it} + \Xi_{it}^{1st} + \Xi_{it}^{2nd}\right)}. \tag{14}$$

Solving equation (14) by k_i provides the portion of total assets that each bank has to liquidate. Further, we assume that a bank in default is totally liquidated, i.e.,

$$k_i = 1, \qquad \text{i is in default.} \tag{15}$$

3.3.2 Fire-sales contagion among funds

Building on (Luu et al., 2018), we assume that funds have a target VaR. First and second round losses have an impact on funds' exposure to risk for two reasons: (1) total exposures are modified, and (2) a loss has already been absorbed. Assuming that market volatility is not influenced by the alignment to a climate policy, we compute the amount of assets that funds have to liquidate in order to go back to their initial VaR level.

Using time series of funds' prices, we estimate the original VaR of fund i $\mathrm{VaR}(0)_i$.

Let us define the relative $\overline{\mathrm{VaR}}$ of fund i with respect to fund's i initial total assets

$$\overline{\mathrm{VaR}}_i = \frac{\mathrm{VaR}(0)_i}{A(0)_i}. \tag{16}$$

The new value of assets after first and second rounds is

$$A(2)_i = A(0)_i + \Xi_i^{1st} + \Xi_i^{2nd}. \tag{17}$$

While the balance sheet of funds is shrank by the effect of first and second rounds shocks, total losses induced by market volatility also shift the VaR level towards the left. The new level of VaR thus is

$$\mathrm{VaR}(2)_i = A(2)_i \cdot \overline{\mathrm{VaR}}_i - \Xi_i^{1st} - \Xi_i^{2nd}, \tag{18}$$

where we assumed that the distribution of shocks due to market volatility has not been modified by the climate policy but only depends on the demand and supply dynamics. Since, by construction, $\mathrm{VaR}(2)_i > \mathrm{VaR}(0)_i$, each fund i reacts by liquidating a portion k_i of its assets. The new value of VaR after liquidation thus reads as

$$\mathrm{VaR}(3)_i = (1 - k_i) \cdot A(2)_i \cdot \overline{\mathrm{VaR}}_i - \Xi_i^{1st} - \Xi_i^{2nd}. \tag{19}$$

Imposing $\mathrm{VaR}(3)_i = \mathrm{VaR}(0)_i$ one solves for k_i.

3.3.3 Asset price impact of fire-sales

The sudden liquidation of portion of asset classes add downward pressure on asset prices. We assume the price impact function to be similar to the one presented in (Cifuentes et al., 2005). More in detail, the price per units of assets after the liquidation p_{cs}^{after} is a function of the relative liquidation K_{cs} and of the price before the liquidation p_{cs}^{before}

$$p_{cs}^{\text{after}} = p_{cs}^{\text{before}} \cdot e^{-\alpha \frac{\sum_i A(1)_{ics} k_i}{\sum_i A(1)_{ics}}} = p_{cs}^{\text{before}} \cdot e^{-\alpha K_{cs}}. \tag{20}$$

where $A(1)_{cs}$ is the value of the sector s in country c after the introduction of the climate policy, and $-\alpha$ is the market liquidity.

While liquidating at a higher price, what remains in banks' and funds' balance sheets loses value because of an increase in supply. By defining the relative price drop due to liquidation as

$$\bar{p}_{cs} = \frac{p_{cs}^{\text{after}}}{p_{cs}^{\text{before}}} \tag{21}$$

third round shock is thus written as

$$\Xi_i^{3rd} = \sum_c \sum_s (1 - k_i) \cdot A(1)_{ics} \cdot (1 - \bar{p}_{cs}). \tag{22}$$

Notice that, in the spirit of Greenwood et al. (2015), banks and funds do not account for other institutions reaction. An equilibrium would be reached by iterating the dynamics several times. In order to avoid losses due to asset fire-sales to increase uncontrollably we only compute one liquidation iteration. As discussed in Greenwood et al. (2015), under certain assumptions the dynamics would converge to a non-zero fixed point. However, given that there is a considerable amount of asset overlapping within the Mexican banking system, we calibrated the Asset Fire-Sales dynamics using a parameter which made less severe the price impact function also because most of the overlapping is caused by the holding of government debt, which are the most liquid securities in the market and which have full government support. The liquidity parameter determines the market impact of asset liquidation on asset price. Following Cifuentes et al. (2005) we use an exponential function. Cifuentes et al. (2005) set alpha to ln(2), which, in case of a total liquidation of the asset classes, corresponds to a price drop of 50%. We set alpha to ln(4/3) to reflect a lower market impact of sales and thus a higher level of liquidity in the market. This reflects the situation of a liquid market since the entire liquidation of an asset class would decrease its price to only 75% of its initial value. This assumption is motivated by the fact that most of the common asset holdings consist of Mexican government bonds and that these securities are the most liquid securities in the Mexican bond market.

The liquidity is set up in this way precisely because of the reasons already explained in the text: the Mexican government securities are by far the most liquid securities in the bond market; therefore, the assumption is a reasonable one. Moreover, despite having such a price impact constant, there is still an important effect on the second round losses.

Now, once we have all the elements of the stress testing model we used as input the data collected to perform the exercise for the Mexican financial system including banks' direct exposures to carbon intensive sectors, interbank exposures, funds' exposures to energy intensive sectors and bank to funds exposures.

3.4 Fourth round: losses transferred to external creditors

While banks' external creditors are first in seniority of payments, it is possible that losses are too large to be absorbed by their capital and their interbank liabilities. To compute the amount of losses that is transferred to external creditors, which also include depositors, we reconstruct the balance sheet identity

$$\Xi_i^{4th} = \min\left\{0\,,\ \Xi_i^{1st} + \Xi_i^{2nd} + \Xi_i^{3rd} + E(0)_i + \sum_j L_{ij}^b\right\}. \tag{23}$$

3.5 Properties of the contagion dynamics

In order to further contribute to the discussion on climate transition risk, we formalise the dependence of financial losses on climate policy targets and market conditions.

In our model, it is possible to show analytically that total loss of bank i due to financial contagion Ψ_i depends in a predictable way on the main parameters. In particular, as one may expect, Ψ_i is non-decreasing with the magnitude of climate policy shock k (with $k < 0$), and with asset price volatility σ. Conversely, Ψ_i is non-increasing with the recovery rate R and with the market liquidity $-\alpha$. These properties are stated in Lemma 1.

Lemma 1. *Dependence of financial losses on contagion parameters. Under the assumption of a feasible valuation function introduced in Section 2:*

- *Losses are non-decreasing with the magnitude of the initial shock k, and with the asset price volatility σ.*
- *Losses are non-increasing with the recovery rate R, and with the market liquidity $-\alpha$.*

See Annex A for the complete proof of this Lemma. In turn, Lemma 1 implies the following set of properties, formalised in Lemma 2. Both individual and systemic financial losses from a disorderly transition are non-decreasing with the time of the transition and the stringency of climate targets. Conversely, financial losses are non-increasing with the strength of market conditions.

Lemma 2. *Dependence of financial losses on transition parameters. Under the assumptions of market conditions formalised in Definition 1 and of a feasible valuation function formalised in Definition 2:*

- *Losses are non-increasing with the strength of market conditions.*
- *Losses are non-decreasing with the time of the transition, and with the stringency of climate targets.*

See Annex A for the complete proof of this Lemma. Using the previous Lemma 2, it is possible to show how financial losses depend on the interplay between market conditions and climate policy shock scenarios. The result is formalised in Proposition 1.

Proposition 1. ***Financial losses and interplay between market conditions and climate policy shock scenarios.*** *If the valuation function $\mathbb{V}$ is feasible, under the same financial network structure, recovery rate R, market volatility σ, and market liquidity α, losses suffered by each bank i after financial contagion can not be smaller if the initial shock k is smaller.*

- *Stricter climate targets could be reached at the same financial loss with an earlier (still disorderly) transition.*
- *Stricter climate targets could be reached at the same financial loss with if market conditions are strengthened.*

See Annex A for the complete proof of this proposition. Indeed, Proposition 1 contribute to the discussion on the effects on financial stability of climate transition risk. In particular, the proposition show that an early climate policy transition supported by strong market conditions triggers less financial losses than a late transition supported in scenario of weak market conditions. Similarly, they imply that total losses can be mitigated strengthening market conditions, and/or anticipating the time of the climate policy transition.

Additionally, we use Lemma 2 and equation (6) to show how total losses depend on financial leverage, defined as the ratio between banks' assets and capital.

Proposition 2. ***Financial losses and brown-leverage.*** *Given a climate policy scenario p, under the assumption of limited liabilities, first round financial losses* Ψ_i^{1st} *are proportional to the shock k and the leverage towards brown sectors, i.e.*

$$h_i^{1st} = \max\left\{-1\,,\ \sum_c \sum_{s^*} \Lambda_{ics^*} k_{cs^*}\right\}, \tag{24}$$

where s^* *labels sectors that are brown and are negatively shocked in our exercise (i.e., "Fossil-Fuel" and "Utilities"),* $\sum_c \sum_{s^*} \Lambda_{ics^*}$ *is the* ***brown-leverage*** *of bank i, and* h_i^{1st} *is the relative equity loss of bank i after the first round.*

Notice that the relative equity loss h_i^{1st} can also be expressed as

$$h_i^{1st} = \frac{-\Xi_i^{1st}}{E_i(0)}. \tag{25}$$

Proposition 2 shows that first round losses are larger for banks that are not yet aligned with climate transition targets.

4 Data

The data used for this work comes from many different sources and repositories at Banco de Mexico. After the 1994 financial crisis in Mexico, financial authorities reached a wide consensus on the data to be collected from the financial system and on the mechanisms which would allow them to share such data. For this reason in Mexico there is a comprehensive coverage of the banks' exposures, as well as for some other financial intermediaries.

The exposures considered in this work come from the regulatory reports that the banks' supervisor and the central bank collect from financial intermediaries. This data comprises the following information:

- Banks loans
- Interbank loans and deposits
- Securities holdings of banks, funds and brokerage houses
- Derivatives exposures among banks and brokerage houses
- Interbank foreign exchange transactions

The data sources with the least frequency of availability is monthly data, which is why the data used to conduct the analysis corresponds to the end of june, 2018 (for all the data sources the data is on a daily basis, with the exception being the loans data, which is monthly). In the following subsections we will provide more detail on each type of exposure and how it was aggregated in order to be used along with the macro model to estimate the impact of climate change in the financial system.

4.1 Banks' exposures data

The data used to compute the exposures of banks and brokerage houses to economic sectors which might be directly affected by the climate change comes from two important sources: i) a regulatory report known as the RC04 which collects all the outstanding loans information (at the loan level) from every bank in Mexico, including development banks at the end of the month; and ii) the holdings of securities of banks (including development banks), brokerage houses and investment funds with a daily frequency.

Individual loans and bonds data include the classification of the borrower/issuer according to the the NAICS[11] sector code.We have mapped the NAICS codes into NACE codes [12]. Then, the mapping from NACE codes to CPRS sectors has been carried out following Battiston et al. (2017)[13]. After the mapping an aggregation of the exposures has been computed for each bank and fund and for each CPRS sector.

4.2 Funds' exposures data

In addition to the information on securities holdings by banks and brokerage houses we also obtained the securities positions for investment funds in Mexico. Such data comes from a different repository also held at Banco de México which contains daily information on the holdings of investment funds at the issuance level. The procedure to obtain the fund's exposures to different economic sectors was

[11] `https://www.naics.com/search-naics-codes-by-industry/`

[12] `https://ec.europa.eu/eurostat/web/products-manuals-and-guidelines/-/KS-RA-07-015`

[13] A table with the mapping is available in the supplementary material of that reference

very similar to the banks' case. Having the securities identified by the ISIN code, the NACE code was obtained and from there the mapping between NACE and CPRS was used.

The funds' exposures to banks and brokerage houses was obtained from the same data source that is used to perform the contagion studies at the Mexican central bank.

The VaR used in the fire sales dynamics comes from the empirical quarterly return distribution for each fund (the 90%, 95%, 99% and 99.9% VaR were obtained). The history of available prices is different depending on the individual fund and ranges from December 2008 to December 2018. On average 600 data points were used to calculate each VaR; the funds' prices were obtained using Morningstar (Morningstar, nd). The coverage of the prices was not complete, since only for half of the funds present in our data (around 300) price information was found. In order to fill the gaps we have computed the VaR, at each confidence level, for each fund for which we have data. Then, we have used the average result for the funds for which data is not available. This allows us to still keep some heterogeneity across funds and fill the data gaps.

4.3 Interbank exposures data

The interbank exposures are obtained from a database which is mainly used to conduct the contagion studies done for financial stability purposes at Banco de México since 2006. This database consists of the outstanding exposures at the pair-level on a daily frequency for a large number of financial intermediaries, including commercial banks, development banks, brokerage houses and investment funds among others. The exposures are computed considering information from unsecured loans, cross holdings of securities, derivatives and foreign exchange related exposures. This data set has been explained and used in many previous works such as Martinez-Jaramillo et al. (2010), Solorzano-Margain et al. (2013), Martinez-Jaramillo et al. (2014), Poledna et al. (2015), Molina-Borboa et al. (2015), Batiz-Zuk et al. (2016) and Anand et al. (2017) among others.

4.4 Banks-Funds' exposures data

This data also comes from the contagion data set resident at Banco de Mexico mentioned in the previous section, in such database exposures are computed among most of the institutions in the Mexican financial system. In particular investment funds hold banks' securities and in this way are exposed to them.

Summarizing: the data used to perform the numerical exercises have different periodicity; therefore, the time period depends on the information set in question. For example, outstanding interfinancial exposures, credit exposures and securities holdings are computed for only one period of time. For the case of pension funds exposures, as there was a need to compute the VaR in order to develop the reaction rule a much longer period was used. However, once the funds reaction rule is calibrated for each fund, then only a single snapshot of the exposures, booth interfinancial and to the carbon intensive sectors, is used. Specifically, the data used to carry out the analysis corresponds to the end of june, 2018.

5 Results

5.1 Descriptive statistics of climate relevant exposures

We first carry out a descriptive statistics of the exposures of financial actors towards the climate policy relevant sectors, CPRS, as defined in the Section Methods. Figure 3 shows the aggregated exposures of banks and investment funds to CPRS in billions of Mexican pesos. The subsectors of the financial sector are grouped together and labelled as "Finance" and include exposures of banks on interbank loans. The remaining sectors are grouped and labelled as "Other" and include a large portion of investments in Mexican sovereign bonds. In the following sections, we will examine how shocks on the CPRS impact directly or indirectly on banks and funds. We will see that while exposures to CPRS determine the first round of losses, interbank loans determine the second round of the contagion process and exposures to sovereign bonds play a role in the third round. Figure 4 shows the relative exposures to CPRS of banks and investment funds as percentage of their respective total assets.

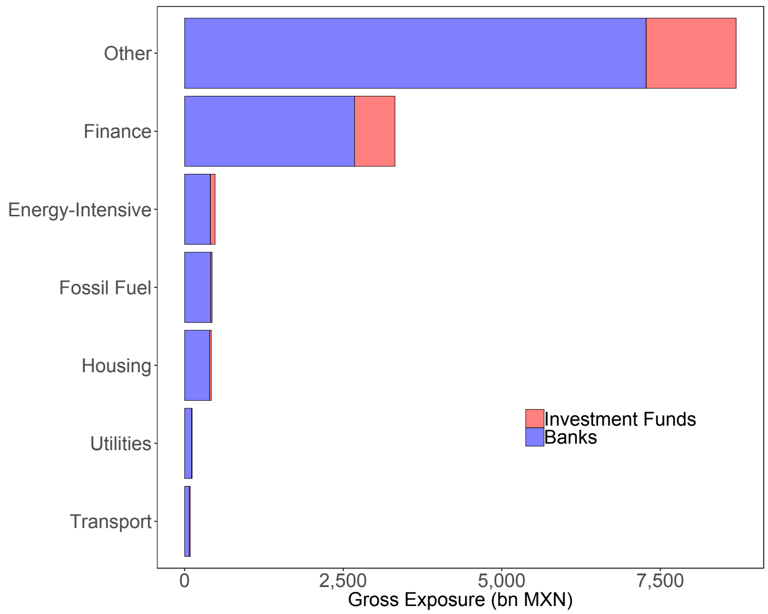
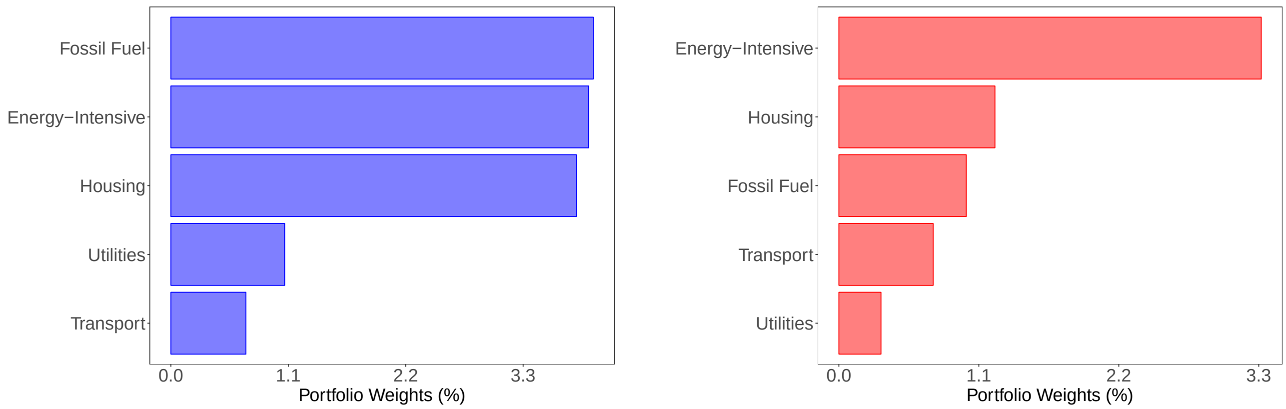


Figure 3: **Exposures to CPRS sectors of banks and investment funds in billions of Mexican pesos.** The x-axis shows banks' and funds' gross exposures, in billions of Mexican pesos, towards the Mexican sectors. The y-axis lists the sectors to which banks and funds are exposed, sorted per size. To compare the size of CPRS sectors to the actual size of banks' and funds' balance sheets, we included also the sector "Finance" an the sector "Other", where we put everything which is not included in the CPRS taxonomy. The overlap on those sectors will play a major role on the fire-sales dynamics, since losses due to fire-sales are due to common asset exposures. Blue bars show the banks' exposures, red bars show funds' exposures. To grasp the magnitude of the amounts, using the MXN-USD exchange from the reference date (19.625 MXN per USD), $7,500 bn MXN correspond to approximately $382.2 bn USD.

The above figures show that banks' and funds' exposures to CPRS are very small in comparison to the Other and Finance sectors. They are also smaller in comparison to similar analysis carried out for EU banks (Battiston et al., 2017). This finding may be surprising considering the fact that the contribution to GVA of the sectors included in the CPRS sectors fossil and utility is at least as large as in the EU. It can be explained by some specific features of the Mexican economy. The largest oil and the electricity generation companies in Mexico (i.e. PEMEX[14] and CFE[15]) are state-owned. We do observe some loans of banks to these companies as well as investments in corporate bonds. However, these companies receive most funding from the state and thus these exposures do not appear in the dataset. In turn, banks are heavily exposed to sovereign bonds. A possible way to estimate the indirect exposures of banks to PEMEX and CFE would be to compute how much of the funds from

[14] Petróleos Mexicanos

[15] Federal Electricity Commission



(a) Banks

(b) Investment funds

Figure 4: **Break-down of the exposures to CPRS sectors for banks and investment funds relative to total assets.** The x-axis shows the exposure, relative to total assets, towards firms resident in Mexico and operating in the CPRS sectors. sectors. The y-axis lists the CPRS sectors to which banks and funds are exposed, sorted by relative exposure. **Left:** banks' portfolio composition. **Right:** investment funds' portfolio composition.

the issuance of Mexican sovereign bonds was deployed to fund such companies. Unfortunately, this estimation is not possible at this stage. Moreover, loans that could be related to the transport sector (e.g. to carry out private transportation business) might be classified as loans to households due to the large role of the informal economy in the overall Mexican economy.

5.2 Climate stress test: mild scenario

From section 2 we recall, that in this paper we refer to a shock scenario as the combination of: i) a *market conditions scenario* i.e., a range of values for the parameters recovery rate R, market volatility σ, market elasticity α, and the funds' VaR; and ii) a *climate policy shock scenario*, i.e., a set of shock arising from the late and disorderly alignment from BAU trajectory to a set of climate target trajectories.

We first focus on a mild shock scenario determined by the switch, estimated under the GCAM model, between two policy scenarios, namely from the business-as-usual climate policy (no policy) to the LIMITS-Ref-Pol-500 scenario (see Appendix for a description of the climate policies scenarios). The parameters are set as follows: interbank recovery rate coefficient $R = 0.5$, market volatility $\sigma = 1.0$, market liquidity $\alpha = \ln 4/3$, and funds' $VaR = 1\%$. Figure 5 shows the total losses in the financial system (banking sector and investment funds altogether) in Mexican pesos triggered by a disorderly realignment from the policy scenario BAU to LIMITS-RefPol-500, estimated with the model GCAM. The x axis represents time in period of 5 years, along the climate policy scenarios. The y axis represent the magnitude of the losses in billion of Mexican pesos that would occur in all the stages of the financial contagion modelled (around \$600 bn pesos, or \$30.6 USD), as described in the Section Methods.

It is important to understand the correct meaning of the time dimension in this figure. The time scale of the climate stress-test is meant here to be in relatively short term, about 6 months. The time evolution displayed here, refers to the evolution of the magnitude of the expected losses, conditional to the shock at the same given period. The magnitude of the shock evolve in time because the climate policy trajectories evolve over the years and some tend to diverge. For instance, switching disorderly from BAU to LIMITS-Ref-Pol-500 implies a bigger shock if this happens in 2050 than if this happens in 2025. Figure 6 shows the losses for banks in percentage of regulatory capital (left), and for funds in percentage of total assets (right) under the same scenario and parameters. The first round losses are relatively small. For instance in 2030 they represent about 2% of capital for banks and about 0.2% of total assets for funds.

However, direct financial contagion due to bilateral contracts among banks amplifies the losses suffered by banks and funds by a factor that is approximately equal to 2. This result can be observed comparing the red and orange surfaces in Figure 6. Notice that the second-round stage, i.e. the interbank credit contagion, is modelled using the NEVA framework. As described in the Section 2, this means that, by varying the parameters of recovery rate coefficient R and the asset price volatility σ, we move smoothly between the two paradigmatic models of financial contagion, from EN to DR. In particular, for intermediate values of these parameters, i.e. $R > 0$ and $\sigma > 0$, the recovery rate is endogenous as in EN, i.e. the fix point of the clearing payment process, but it is combined with bankruptcy costs (the lower R, the larger the costs) and with risk on the external assets of banks.[16] The final value of interbank assets with face value A^b_{ij}, is then equal to $A^b_{ij}\mathbb{V}_{ij}(T)$, where $\mathbb{V}_{ij}(T)$ is the network coherent valuation function at the equilibrium of the process that considers future shocks arising from market volatility. Although we consider a very liquid market (i.e. $\alpha = \ln 4/3$), for banks the third round, due to contagion via common exposures, amplifies approximately by a further factor 2 the compound losses of first and second rounds. For funds, the amplification factor effect is larger and approximately equal to 7.

5.3 Climate stress test: adverse scenarios

In this section we then consider some adverse yet still plausible climate policy shock scenarios. We now use the WITCH model, to estimate the impact of switching from the business-as-usual climate

[16]Note the distinction between recovery rate, i.e. the fraction of the face value of interbank claims recovered after interbank assets clearing, and the recovery rate coefficient R, i.e. the fraction that can be recovered net of bankruptcy cost.

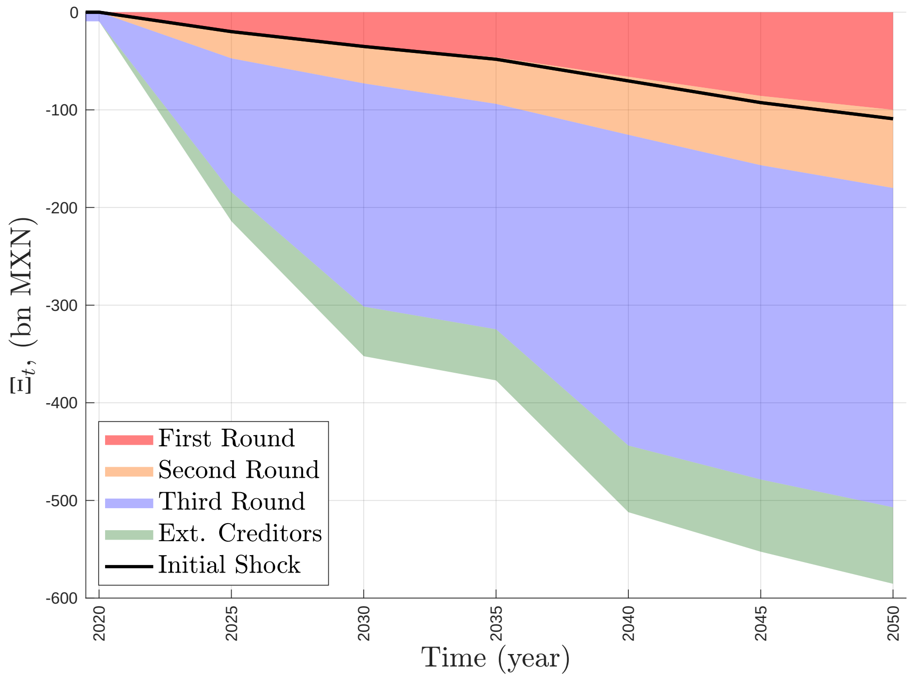
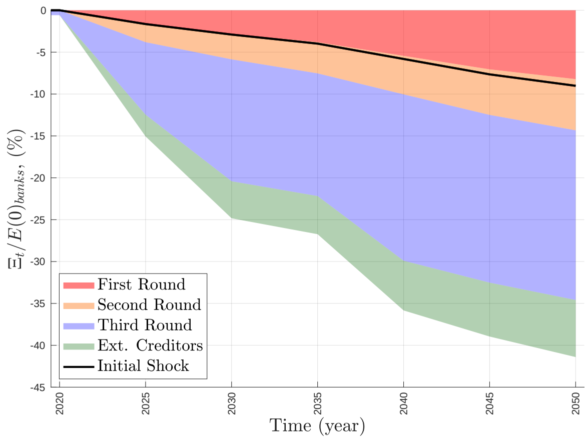


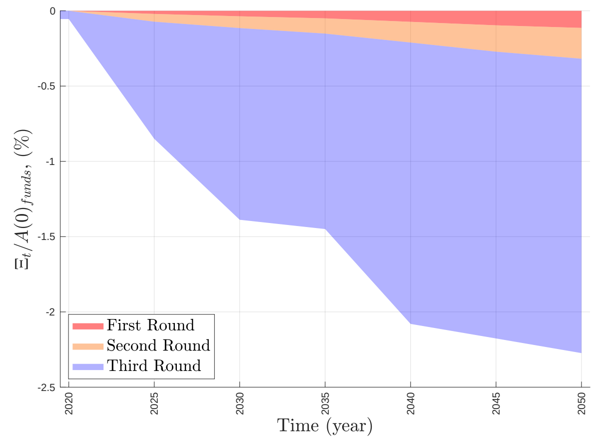
Figure 5: **Profile of losses suffered by the Mexican financial system conditional upon the policy scenario LIMITS-RefPol-500(GCAM).** The x axis represents time in years, along climate policy scenarios. The y axis represent the magnitude of the losses in billions of Mexican pesos. Effect of a shock on the Mexican financial system triggered by a disorderly realignment from the policy scenario BAU to LIMITS-RefPol-500, estimated with the model GCAM. We set interbank recovery rate coefficient $R = 0.5$, and market volatility $\sigma = 1.0$, market liquidity $\alpha = \ln 4/3$, and funds $VaR = 1\%$. The solid black line shows the loss on the asset classes. The red surface shows losses suffered by the Mexican financial system due to direct exposure, the orange surface shows the losses suffered by the Mexican financial system due to direct contagion, the blue surface shows the losses suffered by the Mexican financial system due to indirect contagion, and the green surface shows the losses suffered by creditors of banks which are external to the Mexican financial system.

policy (no policy) to four different possible climate policy scenarios (LIMITS-RefPol-500, LIMITS-StrPol-500, LIMITS-RefPol-450, LIMITS-RefPol-500, see Appendix). The labels RefPol versus StrPol refer instead to the timing of the CO2 emission reduction trajectory under the corresponding climate policy scenario. The smaller is the target level of the CO2 concentration in the atmosphere (450 or 500 parts per million), the more stringent is the climate policy and therefore the larger is the shock in market share affecting the economic sectors. The four climate policy shocks refer here to the switch, estimated under the WITCH model, from the business-as-usual climate policy (no policy) to one of the four climate policy scenario, respectively.

As one may expect, if the parameters of the financial contagion process are the same, the larger



(a) Banks



(b) Funds

Figure 6: **Break down of shock on banks and funds triggered by the policy scenario LIMITS-RefPol-500(GCAM).** The red surface shows the shock due to direct exposure, the orange surface shows the shock due to direct contagion, the blue surface shows the shock due to indirect contagion, and the green surface shows the losses suffered by creditors of banks which are external to the Mexican financial system. The solid black lines shows the monetary loss of the externals that are shocked and indicates the impact on the economic sectors of the introduction of the climate policy. **Left:** the relative equity loss suffered by Mexican banks. **Right:** the shock suffered by Mexican funds. We have set interbank recovery rate $R = 0.5$, market volatility $\sigma = 1.0$, market liquidity $\alpha = \ln 4/3$, and funds $VaR = 1\%$.

the climate policy shock the larger the losses incurred by banks and funds at each stage of contagion. Indeed, the losses computed by the contagion model in each stage are a non decreasing function of the magnitude of the initial shock. Figure 7 illustrates this fact by comparing the total losses in the financial system in billions of Mexican pesos. On the left, we consider the shock of switching disorderly from BAU to StrPol500. On the right, we consider the shock of switching disorderly from BAU to StrPol450, which is stricter than StrPol500. The meaning of the time periods is the same as in the previous figures. The parameters are set as follows: interbank recovery rate coefficient close to $R = 0.5$, market volatility close $\sigma = 0.8$, market liquidity $\alpha = \ln 4/3$, and funds' $VaR = 1\%$.[17]

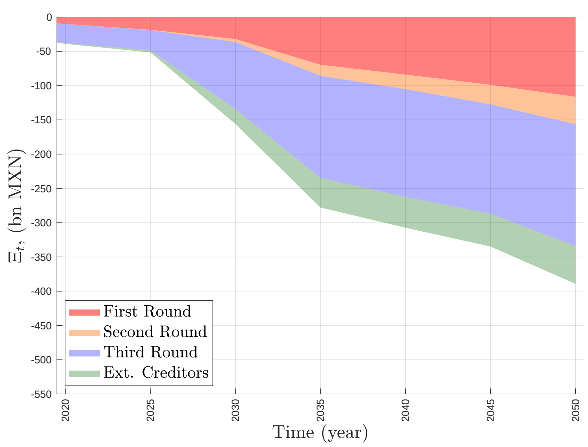
As we can see, in each time period, the losses in the second scenario, above \$500 bn MXN (or \$25.5 bn USD) at the maximum level, are larger or equal than in the first, less than \$400 bn MXN (\$20.4 bn USD). This is due to the fact that losses due to direct exposure, shown by the red surface, are larger in the stricter policy scenario than in the more conservative one. While initial losses are then amplified by the same market conditions, total losses in the policy scenario StrPol-450 are always

[17] Notice that strictly speaking, because the parameters R and σ are drawn from a Beta distribution, we could select two scenarios with values of R and σ that are very close but not identical. In detail, R is drawn from a beta distribution with parameters $\beta(4, 2)$, and σ is drawn from a beta distribution with parameters $\beta(5, 2)$

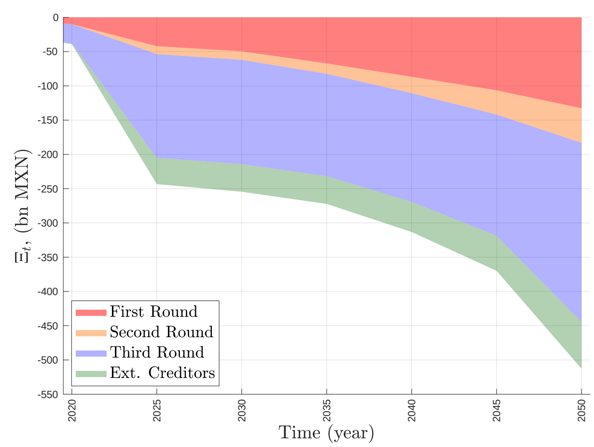
larger than total losses in the policy scenario StrPol-500.

Milder or more adverse climate policy scenarios are not the only determinant of the systemic losses in our model. The interplay between climate policy shock scenarios and financial market conditions is crucial. A milder climate policy shock could lead to larger losses if the market conditions are worse enough. This is illustrated in Figure 8.

We consider two cases. On the left, the climate policy shock scenario StrPol500 is milder but the market conditions are harsher. Indeed, a lower recovery rate coefficient implies larger losses in the interbank network, conditional upon default of counterparties. Larger asset price volatility implies lower expected value of bonds. We observe, that losses are systematically larger in the first case than in the second (above \$350 bn MXN, or \$18.8 bn USD, against less than \$250 bn MXN, or \$12.7 bn USD, at the maximum level, respectively). Additionally, notice that losses triggered by the climate policy StrPol500 in the year 2030 are about the same as losses triggered by the climate policy StrPol450 around year 2023. This implies that, under the same market conditions, an *early*, but still disorderly, alignment to *more demanding* climate targets could have the same impact on the financial system as a *late* and disorderly alignment to *less demanding* climate targets.

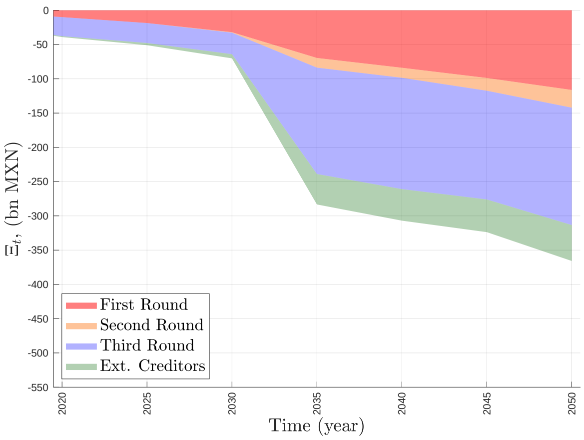


(a) StrPol-500, $R = 0.49334$, $\sigma = 0.90776$

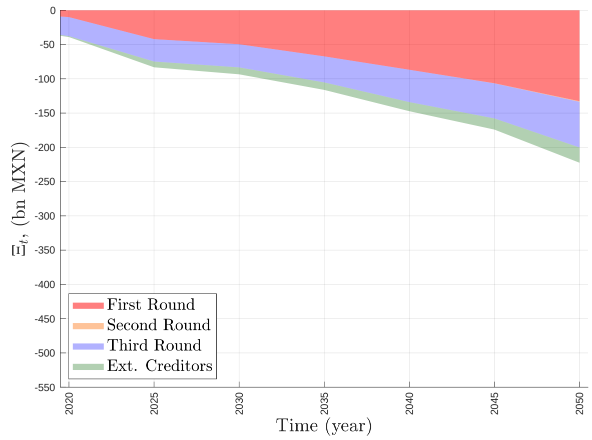


(b) StrPol-450, $R = 0.50470$, $\sigma = 0.90235$

Figure 7: **Comparison of shock suffered by the Mexican financial system in the two different policy scenarios estimated using the WITCH model.** Among all trajectories, we have selected two that have interbank recovery rate R close to $R = 0.5$ and market volatility σ close to 0.9. Further, we have set market liquidity $\alpha = \ln 4/3$, and funds' $VaR = 1\%$. The red surface shows losses suffered by the Mexican financial system due to direct exposure, the orange surface shows the losses suffered by the Mexican financial system due to direct contagion, the blue surface shows the losses suffered by the Mexican financial system due to indirect contagion, and the green surface shows the losses suffered by creditors of banks which are external to the Mexican financial system.



(a) StrPol-500, $R = 0.39607$, $\sigma = 0.80354$



(b) StrPol-450, $R = 0.78736$, $\sigma = 0.38525$

Figure 8: **Comparison of shocks suffered by the Mexican financial system in two different amplification scenarios.** Among all trajectories, we have selected two. **Left:** a mild policy scenario with strict recovery rate R close to 0.4 and market volatility σ close to 0.8. **Right:** a strict policy scenario with conservative recovery rate R close to 0.8 and market volatility σ close to 0.4. In both scenarios, we have set market liquidity $\alpha = \ln 4/3$, and funds' $VaR = 1\%$. The red surface shows losses suffered by the Mexican financial system due to direct exposure, the orange surface shows the losses suffered by the Mexican financial system due to direct contagion, the blue surface shows the losses suffered by the Mexican financial system due to indirect contagion, and the green surface shows the losses suffered by creditors of banks which are external to the Mexican financial system.

5.4 Sensitivity analysis

The interplay between climate policy shock scenarios and market conditions leads to the fact that the magnitude of systemic losses in the financial system is a multi-dimensional surface that depends in a non monotonic way on the parameters.

In each climate policy shock scenario, the losses can vary substantially across the market conditions (i.e. for varying levels of recovery rate R and asset price volatility σ. A first method to provide actionable insights for financial stability, is to characterize the interplay by means of a sensitivity analysis. We focus on the WITCH model and we compare losses at each stage of the contagion process across the parameter space, by varying the recovery rate, the market volatility and the climate policy shock scenarios. The results are reported in Table 4, which can be read as follows. For each year and scenario, we report the values of the shocks on the fossil fuel and utility sectors (corresponding as before to a disorderly switch from a BAU scenario to the chosen climate policy scenario). For instance, in line 15 of Table 4, the shock on the fossil fuel sector and utility sector corresponding to a disorderly switch from BAU to the climate policy scenario StrPol450 are about -15% and -59%, respectively. The first round loss is 0.31% of total asset. Along the columns, from the second round on, we report the Climate Value at Risk for each round of the climate stress test, computed across the realisation of the parameters. Indeed, to analyse the impact of uncertainty on recovery rate and market volatility on the profile of losses suffered by the Mexican financial system relative to initial total assets, for each of the four policy scenarios, we have generate a set of 1000 trajectories. Each trajectory is characterized by a value of the recovery rate R drawn from a Beta distribution with parameters $\beta(4, 2)$ and a market volatility σ also drawn from a beta distribution with parameters $\beta(5, 2)$. For each time period, we then compute the value at risk, in the following referred to as VaR, with a given confidence level p across the set market conditions. The VaR is defined as the value of the loss such that losses larger than VaR occur with probability smaller than p.

For instance, again on line 15 of the Table 4, the figures imply that, given the policy scenario StrPol-450 estimated with the model WITCH, the Mexican financial system has 1% probability to lose at least 1.34% of its total assets after a third round, under the assumptions that interbank recovery rate and market volatility are drawn from Beta distributions with the parameters discussed above.

5.4.1 Climate scenario envelope analysis

A second, more intuitive, method to provide actionable insights for financial stability from the multidimensional surface of systemic losses is what we call here a *climate scenario envelope analysis*. Indeed the necessity to use the climate envelope analysis to study the impact of a climate policy shock in presence of uncertainty on market conditions was not stressed enough. We now discuss more in detail the value added from studying climate transition risk using the climate envelope analysis. Indeed, financial losses induced by a climate policy shock depend on a wide range of parameters. In order to visualize the evolution of climate transition risk in time and accounting for uncertainty on market conditions (recovery rate, market volatility, and market liquidity) we introduce here a second, more intuitive, method. This method, that we call climate scenario envelope analysis, allows to provide actionable insights for financial stability from the multidimensional surface of systemic losses. Furthermore, since the ex-ante estimation of market conditions is difficult, the envelope analysis helps to quantify the potential impact of a climate policy shock both from the point of view of the regulator and from the point of view of financial institutions.

We then define an *envelope of trajectories* as follows. First we consider the subset of trajectories obtained when the parameters related to both climate policy shocks and market conditions (recovery rates, market volatility, market elasticity) are confined with some specified ranges. Second, the envelope of trajectories is the surface bounded by the minimum and maximum shocks at each time period.

In Figure 9a we show two climate envelopes one above the other. The upper climate envelope, highlighted in blue color code, illustrates the profile of losses in a mild scenario where the climate policy scenario is less demanding (RefPol-500). The second climate envelope, highlighted in red color code, illustrates the profile of losses in a scenario where the climate policy scenario is more demanding (RefPol-450). Additionally, inside each envelope, we show each individual trajectory of losses. The figure shows that, while one policy scenario is more stringent than the other, the interplay with market conditions creates a large surface where the two envelopes overlap. All climate policy shocks have been estimated using the WITCH model and we set market liquidity $\alpha = \ln 4/3$ and funds $VaR = 1\%$. Since recovery rate R and market volatility σ are drawn from Beta distributions the upper and lower bound match with the losses estimated with well established models of financial contagion. The upper bound corresponds to the (Eisenberg and Noe, 2001) estimation (i.e., when $R = 1$ and $\sigma = 0$). The lower bound corresponds to the (Battiston et al., 2012b) estimation (i.e., when $\sigma = 1$) with recovery rate $R = 0$.

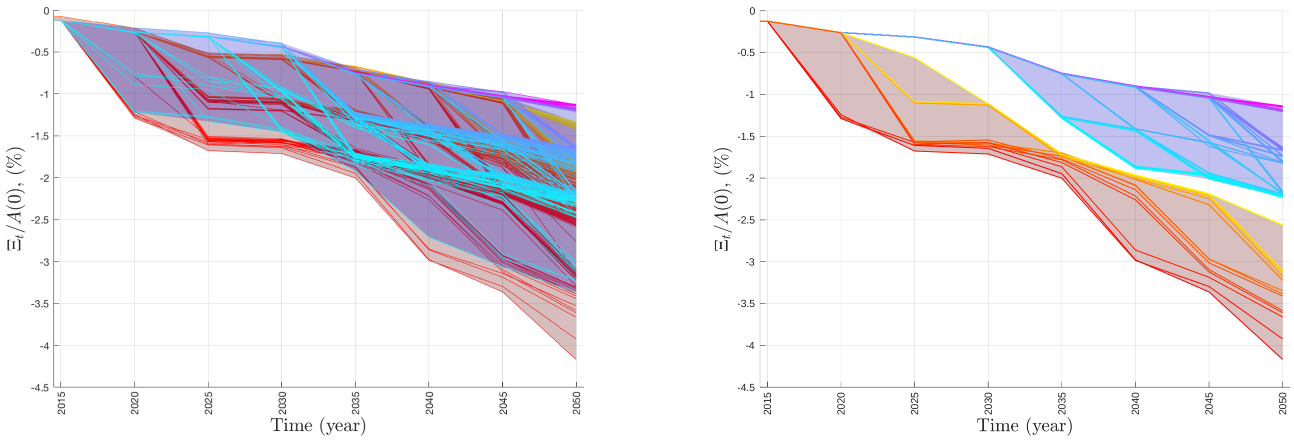
On Figure 9b we only show the subset of trajectories that are within specific ranges of market conditions. Trajectories in the blue envelope are such that recovery rate R is between 0.4 and 0.8, and market volatility σ is between 0.6 and 0.8. Indeed, a high recovery rate and a low market volatility lead to lower level of amplification losses in the contagion process Roncoroni et al. (2018). Trajectories in the red envelope are such that the recovery rate R is between 0.8 and 1.0, and market volatility σ is between 0.0 and 0.4. More adverse market conditions are such that amplification of losses is larger. Because total losses are non decreasing when recovery rate R decreases, market volatility σ increases, or the climate policy shock becomes more negative we managed to define two envelopes that are disjoint. This can always be reached by selecting ranges for market conditions that are non overlapping. Because in the blue envelope market volatility is low, loss amplification starts late in time and has a small effect due to large recovery rate. In fact, the shock only reached 2% of total assets. Because in the red envelope market volatility is large, loss amplification starts early in time and has a large effect due to low recovery rate. The initial shock is amplified up to more than 4% of total assets.

The climate envelope scenario analysis is thus a simple graphic method that can be used to compare bundles of trajectories across a wide range of climate policy scenarios and market conditions scenarios.

6 Conclusion and policy implications

In this paper we extend the framework of the climate stress test of the financial system to analyze the effects on financial stability of the interplay of climate policy shocks and market conditions.

We develop a climate stress test framework to estimate the direct and indirect impact of a late and disorderly alignment to climate targets. We consider a financial system composed of banks and investment funds. The methodology combines the estimation of losses arising both from interbank distress contagion as well as from common asset exposures. The valuation of interbank claims is



(a) RefPol-500 and RefPol-450 envelopes.

(b) RefPol-500 and RefPol-450 envelopes, comparison of market conditions.

Figure 9: **Climate Scenario Envelope Analysis of two climate policy scenarios.** The first envelope is highlighted in **blue** and is characterized by the LIMITS trajectory of the policy scenario LIMITS-RefPol-500. The second envelope is highlighted in color code **red** and is characterized by the LIMITS trajectory of the policy scenario LIMITS-RefPol-450. The figure on the **left** shows the entire set of trajectories while the figure on the **right** focuses on two specific market condition scenarios. In particular, each trajectory in the blue envelope corresponds to a market volatility σ between 0.6 and 0.8, and an interbank recovery rate R between 0.4 and 0.8. Each trajectory in the red envelope corresponds to a market volatility σ between 0.8 and 1.0, and an interbank recovery rate R between 0.0 and 0.4. The color of each trajectory has been chosen to highlight the ranking of losses at year 2050. All climate policy shocks have been estimated using the WITCH model and we set market liquidity $\alpha = \ln 4/3$ and funds $VaR = 1\%$.

carried out before maturity and accounts for the endogenous (i.e., network coherent) recovery rate of banks Eisenberg and Noe (2001); Battiston et al. (2012b); Barucca et al. (2016). Contagion via common exposures assumes a reaction of financial institutions in order to get to the initial balance sheet constraints Kiyotaki and Moore (2002); Caballero and Simsek (2013); Greenwood et al. (2015).

We then apply our methodology to a supervisory dataset including the exposures of the Mexican banks and investment funds to climate policy relevant sectors. We observe small direct exposure to climate policy relevant sectors (in particular to fossil utility and transportation), however this may be due in part to the specific characteristics of the Mexican economy (e.g., the level of informality of the economy, see Section 5.1).

For our climate stress-test we consider climate scenarios that are a combination of climate policy shocks scenarios and market conditions scenarios. Despite the small direct exposure, we identify climate policy scenarios and market conditions where losses due to financial contagion are large.

In a mild scenario (i.e., transition towards a less demanding climate target, and market conditions characterized by a lower level of risk), we find losses ranging between 1% and 2% of total assets of the Mexican financial system. In a more adverse scenario (i.e. where the climate policy scenario is more stringent and triggers a negative shock of larger magnitude, and market conditions are such that amplification is larger) we find that systemic losses range between 2.5% and 4% of initial total assets. Our findings show that the total losses for the financial system result from the interplay between climate policy shocks and market conditions. Finally, we develop a graphic method to compare the levels of financial stability under different climate policy scenarios in a range of market conditions.

Notice that first contribution of this paper is methodological. The model can be applied to any jurisdiction or country as long as a data set similar to the one described here is available. The application of the model to case of Mexico has the value of illustrating the kind of insights that can be drawn from the analysis. We do not claim that the specific figures found for Mexico would apply to other countries. However, all the analytical results in Section 3.5 stress-test hold irrespectively of the country. In particular, while the magnitude of the effects investigated here may depend on the country, the direction of the effect holds more in general.

Our results have three main policy implications which are supported both by analytical and empirical results. As we have seen, in the mild shock scenario the systemic losses are relatively contained but losses increase when the disordered alignment to climate targets occurs later in time. Thus the first policy implication is that, if the alignment of the real economy to climate targets cannot be avoided to be disorderly, then financial institutions have an incentive for such an alignment to occur as early as possible because financial losses would be smaller.

Further, a late and disorderly transition to a mild climate policy shock scenario implies relatively large losses for the financial system. However, under the same market conditions, the disorderly transition to a stricter scenario may lead to the same level of losses if the alignment occurs earlier. The second policy implication is that a country could reach a more stringent climate target, if the alignment occurs earlier, at the same cost (in terms of financial losses) of reaching a less stringent target with a later alignment.

Finally, we show that aligning to a milder climate policy scenario might lead to larger losses than aligning to a more stringent climate policy scenario if market conditions are riskier. Thus, the third policy implication is that in the face of a tighter climate policy shock, it is possible to contain the adverse effect of financial contagion if the market conditions are strengthened enough.

Several limitations apply to our data and to our model, which should be taken into account when considering the results and their policy implications.

A first limitation of our model, is that it assumes a mechanic transmission of the shock along chains of financial contracts which are taken as exogenous and constant in time. For instance, conditional to the shock, we assume that the banks suffer a loss on their balance sheet without being able to anticipate the loss and reallocate their portfolio. Further, its loss translates in a decrease in value of the obligation it has issued on the interbank credit market, thus propagating the loss to its counterparties. Again, the counterparties are not able to anticipate and avoid this loss. Nonetheless, this approach is common to most models of financial contagion in the interbank market and similar approaches have been long used for policy purposes Henry and Kok (2013). As demonstrated by the financial events of 2008, as well as by the policy events of the recent years (e.g. Brexit, Paris Agreement achievement, US withdrawal from Paris Agreement), market players are not always able to anticipate shocks nor to rebalance in time their portfolios of interbank contracts. In particular, they do not have full information on the network of contracts among counterparties. The value of this approach is to estimate the losses for the financial system in severe yet plausible scenarios. While those scenario are stylized the analysis may provide insights on the upper bounds of the losses in paradigmatic situations.

A second limitation regard the third stage of the contagion process, i.e. the fire sales. While agents do react to the shock by trying to maintain their risk management targets (leverage for banks and Value at Risk for funds), they do not internalize the impact of their own reaction and other agents' reaction. However, if they did, this would lead to an overall larger drop in asset price values. Therefore, this assumption implies a conservative estimate of the losses to sudden liquidation of common assets. Notice that this feature applies also to established models of common asset contagion Caccioli et al. (2014); Greenwood et al. (2015).

A third limitation concerns the probability distribution of idiosyncratic shocks on banks' external assets occurring between the time of valuation and the time of the maturity. While a uniform distribution of shocks is unrealistic, it represents an upper bound on the tails of the loss distribution of a defaultable bond (see discussion in Section 3.2). Future work should address this limitation by empirically calibrating the distribution of stochastic shocks induced by market volatility.

A fourth limitation regards the fact that a large portion of the holdings of banks and funds consists of sovereign bonds. Their value is indirectly affected by climate policy shocks because they may decrease their fiscal revenues and thus decrease the sovereign's ability to pay the coupons and the face value (Battiston and Monasterolo, 2019).

Among the avenues for future research we list here two possible avenues for future research to further develop and improve the methodology. First, there is need to empirically calibrate the volatility of external assets in order to better model future stochastic shocks and probability of default of financial institutions, in particularly banks. Second, we plan to extend the methodology including the sovereign bond channel in order to also capture financial institutions' indirect exposure to climate transition risk.

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A Proofs of propositions

Lemma 1: Under the assumption of the feasible valuation function introduced in Section 2:

- Losses are non-decreasing with the magnitude of the initial shock k, and with the asset price volatility σ.
- Losses are non-increasing with the recovery rate R, and with the market liquidity $-\alpha$.

Proof. From the definition of feasible valuation function, it follows that $\mathbb{V}(s_1) \leq \mathbb{V}(s_1)$, if $s_1 \leq s_1$ because the equity of banks is non-decreasing with the shock. Since the equity of banks is a non-decreasing function of $\mathbb{V}$, losses are non-decreasing with the magnitude of the initial shock k.

The valuation function we use in this paper $\mathbb{V}$ is a non-increasing function with the market volatility σ. Since the equity of banks is a non-decreasing function of $\mathbb{V}$, losses are non-decreasing with the asset price volatility σ.

The valuation function we use in this paper $\mathbb{V}$ is a non-decreasing function with the recovery rate R. Since the equity of banks is a non-decreasing function of $\mathbb{V}$, losses are non-increasing with the recovery rate R.

The price impact of liquidation we use in this paper $\mathbb{V}$ is a non-decreasing function with the market liquidity $-\alpha$. Since the equity of banks is a non-decreasing function of the price of their assets, losses are non-increasing with the recovery rate R. □

Lemma 2: Under the assumption of the feasible valuation function introduced in Section 2:

- Losses are non-increasing with the strength of market conditions.
- Losses are non-decreasing with the time of the transition, and with the stringency of climate targets.

Proof. Strong market conditions are characterized by large interbank recovery rate R, large market liquidity $-\alpha$ and small asset price volatility σ. Since losses are non-decreasing with asset price volatility σ, and are non-increasing with the recovery rate R, and with the market liquidity $-\alpha$, Lemma 1 proves that osses are non-increasing with the strength of market conditions.

The gap between BAU and any climate policy p is non decreasing in time, thus the first round shock induced by a late and disorderly transition from BAU to p is non-increasing in time. Applying Lemma 1 proves that losses are non-decreasing with the time of the transition.

In respect to less stringent climate targets, more stringent climate targets are characterized by trajectories of economics activities that diverge more from BAU. This is due to the fact that to reach more stringent climate targets brown/green activities should be reduced/increased more. Since the magnitude of the initial shock is increasing with the divergence of trajectories of economics activities, applying Lemma 1 proves that losses are non-decreasing with the stringency of climate targets. □

Proposition 1: Financial losses and interplay between market conditions and climate policy shock scenarios.

If the valuation function $\mathbb{V}$ is feasible, under the same financial network structure, recovery rate R, market volatility σ, and market liquidity α, losses suffered by each bank i after financial contagion can not be smaller if the initial shock k is smaller. In detail

- Stricter climate targets could be reached at the same financial loss with an earlier (still disorderly) transition.
- Stricter climate targets could be reached at the same financial loss with if market conditions are strenghtened.

Proof. Lemma 2 shows that losses are increasing with the time of the climate policy transition. Therefore, it is possible to reduce losses anticipating the transition. By construction of the IAM model used to build LIMITS trajectories, there always is a point in time where BAU and each climate policy trajectories coincide. When BAU and p coincide, no shock is induced by a disorderly transition. For this reason, it is always possible to anticipate the transition enough to find a moment in time which satisfies the proposition.

Lemma 2 shows how the strenght of market conditions influences losses due to financial contagion. In particular, setting $R = 1, \sigma = 0, -\alpha = -1$ reduces to the minimum losses due to financial contagion. For this reason, influencing market conditions it is always possible to minimize losses. □

Proposition 2: Financial losses and brown-leverage. Given a climate policy scenario p, under the assumption of limited liabilities, first round financial losses are proportional to the shock k and the leverage towards brown sectors, i.e.

$$h_i^{1st} = \max\left\{-1\,,\ \sum_c \sum_{s^*} \Lambda_{ics^*} k_{cs^*}\right\}, \tag{26}$$

where s^* labels sectors that are brown and are negatively shocked in our exercise (i.e., “Fossil-Fuel” and “Utilities”), Λ_{ics^*} is the *brown-leverage* of bank i, and h_i^{1st} is the relative equity loss of bank i after the first round.

Proof. The equation to prove is obtained by dividing Equation (6) by bank i’s equity. It then follows that financial losses are proportional the leverage towards brown sectors. □

B LIMITS - climate policy scenarios database

In this section we describe the main characteristics of the forward looking scenarios of economic trajectories that we use. In this paper we consider the scenarios elaborated by the international scientific consortium LIMITS and reviewed by the IPCC. Among all the LIMITS trajectories, we select the StrPol and RefPol climate policy scenarios which are aligned to the 2C target. Conditioned to climate policies' introduction and/or implementation, in this paper we use the LIMITS database to compute the market shares shocks for several economic activities in primary and secondary energy (e.g., primary energy from gas, electricity produced hydroelectric power plants).

As illustrated in Table 3 and in (Battiston et al., 2019), the characteristics of the LIMITS trajectories are the following:

- The **level of ambition** in emission reduction in the **near-term** (2020): reference policy 'weak' corresponds to unconditional Copenhagen Pledges; more 'stringent' based on conditional Copenhagen Pledges.
- The **level of ambition** in emission reduction in the **long-term** (2100): no target or concentrations targets of 450 or 500 ppm CO_2-equivalent.
- **Fragmented action until**: indicates the level of international cooperation and coordination until 2020.

500 parts per million (ppm) and 450 ppm refer to the concentration of CO_2 at the end of century consistently with the 2°C aligned scenarios. As in IPCC WGII (2014), these levels of CO_2 concentration are associated to two different policy scenarios, i.e. the Reference Policy (RefPol), and the Strong Policy (StrPol). While both scenarios share the assumption of fragmented countries' action, the RefPol policy scenario assumes a weak near-term target by 2020 and StrPol assumes a stringent near-term target by 2020. The 500 and 450 ppm scenarios are associated to a probability of exceeding the 2°C target by 35-59% and 20-41% respectively (Meinshausen et al., 2009).

C Summary of losses due to direct and indirect contagion

In this section we summarize losses due to contagion in different policy scenario and under different market conditions. For each scenario and model, the two tables show the following quantities: 1) the relative shock to the CPRS, 2) losses suffered by banks in the three stages of contagion expressed as percentage of total initial investment, and 3) gross losses suffered by external creditors expressed in thousands of Mexican pesos. For all results, we set market liquidity $\alpha = \ln 4/3$ and funds $VaR = 1\%$.

Scenario Class	**Scenario Name**	**Scenario Type**	**Level of Ambition (near term)**	**Level of Ambition (long term)**	**Fragmented Action Until**
No policy	BAU	Baseline	None	None	N/A
Delayed policy	RefPol-450	Climate Policy	Weak	450 ppm	2020
Delayed policy	StrPol-450	Climate Policy	Stringent	450 ppm	2020
Delayed policy	RefPol-500	Climate Policy	Weak	500 ppm	2020
Delayed policy	StrPol-500	Climate Policy	Stringent	500 ppm	2020

Table 3: LIMITS scenarios characteristics. Source (Kriegler et al., 2013)

Each statistics refers to 500 realizations where market volatility σ has been randomly generated following a beta distribution with parameters $\beta(5,2)$ and recovery rate has been generated following a beta distribution with parameters $\beta(4,2)$. For instance, line 31 shows that the WITCH model estimates that the introduction of the StrPol-450 policy scenario would decrease by 51.68% the value of loans to the sector Fossil-Fuel. Similarly, the loans granted to the the Utilities sector would lose 79.05% of their value. Those two shocks would trigger a devaluation of assets of the Mexican financial system due to direct exposure equal to 0.82%. For 1% of the realizations, financial contagion due to direct exposure would further decrease the value of total assets of the financial system of 1.24%. Further, financial contagion due to liquidation of common assets would decrease the value of total assets of the Mexican financial system of 2.87%. Finally, the losses that are too large to be absorbed by banks' capital and are transmitted to external creditors is 3.30% of banks' initial capital.

Index	Year	Model	Scenario	Fossil Fuel shock	Utilities shock	1^{st} Round	2^{nd} Round VaR1%	3^{rd} Round VaR1%	Ext. VaR1%
1.	2015	WITCH	RefPol-450	0.17	-0.71	-0.01	-0.01	-0.12	-0.12
2.	2015	WITCH	RefPol-500	0.17	-0.71	-0.01	-0.01	-0.12	-0.12
3.	2015	WITCH	StrPol-450	0.18	-0.78	-0.01	-0.01	-0.13	-0.13
4.	2015	WITCH	StrPol-500	0.18	-0.78	-0.01	-0.01	-0.13	-0.13
5.	2020	WITCH	RefPol-450	-0.37	-5.69	-0.08	-0.09	-0.26	-0.27
6.	2020	WITCH	RefPol-500	-0.37	-5.69	-0.08	-0.08	-0.25	-0.27
7.	2020	WITCH	StrPol-450	-0.80	-10.73	-0.06	-0.06	-0.23	-0.24
8.	2020	WITCH	StrPol-500	-0.80	-10.73	-0.06	-0.06	-0.23	-0.24
9.	2025	WITCH	RefPol-450	-6.37	-49.01	-0.28	-0.39	-1.32	-1.57
10.	2025	WITCH	RefPol-500	-2.33	-32.53	-0.11	-0.18	-0.78	-0.90
11.	2025	WITCH	StrPol-450	-5.67	-45.90	-0.26	-0.35	-1.28	-1.52
12.	2025	WITCH	StrPol-500	-2.33	-31.40	-0.11	-0.14	-0.73	-0.84
13.	2030	WITCH	RefPol-450	-15.30	-59.27	-0.30	-0.42	-1.34	-1.59
14.	2030	WITCH	RefPol-500	-7.57	-35.45	-0.20	-0.29	-1.22	-1.44
15.	2030	WITCH	StrPol-450	-14.73	-58.31	-0.31	-0.41	-1.34	-1.59
16.	2030	WITCH	StrPol-500	-7.50	-35.55	-0.20	-0.27	-1.19	-1.42
17.	2035	WITCH	RefPol-450	-23.44	-64.54	-0.42	-0.59	-1.52	-1.77
18.	2035	WITCH	RefPol-500	-14.60	-35.75	-0.43	-0.59	-1.51	-1.78
19.	2035	WITCH	StrPol-450	-22.84	-63.23	-0.41	-0.55	-1.49	-1.75
20.	2035	WITCH	StrPol-500	-14.32	-35.36	-0.43	-0.55	-1.50	-1.78
21.	2040	WITCH	RefPol-450	-32.22	-69.44	-0.54	-0.80	-1.85	-2.13
22.	2040	WITCH	RefPol-500	-20.33	-38.02	-0.52	-0.74	-1.72	-2.00
23.	2040	WITCH	StrPol-450	-31.60	-68.19	-0.53	-0.74	-1.78	-2.06
24.	2040	WITCH	StrPol-500	-20.00	-37.58	-0.52	-0.69	-1.66	-1.93
25.	2045	WITCH	RefPol-450	-41.20	-74.53	-0.66	-1.01	-2.60	-2.99
26.	2045	WITCH	RefPol-500	-26.65	-41.97	-0.61	-0.92	-2.01	-2.33
27.	2045	WITCH	StrPol-450	-40.35	-73.32	-0.66	-0.96	-2.55	-2.93
28.	2045	WITCH	StrPol-500	-26.26	-41.42	-0.61	-0.84	-1.84	-2.14
29.	2050	WITCH	RefPol-450	-52.54	-80.06	-0.82	-1.28	-2.91	-3.35
30.	2050	WITCH	RefPol-500	-34.87	-48.66	-0.72	-1.11	-2.73	-3.15
31.	2050	WITCH	StrPol-450	-51.68	-79.05	-0.82	-1.24	-2.87	-3.30
32.	2050	WITCH	StrPol-500	-34.22	-47.85	-0.72	-1.02	-2.60	-3.00

Table 4: Summary of evolution in time of contagion for a given model and scenario