1. ASSESSING SYSTEMIC RISK IN THE LUXEMBOURG BANKING SECTOR : A DELEVERAGING APPROACH

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ABSTRACT

This paper applies a new methodology for measuring systemic risk to the Luxembourg banking sector. The model involves an exogenous shock to assets which leads to equity losses, increasing leverage. Banks then return to their previous level of leverage through selling assets, which impacts prices and leads to losses for banks holding these assets. Systemic risk is measured by the percentage in which equity decreases across the entire banking sector from deleveraging, and is decomposed to identify the risk contribution of individual banks and asset classes over time. This measure is shown to serve as a leading indicator of distress, and is applied to demonstrate that the Basel III capital requirements have extensive capacity to reduce risk associated with deleveraging through fire sales.

1 INTRODUCTION

Systemic risk has become an increasingly important area of concern since the onset of the global financial crisis. In particular, the propagation of financial distress throughout the banking sector has demonstrated the need to better understand the buildup and impact of risks affecting the financial system as a whole. This paper provides a quantitative assessment of systemic risk in the Luxembourg banking sector using the empirical framework of Greenwood, Landier, and Thesmar (2015). The model involves an exogenous shock to assets which leads to equity losses, increasing leverage. Banks then return to their previous level of leverage through selling assets, which impacts prices and leads to losses for banks holding these assets. Systemic risk is measured by the percentage in which equity decreases across the entire banking sector from deleveraging.

This methodology provides a number of useful insights into risk related to deleveraging through fire sales in the Luxembourg banking sector. First, the output of the model is used to construct an index which shows how the vulnerability of the Luxembourg banking sector evolves over time. Second, the model measures each individual bank's risk contribution, thereby identifying the banks which contribute most to system-wide vulnerability. Third, the model measures the risk contribution of specific asset classes. Fourth, the model captures the susceptibility of each bank to be hurt by other banks, which differs from the capacity to contribute to risk. Fifth, the vulnerability index is shown to have predictive capacity and can be used as an early warning indicator for financial distress. Lastly, this balance sheet-based approach provides different information that market-based risk measures may not identify, such as the buildup of risk during periods of low volatility. This feature allows the model to complement other measures of risk.

The rest of this paper is organized as follows. Section 2 describes the structure and assumptions of the model, section 3 describes the data, and section 4 discusses the results. Section 5 covers the resilience of the Luxembourg banking sector in stressed scenarios. Section 6 examines the capability of the aggregate vulnerability index to serve as a leading indicator. Section 7 explores the impact of the Basel III regulatory framework and its capacity to reduce systemic risk in Luxembourg. Section 8 concludes.

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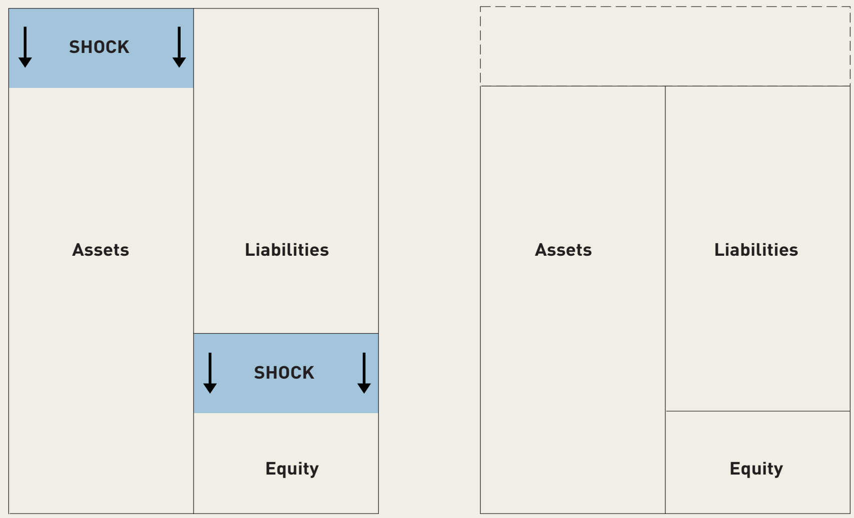
2 MODEL

The following methodology developed by Greenwood et al. (2015) is applied to the Luxembourg banking sector. This approach accounts for both the time-varying and cross-sectional components of systemic risk (Borio, 2003). At the initial stage, each bank's leverage ratio is assumed to be its target level of leverage which it seeks to maintain over time.[2] Maintaining leverage is a realistic assumption, as Adrian and Shin (2010) empirically demonstrate that banks target fixed leverage ratios. At time *t* each bank receives a shock in which assets decline by 1%. This decline in assets is accompanied by an equivalent decline in equity, which increases leverage. This is shown in Figure 1.

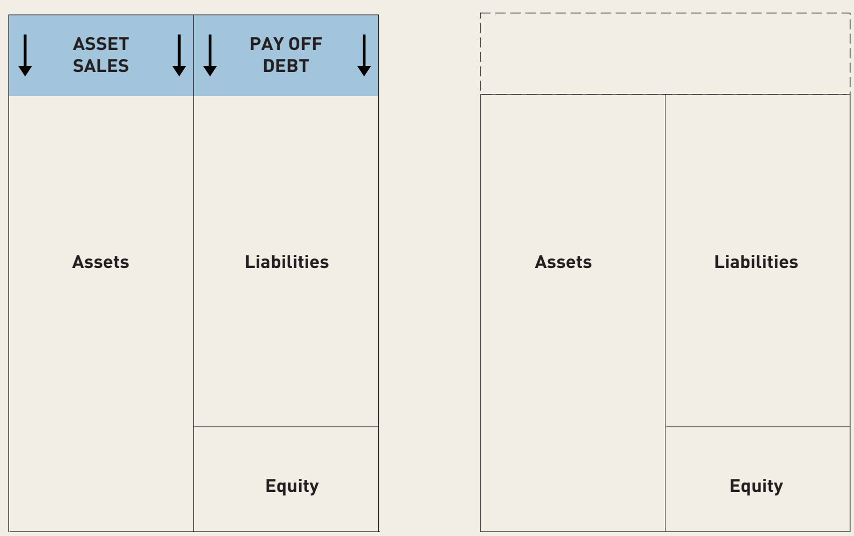
Figure 1
Exogenous shock leads to a decrease in assets and equity



Note: The left diagram shows the impact of the shock on assets and equity, while the right diagram shows the structure of the balance sheet after the shock occurs.

In order to return to target leverage, at time $t + 1$ banks sell assets in proportion to their holdings, which is illustrated in Figure 2. Each bank sells an amount of assets such that its capital structure after asset sales is proportional to its original debt and equity mix before the exogenous shock occurs. In this way, asset sales allow the bank to return to its previous level of leverage.

Figure 2
Return to target leverage by selling assets to pay off debt



Note: Assets are sold and the proceeds are used to pay off debt, as shown in the left diagram. This reduces the leverage of the firm, bringing it back to its original debt-to-equity ratio as shown in the right diagram.

Let there be N banks, each which hold a portfolio of K assets. Let *A* be an N x N diagonal matrix representing the total value of assets on each bank's balance sheet. Let *M* be an N x K matrix of the weights of the individual assets that banks hold. Let *B* be an N x N diagonal matrix representing each bank's

2 Within the context of this study, leverage is defined as a bank's debt-to-equity ratio, with equity defined as total capital and debt defined as assets minus equity. Leverage is capped at 50.

target leverage ratio. Let R be an N x 1 vector of asset shocks, in this case 1%. The amount of assets that must be sold at time $t + 1$ to return to target leverage is defined as ϕ in equation (1).

$$\phi_{t+1} = M'_t B_t A_t R_t \tag{1}$$

Although asset sales result in banks achieving their target leverage, this also impacts prices. Let L be a K x K diagonal matrix that defines the price impact for a given amount of assets sold. The matrix is calibrated with a price movement of 10 basis points for every €10 billion in sales of a particular asset type, which is the value used by Greenwood et al. (2015). Since L is a diagonal matrix, sales from one asset class do not directly impact the prices of other asset classes. Let P be a K x 1 vector of the price impact from assets sold. Combining L with equation (1) produces equation (2).

$$P_{t+1} = L\phi_{t+1} \tag{2}$$

The price impact vector P is used to generate W, an N x 1 vector of weighted bank portofolio losses measured in relative terms. W is computed by pre-multiplying equation (2) by M:

$$W_{t+1} = M_t L M'_t B_t A_t R_t \tag{3}$$

Building off the framework established in equations (1), (2), and (3), the aggregate vulnerability of the banking sector is represented by the term AV in equation (4). 1 is an N x 1 vector of ones and E is the total amount of equity across all banks before deleveraging occurs. The numerator can be interpreted as the total amount of losses in euro that the banking sector faces as a result of deleveraging. This value is normalized by dividing by the total amount of equity in the banking sector. The aggregate vulnerability risk term AV in equation (4) can be interpreted as the percentage in which equity decreases across the banking sector as a result of deleveraging.

$$AV_{t+1} = \frac{1' A_t M_t L M'_t B_t A_t R_t}{E_t} \tag{4}$$

This formula reveals several properties about how deleveraging through fire sales contributes to systemic risk. First, size plays a significant role. A greater amount of aggregate banking assets leads to higher total risk. Second, bank interconnectedness is important. The more that banks hold large asset classes that are also held by other banks, the greater the losses across the banking sector from deleveraging. Third, the more levered banks are, the more severe losses the system will face. Fourth, the more that banks are exposed to assets which are shocked, the greater their risk. Therefore, if only certain asset classes receive shocks while others remain resilient to financial distress, those banks with the greatest holdings of assets which decline in value are the most adversely affected.

Although the term AV in equation (4) represents the aggregate level of risk across the banking sector, this term can be decomposed to identify the contribution of each individual bank n to aggregate vulnerability. This is shown in equation (5). The term δ_n is an N x 1 vector of zeros except for the n^{th} term, which is 1.

$$AV_{n,t+1} = \frac{1' A_t M_t L M'_t B_t A_t \delta_n \delta_n' R_t}{E_t} \tag{5}$$

Summing up each term of the individual risk contribution of each bank in equation (5) yields the total aggregate vulnerability of the entire banking sector shown in equation (4). The summation effect is shown in equation (6).

$$\sum_{n=1}^{N} AV_{n,t+1} = AV_{t+1} \tag{6}$$

Equation (5) allows for a comparison of the individual risk contribution of each bank. This produces a ranking in which the banks contributing the most to aggregate vulnerability can be identified. In addition to having a metric that identifies the degree to which banks contribute to aggregate vulnerability, it can also be shown to what extent the risk of the system as a whole contributes to the vulnerability of each bank. It is possible to have a bank that is highly vulnerable to systemic risk without largely contributing to systemic risk. An example of this is a small, highly levered bank. In equation (7), let *e* represent an individual bank's equity and *IV* represent an individual bank's indirect vulnerability. *IV* is interpreted as the percentage of equity of bank *n* that decreases as a result of all other banks deleveraging.

$$IV_{n,t+1} = \frac{\delta_n{}' A_t M_t L M'{}_t B_t A_t R_t}{e_{n,t}} \tag{7}$$

In equation (8), *IC* represents the interconnectedness between two banks, *m* and *n*. Suppose there is a shock only to bank *m*'s assets, which causes bank *m* and only bank *m* to deleverage. This shock can be represented by $\sigma\delta_m$, where σ is a scalar representing the magnitute of the shock and δ_m is a vector of zeros except for the m^{th} term which is 1. Equation (8) models the percentage decrease in bank *n*'s equity as a result of bank *m* deleveraging.

$$IC_{m,n,t+1} = \sigma \frac{\delta_n{}' A_t M_t L M'{}_t B_t A_t \delta_m}{e_{n,t}} \tag{8}$$

Bank *n* faces higher risk from bank *m* deleveraging when both banks are highly levered and both hold similar assets.

3 DATA

Quarterly balance sheet data for Luxembourg banks is used from 2003Q2 to 2015Q3.[3] Assets are disaggregated into 13 asset classes, which fall into the categories of loans, debt, and shares. Each asset class and its corresponding weight is shown in Table 1. Loans to credit institutions is the largest asset class, accounting for 38.5% of total banking assets. Euro area sovereign debt is 4.8% of assets, while equity is 1.0%.

Table 1:

Disaggregation of Luxembourg banking assets

ASSET CLASS	WEIGHT
Loans	
Credit institutions	38.5%
Non-financial corporations	10.2%
Households	8.2%
Other financial institutions	6.0%
General government	1.1%
Investment funds	1.0%

3 Branches have been excluded from the scope of the analysis.

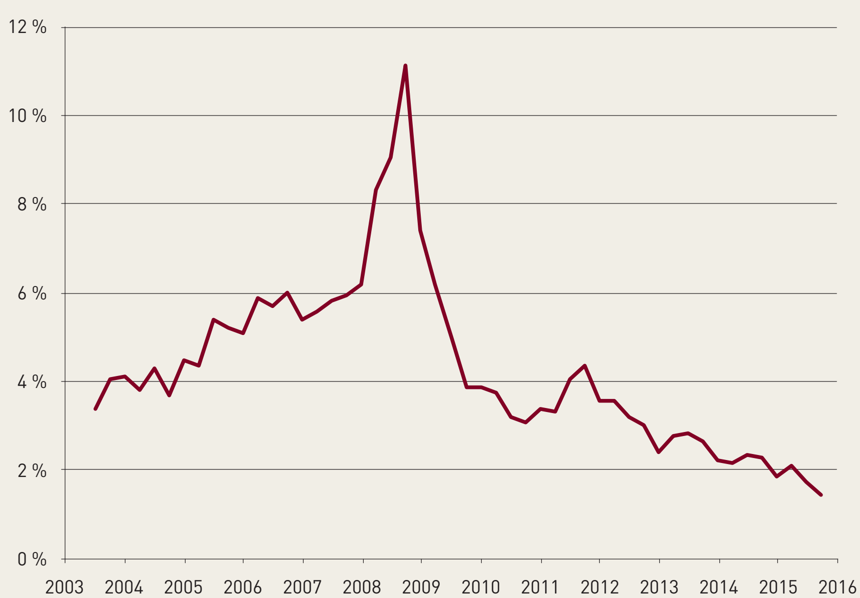
ASSET CLASS	WEIGHT
Debt	
Credit institutions	8.8%
Euro area sovereigns	4.8%
Other financial institutions	4.4%
General government	1.9%
Non-financial corporations	0.6%
Shares	
Equity	1.0%
Investment funds	0.7%

Source: BCL calculations. Values represent a weighted average across all banks in 2015Q3 excluding branches. Weights do not add up to 1 because some assets held by banks do not fall within the asset classes shown in the table (sum=87.2%).

4 RESULTS

Figure 3 shows the aggregate vulnerability (AV) index for the Luxembourg banking sector. The value of the index can be interpreted as the percentage in which equity would decrease across all banks from deleveraging in response to a 1% shock to assets. As shown in Figure 3, there is a steady buildup of risk in the years preceding the financial crisis. The index spikes in 2008Q1, significantly increasing from previous levels. At its peak in 2008Q3, equity would have declined by 11.1% from deleveraging due to a 1% asset shock. In the periods that follow, the index rapidly decreases to 4% and remains subdued throughout the remainder of the observed time period. In the most recent observation of 2015Q3, the index is at 1.4%, indicating low risk.

Figure 3
Aggregate vulnerability index for the Luxembourg banking sector



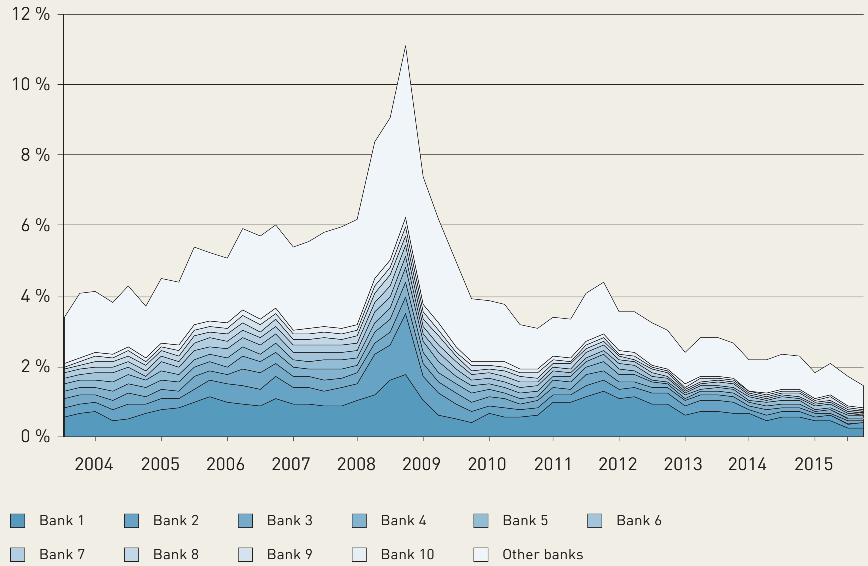
Source: BCL calculations. The AV index shows the percentage in which equity would decrease across all banks from deleveraging in response to a 1% shock to assets.

The AV index is disaggregated at the bank level to show the individual contribution of each bank. Figure 4 shows the risk contribution of the 10 banks with the highest aggregate vulnerability, with all of the remaining banks combined into a single category. The composition of these 10 banks varies over time as institutions drop in and out of this group. Due to the linear properties of the model, the sum of the risk contribution of each individual bank in Figure 4 is equal to total aggregate vulnerability in Figure 3. In 2015Q3, 55% of total aggregate vulnerability was concentrated in the top 10 banks, while 32% was concentrated in the top 3 banks. This is a significant decrease from 2011Q4, when 69% was concentrated in the top 10 banks, and 44% was concentrated in the top 3 banks.

Table 2 shows the 10 banks with the highest aggregate vulnerability and their corresponding sizes in 2015Q3. Relative AV is defined as the percentage contribution to total aggregate vulnerability. This table illustrates that a financial institution's contribution to risk is not necessarily determined by its size. According to Table 2, bank A, which has the highest AV and largest size, accounts for 18.6% of total AV in the banking sector and 13.3% of total banking assets. This bank generates a relatively large amount of risk compared to its size. On the other hand, some banks provide a relatively low amount of AV compared to their total assets. For example, bank E contributes only 4.0% of total AV, but has assets equivalent to 7.4% of the banking sector. The 10 banks in Table 2 together account for 55% of total AV and 49% of total assets. This indicates that on an aggregate level, these banks exhibit a greater degree of risk than is reflected by their size alone.

Figure 4

Aggregate vulnerability index decomposed by bank



Source: BCL calculations. For each time period, the risk contribution of the 10 banks with the highest aggregate vulnerability is shown, while the risk contribution of all other remaining banks is combined into a single category.

Table 3 shows the relationship between aggregate vulnerability and size for the 10 banks with the largest asset holdings in 2015Q3. Bank K has a significantly lower contribution to total AV than share of assets in the banking sector, and is ranked 5 in asset size and 23 in AV. In this case, bank K's share of assets is nearly 4 times larger than its share of AV. The largest 10 banks together comprise 52% of total AV and 56% of assets. Therefore, this group of banks has a lower level of risk than their asset size suggests.

Table 2:

Banks with highest aggregate vulnerability

BANK NAME	RELATIVE AV	TOTAL ASSETS	AV RANK	SIZE RANK
Bank A	18.6%	13.3%	1	1
Bank B	8.1%	7.3%	2	3
Bank C	5.2%	3.9%	3	6
Bank D	4.9%	6.3%	4	4
Bank E	4.0%	7.4%	5	2
Bank F	3.5%	2.0%	6	16
Bank G	3.3%	2.7%	7	9
Bank H	2.9%	2.6%	8	11
Bank I	2.5%	2.6%	9	12
Bank J	2.4%	0.9%	10	27
Total	**55.4%**	**49.0%**		

Source: BCL calculations. Values are as of 2015Q3. Relative AV is defined as the percentage contribution to total aggregate vulnerability. Total assets are defined as the percentage of all banking sector assets excluding branches. Banks are ordered from largest to smallest by aggregate vulnerability.

Table 3:

Banks with largest asset holdings

BANK NAME	RELATIVE AV	TOTAL ASSETS	AV RANK	SIZE RANK
Bank A	18.6%	13.3%	1	1
Bank E	4.0%	7.4%	5	2
Bank B	8.1%	7.3%	2	3
Bank D	4.9%	6.3%	4	4
Bank K	1.5%	5.6%	23	5
Bank C	5.2%	3.9%	3	6
Bank L	2.4%	3.6%	11	7
Bank M	1.9%	3.5%	17	8
Bank G	3.3%	2.7%	7	9
Bank N	2.3%	2.6%	12	10
Total	**52.2%**	**56.2%**		

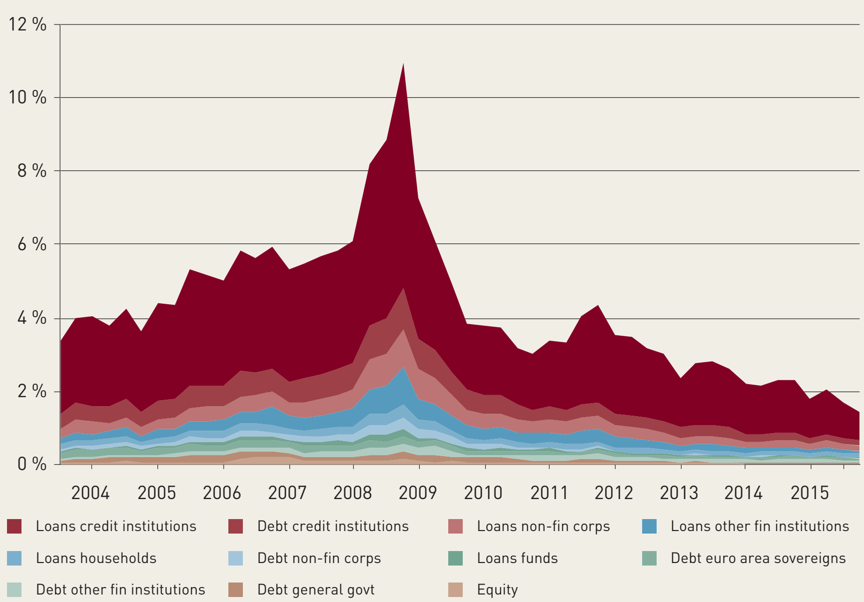
Source: BCL calculations. Values are as of 2015Q3. Relative AV is defined as the percentage contribution to total aggregate vulnerability. Total assets are defined as the percentage of all banking sector assets excluding branches. Banks are ordered from largest to smallest by total assets.

The distinction between bank size and risk contribution is important within the context of systemic risk. The model offers an alternative framework for identifying the most systemic banks. In particular, it provides new information to measure systemic risk that cannot be determined by asset size alone. This important feature suggests that identifying the largest banks as the most risky does not provide a comprehensive assessment, and excludes many of the institutions that in fact contribute most to risk from a bank deleveraging perspective.

Figure 5 shows the aggregate vulnerability index decomposed by asset class. Loans to credit institutions contribute approximately half of total AV, while debt issued by credit institions, loans to non-financial corporations, and loans to other financial institutions also play a substantial role. It can be observed that the relative risk contribution of each asset class does not exhibit significant variation over time.

Figure 5

Aggregate vulnerability index decomposed by asset class



Source: BCL calculations. Loans to general government and investment fund shares are not displayed in this figure due to their small risk contribution throughout the observed time period.

Table 4 shows the relationship between aggregate vulnerability and size for each asset class in 2015Q3. As seen in the table, a sizable difference persists between relative AV and assets in several cases. The most pronounced discrepancy is for loans to credit institutions, which has a relative AV of 53.3% and assets of 44.2%. Relative AV is 9.1% higher than assets, indicating that the risk contribution of this asset class exceeds that of its size. Loans to households have a relative AV of 6.3% and an asset weight of 9.4%, which shows its contribution to risk is relatively less than its size. Measuring the relative AV of each asset class is important because it provides additional information that exposure alone cannot account for. As the table indicates, an asset class may exhibit a degree of aggregate vulnerability that is either in line with its relative size or diverges.

Table 4:

Aggregate vulnerability and size of asset classes

ASSET CLASS	RELATIVE AV	ASSET WEIGHT
Loans to credit institutions	53.3%	44.2%
Loans to non-financial corporations	10.8%	11.7%
Debt credit institutions	9.2%	10.1%
Loans to households	6.3%	9.4%
Loans to other financial institutions	5.5%	6.8%
Debt euro area sovereigns	4.4%	5.5%
Debt other financial institutions	4.7%	5.0%
Debt general government	1.7%	2.2%
Loans to general government	0.8%	1.2%
Equity shares	0.7%	1.2%
Loans to investment funds	1.2%	1.1%
Investment fund shares	0.8%	0.8%
Debt non-financial corporations	0.5%	0.7%
Total	**100%**	**100%**

Source: BCL calculations. Values are as of 2015Q3. Relative AV is defined as the percentage contribution to total aggregate vulnerability. Values for total assets exclude branches and have been adjusted such that they sum to 100%, allowing for comparability to relative AV.

In addition to aggregate vulnerability (AV), which measures the degree to which banks contribute to systemic risk through deleveraging, another measure will now be considered which shows how vulnerable individual banks are. Indirect vulnerability (IV) measures the percentage of equity a bank loses as a result of all other banks deleveraging from a shock. A bank with a high contribution to systemic risk is not necessarily vulnerable, and vice versa. Table 5 shows the 10 banks with the highest IV. The average IV for all Luxembourg banks is 17.5%. Bank O has the highest IV and would lose 267.8% of its equity from other banks engaging in deleveraging. Although losing more than 100% of equity is not realistic in practice, this measure is still useful because it illustrates the magnitude of a bank's vulnerability to the system as a whole. The model also provides a ranking of the most vulnerable institutions. Such a ranking is useful in its own right to identify which banks are the most susceptible to losses from fire sales due to system-wide deleveraging. In addition, it allows us to better understand to what extent banks that significantly contribute to financial distress are prone to be hurt by other banks. Table 5 provides additional insight into this relationship.

The 10 banks with the highest IV tend to have AV rankings that are much lower. Only one of the banks in the top 10 IV ranking has a corresponding AV ranking that is also in the top 10, which is bank J. This bank has both a high level of vulnerability and contribution to systemic risk from deleveraging. However, overall, the remaining banking entities in Table 5 have lower AV rankings. For example, bank R has an IV rank of 4, but an AV rank of 24. This suggests a high degree of vulnerability but a relatively low contribution to systemic risk from deleveraging. Assessing both IV and AV is important in terms of gaining a holistic understanding of a bank's risk profile.

Table 5:

Banks with greatest indirect vulnerability as a fraction of equity

BANK NAME	IV	IV RANK	AV RANK
Bank O	267.8%	1	21
Bank P	56.9%	2	14
Bank Q	49.8%	3	18
Bank R	43.0%	4	24
Bank S	42.5%	5	58
Bank J	41.4%	6	10
Bank T	37.3%	7	34
Bank U	35.8%	8	35
Bank V	34.9%	9	57
Bank W	33.0%	10	37
Average of all banks	17.5%		

Source: BCL calculations. Values are as of 2015Q3.

The next metric analyzed is interconnectness between individual financial institutions. Within the context of this study, interconnectedness (IC) refers to the percentage in which equity declines in one bank as the result of a single other bank deleveraging after a 1% asset shock. Interconnectedness is calculated for every combination of two banks in the Luxembourg banking sector. The results for a select sample of interconnected banks are shown in Table 6. The values represent the amount by which equity declines for the bank in the left column as a result of the bank in the corresponding top row deleveraging. A prominent feature of the interconnectedness matrix is that it is not symmetric. For example, the interconnectedness between bank A and F is not the same as the interconnectedness between bank F and A. When bank A and only bank A deleverages as a result of an asset shock, bank F loses 0.7% of its equity. However, if bank F deleverages, bank A loses only 0.1% of its equity. This highlights the distinction that a bank's ability to adversely impact other banks differs from its suceptiblity to be be harmed by other banks.

The most interconnected financial institutions are bank L and bank O. When bank L deleverages, bank O loses 5.4% of its equity. This figure is particulary severe due to the relatively low amount of equity held by bank O. A bank with stronger capitalization could better withstand an equivalent loss. Alternatively, when bank O delevers, bank L only loses 0.1% of its equity. This can be explained by the fact that bank L has a balance sheet that is almost 4 times that of bank O. In addition, bank L has half the leverage that bank O does. These factors show that bank L has stronger potential to negatively impact bank O than vice versa. In fact, bank O is highly interconnected with all of the other banks shown in Table 6, which is illustrated in the last row of the table. This result is consistent with Table 5, which identifies bank O as the most vulnerable financial institution in the Luxembourg banking sector.

Table 6:

Interconnectedness matrix for select financial instutions

	B	D	A	C	F	P	O	J	L	O
B		0.1%	0.2%	0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%
D	0.1%		0.3%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
A	0.1%	0.1%		0.1%	0.1%	0.1%	0.1%	0.1%	0.1%	0.0%
C	0.1%	0.2%	0.4%		0.1%	0.0%	0.0%	0.1%	0.1%	0.1%
F	0.1%	0.2%	0.7%	0.1%		0.1%	0.1%	0.1%	0.1%	0.0%
P	0.2%	0.3%	1.5%	0.3%	0.3%		0.2%	0.2%	0.2%	0.0%
O	0.3%	0.4%	1.6%	0.3%	0.3%	0.2%		0.2%	0.2%	0.1%
J	0.3%	0.3%	1.2%	0.2%	0.2%	0.1%	0.1%		0.2%	0.1%
L	0.1%	0.1%	0.3%	0.1%	0.0%	0.0%	0.0%	0.0%		0.1%
O	3.0%	3.3%	4.0%	2.7%	0.6%	0.4%	0.4%	1.5%	5.4%	

Source: BCL calculations. Values are as of 2015Q3. Interconnectedness is measured as the loss in equity of the bank in the left column as a result of the bank in the corresponding top row deleveraging after a 1% asset shock.

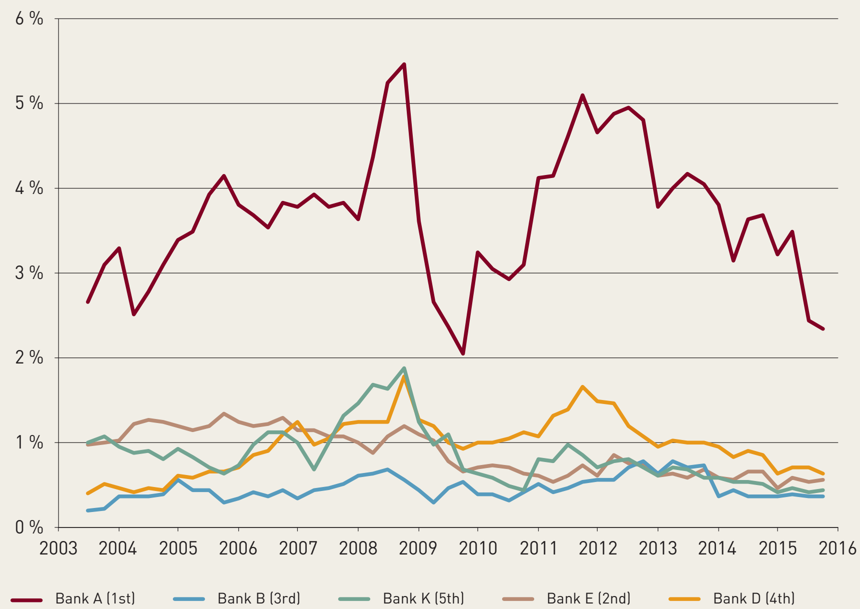
5 SCENARIO ANALYSIS

This section presents the impact of several stressed scenarios on the Luxembourg banking sector. The first scenario involves how failure of a single bank would affect the total level of equity in the banking sector. Bank failure is triggered by the equity of a particular institution being entirely wiped out. This is taken into account by first writing down assets such that the equity of a particular bank is eliminated, initiating bankruptcy. Thereafter, all remaining assets are liquidated, which impacts asset prices and in turn the balance sheets of all other banks holding these assets. The bank failure scenario is represented in equation (9), where *F* indicates the failure of bank *n*. θ_n is an N x 1 vector of zeros, except for the entry corresponding to failing bank *n*, which is equal to 1. The variables $a_{n,t}$ and $e_{n,t}$ correspond to the value of total assets and total equity for failing bank *n* at time *t*.

$$F_{n,t+1} = \frac{1' A_t M L M' \theta_n \theta_n' (a_{n,t} - e_{n,t})}{E_t} \quad (9)$$

The outcome of this scenario can be interpreted as the percentage of equity in the entire banking sector that would be eliminated as the result of a single bank failing. Figure 6 shows the impact of each of the five largest banks failing on an individual basis.

Figure 6
Impact of bank failure on equity in the Luxembourg banking sector



Source: BCL calculations. Rankings correspond to asset size in 2015Q3.

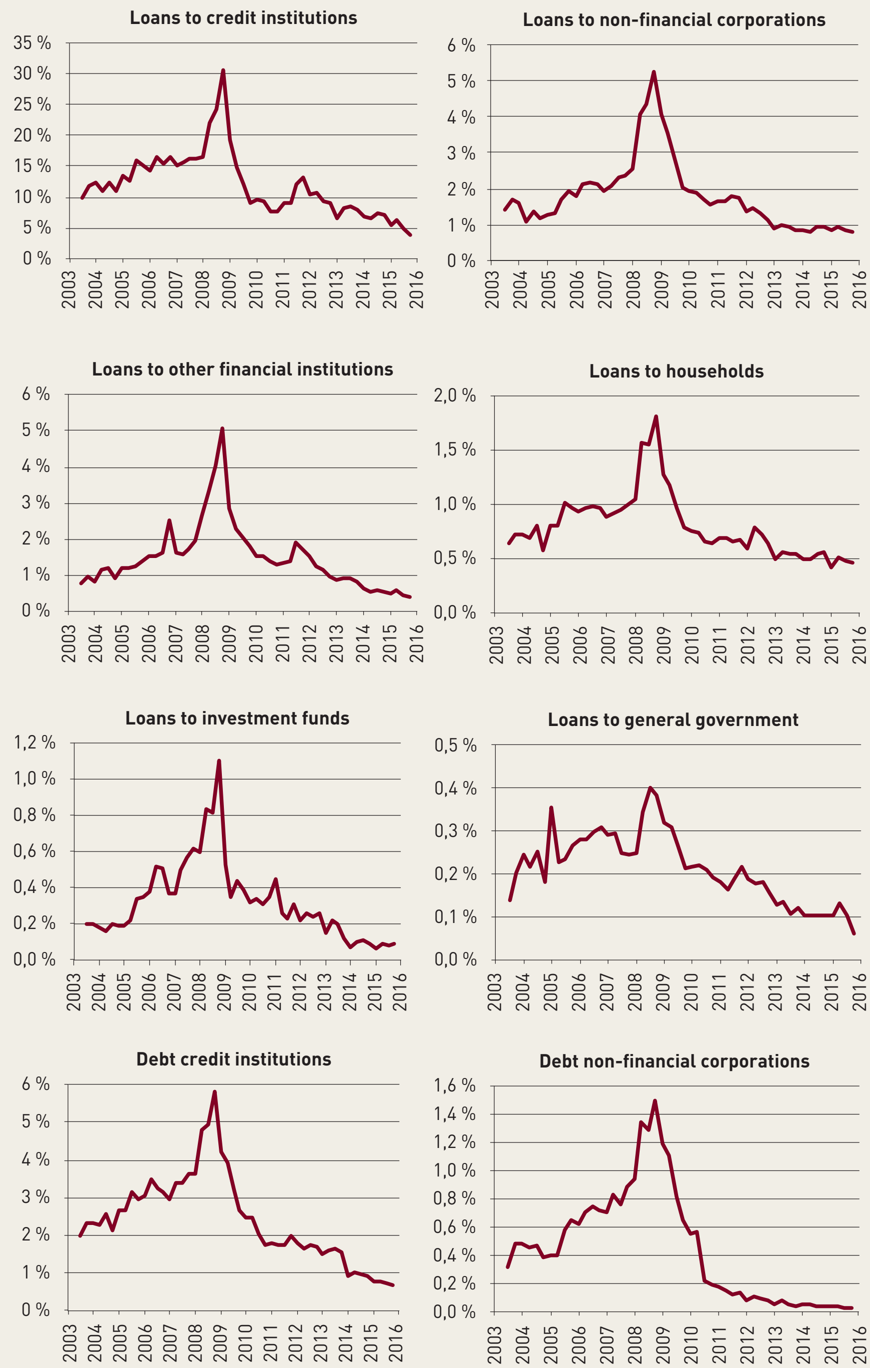
Failure of bank A, the largest bank in 2015Q3, would result in a 2.4% decrease in total banking equity. This figure has been steadily declining for this institution since 2012. The second, third, fourth, and fifth largest banks would cause equity decreases of 0.57%, 0.36%, 0.63%, and 0.43%, respectively in 2015Q3. Note that despite bank B being larger than bank D and bank K, it has less of a severe impact than both other institutions on system-wide equity losses resulting from its failure.

The next scenario involves examining the resiliency of the banking sector to shocks in individual asset classes. A shock is applied to each asset class on an individual basis, which produces a decline in bank equity for each observed time period. The model for applying asset shocks is shown in equation (10). Z represents the percentage of equity that would decline in the Luxembourg banking sector at time $t+1$ from deleveraging after a shock to asset class k and no other asset classes. The term λ_k is a K x 1 vector of zeros except for the k^{th} term, which is 1. Q is a K x 1 vector of asset shocks which indicates the amount by which the value of the entire asset class is written down.

$$Z_{k,t+1} = \frac{1' A_t M_t L M'_t B_t A_t M_t \lambda_k \lambda_k' \, Q_t}{E_t} \tag{10}$$

In the following scenario, each asset class is individually shocked by 5%. The results for all 13 asset classes are shown in Figure 7. According to the first graph in Figure 7, a 5% shock in the value of loans to credit institutions would result in a 3.9% decline in equity across the banking sector in 2015Q3 from deleveraging. This asset class has the greatest impact on equity losses. The next most systemic asset class is loans to non-financial corporations, which would cause a 0.8% decline in banking equity as the result of a 5% shock. Most of the individual asset class shocks reach their peaks between 2008 and 2009. However, euro area sovereign debt and general government debt experienced elevated levels of risk before the crisis. At its highest historical peak, investment fund shares would only cause a 0.45% decrease in banking equity if shocked by 5%.

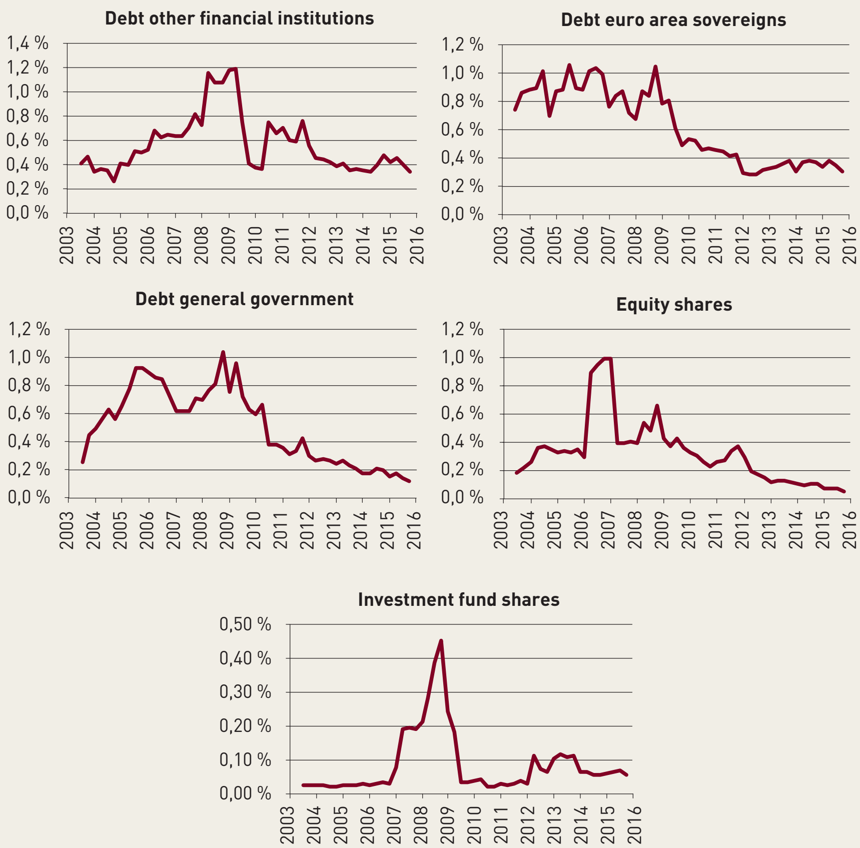
Figure 7
Impact of asset class shocks on equity in the Luxembourg banking sector



Source: BCL calculations.

Figure 7

Impact of asset class shocks on equity in the Luxembourg banking sector



Source: BCL calculations.

6 AGGREGATE VULNERABILITY AS A LEADING INDICATOR

In addition to its usefulness in measuring risk related to deleveraging within the banking sector, individual financial institutions, and specific asset classes, the AV index can be used as a leading indicator of distress. Duarte and Eisenbach (2014) show that the dynamic evolution of the AV index has predictive capacity for the US financial sector. This section will examine to what extent the AV index serves as a leading indicator for GDP and unemployment in Luxembourg.

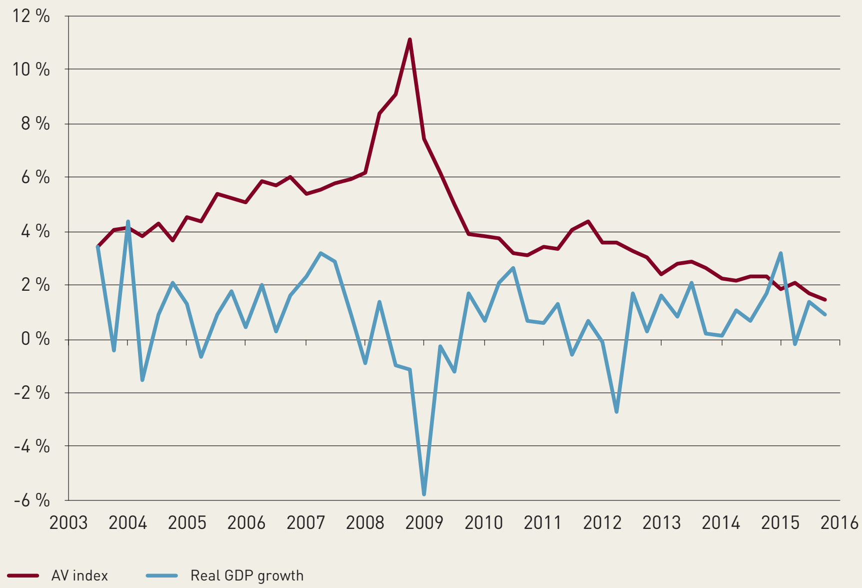
Figure 8 shows the AV index compared to real GDP growth. As the graph illustrates, the two time series tend to move in opposite directions. This is an intuitive result which suggests that an increase in AV is associated with a decline in real GDP. Furthermore, the AV index often moves before real GDP growth. For example, the AV index peaks in 2008Q3 then declines after, while real GDP growth reaches its lowest point in 2008Q4, increasing thereafter.

The AV index and unemployment growth are shown in Figure 9. These series appear to have similar movements, although the AV index often moves before unemployment growth. This feature is especially pronounced during the period of highest financial distress, when the AV index peaks in 2008Q3, and unemployment growth reaches its maximum value in 2009Q1. Despite visual representations that suggest the AV index may be a leading indicator for both unemployment growth and real GDP growth, econometric analysis is conducted to determine whether this relationship is statistically significant.

Granger-causality is employed for assessing the predicative capacity of the AV index. The first difference is taken for each time series to ensure stationarity. The change in real GDP growth and change in unemployment growth are each tested independently to determine whether they Granger-cause change in the AV index. The reverse test is also conducted to examine whether change in real GDP growth and change in unemployment growth Granger-cause change in the AV index.

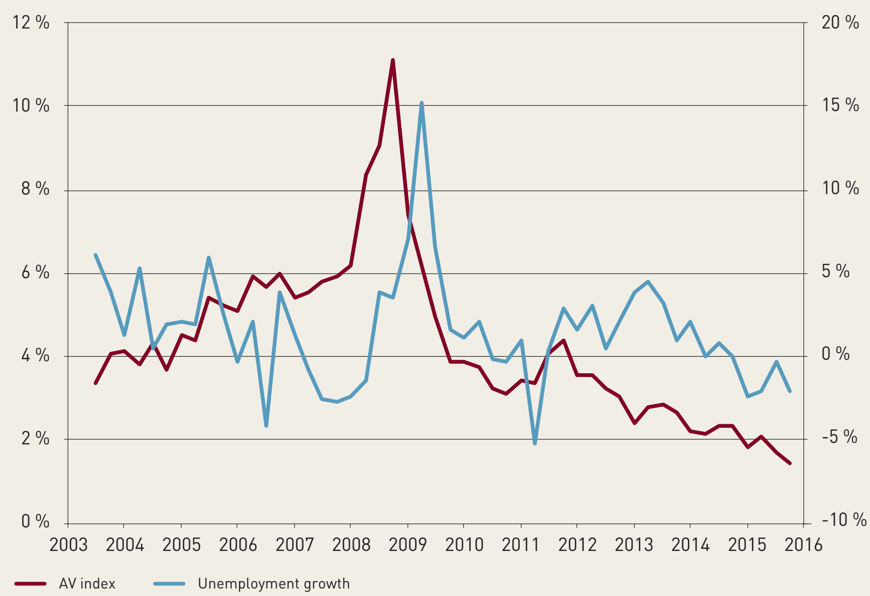
The results of the Granger-causality tests for AV and real GDP growth are shown in Table 7. The null hypothesis is that X does not Granger-cause Y. The upper portion of the table indicates that the null hypothesis being tested is that change in the AV index does not Granger-cause change in real GDP growth.

Figure 8
Aggregate vulnerability index and real GDP growth



Source: BCL calculations and STATEC. Real GDP growth is defined as the seasonally adjusted percentage change in real GDP from the previous quarter.

Figure 9
Aggregate vulnerability index (left axis) and unemployment growth (right axis)



Source: BCL calculations and STATEC. Unemployment growth is defined as the seasonally adjusted percentage change in the unemployment rate from the previous quarter.

Table 7:

Granger-causality results for aggregate vulnerability and real GDP

LAGS	X	Y	F-STATISTIC	P-VALUE	
1	AV	GDP	5.8191	0.0200	*
2	AV	GDP	7.4985	0.0016	**
3	AV	GDP	8.0758	0.0003	***
4	AV	GDP	5.8730	0.0010	**
5	AV	GDP	4.1922	0.0046	**
6	AV	GDP	3.2442	0.0141	*
7	AV	GDP	2.7999	0.0251	*
8	AV	GDP	2.2381	0.0607	
1	GDP	AV	1.6339	0.2077	
2	GDP	AV	0.8415	0.4382	
3	GDP	AV	0.4166	0.7421	
4	GDP	AV	0.6338	0.6417	
5	GDP	AV	0.4689	0.7966	
6	GDP	AV	0.6292	0.7056	
7	GDP	AV	0.8298	0.5718	
8	GDP	AV	1.5471	0.1935	

*Note: The null hypothesis is that X does not Granger-cause Y. The variable AV represents change in the AV index, while GDP represents the change in real GDP growth. * = $p < 0.05$, ** = $p < 0.01$, *** = $p < 0.001$.*

The findings show that the null hypothesis is rejected for tests from 1 to 7 lags, and change in the AV index does in fact Granger-cause change in real GDP growth. Depending on the length of the lag, results are significant at the 0.05, 0.01, and 0.001 levels. In the lower portion of the table, we fail to reject the null hypothesis that the change in real GDP growth Granger-causes change in the AV index at all lags. This suggests the relationship between these two variables is only one way, and the change in the AV index can help predict the change in real GDP growth, but not vice versa.

The results of the Granger-causality tests for AV and unemployment growth are shown in Table 8. The upper portion of the table shows that the null hypothesis is rejected for tests from 2 to 8 lags, demonstrating change in the AV index does in fact Granger-cause change in unemployment growth. Results are significant at the 0.05, 0.01, and 0.001 levels. In the lower portion of the table, we fail to reject the null hypothesis that the change in unemployment growth Granger-causes the AV index at all lags. This outcome demonstrates that change in the AV index can help predict the change in unemployment growth, although the reverse is not true.

Table 8:

Granger-causality results for aggregate vulnerability and unemployment

LAGS	X	Y	F-STATISTIC	P-VALUE	
1	AV	UNEMPL	0.0509	0.8225	
2	AV	UNEMPL	9.1311	0.0005	***
3	AV	UNEMPL	8.4962	0.0002	***
4	AV	UNEMPL	6.2467	0.0006	***
5	AV	UNEMPL	4.7318	0.0023	**
6	AV	UNEMPL	3.6504	0.0077	**
7	AV	UNEMPL	3.7424	0.0059	**
8	AV	UNEMPL	3.2504	0.0119	*
1	UNEMPL	AV	0.0037	0.9516	
2	UNEMPL	AV	2.3329	0.1095	
3	UNEMPL	AV	1.7383	0.1751	
4	UNEMPL	AV	1.1833	0.3346	
5	UNEMPL	AV	1.6880	0.1650	
6	UNEMPL	AV	1.3177	0.2799	
7	UNEMPL	AV	1.0689	0.4096	
8	UNEMPL	AV	0.9350	0.5066	

Note: The null hypothesis is that X does not Granger-cause Y. The variable AV represents change in the AV index, while UNEMPL represents the change in unemployment growth. $*$ *=* $p < 0.05$*,* $**$ *=* $p < 0.01$*,* $***$ *=* $p < 0.001$*.*

It can be concluded that change in the AV index Granger-causes both change in real GDP growth and change in unemployment growth. However, an important caveat to this analysis is that Granger-causality does not necessarily imply a true causal relationship. Instead, it indicates that past values of change in the AV index are useful for predicting change in real GDP growth and unemployment growth. According to the results, it can be concluded that change in the AV index serves as a leading indicator for both change in real GDP growth and change in unemployment growth, especially during periods of heightened financial distress. Although it has not been determined whether the AV index strictly causes the other examined variables, it nonetheless provides a useful indication of future real GDP growth and unemployment growth in Luxembourg.

7 IMPACT OF BASEL III CAPITAL REQUIREMENTS

The Basel Committee on Banking Supervision has introduced a number of capital requirements through the Basel III regulatory framework. One of the core purposes behind these measures is "raising the quality, consistency and transparency of the capital base."[4] These capital requirements ensure a minimum level of Common Equity Tier 1 capital, total Tier 1 capital, total capital, and a capital conservation buffer, among other conditions.[5] A phase-in scheme has been developed that began in 2013 and will reach completion on 1 January 2019. The corresponding levels for each year are shown in Table 9. All figures in the table are shown as a percentage of risk-weighted assets.

4 Basel Committee on Banking Supervision (2011), p. 2.
5 In addition to capital requirements, a Basel III regulatory leverage limit is being developed which may also impact deleveraging risk. This measure is foreseen to come into force on 1 January 2018.

Table 9:

Phase-in for Basel III capital requirements in Luxembourg

MINIMUM CAPITAL	2013	2014	2015	2016	2017	2018	2019
Common Equity Tier 1	3.5%	4.0%	4.5%	4.5%	4.5%	4.5%	4.5%
Tier 1 capital	4.5%	5.5%	6.0%	6.0%	6.0%	6.0%	6.0%
Total capital	8.0%	8.0%	8.0%	8.0%	8.0%	8.0%	8.0%
Capital conservation buffer	0%	2.5%	2.5%	2.5%	2.5%	2.5%	2.5%
Total capital plus buffer	8.0%	10.5%	10.5%	10.5%	10.5%	10.5%	10.5%

Source: Basel Committee on Banking Supervision. All dates are as of 1 January. Luxembourg introduced a fully phased-in capital conservation buffer of 2.5% at the beginning of 2014.

This section will now explore the impact of the Basel III capital requirements on the Luxembourg banking sector. The analysis involves retroactively adjusting the AV index to assess the level of aggregate vulnerability that would have been realized if banks held capital levels that met the future Basel III requirements. The minimum amount of capital banks must maintain in Luxembourg is 10.5%, while the scenario considered involves banks maintaining a total capital ratio of at least 12.5%.

The methodology behind simulating the impact of the Basel III capital requirements on the Luxembourg banking sector is as follows. First, the total amount of Tier 1 and Tier 2 capital as a percentage of risk-weighted assets is computed for each bank. If the Tier 1 capital ratio is less than 10.5%, Tier 1 capital is upwardly adjusted to this value. The same methodology is applied to Tier 2 capital if it is below 2%.[6] However, if these capital ratios are met, no modifications are made. The adjustment process is shown in equations (11) and (12). The amount of additional capital each bank holds in this scenario in excess of their actual capital is represented by ξ and φ for Tier 1 and Tier 2 capital respectively. The adjusted equity value is shown in equation (13). Leverage is recomputed with the adjusted equity value as illustrated in equation (14).

$$\frac{\text{Tier 1 Capital} + \xi}{\text{RWA}} = 10.5\% \tag{11}$$

$$\frac{\text{Tier 2 Capital} + \varphi}{\text{RWA}} = 2\% \tag{12}$$

$$\text{E}_{\text{Adjusted}} = \text{E}_{\text{Original}} + \xi + \varphi \tag{13}$$

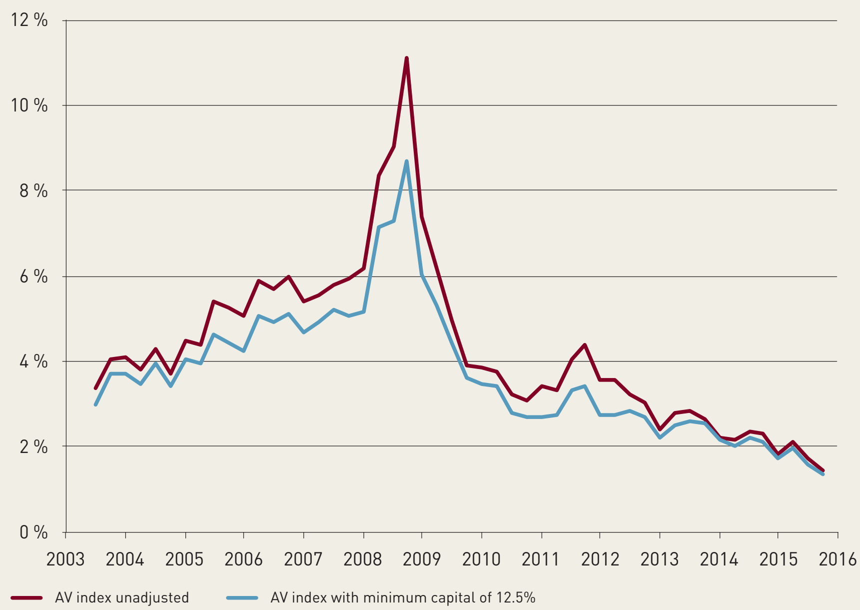
$$\text{Leverage}_{\text{Adjusted}} = \frac{\text{A}_{\text{Original}} - \text{E}_{\text{Adjusted}}}{\text{E}_{\text{Adjusted}}} \tag{14}$$

Figure 10 shows the evolution of the aggregate vulnerability index over time, as well as the adjusted values of the index if banks in each time period held a minimum capital level of 12.5%. This analysis provides insight into the effectiveness of the Basel III capital requirements in reducing deleveraging risk in the Luxembourg banking sector. In 2003, there is very little difference between the baseline scenario and the adjusted scenario. However, in the years building up to the global financial crisis, the gap between the two scenarios steadily increases, reaching its maximum value of 2.45% in absolute terms at

6 In the event that Tier 2 capital is less than the 2% threshold, any Tier 1 capital in excess of 10.5% is counted toward the Tier 2 ratio. If the ratio is still less than 2% then Tier 2 capital is upwardly adjusted.

the end of 2008Q3. This suggests that during the peak of the financial crisis, if banks were capitalized with a minimum of 10.5% Tier 1 capital and 2% Tier 2 capital, the value of the aggregate vulnerability index would have been 8.7% instead of 11.1%. This is equivalent to a 22% reduction in risk associated with fire sales driven by deleveraging.[7]

Figure 10
Aggregate vulnerability index adjusted for Basel III capital framework



Source: BCL calculations.

The Basel III capital requirements have a strong capacity to reduce risk in the Luxembourg banking sector. This is especially apparent during periods of financial distress, when additional capitalization is shown to have the most dramatic impact on risk reduction. Increased capital levels therefore strengthen the stability of the banking system as a whole, and help develop resistance to potentially adverse effects of future crises.

8 CONCLUSION

This paper applies a new method of assessing systemic risk to the Luxembourg banking sector. When all banks face an exogenous shock, they sell assets to return to target leverage, which impacts prices and causes banks holding those assets to realize losses in equity. The model incorporates bank size, leverage, and interconnectedness to show how much equity would be lost across all banks. Risk is decomposed to measure the contribution of individual banks and asset classes.

This study provides a number of systemic risk measurements that are useful from a policy perspective on a system-wide or individual bank level. Excessive risk observed in the Luxembourg banking sector as a whole could signal the need to implement mitigating measures. Additionally, individual banks that significantly contribute to risk or exhibit considerable vulnerability can be identified. The model offers insight into both the cross-dimensional aspect of risk as well as its buildup over time.

The Luxembourg banking sector currently shows low signs of risk as measured by aggregate vulnerability, and remains resilient to scenarios of financial distress. Furthermore, the aggregate vulnerability index is shown to have predictive capacity in relation to both real GDP and unemployment. An important contribution of this study is investigating the impact of the Basel III capital requirements on risk related to fire sales from deleveraging. The results indicate that maintaining capital levels which meet the Basel III requirements substantially strengthens the stability of the Luxembourg banking sector.

7 (8.7 / 11.1) – 1 = 22% reduction.

REFERENCES

Adrian T. and H. Shin (2010): "Liquidity and leverage", Federal Reserve Bank of New York, *Staff Reports*, No. 328.

Borio C. (2003): "Towards a macroprudential framework for financial supervision and regulation?", *BIS Working Papers*, No. 128.

BCBS (2011): "Basel III: A global regulatory framework for more resilient banks and banking systems", June, BCBS: Basel Committee on Banking Supervision.

Duarte F. and T. Eisenbach (2014): "Fire-sale spillovers and systemic risk", Federal Reserve Bank of New York, *Staff Reports*, No. 645.

Greenwood R., A. Landier and D. Thesmar (2015): "Vulnerable banks", *Journal of Financial Economics*, Vol. 115, 471–485.