FRANCE

October 2019

FINANCIAL SECTOR ASSESSMENT PROGRAM

TECHNICAL NOTE—BALANCE SHEET RISKS AND FINANCIAL STABILITY

This Technical Note on Balance Sheet Risks and Financial Stability on France was prepared by a staff team of the International Monetary Fund as background documentation for the periodic consultation with the member country. It is based on the information available at the time it was completed on October 1, 2019.

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BALANCE SHEET RISKS AND FINANCIAL STABILITY

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Glossary

ACPR	Autorité de Contrôle Prudentiel et de Résolution
AMF	Autorité des Marchés Financiers
BdF	Banque de France
BIS	Bank for International Settlements
CIU	Collective Investment Undertaking
EA	Euro Area
ECB	European Central Bank
HCSF	Haut Conseil de Stabilité Financière
LEI	Legal Entity Identifier
MFI	Monetary Financial Institution
MMF	Money-market Fund
NFC	Non-financial Corporation
OFI	Other Financial Institution
PROTIDE	Production de statistiques de titres en détention
TCEP	Tableau complémentaire aux éléments de placements

MACROFINANCIAL RISK AND CAPITAL GAP (CAP-GAP) ANALYSIS

A. Executive Summary[1]

1.   Macroprudential policy setting faces the challenge of identifying growth of financial and macroeconomic variables above and below potential. The gaps between actual performance and potential are crucial for policy makers but are unobserved. This is especially true for financial variables such as capital and risk of default of borrowers (firms and banks) and lenders (banks and households).

2.   Against this backdrop, a macrofinancial structural model is presented that captures (i) sectoral dynamics of firms and banks and feedbacks between them, (ii) capital and default risk dynamics of each sector, (iii) capital and risk gaps i.e., deviations of capital and default risk from potential (the welfare maximizing optimum), and it provides (iv) a quantitative method for measurement.

3.   The *potential* levels of capital and default risk are defined as the ones that a central planner would choose in a world where corporate and bank capital levels are flexible. In contrast, the decentralized economy presented here assumes that over the sample period that banks and firms accumulate capital mostly by retaining earnings. Equity issuance and payouts are captured by shocks to accumulated capital. So, like the concept in monetary policy of output gap between sticky and flexible prices, capital and risk gaps arise between sticky and flexible capital structures.

4.   While the analysis is silent on the implementation of the optimal capital levels, i.e., on the instruments at the disposal of the macroprudential authority to mitigate the sluggishness of capital accumulation, it can be used a signaling device to indicate when macroprudential action is necessary. Any policy measure could be used, as long as it closes capital and risk gaps considering the general equilibrium effects. The model can then be used to measure whether the policy intervention was successful.

5.   The model is taken from French aggregate publicly available data and estimated with Bayesian estimation techniques.

6.   We find that default risk fluctuates during time between being too high and too low. Risk is too high (when the risk gap reaches positive territory) during four episodes: prior to the Technology Crisis, prior to the Global Financial Crisis, prior to the Sovereign Debt Crisis, and now. The default risk gap in the corporate sector was particularly elevated during the Technology Crisis,

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[1]This chapter was prepared by Fabian Lipinsky and Mirela Sorina Miescu.

and now, although default risk is now relatively low in absolute terms. Default risk of the banking sector was particularly elevated during the Global Financial Crisis and appears now adequate.

7.   With respect to capital, again, four episodes stand out where more corporate capital is needed marked by a positive gap: prior to the Technology Crisis, prior to the Global Financial Crisis, prior to the Sovereign Debt Crisis, and now. Bank capital which was too low during the Global Financial Crisis and the Sovereign Debt Crisis, has strengthened significantly, and appears now to be adequate.[2]

8.   The analysis implies that firms should be encouraged to strengthen their equity capital base by retaining earnings or issuing equity. This could be done also indirectly by publishing related research.

B.   Introduction

Motivation

- Macroprudential policy setting faces the challenge of identifying growth of financial and macroeconomic variables above and below potential.

- The gaps between actual performance and potential are crucial for policy makers but are unobserved. This is especially true for financial variables such as capital and risk of default of borrowers and lenders.

- The global financial crisis has highlighted the importance of monitoring both balance sheets of borrowers and lenders as well as the relevance of risk and uncertainty shocks as driver of the business cycle.

- If for example capital is too low and default risk is too high, policy makers could seek policies to increase the capital base of agents or to decrease debt.

- The question arises of how to quantify capital needs and risks associated to borrowers' and lenders' balance sheets and determine capital and risk gaps e.g., deviations of capital and risk from potential that can be used by policy makers to calibrate macroprudential tools.

Contribution

9.   Against this backdrop, a macrofinancial structural model is presented that captures (i) sectoral dynamics of nonfinancial firms and financial intermediaries and feedbacks between them, (ii) default risk in each sector, (iii) capital and risk gaps, and it provides (iv) a quantitative method for measurement.

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[2]The analysis is solely based on aggregate data. Single institutions and their capital adequacy are not subject of the analysis.

- *Sectoral dynamics.* The model simulates the joint balance sheet dynamics of borrowers (nonfinancial firms) and lenders (financial intermediaries). Balance sheet strength of borrowers crucially impacts balance sheet strength of lenders, and vice versa.

- *Risk.* The model differentiates between two types of risk originating from variation in borrowers' asset returns: nonfinancial firm cross-sectional variation in asset returns (idiosyncratic risk), and aggregate variance in asset returns (aggregate risk). As shown below, idiosyncratic risk can be measured by default risk of nonfinancial firms derived from corporate credit spreads; aggregate risk can be measured by default risk of financial intermediaries derived from financial credit spreads.

- *Gaps.* The framework measures capital and risk gaps that may arise at borrowers or at lenders and are closely linked.

- *Measurement.* A quantitative method is provided to measure gaps in a theoretically sound framework.

Literature Review

10.   The model is based on Christiano, Motto and Rostagno (2014) who focus on the balance sheet dynamics of firms and firm default. They show that variations in idiosyncratic risk are an important driver for business cycle fluctuations.

Figure 1. Literature Review

Source: IMF staff.
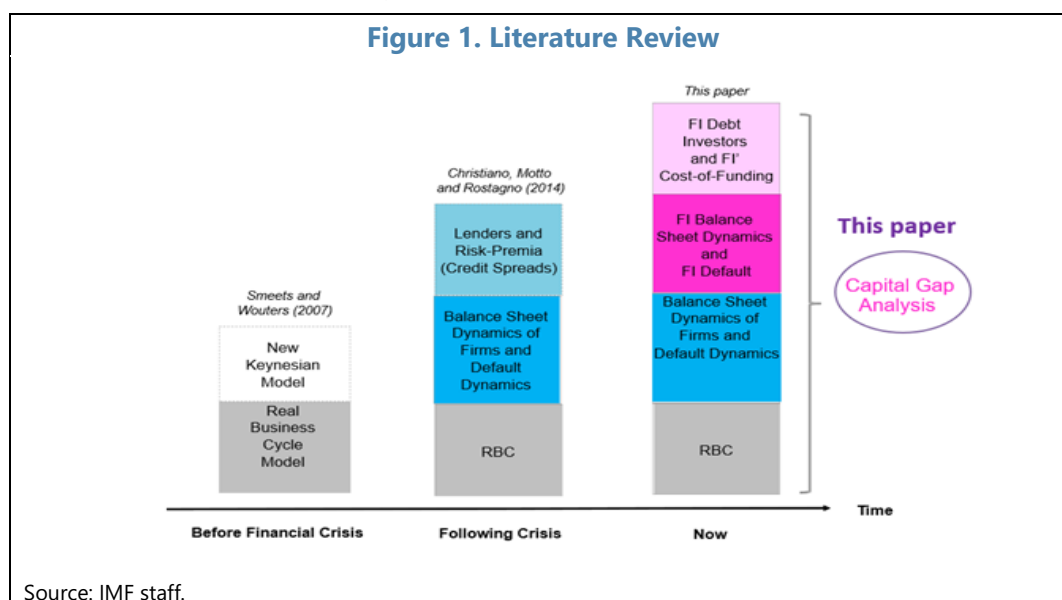
11.   The framework is extended with defaulting financial intermediaries, and financial intermediary debt investors. Aggregate risk is an important driver of the probability of default of financial intermediaries. In comparison to existing models with financial intermediary or bank default, default is due to aggregate risk.

12.   Both frameworks follow the financial accelerator literature in that capital is accumulated mostly out of retained earnings, implying that capital is sticky. In addition, welfare-maximizing capital and risk measures are calculated that result from the optimal trade-off of the tax-benefits of debt and the cost of default and serve as a benchmark for the performance of the economy and the financial system and allow to quantify capital and risk gaps.

C.   High-level Summary of the Model

13.   A general equilibrium model has been developed that seeks to assess how capital and default risk of nonfinancial firms and financial intermediaries changes over time and whether capital and risks are too low or too high at a given point in time, providing a signal for policy makers when to loosen or tighten macroprudential policy measures.

- *The model.* The core of the model builds a standard real business cycle model. The core is enhanced with a financial system that has three set of agents. Financial intermediaries borrow funds from financial investors and on-lend the funds to nonfinancial firms. Financial investors also hold the equity of nonfinancial firms and financial intermediaries.

- *Idiosyncratic and aggregate risk*. Nonfinancial firms acquire assets that yield a return subject to idiosyncratic and aggregate productivity shocks.

- *Nonfinancial firm default and idiosyncratic risk*. Nonfinancial firms default if the value of end-of-period assets falls below the value of liabilities, or equivalently if its idiosyncratic productivity falls below a certain default threshold. The probability of default of nonfinancial firms depends on firms' balance sheet strength, aggregate productivity, and the cumulative distribution function of idiosyncratic productivity.

- *Financial intermediary loan portfolio.* Financial intermediaries return on the loan portfolio consists of two parts. Financial intermediaries receive the interest and principal payment from non-defaulting firms and recover the assets from defaulted firms.

- *Financial intermediary default and aggregate risk*. Financial intermediaries' default if the value of end-of-period assets falls below the value of liabilities, or equivalently if aggregate productivity falls below a certain default threshold. Hence, the probability of default of financial intermediaries depends on balance sheet strength of borrowers and financial intermediaries and the distribution function of aggregate productivity.

- *Deviation of capital from potential.* Nonfinancial firms and financial intermediaries accumulate capital out of retained earnings, according to an exogenously given law motion. In addition to capital accumulated out of retained earnings, the model determines the optimal capitalization that maximizes profits trading off the tax benefits of debt versus the cost of default. The difference between welfare maximizing optimal capital and own capital accumulated out of retained earnings, provides the deviation from potential, the capital gap.

- **_Deviations of risk, lending and funding from potential._** The solution of the model with capital accumulated out of retained earnings can be compared to the solution of the model with optimal capital. The comparison allows to determine deviations from potential of capital, default risk, lending, and funding. The deviations from potential provide signals for policy makers when to tighten or loosen macroprudential policies.

- **_Application to French data._** The model is brought to the data by fitting macroeconomic and financial time series and estimating the shocks that are in the model. The parameters of the model are estimated to maximize the likelihood of observing the data. In addition to the solution of the model, the model is solved for the welfare-maximizing optimum (the potential), and deviations from potential are calculated.

14.   The following sections describe the model in greater detail.

D.   Detailed Description of the Model[3]

Core of the Model

15.   The core of the model builds a standard real business cycle model (RBC model) with exogenous government spending and investment adjustment cost. It has four macroeconomic shocks: total factor productivity, government spending, investment efficiency, and labor market tightening (disutility of labor). The core of the model is augmented with a financial system.

The Financial System

16.   The financial system comprises three set of agents: nonfinancial firms, financial intermediaries, and financial investors, ultimately households.

17.   Financial intermediaries use own funds and funds raised from financial investors in the form of deposits and whole-sale funding to issue loans. Nonfinancial firms use the proceeds from the loans together with own funds to acquire productive assets.

- Funding constraints of nonfinancial firms and financial intermediaries:

$$q_t k_t = n_t^F + b_t \qquad\qquad b_t = n_t^B + d_t$$

18.   The acquisition of assets of nonfinancial firms gives rise to two financial shocks, as described in the following: cross-sectional return-on-asset variance of nonfinancial firms (idiosyncratic risk), and aggregate return-on-asset variance of nonfinancial firms (aggregate risk).

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[3]For the basis setup of the model, the standard shocks and the estimation see Christiano, Motto and Rostagno (2014). For further details of the contribution of this paper and the optimality conditions see Appendix I. Beyond this, more detail will be disclosed in an upcoming working paper.

Nonfinancial Firms, Firm Default, and Probability of Default

19.   The cashflow of nonfinancial firms consist of an initial outlay of own funds. Next period nonfinancial firms receive a return on invested assets and pay back debt. The return on assets is subject to an idiosyncratic and aggregate productivity shock. Firms' income is taxed, and future cash-flows are discounted at a stochastic discount factor.

- Expected cashflow of nonfinancial firms:

$$E_t \left[-n_t^F + M_{t+1} \left[\max\left(z_{t+1} \varepsilon_{i,t+1} R_{k,t+1} k_t - R_{b,t} b_t \right) (1-\tau), 0 \right] \right]$$

20.   Nonfinancial firms default if the value of end-of-period assets falls below the value of liabilities, or if its idiosyncratic productivity falls below a certain default threshold.

- Nonfinancial firm default:

$$\varepsilon_{i,t+1} < \varepsilon_{t+1}^z \equiv \frac{R_{b,t} b_t}{z_{t+1} R_{k,t+1} k_t}$$

21.   The probability of default of nonfinancial firms depends on firms' balance sheet strength, aggregate productivity, and the cumulative distribution function of idiosyncratic productivity.

- Model-based through-the-cycle PD:

$$PD^F \left(\varepsilon_{t+1}^z \right) = Prob \left(\varepsilon_{i,t+1} < \varepsilon_{t+1}^z \right) = F \left(\varepsilon_{t+1}^z, \sigma_{\varepsilon,t+1} \right)$$

Financial Intermediaries, Intermediary Default and Probability of Default

22.   The cashflow of financial intermediaries consist of an initial outlay of own funds. Next period financial intermediaries receive a return on the loan portfolio and pay back received funding. Income is taxed.

- Expected cashflow of financial intermediaries:

$$E_t \left[-n_t^B + M_{t+1} \left[\max\left(R_{B,t+1} b_t - R_{d,t} d_t \right) (1-\tau), 0 \right] \right]$$

23.   The return on the loan portfolio consists of two parts. Financial intermediaries receive the interest and principal payment from non-defaulting firms and recover the assets from defaulted firms. Default is subject to screening cost.

- Return on loan portfolio at time t+1:

$$R_{b,t} b_t (1 - PD(\varepsilon_{t+1}^z)) + \int_0^{\varepsilon_{t+1}^z} \varepsilon_{i,t+1} z_{t+1} R_{k,t+1} k_{t+1} (1-\mu) dF - R_{d,t} d_t$$

24.   The expression can be rewritten to receive model-based loss-given default (LGD) and expected losses.

- Model-based expected loss and LGD:

$$B_t\,(1 - PD(\varepsilon_{t+1}^z)LGD(\varepsilon_{t+1}^z)) - D_t$$

$$B_t \equiv R_{b,t}b_t \qquad\qquad D_t \equiv R_{d,t}d_t$$

- Model-based loss rate:

$$l_{t+1} = PD(\varepsilon_{t+1}^z)LGD(\varepsilon_{t+1}^z)$$

25.   Financial intermediaries default if the value of end-of-period assets falls below the value of liabilities, or if aggregate productivity falls below a certain default threshold. Hence, the probability of default of financial intermediaries depends on balance sheet strength of borrowers and financial intermediaries and the distribution function of aggregate productivity. For simplicity it is assumed that aggregate productivity takes a fixed value above and below the default threshold.

- PD of FIs depends on borrower and bank balance sheet strength and aggregate risk

$$\text{PD}^B(z_{t+1}^*) = \text{Prob}(z_{t+1} < z_{t+1}^*) = \pi^D(z_{t+1}^*,\sigma_{z,t+1})$$

- Default threshold:
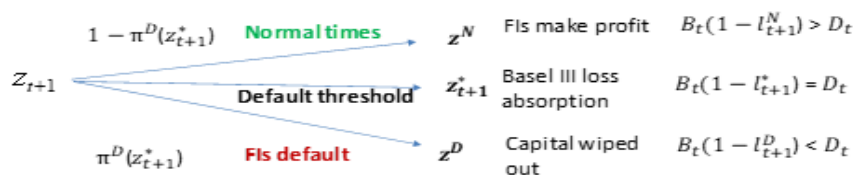
Financial Investors

26.   Financial investors (or mutual funds) hold the equity in nonfinancial firms and financial intermediaries and provide funding in the form of deposits and wholesale funding to financial intermediaries. Financial investors receive funding in case the financial intermediary doesn't default and receive the assets of intermediaries in case of default.

- Expected cashflow of financial investors:

$$\text{E}_t\left[-d_t + M_{t+1}\left[D_t\left(1 - \pi^D\left(z_{t+1}^*\right)\right) + \pi^D\left(z_{t+1}^*\right)B_t\left(1 - l\left(\varepsilon_{t+1}^D\right)\right)\left(1 - \mu_B\right)\right]\right]$$

Capital Accumulation and Agents' Optimization

27.   Nonfinancial firms and financial intermediaries accumulate capital out of retained earnings, according to an exogenously given law of motion (below; derivation see Appendix I). A

constant fraction of earnings is distributed as dividends, while the remainder is retained, as in the standard financial accelerator literature as in Bernanke, Gertler and Gilchrist (1999).[4]

$$n_{F,t} = \frac{R_{k,t}}{q_{t-1}} \left(n_{F,t-1} + n_{B,t-1} + d_{t-1} \right) \left(s_{F,t}^N \left(1 - G\left(z_t^*\right)\right) + s_{F,t}^D G\left(z_t^*\right)\right) (1 - \tau)(1 - \gamma_F)$$

$$n_{B,t} = \left(\frac{R_{k,t}}{q_{t-1}} \left(n_{F,t-1} + n_{B,t-1} + d_{t-1} \right) s_{B,t}^N - R_{d,t-1} d_{t-1} \right) \left(1 - G\left(z_t^*\right)\right)(1 - \tau)(1 - \gamma_{B,t})$$

28.   Given the model set-up, the model solution is found by letting nonfinancial firms maximize their cashflow, taking the cashflows of financial intermediaries and financial investors as given, assuming both make zero profits.

29.   Given an initial capital position, nonfinancial firms scale up their balance sheets (by scaling up financial-intermediaries balance sheet) financed through liabilities to maximize future profits.

30.   The optimal lending rate and financial intermediaries' cost-of-funding is determined by the trade-off between the cost-of-default and tax-benefits of debt. Consequently, nonfinancial firms maximize with respect to three choice variables: financial intermediaries' funding and hence nonfinancial firms' liabilities, lending rates, and financial intermediaries' cost-of-funding.

Financial Frictions and Optimality

31.   There are three financial frictions in the model:

- **Income of nonfinancial firms and financial intermediaries is tax-deductible, while income of financial investors is not (see cashflows).** So, more intermediated funding between financial intermediaries and financial investors results in a tax-benefit. This is called "the benefit of financial intermediation".

- **Defaults of nonfinancial corporates trigger a screening cost.**

    i. The optimal lending rate is determined trading off the benefit of financial intermediation associated to non-defaulting loans versus the cost of default.

- **Defaults of financial intermediaries result in lower productivity.**

    i. Financial intermediaries' cost-of-funding is determined by trading off the benefit of financial intermediation associated with more funding versus the productivity loss in case of default.

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[4]Equity capital adjustment cost could be added as an alternative to exogenous capital accumulation as in Gourio, Kashyap, and Sim (2018). In both cases, exogenous capital accumulation and the use of adjustment cost, capital is sticky. Identified capital gaps may differ if adjustment cost were used.

The Capital Gaps

32.   In the model, capital is sticky, and capital is accumulated out of retained earnings, as in Christiano, Motto and Rostagno (2014). Nonfinancial firms have three choice variables.

33.   In comparison to the model solution, the optimal welfare-maximizing optimal solution can be calculated, assuming a flexible capital structure and solving also for the optimal level of capital of nonfinancial firms and financial intermediaries. This maximization problem has five choice variables–two more than the model solution.

- Optimal capitalization:

$$\max_{\{d_t, R_{d,t}, R_{b,t}, n_t^F, n_t^B\}} E_t \left[-\lambda_t n_t^F + \beta\lambda_{t+1} \left[\max\left(z_{t+1}\varepsilon_{i,t+1}R_{k,t+1}k_t - R_{b,t}b_t \right)(1-\tau), 0 \right] \right]$$

Subject to:

- Funding constraints of entrepreneurs and banks:

$$q_t k_t = n_t^F + b_t \qquad b_t = n_t^B + d_t$$

- FI participation and FI capital constraint:

$$E_t \left[-\lambda_t n_t^B + \beta\lambda_{t+1} \left[\max\left(B_t(1 - PD(\varepsilon_{t+1}^z)LGD(\varepsilon_{t+1}^z)) - D_t \right)(1-\tau), 0 \right] \right] \geq 0$$

$$B_t(1 - PD(\varepsilon_{t+1}^*)LGD(\varepsilon_{t+1}^*)) - D_t \geq 0$$

- Wholesale FI debt investor participation constraint:

$$E_t \left[-\lambda_t d_t + \beta\lambda_{t+1} \left[D_t\left(1 - \pi^D(z^*_{t+1})\right) + \pi^D(z^*_{t+1})B_t\left(1 - l(\varepsilon^D_{t+1})\right)(1 - \mu_B) \right] \right] \geq 0$$

- Default thresholds:

$$\varepsilon_{t+1}^N \equiv \frac{R_{b,t}b_t}{z^N R_{k,t+1}k_t} \qquad \varepsilon_{t+1}^* \equiv \frac{R_{b,t}b_t}{z^*_{t+1}R_{k,t+1}k_t} \qquad \varepsilon_{t+1}^D \equiv \frac{R_{b,t}b_t}{z^D R_{k,t+1}k_t}$$

34.   The difference between welfare maximizing optimal capital and own capital accumulated out of retained earnings, provides the deviation from potential, the capital gaps. So, similar to the well-known concept in monetary policy of output gap between sticky and flexible prices, the capital gaps between sticky and flexible capital are calculated.

Deviation of Risk from Potential: Risk Gaps

35.   Deviations of capital from potential imply deviations of risk from potential, both nonfinancial firm default risk and financial intermediary default risk.

36.   The solution of the model with capital accumulated out of retained earnings can be compared to the solution of the model with optimal capital. The comparison allows to

determine deviations from potential of capital, default risk, lending, and funding. The deviations from potential provide signals for policy makers when to tighten or loosen macroprudential policies.

E.   Empirical Strategy and Application to France

37.   The model is brought to the data by fitting macroeconomic and financial quarterly time series between 2000:Q4 and 2018:Q2:

- *Macroeconomic time series*: output, investment, employment, and consumption (all demeaned percentage changes).

- *Financial time series*: corporate credit spread (demeaned percentages), financial credit spread (demeaned percentages), and aggregate bank capital (demeaned percentage changes).

38.   The Metropolis-Hastings algorithm is used to find parameters that maximize likelihood of having observed data (Bayesian estimation). Standard parameters were calibrated. Models with frictions as presented herein improve the model fit of observed data relative to the standard RBC model.[5]

39.   A shock decomposition provides the shock realizations during the historical time period that led to the data:

- *Macroeconomic shocks***:** total factor productivity ('ey'), government spending ('eg'), investment efficiency ('ei'), and labor market tightening (disutility of labor, 'en').

- *Financial shocks:* cross-sectional return-on-asset variance of nonfinancial firms (idiosyncratic risk,'eF'), aggregate return-on-asset variance of nonfinancial firms (aggregate risk, 'eB'), and financial intermediary income shock ('ek'), altering capital accumulation of financial intermediaries out of retained earnings.

40.   In addition to the solution of the model, the model is solved for the optimum (the potential), and deviations from potential are calculated. Deviations from potential of capital of nonfinancial firms, capital of financial intermediaries, default risk of nonfinancial firms, and default risk of financial intermediaries are reported. The gaps may guide the authorities in setting macroprudential policies.

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[5]For a check of the plausibility of the model and matching of moments see Christiano, Motto and Rostagno (2014). It is likely that including financial credit spreads in addition to corporate credit spreads increases the fit of the model even further.

F. Results–Gap Analysis

Default Risk Dynamics

41.   Figures 2 and 3 show the demeaned probability of default of the firm and of the banking sector (the black line). Default risk spiked during the 2009 Global Financial Crisis and during the 2012 European Sovereign Debt Crisis. According to the model, default risk is currently low, as credit spreads are low.

42.   The shock decomposition reveals what shocks are driving default probabilities. The three most important shocks are cross-sectional, idiosyncratic risk shocks (represented by the yellow bars 'eF'), aggregate risk shocks (light blue bars 'eB'), and productivity shocks (blue bars 'ey'). Corporate default risk is driven to a significant extent by cross-sectional, idiosyncratic risk. Banking default risk is mostly driven by aggregate risk.

Figure 2. France: Corporate Probability of Default

(quarterly; demeaned)

Firm risk (black line) strongly affected by idiosyncratic risk (yellow bars, 'eF').

Note: The figure shows the demeaned probability of default of the corporate sector. The x-axis denotes the year. The y-axis denotes percentages (0.01 equals to 1 percent).
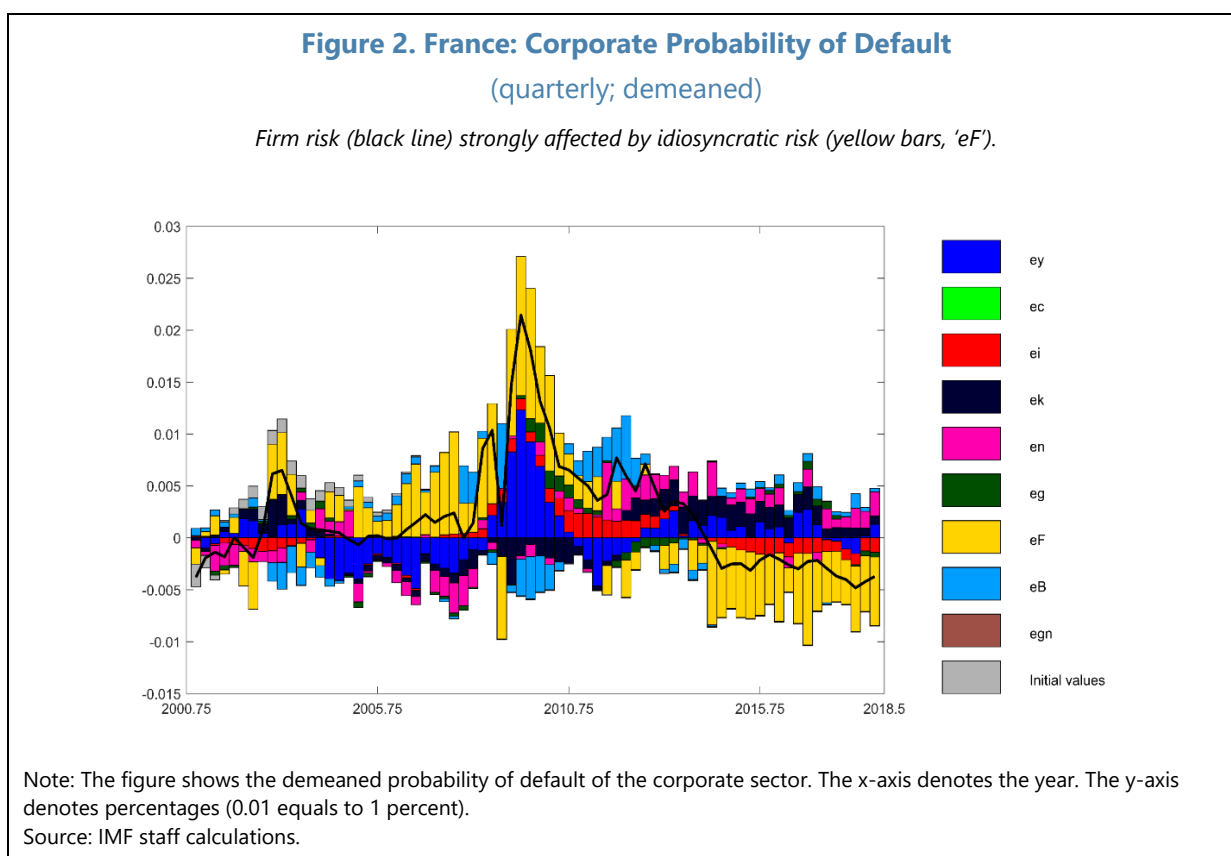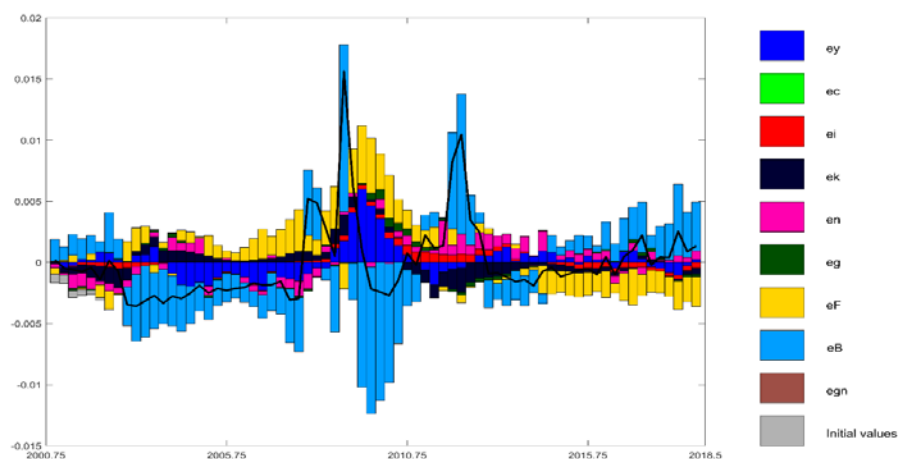Source: IMF staff calculations.

Figure 3. France: Banking Sector Probability of Default

(quarterly; demeaned)

Bank risk (black line) strongly affected by aggregate risk (light blue bars, 'eB').

Note: The figure shows the demeaned probability of default of the banking sector. The x-axis denotes the year. The y-axis denotes percentages (0.01 equals to 1 percent).
Source: IMF staff calculations.

Risk Gaps

43.   Figures 4 and 5 show the deviations of the probability of default from the welfare-maximizing optimum. Risk fluctuates during time between being too high and too low. Risk is too high (when the risk gap reaches positive territory) during four episodes: prior to the Technology Crisis, prior to the Global Financial Crisis, prior to the Sovereign Debt Crisis, and now. Default risk in the corporate sector was particularly elevated during the 2002 Technology Crisis, and now, although it is now low in absolute terms. Default risk of the banking sector was particularly elevated during the Global Financial Crisis and appears now adequate.

Figure 4. France: Corporate Risk Gap (Corporate PD–Optimal PD)

Firms' risk gap (black line) is elevated.

Note: The figure shows the gap of default risk of the nonfinancial corporate sector. The x-axis denotes the year. The y-axis denotes percentages (0.005 equals to 0.5 percent excessive default risk in absolute terms).
Source: IMF staff calculations.

Figure 5. France: Banking Risk Gap (Bank PD–Optimal PD)

Banks' risk gap (black line) is about adequate.
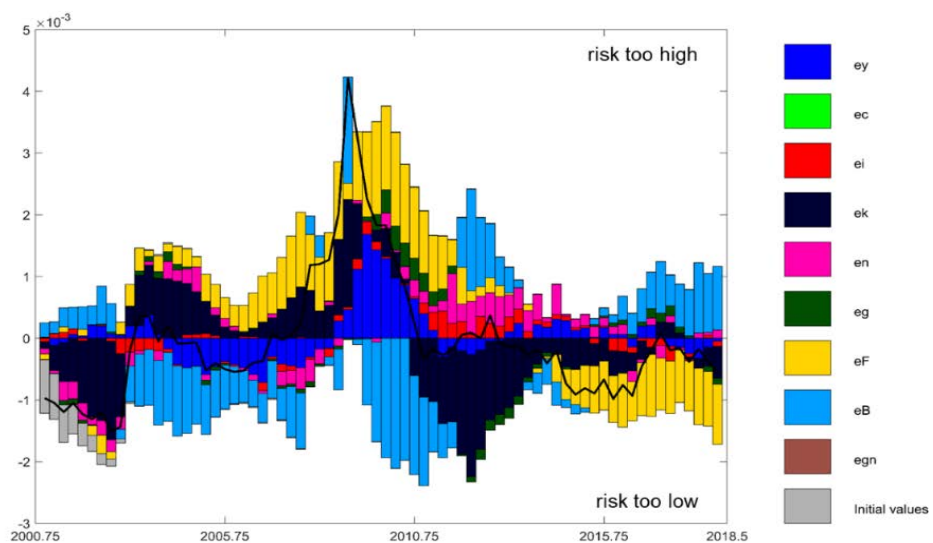
Note: The figure shows the gap of default risk of the banking sector. The x-axis denotes the year. The y-axis denotes percentages (0.005 equals to 0.5 percent excessive default risk in absolute terms).
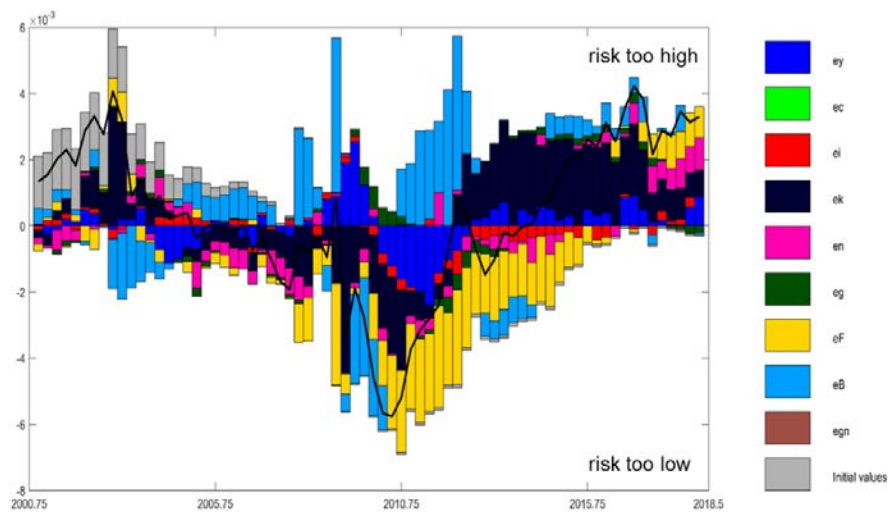Source: IMF staff calculations.

Capital Gaps

44.   Figures 6 and 7 show the deviations of firm capital and banking capital from the welfare maximizing optimum in percentage deviations. Again, four episodes stand out where more corporate capital is needed marked by a positive gap: prior to the Technology Crisis, prior to the Global Financial Crisis, prior to the Sovereign Debt Crisis, and now. Bank capital was too low during the Global Financial Crisis and the Sovereign Debt Crisis and appears now to be adequate.

Figure 6. France: Corporate Capital Gap ((Optimal Capital–Corporate Capital)/Corporate Capital)

Firms should strengthen their capital base.
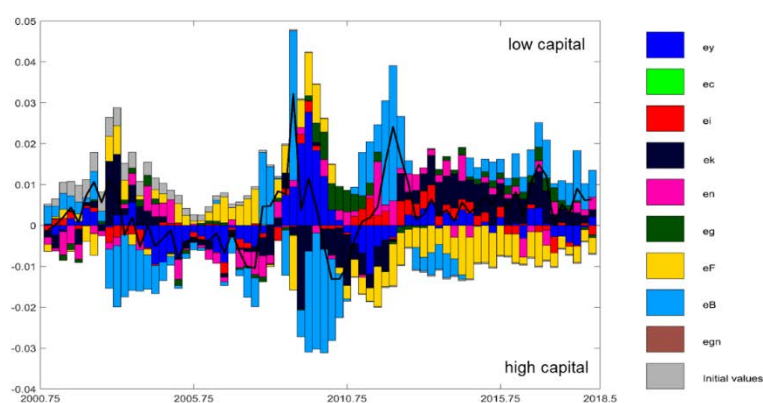
Note: The figure shows the gap of aggregate capital of the nonfinancial corporate sector. The x-axis denotes the year. The y-axis denotes percentages (0.05 equals to a 5 percent gap relative to the total market cap).
Source: IMF staff calculations.

Figure 7. France: Banking Capital Gap ((Optimal Cap–Bank Cap)/Bank Cap)

Banks capital base has improved significantly.
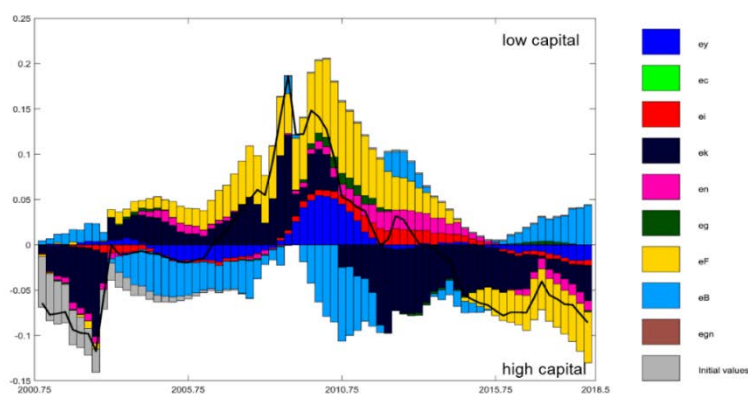
Note: The figure shows the gap of aggregate capital of the banking sector. The x-axis denotes the year. The y-axis denotes percentages (0.2 equals to a 20 percent gap relative to the nominal amount of aggregate capital).
Source: IMF staff calculations.

G. Results–Macro Stress Test

Scenario Generation

45.   During the historical period, the worst downturn was during the Global Financial Crisis. Consequently, the stress test asks what the effect of the Global Financial Crisis on the French economy would be today. For this, the structural shocks were reconstructed from the historical time series. The shocks of the Global Financial Crisis during 2008–2011 were applied now to simulate the macro stress test between 2018–2021.

Stress Test Results

46.   The stress tests show that bank capital is about adequate, while more corporate capital is needed under adverse conditions. Firms a more vulnerable than banks at the current juncture. Nevertheless, corporate and banking risk gaps are elevated under adverse conditions. The corporate risk gap reaches unprecedented highs, while the bank risk gap is considerably lower than during the Global Financial Crisis, if stress intensifies. Figure 8 shows the results of the macro stress test.

Figure 8. France: Gap Analysis of Default Risk and Capital of Nonfinancial Corporates and Banks, and Macro Stress Test

Default risk of the nonfinancial corporate sector has been too high, and capital too low, while bank default risk and aggregate bank capital appear adequate.

Note: The figure shows gaps of default risk and aggregate capital of the nonfinancial corporate sector and the banking sector. The x-axis denotes the year. The y-axis denotes percentages (in the case of risk 0.005 equ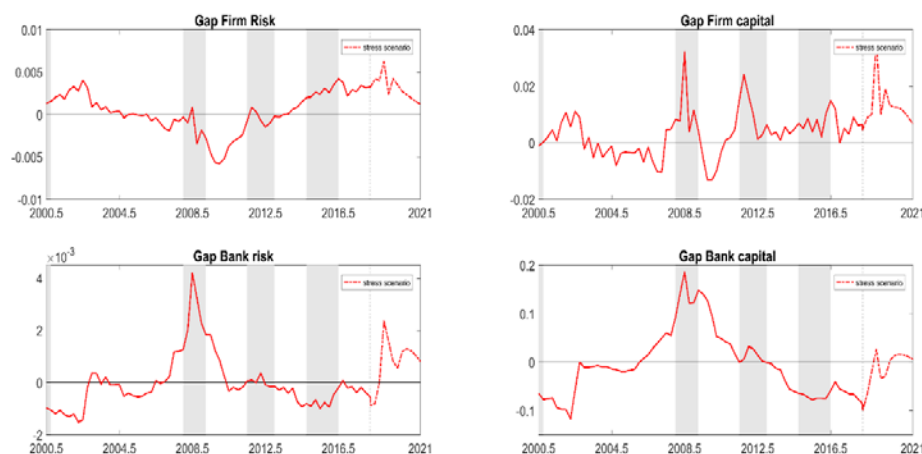als to 0.5 percent excessive default risk in absolute terms; in the case of capital 0.2 equals to a 20 percent gap relative to the nominal amount of aggregate capital). The grey bars highlight recession periods of France's economy. The dotted red line simulates a crisis period that is in magnitude like the Global Financial Crisis.
Source: IMF staff calculations.

H. Implications for Macroprudential Policy Setting

47.   Whenever the analysis reveals risk and capital gaps, it implies that capital should be increased in the respective sector by earnings retention or issuance of equity. Alternatively, any policy measure could be used, as long as it closes capital and risk gaps considering the general equilibrium effects (even though certain macroprudential tools are not part of the model they alter the observed data and hence change the gaps). Consequently, the model can be used as a signaling device when macroprudential intervention is needed (ex-ante and contemporaneous), and whether macroprudential action was successful (ex-post) e.g., whether gaps were closed. The analysis implies that more capital or macroprudential intervention was needed before[6] and/or during four episodes: the Technology Crisis (firm capital), the Global Financial Crisis (firm and bank capital), the Sovereign Debt Crisis (mainly firm but also bank capital), and now (firm capital).

INTERCONNECTEDNESS AND CONTAGION: SELECT ISSUES

A. Executive Summary[7]

48.   The chapter is an attempt to better understand some issues on the interconnectedness within the French financial system. The French financial system is characterized by globally active financial conglomerates with business lines across banking, insurance, and asset management. Ongoing work by the French authorities and the IMF have highlighted the policy significance of the resulting cross-sector and cross-border links.

49.   The analysis is based on three different datasets that provide complementary perspectives on interconnectedness, assessing exposures and contagion. Three approaches are applied. First, direct exposure is assessed through network visualization and summary statistics. Second, clusters of common exposure are identified by examining the extent to which different portfolios overlap. Finally, the analysis on banks is complemented by a contagion exercise using interbank loan data to compensate for the relatively low coverage achieved for banks and marketable securities dataset used for exposures analysis.

50.   The overall composition of direct exposures has been shifting for French financial entities. Across the board exposures to non-financial corporations (NFCs) have increased. There are significant shifts in the portfolio composition, but these vary across sectors. Banks have reduced exposures to domestic monetary financial institutions (MFIs) in favor of other domestic nonbank financials and French government securities. Insurers, on the other hand, have significantly drawn down exposures to foreign non-MFIs in favor of securities issued by the French government and foreign nonbank financials. Investment funds have invested away from domestic MFIs and the

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[6]A more forward-looking result may be obtained by using leverage or coverage ratios instead of credit spread data.

[7]This chapter was prepared by Vassili Bazinas.

French government but increased domestic and cross-border holdings across every other counterparty sector, most notably non-MFIs.

51.   Network analysis suggests increased individual diversification but shifts in cross-border exposures have resulted in increasingly strong clusters of common exposure. First, a cluster of overlapping portfolios is centered around mixed funds and includes equity, bond, and other funds. The second cluster consists of banks and insurers. The two clusters are linked through the common exposure of insurers and mixed funds. While common exposure is lower for banks and insurers relative to the last FSAP, the current upward trend needs close monitoring. Additionally, common exposure among the cited fund sectors has been increasing steadily, suggesting that diversification of idiosyncratic counterparty risk may be generating additional aggregate risk. These trends can be monitored by examining more narrowly how portfolios comove.

52.   Domestically, the network between financial entities is organized in hubs around insurers and banks that in turn has consequences for common exposure. Funds form hubs around insurers through liabilities and around banks through assets. On the asset side, clusters of domestic common exposure are organized around bond and mixed funds. The first cluster contains bond, money market, and other funds, while the second cluster contains mixed funds, banks, and insurers. On the liabilities side, all funds are clustered around mixed funds.

53.   From a financial stability viewpoint, French banks are less inwardly vulnerable to cross-border interbank contagion since the last FSAP, as well as less outwardly contagious. Vulnerability risk emanating from cross-border exposures in interbank loans has declined. Contagion risk emanating from the French banking system has declined slightly since the last FSAP. Spillovers from France have the greatest impact within the EA, while spillovers to France emanate principally from outside the EA.

54.   The authorities should close the remaining data gaps and monitor risks arising from common exposure at different levels of aggregation. The absence of assets other than marketable securities is partially by construction of the datasets and partially by restricted third-party access. Particularly, the absence of exposures between French-domiciled banks and insurance companies may affect cross-sector interconnectedness results for domestic exposures. Additionally, reliable information on financial group identification would add another dimension to the risk analysis. Thus, the authorities' plans to complete the construction of this data during 2019 is important. The cross-border interconnectedness results are relatively more robust due to the almost total coverage of financial entities' assets. A separate contagion exercise is carried out on interbank loan data at the country level to address coverage for banks, but compilation of regulatory capital data at the entity level would permit more detailed analysis of domestic exposures.

B.   Introduction

55.   One of the drivers of systemic risk is the nature and extent of interconnectedness across the different components of the financial system. As one of the largest financial systems, France is host to a range of Euro Area (EA) and non-EA banks, insurers, and asset managers. A

distinctive feature of the French financial system is the prevalence of internationally-active groups with diversified exposures across sectors and borders. An examination of these structural features can help complement intra-sector stress tests.

56.   The work undertaken thus far underscores the importance of interconnectedness across sectors and within financial groups. The Haut Conseil de Stabilité Financière (HCSF), the macroprudential authority in France, has an ongoing work agenda examining cross-sector contagion. The role of funds and asset managers is examined extensively in Benhami et al. (2018), who compile a unique dataset of bilateral exposures between funds and banks, and between funds and insurance companies. Among other things, they find that funds are not more exposed to entities from the same group than to other entities on the asset side; the opposite is true on the liabilities side of funds. Similarly, banks' and insurance companies' exposures to funds from the same group vary between 1 percent to 6 percent of total assets. In other work by the Autorité de Contrôle Prudentiel et de Résolution (ACPR), Hauton and Héam (2015) find that insurance components within groups are more exposed to the banking component but diversification at the group level increases resilience.

57.   The FSAP analysis exploits three different datasets to obtain complementary perspectives on interconnectedness. First, the most general dataset covers domestic and cross-border exposures in marketable securities[8] on a unilateral reporting basis for banks, insurers, and funds; the coverage is almost complete for insurers and funds, but banks hold a relatively small share of assets in marketable securities. The three datasets are combined to assess general trends in direct total exposures and specific trends in direct cross-border exposures. Second, a dataset based on bilateral reporting is used to assess interconnectedness for domestic assets and liabilities between French financial entities; coverage is relatively lower but more granular, permitting a more complete assessment of network properties. Finally, Bank for International Settlements (BIS) consolidated banking statistics are used to complement the analysis on banks by examining interbank loans at the country aggregation level.

58.   The interconnectedness analysis centers on direct exposure, common exposure, and contagion in networks. Direct exposures are physical assets and liabilities between entities. A portfolio of diversified direct exposures can minimize idiosyncratic (counterparty) risk and thereby also minimize first-round contagion effects. Direct exposures are assessed through network visualization and summary statistics. Common exposure refers to portfolio overlap and indicates the extent to which entities may be susceptible to similar shocks. Entities that diversify idiosyncratic risk against counterparties may still be susceptible to risk from common exposure if other entities have diversified their direct exposures in a similar manner. If entities do not account for common exposures, they may inadvertently create clusters with elevated aggregate risk; second-round contagion effects are an example of common exposure. Common exposure is assessed by constructing a measure that identifies clusters of similar entities following Giudici, Sarlin and Spelta

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[8]Marketable securities are comprised of equity, debt securities, and fund shares. Assets are assumed to be marked-to-market.

(2017). Finally, we carry out the contagion exercise of Espinosa-Vega and Solé (2011) specifically on a network of interbank loans for which adequate data are available.

59.   Results for banks, insurers, and funds suggest varying narratives on risks to financial stability stemming from interconnectedness. First, the data suggest a shifting composition of total exposures held by the French financial system domestically and across borders. Specifically, banks, insurers, and funds have all significantly increased exposure to NFCs. More narrowly, banks have invested away from domestic MFIs, insurers have increased exposure to the French government, and funds have reduced exposure to domestic MFIs and to the French government while increasing exposures in every other sector domestically and abroad. Second, the domestic network between financial entities is organized in hubs around insurers and banks; funds form hubs around insurers through liabilities and around banks through assets. Third, while network analysis suggests increased individual diversification in cross-border exposures, shifting cross-border exposures have resulted in increasingly strong clusters between equity, bond, mixed, and other funds, as well as between banks, insurers, and mixed funds. Fourth, domestic out-flow common exposures are organized around bond and mixed funds; the first cluster contains bond, other, and money market funds, while the second cluster contains mixed funds, banks, and insurers. Fifth, domestic in-flow common exposure consists of one cluster comprised of all funds; this is likely due to the structure of the data. Sixth, French banks are less inwardly vulnerable to cross-border interbank contagion since the last FSAP, as well as less outwardly contagious. Spillovers from France have the greatest impact within the EA, while spillovers to France emanate principally from outside the EA.

60.   This note is structured into the following sections. The data used in the FSAP analysis are first discussed briefly, including a discussion of data gaps. Subsequently, cross-border exposures are assessed jointly for banks, insurers, and funds. The third section examines interconnectedness stemming from domestic bilateral exposures, while the fourth section carries out an interbank contagion exercise at a country-level consolidation. The last section offers concluding observations. A summary of the data and methodologies employed is available in Appendices II and III.

C.   Data Overview

Datasets used in the FSAP are categorized into unilateral (domestic and cross-border) exposures and bilateral (domestic) exposures. The data sources used by the French authorities to construct the datasets is also described, including data gaps.

Coverage

61.   The interconnectedness analysis uses data compiled for the HCSF on contagion. The HCSF has initiated a long-term work agenda on cross-sector contagion. The first step of this effort has been the creation of a dataset on bilateral exposures in marketable securities across sectors, compiled originally in Benhami et al. (2018). The data collection remains a work in progress; exposures between banks and insurance companies are missing, as are exposures beyond

marketable securities. The authorities plan to expand[9] and exploit this data in a model to assess shock propagation through interconnectedness.[10] The data cover exposures in marketable securities held by French-domiciled banks, insurance companies, and funds. Marketable securities include debt, equity, and fund shares.

62.   The data used in the cross-border assessment are collected unilaterally and reflect the complete exposures in marketable securities for banks, insurance companies, and funds. For banks, holdings data are collected from the Production de statistiques de titres en détention (PROTIDE), listing securities held by individual entities. For insurance companies, holdings data are collected from the Tableau complémentaire aux éléments de placements (TCEP) in Solvency I and Solvency II reporting, listing securities holdings for individual entities; a structural break with the implementation of Solvency II in January 2016 creates qualifiers for interpreting the data. Finally, for funds, data on the investment portfolios of French collective investment undertakings (CIU) are collected by the BdF at a security level. These data thus represent both domestic and cross-border positions in marketable securities for the French financial system. Data are provided annually for banks (2008–2017) and insurance companies (2011–2017) and quarterly for funds (2008–2017).

63.   The data used in the domestic assessment represent bilateral exposures in marketable securities to and from French-domiciled funds. The data used in the cross-sector interconnectedness assessment constitute a subset of the data used in the cross-border assessment. The distinction arises from the effort to create a dataset of bilateral exposures in marketable securities between French-domiciled financial institutions using data from reported asset holdings. On the asset side, the data provide funds' domestic holdings with respect to banks and insurance companies. On the liabilities side, the data show all financial domestic holders of French-domiciled funds' shares, which are compiled from banks' and insurance companies' reported holdings. Data are provided annually between 2010–2016.

64.   While the unilateral dataset captures a larger share of exposures, the bilateral dataset provides deeper granularity for domestic exposures. The unilateral dataset coverage relative to total assets is 10.5 percent for banks, 92.7 percent for insurers, and 96.3 percent for funds. The coverage of the bilateral dataset is much smaller at 2.2 percent for banks, 29.8 percent for insurers, and 25.7 percent for funds,[11] but has the benefit of showing party-to-party exposures. Overall, the unilateral dataset covers EUR 4.8 trillion in assets (of which EUR 1.1 trillion to French financial entities), while the bilateral dataset covers EUR 835 billion in assets between French financial entities.

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[9]The authorities are currently incorporating direct exposures in marketable securities between banks and insurance companies.

[10]In an initial model, the HCSF will assess direct and indirect exposures with two main channels: losses through mark-to-market accounting of securities; and losses due to potential defaults. Eventually, behavioral aspects examining asset fire sales and investor runs will be incorporate. The authorities aim to complete this work in 2019.

[11]The much smaller coverage of assets in the bilateral dataset results from the restriction that holders and issuers are French-domiciled financial entities.

Gaps

65.   In the bilateral dataset, exposures in marketable securities between banks and insurers are not readily accessible. Also missing are exposures in instruments other than marketable securities for all types of financial entities in the unilateral and bilateral datasets. The partial completeness of the data means that interconnectedness may be understated, primarily along two dimensions. First, domestic interbank exposures across all instruments are missing; marketable securities of other French banks constitute 1.6 percent of total assets, but exposure through interbank loans is much higher at 31 percent of total assets.[12] Second, bilateral exposures between banks and insurance companies are missing; insurers hold 11 percent of their balance sheet in securities issued by French banks.

66.   While the first omission is related to third-party access, the second omission relates to the stage of completion of the HCSF's work agenda.[13] The cross-border interbank contagion analysis uses loans to capture a missing dimension of interconnectedness for banks. Also, a closer examination of trends within and across financial groups would have necessitated information on which entity-level banks, insurers, and funds (or asset managers) form part of a specific financial group. This remains work in progress, so information on financial group membership was not available for this analysis.

D. Cross-border Interconnectedness

This section details the cross-border interconnectedness analysis undertaken using the unilateral reporting dataset provided by the HCSF. Direct exposures are assessed by providing network visuals and descriptive statistics. Common exposures are further examined by employing the common exposure framework of Giudici, Sarlin and Spelta (2017).

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[12]The omission of interbank loans is due to restrictions on data access with the ECB. Data on large interbank exposures is owned by the ECB and only made available on-site in Frankfurt, despite being collected by the BdF in Paris. Data on marketable securities is collected by the French regulatory authorities (BdF, ACPR, AMF) and only accessible at the open data room of the BdF in Paris. The interconnectedness analysis was carried out using the data on marketable securities provided directly by the French authorities in Paris.

[13]Bilateral exposures between banks and insurance companies are missing because the cross-sector interconnectedness dataset is constructed by matching holders and issuers in two databases of securities holdings reports. Specifically, banks report their securities holdings at the entity-level, identified by their SIREN code (French official identifier); issuers are also identified by their SIREN. Insurance companies report at the entity-level and are identified by their SIREN, but issuers are instead identified by a separate Legal Entity Identifier (LEI). To report bilateral exposures between banks and insurance companies, therefore, a correspondence between SIREN and LEI must be achieved. There are several obstacles with reporting to overcome: (i) first, LEI is provided on a voluntary basis; (ii) second, LEI may vary over time, for instance due to mergers and acquisitions; (iii) third, an LEI could be reported for various levels of aggregation, for instance the holding company as opposed to the individual entity. Work through the HCSF is ongoing to complete the cross-sector interconnectedness dataset within 2019.

Direct Exposures in Cross-border Marketable Securities

67.   **Total exposures in marketable securities across banks, insurance companies, and funds stand at EUR 4.8 trillion, an increase of 27 percent since 2011.** Insurance companies and funds have dramatically increased their total exposures since the Euro Area crisis, while banks' total exposures have declined slightly. In 2017, total exposures for insurance companies have increased to EUR 2.4 trillion (+36 percent since 2011), decreased to EUR 896 billion (-12 percent since 2011) for banks, and increased to EUR 1.5 trillion (+30 percent since 2011) for funds.

68.   **Cross-border exposures in marketable securities have increased in aggregate since the last FSAP but not proportionally to domestic exposures overall due to sector trends.** Insurers and funds have increased cross-border exposures to EUR 1.15 trillion and EUR 784 billion in 2017 (+25 percent and +47 percent since 2011). As a share of total exposures in marketable securities, however, cross-border exposures for insurers and funds account for 49 percent and 52 percent in 2017 (-2 percent and +8 percent since 2011).[14] Banks drastically reduced their cross-border marketable securities holdings in the aftermath of successive crises in 2008 and 2010 in favor of domestic alternatives. While cross-border exposures for banks have been reduced to EUR 375 million in 2017 (-39 percent since 2011), this has been offset by a proportional increase in domestic exposures; since 2011, cross-border exposures continue to comprise a steady share of 42 percent of all marketable securities holdings.[15]

69.   **French financial entities maintain a global presence but are most heavily invested in the Euro Area, the United States, and the United Kingdom.** Banks, insurers, and funds have a comparable geographic footprint, maintaining diversified exposures around the globe but focused in a few markets (see Figure 10). Since 2012, changes have largely been proportional at the country level.

70.   **At the country-sector level, trends in domestic and cross-border exposures for banks, insurers, and funds imply a shifting composition (see Figure 9).** Changes in the composition of French financial institutions' holdings are evident from Figure 17. Broadly, there has been a significant shift toward domestic and foreign NFCs across banks, insurers, and funds. Banks' domestic exposures to the French government form the most substantial individual exposure, while exposure to domestic nonbank financials has been steadily increasing. Insurance companies have significantly increased exposures to the French government but also to nonbank financials. Insurers' cross-border exposures are concentrated in monetary financial institutions (MFIs) and NFCs. Funds' overall declining exposures to domestic MFIs since 2011 has been offset by increased exposure to

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[14]When examining an institution's total cross-border exposures, this may be understated if the indirect cross-border exposure through the holding of domestic fund shares is not considered. Data based on the look-through principle, however, were only available for insurance companies.

[15]A caveat for funds and banks is that data are not available for the ultimate exposure, as they were for insurance companies; this means that cross-border exposures are understated. This is likely not a significant issue for French banks, since banks' holdings of French funds amount to 0.42 percent of total assets.

NFCs and other French funds. The fastest-growing exposures for funds, however, have been to foreign non-MFIs and NFCs.

71.   Exposures are predominantly comprised of debt securities. Banks hold most of their domestic and cross-border exposures in debt securities; 80 percent for domestic positions and 69 percent for cross-border positions. Similarly, insurance companies' exposures are primarily in debt securities (76 percent for domestic and 72 percent for cross-border securities), but domestic exposures in equity have increased since 2015.[16] Finally, funds hold mostly debt securities domestically and abroad. Since 2012, funds have invested increasingly in domestic equities and other domestic funds, so that the domestic positions are evenly split between debt (33 percent), equity (33 percent), and fund shares (34 percent). Abroad, French funds are primarily invested in debt securities (55 percent), followed by equity (33 percent) and foreign fund shares (12 percent).
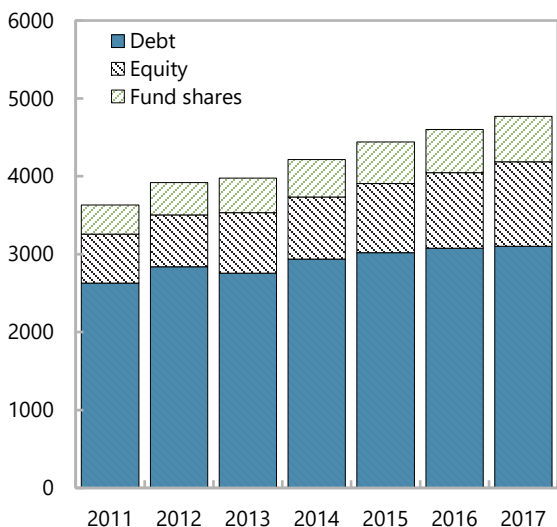
72.   The direct exposure network properties further reflect the evolving composition of cross-border exposures at the country-sector level. Examining the network of exposures of French financial entities to country-sector counterparties lends further support to the narrative of changing composition. The number of counterparties (vertices) for banks has remained relatively constant, while the number of connections (edges) has declined (Figure 11). This indicates that fewer banks are invested in cross-border counterparties in 2017, coinciding with the reduced aggregate cross-border positions. With fewer connections and a similar number of country-sector counterparties, heterogeneity in cross-border exposures for banks, prima facie, is relatively higher; international banks have drawn down cross-border positions while maintaining counterparties, while smaller banks have withdrawn from exposures to cross-border counterparties. For insurance companies and funds, increased aggregate cross-border positions have coincided with a larger number of counterparties and connections, suggesting increased individual diversification. To the extent that a greater number of insurers and fund sectors are holding similar exposures that diversify away idiosyncratic risk, however, it is not immediately clear whether aggregate risk is increasing as a result. Common exposures are subsequently examined in greater detail to ascertain whether French financial entities are subject to similar risks from their holdings of marketable securities.

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[16]A caveat here is that there is a structural break in the data for insurance companies in 2016 due to the implementation of Solvency II reporting. Consequently, comparisons across time should be interpreted cautiously.

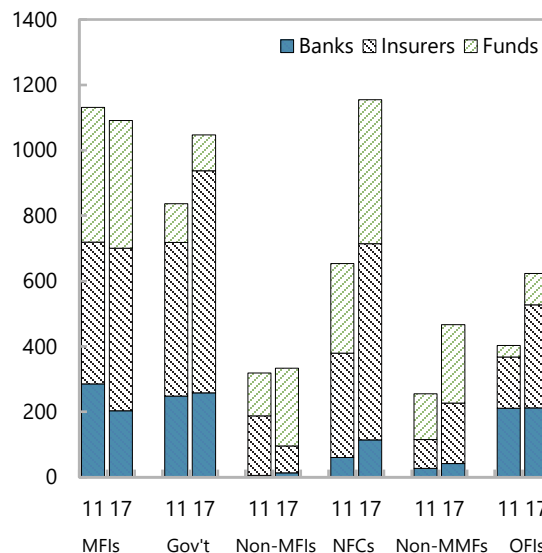**Figure 9. France: Composition of Exposures in the Unilateral Dataset**

Exposures are mainly held in debt securities.

Total Positions
(EUR billion)

Exposures have increased across all major counterparty countries and domestically, driven by insurers and funds.

Exposures by Counterparty Country
(EUR billion, FR lhs others rhs)

Increased exposures since 2011 are primarily due to high insurance and fund holdings of NFCs.

Exposures by Counterparty Sector
(EUR billion)
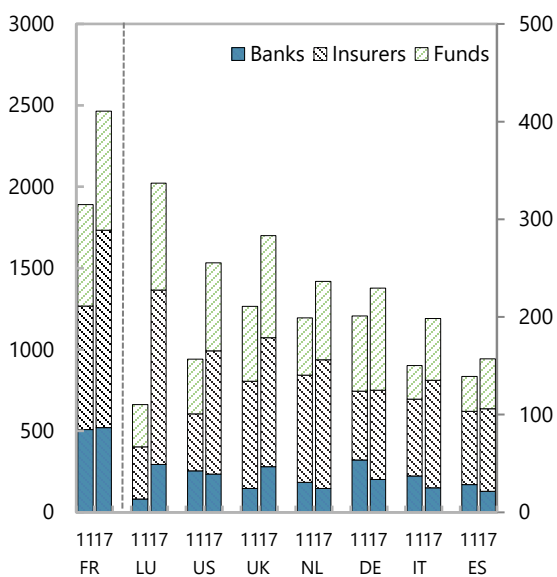
Overall, domestic (FR) and cross-border (XB) exposures have increased across almost every counterparty sector, but changes in NFC holdings dominate.

Exposure Change by Counterparty Country and Sector
(Proportion of total exposure change, 2011-2017)
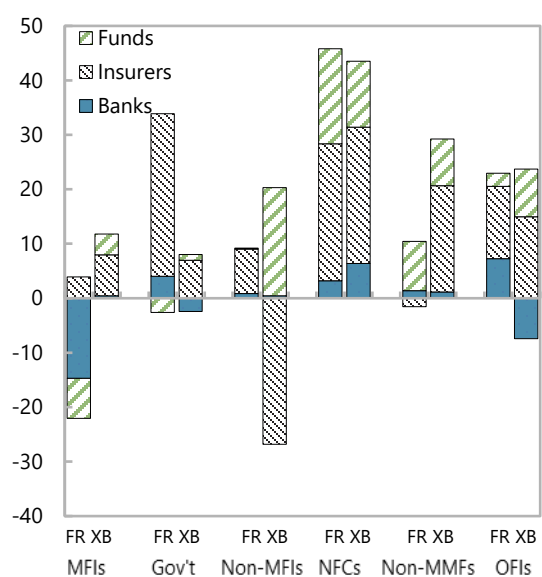
Source: Haut Conseil de Stabilité Financière (HCSF).

Figure 10. France: Direct Cross-border Exposures of French Financial Entities

Banks, insurers, and funds maintain a global presence, with exposures focused in the EU, the US, and the UK. The highest individual exposure is to Luxembourg, with marketable securities holdings amounting to EUR 337 billion.
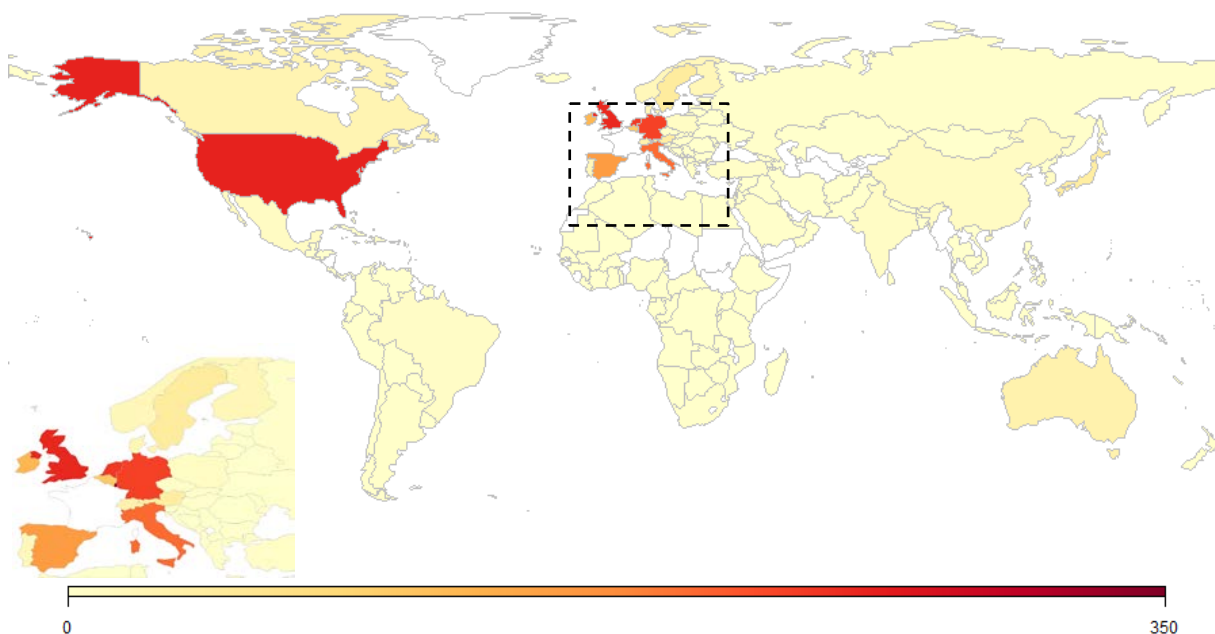
Cross-border exposures in marketable securities have increased in magnitude since 2012, driven by insurers' and funds' increased exposures within the EU; banks' total cross-border exposures over the same period have declined.
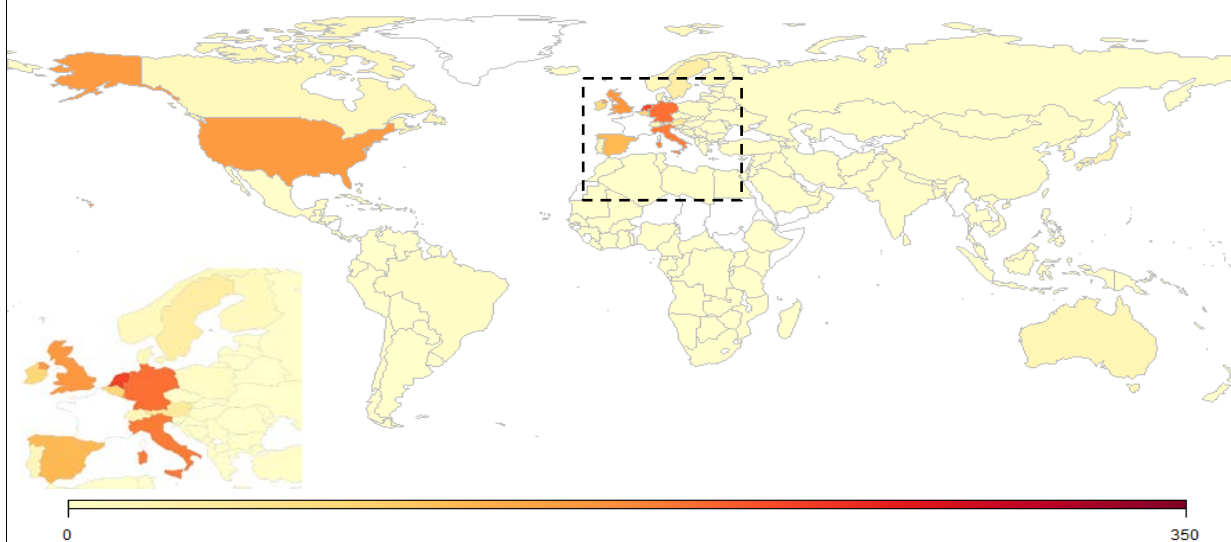
Note: Units are in EUR billion.
Source: Haut Conseil de Stabilité Financière (HCSF).

Figure 11. France: Direct Cross-border Exposure Network Properties in Unilateral Dataset

The number of counterparties has remained constant, while linkages have been declining, indicating a retreat of banks from cross-border exposures.

Network Summary of Bank Cross-border Exposures
(Count, by country-sector)

Insurance companies have diversified cross-border exposures across more counterparties; a break in 2016 due to Solvency II should be considered.
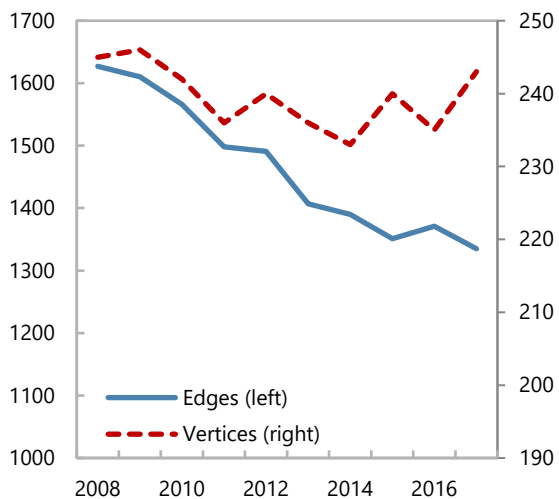
Network Summary of Insurer Cross-border Exposures
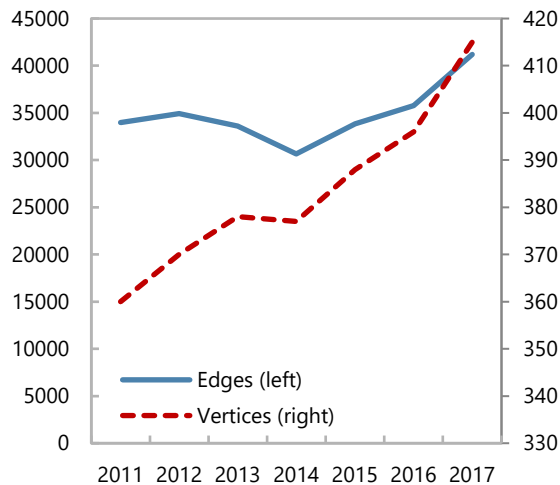
Similarly, funds have diversified exposures across a greater number of cross-border counterparties.

Network Summary of Fund Cross-border Exposures
(Count, by country-sector)
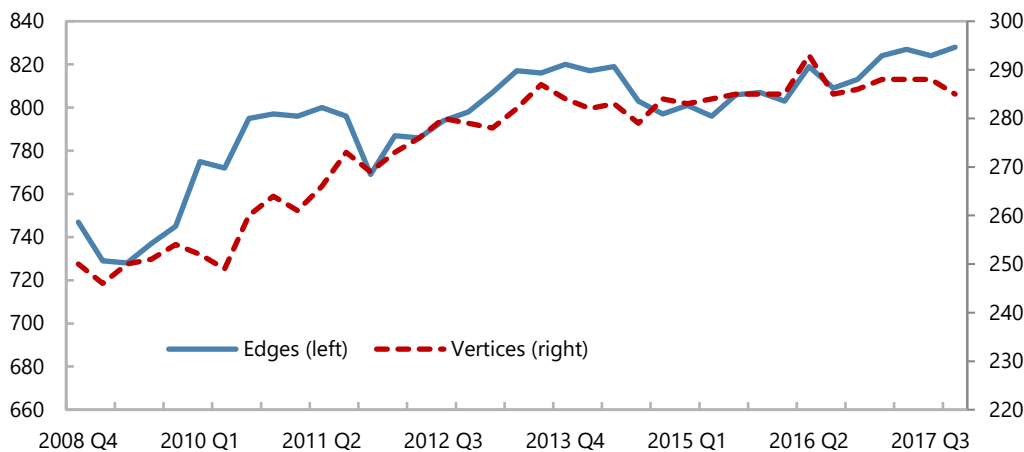
Source: Haut Conseil de Stabilité Financière (HCSF).

Common Exposures in Cross-border Marketable Securities

73.   An assessment of risks stemming from common exposures in assets requires a more careful examination of direct exposures. The previous section summarized the properties of the unilateral datasets and the resulting direct networks for banks, insurers, and funds. Common

exposure networks are helpful to determine whether a subset of financial entities is susceptible to similar market risks stemming from their cross-border holdings of marketable securities. Whereas direct exposure networks represent exposures in physical assets and liabilities, common exposure networks represent exposures in terms of composition similarity in portfolios of assets and liabilities.[17]

74.   The common exposure analysis examines the similarity in the composition of French financial entities' portfolios. The methodology in Giudici , Sarlin and Spelta (2017) uses a linear transformation of distance to define the similarity between portfolio vectors, which the authors call *out-flow common exposure* for assets and *in-flow common exposure* for liabilities.[18] There is a one-to-one correspondence between the correlation of two vectors and distance; we favor the use of distance because the objective is to identify clusters that are most similar.[19] If two entities have a greater proportion of their asset portfolio invested in similar counterparties, the out-flow common exposure will be higher; equivalently, correlation will be higher, and distance will be lower. Larger exposures to similar counterparties relative to the rest of the portfolios will mean that entities are exposed to greater common risk. Given the unilateral nature of the datasets under consideration in this section, similarities only on the asset side are examined. The analysis is carried out for banks, insurers, and types of funds, where counterparties consist of cross-border exposures at the country-sector level. Significance can be assessed based on a t-test of the correlation coefficient.[20] For out-flow cross-border assets, significance is achieved at all conventional levels for every out-flow common exposure measure reported.

75.   Common exposure risk for cross-border asset holdings is relatively high within the fund sector, as well as between banks and insurers. Table 1 characterizes common exposure risk using the methodology of Giudici, Sarlin and Spelta (2017). The out-flow common exposure between pairs of entities is shown below the diagonal, while a percent change since 2012 is shown above the diagonal. The out-flow common exposure is high between equity and mixed funds (1.32), bond and mixed funds (1.24), mixed and other funds (1.40), and equity and other funds (1.17), suggesting the presence of a cluster. Elsewhere, common exposures between insurers and banks and between insurers and mixed funds are relatively high (1.20 and 1.19), suggesting the presence

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[17]Over a graph, the direct network will be represented by edges corresponding to holdings in marketable securities. For a common exposure network, however, edges in a graph represent the proximity in portfolio and funding composition.

[18]Further details are provided in Appendix III.

[19]This is very common in the network analysis literature.

[20]The following t-statistic can be used to assess significance of correlation:

$$t = r\frac{\sqrt{n-2}}{\sqrt{1-r^2}},$$

where *r* is the correlation coefficient and *n* is the number of degrees of freedom. For 2026 degrees of freedom, the one-sided test (positive correlation since we are interested in similarity) has a 1 percent, 5 percent, and 10 percent critical values at 2.33, 1.96, and 1.28; these correspond to out-flow common exposures (correlations) of 0.64 (0.07), 0.62 (0.05), and 0.61 (0.04). We are interested in one-sided significance, because we want to identify clusters by similarity of portfolio composition.

of a second cluster. A final comment is that bond funds have highly significant overlap with every other sector. Common exposure indicates the extent to which portfolios overlap proportionally, so that if a shock affects one, it is likely to affect all.

76.   Fund sectors may have individually diversified direct exposures, but the funds industry overall is susceptible to elevated aggregate risk through common cross-border exposures. While examining direct exposures, we found that funds had increased cross-border exposures overall, resulting in a network with more vertices and edges; this suggested that perhaps individually, fund sectors were diversifying idiosyncratic counterparty risk. By assessing the similarity in portfolio composition, however, we find that any potential individual diversification by fund sector has also led to increased aggregate risk for the funds industry; increasingly, fund sectors are investing in the same country-sector counterparties, forming a cluster of common exposure.

77.   Despite declining cross-border exposures for banks and increasing cross-border exposures for insurers, common exposure is also elevated. Banks and insurers have displayed opposite tendencies in direct cross-border exposures. Nonetheless, there is significant portfolio overlap at the country-sector level, so that both are susceptible to similar shocks. If domestic exposures from the unilateral dataset are also considered, common exposure for banks and insurers rises to 1.46, driven by the shift in portfolio composition of insurers toward French government bonds.

78.   Some recent trends in cross-border common exposures must be monitored. Figure 12 shows the evolution between pairs of entities with significant common exposures trending upward in recent years. While generally not higher than in 2012 (as indicated above the diagonal in Table 1), common exposure in all pairs has been increasing since 2015. Particularly, a cluster of common exposure is being formed between equity, bond, mixed, and other funds. Insurers are on the periphery of this cluster through their common exposure with mixed funds, while banks are connected through common exposure with insurers. Since 2015, the strength of these relationships has been increasing, suggesting that shocks affecting the cited fund sectors will also impact insurers. Banks are more likely to be affected by shocks that are common only to insurers.

Table 1. France: Common Exposures in Cross-Border Assets								
	Equity	Bond	Mixed	Hedge	Other	Bank	Insurer	MMF
Equity		1%	11%	-4%	-13%	3%	17%	13%
Bond	1.04		11%	10%	-17%	-15%	-15%	4%
Mixed	1.32	1.24		-34%	1%	-8%	7%	7%
Hedge	0.76	1.02	0.87		-13%	29%	-11%	12%
Other	1.17	1.08	1.40	0.87		-3%	1%	-8%
Bank	0.71	0.95	0.80	1.10	0.85		-2%	-2%
Insurer	0.96	0.99	1.19	0.83	1.10	1.20		-22%
MMF	0.80	1.01	0.81	0.79	0.80	0.93	0.93	

Note: The lower triangle shows out-flow (asset) common exposure between two sectors for 2017; this is scaled between 0 and 2. A higher value indicates higher similarity in exposures. The upper triangle shows the percent change since 2012. See Appendix III for further details.
Source: Haut Conseil de Stabilité Financière (HCSF) and IMF staff.

Figure 12. France: Significant Trends in Cross-border Common Exposure

The cross-border portfolio composition of certain funds and those of banks and insurers have been increasing in similarity of exposures over the sample, indicating increased susceptibility to common shocks.

Common Exposure Trends in Cross-border Assets
(Index)
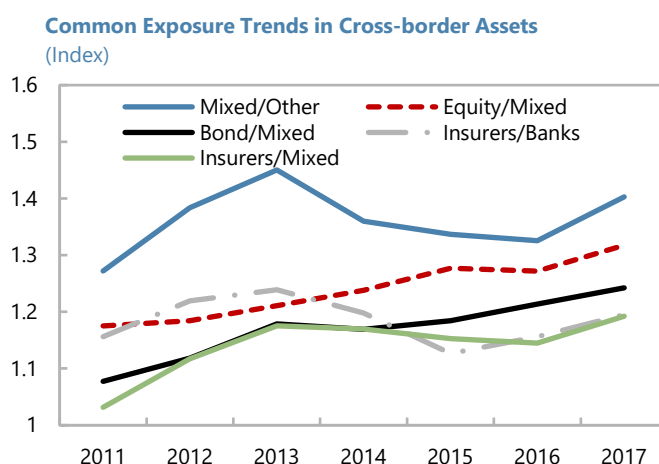
Source: Haut Conseil de Stabilité Financière (HCSF) and IMF staff calculations.

E.   Domestic Interconnectedness

To complement the cross-border analysis undertaken using unilaterally reported data, this section examines domestic exposures using the more granular bilateral reporting dataset for domestic exposures constructed by the HCSF (Benhami et al., 2018). Direct exposures are assessed by providing network visuals and descriptive statistics. Common exposures are further examined by employing the common exposure framework of Giudici, Sarlin and Spelta (2017).

Direct Exposures in Domestic Marketable Securities

79.   The bilateral dataset provides unique insight into direct exposures across sectors, but careful interpretation is necessary. Total domestic exposures in marketable securities held by domestic financial entities stand at EUR 1.1 trillion. The bilateral reporting dataset covers EUR 835 billion of assets at a greater granularity, for instance by showing party-to-party holdings even for funds. The lower coverage of total assets is primarily due to the omission of insurance companies' exposure to marketable securities issued by banks.

80.   Funds are connected to insurance companies through liabilities and to banks through assets. Domestic exposures in the bilateral dataset are dominated by insurance companies holding fund shares issued primarily by mixed and money market funds (Figures 13 and 14). Banks' relatively low positions reflect the nature of the data, in the sense that marketable securities comprise a much smaller proportion of banks' balance sheets relative to insurance companies and funds. However, a significant portion of funds' domestic holdings in marketable securities is comprised of debt issued by banks.

81. **While aggregate exposures are increasing, there is greater consolidation among counterparties.** The first panel in Figure 15 shows the number of vertices and edges, representing the total number of counterparties and direct exposures, respectively. The number of vertices has been steadily declining throughout the entire sample, indicating a lower number of counterparties with exposures in assets and liabilities. The number of edges has also been steadily declining. Taken jointly with increased domestic exposures, this suggests consolidation and increased interconnectedness between funds and the rest of the financial system.

82. **The domestic network has become slightly less sparse, and therefore more interconnected.** The second panel in Figure 15 shows the density of the network and the average distance. The density of a network is the ratio of edges relative to the total number of possible edges that would arise if the graph were fully connected,[21] while average distance measures the average number of edges along the shortest path between two vertices in a graph. The domestic network in 2017 is comprised of 9,670 funds, 132 banks, and 130 insurance companies, amounting to 9,932 vertices in total. From these vertices, there are a total of 61,348 edges representing an exposure from a bank or insurance company to a fund. With a density of 0.06 percent, the network is relatively sparse, although in line with the literature on financial networks. Additionally, the average distance is 3.24 and varies between 1 and 14, so that any two vertices are, on average, connected through 2 or 3 other vertices. The low density and average distance suggest that some financial entities are acting as hubs; that is, many financial entities form clusters through 2 or 3 other well-connected financial entities.

83. **The network is clustered around a few well-connected banks and insurance companies and many sparsely-connected funds.** The third panel of Figure 15 shows the cumulative degree density distribution for the network in 2008 and in 2017. The degree represents the number of inward- and outward-oriented edges connected to a vertex. The cumulative distribution shows that 75 percent of the probability mass is concentrated below 10 in 2017, indicating that 75 percent of all financial entities in the sample are connected to at most 10 other entities. Nonetheless, there exists a very small number of entities with more than 1000 links; these include three banks and six insurance companies. Over time, the distribution has shifted left so that the highly-connected entities are progressively less connected; alternatively, there are fewer highly-connected entities.

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[21]A graph or network is said to be fully connected if every vertex is connected by an edge to every other vertex. If V represents the number of vertices, then $V(V-1)$ represents the total number of potential edges. If E represents the number of edges, then $E/[V(V-1)]$ represents the network density.

Figure 13. France: Composition of Domestic Exposures in the Bilateral Dataset

Insurers hold most of the marketable securities issued by nonbanks domestically.

Domestic Marketable Securities by Holder
(EUR billion)
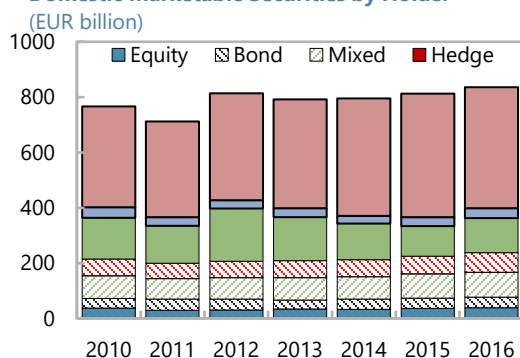
Mixed and money-market funds are the most active domestic nonbank issuers.

Domestic Marketable Securities by Issuer
(EUR billion)
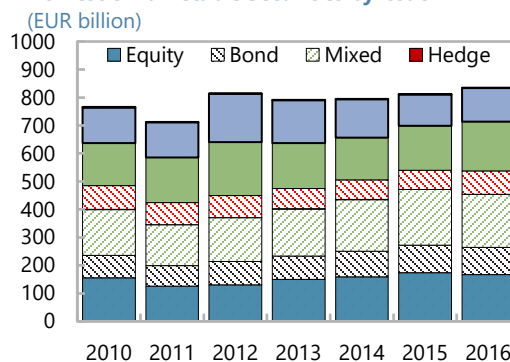
There are 9,670 French-domiciled funds with exposures to other French-domiciled financial institutions.

Composition by Count
(Number)
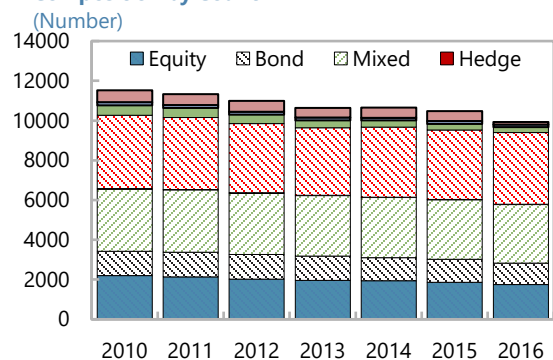
Banks hold only a small but increasing size of shares in French-domiciled funds.

Balance Sheet Marketable Securities for Banks
(EUR billion)
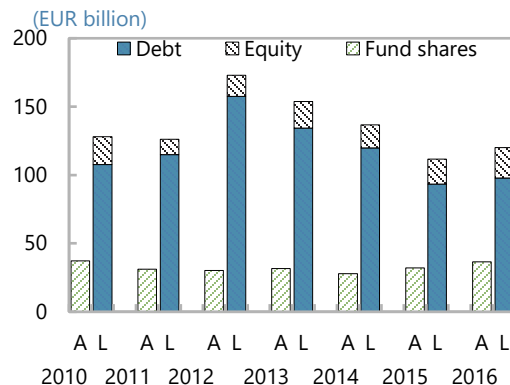
Insurance companies hold most fund shares issued by French-domiciled.

Balance Sheet Marketable Securities for Insurers
(EUR billion)
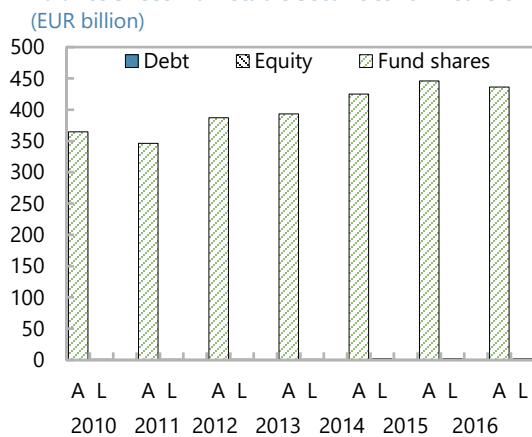
French-domiciled funds hold increasingly more fund shares and fewer bonds.

Balance Sheet Marketable Securities for Funds
(EUR billion)
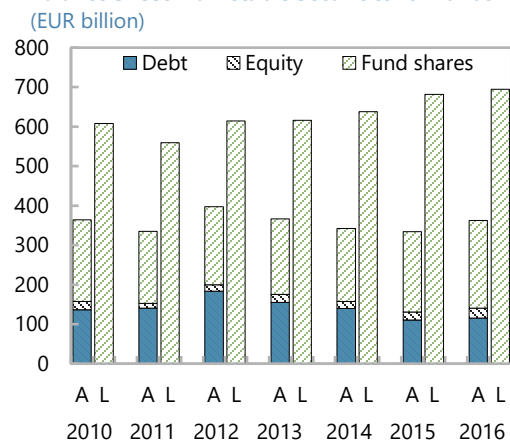
Source: Haut Conseil de Stabilité Financière (HCSF).

Figure 14. France: Network Visualization of Cross-sector Exposures

Exposures in the bilateral dataset are mainly held by insurers. Edges are colored according to the holder, thereby indicating cross-sector positions as assets. Vertex size is scaled according to total assets.
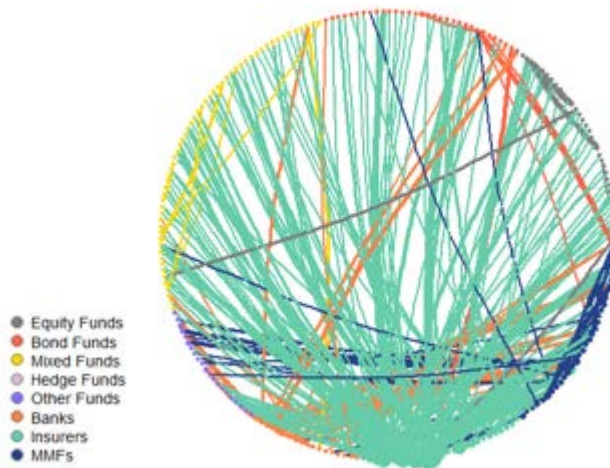
Exposures in the bilateral dataset are issued by mixed and money market funds. Edges are colored according to the issuer, thereby indicating cross-sector positions as liabilities. Vertex size is scaled according to total assets.
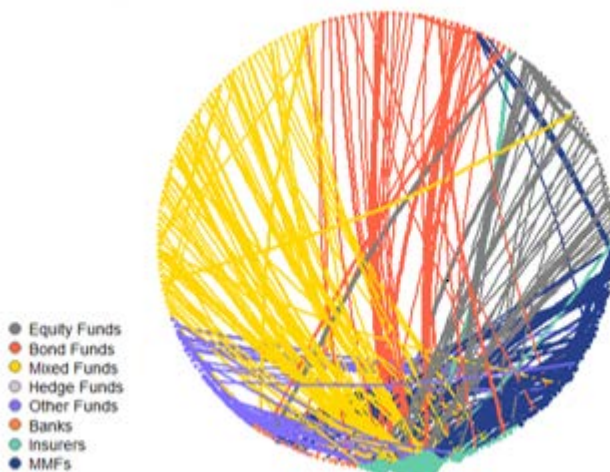
Note: Only exposures over 1 billion EUR shown.
Source: Haut Conseil de Stabilité Financière (HCSF).

Figure 15. France: Direct Exposure Network Properties in Bilateral Dataset

The number of counterparties and connections in the network have been declining, suggesting consolidation in the financial system.

The complexity of the network is stable over time, with most entities connected to each other through 2–3 highly-connected entities acting as hubs.

Network Summary of the Financial System
(Count)

Network Density and Average Distance
(Number of edges left, percentage right)
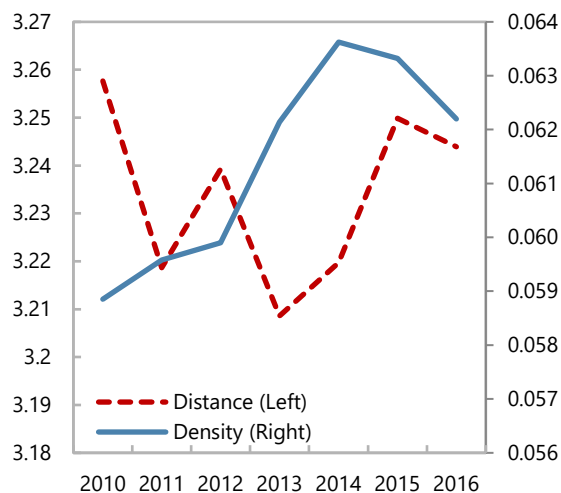
A clustering effect is evident from the small number of highly-connected entities.

Cumulative Degree Distribution
(Probability mass, logarithmic scale)
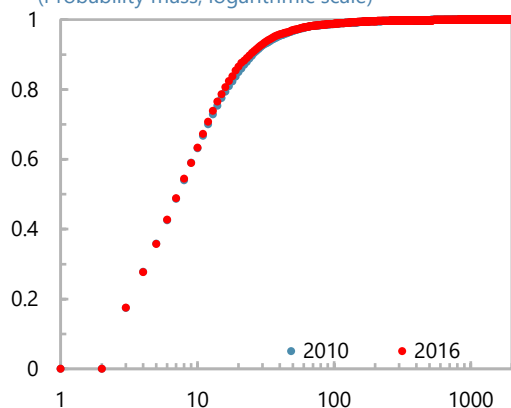
Source: Haut Conseil de Stabilité Financière (HCSF).

Common Exposures in Domestic Marketable Securities

84.   A nuanced assessment of risks resulting from direct exposures requires an examination of common exposure. The results of the previous section indicated the presence of clusters around insurers (liabilities) and banks (assets) in the domestic network. Shifting focus from direct to common exposure, we can assess the extent to which overlapping portfolios may present an indirect risk. Interpretation of results are tempered by the low coverage of the bilateral dataset

that includes 2.2 percent of banks' total assets, 29.8 percent of insurers' assets, and 25.7 percent of funds' assets. The analysis is carried out for banks, insurers, and types of funds, where counterparties consist of domestic financial institutions. Significance can be assessed based on a t-test of the correlation coefficient, and a common exposure of 1.07 is significant at the 1 percent level.[22]

85.   **On average, diversification of idiosyncratic risk does not lead to increased aggregate risk through common exposure.** Figure 17 shows the out-flow common exposure relative to the average portfolio in the sample (red) and total direct exposure (blue). The average out-flow common exposure reaches low levels of significance for a subset of entities considered.

86.   **Common exposure in assets is high, however, between bond, other, and money market funds, as well as between banks, insurers, and mixed funds.** Table 2 characterizes common exposure risk using the methodology of Giudici, Sarlin and Spelta (2017). The out-flow common exposure between pairs of entities is shown below the diagonal, while a percent change since 2012 is shown above the diagonal. Two clusters seem to exist. First, bond funds have significant common exposure with other funds (1.40) and with MMFs (1.40). Second, banks and insurers[23] have significant domestic common exposure (1.30), as well as with mixed funds (1.20 and 1.52). Thus, domestic portfolios within the fund industry display some overlap, though slightly different to the overlap observed for cross-border exposures, while banks and insurers display overlap in portfolios of both domestic and cross-border exposures.

87.   **On the liabilities side, funds display significant common exposure.** Figure 18 shows the in-flow common exposure with respect to the average portfolio in the sample (red) and total direct exposure (blue). For all funds except MMFs, common exposures have increased concurrently with direct exposures; not only are funds exposed to their counterparty, but they are also exposed to each other indirectly through common funding shocks. Table 3 shows the in-flow common exposure between pairs of entities below the diagonal, while a percent change since 2012 is shown above the diagonal. Here we see a cluster of common exposure forming for the entire fund industry, centered around mixed funds; that is, the funding composition of mixed funds overlaps most strongly with equity (1.77), bond (1.80), hedge (1.82), and other funds (1.76); MMFs exist on the periphery of this cluster, though significant funding overlap (1.40) is still evident. The difference is stark for banks and insurance companies that show no funding overlap with the rest of the financial system. The results here are likely dominated by the structure of the domestic dataset, where funds are connected through a few insurers on the liabilities side.

88.   **Some recent trends of out- and in-flow common exposure should be monitored.** Figure 16 shows the evolution between pairs of entities with significant common exposures. Since 2013,

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[22]For 14 degrees of freedom, the one-sided test has 1 percent, 5 percent, and 10 percent critical values at 2.62, 1.76, and 1.35; these correspond to out- and in-flow common exposures (correlations) of 1.07 (0.57), 0.93 (0.43), and 0.85 (0.34).

[23]Unit-linked insurance is not distinguishable in the domestic dataset, meaning that some of the risk attributed to insurance companies will be borne by end-investors. Thus, out-flow common exposure of insurers may be slightly overstated, particularly with respect to mixed funds. Further work is necessary to distinguish out-flow common exposure of insurers that is related to unit-linked products.

both clusters identified previously by significant out-flow common exposure have shown an upward tendency, indicating that despite any potential diversification of idiosyncratic counterparty risk individually, the portfolios are increasingly overlapping. As well, the cluster identified by significant in-flow common exposure has been increasing in proximity of funding composition over the entire sample.

89.   Results on domestic common exposures should be interpreted cautiously. The data do not cover significant balance sheet exposures for banks, so that the impact of high common exposure may not be very consequential. Additionally, the disaggregated nature of the data means that some of the results may be driven by the group ownership structure. Information on groups was not made available to the mission, but this is something that could be explored by the authorities.[24]

Table 2. France: Common Exposures in Domestic Assets

	Equity	Bond	Mixed	Hedge	Other	Bank	Insurer	MMF
Equity		1%	4%	1%	-3%	-13%	-8%	11%
Bond	0.54		8%	1%	37%	24%	14%	-14%
Mixed	0.92	0.64		-35%	-17%	-10%	3%	-5%
Hedge	0.48	0.96	0.73		-34%	-24%	-19%	7%
Other	0.67	1.40	0.96	0.88		-15%	-13%	14%
Bank	0.48	0.75	1.20	0.94	1.13		4%	4%
Insurer	0.81	0.43	1.52	0.77	0.75	1.30		-2%
MMF	0.69	1.40	0.54	1.08	1.08	0.53	0.36	

Notes: The lower triangle shows out-flow (asset) common exposure between two sectors for 2016; this is scaled between 0 and 2. A higher value indicates higher similarity in exposures. The upper triangle shows the percent change since 2011. See Appendix III for further details.
Source: Haut Conseil de Stabilité Financière (HCSF) and IMF staff.

Table 3. France: Common Exposures in Domestic Liabilities

	Equity	Bond	Mixed	Hedge	Other	Bank	Insurer	MMF
Equity		2%	-1%	-1%	6%	0%	-7%	-3%
Bond	1.68		1%	1%	7%	0%	10%	0%
Mixed	1.77	1.80		1%	7%	-2%	3%	-2%
Hedge	1.69	1.65	1.82		6%	-4%	0%	-2%
Other	1.64	1.66	1.76	1.79		-17%	8%	-4%
Bank	0.39	0.38	0.40	0.41	0.52		3%	2%
Insurer	0.45	0.48	0.40	0.36	0.36	0.48		14%
MMF	1.34	1.42	1.43	1.41	1.60	0.76	0.34	

Notes: The lower triangle shows out-flow (asset) common exposure between two sectors for 2016; this is scaled between 0 and 2. A higher value indicates higher similarity in exposures. The upper triangle shows the percent change since 2011. See Appendix III for further details.
Source: Haut Conseil de Stabilité Financière (HCSF) and IMF staff.

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[24]Hauton and Héam (2015) find that diversification occurs at the group level, so that perhaps common exposure risks are slightly overstated. Benhami et al. (2018) report that intra-group exposures do not exceed 4 percent of total group assets.

Figure 16. France: Significant Trends in Domestic Common Exposures

Positive trends in domestic asset holdings between banks, insurers, and mixed funds complement the results found for cross-border holdings of the same financial entities.

Common Exposure Trends in Domestic Assets
(Index)
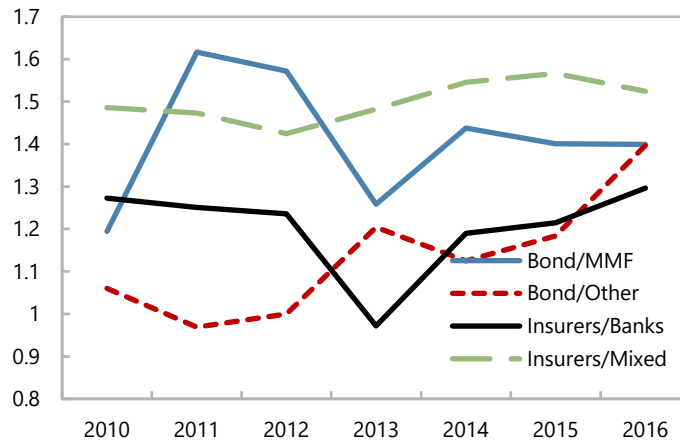
Despite the structure of the bilateral dataset emphasizing the fund industry, comparisons over time indicate that funding similarity in the funds industry has increased markedly in recent years.

Common Exposure Trends in Domestic Liabilities
(Index)
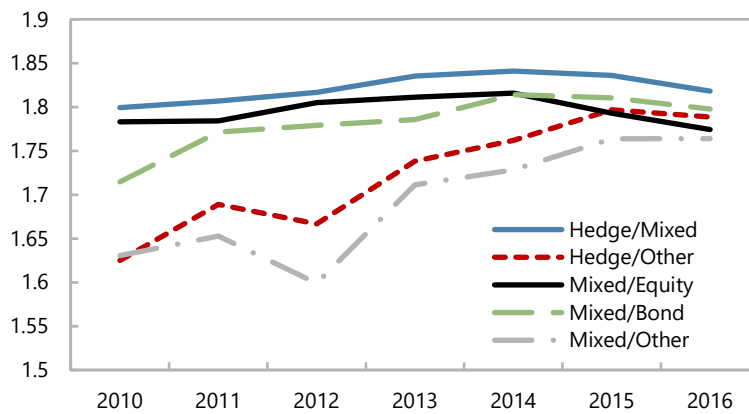
Source: Haut Conseil de Stabilité Financière (HCSF) and IMF staff.

Figure 17. France: Common Exposures in Assets Relative to the Average Domestic Portfolio
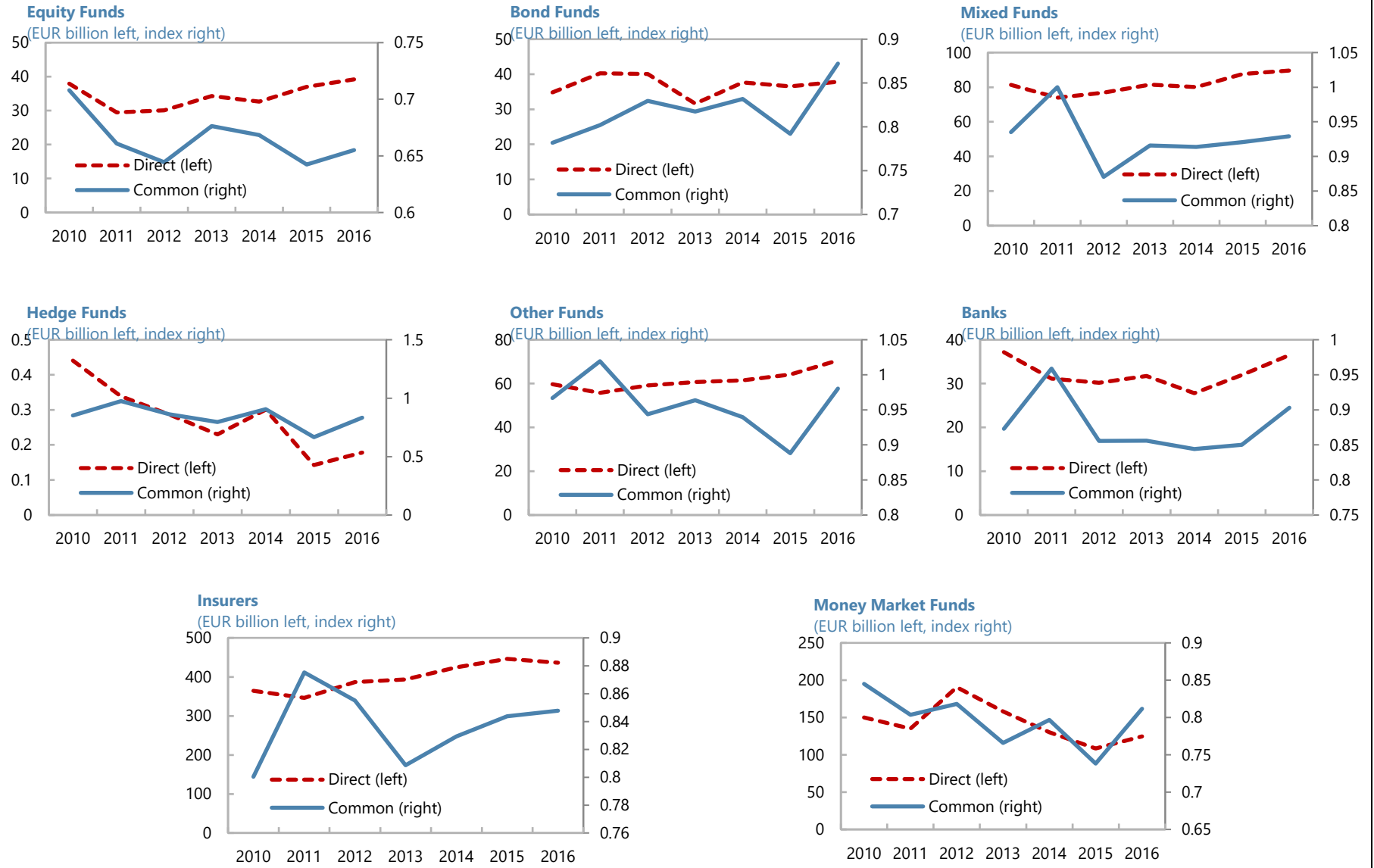
Source: Haut Conseil de Stabilité Financière (HCSF) and IMF staff.

Figure 18. France: Common Exposures in Liabilities Relative to the Average Domestic Portfolio

Equity Funds
(EUR billion left, index right)

Bond Funds
(EUR billion left, index right)

Mixed Funds
(EUR billion left, index right)

Hedge Funds
(EUR billion left, index right)

Other Funds
(EUR billion left, index right)

Banks
(EUR billion left, index right)

Insurers
(EUR billion left, index right)

Money Market Funds
(EUR billion left, index right)

Direct (left)
Common (right)
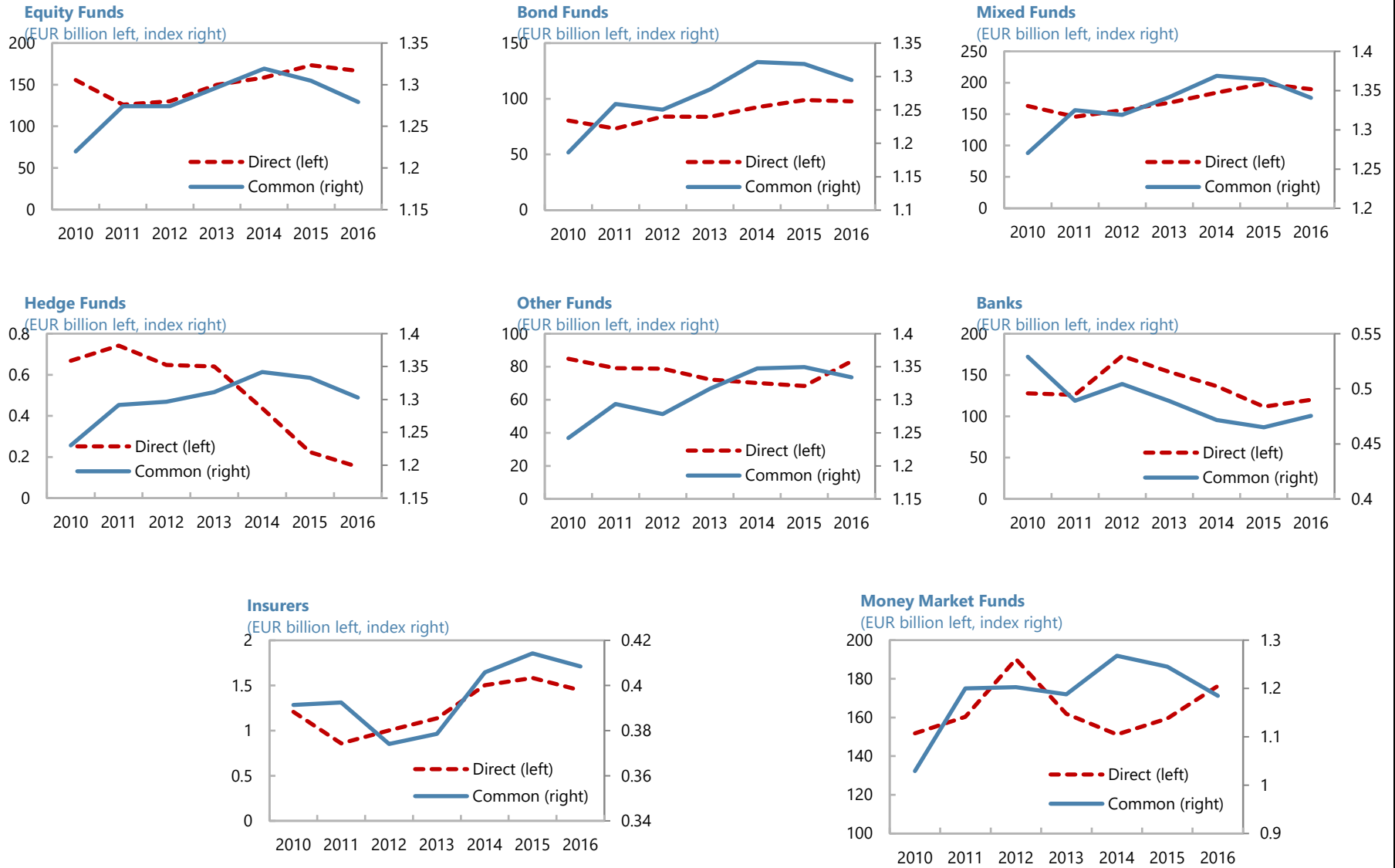
Source: Haut Conseil de Stabilité Financière (HCSF) and IMF staff.

F. Cross-border Interbank Contagion

Combining bilateral exposure data with data on regulatory capital permits an analysis of contagion effects for the French banking sector. Contagion risk for the international interbank exposures are assessed using BIS data and employing the methodology in Espinosa-Vega and Solé (2011).

90. **Data from the Bank for International Settlements (BIS) were paired with regulatory capital data from various sources to assess cross-border interbank contagion at the international level.** Marketable securities were shown earlier to form a small share of French banks' balance sheets, across borders and domestically. Bilateral exposure data in loans and derivatives between banking systems are used to complement the earlier analysis in cross-border interconnectedness, thus capturing a more significant dimension for French banks. Inward and outward spillovers are assessed using the model of Espinosa-Vega and Solé (2011) and pairing bilateral exposure data with capital data; this permits an assessment of the capacity of entities to absorb losses.

91. **The contagion risk exercise highlights the direct and indirect exposures of banking systems.** Previously, the interconnectedness analysis attempted to determine the level of direct and indirect exposures of French financial institutions with respect to their investment portfolios and funding, as the data permitted; this highlighted the potential risk channels without, however, simulating shocks to assess the importance of direct and indirect interconnectedness.

92. **Several assumptions were made to employ the stylized model of Espinosa-Vega and Solé (2011) for banks.** A credit shock is simulated by assuming that the banking system of a country defaults on its interbank loans, with a loss-given-default of 100 percent. Furthermore, a credit-and-funding shock is simulated by assuming that the banks are only able to recover 65 percent of the lost funding from a default entity, while also assuming a 50 percent discount rate on assets that a bank may be forced to sell cover the funding gap.

93. **French banks are less vulnerable and slightly less contagious than during the last FSAP.** Figure 19 shows the inward and outward spillover of French banks relative to the global interbank network for a credit-and-funding shock. Indices are calculated as the total losses incurred and caused relative to total capital.[25] Vulnerability risk emanating from cross-border exposures in interbank loans has declined significantly. Contagion risk emanating from the French banking system remains among the highest in the world and has declined very slightly since the last FSAP. These findings complement the narrative developed for marketable securities, whereby French banks have reduced and diversified cross-border exposures, thereby increasing their presence in relatively smaller (less capitalized) banking systems.
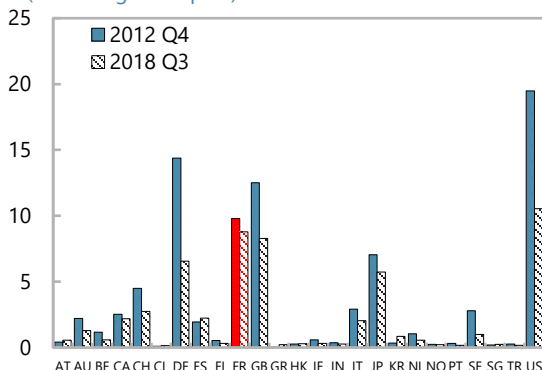
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[25]For further details, see Appendix III.

94. **Spillovers from France have the greatest impact within the EA, while spillovers to France emanate principally from outside the EA.** The third panel in Figure 19 shows outward contagion from the French banking system to other countries. Within the EA, the Netherlands, Ireland, Belgium, and Italy are susceptible to shocks from France; outside the EA, the United Kingdom is similarly susceptible. The fourth panel in Figure 19 shows the inward contagion to the French banking system. In this instance, France is susceptible primarily to shocks from outside the EA; specifically, the United Kingdom, the United States, and Japan. Within the EA, Germany is the primary source of inward vulnerability for France.

95. **Spillovers to France have declined since the last FSAP.** While the French banking system is susceptible to credit and to credit-and-funding shocks from outside the Euro Area, these have notably declined since 2012 Q4, particularly with respect to the United States. This has translated into an overall lower vulnerability index in simulations.

Figure 19. France: Cross-border Interbank Contagion

French banks are as contagious as during the last FSAP in 2012...

...though at the same time relatively less vulnerable.

Contagion Index, Credit and Funding Shock
(Percentage of capital)

Vulnerability Index, Credit and Funding Shock
(Percentage of capital)
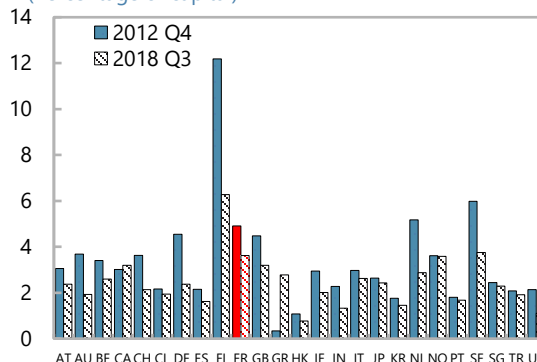
The Netherlands, the United Kingdom, Ireland, Italy, and Belgium, are most susceptible to French banks...

...while French banks are most exposed to the United Kingdom, Germany, and the United States.

Contagion from France, Credit and Funding Shock
(Percentage of capital)

Contagion to France, Credit and Funding Shock
(Percentage of capital)
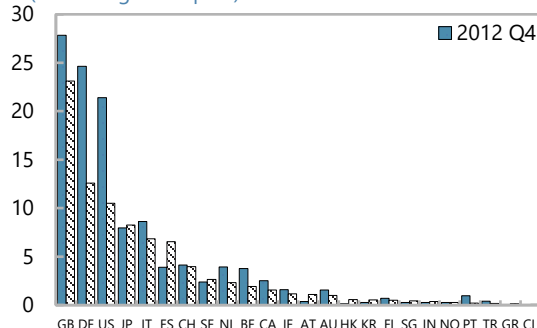
Source: Bank for International Settlements (BIS) and IMF staff calculations.

G. Concluding Remarks

96.   This note has examined some issues in cross-sector interconnectedness stemming from domestic and cross-border exposures. We used unilateral reporting datasets with broad coverage to assess exposures overall and a more granular bilateral reporting dataset with narrower coverage to assess domestic exposures. We provided network visuals and summary statistics to characterize direct exposures, while at the same time examining similarity in portfolio compositions to characterize indirect exposures. To complement the analysis for banks, we used BIS data on interbank loans and carried out a contagion exercise.

97.   The overall composition of exposures has been shifting for French financial entities. Across the board, there have been large investments in marketable securities issued by domestic and foreign NFCs. Banks have reduced exposures to domestic MFIs in favor of other domestic nonbank financials and the French government. Insurers, on the other hand, have significantly drawn down exposures to foreign non-MFIs in favor of securities issued by the French government and foreign nonbank financials. Finally, funds have invested away from domestic MFIs and the French government but increased domestic and cross-border holdings across every other counterparty sector, most notably non-MFIs.

98.   The analysis shows two interlinked clusters characterized by common exposures that should be monitored. Common exposure indicates the extent to which portfolios overlap, exposing entities to common shocks. We identified two clusters of elevated common exposure risk. The first cluster is centered around mixed funds and includes equity, bond, and other funds. The second cluster consists of banks and insurers. The two clusters are linked through the common exposure of insurers and mixed funds. While common exposure is lower for banks and insurers relative to the last FSAP, the current upward trend should be monitored. Additionally, common exposure among the cited fund sectors has been increasing steadily, suggesting that diversification of idiosyncratic counterparty risk may be generating additional aggregate risk. Trends can be monitored by examining more narrowly how portfolios comove.

99.   The nature of the domestic direct exposures implies the formation of hubs around insurers and banks that in turn has consequences for common exposures. Funds form hubs around insurers through liabilities and around banks through assets. On the asset side, domestic common exposures are organized around bond and mixed funds. The first cluster contains bond, other, and money market funds, while the second cluster contains mixed funds, banks, and insurers. On the liabilities side, all funds are clustered around mixed funds with significant common exposure that is partially attributable to the nature of the dataset. Trends in common exposure for the clusters identified should be monitored as these generally display an upward tendency since 2013.

100.   The analysis of contagion, based on aggregate interbank data at the country level, reveals that French banks are less vulnerable and contagious since the last FSAP. Domestic and cross-border holdings of banks in marketable securities comprise just 10.5 percent of banks assets, whereas the coverage for insurers and funds was almost complete. BIS consolidated banking

statistics were used in combination with aggregated regulatory capital data to assess the ability of the French banking system to absorb shocks. The analysis showed that the French banking system is slightly less vulnerable and contagious since the last FSAP. The main sources of contagion for the French banking system are the United Kingdom, the United States, the Euro Area, and Japan, while the main sinks of contagion from the French banking system are the Euro Area and the United Kingdom.

101.   Significant gaps remain, but the French authorities have a comprehensive agenda in place. Some gaps in the data remain that could affect the magnitude of various identified effects. Domestic bilateral holdings of marketable securities are not currently available for banks and insurers, though the French authorities are well underway in completing this dataset. Gaps across other types of exposures could not be surmounted. Nonetheless, the French authorities are able to monitor a broader coverage of exposures and are working towards a more complete understanding of cross-sector and intra-group holdings by completing data gaps and progressing on contagion research.

Appendix I. Capital and Risk Caps Technical Appendix

This appendix describes the model used to compute capital and risk caps.

Asset Accumulation and Accounting Identities
Firms finance asset purchases $q_t k_t$ with net worth e.i. equity $n_{F,t}$, and debt b_t. Financial intermediaries raise funding through capital $n_{B,t}$, deposits, and wholesale funding d_t. The budget constraints of firms and financial intermediaries are:

$$q_t k_t = n_{F,t} + b_t$$
$$b_t = n_{B,t} + d_t$$
$$q_t k_t = n_{F,t} + n_{B,t} + d_t$$

Firms
The cashflow of firms consist of an initial outlay of own funds. In addition, firms raise debt. Own funds and debt is used to acquire productive assets. Next period firms receive a return on invested assets $R_{k,t+1}$ and pay back debt at rate $R_{b,t} = 1 + i_{b,t}$. The return on assets is subject to an idiosyncratic ($\varepsilon_{i,t+1}$) and aggregate (z_{t+1}) productivity shock. Firms' income is taxed at rate τ, and future cash-flows are discounted at the stochastic discount factor (M_{t+1}) of firm-owning households.

$$-n_{F,t} + E_t \left(M_{t+1} max \left((z_{t+1}\varepsilon_{i,t+1} R_{k,t+1} k_t - R_{b,t} b_t)(1-\tau), 0 \right) \right)$$

Firms default if the value of end-of-period assets falls below the value of liabilities, or if its idiosyncratic productivity falls below a certain default threshold.

$$\varepsilon_{i,t+1} < \varepsilon_{t+1}^z \equiv \frac{R_{b,t} b_t}{z_{t+1} R_{k,t+1} k_t}$$

The probability of default of firms depends on firms' balance sheet strength, aggregate productivity, and the cumulative distribution function of idiosyncratic productivity.

$$PD^F \left(\varepsilon_{t+1}^z \right) = Prob \left(\varepsilon_{i,t+1} < \varepsilon_{t+1}^z \right) = F \left(\varepsilon_{t+1}^z, \sigma_{\varepsilon,t+1} \right)$$

Firms' cash flow can be rewritten, writing out the integral over idiosyncratic risk and introducing some useful notation:

$$-n_{F,t} + E_t \left(M_{t+1} \left(\int_{\varepsilon_{t+1}^z}^{\infty} (z_{t+1}\varepsilon_{i,t+1} R_{k,t+1} k_t - R_{b,t} b_t) f(\varepsilon_{i,t+1}) d(\varepsilon_{i,t+1}) \right)(1-\tau) \right)$$
$$-n_{F,t} + E_t \left(M_{t+1} \left(z_{t+1} R_{k,t+1} k_t (1 - \Delta(\varepsilon_{t+1}^z)) - R_{b,t} b_t (1 - F(\varepsilon_{t+1}^z)) \right)(1-\tau) \right)$$
$$-n_{F,t} + E_t \left(M_{t+1} \left(z_{t+1} R_{k,t+1} k_t (1 - \Gamma(\varepsilon_{t+1}^z)) \right)(1-\tau) \right)$$

Capital and Risk Caps Technical Appendix (continued)

where

$$\Delta\left(\varepsilon_{t+1}^{z}\right) \equiv \int_{0}^{\varepsilon_{t+1}^{z}} \varepsilon_{i,t+1} f\left(\varepsilon_{i,t+1}\right) d\left(\varepsilon_{i,t+1}\right)$$

$$\Gamma\left(\varepsilon_{t+1}^{z}\right) \equiv \Delta\left(\varepsilon_{t+1}^{z}\right) + \varepsilon_{t+1}^{z}\left(1 - F\left(\varepsilon_{t+1}^{z}\right)\right)$$

It becomes obvious that due to debt-financing, firms receive a share equal to $1 - \Gamma\left(\varepsilon_{t+1}^{z}\right)$ of firms earnings.

Financial Intermediaries

The cashflow of financial intermediaries consist of an initial outlay of own funds. In addition, financial intermediaries raise deposits and wholesale funding to finance loans. Next period financial intermediaries receive a return on the loan portfolio and pay back received funding at rate $R_{d,t} = 1 + i_{d,t}$.

$$-n_{B,t} + E_t\left(M_{t+1} max\left(\left(R_{B,t+1}b_t - R_{d,t}d_t\right)(1 - \tau), 0\right)\right)$$

The return on the loan portfolio consists of two parts. Financial intermediaries receive the interest and principal payment from non-defaulting firms and recover the assets from defaulted firms. Default triggers a cost of default equal to a fraction μ of firms' earnings.

$$R_{B,t+1}b_t \equiv R_{b,t}b_t\left(1 - F\left(\varepsilon_{i,t+1}^{z}\right)\right) + \int_{0}^{\varepsilon_{t+1}^{z}} z_{t+1}\varepsilon_{i,t+1}R_{k,t+1}k_t f\left(\varepsilon_{i,t+1}\right) d\left(\varepsilon_{i,t+1}\right)(1 - \mu)$$

Financial intermediaries' cash flow can be rewritten:

$$-n_{B,t} + E_t\left(M_{t+1} max\left(\left(z_{t+1}R_{k,t+1}k_t\left(\Gamma\left(\varepsilon_{t+1}^{z}\right) - \mu\Delta\left(\varepsilon_{t+1}^{z}\right)\right) - R_{d,t}d_t\right)(1 - \tau), 0\right)\right)$$

Financial intermediaries receive a share $\Gamma\left(\varepsilon_{t+1}^{z}\right)$ of firms' earnings minus screening costs. Financial intermediaries default if the value of end-of-period assets falls below the value of liabilities, or if aggregate productivity falls below a certain default threshold. Hence, the probability of default of financial intermediaries depends on balance sheet strength of borrowers and financial intermediaries and the distribution function of aggregate productivity.

$$PD^{B}\left(z_{t+1}^{*}\right) = Prob\left(z_{t+1} < z_{t+1}^{*}\right) = G\left(z_{t+1}^{*}, \sigma_{z,t+1}\right)$$

To differentiate normal states of the world with states in which financial intermediaries default, we assume that productivity is lower in case of default. For simplicity it is assumed that aggregate productivity takes a fixed value above (z^{N}) and below (z^{D}) the default threshold z_{t+1}^{*}.

Capital and Risk Caps Technical Appendix (continued)

$$\text{Normality}: (1 - G(z_{t+1}^*))$$

$$(z_{t+1} > z_{t+1}^*) \to z_{t+1} = z^N \to \varepsilon_{t+1}^N \equiv \frac{R_{b,t}b_t}{z^N R_{k,t+1}k_t}$$

$$\text{Threshold}: z_{t+1}^* R_{k,t+1}k_t \left(\Gamma(\varepsilon_{t+1}^*) - \mu\Delta(\varepsilon_{t+1}^*)\right) - R_{d,t}d_t = 0$$

$$z_{t+1} = z_{t+1}^* \to \varepsilon_{t+1}^* \equiv \frac{R_{b,t}b_t}{z_{t+1}^* R_{k,t+1}k_t}$$

$$\text{Default}: G(z_{t+1}^*)$$

$$(z_{t+1} < z_{t+1}^*) \to z_{t+1} = z^D \to \varepsilon_{t+1}^D \equiv \frac{R_{b,t}b_t}{z^D R_{k,t+1}k_t}$$

Joint Maximization

Firms' cashflow and maximisation problem is:

$$\mathcal{L} = -n_{F,t} + E_t \left(M_{t+1} \frac{R_{k,t+1}}{q_t} (n_{F,t} + n_{B,t} + d_t) \left(s_{F,t+1}^N (1 - G(z_{t+1}^*)) + s_{F,t+1}^D G(z_{t+1}^*)\right) \right)(1 - \tau)$$

Financial intermediaries' cashflow and participation constraint is:

$$+ \lambda_t^B \left\{ -n_{B,t} + E_t \left(M_{t+1} \left(\frac{R_{k,t+1}}{q_t} (n_{F,t} + n_{B,t} + d_t) s_{B,t+1}^N - R_{d,t}d_t\right) (1 - G(z_{t+1}^*)) \right)(1 - \tau) \right\}$$

Mutual funds' cashflow and participation constraint is:

$$+ \lambda_t^I \left\{ -d_t + E_t \left(M_{t+1} \left(R_{d,t}d_t (1 - G(z_{t+1}^*)) + G(z_{t+1}^*) \frac{R_{k,t+1}}{q_t} (n_{F,t} + n_{B,t} + d_t) s_{B,t+1}^D (1 - \mu_B) \right) \right) \right\}$$

The default threshold is:

$$+ E_t \left(M_{t+1} \lambda_{t+1}^V \left(\frac{R_{k,t+1}}{q_t} (n_{F,t} + n_{B,t} + d_t) s_{B,t+1}^* - R_{d,t}d_t\right) \right)$$

Where the respective share in the earnings are defined as:

$$s_{F,t+1}^N = z^N (1 - \Gamma(\varepsilon_{t+1}^N))$$

$$s_{F,t+1}^D = z^D (1 - \Gamma(\varepsilon_{t+1}^D))$$

$$s_{B,t+1}^N = z^N (\Gamma(\varepsilon_{t+1}^N) - \mu\Delta(\varepsilon_{t+1}^N))$$

$$s_{B,t+1}^D = z^D (\Gamma(\varepsilon_{t+1}^D) - \mu\Delta(\varepsilon_{t+1}^D))$$

$$s_{B,t+1}^* = z_{t+1}^* (\Gamma(\varepsilon_{t+1}^*) - \mu\Delta(\varepsilon_{t+1}^*))$$

Capital and Risk Caps Technical Appendix (continued)

Firms and financial intermediaries accumulate capital out of retained earnings:

$$n_{F,t} = \frac{R_{k,t}}{q_{t-1}}\left(n_{F,t-1} + n_{B,t-1} + d_{t-1}\right)\left(s_{F,t}^N\left(1 - G\left(z_t^*\right)\right) + s_{F,t}^D G\left(z_t^*\right)\right)(1-\tau)(1-\gamma_F)$$

$$n_{B,t} = \left(\frac{R_{k,t}}{q_{t-1}}\left(n_{F,t-1} + n_{B,t-1} + d_{t-1}\right)s_{B,t}^N - R_{d,t-1}d_{t-1}\right)(1 - G\left(z_t^*\right))(1-\tau)(1-\gamma_{B,t})$$

Optimality Conditions

Substituting $\phi_{D,t} \equiv \frac{R_{d,t}d_t}{k_t}$ and $\phi_{B,t} \equiv \frac{R_{b,t}b_t}{k_t}$, we receive the following first order conditions with respect to $d_t, \phi_{D,t}, z_{t+1}^*$ and $\phi_{B,t}$.

First order conditions:

∂d_t:

$$\lambda_t^I = E_t\left(M_{t+1}\frac{R_{k,t+1}}{q_t}X_{t+1}\right)$$

where

$$X_{t+1} \equiv \lambda_t^F\left(s_{F,t+1}^N\left(1 - G\left(z_{t+1}^*\right)\right) + s_{F,t+1}^D G\left(z_{t+1}^*\right)\right)(1-\tau)$$
$$+ \lambda_t^B s_{B,t+1}^N\left(1 - G\left(z_{t+1}^*\right)\right)\left(\left(\Gamma\left(\varepsilon_{t+1}^z\right) - \mu\Delta\left(\varepsilon_{t+1}^z\right)\right)1 - \tau\right) + \lambda_t^I s_{B,t+1}^D G\left(z_{t+1}^*\right)(1 - \mu_B)$$
$$+ \left(\lambda_t^I - \lambda_t^B(1-\tau)\right)s_{B,t+1}^*\left(1 - G\left(z_{t+1}^*\right)\right)$$

$\partial\phi_{D,t}$:

$$E_t\left(M_{t+1}\left(\left(\lambda_t^I - \lambda_t^B(1-\tau)\right)\left(1 - G\left(z_{t+1}^*\right)\right) - \lambda_{t+1}^V\right)k_t - A'\left(\phi_{D,t}\right)\right) = 0$$

$\partial z_{t+1}^*\left(s_{t+1}\right)$:

$$-g\left(z_t^*\right)Z_t + \lambda_t^V\left(\Gamma\left(\varepsilon_t^*\right) - \mu\Delta\left(\varepsilon_t^*\right) + z_t^*\frac{\partial\varepsilon_t^*}{\partial z_t^*}\frac{\partial\left(\Gamma\left(\varepsilon_t^*\right) - \mu\Delta\left(\varepsilon_t^*\right)\right)}{\partial\varepsilon_t^*}\right) = 0$$

where

$$Z_t \equiv \lambda_{t-1}^F\left(s_{F,t}^N - s_{F,t}^D\right)(1-\tau)$$
$$+ \lambda_{t-1}^B s_{B,t}^N(1-\tau) - \lambda_{t-1}^I s_{B,t}^D(1 - \mu_B)$$
$$+ \left(\lambda_{t-1}^I - \lambda_{t-1}^B(1-\tau)\right)s_{B,t}^*$$

Substituting:

Capital and Risk Caps Technical Appendix (concluded)

$$\Gamma\left(\varepsilon_t^*\right) = \Delta\left(\varepsilon_t^*\right) + \varepsilon_t^*\left(1 - F\left(\varepsilon_t^*\right)\right)$$

$$\frac{\partial \varepsilon_t^*}{\partial z_t^*} = -\frac{\varepsilon_t^*}{z_t^*}$$

$$\frac{\partial\left(\Gamma\left(\varepsilon_t^*\right) - \mu\Delta\left(\varepsilon_t^*\right)\right)}{\partial \varepsilon_t^*} = 1 - F\left(\varepsilon_t^*\right) - \mu f\left(\varepsilon_t^*\right)\varepsilon_t^*$$

Gives:

$$-g\left(z_t^*\right) Z_t + \lambda_t^V\left(\Delta\left(\varepsilon_t^*\right)\left(1 - \mu\right) + \mu f\left(\varepsilon_t^*\right)\varepsilon_t^{*2}\right) = 0$$

$$\lambda_t^V = \frac{g\left(z_t^*\right) Z_t}{\Delta\left(\varepsilon_t^*\right)\left(1 - \mu\right) + \mu f\left(\varepsilon_t^*\right)\varepsilon_t^{*2}}$$

The first order condition of financial intermediaries' funding and default threshold equate the tax benefit associated with a higher collateral value $\lambda_t^V\left(\Delta\left(\varepsilon_t^*\right)\left(1 - \mu\right) + \mu f\left(\varepsilon_t^*\right)\varepsilon_t^{*2}\right)$ with the expected loss of productivity associated to more intermediary defaults $g\left(z_t^*\right) Z_t$.

$\partial\phi_{B,t}$:

$$\begin{aligned}
E_t(M_{t+1}(&-\lambda_t^F\left(\left(1 - F\left(\varepsilon_t^N\right)\right)\left(1 - G\left(z_{t+1}^*\right)\right) + \left(1 - F\left(\varepsilon_t^N\right)\right) G\left(z_{t+1}^*\right)\right)\left(1 - \tau\right) \\
&+ \lambda_t^B\left(1 - F\left(\varepsilon_t^N\right) - \mu f\left(\varepsilon_t^N\right)\varepsilon_t^N\right)\left(1 - G\left(z_{t+1}^*\right)\right)\left(1 - \tau\right) \\
&+ \lambda_t^I\left(1 - F\left(\varepsilon_t^D\right) - \mu f\left(\varepsilon_t^D\right)\varepsilon_t^D\right) G\left(z_{t+1}^*\right)\left(1 - \mu_B\right) \\
&+ \lambda_{t+1}^V\left(1 - F\left(\varepsilon_t^*\right) - \mu f\left(\varepsilon_t^*\right)\varepsilon_t^*\right) k_t - A'\left(\phi_{B,t}\right))) = 0
\end{aligned}$$

The agent chooses debt by trading off the benefit of financial intermediation $\lambda_{t+1}^V\left(1 - F\left(\varepsilon_t^*\right) - \mu f\left(\varepsilon_t^*\right)\varepsilon_t^*\right)$ against the cost of default of nonfinancial firms $\mu f\left(\varepsilon_t^z\right)\varepsilon_t^z$ in different states of the world. So, issuing more loans is profitable as it increases the size of financial intermediaries' balance sheets and the tax income from it, but more loans also result in more defaults and a higher cost of default.

Deviations from Potential

Similar to the concept of output gap between sticky and flexible prices, we calculate capital and risk gaps between sticky and flexible capital structures. For the flexible capital structure benchmark economy, first order conditions with respect to $n_{F,t}$ and $n_{B,t}$ are taken, implying:

$$\lambda_t^B = \lambda_t^I = 1$$

Appendix II. Data and Methodologies

Domain	FSAP Methodology
Cross-border interconnectedness analysis	Data • Domestic and cross-border exposures in marketable securities at the entity level for banks and insurers (annually, 2008–2017 and 2011–2017), as well as at the sector-level for funds (quarterly, 2008–2017), are utilized. Reporting is unilateral and relies on the assets of holders, resulting in networks between French-domiciled entities and foreign and domestic counterparties. Sources include BdF, ACPR, and AMF. Approach implemented • The objective is to understand direct and indirect exposures. • Direct exposures are assessed by network visualization and network summary statistics. • Indirect exposures are assessed using the method of Giudici, Sarlin, and Spelta (2017), which examines portfolio-composition similarity. The distance between an entity's portfolio and those of other entities indicates similarity. Lower distance/higher similarity means that entities invest similar proportions of their portfolio in other counterparties and therefore have overlapping portfolios; thus, they will be vulnerable to a similar set of shocks. The analysis is carried out by categorizing all banks and insurers in one respective group while differentiating funds by business model.
Domestic interconnectedness analysis	Data • Domestic exposures in marketable securities at the entity level for banks, insurers, and funds (annually, 2010–2016) are utilized. Reporting is bilateral but incomplete and relies on the assets of holders; only links between funds-banks and funds-insurers are covered. This creates bilateral networks between funds-banks and funds-insurers. Sourced from the HCSF. Approach implemented • Direct exposures are assessed by network visualization and network summary statistics. • Indirect exposures are assessed using the method of Giudici, Sarlin, and Spelta (2017), which examines portfolio-composition similarity. Since bilateral data are available for domestic exposures, the analysis can be carried out both for assets and liabilities; for the latter, all assets are summed up. The analysis is carried out by categorizing all banks and insurers one respective group while differentiating funds by business model.
Cross-border interbank contagion analysis	Data • Interbank loan exposures are used alongside capital data for 2012:Q4 and 2018:Q4. The analysis is be carried out at the national level for banks only. Sourced from the BIS consolidated banking statistics. Approach implemented • The objective is to assess inward and outward contagion risk based on the method of Espinosa-Vega and Solé (2011). • For a calibrated credit and funding shock, sequential defaults among national banking sectors are triggered if capital is insufficient to cover losses. The algorithm stops once no more failures take place. Inward and outward measures are computed as functions of lost and total capital, indicating the level of vulnerability and contagiousness of banking systems. • Countries included: Austria, Australia, Belgium, Canada, Switzerland, Chile, Germany, Spain, Finland, France, Greece, the United Kingdom, Hong Kong Special Administrative Region, Ireland, India, Italy, Japan, Korea, the Netherlands, Norway, Portugal, Sweden, Singapore, Turkey, and the United States.

Appendix III. Interconnectedness and Contagion Technical Appendix

A. Graphical Model Terminology

A *graph* or *network* is a collection *G* of vertices *V* and edges *E*. A graph is said to be *directed* if edges are oriented between vertices and *undirected* otherwise. The *degree* of a vertex is the number of edges connected to the vertex. For directed graphs, the *degree* can refer alternatively to edges that originate or conclude at a vertex, or both. A *fully connected* graph is one where all vertices are connected to all other vertices. The *density* of a graph is the ratio of the total number of edges to the total possible number of edges i.e., those in a fully connected graph. A *path* between two vertices refers to the set of edges connecting those vertices. The *average distance* refers to the average number of edges along the shortest paths for all pairs of vertices in a graph.

B. Direct and Common Exposure Networks

The usual definitions of systemic risk include references to events that affect a broad array of financial institutions in a significant way. In other words, a risk is systemic if it simultaneously affects many market participants, so that losses spread throughout the system. Network models are helpful to understand contagion effects and have been broadly implemented. A *direct network* represents the physical flow of funds between entities in the form of assets and liabilities. A *common exposure network*, on the other hand, represents the proximity in exposure composition between entities, which can be distinguished either in terms of assets (portfolio composition) or liabilities (funding composition). The methodology implemented to assess the strength of direct and common exposure networks is that of Giudici, Sarlin and Spelta (2017). This is briefly detailed below.

Direct Network

A direct network can be defined over a graph comprised of edges w_{ijt} representing quantities lent from *j* to *i* at time *t*. The direct *in-strength* of an entity *i* in a direct network is the sum of all inward exposures $S_{it}^{in} = \sum_j w_{ijt}$, while the direct *out-strength* of an entity *j* is symmetrically defined as $S_{it}^{out} = \sum_i w_{ijt}$.

Common Exposure Network

A common exposure network can be defined over a graph where the edges represent a function of the correlation between vertices. Define the vector $In^{it} \in R^{1 \times N}$ as the quantities lent to entity *i* by all other entities at time *t*. Symmetrically, define the vector $Out^{it} \in R^{1 \times N}$ as the quantities lent by entity *i* to all other entities.

An *in-flow common exposure network* is defined over a graph comprised of edges

$$d_{ijt}^{In} = 2 - \sqrt{2\left(1 - C_{In^{it}, In^{jt}}\right)},$$

where $C_{In^{it},In^{jt}}$ is the correlation between funding compositions of i and j; this describes the funding similarity between two entities. Symmetrically, an *out-flow common exposure network* is defined over a graph comprised of edges

$$d_{ijt}^{Out} = 2 - \sqrt{2(1 - C_{Out^{it},Out^{jt}})},$$

where $C_{Out^{it},Out^{jt}}$ is the correlation between the portfolio compositions of i and j; this describes the portfolio similarity between two entities.

Based on the definition of a common exposure network, two summary measures are calculated. For common exposure network, the in-strength is defined by $K_{it}^{In} = \sum_j d_{ijt}^{In}$, and the out-strength is defined symmetrically by $K_{it}^{Out} = \sum_i d_{ijt}^{Out}$.

C.   Contagion Risk

Contagion risk can be assessed by examining bilateral exposure data alongside regulatory capital data. The combination permits an analysis of when direct and common exposures become costly. The methodology implemented to assess the strength of contagion risk within the international interbank network is that of Espinosa-Vega and Solé (2011). This is a stylized model of banks' balance sheets that is commonly employed across FSAPs.

The starting point is a stylized balance sheet identity for a bank i, written as

$$\sum_j x_{ji} + a_i = k_i + b_i + d_i + \sum_j x_{ij},$$

where x_{ji} represents i claims on j, a_I represents other assets, k_I represents capital, b_I represents borrowing excluding interbank loans, and d_i represents deposits.

Assumptions on the impact of credit and funding shocks initiate inter-period dynamics of the model. A credit shock is stylized by assuming an entity or a set of entities default on their obligations with a loss-given-default of λ. If h defaults, the effect on i is characterized by

$$\sum_{j \neq h} x_{ji} + (1 - \lambda)x_{hi} + a_i = (k_i - \lambda x_{hi}) + b_i + d_i + \sum_j x_{ij},$$

so that if capital is insufficient to cover losses, i will default as well. A credit-and-funding shock is stylized by assuming that i is only able to replace a fraction $1 - \rho$ of the lost funding from a defaulted entity h. This means that i must sell assets worth $(1 + \delta)\rho x_{ih}$ to cover its funding shortfall, where δ represents the degree of distress in asset markets. Therefore, the effect on i is characterized by

$$\sum_j x_{ji} - (1 + \delta)\rho x_{hi} + a_i = (k_i - \delta\rho x_{hi}) + b_i + d_i + \sum_j x_{ij} - \rho x_{ih},$$

and i will default if it cannot absorb the funding shortfall cost induced by a fire sale of its assets.

The algorithm simulates failures of entities included in the analysis and stops when no more failures occur. Based on the number of failures suffered or induced, contagion (outward spillover) and vulnerability (inward spillover) may be assessed. Specifically, the present analysis focuses on the contagion index of an entity i

$$\mathrm{CI}_h = 100\frac{\sum_{i \neq h} l_{hi}}{\sum_{i \neq h} k_i},$$

where losses l_{hi} of i from the default of h can alternatively be λx_{hi} under a credit shock and $\delta \rho x_{hi}$ under a credit-and-funding shock. Additionally, the vulnerability index of an entity i is calculated as

$$\mathrm{VI}_i = 100\frac{\sum_{h \neq i} l_{hi}}{(n-1)k_i},$$

where n represents the number of entities in the network.

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