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The interdependencies of Canadian financial institutions: an application to climate transition shocks

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Abstract

We develop a methodological framework that captures the indirect—or systemic—implications of market, credit and liquidity shocks. We apply this framework using data from the Canadian financial system and a combination of shocks coherent with a delayed climate transition scenario towards a low carbon economy. We examine the direct effects on financial system entities through their positions on public and private assets and derivatives portfolios of deposit-taking institutions, life insurance companies, pension funds and investment funds. To assess the indirect effects from the potential spread across an interconnected financial system, we extend an agent-based model to explore shock transmission channels such as cross-holding positions, business similarities, common exposures and fire sales. This model considers behavioral assumptions and rules, allowing us to understand the interconnectedness of the financial system. This work strengthens our understanding of how distinct entities within the financial system could be impacted by and respond to climate transition risks and opportunities, and of the potential channels through which those risks and opportunities may spread. More generally, this work contributes to building standardized systemic risk assessment and monitoring tools to control potential systemic risks.

Topics: Climate change; Financial stability; Financial institutions; Financial markets; Economic models
JEL codes: Q54, C63, G01, G10, G20

Résumé

Nous développons un cadre méthodologique qui permet de saisir les implications indirectes - ou systémiques - des chocs de marché, de crédit et de liquidité. Nous appliquons ce cadre en utilisant des données du système financier canadien et une combinaison de chocs cohérents avec un scénario de transition climatique retardée vers une économie à faible émission de carbone. Nous examinons les effets directs sur les entités du système financier à travers leurs positions sur les actifs publics et privés et les portefeuilles de produits dérivés des institutions de dépôt, des compagnies d'assurance-vie, des fonds de pension et des fonds d'investissement. Pour évaluer les effets indirects de la propagation potentielle dans un système financier interconnecté, nous étendons un modèle basé sur les agents pour explorer les canaux de transmission des chocs tels que les positions croisées, les similitudes commerciales, les expositions communes et les ventes forcées. Ce modèle prend en compte des hypothèses et des règles comportementales, ce qui nous permet de comprendre l'interconnexion du système financier. Ce travail renforce notre compréhension de la manière dont des entités distinctes au sein du système financier pourraient être affectées par les risques et les opportunités liés à la transition climatique et y répondre, ainsi que des canaux potentiels par lesquels ces risques et opportunités peuvent se propager. Plus généralement, ces travaux contribuent à la mise en place d'outils normalisés d'évaluation et de suivi des risques systémiques afin de contrôler les risques systémiques potentiels.

Sujets : Changements climatiques; Stabilité financière; Institutions financières; Marchés financiers; Modèles économiques
Codes JEL : Q54, C63, G01, G10, G20

1. Introduction

Systemic risk in biological terms is defined as a possible global disaster arising from the behaviour of a single individual of the species that coexist in the same environment. Likewise in Economics, systemic risk is the threat of a system breakdown because the effects of the interactions among individuals are undervalued, i.e. negative externalities arise from the relationship between economic agents. As systemic risk affects all sectors, it should be evaluated not only within sectors, but also between sectors. There are relevant features in the financial system that make financial sectors susceptible to these systemic risk sources, e.g. externalities through transmission channels, asymmetric information due to agency problems and powerful feedback and amplification mechanisms such as fire sales and herd behaviour. Building a resilient financial sector able to prevent spread of a breakdown in the economic system is an important target for supervisory authorities, as irregular performance of the financial system could reduce the effectiveness of monetary policy, hampering the economic and financial well-being of the citizens. Analytical tools enabling the timely identification of shocks and sources of risk that could lead to systemic events can help policymakers to assess the likely spread of individual problems in the financial system during crisis periods and to calibrate prudential instruments in tranquil times.

We present a model that captures the system-wide amplifications of market, credit and liquidity shocks to peers and other financial sectors. The model describes propagation of shocks in a network of deposit-taking institutions, life insurance companies, investment funds and pension funds, where the role of each player in the model might aggravate or mitigate the effects of shocks on the financial system depending on their business model, how exposed they are to shocks, and which types of interlinkages exists with other market players. We extend the framework presented in Hałaj (2018) by addinglife insurance and pension funds. The contagion process of this framework allows for credit deterioration and different fire sales sensitivities as a function of the type of assets sold. The model also includes intersectoral lending, cross-holding effects through equities and funds' participations and the liquidity effects of derivatives. We use our model to assess the response of the Canadian financial system to the materialization of a 2ºC delayed climate transition scenario.

We contribute to the research on financial stability and systemic risk in the following way. We link potential spillovers between liquidity and solvency as Hałaj (2018) proposed, extending the analysis to life insurance companies and pension funds, adding the role of margin calls. Second, we consider how derivatives and credit deterioration might lead to liquidity issues, which could aggravate overall liquidity conditions through the intersectoral lending channels. To our knowledge, no study has analysed the role of derivatives, intersectoral lending linkages and credit deterioration in the pension fund sector. Cont et at. (2020) analyse the linkages between liquidity and solvency in the banking sector, including the effects of derivatives and credit deterioration on the liquidity status of the financial institution. These features are not considered in Hałaj (2020), which is an application of Hałaj (2018) using Canadian data. The focus of Puhr et al. (2012) is the banking sector, where they analyse the relationship between solvency and liquidity via the increase of collateral needs (margin calls) and increase in funding costs due to a deterioration of solvency conditions. Fricke and Fricke (2017) focus on equity funds, while Cetorelli et al. (2016) and Gourdel and Sydow (2023) study different types of investment funds. Calimani et al. (2019) find that investment funds play a key role to exacerbate contagion. They focus on the fire sales mechanisms without looking at the cross-holding positions between banks and investment funds. Aikman et al. (2019) and Sydow et al. (2021) only analyse the systemic implications of banks and investment funds. Caccioli et al. (2020) also consider insurance companies within the analysis, including equity and debt securities. Barucca et al. (2021) and Chrétien et al. (2020) consider the insurance sector together with banking and investment fund sectors in their modeling. Third, we assess the fire sales contagion by taking into account the effects of sales pressure on prices for different types of asset types. Also, we compute different sensitivities based on quantile regression (see Fukker et al., 2022). The fire sales have an effect on credit deterioration for fixed-income instruments, transforming PDs of the different assets in endogenous variables of the model. Cont and Schaanning (2017) analyse the effect of fire sales in the banking sector, where firms have to sell assets to keep the leverage ratio below a certain threshold. Greenwood et al. (2015) study the relationship between system-wide deleveraging and contagion via fire sales in the banking sector. Duarte and Eisenbach (2021) build a vulnerability index for the banking sector, based on their exposure to fire sales. Fourth, we trace back the contagion between institutions, which allows us to build some contagion indicators based on network analysis (see for instance Bardoscia et al. , 2021). Fifth, we investigate the role of pension funds in the financial system, which has not been analysed deeply enough in the literature. Douglas and Roberts-Sklar (2018) focus on the behaviour of defined benefit pension funds in UK, and their reaction to change in yields, equity prices and longevity expectations. Bédard-Pagé et al. (2021) describe the behaviour of Canadian pension funds during the COVID crisis, where they faced liquidity issues due to margin calls and funding instabilities in the commercial paper market. We take into account these potential liquidity issues together with the discussion with Canadian pension funds' asset managers about the behaviour and reaction of pension funds, with a focus on the climate transition.

Another strand of literature investigates empirically the effects of climate transition on the financial system. Our contribution to this area is the application of our methodological framework to assess the spread of climate transition shock on the Canadian financial system by using supervisory data from OSFI, AMF, third-party data from Lipper and bilateral agreements with several pension funds. This is the first climate exercise done with Canadian data. Roncoroni et al. (2021) uses Mexican financial system data to analyse the transmission of climate transition within the banking and investment funds' sectors. Gourdel and Sydow (2023) consider EU investment funds to assess the propagation of climate transition and physical shocks, Battiston et al. (2017) focus on the response of banking sector in Europe to climate transition, and Dubiel-Teleszynski et al. (2022) make an application to EU data of banks, investment funds and insurance companies.

We illustrate how a set of shocks, coherent with the materialization of a delayed climate transition scenario, transmits through the Canadian financial system. Our findings show modest impacts, which partly reflects the limited exposure of Canadian financial entities to sectors of the economy that may be negatively impacted by the transition. Despite this limited exposure, the interconnections revealed in this study play a role in spreading the impacts of the climate transition risk to the overall financial system. In particular, common exposures, fire sales and cross-holding positions were found to be important transmission channels. Pension funds and deposit-taking institutions—in contrast to life insurance companies—invest a significant portion of assets in high-yield loans in climate-related sectors. The fact that these entities take more risk in private markets is useful in helping us understand the spread of a climate transition shock. Investment funds' sector is the main contributor to the spread of these shocks, as being more procyclical and susceptible to redemption shocks than other types of financial entities. Pension funds allow to mitigate the contagion effects due to their potential role as buyers for the undervalued assets. Given their size, long-term investment horizons, stable contributor base and diverse investment strategies, pension funds might be interested in capitalizing on these undervalued assets as potential future opportunities.

The rest of the paper is structured as follows. In Section 2, we present the model, outline the datasets employed to conduct the analysis, and briefly describe the delayed climate transition scenario. In Section 3, we present the results, and Section 4 draws conclusions.

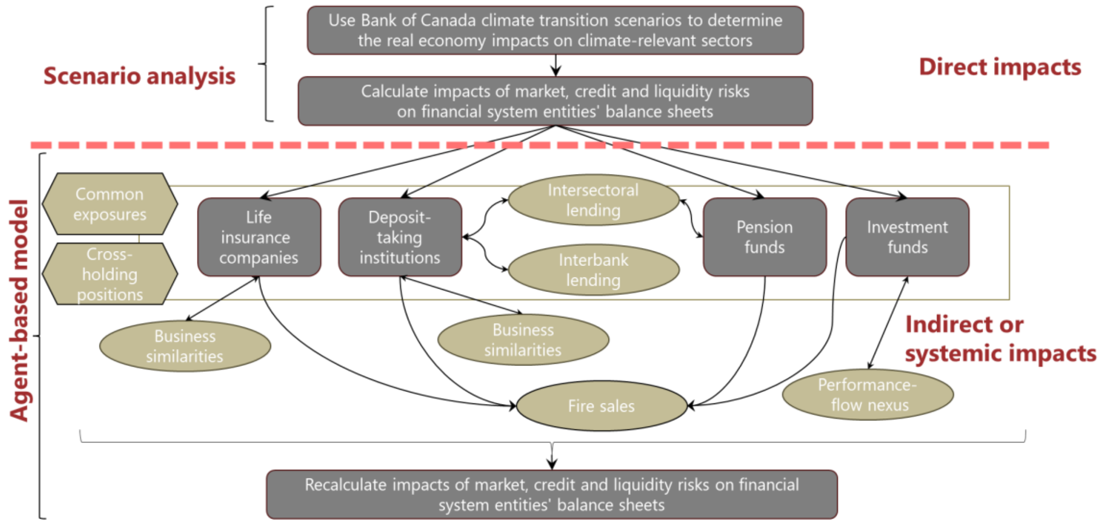
2. Methodology

2.1. Model

To model the connections in the financial system, we rely on an Agent Based Model (ABM) structure. The agent-based model describes a system of connected agents – here financial market participants – and serves as a framework to study how the shock propagation might occur. It depends on the type of connections that the players have between them. This type of model allows to reflect complex patterns in the financial system using balance sheet items and behavioural rules that drive the actions of the agents. Agent-based models (ABMs) can thereby provide rich analytical insights about the systemic implications of a given shock. Both entity-specific details (like risk profiles and portfolio characteristics) and commonalities and financial linkages across entities are core features of the financial system that can be modelled through an ABM. Notably, this approach is useful to model adverse conditions, such as in the case of a sharp adjustment of asset valuations due to a stressful climate transition shock.[1]

Figure 1 presents an overview of the transmission channels considered in our study.

Figure 1: **Systemic effects—and their transmission channels—following climate transition shock**



Common exposures and fire sales

Common exposures in assets are indirect connections among financial institutions through their investment in similar asset holdings. In this study, entities share a common exposure when they invest in the same asset class issued from the same economic sector and region. We define common exposures using the climate-relevant public assets (equity or debt) held by the financial entities within the scope of our study. We focus on publicly traded assets because they are priced by the market, which allows entities to gain liquidity by selling them but might also expose entities to mark-to-market losses due to fire sales.[2] The greater the overlapping exposures to a given set of assets, the more vulnerable an entity may be to a given shock affecting those assets.

Common exposures can lead to systemic losses when an asset price decreases sharply, either because of a shock to that asset or because of selling pressure in secondary markets, such as in a fire sale. Fire sales could lead to securities being sold at large discounts due to a liquidity shortage. This situation can create opportunities for value investors willing to buy undervalued assets with recovery potential. However, fire sales pose challenges for investors

[1] ABMs are well suited to capture stylized facts of the financial system, including periods of turmoil (e.g., out-of-equilibrium behaviours, multiple decision rules, heterogeneous and disaggregated balance sheets, and non-linear dynamics and spillovers). But it is worth noting a few of the drawbacks of ABMs. One drawback relates to parameter calibrations, where historical data may not be accurate depictions of actual values, which might not yet be observed. Another drawback is the stability of the model, which is highly dependent on the parameter selection. For more details on ABMs, see Lux and Zwinkels (2018).

[2] In contrast, private assets are illiquid and priced at book value.

because of increased mark-to-market losses and herd behaviour, potentially leading to larger losses.[3]

Business similarities

When the asset allocation among financial institutions for a given type of financial entity (e.g., banking sector) is similar, this could indicate potential exposure to similar risks. If an entity faces solvency issues after a shock (such as a climate transition shock), this could be informative about the solvency positions of similar entities, leading to an increase in funding costs.[4]

In our framework application, we consider how information contagion between entities with similar business models could imply higher funding costs when one entity is facing solvency issues after a climate transition shock.

Cross-holding positions

Cross-holding positions refer to entities owning investment (e.g., through shares) in other financial entities. This exposure implies that the financial performance of an entity directly influences its investor, thus potentially amplifying losses in the financial system.

Interbank and intersectoral lending

Lending channels between banks (i.e., interbank lending) or between banks and pension funds (i.e., intersectoral lending) keep liquidity flowing in the financial system. If a lender faces liquidity constraints, this could curtail the lending facilities to other counterparties. The borrower would carry a cost of replacement of the discontinued funding sources.

Performance-flow nexus

The performance-flow nexus is an amplification channel specific to open-ended mutual funds.[5] Large redemptions, triggered by the poor performance of funds, may drive fund managers to sell assets at lower prices to cover withdrawals, burdening remaining investors. This creates a "first-mover advantage" and triggers herding behaviour, which makes it difficult for fund managers to meet all redemption requests. Thus, losses can lead to redemptions, which in turn result in further losses.

[3] Common exposures can have positive effects in normal times, such as diversification benefits and risk sharing. But they can also have negative effects in downturns through the amplification of losses and contagion. These effects can have adverse consequences for the real economy by reducing credit availability, investment opportunities and consumer confidence. See, for example, Acemoglu, Ozdaglar and Tahbaz-Salehi (2015) and Abad et al. (2022).
[4] Borrower default risk can also inform lender solvency risks (see Ahnert and Georg [2018]) and other lenders' solvency situations if a common systematic factor is shared (see Acharya and Yorulmazer [2008]). See Wang, van Lelyveld and Schaumburg (2019) for a discussion of information contagion through business model similarities.
[5] This channel has been observed in corporate bond funds (Goldstein, Jiang and Ng 2017; Dötz and Weth 2019) and equity funds (Chen, Goldstein and Jiang 2010). The performance-flow nexus has been introduced in several resilience exercises for mutual funds (Arora and Ouellet Leblanc 2018; ESMA 2019; Gourdel and Sydow 2022; Ojea-Ferreiro 2020; Fricke and Fricke 2021).

The model is composed of a sequence of 8 steps that occur sequentially in a financial system of banks, pension funds, open-ended mutual funds[6] and life insurance companies.[7] Some of these steps are only activated for some players, as the transmission and amplification channels might be different for each type of agent.

The agents determine their actions in isolation, but their decisions impact other market participants through the channels previously mentioned, creating complex multidimensional connections which can propagate the shock. We focus on two types of key metrics to decide if a market participant is taking an action: solvency ratio and liquidity ratio. Pension funds and investment funds focus on liquidity ratio, while life insurance companies focus on solvency ratio. Banking sector considers both liquidity and solvency ratios. We do not consider profit maximization-based on balance sheet optimisation, leverage ratio or ALM measures as we are looking at short-term horizons.[8]

Let us define the solvency ratio of institution i (τ^i) as the ratio between equity (e^i) and the risk weighted assets (Ω^i), which are the product of their assets (a_n^i) multiplied by some risk weights (ω_n^i):

$$\tau^i = \frac{e^i}{\Omega^i} = \frac{e^i}{\sum_n a_n^i \omega_n^i}$$

The solvency threshold to take actions is set at 10.5% for domestic systemically important bank (DSIBs) and 7% for small and medium-sized deposit-taking institutions (SMSBs).[9] The default solvency threshold for deposit-taking institutions is 4.5%. For life insurance companies, there are two definitions of solvency depending on the assets which are considered to define the equity bucket. Total LICAT has a threshold of 100%, while Core LICAT, which is more restrictive with the definition of equity, is set at 70%. Default threshold are set at 90% and 55% for Total LICAT and Core LICAT, respectively.

The liquidity ratio or liquidity coverage ratio (LCR) is defined as the ratio between the High Quality Liquid Assets (HQLA) and the liquidity needs considered by the institution (Λ). We could interpret the liquidity weights indicating the inflow (k_n^i) and outflow (λ_n^i) rates of the assets (a_n^i) and liabilities (l_n^i) held by the institution:

$$LCR^i = \frac{\sum_n a_n^i k_n^i}{\Lambda^i} = \frac{\sum_n a_n^i k_n^i}{\sum_n l_n^i \lambda_n^i}$$

[6] Although we model mutual funds as active players, we consider the whole investment fund sector, as they would play a passive role in terms of cross-holding contagion, without taking any active in relation with liquidity measures. Appendix provides more information about the intra-fund contagion via cross-holdings.

[7] Appendix provides a summary of the decision tree of the different types of agents in our model.

[8] ABMs usually assume some kind of limited rationality which could be suboptimal (Lux and Zwinkels, 2018).

[9] These thresholds are based on the different buffers that deposit-taking institutions must hold. DSIBs should keep an extra 2.50% for the Domestic Stability Buffer (DSB) and a CET1 surcharge equal to 1% of RWAs at the end of 2021.

Note that the liquidity needs of an institution (Λ^i) increases if the margin calls from derivative positions increases or if the short positions generate losses. We set the LCR threshold to 1, such that agents will begin to sell assets if their liquidity needs are higher than the liquidity held by the institution.

We will now describe the sequence of steps in the model in a general framework, where institutions can suffer market, credit and liquidity shocks. Market shocks decrease their asset value and its equity, due to the equality $\sum_n a_n^i = \sum_n l_n^i + e^i$. Hence, when asset values are reduced the solvency ratio is affected. That decrease in asset value could imply also a lower liquidity ratio if the asset n (a_n^i) suffering the market loss has an inflow ratio higher than zero, i.e. $k_n^i > 0$. Credit shocks can decrease asset values due to increased default risk, affecting solvency ratios through the decrease of equity and a potential increase of risk weighted assets if the credit deterioration is large enough. Also, the credit deterioration might imply that the asset is no longer considered high-quality, i.e. $k_n^i = 0$, generating an impact on the liquidity ratio. Finally, liquidity shocks, which could be a consequence of deposit run-offs for banks or redemption shocks for open-ended mutual funds, derivative-related losses and margin calls and the increase of liquidity needs from short positions can increase the denominator of the LCR.

1) Eligible or cash-equivalent assets

This step is only applicable to the banking sector and occurs in the case of liquidity distress. As this sector can borrow money from the central banks against good quality collateral, we consider if the high-quality assets are enough to gather enough liquidity to face liquidity constraints. If we assume that the eligible assets are a set of ε assets within the N number of assets, i.e. $\varepsilon \in N$, the bank has enough liquidity if the follow inequality holds:

$$\sum_{n \in \varepsilon} (1 - h_n) a_n^i \geq \Lambda^i$$

Where h_n is a haircut associated with an asset n. If banks access repo contracts to cover funding outflows, the cost of the repo impacts the profits and losses of that institution. We set the repo cost at 25 bps, aligned with Hałaj (2020). Also, we apply an include an extra haircut of the repoed security following Hałaj (2020), which impacts the denominator of the solvency ratio.

Similarly, asset managers of investment funds and pension funds might use part of their assets which could be considered as cash-equivalent or High Quality Liquid Assets (HQLA), which could be used to gather enough liquidity without affecting market prices. Appendix shows some details on the calibration of the haircut or liquidity weights for those agents. For the banking sector we use the haircuts indicated by OSFI in the Liquidity Adequacy Requirements (LAR).

2) Interbank funding

Banks which are not able to gather enough liquidity from their eligible assets would stop rolling over their credit to the interbank market. The debtor would search other lenders to keep their lending facilities, which would imply a cost of searching as an externality.

The decrease in equity from cost of searching will be reflected in a decrease in the assets side, as the assets must be equal to liabilities and equities, i.e. the new equity amount e^{i*} for the debtor would be:

$$e^{i,2} = e^{i,1} - \sum_{k \in \mathcal{B}} c\, l_{ik}$$

Where l_{ik} is the liability of debtor i with bank k. Bank k is within the set of $\mathcal{B}$ banks which are facing liquidity issues. c is the cost of search, which we set to 50 bps, which is more conservative than Hałaj (2020).

3) Intersectoral funding

Bédard-Pagé et al. (2021) indicates that pension funds are the main counterparties of banks in the REPO market. The introduction of this player in the model implies an extension of the interbank lending to intersectoral lending. We apply the previous step to the lending relationship between pension funds and banks if either is suffering liquidity issues. We use the EBET-2L and 2A OSFI returns to estimate the short-term REPO contracts between banks and pension funds. EBET-2L provides a good coverage of DSIBs debtors with pension funds, indicating some maturity buckets.[10] Unfortunately, the EBET-2A doesn't provide enough detail about the lending maturity, so we assume that 90% of the REPOs lent by banks to pension funds are short-term lending based on expect advice.

4) Fire sales

If liquidity conditions are still below the threshold or solvency conditions are at risk, market participants sell a share of their assets to gather capital and liquidity. This step affects all the players, either directly through the sell of assets or the price adjustment from the extra selling pressure in the secondary market if a large enough amount is sold.

We assume an exponential price impact function, widely used in the literature[11] to assess how the volume sold (V) would affect a price change $\Psi_{\phi}(V)$ via the sensitivity of the market to a certain of volume sold (α), i.e.

$$\Psi_{\phi}(V) = (1 - \exp(-V\alpha))$$

The fire sales are extremely sensitive to the value of α, so as a robustness check, we estimate this value for different types of climate related assets using quantile regression, similarly to Fukker et al. (2022). Appendix introduces the methodology we are using for the estimation of

[10] We assume that just short-term lending would be affected, which corresponds to REPOs with maturity within one month.

[11] See, for instance, Schnabel and Shin (2002), Cifuentes, Feruci and Shin (2005), Cont and Schaanning (2017)

these values. Unfortunately, data from EIKON is well-populated for stock assets but it fails to capture a sample large enough for debt instruments. We rely on the ratio between equity and debt of non-financial corporations from Fukker et al. (2022) to get the α for debt instruments through the adjustment the price sensitivity of equity. We also follow Hałaj (2020) to set the OLS estimation of non-climate-related (non-CRS) assets. We use the OLS estimation and the 5th percentile to assess the effects of the climate shock under two different calibrations of those parameters.

The mark-to-market adjustment would imply that the new amount reported for asset n would be:

$$a_n^{i,4} = a_n^{i,3}(1 - \exp(-V_n \alpha_n))$$

Consequently, the equity adjustment due to large asset sell by market participants would be

$$e^{i,4} = e^{i,3} - \sum_{k \notin \varepsilon} a_n^{i,3}(1 - \exp(-V_k \alpha_k))$$

where V_k is the volume of asset k sold in the market and α_k is the sensitivity price associated with that asset. Regarding the selling strategy, we focus on a horizontal slicing, i.e. selling equal shares of assets in the market to keep the portfolio composition constant, instead of a waterfall or vertical slicing, where the most liquid assets are sold in a first place. We decide to focus on this strategy as it generates higher impact on the financial system[12]

The institutions might hold some fixed-income instruments that they do not plan to sell and therefor could assess at book value instead of market value, i.e. Hold to Maturity (HtM) assets. When dealing with price changes in the secondary market for bond instruments, we consider that a price change is just a market impact or if that price change might affect funding capacity of the issued firm.

Market risk would be translated in the change of the yield to maturity of the bond[13] In terms of contagion, this means that the contagion through market institutions would occur only if several participants are selling the asset in different loops. For instance, institution A is selling bond type X after the evaluation of the first-round effects. Institution B doesn't sell, but then, due to the second-round losses in its equity position from fire sales, institution B decides to sell part of its bond portfolio in the following loop, getting the impact of the sell pressure from institution A in the previous iteration. If institution B is not selling the bond, it doesn't matter what happens in the secondary market, as it is facing only credit risk.

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[12] See, for instance ESMA(2019), Arora and Ouellet Leblanc (2018) and Arora et al. (2019). For instance, in normal times, investments in bond funds are more liquid than investments in bonds partly because fund managers can match redemptions with cash from new investors. Bond fund managers will also sell less-liquid assets, i.e. vertical slicing, to maintain the liquidity of their portfolio when they fear that the liquidity needs will continue in time, e.g. several redemption requests.

[13] See Appendix for a formulation of the bond equation).

If the change in price affects the funding capacity of the firm, its current credit risk would be affected. This would imply an impact in the portfolio of the remainder institutions, no matter if they are selling or holding its debt position. Also, the PD becomes endogenous, as it would change not only due to the climate transition shock, but also from the second-round interactions. The introduction of endogenous PDs in the model and studying how change in PD might imply changes in the credit quality of the portfolio is one of our contribution in the modeling section. Interesting the initial LGD plays a key role explaining the change in the PD.

5) Funding cost increase due to solvency deterioration

If after the decrease in the solvency ratio compared to the initial step (Δ^{τ}) is higher than a certain threshold the bank or life insurance company will face a higher funding cost. A severe drop of the capital ratio could be seen as a signal to the funding market, showing a higher risk of default. Lenders would revise their risk premia, implying a higher funding cost. The funding cost increase would be higher when the liabilities have longer maturities (μ_m^i). The bigger is the solvency ratio change with respect to the threshold, the higher would be the funding cost. The sensitivity of the funding conditions to changes in solvency position (ϕ_m) also may be relevant, as the market could be more sensitive in distress periods and less sensitive in normal times.

Hence, we could define the change in equity as:

$$e^{i,5} = e^{i,4} - \sum_{m \in M} \phi_m \left(\frac{e^{i,0}}{\Omega^{i,0}} - \frac{e^{i,4}}{\Omega^{i,4}} - \Delta^{\tau} \right)^{+} l_m^i \mu_m^i$$

Where $e^{i,5}$ indicates the equity of institution i after the direct effects on funding costs, $e^{i,4}$ indicates the equity of institution i after the fire sales and $e^{i,0}$ indicates the equity level at the beginning of the iteration. $\Omega^{i,4}$ is the risk weighted assets after fire sales, while $\Omega^{i,0}$ indicates the risk weighted assets at the beginning of the iteration. The risk weighted assets would change over the iteration from the previous steps (e.g. search cost of lender would decrease cash holdings, new repo positions increase risk weights, fire sales would decrease the mark-to-market value and might generate a credit deterioration which increases risk weights, …). This step would work for banks and life cos, as these are the institutions which build solvency ratios in a regular basis. We set $\phi_m = 1$ and $\Delta^{\tau} = 100$ bps for banks following Hałaj (2018). Also, Hałaj (2020) uses the threshold of 100 basis points for Canadian banks. For life insurance companies, we set the threshold at 450 basis points for Core LICAT and 800 basis points for Total LICAT from visual analysis of LICAT and LIFE returns from federal-regulated Canadian life insurance companies.

6) Business similarity

We consider the indirect consequences on the funding costs to other banks with a similar business model. We define a similar business model as firms with similar funding and investment strategies, captured via the cosine similarity ($\theta_{i,j}$) between institutions i and j, i.e.,

$$\theta_{i,j} = \frac{\sum_n a_n^i a_n^j + \sum_m l_m^i l_m^j}{\sqrt{\sum_n (a_n^i)^2 + \sum_m (l_m^i)^2}\sqrt{\sum_n \left(a_n^j\right)^2 + \sum_m \left(l_m^j\right)^2}}$$

where a_n^i is the asset n of firm i and l_m^i is the liability m of firm i.

If two firms have a cosine similarity higher than a certain threshold τ_{peers}, i.e. $\theta_{i,j} > \tau_{peers}$, we would have a contagion between i and j if any of them is facing a higher funding cost due to the solvency deterioration. The threshold of the cosine similarity is set at 95% for banks as in Hałaj (2018) and 98% for life insurance companies, based on visual analysis on federal-regulated life insurance companies.

The repricing risk, in case any firm of the peers increases its funding costs as a consequence of the solvency deterioration, affects the maturing and rolled-over volumes of the institution's funding. For a bank I affected by a solvency deterioration of firm j, the new equity would be

$$e^{i,6} = e^{i,5} - \sum_m \psi_m l_m^i \mu_m^i \, \mathbb{I}_{\{\theta_{i,j} > \tau_{peers}\}}$$

where ψ_m is the additional cost of funding for banks with similar in business model. Following Hałaj (2018), we set $\psi_m = 50$ bps, while for life-cos is set ψ_m =100 bps.

7) Cross-holding contagion

The cross-holding contagion would be a result of financial institutions holding equity and debt instruments from other financial firms.

The equity returns are built for banks and life insurance companies based on their percentage change in equity value, while for the investment funds we compute the change in the total assets under management (AuM) from the beginning of the iteration up to this step. Given the asset portfolio of each market participants, we can compute the effects of the decrease in value of one firm into the rest of the market players.[14]

For the debt positions, we follow Hałaj (2018) putting the focus on default events, without considering the credit deterioration in terms of debt pricing. We assume a LGD=40 aligned with Hałaj(2018,2020) for banks and life insurance companies. Default will occur if the solvency ratio is below the default threshold after all the previous steps.[15]

If an institution i defaults and institution j holds debt issued by firm i, the shock received by firm j in its equity position would be

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[14] However, the coverage is not perfect. We can get the positions of investment funds in participations or equity shares in other investment funds, banks and life insurance companies. For life insurance companies, we can capture banks, other life insurance companies and investment funds. For banks, the investment in other market participants is limited to the DSIBs through the EBET-2A returns, but no information is available for SMSBs. Finally, the positions of pension funds is only known for investment funds, being the coverage we were able to capture quite diverse depending on the pension fund.

[15] Note that default will be also translated into a lender search for the borrowers in the intersectoral and interbanking sectors, implying a search cost, as described in steps 2 and 3.

$$e^{j,7} = e^{j,6} - LGD_i w_{i,j}$$

Where $w_{i,j}$ is the debt position of institution j invested in institution i. This change in equity will be reflected in a decrease in risk weighted assets, as a share of $(1 - LGD_i)$ will be part of cash holdings and the remaining LGD_i will have a value of zero. If institution j falls below its solvency default threshold due to their defaulted position in firm i, a cascade of defaults will start[16]

8) Performance- flow nexus

The bad performance of an open-ended fund, reflected in a significant devaluation of assets under management, could trigger behavioural redemptions. In particular, the mismatch between the redemption terms and the liquidity of the investment funds generates an externality that can trigger an herb behaviour within the investors.

This problem is created by investors who withdraw large amounts of their investment from the fund. Large redemptions force the fund manager to sell part of the portfolio at a lower price, in order to obtain sufficient liquidity to be able to cover these withdrawals. Therefore, the cost of withdrawing from the fund is borne by the remaining investors. This creates an incentive to redeem the investment before other investors, known as the "first-mover advantage", which triggers herding behaviour among investors and makes it difficult for the fund manager to meet all redemption requests.

Hałaj (2018) captures the non-linear relationship as a redemption of 3% when the change in AuM is below- 6%. We estimate the relationship between weekly flows and returns change for different quantiles for equity funds, bond funds and other funds. The literature has point out to differences between equity and bonds funds in terms of flows[17], which motivate the calibration in terms of the type of mutual fund.

Our estimates provide a outflow similar to Hałaj (2018) for equity funds, where a decrease of 6% generates an outflow of 2%, but the outflows are milder for bonds (0.6%) and other funds (1.26%).

$$f_{equity} = \begin{cases} 0\ if\ r > -1.45\% \\ 0.18r\ if - 2.05\% < r \leq -1.45\% \\ 0.22r\ if - 5.95\% < r \leq -2.05\% \\ 0.35r\ ifr \leq -5.95\% \end{cases}$$

$$f_{bond} = \begin{cases} 0\ if\ r > -1.25\% \\ 0.04r\ if - 5.35\% < r \leq -1.25\% \\ 0.1r\ if\ r \leq -5.35\% \end{cases}$$

16 More details on how the algorithm for the cascades of defaults would work is provided in Appendix A from Hałaj (2018).

17 See, for instance, Goldstein, Jiang and Ng 2017; Dötz and Weth (2019) and Chen, Goldstein and Jiang (2010).

$$f_{other} = \begin{cases} 0 \; if \; r > -1.05\% \\ 0.03r \; if -1.55\% < r \leq -1.05\% \\ 0.04r \; if -3.05\% < r \leq -1.55\% \\ 0.13r \; if -3.85\% < r \leq -3.05\% \\ 0.24r \; if \; r \leq -3.85\% \end{cases}$$

2.2. Data

2.2.1. Data sources

We rely on a variety of data sources to capture representative datasets of four major types of financial entities: deposit-taking institutions, life insurance companies, pension funds and investment funds.

The data collection process is multifaceted, involving reliance on various sources and arrangements.

- We use regulatory returns from OSFI for federally regulated deposit-taking institutions and life insurance companies; data for these entities regulated in the province of Quebec are obtained through a data sharing agreement with the AMF.
- Collaboration with several Canadian pension funds and asset managers of pension funds allows us to acquire detailed data on their exposures to climate-relevant sectors, covering both long and short positions in their portfolios of public and private assets and derivatives.[18]
- For investment funds, we use data from a third-party provider, Lipper, a Refinitiv Company. These data include information on approximately 2,000 open-ended mutual funds and exchange-traded funds (ETFs) in Canada.

All entities and funds we consider are based in Canada, though as previously mentioned, the analysis includes a worldwide coverage of their assets.[19] **Table 1** presents the data sources used in the scenario analysis to examine the direct effects of climate transition risk on distinct financial entities. The ABM model was calibrated using some of the data sources described above as well as others. **Table 2** provides further details.

[18] Box 1 presents highlights from this collaboration.

[19] Our study presents results for Canadian-domiciled open-ended mutual funds and ETFs. The mutual funds and ETFs are limited to equities, bonds, mixed assets, and others (including alternatives, money markets). Funds with asset compositions like real estate and commodities are outside the scope of our study. The ABM model includes investment funds domiciled in Canada, the United States or abroad that received investment from a Canadian financial entity. The inclusion of foreign entities intensifies market selling pressure, amplifying the fire sale effects.

Table 1: Data sources for direct effects

Financial system entity or type of assets	Loans or private debt	Bonds*	Public equities*	Private equities	All other assets and metrics	Derivatives
Deposit-taking institutions	OSFI (A2, RAPID2 BF), AMF	OSFI (B2), AMF		—	OSFI (M4, NCCF, LCR, BCAR), AMF	—
Life insurance companies	OSFI (IPMT), AMF			—	OSFI (IPMT, LICAT), AMF	—
Pension funds	Voluntarily provided by participating pension funds					
Investment funds	—	Lipper, a Refinitiv Company		—	Lipper, a Refinitiv Company	—

*Where relevant, Eikon, a Refinitiv Company is used to complete public securities information.
Note: OSFI is the Office of the Superintendent of Financial Institutions; AMF is the Autorité des marchés financiers; A2 is OSFI's Non-Mortgage Loans return; B2 is OSFI's Securities return; M4 is OSFI's Balance Sheet return; LCR is OSFI's Liquidity Coverage Ratio Reporting Form; NCCF is OSFI's Net Cumulative Cash Flow Reporting Form; RAPID2 BF is OSFI's Wholesale Transaction return; BCAR is OSFI's Basel Capital Adequacy Reporting return; IPMT is OSFI's Investment Portfolio Monitoring Template; LICAT is OSFI's Life Insurance Capital Adequacy Test return.

Table 2: Data sources for systemic (or indirect) effects

Financial system entity or transmission channel	Common exposures	Cross-holding positions	Interbank lending	Intersectoral lending	Business similarities	Fire sales
Deposit-taking institutions	OSFI (B2, NCCF), AMF	OSFI (EB/ET-2A)	OSFI (EB/ET-2L)		OSFI (NCCF), AMF	Eikon, a Refinitiv Company
Life insurance companies	OSFI (IPMT), AMF		n/a	—	OSFI (LICAT, LIFE), AMF	
Pension funds	Voluntarily provided by participating pension funds**		n/a	OSFI (EB/ET-2A)*	n/a	
Investment funds	Lipper, a Refinitiv Company		n/a	—	—	

*90% of the intersectoral lending positions reported by banks to pension funds are assumed to be short-term.
**Cross-holding positions for pension funds cover only investment funds.
Note: Where data are unavailable, calibrations from other research are used. For example, Fukker et al. (2022) is used for debt price sensitivities to selling pressures and Hałaj (2020) for funding shocks due to decreasing solvencies. OSFI is the Office of the Superintendent of Financial Institutions; AMF is the Autorité des marchés financiers; B2 is OSFI's Securities return; EB/ET-2A and 2L are OSFI's Interbank and Major Exposures returns; NCCF is OSFI's Net Cumulative Cash Flow Reporting form; LICAT is OSFI's Life Insurance Capital Adequacy Test return; IPMT is OSFI's Investment Portfolio Monitoring Template; LIFE is OSFI's harmonized quarterly and annual supplement return on life insurance.

2.2.2. Data of Canadian financial institutions: climate-related and systemic-related information.

Total financial system climate-relevant exposures

Panels a to d in **Chart 1** show the initial exposures of climate-relevant assets for the financial system entities within the scope of our study, which collectively manage a substantial portion of the Canadian financial system (total assets approximately $14.5 trillion). These climate-relevant exposures include assets of the following types:

- loans or private debt
- bonds
- public equity
- private equity (for pension funds only)

The financial system's overall climate-relevant exposures within the scope of our study constitute about 8% of total assets. However, exposures vary across the different types of entities. For instance, deposit-taking institutions have under 4% exposure to climate-relevant assets, while life insurance companies have about 19%.

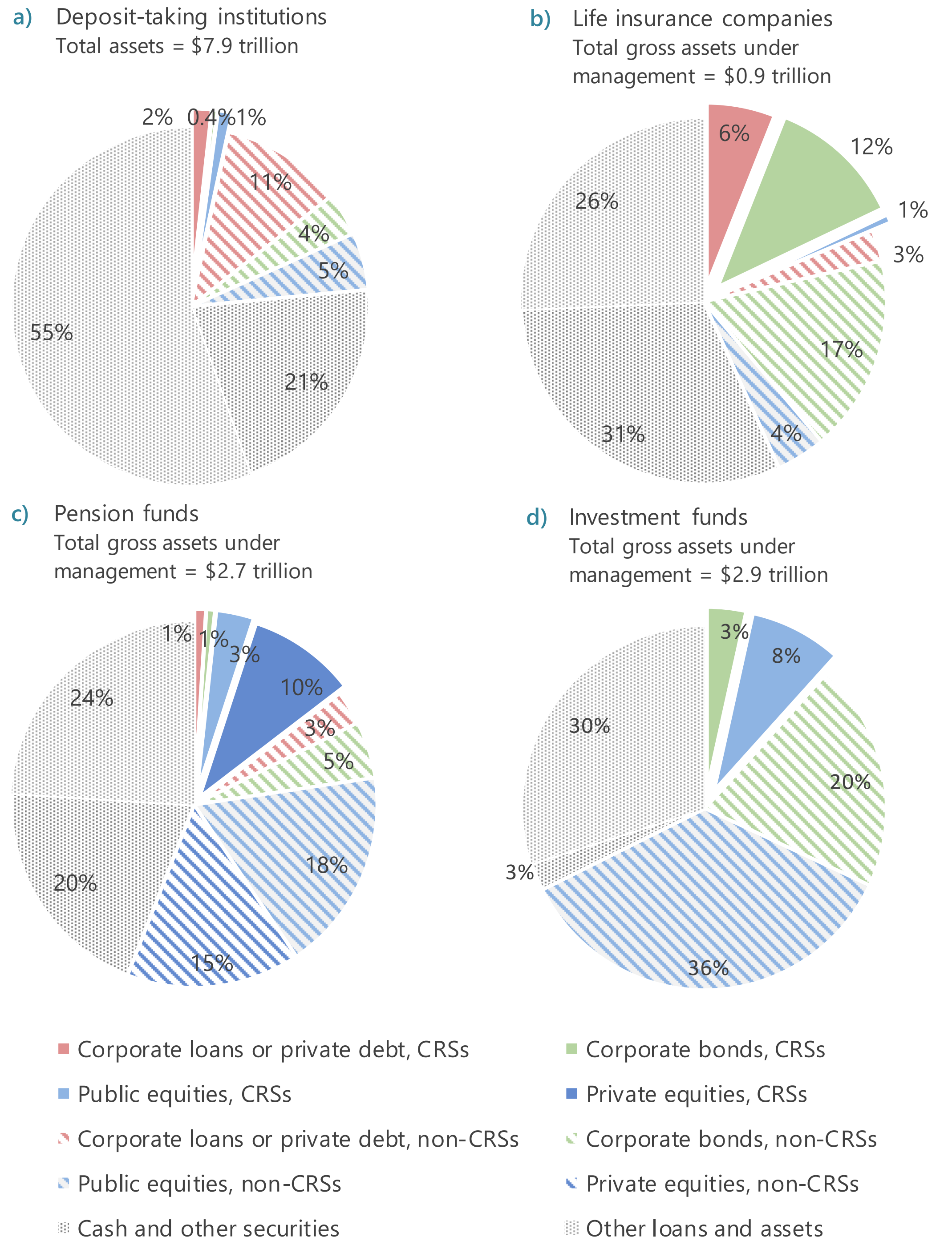
Exposures also vary across different types of entities in terms of their asset allocations. While life insurance companies tend to have a higher allocation in climate-relevant bonds and loans, pension funds' and investment funds' portfolios contain more climate-relevant equities, with pension funds holding a significant amount of climate-relevant private equities.

Common exposures to climate-relevant assets

Understanding how these exposures are shared within the financial system may also provide insight around potential climate-related systemic vulnerabilities. **Chart 2** shows how Canadian financial system entities are linked through their common exposures in climate-relevant assets (when they hold public assets in the same climate-relevant sector and region). The chart helps give a sense of the financial system's climate interconnectedness.[20] We focus on publicly traded assets due to their expected liquidity and potential to trigger contagion via

[20] We follow the approach of Pool, Stoffman and Yonker (2015) to define the portfolio overlap measure.

Chart 1: Climate-relevant asset exposures for financial system entities in scope of our study



Note: CRS is climate-relevant sector. Components in grey are assets outside of the study's scope (e.g., residential and commercial mortgages, sovereign bonds).

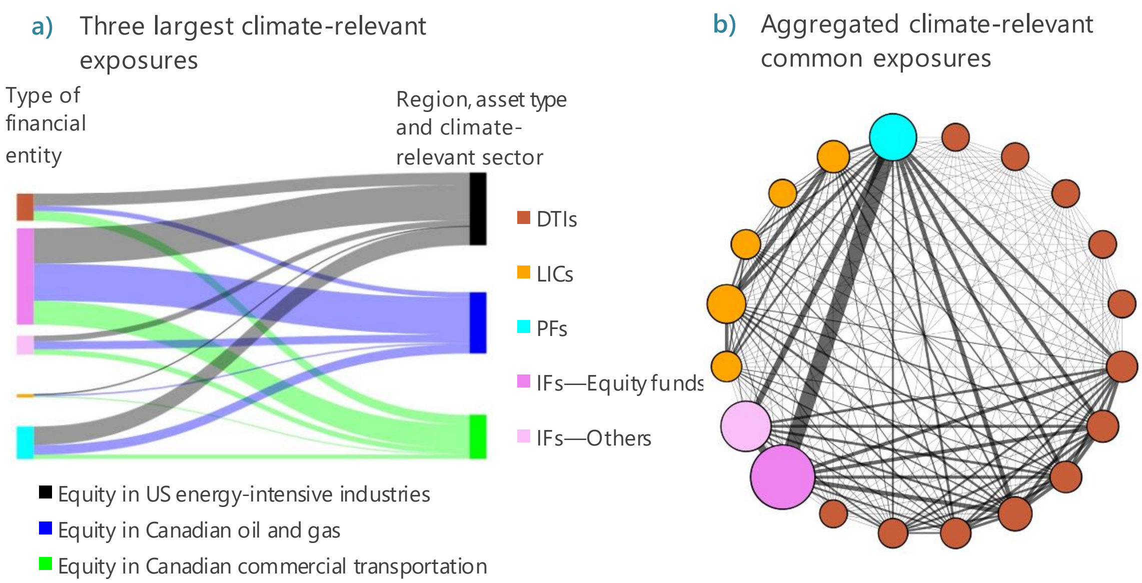
Sources: Office of the Superintendent of Financial Institutions; Autorité des marchés financiers; proprietary data from Canadian pension funds; Lipper, a Refinitiv Company; Eikon, a Refinitiv Company and Bank of Canada calculations
Last observations: deposit-taking institutions, life insurance companies, investment funds and most pension funds, December 2021; remaining pension funds, March 2022

fire sales. For example, despite pension funds holding approximately 15% of their assets in climate-relevant sectors, most of these assets are not publicly traded (**Chart 1**, panel c), limiting their exposure to contagion and fire sales.

The three largest common exposures are held primarily by deposit-taking institutions, pension funds and investment funds (mainly equity funds), mostly through their equity positions in both energy-intensive industries in the United States and in oil and gas and commercial transportation in Canada (**Chart 2**, panel a). **Chart 2**, panel b shows the aggregation of linkages for all financial system entities across all public asset types, climate-relevant sectors, and regions. The larger the node, the more an institution is exposed through climate-relevant assets. The thicker the line, the larger the common exposure among entities. Large common positions among different financial entities represent stronger connections, which in turn potentially play a role in shock transmission and spread. Pension funds, the six largest deposit-taking institutions, and investment funds have the strongest common exposure connections. **Chart 2**, panel b also highlights the potential role of investment funds, especially equity funds, in acting as climate transition shock propagators in the Canadian financial system.

Chart 2: Climate-relevant common exposures across the Canadian financial system

Public assets only, by region, asset type and climate-relevant sector



Note: DTIs are deposit-taking institutions; LICs are life insurance companies; PFs are pension funds; IFs are investment funds.

Sources: Office of the Superintendent of Financial Institutions; Autorité des marchés financiers; proprietary data from Canadian pension funds; Lipper, a Refinitiv Company; Eikon, a Refinitiv Company; and Bank of Canada calculations
Last observations: DTIs, LICs, IFs and most PFs, December 2021; remaining PFs, March 2022

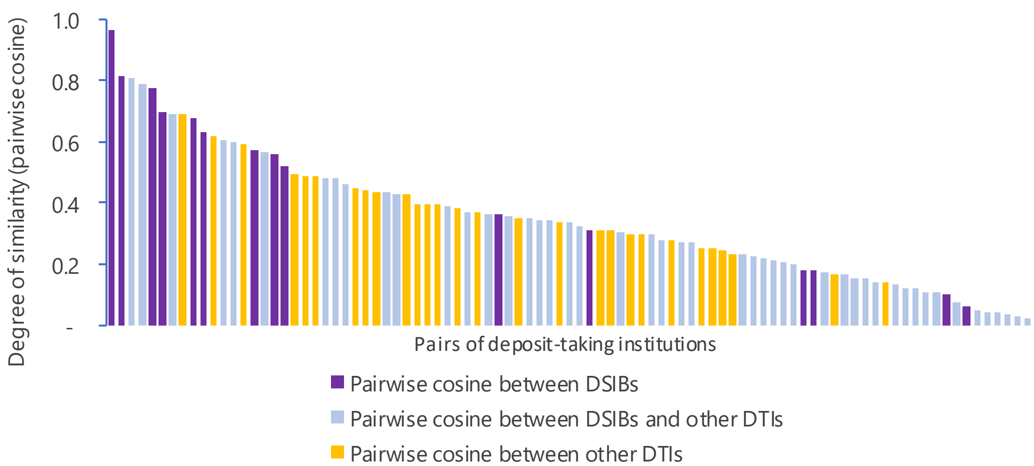
The following three charts shed light on some of the transmission and propagation channels discussed in section 2—namely business similarities, cross-holding positions and interbank and intersectoral lending. As discussed in section 2, these channels help inform our understanding of the financial system's connectivity as well as how a shock, such as a climate transition shock, may spread among entities.

Business similarities

We use cosine similarity to assess business similarities. **Chart 3** shows the pairwise cosine measures for the balance sheet items (e.g., equities) of the deposit-taking institutions in our study. Most pairwise cosine measures between each of the six largest Canadian banks (known as domestic systemically important banks, or DSIBs) and the other deposit-taking institutions are below 0.4, suggesting mild business similarities.[21] However, the situation is different among the six largest Canadian banks themselves. The average cosine measure is about 0.5, and nine pairwise measures exceed this average, suggesting strong business similarities among the six DSIBs. Because of this, if any of these entities were to experience financial distress due to a climate transition shock, they would likely face higher funding costs given their perceived similar risk exposure. For life insurance companies (not shown in Chart 3), we find strong business similarities among them, with all cosine measures exceeding 0.95. This implies that they would also experience potential increases in funding costs should one of them face solvency issues.

Chart 3: Business similarities across deposit-taking institutions

Pairwise cosine measures between deposit-taking institutions, ordered from largest to smallest



Note: DSIBs are domestic systemically important banks; DTIs are deposit-taking institutions.

Sources: Office of the Superintendent of Financial Institutions, Autorité des marchés financiers and Bank of Canada calculations
Last observation: December 2021

Cross-holding positions

Table 3 shows the level of cross-holding positions among different types of financial entities of the Canadian financial system. It shows that investment funds invest heavily in each

[21] Values range from 0 to 1, where 1 indicates identical allocation of balance sheet items and 0 indicates completely different allocations. Details of the construction of this measure are provided in Hałaj (2018).

other—up to 30% of their portfolios are composed of shares of other investment funds. Should these funds be impacted by a climate transition shock, they could act as a potential source of transmission and amplification. **Table 3** also highlights several data gaps that hinder our ability to obtain a complete picture of the cross-holding positions within the Canadian financial system.

Table 3: Level of cross-holding positions among financial system entities

Percentage of total assets, by type of asset and holding entity

		Type of entity—issuer				
Type of asset	**Type of entity—holder**	**Deposit-taking institutions**	**Life insurance companies**	**Pension funds***	**Investment funds**	**Total**
Debt	DSIBs**	0.11	0.01	0.11	0.01	0.23
	Life insurance companies	0.62	0.04	0.03	—	0.69
	Pension funds*	—	—	—	—	—
	Investment funds	2.12	0.24	0.08	—	2.44
Shares	DSIBs**	0.34	0.03	n/a	0.03	0.40
	Life insurance companies	0.50	0.07	n/a	0.04	0.61
	Pension funds	—	—	n/a	0.98	0.98
	Investment funds***	3.18	0.53	n/a	30.32	34.03

* Debt issued by pension funds is not presented due to study's exclusion of liability data.
** Data on cross-holding positions are available only for domestic systemically important banks (DSIBs).
*** Investment funds as a type of holder are restricted to open-ended mutual funds and exchange-traded funds domiciled in Canada. Depending on the data source used, investment funds as a type of issuer may include real estate funds or other funds.

Sources: Office of the Superintendent of Financial Institutions; Autorité des marchés financiers; proprietary data from Canadian pension funds; Lipper, a Refinitiv Company; Eikon, a Refinitiv Company; and Bank of Canada calculations
Last observations: deposit-taking institutions, life insurance companies, investment funds and most pension funds, December 2021; remaining pension funds, March 2022

Interbank and intersectoral lending

The level of interbank and intersectoral lending among DSIBs, and between DSIBs and pension funds, is shown in **Table 4**. We shed light on these types of entities because of their important role in the lending space of the Canadian financial system. Our analysis suggests that this is not an important potential propagation channel, as represented by their relatively low shares of total expected liquidity outflows of DSIBs and pension funds. Of note, the fact that our shock affects the asset side only may also explain the low relevance of this channel.

Table 4: Interbank and intersectoral lending

Percentage of total expected liquidity outflows of the borrower, by type of entity

	Type of entity—lender	
Type of entity—borrower	**DSIBs***	**Pension funds**
DSIBs*	1.01	1.71
Pension funds	6.93	—

*DSIBs are domestic systemically important banks. Non-DSIBs were not considered due to a lack of data on their intersectoral lending or borrowing counterparties.

Sources: Office of the Superintendent of Financial Institutions, proprietary data from Canadian pension funds; and Bank of Canada calculations
Last observations: DSIBs and most pension funds, December 2021; remaining pension funds, March 2022

2.3. 2°C delayed climate transition scenario

Scenario analysis is a tool that is used to deal with a high degree of uncertainty. Climate transition risks - in particular - have long time horizons with high uncertainty about how policy, technology and socio-economic factors might evolve.

Hence, the scenarios developed for this exercise are not meant to be forecasts or to be comprehensive. They explore plausible but intentionally adverse global transition pathways consistent with achieving specific climate targets.

The purpose was to look at stressful scenarios, where the transition relies on significant structural change at the industry level and capture how climate transition factors may drive changes in the economy and the financial system. As such, the scenarios rely conservatively on future technology availability and public policy measures that could ease the transition.

The scenarios are aligned with those developed by the Network for Greening the Financial System - the NGFS - that are currently being used by other central banks and supervisors for climate-related risk assessment purposes. The alignment is generally in terms of the scenario narratives as well as in terms of the paths of global emissions and carbon price.

However, the Bank developed its own scenarios for the pilot to provide economic and financial data at the relevant geographic and sectoral level for the Canadian economy and financial system. Finally, our scenarios focus just on climate transition risk – not on climate physical risk – and are driven by global climate policy action – not just domestic action.[22]

The scenarios vary in two broad dimensions: first, the ambition and timing of global climate policy, and second, the technological change. The first scenario is our reference or baseline

[22] For recent Bank staff work on physical-related climate risk, see Johnston et al. (2023).

scenario. It reflects climate policies in place at the end of 2019. At the time of the pilot, we took this point in time to abstract from the effects of COVID. This baseline scenario implies a continued rise in emissions and an increase in average global temperature in the range of 2.9 to over 3 degrees Celsius by end of century. **Table 5** summarizes the different assumptions in the climate scenarios.

The scenario employed to measures losses compared to the baseline is the 2°C delayed scenario, where global action to limit global warming to below 2 degrees Celsius is delayed by 10 years – starting in 2030. This scenario takes full advantage of commercially available technologies – such as wind, solar, electric vehicles, and energy efficiency improvements and limited reliance on negative emissions technologies. The scenario can't rely on technologies that are not yet commercially available or face scalability issues. Table 5 summarize the main characteristics of the scenarios used in this study.

The main model used to build our scenarios is the Economic Projection and Policy Analysis – or EPPA model - developed at the MIT. The EPPA model provides projections of world economic development at a multi-country and multi-sector level, including the economic implications of greenhouse gas emissions, conventional air pollution, land-use change, food demand, and natural resource use. It also has a rich representation of technologies. This model has the ability to capture the sectoral restructuring along the transition. More information about the regional and sectoral coverage of the EPPA model can be found in Chen et al. (2022).

Table 5: Scenarios employed to build the market, credit and liquidity shocks

Scenario	Climate policy ambition and timing	Technological change
Baseline (2019 policies)	The world follows a path consistent with climate policies in place at the end of 2019, implying a continued rise in emissions and an increase in average global temperature in the range of 2.9–3.1°C by 2100. Forestry continues on a global trend of being a net source of emissions through mid-century.	The pace of technological change is slow. The availability of carbon dioxide removal (CDR) technologies is limited.
Below 2°C delayed	After a decade of following 2019 policy frameworks, collective global action to align with a 2oC target begins in 2030. A steeper transition is needed to make up for the additional decade of a continued rise in emissions. Delayed investments, planning and management prohibit forests from becoming a net sink by mid-century.	The pace of technological change is moderate. The availability of CDR technologies is limited.

The output of the EPPA model is employed to generate price changes in equity instruments via a dividend discount model, a change in the probability of default (PD) via a Merton model and a change in the Loss Given Default(LGD) via a Frye-Jacobs relationship with the PD. For the sake of brevity and due to the aim of this study focuses on the propagation mechanisms of Canadian financial system, we refer to Hosseini et al. (2022) for a detailed formulation of the price and PD change equations.

Including liquidity risk is key in understanding systemic risk. The **liquidity risk assessment method** is another extension of the pilot project's methods. Consistent with the goals of this study, the inclusion of a liquidity risk channel can inform us of the difficulties entities may face in meeting their short-term financial obligations. This could be due to an inability to convert their assets into cash without incurring a substantial loss. Specifically, we examine the liquidity held by financial system entities before the climate transition shock and their liquidity needs after the shock.

The liquidity held by a given entity is determined by weighting its asset positions by a Basel III-based liquidity factor.[23] We calculate liquidity measures for deposit-taking institutions, open-ended mutual funds (for investment fund entities) and pension funds. We assume that the cash flow on the liquidity coverage ratio framework for deposit-taking institutions follows the run-off rate from OSFI and the Autorité des marchés financiers (AMF) net cumulative cash flow returns. For open-ended mutual funds, we use historical data to estimate the expected cash outflows through redemptions. Finally, while pension funds have predictable outflows to pay their beneficiaries, they face relatively less-predictable liquidity constraints from their derivative positions.[24] Because of this, increased liquidity needs for derivatives positions are captured by a volatility-based measure (Standard Portfolio Analysis of Risk, or SPAN) for equity-related derivatives and a Monte Carlo simulation for debt-related derivatives.[25]

3. Illustrative application on climate transition shocks

3.1. Key assumptions

To support the interpretation of the findings generated from our application of the framework, we note key data constraints and other analytical limitations. Our suite-of-model data requirements and our efforts to secure a representative sample of financial entities within the scope of our study encountered some challenges, including data quality, granularity and availability. Therefore, several assumptions were needed to apply the methodological framework.

Notably, our analysis lacks detailed asset-level information, especially for identifying assets impacted by climate-relevant sectors of the Canadian economy. This is particularly evident for

[23] See Bank for International Settlements (2013).
[24] See Bédard-Pagé et al. (2021).
[25]. Appendix contains the details to generate the liquidity shocks in derivative markets.

federally regulated deposit-taking institutions and life insurance companies. For deposit-taking institutions, some regulatory return categories do not align well with our classification of climate-relevant sectors.[26] For life insurance companies, data on private equities are available but not usable in our framework because the classification system used in the returns cannot be leveraged for climate analysis. In contrast, our data partnerships with the AMF and Canadian pension funds provide detailed asset-level information on climate-relevant sectors. However, these partnerships are time-limited.

Beyond the data challenges, the application of the framework faces several analytical limitations.[27] The analysis focuses only on climate transition risk, excluding other concurrent shocks related to physical impacts of climate change.[28] Our study also excludes other transition-related implications on inflation, interest rates and real economy feedback loops. It focuses on the asset side of the balance sheet, not the liability side, which can also be affected by climate transition. Moreover, while we do include a wide range of assets, not all assets and sectors potentially impacted by climate transition are considered, such as infrastructure, real estate and sovereign bonds. Furthermore, while market intelligence gathering with financial system entities and authorities allows us to include some behavioural rules in the ABM, the main sources of reaction and decision are the key metrics (e.g., total assets, liquidity coverage ratios).[29] Lastly, a static balance sheet is assumed for analytical tractability, limiting portfolio adjustments in response to changing conditions. The static balance sheet assumption serves as a reasonable approximation of an entity's response in the short term, though it can misrepresent an entity's planning around the climate transition to mitigate potential losses.

3.2. Results

The charts in this section show the results from applying our methodological framework. These charts illustrate findings on both the direct effects (through scenario analysis) and systemic effects (through agent-based modelling) after the climate transition shock has occurred. Recall that the shock used in this study originated from the most stressful climate transition scenario—the **below 2°C delayed** scenario. The shock's impacts shown in the charts in this section are relative to the baseline scenario (2019 policies).

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[26] For instance, the OSFI B2 return includes security holdings in the entire manufacturing sector, which comprises both climate-relevant and non-climate relevant sectors. To estimate holdings in each subsector, we assume that the securities' share aligns with the subsector's securities share in the overall non-financial corporate securities market.
[27] On climate data gaps, more broadly, as part of its work on climate, OSFI issued its draft "Climate Risk Returns for Federally Regulated Financial Institutions (FRFIs)" for industry consultation in June 2023. Once finalized, the returns will collect climate-related data elements directly from FRFIs, representing an important milestone for the quantification of potential exposures. The draft was designed in partnership with the Bank of Canada and the Canada Deposit Insurance Corporation. A report on the consultations, which closed on September 30, 2023, will be published in early 2024.
[28] For recent Bank staff work on physical-related climate risk, see Johnston et al. (2023).
[29] Further, consistent with the objectives of this study, we assume a horizontal slicing approach in the selling strategy, because this approach generates larger losses from the fire sales. More information about selling strategies is provided in Arora and Ouellet Leblanc (2018).

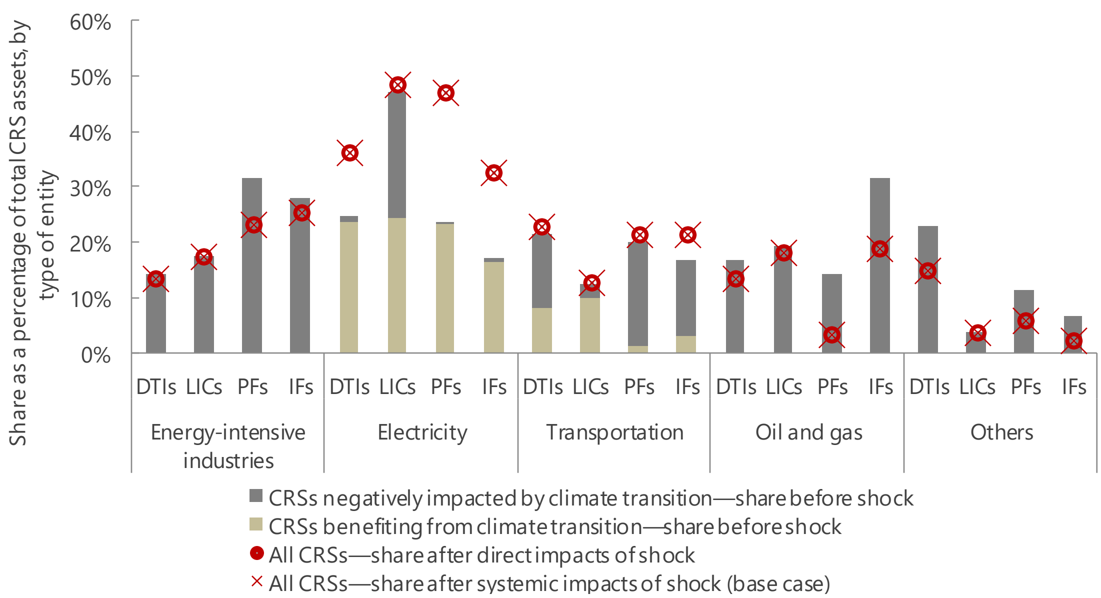
Investment allocation across climate-relevant sectors

Chart 4 presents the asset allocations across climate-relevant sectors for each type of financial entity. The grey and tan bars show the initial share of climate-relevant sector assets before the climate transition shock. Deposit-taking institutions, life insurance companies and pension funds exhibit similar asset allocations in sectors that benefit from our transition scenarios, with about one-third of their climate-relevant assets invested in these sectors. In contrast, investment funds have the smallest stake in these sectors, with less than one-fifth of their climate-related assets allocated in these sectors.

Chart 4 also shows how both the direct effects (red circles) and systemic effects (red Xs) of the climate transition shock can change the weighting of climate-relevant sectors relative to the total climate-related holdings of different financial entity types. Because we assume static balance sheets, changes to asset valuations in each sector after the shock change the relative weight of that sector in the entities' portfolios. As asset valuations fluctuate because of the shock, the shares of exposures to sectors that benefit from the transition scenarios increase. This is the case for deposit-taking institutions, life insurance companies and pension funds in the electricity sector. However, despite their important exposure to this sector, life insurance companies' shares increase less than those of pension funds, given that life insurance companies invest more heavily in bonds. Bonds generally fluctuate less in our transition scenarios compared with equities, which are more sensitive to changes in expected future cash flows and discount rates (shown later in **Chart 7**, panel b).

Chart 4: Share of exposures by type of climate-relevant sector

Each type of entity sums to 100%, impacts are percentage-point change, relative to baseline



Note: CRS is climate-relevant sector; DTIs are deposit-taking institutions; LICs are life insurance companies; PFs are pension funds; IFs are investment funds.

Sources: Office of the Superintendent of Financial Institutions; Autorité des marchés financiers; proprietary data from Canadian pension funds; Lipper, a Refinitiv Company; Eikon, a Refinitiv Company; and Bank of Canada calculations

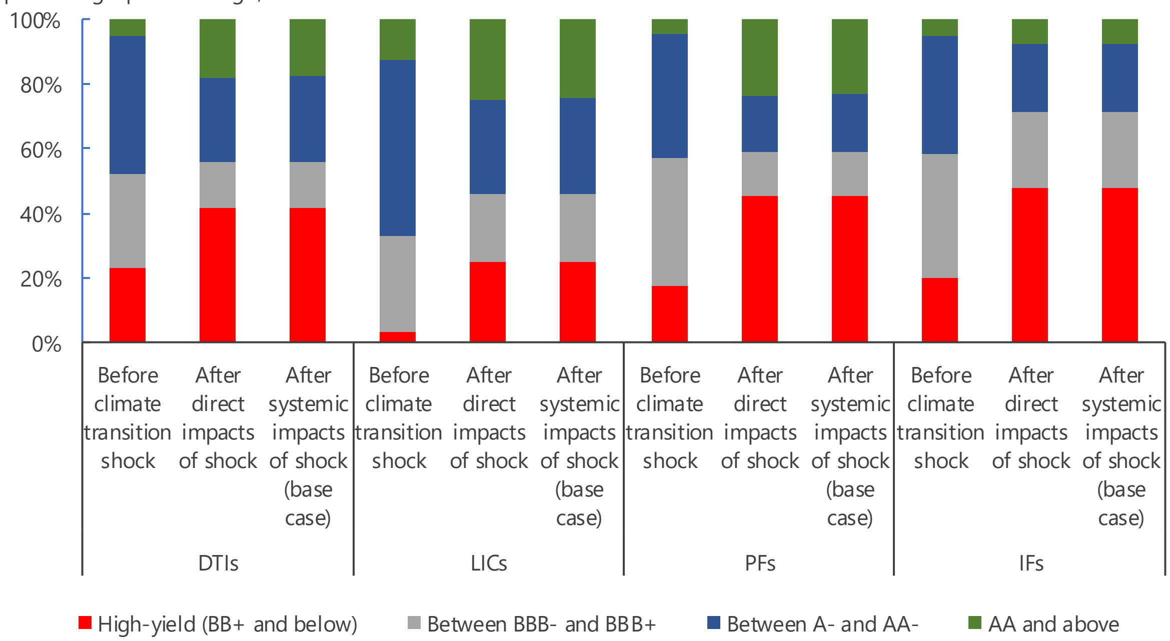
Last observations: DTIs, LICs, IFs and most PFs, December 2021; remaining PFs, March 2022

Allocation of debt holdings by credit rating

Financial entities' risk-taking behaviour concerning their climate-relevant assets also sheds light on the potential effects of a climate transition shock.[30] **Chart 5** and **Chart 6** illustrate the role of this informative dimension for climate-relevant bonds as well as climate-relevant loans and private debt. Life insurance companies hold 95% of their pre-shock climate-relevant bonds and loans allocation in the investment-grade space. Pension funds, meanwhile, exhibit a riskier pre-shock investment profile, with a significant portion of their climate-relevant private debt falling into the high-yield space.[31] Investment funds also hold a notable percentage of their climate-relevant corporate bond portfolio in high-yield securities.

Chart 5: **Share of climate-relevant bond exposures, by bond credit rating**

Percentage of total climate-relevant corporate bonds, weighted average for each type of entity, impacts are percentage-point change, relative to baseline



Note: DTIs are deposit-taking institutions; LICs are life insurance companies; PFs are pension funds; IFs are investment funds.

Sources: Office of the Superintendent of Financial Institutions; Autorité des marchés financiers; proprietary data from Canadian pension funds; Lipper, a Refinitiv Company; Eikon, a Refinitiv Company; and Bank of Canada calculations
Last observations: DTIs, LICs, IFs and most PFs, December 2021; remaining PFs, March 2022

Charts 5 and 6 also show that the allocation of credit risk becomes riskier as the climate-relevant bonds and loans are negatively impacted by the climate transition shock, migrating

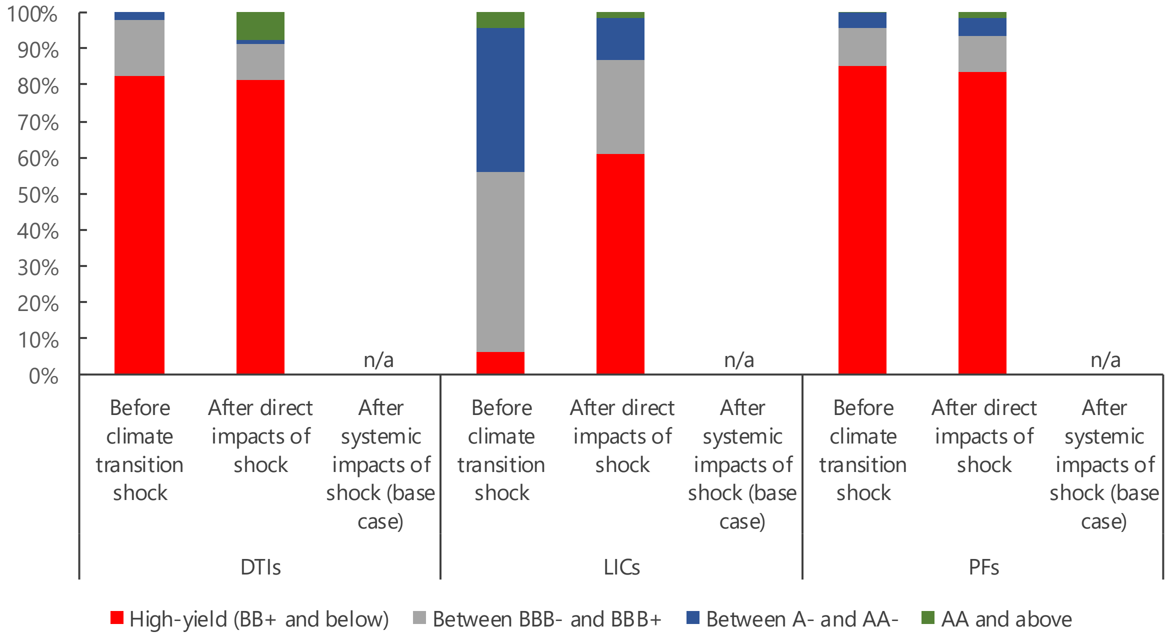
[30] In this study, the riskiness of an asset is based on its credit rating. Higher credit ratings indicate lower risk and higher credit quality, while lower credit ratings indicate higher risk and lower credit quality.

[31] This corroborates a trend that indicates pension funds are taking more risk in private markets. However, through the negotiation of covenants, pension funds have a tighter hold on the terms of private debt contracts. For example, contract terms may incorporate details around a firm's climate transition plans, serving to mitigate climate-related risk.

from investment-grade to the high-yield credit rating (shown in the charts by the increasing length of the red bars after the climate shock). This is particularly evident in the average risk profile of climate-relevant bond portfolios of pension funds and investment funds. Conversely, the credit ratings of climate-relevant assets in those sectors that stand to benefit from the transition see an improvement following the direct impacts (shown by the increasing length of the green and blue bars in **Chart 5** and **Chart 6**). This is particularly noteworthy for all entity types except investment funds, given their exposure to sectors that benefit from the transition.

Chart 6: Share of climate-relevant loan and private debt exposures, by loan or private debt credit rating

Percentage of total climate-relevant corporate loans and private debt, weighted average for each type of entity, impacts are percentage-point change, relative to baseline



Note: No systemic impacts occur for loans and private debt because of the absence of trade in secondary markets. DTIs are deposit-taking institutions; LICs are life insurance companies; PFs are pension funds; IFs are investment funds.

Sources: Office of the Superintendent of Financial Institutions; Autorité des marchés financiers; proprietary data from Canadian pension funds; and Bank of Canada calculations
Last observations: DTIs, LICs, IFs and most PFs, December 2021; remaining PFs, March 2022

Credit, market and liquidity risk impacts

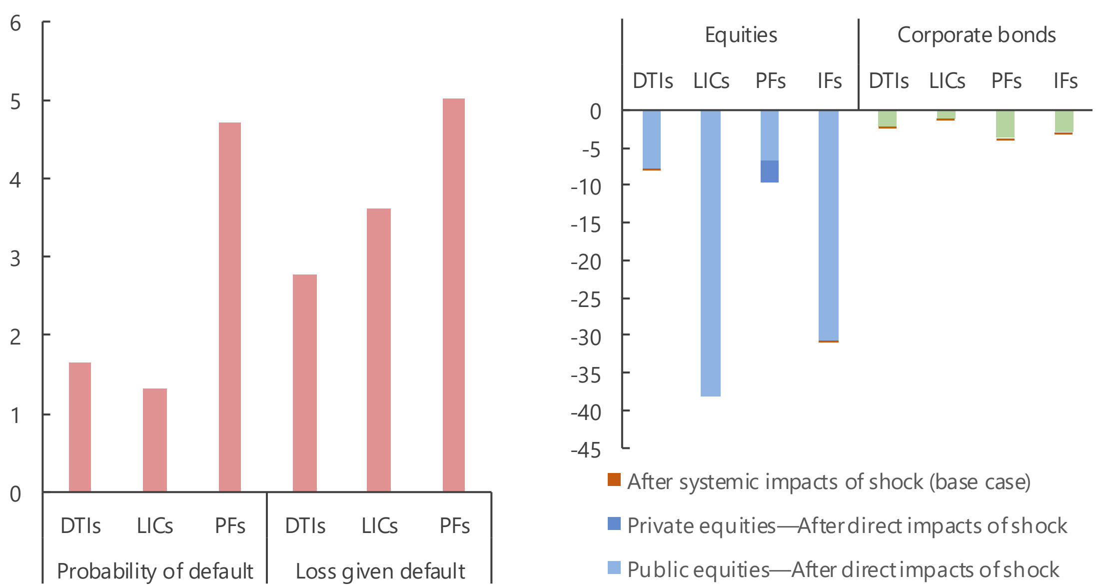
Chart 7 shows the direct effects on credit and market risks for the portfolios held by financial system entities after the climate transition shock. Deposit-taking institutions face a notable increase in credit risk in their climate-relevant loans portfolio (**Chart 7**, panel a). Their climate-relevant equities also experience significant market valuation impacts, while the effects on bonds are relatively minor (**Chart 7**, panel b). However, as we show later, the valuation of total assets in deposit-taking institutions' portfolios are not materially affected due to their relatively low initial exposure to climate-relevant assets.

Life insurance companies experience lower credit risk impacts than deposit-taking institutions, which is consistent with their allocation of climate-relevant assets and risk-taking behaviour. Moreover, despite a considerable decrease in equity valuations, the overall impact is small due to life insurance companies' limited investment in climate-relevant equities. Pension funds' riskier investment profile contributes to the potential for greater losses, with a substantial increase in the average probability of default on their climate-relevant private debt portfolio. However, they face a relatively smaller decline in their average climate-relevant equity valuations, primarily from their public equity portfolio. Like other entities, investment funds show moderate credit risk impacts but face significant decline in their equity valuations.

Chart 7: Direct and systemic credit and market risk impacts on climate-relevant assets
Percentage-point change, relative to baseline, weighted average of climate-relevant assets, by type of entity

a) Probability of default and loss given default, climate-relevant corporate loans and private debt

b) Market valuations, climate-relevant corporate bonds and equities

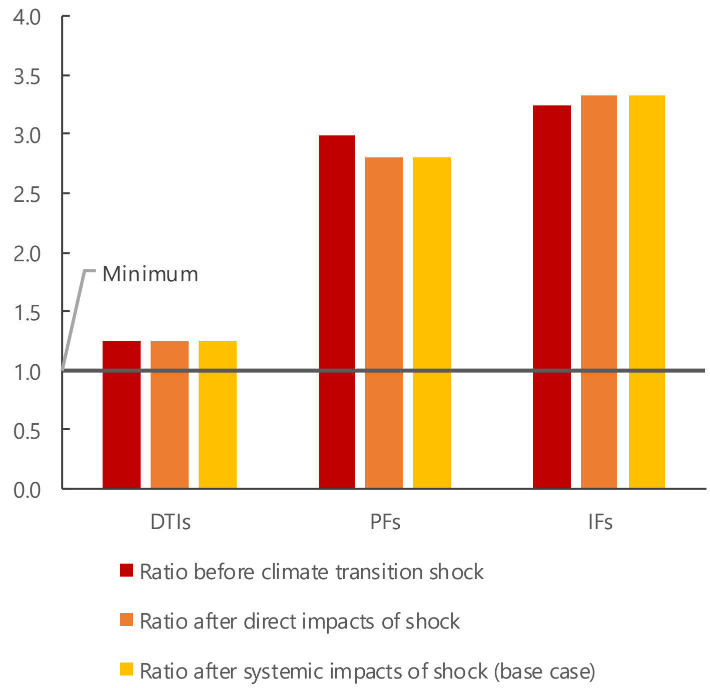


Note: No systemic impacts occur for loans and private debt because of the absence of trade in secondary markets. DTIs are deposit-taking institutions; LICs are life insurance companies; PFs are pension funds; IFs are investment funds.

Sources: Office of the Superintendent of Financial Institutions; Autorité des marchés financiers; proprietary data from Canadian pension funds; Lipper, a Refinitiv Company; Eikon, a Refinitiv Company; and Bank of Canada calculations
Last observations: DTIs, LICs, IFs and most PFs, December 2021; remaining PFs, March 2022

A financial system's vulnerability to a climate transition shock may also be informed by impacts on the liquidity ratios of the different entities. **Chart 8** assesses how the liquidity ratio is impacted by the revaluation of assets, and in the specific case of pension funds, by the losses and margin calls from their derivatives exposures. It shows that liquidity ratios for all types of financial entities remain, on average, well above the threshold for the liquidity coverage ratio for deposit-taking institutions or expected outflows for pension funds and investment funds. This suggests that the financial entities have adequate liquidity to meet their obligations and cope with potential shocks.[32]

Chart 8: Direct and systemic impacts on liquidity ratios
Liquidity coverage ratios, by type of entity



Note: DTIs are deposit-taking institutions; LICs are life insurance companies; PFs are pension funds; IFs are investment funds.

Sources: Office of the Superintendent of Financial Institutions; Autorité des marchés financiers; proprietary data from Canadian pension funds; Lipper, a Refinitiv Company; Eikon, a Refinitiv Company; and Bank of Canada calculations
Last observations: DTIs, LICs, IFs and most PFs, December 2021; remaining PFs, March 2022

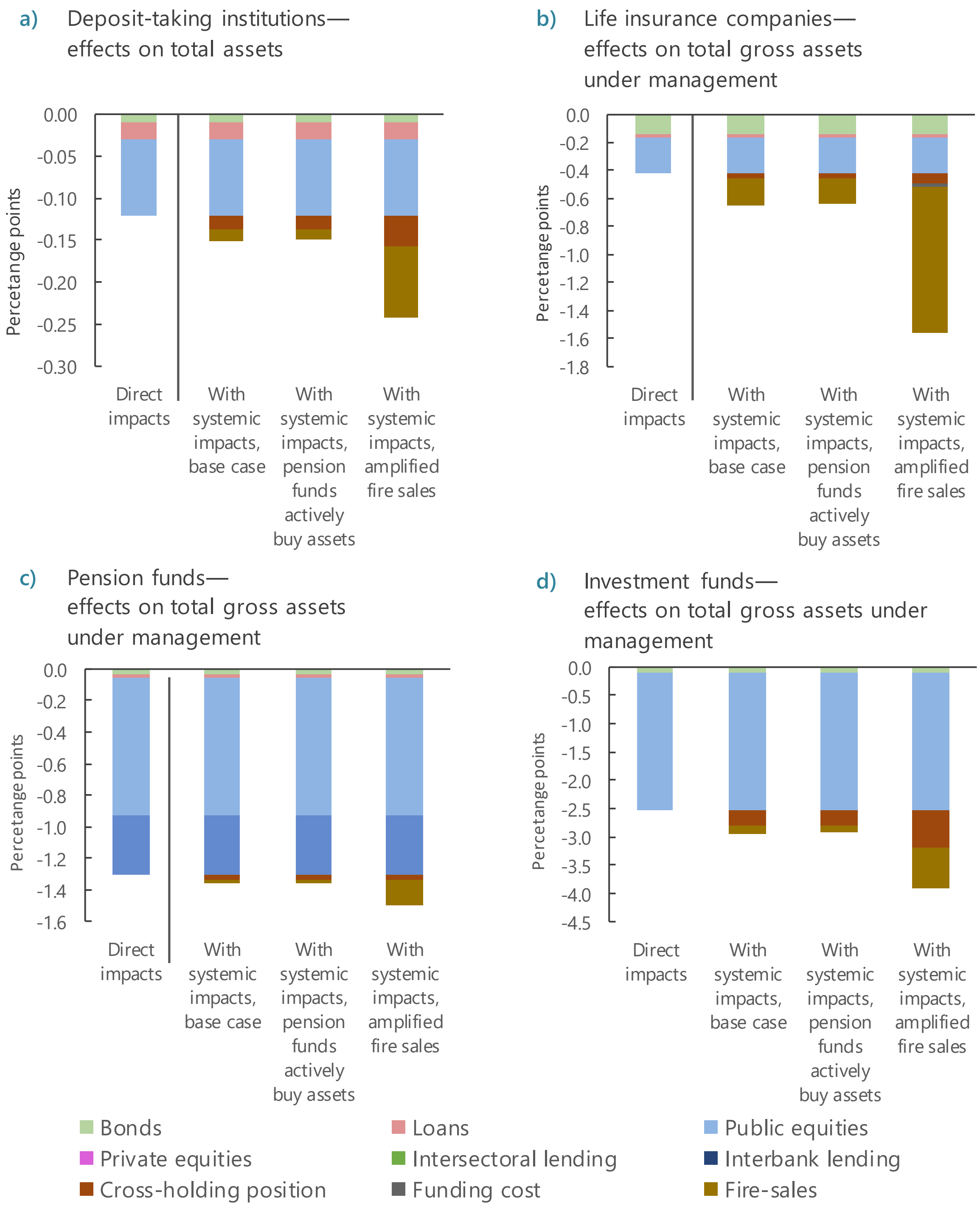
Asset valuation impacts by transmission channel

The panels in **Chart 9** show the changes in total asset valuations for different financial entities' portfolios. For deposit-taking institutions, life insurance companies and pension funds, the total asset valuations experience a minor to milder decline after the direct effects of the climate transition shock (first column in all panels). The deposit-taking institutions' relatively low initial exposure to climate-relevant assets, and life insurance companies' and pension funds' diversified portfolios, help mitigate direct impacts. Investment funds, in contrast, face greater direct effects, with a notable decline in their total gross assets under management, especially for equity funds.[33]

[32] See Appendix D for technical details about the liquidity risk methodology used in this study.
[33] Additional findings for investment funds, including the larger decline for equity funds, are shown in Appendix C.

Chart 9: Direct and systemic effects on total assets

Percentage-point change, relative to baseline



Sources: Office of the Superintendent of Financial Institutions; Autorité des marchés financiers; proprietary data from Canadian pension funds; Lipper, a Refinitiv Company; Eikon, a Refinitiv Company; and Bank of Canada calculations

Last observations: deposit-taking institutions, life insurance companies, investment funds and most pension funds, December 2021; remaining pension funds, March 2022

Though we observe mild direct effects of the climate transition shock, systemic effects may amplify these initial losses. To provide insights around this finding, the panels in **Chart 9** also present the transmission channels under the three alternative fire sale cases discussed in section 2:

- **base case**—baseline parametrization for fire sales in our agent-based model
- **pension funds actively buy assets**—pension funds actively buy climate-transitioning assets (i.e., assets that may help with the climate transition) sold by investment funds facing liquidity needs
- **amplified fire sales**—asset sales (mainly by investment funds) have a bigger effect on the falling asset prices, reflecting the non-linearities between selling volumes and price changes

Our analysis shows that even in the base case, mild direct effects—mostly triggered by fire sales—can increase significantly when accounting for these channels. While pension funds can lessen systemic effects through their active buying, the purchases are not large enough to absorb all undervalued assets. Finally, in the amplified fire sales case, the fallout from fire sales is significantly larger, triggering an increase in funding costs for life insurance companies and doubling the impact on investment funds' cross-holding positions.

Tracing back systemic effects by type of financial system entity

Chart 10 presents a breakdown of systemic effects of the climate transition shock by type of financial system entity. It traces these effects back to the type of entity that caused them. For example, in our fire sales base case, approximately 20% of investment funds' losses caused by systemic channels are attributable to the role of deposit-taking institutions.

In our fire sales base case, the climate transition shock prompts only investment funds to conduct fire sales. This sudden sell-off of assets leads to a decrease in asset prices, causing a devaluation of similar assets held by other financial system entities, thereby spreading the impacts across the financial system. **Chart 10**, panel a shows that most systemic effects in our framework application can be traced back to investment funds, with the effects for life insurance companies and pension funds primarily attributable to investment funds.

Chart 10, panel b shows the financial system's vulnerabilities related to its network connections following the climate transition shock. The node size represents the systemic impact on each entity, standardized by the entity's total assets.[34]

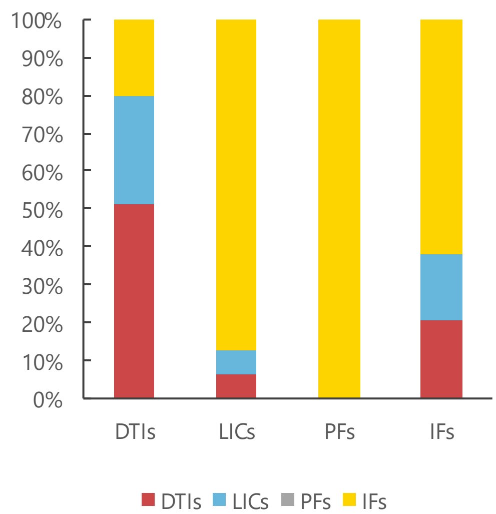
The chart also delineates the pathways of both direct and systemic impacts, tracing them back to their originating institutions. Blue lines indicate increases in total asset valuations. For

[34] The standardization prevents the bias toward the largest institutions. Notably, a large institution could suffer a higher impact in absolute terms, though proportionally, the hit might be less material than the one suffered by other smaller institutions.

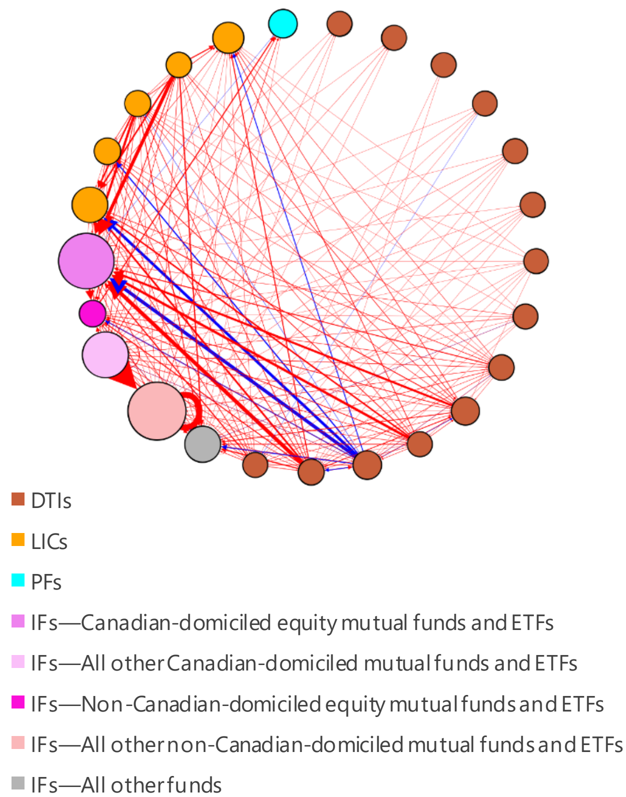
example, deposit-taking institutions (DTIs) that benefit from the transition will contribute to increases in the asset valuations of investment funds and life insurance companies that hold shares in the DTIs. Conversely, red lines indicate losses, including those stemming from the systemic effects from cross-holding positions or fire sales.

Chart 10: Origination of systemic effects by entity type

a) Aggregated origination of systemic effects (base case) by entity type



b) Directional origination of systemic effects (base case) by entity type



Note: DTIs are deposit-taking institutions; LICs are life insurance companies; PFs are pension funds; IFs are investment funds.

Sources: Office of the Superintendent of Financial Institutions; Autorité des marchés financiers; proprietary data from Canadian pension funds; Lipper, a Refinitiv Company; Eikon, a Refinitiv Company; and Bank of Canada calculations
Last observations: DTIs, LICs, IFs and most PFs, December 2021; remaining PFs, March 2022

Additionally, the investment funds are broken down into five distinct fund types, differentiating between equity mutual funds/exchange-traded funds (ETFs) and non-equity mutual funds/ETFs, such as mixed assets, bonds and alternatives. This categorization helps assess how these funds' investment strategies may affect shock propagation. We also separate Canadian from foreign investment funds. **Chart 10**, panel b reveals that Canadian equity mutual funds/ETFs exhibit greater vulnerability than their foreign counterparts, as indicated by the larger node sizes. In contrast, non-equity funds demonstrate comparable levels of vulnerability both domestically and internationally.

Foreign investment funds are shown to play a significant role in transmitting systemic impacts, evidenced by the numerous arrows emanating from these nodes. For instance, the most substantial line connecting to the pension fund node originates from foreign equity funds. Notably, investment funds act as conduits for shock transmission across financial institutions, linking entities without direct cross-holding relationships. This is exemplified by the profits (**Chart 10**, panel b, blue arrows) flowing from the banking sector to Canadian equity funds, which hold shares in the DTIs. A thinner blue line from the Canadian equity funds to the pension fund node illustrates the interconnection between the banking sector and pension funds, mediated by the pension funds' stakes in investment funds, which in turn possess shares of the banking sector.

4. Conclusion

We develop a methodological framework to inform the understanding of the propagation of shocks across the financial system. This framework relies on an agent-based model fed by input data from a scenario analysis, allowing us to gain insights into the direct effects and systemic implications of the materialization of different kind of shocks. We apply the framework to Canadian financial system data to help draw financial stability insights after a climate transition shock.

The application of the framework deepens our understanding of how climate transition risk may directly impact distinct financial system entities. We explore factors such as the entities' exposures to climate-relevant assets, risk-taking behaviour, size and investment horizon, business models and asset mixes (e.g., whether the entities are active in public or private markets). This gives us greater insight into how distinct financial entity types are impacted by and may respond to climate transition risk.

Our application shows that although systemic factors may spread and amplify the direct effects of a climate transition shock, assessing the initial exposures of climate-related sectors provides insight into the risks that financial entities face. Evaluating portfolio allocations by sector and asset type reveals how entities' exposures to sectors that benefit from the transition may make some entities less susceptible to transition shocks.

The size of the financial system entity also plays an important role in its ability to understand and adapt to climate shocks. Larger entities often have more diversified portfolios and further developed capacities to assess climate risk, making them better equipped to navigate the challenges posed by transition shocks. Other factors, such as the entity's risk management strategies, sectoral focus, and regulatory environment, also play a role.

Investment horizons are another factor in understanding transition risk. Entities with long investment horizons like pension funds and life insurance companies may act as dampeners within the financial system during a transition shock. Their long-term focus, evidenced by the longer average maturity of their assets relative to other entities, may lead them to seek bargains in sectors negatively impacted by the transition shock, thereby acting as a stabilizing force. In contrast, deposit-taking institutions, and particularly investment funds, may have the opposite effect. Shorter investment horizons, and dependence on more fragile funding sources for investment funds, lead these entities to become procyclical and increase volatility in fire-sale environments.

In addition, our analysis sheds light on how shocks may spread across entity types and potentially create systemic implications. Notably, common exposures help to identify the degree of portfolio interconnectedness in the financial system. Further, despite low initial direct exposures and financial impacts on financial system entities, some transmission channels such as cross-holding positions and fire sales may amplify direct effects. In addition, depending on the type of financial system entity, we find that some are more prone to act as a propagator of a transition shock in the financial system (i.e., investment funds) rather than a shock absorber (i.e., pension funds).

Our study also highlights several analytical challenges and limitations. Data challenges were a primary limitation in this study. The analysis excludes other types of risks that could occur concurrently with or compound the climate transition risk (e.g., climate-related physical risk, and transition-related inflation risk, interest rate risk, and real economy feedback loops). It also does not include some types of assets and economic sectors that could be sensitive to climate transition shocks (e.g., residential and commercial real estate, sovereign bonds, commodities, and mining sectors others than coal). Further, we do not include the liability side of balance sheets/portfolios for most of the financial institutions (partly due to data limitations) and assume a static balance sheet.

Our insights and limitations underscore the need for further analytical efforts that encompass a broader range of asset types and sectors. This can help provide a more comprehensive understanding of the impact of financial risks across the financial landscape. This work does strengthen our knowledge of how distinct financial system entities may be impacted by and respond to financial risks and opportunities, and of the potential channels through which those risks and opportunities may spread across the financial system. More generally, our work contributes to building standardized systemic risk assessment and monitoring tools.

References

Abad, J., M. D'Errico, N. Killeen, V. Luz, T. Peltonen, R. Portes T. and Urbano. 2022. "Mapping Exposures of EU Banks to the Global Shadow Banking System." *Journal of Banking & Finance* 134:106168.

Acemoglu, D., A. Ozdaglar and A. Tahbaz-Salehi. 2015. "Systemic Risk and Stability in Financial Networks." *American Economic Review* 105 (2): 564–608.

Acharya, V. V. and T. Yorulmazer. 2008. "Information Contagion and Bank Herding." *Journal of Money, Credit and Banking* 40 (1): 215–231.

Ahnert, T. and C-P. Georg. 2018. "Information Contagion and Systemic Risk." *Journal of Financial Stability* 35 (C): 159–171.

Aikman, D., Chichkanov, P., Douglas, G., Georgiev, Y., Howat, J. and King, B., 2019. Bank of England Staff Working Paper No. 809 System-wide stress simulation.

Arora, R., G. Bédard-Pagé, G. Ouellet Leblanc and R. Shotlander. 2019. "Bond Funds and Fixed-Income Market Liquidity: A Stress-Testing Approach" Bank of Canada Technical Report No. 115.

Arora, R. and G. Ouellet Leblanc. 2018. "How Do Canadian Corporate Bond Mutual Funds Meet Investor Redemptions?" Bank of Canada Staff Analytical Note No. 2018-14.

Altman, E.I., Brady, B., Resti, A. and Sironi, A., 2005. The link between default and recovery rates: Theory, empirical evidence, and implications. The Journal of Business, 78(6), pp.2203-2228.

Altman, E.I. and Kalotay, E.A., 2014. Ultimate recovery mixtures. Journal of Banking & Finance, 40, pp.116-129.

Bardoscia, M., Barucca, P., Battiston, S., Caccioli, F., Cimini, G., Garlaschelli, D., Saracco, F., Squartini, T. and Caldarelli, G., 2021. The physics of financial networks. Nature Reviews Physics, 3(7), pp.490-507.

Barucca, P., Mahmood, T. and Silvestri, L., 2021. Common asset holdings and systemic vulnerability across multiple types of financial institution. Journal of Financial Stability, 52, p.100810.

Battiston, S., Mandel, A., Monasterolo, I., Schütze, F. and Visentin, G., 2017. A climate stress-test of the financial system. Nature Climate Change, 7(4), pp.283-288.

Bédard-Pagé, G., Bolduc, D., Demers, A., Dion, J.P., Pandey, M., Berger-Soucy, L. and Walton, A., 2021. COVID-19 crisis: Liquidity management at Canada's largest public pension funds. (No. 2021-11). Bank of Canada Staff Analytical Note.

Caccioli, F., Ferrara, G. and Ramadiah, A., 2020. Modelling fire sale contagion across banks and non-banks (No. 878). Bank of England.

Calimani, S., Hałaj, G. and Żochowski, D., 2022. Simulating fire sales in a system of banks and asset managers. Journal of Banking & Finance, 138, p.105707.

Cetorelli, N., Duarte, F.M. and Eisenbach, T.M., 2016. Are asset managers vulnerable to fire sales? (No. 20160218). Federal Reserve Bank of New York.

Chrétien, E., Darpeix, P., Gallet, S., Grillet-Aubert, L., Lalanne, G., Malessan, A., Novakovic, M., Salakhova, D., Samegni-Kepgnou, B. and Vansteenberghe, E., 2020. Exposures through common portfolio and contagion via bilateral cross holdings among funds, banks and insurance companies. Haut Conseil de Stabilitè Financière Working Papers.

Chen, Y.-H. H., E. Ens, O. Gervais, H. Hosseini, C. Johnston, S. Kabaca, M. Molico, S. Paltsev, A. Proulx and A. Toktamyssov. 2022. "Transition Scenarios for Analyzing Climate-Related Financial Risk." Bank of Canada Staff Discussion Paper No. 2022-1

Chernenko, S. and A. Sunderam. 2016. "Liquidity Transformation in Asset Management: Evidence from the Cash Holdings of Mutual Funds." National Bureau of Economic Research Working Paper No. 22391.

Cifuentes, R., Ferrucci, G., & Shin, H. S. (2005). Liquidity risk and contagion. Journal of the European Economic association, 3(2-3), 556-566.

Cont, R. and Schaanning, E., 2017. Fire sales, indirect contagion and systemic stress testing. Indirect Contagion and Systemic Stress Testing (June 13, 2017).

Cont, R., Kotlicki, A. and Valderrama, L., 2020. Liquidity at risk: Joint stress testing of solvency and liquidity. Journal of Banking & Finance, 118, p.105871.

Dötz, N. and M. A. Weth. 2019. "Redemptions and Asset Liquidations in Corporate Bond Funds." Deutsche Bundesbank Discussion Paper No. 11/2019.

Douglas, G. and Roberts-Sklar, M., 2018. Staff Working Paper No. 757 What drives UK defined benefit pension funds' investment behaviour?.

Duarte, F. and Eisenbach, T.M., 2021. Fire-sale spillovers and systemic risk. The Journal of Finance, 76(3), pp.1251-1294.

Dubiel-Teleszynski, T., Franch, F., Fukker, G., Miccio, D., Pellegrino, M. and Sydow, M., 2022. System-wide amplification of climate risk. ECB Macroprudential Bulletin, 17.

European Securities and Markets Authority (ESMA). 2015. "Measuring the Shadow Banking System – A Focused Approach." In *Report on Trends, Risks and Vulnerabilities* No. 2, 2015: 34–38.

European Securities and Markets Authority (ESMA). 2019. "Stress Simulation for Investment Funds." ESMA Economic Report.

Fricke, C. and Fricke, D., 2021. Vulnerable asset management? The case of mutual funds. Journal of Financial Stability, 52, p.100800.

Fukker, G., Kaijser, M., Mingarelli, L. and Sydow, M., 2022. Contagion from market price impact: a price-at-risk perspective (No. 2692). European Central Bank.

Goldstein, I., H. Jiang and D. T. Ng. 2017. "Investor Flows and Fragility in Corporate Bond Funds." *Journal of Financial Economics* 126 (3): 592–613.

Gourdel, R. and Sydow, M., 2023. Non-banks contagion and the uneven mitigation of climate risk. International Review of Financial Analysis, 89, p.102739.

Hałaj, G. 2018. "System-Wide Implications of Funding Risk." Physica A: Statistical Mechanics and its Applications 503: 1151–1181.

Hałaj, G., 2020. Resilience of Canadian banks to funding liquidity shocks. Latin American Journal of Central Banking, 1(1-4), p.100002.

Hosseini, H., C. Johnston, C. Logan, M. Molico, X. Shen and M.-C. Tremblay. 2022. "Assessing Climate-Related Financial Risk: Guide to Implementation of Methods." Bank of Canada Technical Report No. 120.

Huang, J. 2020. "Dynamic Liquidity Preferences of Mutual Funds." *Quarterly Journal of Finance* 10 (4): 2050018.

Johnston, C., G. Vallée, H. Hosseini, B. Lindsay, M. Molico, M.-C. Tremblay and A. Witts. 2023. "Climate-Related Flood Risk to Residential Lending Portfolios in Canada." Bank of Canada Staff Discussion Paper No. 33.

Lux, T. and R. C. J. Zwinkels. 2018. "Empirical Validation of Agent-Based Models." In Handbook of Computational Economics (Vol. 4), edited by C. Hommes and B. LeBaron, 437–488. Oxford, United Kingdom: Elsevier.

Mirza, H., Moccero, D., Palligkinis, S. and Pancaro, C., 2020. Fire sales by euro area banks and funds: What is their asset price impact?. Economic Modelling, 93, pp.430-444.

Ojea-Ferreiro, J. 2020. "Quantifying Uncertainty in Adverse Liquidity Scenarios for Investment Funds." CNMV Bulletin Quarter II: 25–44.

Puhr, M.C., Santos, M.A., Schmieder, M.C., Neftci, S.N., Neudorfer, M.B., Schmitz, M.S.W. and Hesse, M.H., 2012. Next generation system-wide liquidity stress testing. International Monetary Fund.

Schnabel, I. and Shin, H. S., (2002), Foreshadowing LTCM: the crisis of 1763, No 02-46, Papers, Sonderforschungsbreich 504

Sydow, M., Schilte, A., Covi, G., Deipenbrock, M., Del Vecchio, L., Fiedor, P., Fukker, G., Gehrend, M., Gourdel, R., Grassi, A. and Hilberg, B., 2021. Shock amplification in an interconnected financial system of banks and investment funds.

Wang, D., I. van Lelyveld and J. Schaumburg. 2019. "Do Information Contagion and Business Model Similarities Explain Bank Credit Risk Commonalities?" European Systemic Risk Board Working Paper Series No. 94.

Online appendix

Intra-contagion in the fund universe via cross-holding positions

Let us define

$$E(t_1) = A(t_1)1_{\{mx1\}} + F(t_1)1_{\{nx1\}} + C(t_1) - L(t_1)$$

Where $E(t_1) = TNA$ (a vector of Total Net Assets with the length equal to the number of funds), $A(t_1)$ is a NxM matrix, where N is the number of funds and M is the number of market assets. $A(t_1)1_{\{mx1\}}$ of is a vector if the sum of the positions of the market assets of the funds, $F(t_1)$ is a NxN vector where the position i,j indicates the investment in fund j held by fund I, $F(t_1)1_{\{nx1\}}$ is a vector of the amount of the investments in other funds, $C(t_1)$ is a vector of the cash holdings and $L(t_1)$ is a vector of the amount of the liabilities (money borrow to hold short positions[35]).

After the market shock we would have two effects:

- The first one directly in the holdings, i.e. $A(t_2)$
- and the second one in the investment of investments, i.e. $F(t_2)$

$$E(t_2) = A(t_2)1_{\{mx1\}} + F(t_2)1_{\{nx1\}} + C(t_1) - L(t_1) \tag{1}$$

The new value of the holdings in other funds would be the weighted sum of the ratios between TNA between t_2 and t_1, i.e.

$$F(t_2)1_{\{nx1\}} = F(t_1)diag\left(\frac{E(t_2)}{E(t_1)}\right)1_{\{nx1\}} = f(t_1)E(t_2)$$

where

$$f(t_1) = F(t_1)Diag\left(\frac{1}{E(t_1)}\right)$$

Using this identity in Eq. (1) we have:

$$E(t_2) = A(t_2)1_{\{mx1\}} + f(t_1)E(t_2) + C(t_1) - L(t_1) \tag{2}$$

After doing some matrix calculations we get that:

$$[I_n - f(t_1)]E(t_2) = A(t_2)1_{\{mx1\}} + C(t_1) - L(t_1) \tag{3}$$

[35] The short position could be seen as borrow the money at time t to buy an asset at time t+1 and give back the money equivalent of the asset price at time t+1. If the price decreases, you would gain the difference between the money you borrow and the price at time t, if the price increases you will have to cover the increase in prices, as the money you borrow is not enough. In this way the money borrow at time t would be a liability and the change of the price between t and t+1 could be seen as a change in asset/cash holdings.

And finally:

$$E(t_2) = [I_n - f(t_1)]^{-1}\left[A(t_2)1_{\{mx1\}} + C(t_1) - L(t_1)\right] \quad (4)$$

This solution holds if the network is regular, i.e. there are no funds fully owned by other funds.

For funds which are 100% investing in other funds we would have matrix Q, linking the investments of fund investing the full portfolio in other funds.

$$\overbrace{E_W(t_2)}^{Wx1} = \underbrace{Q_{\{W,N\}}}_{WxN} \underbrace{Diag\left(\frac{1}{E_N(t_1)}\right)}_{NxN} \underbrace{E_N(t_2)}_{(NX1)}$$

Where W is the set of funds of funds and $Q_{\{W,N\}}$ indicates in the position i,j the investment of fund i in fund j, where fund j is not fully invested in other funds.

LGD estimation and relationship with PD in climate-relevant assets

Following Altman and Kalotay (2014), we could transform the recovery rates (RR) into the real line by applying an inverse normal, i.e.

$y = \Phi^{-1}(RR)$,

Where $\Phi^{-1}(\ldots)$ is the inverse cumulative distribution function. This transformation implies a relationship between the cumulative distribution of y and the cumulative distribution of the transformed RR, i.e.

$$G(y) = F\big(\Phi(y)\big) = F(RR)$$

The density distribution of y is unknown $(g \ldots)$, and they use a mixture of normal distributions to capture the form, i.e.

$$g(y) = \pi_1\phi(y,\mu_1,\sigma_1) + \cdots + (1 - \pi_1 - \cdots - \pi_{N-1})\phi(y,\mu_N,\sigma_N)$$

Unfortunately, they don't provide the estimated parameters, which would solve a lot of problems as that would be like giving us the distribution of RR. Given the identity between cumulative distributions, we can get the relationship between density distributions, which would be (through the derivative of the cumulative distribution):

$$\frac{\partial G(y)}{\partial y} = g(y) = \frac{\partial F\big(\Phi(y)\big)}{\partial y} = f\big(\Phi(y)\big)\phi(y)$$

Note that we are getting the distribution of the RR by doing

$\frac{g(y)}{\phi(y)} = f\big(\Phi(y)\big)$, which in terms of RR would be $\frac{g\left(\Phi^{-1}(RR)\right)}{\phi\left(\Phi^{-1}(RR)\right)} = f(\mathrm{RR})$

In this paper, they provide the following information: mean (μ_{RR}), variance (σ_{RR}^2), quantile 10% ($q_{0.1}$), quantile 90% ($q_{0.9}$) and the interquartile range (IQR). The definition of these five measures expressed using the density function distribution of the RR:

$$\mu_{RR} = E(RR) = \int_0^1 RRf(RR)\,dRR$$

$$\sigma_{RR}^2 = E(RR^2) - E(RR)^2 = \int_0^1 RR^2 f(RR)dRR - \left(\int_0^1 RRf(RR)\,dRR\right)^2$$

$$0.1 = \int_0^{q_{0.1}} f(RR)\,dRR = F(RR \leq q_{0.1})$$

$$0.9 = \int_0^{q_{0.9}} f(RR)\,dRR = F(RR \leq q_{0.1})$$

$$IQR = q_{0.75} - q_{0.25} = F^{-1}(0.75) - F^{-1}(0.25)$$

where

$0.75 = \int_0^{q_{0.75}} RRf(RR)dRR$ and $0.25 = \int_0^{q_{0.25}} RRf(RR)\,dRR$

The existence of five measures limits our density model to a maximum of five parameters (due to the curse of the dimensionality). A mixture of two normal distributions would have exactly two parameters $(\mu_1, \sigma_1, \mu_2, \sigma_2, \pi_1)$:

$$g(y) = \pi_1 \phi(y, \mu_1, \sigma_1) + (1 - \pi_1)\phi(y, \mu_2, \sigma_2)$$

With the following restrictions: $0 < \pi_1 < 1, \sigma_1 > 0, \sigma_2 > 0, \mu_1 < \mu_2$. The last restriction is imposed by Altman and Kalotay (2014) to speed the convergence of the estimation.

Finally we need to transform the previous five measures in terms of y, instead of RR

$$\mu_{RR} = E(\Phi(y)) = \int_{\Phi^{-1}(0)}^{\Phi^{-1}(1)} \overbrace{\Phi(y)f(\Phi(y))}^{g(y)}\,d\Phi(y) == \int_{-\infty}^{\infty} \Phi(y)f\,\overbrace{(\Phi(y))\phi(y)}^{g(y)}\,dy$$

$$\sigma_{RR}^2 = E(\Phi(y)^2) - E(\Phi(y))^2 = \int_{-\infty}^{\infty} \Phi(y)^2\,\overbrace{f(\Phi(y))\phi(y)}^{g(y)}\,dy - \left(\int_{-\infty}^{\infty} \Phi(y)\,\underbrace{f(\Phi(y))\phi(y)}_{g(y)}\,dy\right)^2$$

$$0.1 = \int_{-\infty}^{\Phi^{-1}(q_{0.1})} \overbrace{f(\Phi(y))\phi(y)}^{g(y)}\,dy$$

$$0.9 = \int_{-\infty}^{\Phi^{-1}(q_{0.1})} \underbrace{f(\Phi(y))\phi(y)}_{g(y)}\,dy$$

$$IQR = \Phi(G^{-1}(0.75)) - \Phi(G^{-1}(0.25))$$

Note that this last expression comes from the fact that

$y = \Phi^{-1}(RR)$ and $G(y) = F(RR)$, so we expressed y as the inverse of $G(\dots)$, i.e. $G^{-1}(u) = \Phi^{-1}(RR)$ and we apply the normal cdf to both sides of the equation:

$\Phi\left(G^{-1}(u)\right) = \Phi\left(\Phi^{-1}(RR)\right) = RR$

Finally, it is just a matter of estimating the parameters which would give us the values of the five measures.

For the PD, we have some quantiles which would correspond to a credit rating, e.g. $q_{0.1} = PD_{AAA}, q_{0.5} = PD_{BBB}, q_{0.9} = PD_C$. We assume that the PD follows a beta distribution and we estimate the parameters which would give us those quantiles in the beta distribution. The beta distribution was chosen due to the fact that it can take several shapes, it is really flexible and the dominium is between 0 and 1 (like the PD).

Finally, we take the correlation parameters between PD and RR in Table 3 from Altman et al. (2005) and we assume a gaussian relationship between the variables. Note that although the relationship is Gaussian, the bivariate distribution is not normal, as the marginals are a beta distribution (for the PD) and transformation from a mixture of gaussian distributions (for the LGD or the RR).

We would like to get conditional distribution of the LDG given the PD, which following the Bayes theorem would be: $f(LGD|PD) = f(LGD, PD)/f(PD)$. Using Sklar theorem we can decompose the joint distribution in a product of marginal distribution and a function c(...) that indicates the dependence between them. Hence, $\frac{f(LGD,PD)}{f(PD)} = \frac{f(LGD)\cancel{f(PD)}c(F(PD),F(LGD))}{\cancel{f(PD)}}$, so we can get the conditional distribution function of the LGD as a product between the marginal pdf and the copula density.

Credit risk assessment in climate-relevant sector bond portfolios

We assess credit risk for climate-relevant sector (CRS) bonds based on the fair valuation of the portfolio given by:

$$V_0(p) = \sum_{t=1}^{T-1} \delta^t \left((1-p_t)^t + Rp(1-p_t)^{t-1}\right)y + \delta^T (1-p_T)^T (y+1),$$

where p_t is the probability of default at time t of the scenario, δ is the discount factor, y is the yield to maturity, R is the recovery rate (i.e., inverse of loss given default), and T is the maturity of bonds. Entities are assumed to have 10-year foresight. After this period, they anticipate constant transition risk impacts until the bond matures. After 2050, a constant net income pathway is assumed.

The valuation impact of the climate change scenario on bond portfolios is calculated by combining the theoretical valuation of the bonds under the baseline scenario (p^B) and the adverse climate transition risk scenario (p^C):

$$\Delta V = \frac{V_0(p^C) - V_0(p^B)}{V_0(p^B)}.$$

Liquidity risk analysis

Liquidity metrics are calculated for deposit-taking institutions (DTIs), pension funds and open-ended mutual funds.

- For **DTIs**: liquidity metrics are based on liquidity coverage ratio (LCR) inflows and outflows from Office of the Superintendent of Financial Institutions and Autorité des marchés financiers regulatory returns.
- For **pension funds**: liquidity metrics are based on the expected outflows provided by pension funds, assuming a 10% cash outflow of total net assets for outliers and accounting for liquidity needs from derivative exposures (see section D.3.3).
- For **open-ended mutual funds**: liquidity metrics are based on the estimation of the highest monthly outflow over five years from historical data, adjusting for a floor outflow based on average historical data and assuming an initial LCR of a least one (see section D.3.2).

Assets of pension funds and open-ended mutual funds are converted into high-quality liquid assets (HQLAs) using a liquidity factor (see section D.3.1).

1 High-quality liquid assets

HQLAs in the LCR are long-position assets expected to provide reliable collateral or cash during market stress. Liquidity weights are applied to each asset class and credit quality as per Basel III bank regulations (BIS 2013). HQLAs are generated by summing the liquidity-weighted shares of different asset classes:

$$HQLA_i = \sum_{q=1}^{N} \omega_{i,q}\, k_q,$$

where $\omega_{i,q}$ represents the proportion of an asset class q in fund *I* and k_q is the liquidity weight (see **Table A-1**).[36]

Table A-1: Liquidity weights for different asset types, by credit rating

Type of funds	CQS1	CQS2	CQS3
Cash	100%	100%	100%
Sovereign debt	100%	85%	50%
Corporate debt	85%	50%	50%
Equity	50%	50%	50%
Fund	Based on the underlying assets		

Note: CQS1 is credit quality step 1 and refers to AAA to AA ratings; CQS2 is credit quality step 2 and refers to A ratings; CQS3 is credit quality step 3 and refers to BBB ratings. Weights are from European Securities and Markets Authority (ESMA), "Stress simulation for investment funds," ESMA Economic Report (September 2019) and Bank for International Settlements, "Basel III: The Liquidity Coverage Ratio and liquidity risk monitoring tools," Basel Committee on Banking Supervision (January 2013).

[36] More details about the use of HQLA in the investment fund universe can be found in ESMA (2015).

2 Redemption flow in open-ended mutual funds

Data from Lipper, a Refinitiv Company, on investment fund flows are used to estimate a fund's liquidity transformation[37] and predict investor redemption responses to the fund's performance.[38] Liquidity transformation is the holdings' shift toward liquid stocks when high market volatility is anticipated due to potential investor redemptions.

The liquidity needs are defined as $\min\left(HQLA_i, max\left(f_{floor}, VaR_{1.7\%}(f_i)\right)\right)$, where $HQLA_i$ is the high-quality liquid asset (see section D.3.1) for fund i. The liquidity needs are the maximum between a floor f_{floor} and a quantile $VaR_{1.7\%}(f_i)$ of the historical flow (standardized by total net assets) for each fund i, which is used to predict potential redemptions.[39] We impose the initial LCR to be at least equal to one, to isolate liquidity needs stemming from climate transition risk only.

3 Derivate-related liquidity needs (for pension funds only)

We use two industry-standard methodologies to evaluate the impact of the climate transition shock on the liquidity needs stemming from equity and debt-related derivatives:

- For equity derivatives, we use the Standard Portfolio Analysis of Risk (SPAN) methodology to determine the initial margin required for a derivative contract.
- For debt-related derivatives, we use Monte Carlo simulations based on the Vasicek (2002) model to calculate the loss of a debt portfolio on which a derivative is built.

Positions provided by pension funds are adjusted using the derivative's delta to equate to a futures position.[40]

Equity underlying

The liquidity needs from equity derivatives arise from (i) increased initial margin requirements and (ii) mark-to-market losses, both increasing the denominator of the pension fund's LCR.

We use the SPAN method to determine the initial margin requirements for equity derivatives. The SPAN method defines the margin interval—that is, the maximum price fluctuation in percent that the derivative contract is expected to have over the predetermined liquidation horizon with the desired level of confidence. For the liquidation horizon and confidence level, we follow common industry calibrations and take the type of derivative—exchange-traded (ET) or over-the-counter (OTC)—into account. Specifically, we set the confidence level to 99.87%, and together with the normal distribution assumption this corresponds to the margin

[37] See Chernenko and Sunderam (2016) and Huang (2020).
[38] See Goldstein, Jiang and Ng (2017).
[39] Historical flows reveal an average maximum outflow of 5% to 20%, varying by investment strategy. For each fund, we calculate the highest historical monthly outflow with a 98.3% probability, equivalent to the highest outflow seen every five years (1/(12 × 5) × 100 = 1.7%). We apply a floor to the outflows to account for limitations in historical data for newly established and small funds, similar to ESMA (2021).
[40] Further adjustments considering the derivative's convexity (gamma) are omitted for simplification.

interval being $MI = 3\sqrt{n}\,\sigma_{260d}$, where the liquidation horizon n = 2 for ET or 5 for OTC derivatives.[41]

The estimate for the volatility of the derivative contract's returns, σ_{260d}, is obtained from an exponentially weighted moving average model:

$$\sigma_{260d} = \sqrt{\frac{(1-\lambda)\sum_{i=1}^{260}\lambda^{i-1}(R_{t-i}-\bar{R})^2}{(1-\lambda^{260})}},$$

where λ = 0.99, balancing time-varying market risk without triggering procyclicality issues.[42]

We employ a time series of returns for a CRS index from Canadian, US and European equity data from Eikon, a Refinitiv Company. We start at the beginning of the COVID-19 crisis to simulate a period of high market volatility. We adjust daily returns based on the climate shock for a sector and a region on top of the price evolution of the COVID-19 crisis.

The initial margin requirement in dollars is the product of the exposure and the margin interval. The increase in initial margin requirement from one day to the next indicates the additional liquidity needed to keep the derivative position open. Finally, as is standard in the industry for equity derivatives, we assume daily settling of gains and losses due to market value changes.

Debt underlying

Derivative debt positions are aggregated by sector and region, and the Vasicek (2002) model is used to generate the Monte Carlo simulations to evaluate the maximum credit loss at a 99.7% confidence level over a five-day liquidation period. The change in maximum credit loss when the probability of default (PD) changes from the initial value to a value under a certain transition scenario (PD_S) is scaled to a five-day loss, aligned with the liquidation period, as:

$$MC = \sqrt{\frac{5}{250}}\,[VaR_{99.7\%}(PD_S) - VaR_{99.7\%}(PD)]$$

where $P\big(CreditLoss(PD) < VaR_{99.7\%}(PD)\big) = 0.997$.[43]

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[41] For similar parameter calibrations used by central counterparties (CCPs) in Canada and Europe, see Odabasioglu (forthcoming) and Boudiaf, Scheicher and Vacirca (2023), respectively.

[42] See, for instance, Brunnermeier and Pedersen (2009) for more information about potential procyclicality issues in the derivatives. See Odabasioglu (forthcoming) for further details on the SPAN methodology, as well as how the calibration of parameters impacts the initial margin requirements.

[43] We use variance reduction techniques to increase the precision of the estimates obtained from the simulation.

Extensions of Hałaj's (2018) agent-based model

We extend Hałaj's (2018) agent-based model (ABM) for each type of entity in scope of this study. We present key design features for two of these extensions: fire sales and the transitioning of assets from being less carbon-intensive or greener (i.e., climate-transitioning assets).

Extension for fire sales

An exponential price impact function (Schnabel and Shin 2002; Cifuentes, Feruci and Shin 2005; Cont and Schaanning 2017; Hałaj 2018, 2020; Fukker et al. 2022) is used to capture the effect of selling pressure on asset price changes:

$$\Psi_{\phi}(V) = (1 - \exp(-V\alpha)),$$

where V is the amount of assets sold by market participants and α is the sensitivity of the price to a certain sold amount. Hałaj (2018, 2020) estimates α = 0.0005 and 0.002 respectively, corresponding to price impacts in basis points for each billion in liquidation in Canadian dollars.

The function's output is highly sensitive to α's value. We use α = 0.002 (Hałaj 2020) for non-climate-relevant sector (CRS) equities. In contrast, for CRS equities, we use data from Eikon, a Refinitiv Company, to estimate the relationship using ordinary least squares estimation and a quantile regression to generate stress in the market. For bond sensitivity, we used Fukker et al.'s (2022) values to rescale the equity price sensitivity and infer the bond price sensitivity for both CRS and non-CRS bonds (i.e., both non-CRS corporate and sovereign bonds). The amplified fire sales case corresponds to the estimate of the fifth percentile.

Extension for climate-transitioning assets

Our scenario analysis provides a useful perspective but does not reflect the opportunities that climate-transitioning assets offer. To tackle this limitation, we model the assets that could be an opportunity over the long run. [44]

We estimate the share of assets able to transition in a sector or sub-sector through the percentage of assets getting the highest environmental rating from Eikon, a Refinitiv Company. We use environmental score grades for about 60,000 firms across Canada, the United States, Europe and Japan to estimate the potential long-term transition of assets sold during fire sales. For instance, 19.83% of firms in the electricity sector have the highest environmental score. This implies that if Can$100 million of electricity equities are sold,

[44] Each firm is assigned to only one sector. For example, a firm generating electricity using only fossil fuel sources would be in the same bucket as a firm generating 51% of its electricity from fossil fuel sources and 49% from renewable sources. The activities in the sector might change in the future, but the initial assessment considers the sectors as constant over time.

pension funds with good liquidity positions could buy Can$19.83 million and transition this firm to the private market. Thus, the final fire sale effect is limited to a selling pressure of Can$81.17 million. The higher the percentage, the more assets that could be absorbed by entities with a long-term horizon.

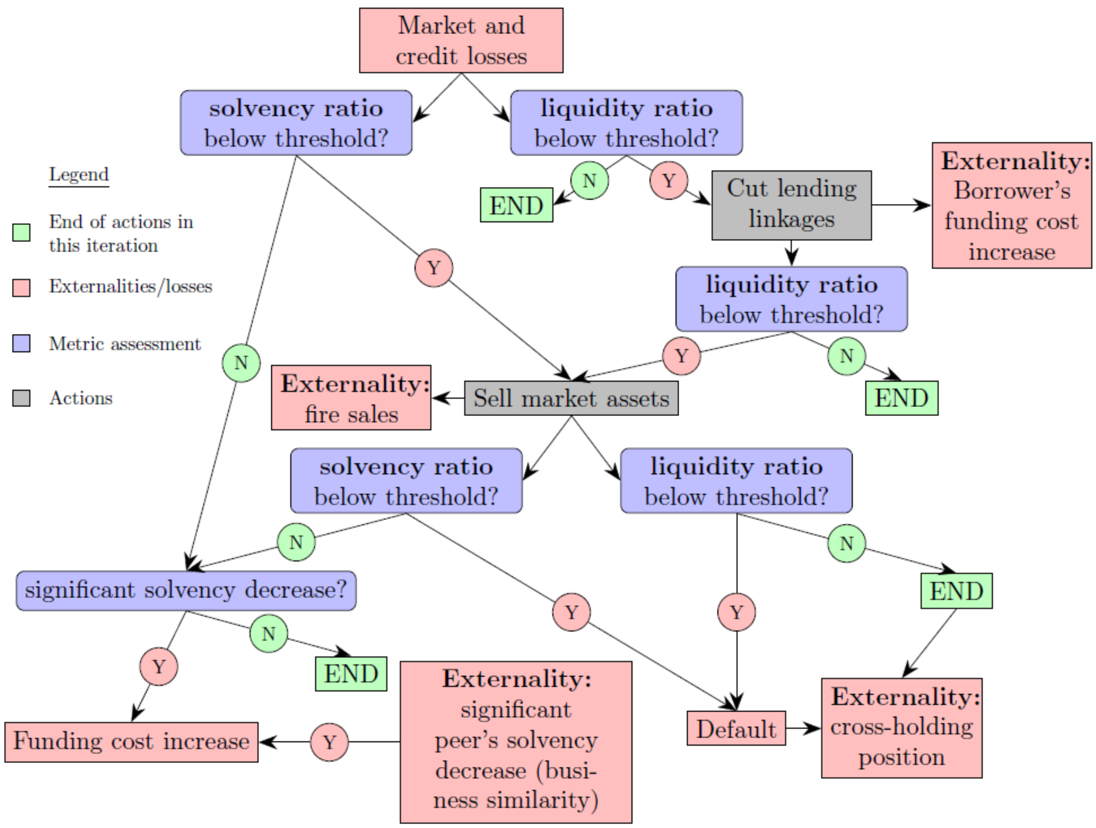
Table A-2: Comparison of this study's model with Hałaj's (2018) agent-based model

	Deposit-taking institutions		Life insurance companies		Investment funds		Pension funds	
Steps in the agent-based model	**Our model**	**Hałaj's (2018) model**	**Our model**	**Hałaj's (2018) model**	**Our model**	**Hałaj's (2018) model**	**Our model**	**Hałaj's (2018) model**
Key metrics and ratios	CET1 LCR	CET1 LCR	LICAT (total and core)		LCR	LCR	LCR	
Interbank lending	✓	✓	✗		✗	✗	✗	
Intersectoral lending	✓	✗	✗		✗	✗	✓	
Fire sales	Based on sector/ sub-sector, asset type and quantile. Consider effects on credit rating.	Common calibra-tion	Based on sector/ sub-sector, asset type and quantile. Consider effects on credit rating.	✗	Based on sector/ sub-sector, asset type and quantile. Consider effects on credit rating.	Common calibra-tion	Based on sector/ sub-sector, asset type and quantile. Consider effects on credit rating. Allow some buying pressure.	✗
Funding shock	✓	✓	✓		✗	✗	✗	
Business similarity	✓	✓	✓		✗	✗	✗	
Cross-holding (equity)	✓	✗	✓		✓	✗	✓	
Cross-holding (debt)	✓	✓	✓		✓	✓	✓	
Performance-flow nexus	✗	✗	✗		✓	✓	✗	

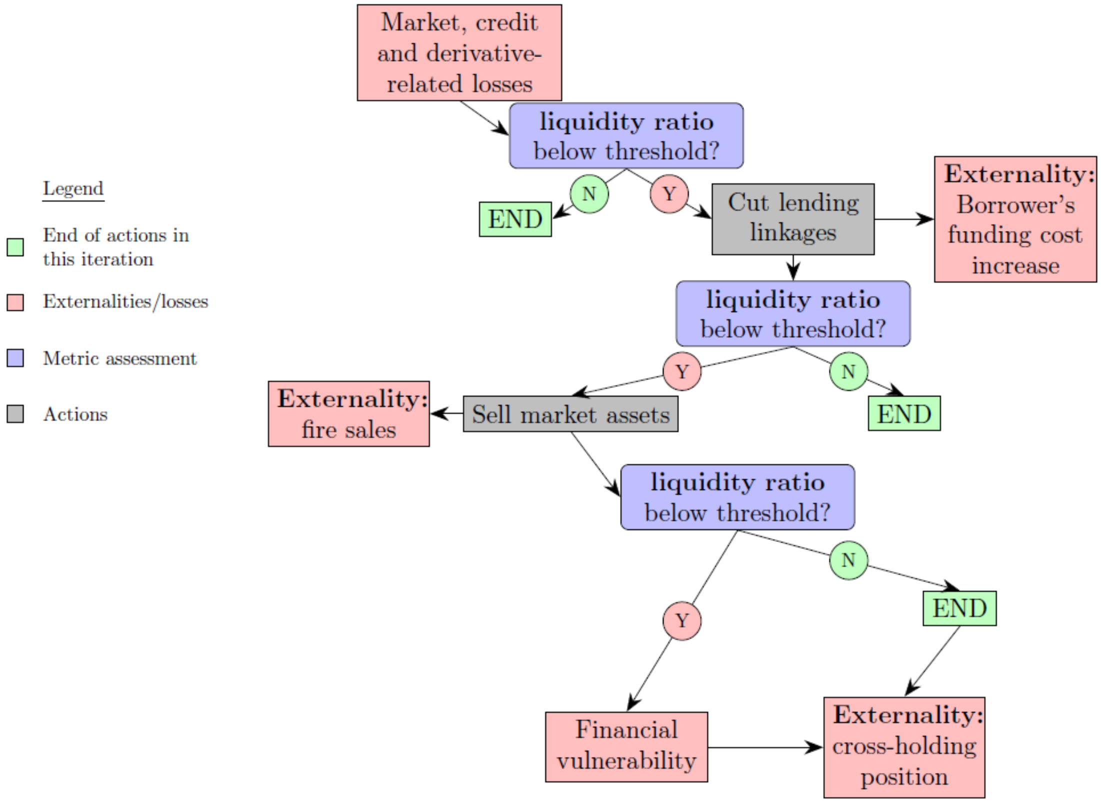
Note: CET1 is Common Equity Tier 1 ratio, LCR is liquidity coverage ratio, LICAT is Life Insurance Capital Adequacy Test.

Decision tree for the different players in the model

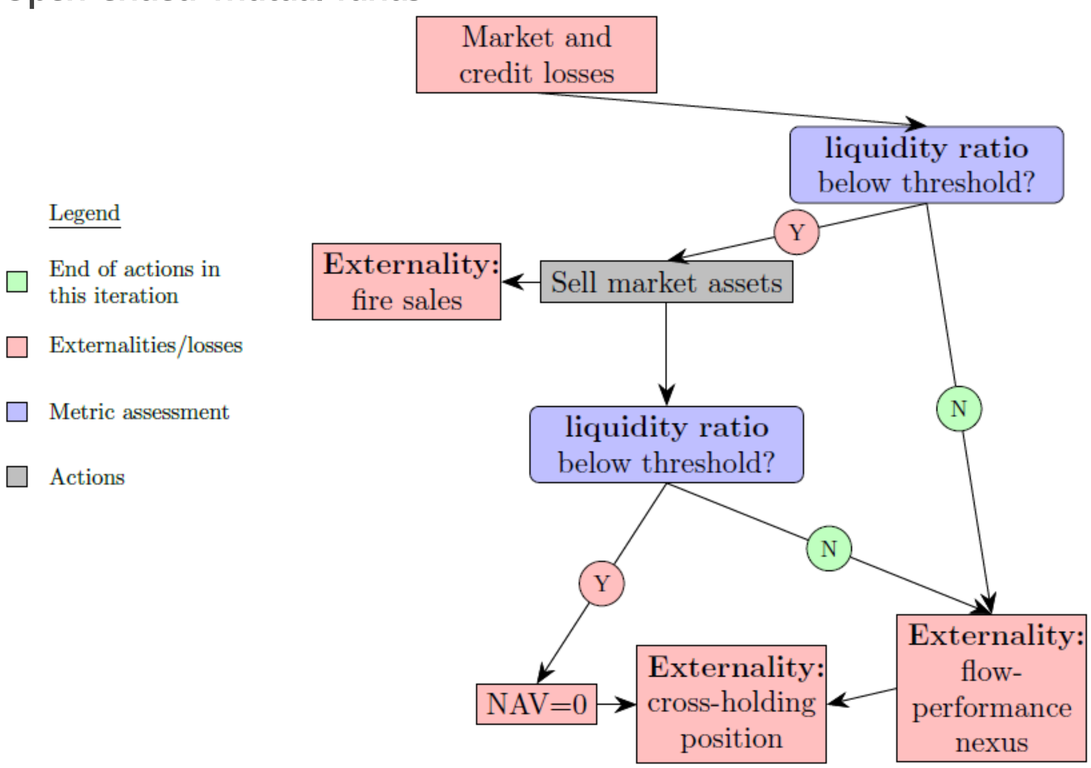
Banks and credit unions



Pension funds



Open-ended mutual funds



Life insurance companies