4 ANNEXES

1. BANK-INVESTMENT FUND INTERCONNECTIONS AND SYSTEMICALLY IMPORTANT INSTITUTIONS IN LUXEMBOURG

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ABSTRACT

Recent international financial market volatility has reinforced the role of the Financial Stability Board's recommendation to enhance monitoring of the linkages between investment funds and the banking sector. Following the global financial crisis, Luxembourg's investment fund sector has exhibited sustained increases in the value of funds' total assets. This increase combined with elevated financial market volatility and risks from emerging market economies suggest that the connections between the investment fund sector and the banking system warrant enhanced monitoring from a macroprudential perspective. The results of this study show that the Luxembourg banking sector has some interconnections with the investment fund industry, notably on the liability side of banks' balance sheets, which may be relevant from a systemic risk perspective. External shocks to the investment fund sector could potentially spread to the domestic banking sector, thereby posing a threat to financial stability.

This paper applies network analysis tools to quantify the structural features of this bank-investment fund network that are relevant from a systemic risk perspective and to determine which banks are most significant within this network based on centrality measures. In a second step, the most pertinent measure is included in the *other systemically important institutions (O-SIIs) framework* to assess if the composition of identified systemic domestic banks changes when investment fund linkages are taken into account. The results reveal that the network of domestic banks and investment funds can be characterized as having a relatively low number of direct connections. Moreover, bank-investment fund and interbank distances are rather small and only a few institutions act as pivots within the network. Such a system could potentially propagate shocks very rapidly.

In terms of connectivity, out of a total of five commonly used measures, betweenness and PageRank appear the most suited for the investment fund and bank network in Luxembourg as the first best captures the banks that constitute pivotal points within the network and the second takes best account of the direct and indirect investment fund and bank connections. Even when the network analysis is not accounted for, this study shows that the standard O-SII assessment is already able to identify a large share of the banks with a high betweenness score as systemic. However, the same is not true for banks with a high PageRank score. When the latter measure is included in the O-SII assessment, two additional custodian banks turn out to be systemic.

1 INTRODUCTION

Links in the form of exposures and liabilities between investment funds and Luxembourg banks are of particular interest for domestic macroprudential authorities given their potential financial stability implications. In the event of a financial crisis, large shocks could be propagated through the financial sector. Indeed, domestic credit institutions' investment fund liabilities amounted to €123 billion or 16% of total assets as of 2016Q4, the majority of it provided by domestic investment funds (87%) and in the form of demand deposits (93%). The 16% share of total assets appears elevated compared to the 2%

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ratio of euro area investment fund deposits at euro area banks.[62] A large share of investment fund deposits could, for instance, be a source of potential risk if the fund sector were to face a significant redemption shock from investors. A redemption shock could potentially trigger a run on bank deposits by these same funds. Such a scenario could occur in market segments where investment funds engage in activities such as liquidity transformation or leverage and simultaneously offer frequent redemptions. If domestic banks suffer a run on their deposits by funds, this might have negative consequences such as fire-sales of part of their assets. Fire sales could trigger losses and defaults on interbank loans, or lead to a stoppage of financing provisions to other banks. Ultimately, this could propagate the shock within the interbank market. It is worth noting that an initial shock arising in the investment fund sector is not likely to occur in isolation or at the national level, but rather in the context of financial turmoil on a European or global scale, for example through a broader reassessment of risk premia. The structure and composition of Luxembourg's investment fund sector make it sensitive to developments and volatility in international financial markets.

Beyond the liability side of the balance sheet, domestic banks' exposure towards investment funds represents €13 billion or 2% of total assets. These exposures appear small but are highly concentrated as one single institution holds 28% and the top-5 institutions 54% of the €13 billion. Thus, it can still constitute a potential channel for contagion as the asset holdings are not fully diversified across banks.

The paper relies on network analysis tools to evaluate financial sector interconnections and focuses on three layers. First, the overall structure of a network consisting of Luxembourg banks' investment fund exposures and liabilities as well as the domestic interbank market exposures will be analysed in order to determine structural features relevant for systemic risk. Second, the institutions that are most important within this network will be identified by using centrality measures. Such measures quantify different aspects of importance within a network, such as the number of links, the distance to other network nodes, or the importance of the connected nodes. Ultimately, the goal will be to determine the most appropriate centrality measure to include as an additional indicator in the O-SII framework in order to ascertain if its explicit inclusion reveals banks to be systemic other than those identified in the standard assessment. The last point is of particular relevance so that macroprudential authorities are not limited to the analysis of existing financial interconnections but have a broad toolkit of measures aimed at fostering banks' resilience. Such a toolkit would include the O-SII framework, which allows authorities to assign additional capital buffers to systemic banks as well as complementary assessment tools. There is a need for additional analytical tools as the standard O-SII assessment has limitations in the sense that it does not entirely account for Luxembourg's specificity regarding investment fund linkages with banks and only considers financial sector interconnections in terms of direct exposures.[63] Reliance on direct exposures alone ignores the indirect exposures created through counterparties' counterparties. This paper aims addressing these national specificities.

62 ESRB EU Shadow Banking Monitor, No 1 / July 2016.

63 The interconnectedness indicators considered are inter-financial system assets and liabilities, as well as debt securities outstanding. See EBA/GL/2014/10 (GL on criteria for the assessment of O-SIIs).

2 NETWORK CONSTRUCTION AND CENTRALITY MEASURES

In this section we outline and describe the network set-up as well as the centrality measures used in the study. The underlying network is taken to be comprised of two components, the Luxembourg interbank market and the market involving investment funds and domestic banks. The interbank network is constructed from banks' large exposure data[64] reported according to regulation (EU) No 575/2013 on prudential requirements for credit institutions.[65] The bank-investment fund network is constructed from individual bank balance sheet data. In this case the more granular large exposure data is not employed since this only includes the asset side of the balance sheet and therefore ignores the more significant liability side.

Within the network model each bank, as well as the investment fund sector as a whole, is represented by a node. These nodes are connected via edges, which can either be directed or non-directed. This means that if bank A has an asset exposure towards bank B and vice versa, then this counts as two separate edges in the directed network and as only one edge that sums up both transactions in the non-directed network. The edges can either all have the same weight, usually equal to one, or they can be weighted according to the exposure amount or its inverse.

A resulting network, be it directed, weighted, or not, can be mathematically represented by an adjacency matrix A. This is an $(n \times n)$ matrix with elements a_{ij} describing the edges of the network, where n is equal to the number of nodes. In a directed network, a_{ij} represents the edge going from node j to node i. Furthermore, if the network is weighted, a_{ij} equals the exposure amount j has towards i.[66] If it is non-weighted, a_{ij} equals one if there is a link and zero otherwise. In a non-directed network, matrix A is symmetric ($a_{ij} = a_{ji}$) because no distinction is made between incoming and outgoing links. If there is a link between nodes i and j, then in the weighted network, a_{ij} equals the sum of asset exposures and liabilities and in the non-weighted network, it equals one. As banks do not lend to or borrow from themselves, the diagonal elements of A are always equal to zero. The following example should illustrate the difference between weighted and non-weighted, as well as directed and non-directed networks. If we consider a network where bank 1 lends an amount of 6 to bank 2, then the four adjacency matrices can be constructed as follows:

$$A_1 = \begin{pmatrix} 0 & 1 \\ 1 & 0 \end{pmatrix},\ A_2 = \begin{pmatrix} 0 & 0 \\ 1 & 0 \end{pmatrix},\ A_3 = \begin{pmatrix} 0 & 6 \\ 6 & 0 \end{pmatrix} \text{ and } A_3 = \begin{pmatrix} 0 & 0 \\ 6 & 0 \end{pmatrix},$$

Here matrix A_1 is non-directed and non-weighted, A_2 is directed but non-weighted, A_3 is weighted but non-directed, and A_4 is directed and weighted.

Based on the interbank-investment fund network, the following five commonly used centrality measures will be considered in order to assess banks' importance: (i) degree centrality, (ii) betweenness centrality, (iii) closeness centrality, (iv) eigenvector centrality, and (v) PageRank.

64 Intra-group exposures within Luxembourg are included. Branches that do not report large exposure data may also be included in case other banks have asset exposures towards them.

65 Regulation (EU) No 575/2013 of the European Parliament and the Council of 26 June 2013 on prudential requirements for credit institutions and investment firms and amending Regulation (EU) No 648/2012.

66 For centrality measures based on distances it can also be the inverse of the exposure amount.

i) Degree centrality

Degree centrality constitutes the most basic indicator to measure a node's importance within a network as it sums up the nodes' edges. In a directed network, one can distinguish between a bank's degree centrality in terms of lending funds (out-degree) and borrowing funds (in-degree). In a non-exposure weighted network, out-degree equals the number of outgoing edges and in-degree the number of incoming edges. In an exposure weighted network, out-degree equals the sum of all asset exposures and in-degree the sum of all liabilities. Formally, out- and in-degree can be respectively written as follows:

$$D_i^{OUT} = \sum_{j=1}^{n} a_{ji} \quad \text{and} \quad D_i^{IN} = \sum_{j=1}^{n} a_{ij} \tag{1}$$

In a directed graph, bank i's overall degree centrality can be obtained as follows:

$$D_i = D_i^{OUT} + D_i^{IN} \tag{2}$$

In a non-directed network, overall degree centrality, out-degree, and in-degree are equivalent:

$$D_i = \sum_{j=1}^{n} a_{ji} = \sum_{j=1}^{n} a_{ij} \tag{3}$$

The standard O-SII framework interconnectedness indicators "intra-financial system assets", "intra-financial system liabilities" and "debt securities outstanding" essentially constitute degree centrality measures for an exposure-weighted directed network.

ii) Betweenness centrality

Betweenness centrality assigns high values to nodes that act as crossroads, thereby controlling network activity. In a non-exposure weighted network, the edges all have the same length while in an exposure weighted network, the length of an edge equals the inverse of the exposure amount. Following Freeman (1979), the betweenness centrality score of node i can be written as follows:

$$B_i = \sum_{i \neq j \neq k} \frac{\rho_{jk}(i)}{\rho_{jk}} \tag{4}$$

with j and k being nodes different from i, ρ_{jk} being the number of shortest paths connecting j and k, and $\rho_{jk}(i)$ being the number of shortest paths connecting j and k that pass through i.

iii) Closeness centrality

Closeness centrality is based on the distance between a node and the other nodes in the network. In a non-exposure weighted network, all edges have the same length while in an exposure weighted network, the length of the edges corresponds to the inverse of their exposure amount. The closeness centrality score of node i is calculated as follows (Freeman, 1979):

$$C_i = \left(\sum_{j=1}^{n} d_{(i,j)} \right)^{-1} \tag{5}$$

with $d(i,j)$ being the shortest distance between nodes j and i. Thus, the closeness centrality score equals the inverse of the sum of all distances between i and the other nodes in the network.

iv) Eigenvector centrality

Eigenvector centrality constitutes an extension of degree centrality. Instead of simply summing up the number or weights of the edges of a node, they are further weighted by the centrality of the nodes to which they connect. The eigenvector centrality score of node i is defined as follows (Newman, 2004):

$$x_i = \frac{1}{\lambda}\sum_{j=1}^{n} a_{ij}x_j \tag{6}$$

with λ being a constant. Thus, in a non-exposure weighted network, the eigenvector centrality score of node i, namely x_i equals the sum of the eigenvector centrality scores of the nodes with which it has a connection divided by λ. This is the case because a_{ij}= 1 if a connection exists and zero otherwise. In an exposure weighted network, the eigenvector centrality score of i equals the sum of the eigenvector centrality scores of the neighbours weighted by the exposure amount a_{ij} and divided by λ. Hence, a node has a higher eigenvector centrality if it is connected to other nodes with a high eigenvector centrality score and in the case of a weighted network if the exposure amount is large. Equation (6) can be rewritten in matrix notation:

$$Ax = \lambda x \tag{7}$$

with A being the adjacency matrix, x an eigenvector of A and λ the corresponding eigenvalue. To guarantee the non-negativity of the obtained centralities, the chosen eigenvector should be associated with the largest eigenvalue of A (Newman, 2004).

v) PageRank

PageRank is a variant of eigenvector centrality that is employed by Google to rank websites according to their importance. A page is considered to be more important depending on the number links from other important websites that lead to it. In this study, the standard PageRank is applied to a directed graph and measures the centrality in terms of incoming links. As noted by Kaltwasser and Spelta (2015), the PageRank score of a website indicates the probability that a random walker who moves around within the web is present at the website in question. Mathematically, it can be written as follows:

$$PR_i^{in} = \alpha \sum_{j=1}^{n} \left[a_{ij} * min\left(\frac{1}{\sum_{k=1}^{n} a_{kj}}, 1\right) + \frac{1}{n} d_j^{out} \right] PR_i^{in} + \frac{1-\alpha}{n} \tag{8}$$

where it is common to assume $\alpha=0.85$. d_j^{out} equals 1 if j has no outgoing links (i.e. $\sum_{k=1}^{n} a_{kj} = 0$) and zero otherwise. In our context, equation (8) describes the importance of a node in terms of the funds it borrowed.

Relative to eigenvector centrality there are three major differences. First, since a directed network is considered, the term $n^{-1}\, d_j^{out}$ is added to assure that a random walker that arrives at a node j without outgoing links (i.e. $a_{ij} = 0$ and $\sum_{k=1}^{n} a_{kj} = 0$) will not get stuck but can leave the node. Second, the term $(1-\alpha)\, n^{-1}$ prevents the same random walker from getting stuck in a sub-graph which might have incoming links but no outgoing links. Third, if node j has outgoing links, the centrality PR_j^{in} will not get fully assigned to node i. Instead node i has to share it with the other neighbours of node j and gets only assigned the fraction $a_{ij} / \sum_{k=1}^{n} a_{kj}$ of PR_j^{in}.

Although less common in standard PageRank applications, an equation similar to (8) can also be written for outgoing links (Kaltwasser and Spelta, 2015):

$$PR_i^{out} = \alpha \sum_{j=1}^{n} \left[a_{ji} * min \left(\frac{1}{\sum_{k=1}^{n} a_{jk}}, 1 \right) + \frac{1}{n} d_j^{in} \right] PR_j^{out} + \frac{1-\alpha}{n} \tag{9}$$

where d_j^{in} equals 1 if j has no incoming links (i.e. $\sum_{k=1}^{n} a_{jk} = 0$) and zero otherwise. Equation (9) gives the PageRank score of node i in terms of the funds it lends out. Equation (8) will be referred to as In-PageRank and equation (9) as Out-PageRank.

vi) Centralisation measures

Based on centrality measures, the structure of a network as a whole can be characterised via centralisation measures. These measures were developed by Freeman (1977) and are calculated from the degree, betweenness and closeness centrality scores of the individual nodes, based on the non-weighted and non-directed network. They describe the tendency of a single node to be more central than all other nodes and are expressed in per cent. An example of a network with 0% centralisation is a fully connected network, i.e. one that has the maximum number of possible edges. A network with 100% centralisation is a star, i.e. a graph in which the only existing edges connect one central node to all other nodes. Centralisation measures can generally be written as follows:

$$C = \frac{\sum_{i=1}^{n} [x^* - x_i]}{max \sum_{i=1}^{n} [x^* - x_i]} \tag{10}$$

where x^* corresponds to the highest centrality score of all nodes, the numerator equals the sum of the differences between x^* and all other centrality scores and the denominator equals the highest possible value of the numerator. As shown in Freeman (1977), the centralisation measures for degree, betweenness and closeness can be written as follows:

$$C_D = \frac{\sum_{i=1}^{n} [D^* - D_i]}{(n^2 - 3n + 2)} \tag{11}$$

$$C_B = \frac{\sum_{i=1}^{n} [B^* - B_i]}{(n^3 - 4n^2 + 5n - 2)} \tag{12}$$

$$C_C = \frac{\sum_{i=1}^{n} [C^* - C_i]}{(n - 2) / (2n - 3)} \tag{13}$$

3 THE OVERALL NETWORK STRUCTURE

Table 1 provides summary statistics of the measures regarding the amounts of financing exchanged within the network. Over the period 2015Q4-2016Q4, asset exposures and liabilities of banks towards investment funds have on average increased by 15% and 11% respectively. The average interbank transaction volume also went up by 50%. The highest investment fund exposure and liability also increased and the highest interbank transaction volume went up by more than €3 billion.[67]

67 This high amount is due to an intra-group transaction. The highest non intra-group transaction equals €1.4 billion.

Table 1:

Volume measures at network level (in million EUR)

	AVERAGE		MAXIMUM	
	2015Q4	2016Q4	2015Q4	2016Q4
Investment fund asset exposure of banks	147	169	3 479	3 602
Investment fund liabilities of banks	1 359	1 506	15 302	16 779
Interbank transactions	40	60	452	3 746

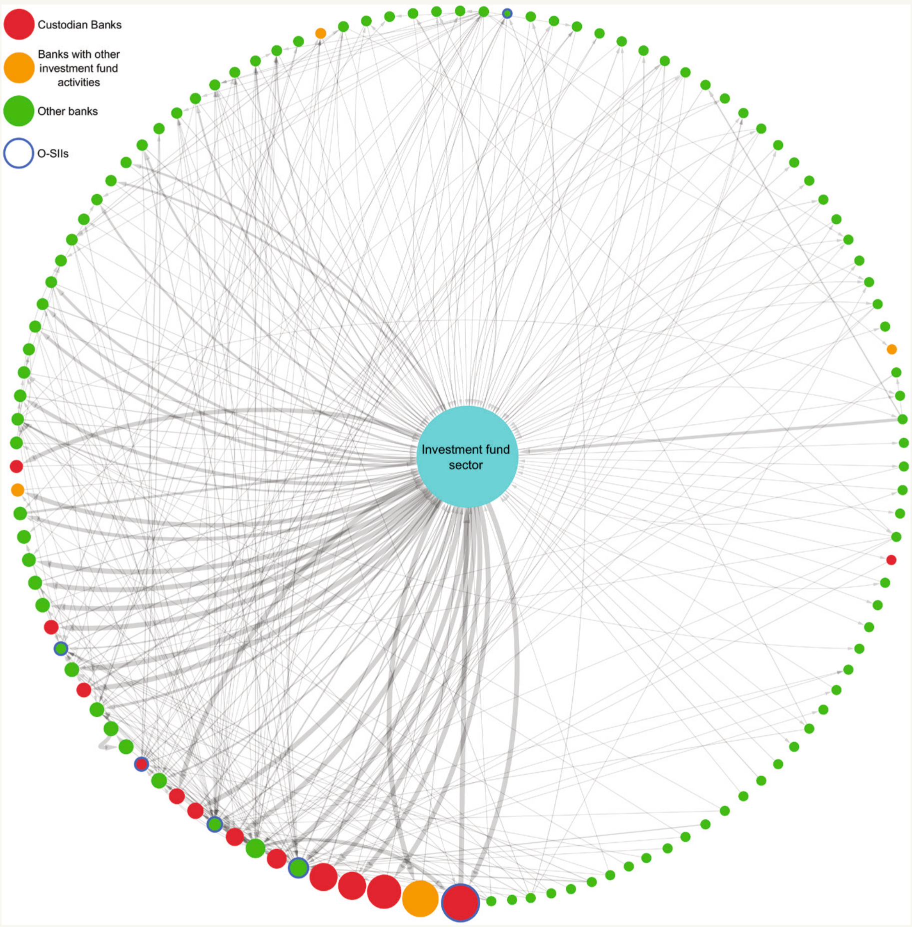
Source: BCL.

Figure 1 provides a graphical representation of the network for 2016Q4. The size of the nodes is proportional to the PageRank score for incoming funds calculated using equation (8). The first observation that can be made from the network visualisation is that the most important banks in the network appear to be custodian banks[68], O-SIIs and one bank pursuing other activities linked to investment funds.[69] The second observation that can be made is that the network is highly centralised on the investment fund sector. Indeed, from the 117 banks active in the network, 92 have a direct connection to the investment fund sector.

Table 2 presents different metrics for quantifying the general network structure in figure 1. The visual depiction of a high grade of network centralisation on the investment fund node is confirmed by the quantitative measures since all three metrics score around 70%. This indicates that the network's shape is closer to a star, with the investment fund node as centre, than to a network where most nodes are equally well connected. This result is worth mentioning as the centralisation measures are calculated from a network that does not include exposure-weighted edges, thereby potentially

Figure 1

The interbank network and bank-investment fund links, 2016Q4



Source: BCL

Notes: Custodian banks are marked in red, banks with other investment fund activities in orange, other banks in green and O-SIIs are depicted with a blue boarder. The size of the bank nodes is proportional to their PageRank score for borrowed funds, based on an exposure weighted network. The highest scoring bank is placed at the bottom and scores decrease clockwise. The direction of the arrows goes from asset holder (lender) to liability issuer (borrower). The thickness of the arrows represents the size of the transferred amount.

68 Custodian banks are defined as the 14 banks with the most assets under custody as of 2015Q4. The definition does not exclude that custodians pursue other lines of business in parallel. One of the 14 banks is not included in the network because it has no interbank nor investment fund link.

69 The information is provided from an internal business model classification scheme of the CSSF.

underestimating the importance of the investment fund node since the amounts involved are usually larger than in the interbank market.

Table 2:

Metrics at the network level

	2015Q4	2016Q4
Degree centralisation (%)	75.3	73.2
Betweenness centralisation (%)	80.0	69.2
Closeness centralisation (%)	75.7	73.2
Diameter	4.0	4.0
Average distance	2.3	2.3
Diameter (only interbank)	8.0	6.0
Average distance (only interbank)	3.0	2.6
Density (%)	2.3	2.6
Average number of interbank connections	3.5	4.0

Source: BCL
Notes: Degree, betweenness and closeness centralisation, as well as the diameter, the average distance and the average number of interbank connections are calculated from a non-weighted undirected network. The density is calculated from a non-weighted directed network.

Distances between nodes within the network appear to be very limited since the network diameter, i.e. the longest distance[70] between any pair of nodes, comprises only four edges. The average distance of 2.3 edges between two nodes is also very short. Given the high level of betweenness centralisation, the short average distance can be to a significant extent explained by the fact that the investment fund node acts as bridge between bank node pairs. However, the 11 percentage point drop in betweenness centralisation over the period 2015Q4-2016Q4, combined with a low and decreasing average distance in the interbank sub-graph suggests that bank nodes may be increasingly acting as bridges within the network instead of the investment fund node. Generally, the short distances between nodes can potentially translate into a heightened threat of contagion following an initial shock in the network, for instance from the investment fund sector. The network also appears to be rather sparse since the density[71] of the network equals 2.6% with four interbank edges per bank. Consequently, a low number of existing edges combined with short distances within the network indicates that several well connected nodes, among which notably the investment fund sector, must act as pivots and could be considered as systemic in the network.

4 RESULTS AT THE NODE LEVEL

To determine the most systemic nodes, the aforementioned centrality measures are calculated. Table 3 summarises the results. Except for in- and out-degree, the score for each node is divided by the sum of the scores of all nodes and multiplied by 10 000 in order to make the indicators more comparable. Hence individual scores are expressed in basis points, the sum of the scores equals 10 000 and all measures have a mean value of 88.

70 Distance refers to the shortest path between two nodes.

71 The density equals the ratio of the effective number of existing edges to the maximum number of possible edges for a directed network.

Table 3:

Centrality results for the nodes

	STD. DEV.	MIN.	MEDIAN	90TH PERC.	MAX.
In-degree	8	0	1	6	76
Out-degree	8	0	1	5	82
Betweenness	630	0	0	106	6 799
Closeness	19	2	93	93	93
Degree	431	0	6	121	4 592
Eigenvector centrality	252	0	4	167	2 032
In-PageRank	342	15	23	109	3 663
Out-PageRank	346	16	23	109	3 671

Source: BCL

Notes: 2016Q4 data. Std. dev. stands for standard deviation, 90th perc. for 90th percentile. Except for in- and out-degree, the sum of the scores per measure equals 10000 and the mean 85. In- and out-degree are calculated from the directed non-weighted network. Betweenness, closeness, degree and eigenvector centrality are calculated from the undirected exposure-weighted network. In- and Out-PageRank refer to the measures for incoming and outgoing funds respectively and are calculated from the directed exposure-weighted network.

For each measure the highest score is obtained by the investment fund node, in line with the previous network centralisation results. The median and 90th percentile values for in- and out-degree respectively also lend support to the finding that only a small number of nodes within the network are very well connected. The betweenness scores are widely dispersed, as indicated by the highest standard deviation of all indicators, and concentrated on only a few nodes since the investment fund sector scores 68% of all points, 12 banks score between 1% and 5% of all points, and 94 banks score 0 points. This illustrates that, apart from the investment fund node, there are only a couple of banks that function as pivots within the network. The very low standard deviation of the closeness indicator further demonstrates that distances between nodes are not only on average very short but that they are distributed almost uniformly. This suggests that the network can be considered as compact.

Degree and eigenvector centrality produce scores that are more evenly distributed than betweenness on the right side of the distribution, with the former having a higher standard deviation due to the much higher score of the investment fund node. Nevertheless, the scores of both measures are still very much concentrated, with the top-10 nodes scoring more than 70% of all points. This is mostly due to the significant investment fund links of a sample consisting mainly of custodian banks. As a consequence, the top-12 most systemic banks identified by degree centrality include 9 custodian banks and the top-12 identified by eigenvector centrality 10 custodian banks, often without significant interbank ties. In addition, despite the fact that degree considers only first-order exposures and eigenvector centrality also higher-order exposures, both measures tend to yield similar results for the sample in question. Indeed, if the investment fund node's score is excluded, the correlation between both measures is 0.97. This indicates that, for this paper's dataset, eigenvector centrality does not add much information to the scores produced by the basic degree measure. This is likely due to the fact that for the network under consideration, eigenvector centrality, unlike PageRank, has the drawback that it assigns the full centrality of the dominant investment fund node to all neighbouring nodes. This means that a bank with a large investment fund connection, but no interbank links, might get a higher centrality score than a bank with a somewhat lower investment fund connection but considerable interbank ties. However, from a systemic risk perspective the latter bank should be more important than the former. Thus, in the context of this analysis, the more sophisticated PageRank measure is better suited for identifying systemic banks. Indeed, both PageRank measures identify a set of banks consisting not only of custodians but also of banks with significant interbank activity as the most systemic banks. Like in- and out-degree, they also make it possible to assess if banks tend to be specialised in either borrowing or lending funds. Correlations[72] between the degree measures and between the PageRank measures are equal to 0.56 and 0.66 respectively, which indicates that banks that are active in lending out funds to the investment fund sector or domestic banks also tend to receive more funds from these entities. Hence, banks that are systemic in terms of their interconnectedness are likely to simultaneously have asset exposures and liabilities towards other nodes in the network.

The ultimate goal of determining the most important banks within the interbank-investment fund network is to include the findings within the O-SII framework in order to assess if the composition of the list of identified systemic banks should be altered. The two measures that are best suited for this purpose are betweenness and PageRank. The former because it identifies a small set of banks that act as likely pivots for spreading shocks towards the rest of the banking sector, the latter because it takes into account first-order and higher-order exposures of banks while giving more weight to interbank connections than eigenvector centrality. In-PageRank, which measures entities importance in terms of receiving funds, should be particularly pertinent as banks' liabilities towards the investment sector are notably higher than their exposures. Degree centrality has the clear drawback vis-à-vis PageRank that it only considers first-order exposures while the closeness measure is not a useful indicator to be included in the O-SII framework as the quantitative difference between most scores is marginal.

5 THE O-SII ASSESSMENT INCLUDING CENTRALITY MEASURES

Table 4 identifies the types of banks that are most important according to PageRank and betweenness. The shares are calculated relative to the sum of all bank scores while excluding the investment fund node. The categories are not mutually exclusive, except for custodian and other investment fund activities. Regarding betweenness, domestically oriented commercial banks (DOCBs)[73] account for 58% of total banking sector scores. Hence, banks with strong links towards the real sector of the Luxembourg economy are also those which are highly active in the interbank market and are positioned as crossroads within the investment fund-interbank network.

Table 4:

Share of total bank centrality scores by type (in %)

	CUSTODIAN	OTHER IF ACTIVITIES	DOCB	O-SII
Betweenness	18	0	58	45
In-PageRank	37	9	10	16
Out-PageRank	32	2	13	25
Average PageRank	35	5	12	20
No. of banks	13	4	7	6

Source: BCL

Notes: 2016Q4 data. "Other IF activities" refers to banks that pursue investment fund activities different from custody services. DOCB refers to domestically oriented commercial bank. Apart from "custodian" and "other IF activities", the categories are not mutually exclusive.

72 Correlations are calculated only from bank scores, i.e. excluding the investment fund node which constitutes a large outlier. If the latter is included, PageRank correlation equals 0.97 and degree correlation 0.93.

73 DOCBs are defined as the seven banks with the highest amount of liabilities from domestic non-financial corporations and households. They account for 85% of the total.

O-SIIs, which include several DOCBs, score almost half of the betweenness points available for the whole banking sector. This indicates that the O-SII framework already accounts to a large extent for the information content of the betweenness indicator. In other words, many banks with high betweenness have already been identified as systemic. This is to a much lesser extent true for banks with high PageRank scores and especially for the In-PageRank, as O-SIIs score 16% of all available points, while institutions with strong investment fund business links such as custodians and banks with other investment fund activities score 46% of all points. We cannot exclude that some banks have not been identified as systemic, although they nevertheless might be "too interconnected to fail". Hence, table 5 presents the number of banks by type that would have been eligible to be identified as an O-SII[74] if some version of PageRank had been included in the 2016 assessment. The standard O-SII assessment is based on four equally weighted criteria, of which one is interconnectedness.[75] Thus, PageRank can either be included as a separate fifth criterion or within the existing interconnectedness criterion. Note that the standard assessment identified six O-SIIs. If included as a fifth criterion, than a 20% weighting appears the most plausible in order to have five equally weighted criteria. Other weights are also included to assess the sensitivity of the results.

Table 5:

Number of O-SIIs with the inclusion of PageRank

PAGERANK INCLUDED AS/IN	INDICATOR	WEIGHT	CURRENT O-SIIS	CUSTODIANS	OTHER BANKS
Separate criterion	In-PageRank	5%	6	0	0
		10%	6	1	0
		15%	6	1	0
		20%	6	2	0
		25%	6	2	1
Separate criterion	Out-PageRank	5%	6	0	0
		10%	6	0	0
		15%	5	0	0
		20%	5	0	0
		25%	5	0	0
Separate criterion	Average PageRank	5%	6	0	0
		10%	6	0	0
		15%	6	0	0
		20%	5	0	0
		25%	5	1	0
Interconnectedness criterion	In-PageRank	5%	6	0	0
	Out-PageRank	5%			

Source: BCL

Notes: 2016 O-SII assessment, based on 2015Q4 data. PageRank can be included as a separate fifth criterion or as indicator within the existing interconnectedness criterion. "Weight" refers to the share with which PageRank enters the O-SII score. "Current O-SIIs" corresponds to the six banks identified in the 2016 standard assessment. "Custodians" refers to the additional number of custodians that were not identified as O-SII in the standard framework. Current O-SIIs already includes two custodians.

74 In this context, being eligible means that a bank scores at least 275 basis points in the O-SII assessment. See EBA/GL/2014/10 (GL on criteria for the assessment of O-SIIs).

75 The other three criteria are size, importance, and complexity/cross-border activity.

If the In-PageRank metric, which captures banks' liabilities towards investment funds, was incorporated as a separate criterion, the six current O-SIIs would still qualify as systemic. Note that the O-SIIs identified to date already include two custodian banks. Additionally, if the weight was 10% or more, one additional custodian would qualify as a systemic bank and at 20% two additional custodians would qualify as such. At 25%, a bank that is very active in the interbank market would also be eligible for being an O-SII. The most plausible weight for a fifth criterion though, as previously mentioned, is 20% as this would make all five criteria equally-weighted. Under the other three scenarios, not all current O-SIIs would qualify as systemic depending on the weighting, without additional custodians or other banks qualifying as such. The only exception is the 25% weighting for the average PageRank. Overall these results appear to be intuitive as many domestic banks, notably custodians, are dependent on inflows of funding from the investment fund sector. As noted previously, those banks' asset exposures are comparably smaller. Given that the largest potential risk arising from interconnections comes from the liability side of banks' balance sheets, In-PageRank seems to be the most appropriate measure and a 20% weighting is the most plausible choice for the O-SII assessment.

6 CONCLUSION

The network consisting of interbank exposures and financial links between banks and investment funds has a rather low number of direct connections, the individual nodes are not too distant from each other and a relatively small set of banks act as pivots within this network. Such a network structure could potentially propagate shocks very rapidly. At a more granular level, the most important institutions functioning as crossroads are domestically oriented commercial banks. Four of these banks have already been identified as systemic under the EBA guidelines for O-SII assessment. On the other hand, the most important institutions in terms of first- and higher-order exposures and liabilities towards investment funds and domestic banks are custodians. So far, only two such banks have been identified as being systemic. A modified O-SII assessment methodology, including a measure to account for this type of centrality, reveals two further custodian banks to be systemic. The results of this study illustrate the effect of including an additional interconnectedness indicator accounting for bank-investment fund linkages in order to enhance the standard O-SII framework in Luxembourg.

REFERENCES

Freeman, L. C. (1979). Centrality in social networks: Conceptual clarification. *Social networks, 1*(3), 215-239.

Kaltwasser, P. R., & Spelta, A. (2015). Systemic risk in the interbank market with heterogeneous agents. *Macro-Risk Assessment and Stabilization Policies with New Early Warning Signals*, SSH.2012.1.3-1.

Newman, M. E. (2004). Analysis of weighted networks. *Physical review E, 70*(5), 056131.

2. THE LOW INTEREST RATE ENVIRONMENT: IMPACT ON LUXEMBOURG BANK PROFITABILITY

Shirin Madani-Beyhurst[76], Jason Mills [77] and Guillaume Queffelec[78]

ABSTRACT

This study analyses the relationship between interest rates and bank profitability in Luxembourg. We use a panel data model to investigate the links between bank profitability measures and a set of bank-specific variables and macro-financial factors, which include the short-term interest rate and the slope of the yield curve. System-GMM estimates show that, despite the negative impact of repricing frictions primarily affecting net interest margins in the short run, in the long run Luxembourg banks profit from a higher level of short-term rates and a steeper yield curve. Moreover, rolling window estimates confirm the non-linear nature of this relationship and indicate that over time, as the short term rate reaches the zero lower bound and the yield curve flattens, the relationship between Luxembourg bank profitability and the level of the rates becomes stronger. As a consequence, low interest rates have an unequivocal negative effect on bank profits, which might constitute a source of vulnerability for Luxembourg banking system in the long run. However, for the time being, we do not observe any significant business model shift toward non-interest income based activities that could amplify systemic risk.

INTRODUCTION

The low interest rate environment is a global phenomenon which is particularly pronounced in advanced economies. The decline of long term rates is often associated with the aftermath of the Global Financial Crisis (GFC) and the slowdown of the world economy, entangled in the down phase of the "financial cycle" and induced by the necessary balance sheet repair and deleveraging of financial intermediaries (Borio (2012)). Monetary policy stimulus has provided support to the post-crisis recovery by easing funding conditions and ultimately it should push long term rates back to their previous trajectory. However, some studies argue that the decline in long term rates began almost three decades ago, suggesting that structural forces drove interest rates down (see Figure 1, Bean et al. (2015), ESRB (2016)). Indeed, a global imbalance between excess saving and reduced investment opportunities, aging populations, increased risk aversion and lower total productivity growth are likely drivers of the slowdown in growth potential of industrialized economies. This reduction in growth leads to a mechanical fall in the equilibrium real interest rate (Bernanke 2005, Gorton 2012 and Summers 2014). If the economy were to settle into "secular stagnation", interest rates across the whole maturity spectrum could remain low for long.

While the materiality of a low for long scenario is still under debate, stress tests at the European level in 2016 adopted low rates for their macroeconomic narratives considering the financial stability challenges they generate. Among the many potential risks induced by a persistent low interest rate environment, pressure on the profitability of credit institutions appears to be one of the most relevant for Luxembourg. The persistently low profitability of credit institutions could eventually have an adverse effect on bank solvency because it limits the ability of credit institutions to meet their regulatory obligations. This could, in turn, encourage banks to take more risks through holding assets with longer maturities, easing lending conditions, increase lending volume. This environment could also force banks to modify

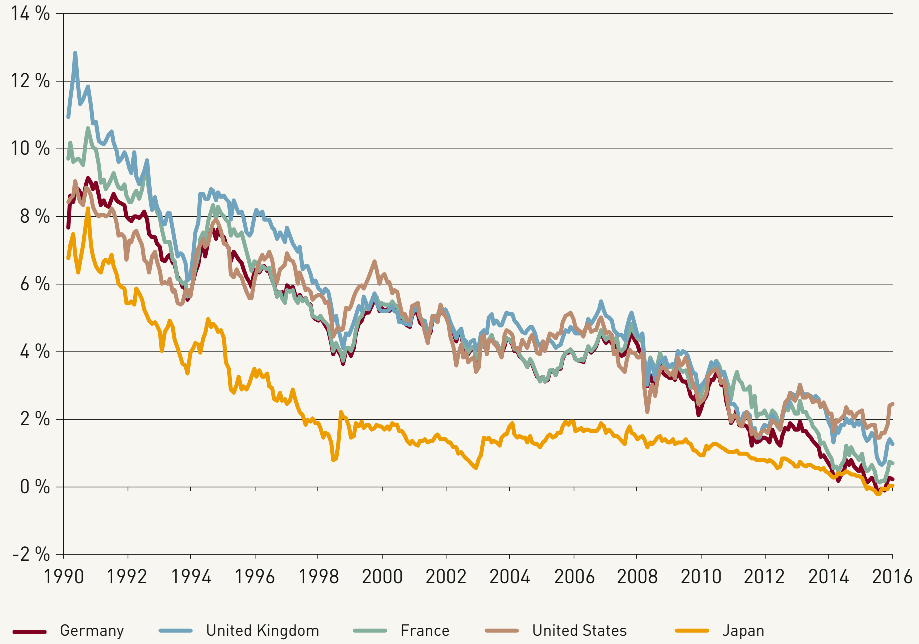
76 Statistics Department, Banque centrale du Luxembourg.

77 Financial Stability Department, Banque centrale du Luxembourg.

78 Financial Stability Department, Banque centrale du Luxembourg.

their business models such that they rely more on non-interest income based activities (revenues from securities and commissions) which, as suggested by Brunnermeier et al. (2012), tend to increase systemic risks.

Figure 1
Ten years government bond yields



Source: Bloomberg

Such risks can arise from constantly evolving business conditions where traditional banks have to adapt to a new set of regulatory requirements, technological innovations (FinTech) and increased competition from online banking and shadow banking (investment funds). In the long run, the low interest rate environment may have important implications for the resilience of the banking sector and the stability of the financial system.

From an economic point of view banks, as intermediaries, are considered profit maximizing monopolies, which earn (transformation) margins by optimally setting the spread between the loan rates and deposit rates to accommodate funding and liquidity needs.[79] For these reasons, the net interest margin (NIM) channel is the usual way of interpreting the deterioration of banks' profitability in a low interest environment because the decline in the level of interest rates and the flattening of the yield curve reduce the spread between the short rate, at which banks finance part of their liabilities, and the long term rate, at which assets are paid. Moreover, since NIM arises from traditional intermediation activity, it often constitutes banks' main source of revenue and historically represents around half of Luxembourg's aggregate banking income.

NIM can be decomposed into three elements, partly owing to the oligopolistic structure of the banking sector, asymmetric information and price rigidities. The first element on the liability side is a commercial margin which is the difference between the deposit rate and the money market rate. Banks can typically mark down the deposit rate from the money market rate because of the low elasticity of demand for deposits. However, these monopoly rents on the liability side decrease as rates converge towards zero because banks are reluctant to pass negative deposit rates to their clients. The transformation margin is the spread between the deposit rate and the lending rate that would be offered in a perfectly competitive environment. This component is directly related to the shape of the yield curve and decreases as the curve flattens. Finally, a commercial margin on the asset side is determined by the difference between the lending rate that would be offered in a perfectly competitive environment and the effective rate paid by the customer. However, this element depends more on rate anticipations

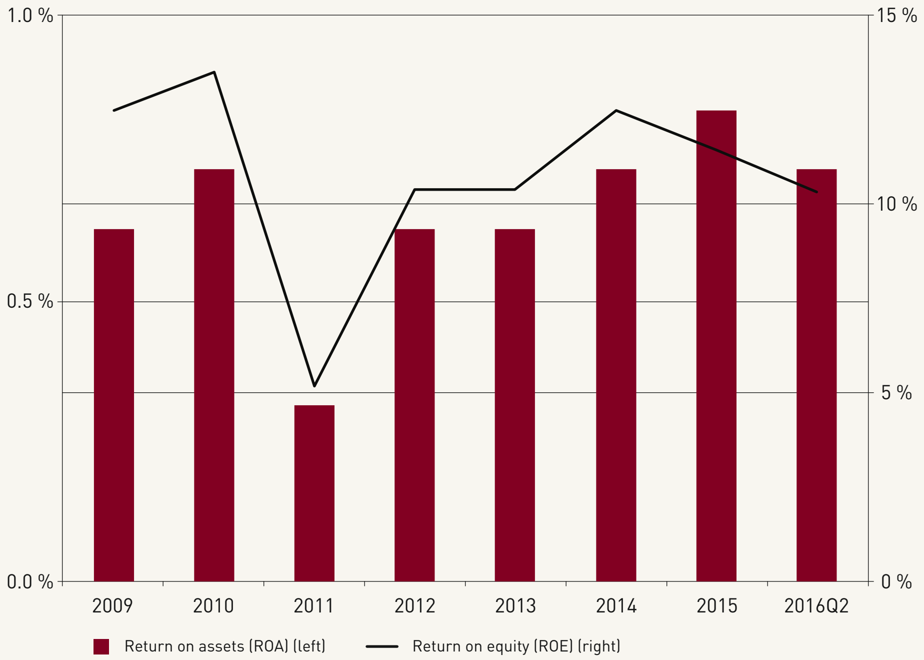
79 See the Monty-Klein model presented by Freixas and Rochet (2008) and the dealer model of Ho and Saunders (1981).

of the bank, its market power and the characteristics of the contract offered to the client (like fixed or variable rate for example).

The econometric study of the determinants of bank profitability and NIM has traditionally been a micro-oriented field focusing on bank-specific characteristics, such as balance sheet structure, the oligopolistic environment or the fiscal and regulatory regime. Nevertheless, a number of papers have analyzed the relationship between economic conditions and bank profitability (Molyneux and Thornton (1992), Demirgüç-Kunt and Huizinga (1999), Saunders and Schumacher (2000) English (2002) among others). These studies confirm the positive relationship between long term interest rates and banks' profits, which is considered to be attributed to their maturity transformation activities. However, the relationship between the short-term rate and profitability appears to be more difficult to capture as seen in certain cases through insignificant parameters or inconsistent coefficient signs from one study to another. Regarding the specific case of Luxembourg, Rouabah (2006) studied the macroeconomic determinants of bank profitability. The results revealed that bank profitability displays co-movements with macroeconomic conditions, but that changes in the short term rates have only a marginal negative impact on banks' profits as measured by return on assets (ROA). The study found no impact on NIM.

More recent papers study bank profitability in a low interest rate environment. The empirical results are important as they suggest that, over time, unusually low interest rates erode bank profitability. Alessandri and Nelson (2015) find a positive relationship between UK banks' profitability and the level of the short term rate and slope of the yield curve. They also found that short run variations of rates compress bank profitability indicating the presence of repricing frictions. Borio et al. (2015) studied the link between the level of interest rates and global banking groups' profitability. Borio showed that these dependencies are positive but are also non linear; i.e. they are reinforcing as the rates and the term premium converge toward zero. Studying 47 countries between 2005 and 2013, Claessens et al. (2016) confirmed this finding. The authors found that between 2007 and 2013, NIM in the US, Euro area, Canada, Japan, and the UK fell by almost 26 basis points due to the decline in interest rates. Regarding the US specifically, the authors found that a low interest rate environment may be associated with decreased profitability. Busch and Memmel (2015) assessed the impact of low interest rates on bank profitability in Germany, and found that German banks have been negatively impacted and that their interest margins for retail deposits have recently declined.

Figure 2
Average return on equity and return on assets of the banking sector



Source: BCL, sample 2009-2016Q2

Combined, these studies suggest the need for further analysis of the relationship between interest rates and bank profitability in Luxembourg. Following Alessandri and Nelson (2015) and Borio et al. (2015) we use panel data models to investigate the links between bank profitability measures and a set of bank-specific variables and macroeconomic factors, which include the short term interest rate and the slope of the yield curve. System-GMM estimates show that, despite the negative impact of repricing frictions in the short run, in the long run Luxembourg banks indeed profit from a higher level of short term rates and a steeper yield curve. Rolling window estimates confirm the non-linear nature of this relationship indicating that over time, as the short term rate reaches the zero lower bound and the yield curve flattens, Luxembourg banks suffered more from the low interest rate environment. Estimates of non-interest income display no significant relationship with the rates, indicating that the low interest rate environment does not act as a push factor for banks to shift toward less stable business models from a systemic risk perspective.

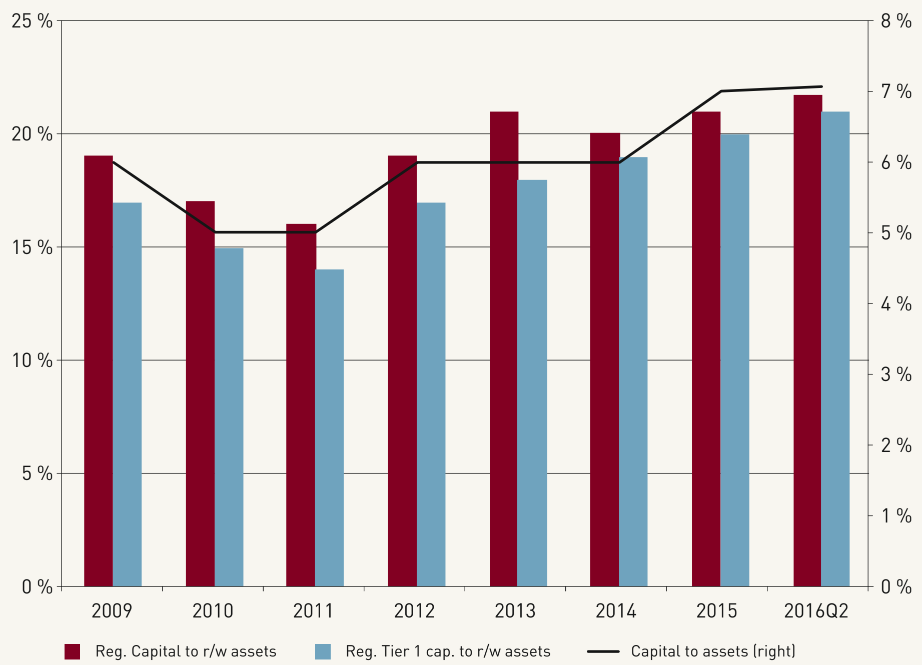
The remainder of the paper is organized as follows. In section 1 we describe the specificities of the Luxembourg banking sector with a focus on the various business models in order to discern the likely consequences of the low interest rate environment on bank profitability. Section 2 presents the empirical approach used in the study, while section 3 presents the results. Finally, the conclusion summarizes the work and addresses potential policy considerations.

1 LUXEMBOURG BANKING SECTOR SPECIFICITIES AND THE LOW INTEREST ENVIRONMENT

Since the Global Financial Crisis, total assets of the Luxembourg banking sector have declined reaching 763 billion euro at the end of 2016 (around 15 times Luxembourg GDP). However, despite a drop in 2011, aggregate profitability has recovered since the crisis (Figure 2) and, although it is still below its pre-crisis levels, remains higher than the European median[80] on average. Indeed, Luxembourg banks do not suffer from the typical legacies of the crisis such as high levels of non-performing loans or costs related to past misconduct.[81]

Current profitability levels allow banks to continue to meet their regulatory obligations and to build and support strong capital positions. As shown in Figure 3, the average Tier 1 ratio of the aggregate Luxembourg banking sector is almost two times the

Figure 3
Capital ratios

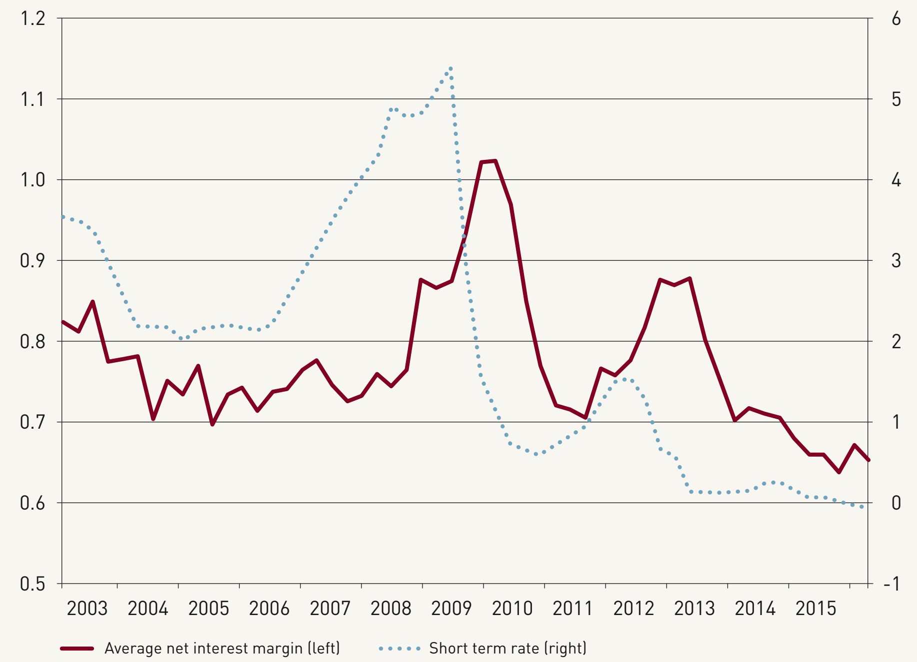


Source: BCL, sample 2009-2016Q2

80 See ESRB risk dashboard, indicators 6.1a and 6.1b, page 29.

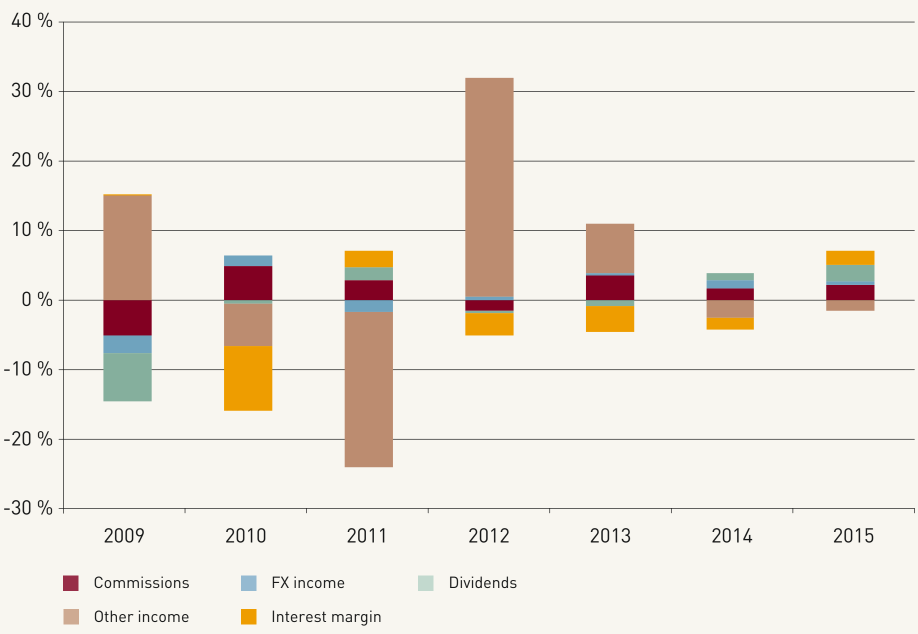
81 Bank of England, Financial Stability Report, November 2016.

Figure 4
Average net interest margin and short term rate (%)



Source: BCL

Figure 5
Contribution of various sources of income to total income growth



Source: BCL

required minimum level of 10.5% in 2016Q2.[82] Luxembourg banks currently have sufficient robustness to absorb adverse shocks.

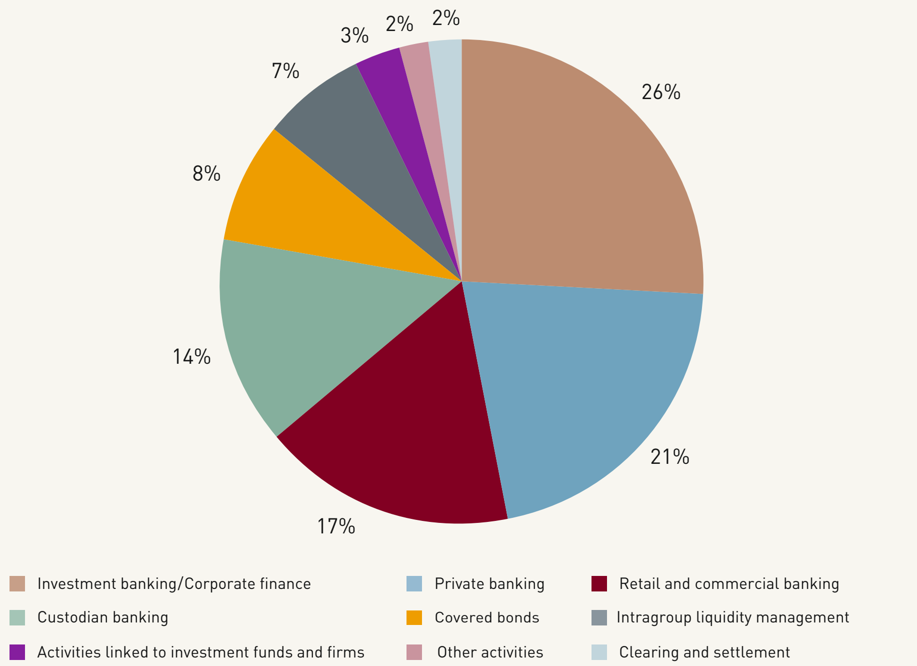
The low interest rate environment is the primary challenge for Luxembourg banks' profitability and future resilience, especially in the event that rates remain low for a prolonged period of time. Figure 4 shows the significant downward trend of aggregate NIM which looks, *a priori*, highly correlated (with a lag) to the level of the short term rate. This tends to be confirmed at the broader European level where 81% of banks participating in the ECB Bank Lending Survey (BLS) in the first quarter of 2016 reported a decline in their net interest income for the past six months.[83] Since NIM has long been structurally low compared to international standards, Luxembourg banks do not rely on NIM as much as their European counterparts. However, NIM still represents 40% of the total income of Luxembourg banks. Hence, it is not clear if banks can fully substitute interest income with other sources of revenue. As shown in Figure 5, even if commissions seem to have supported bank profitability in the recent period, the contribution of the different sources of revenue are very volatile, and so far banks appear

82 See CSSF Regulation 14-01.
83 The April 2016 survey questionnaire included, for the first time, an ad hoc question on the impact of the ECB's negative deposit facility rate (DFR) on their net interest income, lending conditions and lending volume. Banks were asked to consider both the direct and indirect effects of the negative DFR, as there may be indirect effects on banks' financial situation and lending conditions even if the respective bank has no excess liquidity.

to be in a transition phase toward new income sources.

Forecasting bank profitability in a low interest rate environment and the profound structural changes that it can induce is a challenging task because Luxembourg banks, at the aggregate level, may diverge from traditional intermediation activities. In many aspects the Luxembourg banking system displays distinct specificities regarding its size and internationally oriented nature, the importance of the inter-bank and intra-group market and the coexistence of various business models.

Figure 6
Total banking sector asset breakdown by type of business models



Source: CSSF

As shown in Figure 6, traditional retail banking activities, primarily those which are domestically oriented, represent a moderate fraction of the Luxembourg banking system (17%). Other business models focus on niche activities or specific client types by providing financial services to international corporations (investment/corporate banks; 26%), portfolio managers and institutional investors (custodian banks; 14%) or wealthy clients (private banks; 21%). In fact, Luxembourg banks are mostly branches and subsidiaries of global banking groups (93% of 144 banking licenses in 2016) which are internationally oriented (75% of the total amount of loans is granted to foreign entities) and maintain strong relations with their parent banks.

As suggested in Table 1, the inter-bank market plays an important role in Luxembourg banking transactions (see loans to deposit taking corporations). Around 50% of the aggregate total assets of the banking sector are composed of inter-bank loans, of which 80% are intra-group loans.[84] These types of loans usually have a very short maturity and provide either interest income or commission income. For these reasons, Luxembourg banks are often described as net liquidity providers which draw on their deposit base to channel funds to parent banks. From a financial stability perspective the risks related to intra-group loans are mixed. On one hand these risks may be considered very low because the level of liquidity mismatch is practically nonexistent and the default probability of the parent remains low. Moreover, academic literature (Reinhardt and Riddiough (2014)) shows that the intra-bank market contributes to dampen adverse shocks by constituting an alternative source of funding to the inter-bank market when the latter dries up during liquidity or solvency crises. On the other hand, intra-group transactions increase the cross-border interconnectedness of the financial system and represent a possible channel of external contagion. The return of such activities is presumably low since the risk

84 BCL (2016). Revue de stabilité financière. Section 3, page 49.

premium and the term premium are likely marginal. However, large banking groups may find it profitable to manage liquidity in various jurisdictions. Hence, the impact of the low interest rate environment is *a priori* difficult to assess and may be neutral on a significant share of the banking book.

Table 1:

Average total asset breakdown by main balance-sheet items and share of loans with an initial maturity superior to one year

	RETAIL BANKS	M>1 YEAR	PRIVATE BANKS	M>1 YEAR	CUSTODIAN BANKS	M>1 YEAR	INVESTMENT/ CORPORATE BANKS	M>1 YEAR
LOANS	**70.5%**		**76.4%**		**53.7%**		**89.3%**	
Government	3.8%	72%	0.04%	27%	0.01%	100%	0.3%	96%
NFCs	16.4%	75%	11.6%	64%	1%	64%	24.8%	68%
Households	32.8%	95%	10.9%	32%	1%	43%	1.4%	74%
Central Bank	1.9%	2%	9.4%	0%	22%	0%	6.2%	0%
Deposit taking corporations	31.9%	49%	54.9%	24%	64%	12%	62.5%	14%
Financial companies	13.3%	77%	13.1%	45%	12%	0%	4.8%	58%
DEBT SECURITIES HELD	**24%**		**16.9%**		**38.6%**		**7.5%**	
EQUITY	**3%**		**2.5%**		**3.4%**		**1.3%**	
NON FINANCIAL ASSETS	**1%**		**0.5%**		**0.4%**		**0.1%**	
REMAINING ASSETS	**1%**		**1.4%**		**1%**		**1.0%**	
OFF-BALANCE SHEET EXPOSURES TO AVERAGE TOTAL ASSET	**14%**		**5%**		**3.6%**		**35.6%**	

Source: BCL, sample 2015Q3. Off-balance sheet exposures are the sum of credit lines and guarantees.

The Luxembourg domestic banking sector is dominated by several well-established players which correspond to the classical view of retail banks operating in an oligopolistic market. The mortgage credit market is fairly concentrated among the top five banks which account for around 80% of the loans to households for house purchases. This business model typically allows banks to extract monopoly rents through the use of mark-ups and mark-downs since households usually posses little bargaining power. However, as previously stated, those sources of income tend to decline with a flatter yield curve.

As shown in Figure 7b, banks' NIM has been trending downward since 2003. Since most of the stock of mortgage loans (77.5% on average for new loans issued between January 2009 and December 2016) are denominated at a floating rate, the return of those investments decreases and may not be compensated by the reduced losses on an already low level of nonperforming loans and a lesser need for provisions. In fact, households managed to lock in low rates with a higher proportion of fixed rate loans which went from 15% of the new loans issued in January 2003 to 59% in December 2016. It is still possible that banks will continue to expand their loan portfolios due to the strong demand for credit stemming from the residential real estate market. However, as the collateral prices increase, the risk premium shrinks and the net effect is unclear.

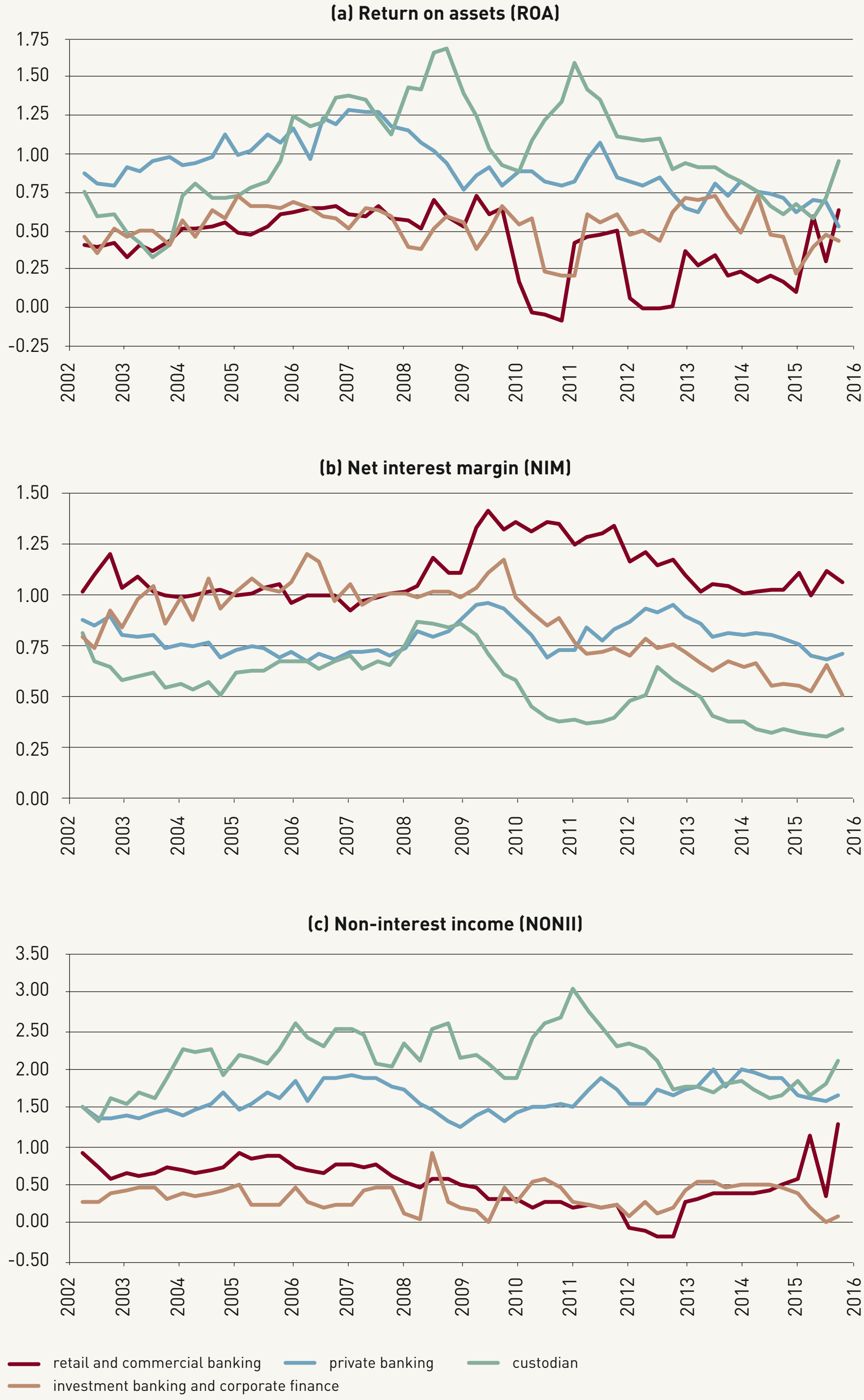
Finally, while retail lenders have diversified their banking books, they still rely primarily on maturity transformation (see table 1, column 1 and 2) and are likely to suffer from the low interest rate environment. As a consequence, the slight increase of NONII at the end of the period (Figure 7c) might suggest that retail banks are looking for other sources of revenues.

Corporate/investment banks usually provide funding solutions to large global firms by underwriting financial instruments (bonds and equity issuance) or syndicated loans, giving support and advice for mergers-acquisitions and accommodating investors' trades via tailored hedging strategies and through their brokers, market making and proprietary trading desks. Table 1 (column 7 and 8) suggests that the corporate banking model dominates in Luxembourg compared to investment banking. Indeed, 89% of banks' balance sheets are composed of loans of which 24.8% are granted to nonfinancial companies. Moreover, their trading books (debt securities held and equity) do not seem to be large enough to conduct significant market based activities. While they have the highest level of off-balance sheet exposures (35.6%) those are credit lines and guarantees presumably granted to NFCs.

As shown in Figure 7b, NIM of corporate banks has approximately halved since 2010 while NONII has not increased significantly over the same period leading to a significant decrease of ROA since 2014. Hence, corporate banks in Luxembourg have not benefited from the positive valuation effects in financial markets and increased securities issuance induced by the low interest rate environment.

Custodian banks collect deposits and assets from corporate and institutional investors. A large part of their activities consists of providing related services to their clients like the collection of incomes from securities (dividends and interest), the execution of transactions, accounting and compliance services and financial reporting for investment funds (computation of net asset value

Figure 7
Profitability by business models
(in %)



Source: BCL

and performance indicators). Custodian services play an important role in the Luxembourg financial sector, particularly for investment funds, which account for a significant portion of financial activity. Luxembourg banks hold a total of 3.5 trillion euros in assets under custody, half of which are held by four entities.

Even if custodian banks may profit from increased investment fund activities, the low interest rate environment is likely to have a negative impact on their profitability as the decrease in ROA suggests (Figure 7a). Indeed, custodian banks do not engage in significant liquidity transformation because of the high volatility of their deposit base and the low level of risk they need to attract clients. Hence, they invest in very liquid short maturity assets as shown in Table 1 and even deposit cash at the central bank (22% of the banking book). Custodian banking is likely the business model most impacted by negative central bank deposit rates and money market rates to the point where they may be reluctant to accept additional deposits as negative rates would be passed on to clients. For this reason, the dynamic of custodian banks NIM closely follows the trajectory of the short term rate (see Figure 4 and Figure 7b).

Finally, private banks are usually smaller structures which provide investment solutions and investment advice to wealthy clients. Table 1 (column 3 and 4) suggests that private banks tend to hold diversified portfolios with balanced maturities in the banking book. While, NIM and NONII seem robust, ROA is clearly on a decreasing trend since the GFC. Their biggest challenge in a low interest rate environment may come from the increased competition from investment funds and universal banks which could be tempted to aggressively attract their client base.

2 EMPIRICAL APPROACH

To evaluate the impact of the low interest rate environment on bank profitability at the aggregate level, we construct a database using quarterly bank-level balance sheet and income statement data from 2002Q1 to 2015Q3 as well as a set of macro-financial variables over the same time period. The dataset contains a sample of 172 banks which cover on average over 75% of total Luxembourg banking sector assets.

We estimate a dynamic panel model with a two-step system GMM[85] estimator proposed by Blundell and Bond (1998) with the Windmeijer's correction (2005) for robust standard errors.[86] The specification has been intensively tested with different panel estimators and control variables. In equation (1) we provide the definitive and robust specification. The model is of the form:

$$\begin{aligned} y_{i,t} = c + \alpha y_{i,t-1} + \beta_0 r_t + \beta_1 \Delta r_t + \beta_2 \Delta r_{t-1} + \beta_3 s_t + \beta_4 \Delta s_t + \beta_5 \Delta s_{t-1} + \beta_6 k_{i,t} + \beta_7 a_{i,t} \\ + \beta_8 a\_vol_{i,t} + \beta_9 hhi_t + \beta_{10}\, gdp_t + \beta_{11} hp_t + \beta_{12} stx_t + \beta_{13} stx\_vol_t + \varepsilon_{i,t} \end{aligned} \tag{1}$$

with $y_{i,t}$ a measure of annual profitability (*ROA, NIM, NONII*), which is based on the last four quarterly values. *ROA* uses pre-tax net income, which ensures that differences in taxation across banks do not impact the results. *NIM* is interest income minus interest expenses over interest bearing assets; *NONII* is fees and commission income as well as foreign exchange income. Each of the profitability measures is normalized by average total assets (*ROA*, *NONII*) or average interest bearing assets (*NIM*).[87]

85 The Hausman test, the Baltagi-Wu test and the Likelihood ratio test suggest respectively the presence of a fixed effect, autocorrelation and heteroskedasticity. Therefore, the lagged dependent variable is correlated with the error term which introduces dynamic panel bias into the estimation process (Nickell, 1981). To overcome this limitation, we use the system GMM estimator.

86 We use the Stata package xtabond2 developed by Roodman (2009).

87 Average total assets for a given bank is defined as [assets(t) + assets(t-4)]/2. Average interest bearing assets for a given bank is defined as [loans and fixed income securities(t) + loans and fixed income securities(t-4)]/2.

The short-term rate r_t is the 3 month euro LIBOR, and s_t is the slope of the yield curve, defined as the German 10-year government bond yield minus the 3 month euro LIBOR. Following Alessandri and Nelson (2015), we introduce the variation of the rates Δr_t and the slope of the yield curve Δs_t at time t and t-1 to capture short run repricing effects. We control for bank-specific variables by adding the ratio of total capital to assets, the natural logarithm of total assets and the volatility of total asset denoted respectively by $k_{i,t}$, $a_{i,t}$ and $a\_vol_{i,t}$. The variable hhi_t is the Herfindahl-Hirschman index, which captures the level of concentration in the banking sector, and is calculated using total assets for each bank. We introduce a set of macro-financial variables to measure the impact of economic activity: gdp_t is the annual growth rate of nominal GDP in the euro area, hp_t is the annual growth rate of Luxembourg home prices, stx_t is the annual growth rate of the Euro Stoxx 50 index, and stx_vol_t is the implied volatility of 30 day options on the Euro Stoxx 50. Financial market data is taken from Bloomberg for stock index returns, implied volatility, and interest rates, and euro area nominal GDP growth is obtained from the ECB Statistical Data Warehouse (SDW), while the residential real estate price index comes from Statec.

We treat bank specific variables as well as lagged dependant variables as predetermined but potentially endogenous and they are introduced as GMM style instruments. All macro-financial variables are considered exogenous and are instrumented by themselves such as in the case for traditional instrumental variables. We run the model on the full sample from 2002Q1 to 2015Q3 to measure the "average" contribution of the rates to the profitability and then investigate the parameters' dynamics and nonlinearities through a rolling window of 22 quarters.

3 RESULTS

Full sample regressions

Since the time span of the sample is large and the instrument count is quadratic in T, we overcome inflation in the instrument count by collapsing the matrix of instruments and restricting the number of lags, so the number of instruments remains below the number of groups. [88] The results on the full sample are displayed in Table 2.

The specification tests demonstrate results close to previous studies. The Hansen test, as well as the separate Difference-in-Hansen tests (named GMM Inst. p and IV inst. p in Table 2) fails to reject the null hypothesis of the validity of instruments. The Arellano-Bond test (A-B AR(2) in Table 2) also fails to reject the null of no autocorrelation of order 2 in the regression residuals.

Net interest margin

For NIM (column 1), both the short term rate and the slope of the yield curve are significant and positive. This shows that higher rates and a steeper yield curve are associated with higher NIM. Hence, a 1 percent increase in the level of the short term rate leads to an increase of NIM by around 0.05% in the long run. This estimate is consistent with Alessandri and Nelson (2015) who find 0.035% increase over a quarter. The increase in the slope of the yield curve has a similar impact compared to the level of the short term rate with a 0.06% increase of NIM following a rise of 1% of the slope. This indicates that Luxembourg banks tend to make significant profits from maturity transformation activities.

Consistent with Alessandri and Nelson (2015), we find that in the short run unexpected changes in rates and the slope of the yield curve have a negative impact on NIM with at least a one period lag persistency

88 The number of lags varies between 32 and 39 over a maximum default value of 55 time periods.

in the case of rates with estimated parameters of similar magnitude. Hence, Luxembourg banks' profitability suffers in the short run from repricing frictions suggesting that following an increase in interest rates, interest bearing liabilities tend to reprice faster than interest bearing assets, leading to a temporary margin compression. Over the long run, Luxembourg banks still profit from higher rates.

Bank specific variables (k, a, a_vol) are significant and positive. This is consistent with the view that bigger banks profit from economies of scale and are better able to handle negative shocks due to a higher degree of portfolio diversification. Moreover, strong capital positions allow banks to roll over short term debt at a lower cost on the money market, leading to a lower level of interest rate risk on the liability side.

The Herfindahl-Hirschman index is significant at the 10% level with an expected positive sign. Indeed, higher concentration gives banks higher market power and the ability to extract monopoly rents from mark-ups of loan rates and mark-downs of deposit rates.

Finally, most of the macroeconomic variables have good explanatory power. GDP growth is significant and positive while market returns and volatility are significant and negative. However, house prices do not seem to be significant.

Return on assets

The results for ROA (column 2) are broadly consistent with the parameters estimated for NIM. The level of the short term rate and the slope of the yield curve are positive and significant with similar magnitude. However, the negative short run repricing effects are less pronounced with Δr_t only significant at the 15% level. This may indicate that, at the portfolio level, interest rate risk is hedged and more difficult to capture with econometric models. However, it does not seem to be possible for Luxembourg banks to counteract the strong decreasing trend in the level of the rates.

Again, bank-specific variables are significant with positive signs. Interestingly the Herfindahl-Hirschman index and GDP are not significant, while home prices are significant at the 10% level and positive. Hence, despite the international orientation of some Luxembourg banking activities, certain banks still profit sufficiently from the residential real estate market to impact the results of the model.

Non-interest income

For NONII most of the rate variables are not significant at any conventional level. Only bank specific variables, GDP growth and market volatility have some explanatory power. While this may be linked to the fact that NONII is an aggregate measure of different sources of income, which can have different sensitivities to rates, this also suggests that Luxembourg banks did not adjusted significantly their business models. This is an important finding as it indicates that banks do not try to compensate lower NIM by increasing revenues from less stable activities. Although, profitability concerns remain, systemic vulnerabilities do not seem to build up outside traditional banking activities.

The concentration measure of the banking system (*hhi*) is significant and negative. This is consistent with Moshirian et al. (2011) who find that a high concentration level leads to lower non-interest income. This negative relationship holds because a high degree of competitiveness in traditional banking activities (deposit and loan market) acts as a push factor for banks to focus more on noninterest income based activities.

Table 2:

System GMM estimation results

	NIM	ROA	NONII
y_{t-1}	**0.700*****	**0.734*****	**0.758*****
	10.84	14.30	15.50
r	**0.047****	**0.053***	0.006
	2.73	1.85	0.25
Δr	**-0.104*****	-0.066+	-0.016
	-3.61	-1.58	-0.34
Δr_{t-1}	-0.04+	-0.018	-0.05
	-1.56	0.54	-1.22
s	**0.062*****	**0.073***	0.033
	2.77	1.81	0.95
Δs	**-0.06****	-0.018	-0.001
	-2.93	-0.51	-0.04
Δs_{t-1}	-0.016	-0.005	-0.009
	-0.72	-0.20	0.31
k	**0.016****	**0.040*****	**0.035*****
	2.26	3.14	3.19
a	**0.256*****	**0.533*****	**0.286***
	4.38	3.35	1.94
a_vol	**0.002*****	**0.001***	**0.001***
	3.76	1.88	1.82
hhi	**0.042***	-0.040	**-0.068*****
	1.84	-1.22	-2.24
gdp	**0.016****	0.002	0.0013
	2.52	0.31	0.11
hp	-0.004	**0.012***	**0.01***
	-1.20	1.80	1.76
stx	**-0.002*****	-0.001+	-0.001
	-4.59	-1.46	-1.31
stx_vol	**-0.003*****	**-0.004*****	**-0.002****
	-4.53	-2.87	-2.17
$cons$	**-6.667*****	**-11.63*****	**-5.979***
	-4.69	-2.87	-1.83
No. Obs	5.162	5.162	5.162
No. Banks	172	172	172
No. Instr	171	168	168
A-B AR(2)	0.800	0.478	0.937
Hansen p	0.517	0.457	0.387
GMM Inst. p	0.440	0.565	0.375
IV inst. p	0.378	0.310	0.323

*Note: += p < 0.15, * = p < 0.1, ** = p < 0.05, *** = p < 0.01. The NIM equation uses the log value of NIM and has one more lagged value of NIM as an independent variable with parameter estimate of 0.1 and p=0.048. In this case, y_{t-2} is treated as a GMM style instrument, pushing the instrument count up.*

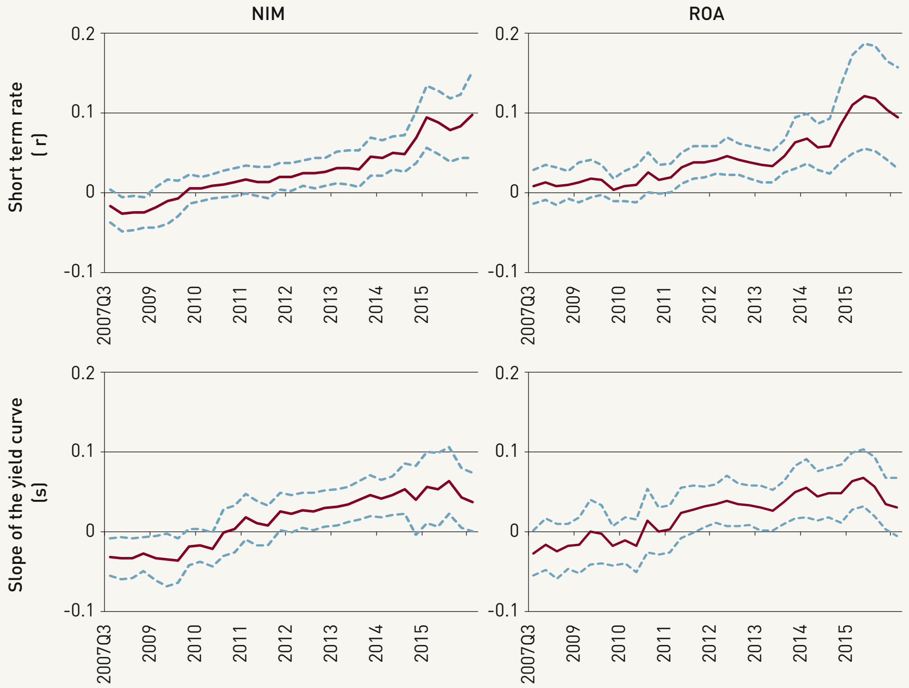
Finally, real estate prices are significant and positive suggesting that the positive impact detected at the portfolio level (ROA) mainly results from commissions related to real estate transactions and not directly from mortgage loans.

Rolling window regressions

According to Borio et al. (2015) the relationships between the rates and profitability measures are highly non-linear; i.e. positive and concave for NIM, negative and convex for NONII and positive and concave for ROA. In the case of NIM, this implies that, as the short term rate converges to the zero lower bound and the yield curve gets flatter, the compression of NIM becomes stronger. On the opposite side, with a sufficiently high level of interest rates, this relationship largely fades away.

We propose to investigate this phenomenon by adopting a different approach compared to Borio et al. (2015) who introduced squared values of the short term rate and the slope of the yield curve in a linear specification. We chose to estimate the same model as equation (1)[89] on a rolling window of 22 quarters, which allows us to track the dynamics of the parameters through time and verify if the relationship has become stronger at the end of the period. The results are presented in Figure 8.

Figure 8
Rolling window system GMM estimations



Note: the figure reports the 22 quarters rolling window system GMM estimates of the parameters associated with the short-term rate and the slope of the yield curve with more parsimonious specifications compared to equation (1). The point estimate is placed at the end of the period. The first data point is 2007Q3; i.e. 2002Q1+22 quarters. The dashed lines represent the 15% confident interval.

The results show an upward trend in the expected values of the estimated parameters. This is particularly true for the relationship between the short term rate and NIM and/or ROA. In fact, hardly any link is detected between rates and profitability measures in sub-samples starting before 2005. This is consistent with Rouabah (2006) who does not find a significant relationship between the rates and profitability in his sample period. Hence, interest rates did not significantly impact profits before the GFC meaning that other structural bank-specific and macroeconomic factors were driving Luxembourg banks' profitability. However, as the rolling window advances, the parameters become different from zero and increase to a level two times above the average estimates on the whole sample. This shows that this relationship is indeed non-linear and that lower rates have impacted bank profitability more as time has passed.

89 To assure the quality of the estimations, the number of instruments is dynamically adjusted in the routine by keeping the number of instruments below the number of groups. Moreover, we use the orthogonal deviation transform to maximize the sample size considering the unbalanced nature of the sample.

CONCLUSION

This article studies the link between interest rates and bank profitability in Luxembourg, with a linear specification estimated on panel data with system GMM over the period 2002Q1 to 2015Q3. Following the approach developed by Alessandri and Nelson (2015) and Borio et al. (2015), we study the impact of the modification in the interest rate structure, the short term rate and the slope of the yield curve on two major elements of banks' income statements; net interest margin, non-interest income, and overall profitability as determined by return on assets. In our analysis we control for macroeconomic factors and bank specific characteristics. We find that in the long run, higher interest rates and a steeper yield curve increase bank profitability. As a consequence, this study reveals that low interest rates have an unequivocally negative effect on bank profits in the long run. However, in the short run, due to asset and liability repricing frictions, we find that a decrease in market rates leads to temporary higher profitability. This study also reveals that Luxembourg banks' NONII does not react at the aggregate level to the rates. Hence, we do not find any evidence of increased systemic risk linked to a surge in non-core banking activities. However, a continued low interest rate environment may eventually raise challenges for banks' resilience and the stability of the financial system in the long run.

As mentioned in section 1, Luxembourg banks have been able to build strong capital positions. Hence, there is no immediate vulnerability for the Luxembourg banking system stemming from the low interest rate environment. Moreover the entry into force of the second pillar of the Banking Union on the resolution of credit institutions on December 2015 provides Luxembourg authorities with the instruments to manage bank solvency issues in an orderly manner. Furthermore, the national macro-prudential authority, the *Comité du risque systemique* (CdRS), closely monitors the buildup of vulnerabilities in the banking system and has at its disposal new macro-prudential instruments (such as the O-SII buffer and the counter-cyclical capital buffer) to improve the resilience of the banking system.

Finally, it is important to recall that the low interest rate environment has implications which go far beyond the scope of monetary and macro-prudential policy. Global imbalances, productivity issues and ultimately the lower growth potential of the advanced economies will likely have to be addressed by structural reforms at the international and European level.

REFERENCES

Alessandri, P. and Nelson, B. (2015). Simple banking: profitability and the yield curve. Journal of Money, Credit and Banking 47, 1 (February 2015), 143-175.

Bean, C., Broda, C., Ito, T., and Kroszner, R. (2015). Low for long? causes and consequences of persistently low interest rates. Geneva Reports on the world economy 17, International Center for Monetary and Banking Studies, October.

Bernanke, B. (2005). The global saving glut and the U.S. current account deficit, March. Remarks by Governor Ben S. Bernanke at the Sandridge Lecture, Verginia association of economists, Richmond, Virginia.

Borio, C. (2012). The financial cycle and macroeconomics: What have we learnt? Working paper 395, Bank for International Settlements, December.

Borio, C., Gambacorta L., and Hofmann, B. (2015). The influence of monetary policy on bank profitability, *BIS Working Papers*, No. 514.

Brunnermeier, M., Dong, G. and Palia, D. (2012). Banks' Non-Interest Income and Systemic Risk. AFA 2012 Chicago Meetings Paper.

Blundell, R. and Bond S. (1998). Initial Conditions and Moment Restrictions in Dynamic Panel Data Models, *Journal of Econometrics*, 87(2), 115-43.

Busch, R. and Memmel, C. (2015). Banks' net interest margin and the level of interest rates, Discussion Papers 16/2015, Deutsche Bundesbank, Research Centre.

Claessens, S., Coleman N., and Donnelly M. (2016). Low-for-long' interest rates and net interest margins of banks in Advanced Foreign Economies, IFDP Notes, Federal Reserve Board, Washington, D.C.

Demirgüc-Kunt, A. and Huizinga, H. (1989). Determinants of commercial bank interest margins and profitability: some international evidence. World Bank Economic Review 13, 2 (1999), 379-408.

ESRB (2016). Final Report of the Joint ATC-ASC-FSC Task Force: Macro-Prudential Issues and Structural Change in a Low Interest Rate Environment. *European Systemic Risk Board*, May 2016.

Freixas, X. and Rochet, J.-C. (2008). Microeconomics of banking. MIT press. Second edition.

Ho, T.S. and Saunders, A. (1981). The determinants of bank interest margins: theory and empirical evidence. Journal of Financial Quantitative Analysis Vol. 16, 581-600.

Molyneux, P. and Thornton, J. (1992). Determinants of European bank profitability: a note. *Journal of Banking and Finance*, 16, 1173-1178.

Moshirian, F., Sahgal, S. and Zhang, B. (2011). Non-interest income and systemic risk : the role of concentration. Working paper.

Nickell, S. (1981). Biases in Dynamic Models with Fixed Effects. *Econometrica*, Vol. 49, No. 6, 1417-1426.

Reinhardt, D. and Riddiough, S. J. (2014). The two faces of cross-border banking flows : an investigation into the links between global risk, arms-length funding and internal capital markets. Working paper 498, Bank of England, April 2014.

Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata, Stata Journal, StataCorp LP, vol. 9(1), pp. 86-136, March.

Rouabah, A. (2006). La sensibilité de l'activité bancaire aux chocs macroéconomiques : une analyse en panel sur les données de banques luxembourgeoises. Cahier d'étude 21, Banque centrale du Luxembourg.

Saunders, A. and Schumacher, L. (2000). The determinants of bank interest rate margins: an international study, Journal of International Money and Finance, Vol. 19, No. 6, 813-832.

Windmeijer's, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. Journal of Econometrics. 126(1), 25-51.

3. HOUSING PRICES AND MORTGAGE CREDIT IN LUXEMBOURG

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ABSTRACT

This paper investigates the interaction between residential housing prices and mortgage credit in Luxembourg over the period 1980Q1-2016Q3. We use a vector error correction framework to model this interaction and allow for feedback effects between the two variables. In the long-run, higher housing prices lead to a mortgage credit expansion, which in turn puts upward pressure on prices. The growing demand for mortgage credit is also sustained by positive net migration to Luxembourg. Construction activity is another important determinant of housing prices, in line with existing supply-side limitations on dwelling availability. While price dynamics are partially explained by these structural factors, our results suggest that residential housing prices are currently characterized by a moderate overvaluation with respect to market fundamentals. This overvaluation is estimated at 5.7% in 2016Q3. Results also show that housing prices have a slow rate of adjustment to deviations from fundamentals (only 2.3% of the misalignment is corrected each quarter) and they do not directly adjust to disequilibria in the mortgage market.

1 INTRODUCTION

The recent financial crisis has demonstrated that developments in the residential real estate market may have severe repercussions on the financial system and the real economy. In addition, more credit-intensive expansions tend to be followed by deeper recessions. This understanding has brought the interaction between housing prices and mortgage credit into the center of the economic policy debate. A growing literature documents the importance of credit growth to housing market dynamics and, in particular, the existence of feedback effects between housing prices and credit in several countries. The work of Fitzpatrick and McQuinn (2007) for Ireland, Oikarinen (2009) for Finland, Brissimis and Vlassopoulos (2009) for Greece, Gimeno and Martinez-Carrascal (2010) for Spain, Anundsen and Jansen (2013) for Norway, or Turk (2015) for Sweden provide country-level studies. For Luxembourg, Di Filippo (2015b) provides an overview of the risks stemming from the mortgage market (both for households and lenders) although credit variables are not directly included in the modeling framework.

This paper contributes to the literature by modeling the interaction between residential housing prices and mortgage credit in Luxembourg over the period 1980Q1-2016Q3. Thus the main variables of interest are the real housing price index and flows of real mortgage loans. The set of fundamentals used in the analysis also includes proxies for construction activity, the real mortgage rate, and demographic variables. Standard unit root tests reveal that the variables are integrated of order one and results from the cointegration tests suggest the existence of two cointegrating relations. We therefore follow the vector error correction model (VECM) approach and interpret the two cointegrating relations as long-run equations for housing prices and credit. A first estimation based on initial identification restrictions suggests that the real construction cost index is weakly exogenous. The main results are then obtained with a restricted VECM analysis. In the long-run, higher housing prices lead to an expansion of mortgage credit, which in turn puts upward pressure on prices. The analysis also confirms the importance of structural factors in the Luxembourg housing market: first, construction activity is an important long-run determinant of property prices, reflecting supply-side limitations on dwelling availability;

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second, demographic factors should be taken into account, as positive net migration to Luxembourg helps sustain the demand for mortgage credit.[91]

While price dynamics are partially explained by these structural factors, we estimate that residential housing prices are currently characterized by a moderate overvaluation with respect to market fundamentals. To this end, we follow the literature and calculate a valuation measure based on the misalignment of the actual price series from the long-run fitted values of the restricted VECM estimation. Since the beginning of 2015, the average overvaluation in the Luxembourg residential real estate market is estimated to be 8.5%, with a value of 5.7% in 2016Q3. For comparison purposes, Turk (2015) estimates that housing prices in Sweden were between 5.5% and 12% above the long-run equilibrium in 2015Q2.

In terms of short-term dynamics of housing prices, the adjustment coefficient is estimated to be 2.3%, which implies that price deviations from fundamentals are corrected at a slow pace. Caldera Sanchez and Johansson (2011) show that there are wide differences across countries in the implied speed of price adjustment, estimating quarterly corrections to be between 2.7% (for Japan and Denmark) and 77.6% (for Poland). These estimates, however, do not consider the inclusion of a long-run equation for mortgage credit. Similarly, the speed of adjustment estimated here is considerably lower than the value of 7.7% documented for Luxembourg by Di Filippo (2015a). Again, this is most likely due to the inclusion of mortgage credit in the analysis. In fact, we find that property prices do not directly adjust to disequilibria in the mortgage market, i.e. the coefficient on the mortgage error correction term is insignificant. On the other hand, regarding the short-term dynamics for mortgages, both error correction terms are statistically significant and negative. The speed of adjustment of mortgage loans is estimated to be 36% per quarter, while a positive deviation of housing prices from their long-run equilibrium leads to a decrease of 13.8% in mortgage loans over the next period. The results therefore suggest that the equilibrium in the mortgage market is restored faster than is the case for housing prices.

The rest of the paper is organized as follows. Section 2 describes the data. Section 3 discusses the methodology. Section 4 presents the initial VECM estimation and the main results. Section 5 concludes.

2 DATA

Data is collected from different sources on residential real estate prices, construction activity and housing supply, mortgage loans and interest rates, as well as demographic factors. The final quarterly sample covers the period between 1980Q1 and 2016Q3. The data on housing price indices for Luxembourg is made available at a quarterly frequency by STATEC. We use the index for new and existing dwellings that has been published online since 2007Q1. Given the short time span, we complete the time-series using historical data compiled from the Central Bank of Luxembourg (BCL) and the *Observatoire de l'Habitat*.

Regarding construction activity and housing supply, we use STATEC information on dwelling permits, housing stock values, and construction cost. The number of dwelling permits includes only residential buildings and it is available at a monthly frequency since 1979M01. Monthly permits are summed over each quarter to obtain a quarterly series. As permits proxy the construction activity, we calculate their moving average over four quarters to account for construction delays and the volatility in the series.

91 The limited supply of dwellings, insufficient to meet demographic pressures, has been highlighted by other studies. Peltier (2011) estimates that, in order to meet the increasing housing demand, 6,500 new dwellings should be built each year between 2010 and 2030. According to STATEC, the number of completed dwellings per year was on average 2,483 between 2010 and 2013.

We also calculate a housing stock series, using lagged permits and available housing stock values.[92] Moreover, we include in the analysis the bi-annual construction cost index and interpolate the series to obtain a quarterly variable.

With respect to mortgage credit, we use BCL data on new mortgage loans granted to domestic households. The data is available quarterly from 1992Q1 onwards, and annually for the period 1978-1991. The annual series is interpolated to a quarterly frequency (using a quadratic match sum approach) and then used to extend the current series backwards. For data on mortgage interest rates, which are available at a monthly frequency starting in 2003M01, we use quarter averages. Moreover, we extend the data backwards by using the growth rates of the quarterly three-month interbank lending rate for Belgium.

The housing market dynamics in Luxembourg are strongly influenced by demographic pressures, with housing demand being driven by an increasing population and a sustained net migration to Luxembourg. To capture this effect, we collected STATEC data on household size, population, and net migration. The average size of resident households is obtained from census data; the information is available every 10 years since 1970, so we linearly interpolate the data to obtain a quarterly series. Annual population estimates are also available since 1970; we apply a quadratic match average method to obtain a quarterly population variable. The average number of households is calculated as the ratio between total population and average size of resident households. Finally, data on annual net migration to Luxembourg is available since 1980 and it is converted to a quarterly frequency using a quadratic match sum process.

The series are seasonally adjusted, rebased to 2010 where applicable, and measured in real terms, i.e. the housing price index, mortgage loans, mortgage rate, and construction cost index are deflated by the consumer price index for Luxembourg. Following the literature, all variables are measured in logs, with the exception of the real mortgage rate, which is measured in per cent *p.a.*[93] The final variables are: real housing price index ($rhpi_t$), building permits (bp_t), housing stock (h_t), real construction cost index (cc_t), real new mortgage loans granted to domestic households (mg_t), real mortgage rate (r_t), average number of households (hh_t) and net migration (mi_t). Table 1 provides summary statistics on the variables, both in levels and first-differences.

92 Although information on the number of existing dwellings is not regularly published by STATEC, this number was estimated to be 135,760 at the end of 1979 and 227,326 in 2015Q1.

93 As net migration equals the number of people migrating to Luxembourg over those who leave, it can in principle be negative. In practice, the only sample year registering a negative value is 1982. Hence, we first linearly interpolate the net migration series between the two adjacent years and then apply the log transformation.

Table 1:

Summary Statistics

PANEL A: VARIABLES IN LEVELS		OBS	MEAN	STDDEV	MIN	MAX	CORR
Real housing price index	$rhpi_t$	147	4.085	0.469	3.291	4.801	0.987**
Building permits	bp_t	147	6.640	0.335	5.923	7.260	0.977**
Housing stock	h_t	147	12.077	0.162	11.822	12.363	0.981**
Real construction cost index	cc_t	147	4.551	0.067	4.402	4.627	0.983**
Real new mortgage loans	mg_t	147	6.069	0.869	4.511	7.303	0.983**
Real mortgage rate	r_t	147	5.577	4.736	-1.285	17.684	0.954**
Average households	hh_t	147	5.129	0.198	4.849	5.520	0.980**
Net migration	mi_t	147	6.690	1.173	2.970	7.989	0.985**

PANEL B: VARIABLES IN FIRST-DIFFERENCES		OBS	MEAN	STDDEV	MIN	MAX	CORR
Real housing price index	$rhpi_t$	146	0.009	0.017	-0.045	0.052	0.580**
Building permits	bp_t	146	0.005	0.056	-0.224	0.239	0.523**
Housing stock	h_t	146	0.004	0.001	0.002	0.011	0.560**
Real construction cost index	cc_t	146	0.001	0.006	-0.014	0.018	0.135
Real new mortgage loans	mg_t	146	0.016	0.075	-0.244	0.269	-0.060
Real mortgage rate	r_t	146	-0.111	0.979	-4.007	3.513	0.054
Average households	hh_t	146	0.005	0.002	0.001	0.011	0.665**
Net migration	mi_t	146	0.013	0.169	-1.066	0.862	0.566**

*Source: BCL calculations. 'Corr' stands for the first-order autocorrelation and ** denotes statistical significance at the 1% level.*

The order of integration was also analyzed, with the results of Augmented Dickey-Fuller (ADF) unit root tests presented in Table 2. The results suggest that the variables are non-stationary in levels. Most variables are stationary in differences, except for the average number of households and the housing stock.

Table 2:

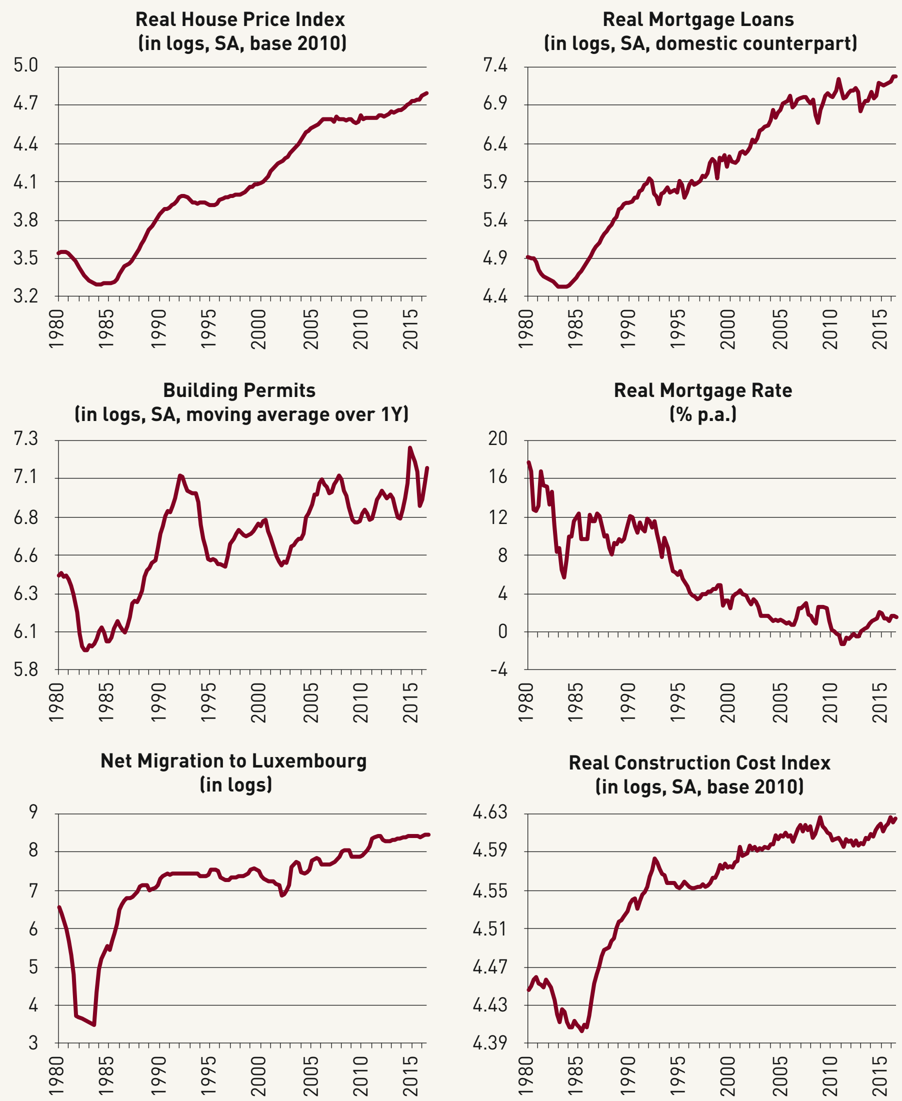
Unit Root Tests

	CONSTANT		CONSTANT + TREND	
	LEVEL	1ST DIFF.	LEVEL	1ST DIFF.
Real housing price index, $rhpi_t$				
Lags	2	1	2	1
Test Statistic	-0.220	-3.621	-3.262	-3.651
Probability	**0.932**	0.006	**0.077**	0.029
Building permits, bp_t				
Lags	5	4	5	4
Test Statistic	-1.387	-3.982	-3.055	-3.998
Probability	**0.587**	0.002	**0.121**	0.011
Housing stock, h_t				
Lags	3	2	3	2
Test Statistic	0.731	-2.773	-3.320	-2.929
Probability	**0.992**	**0.065**	**0.067**	**0.157**
Real construction cost index, cc_t				
Lags	4	3	4	3
Test Statistic	-1.140	-4.102	-2.128	-4.070
Probability	**0.699**	0.001	**0.526**	0.009
Real new mortgage loans, mg_t				
Lags	0	0	0	0
Test Statistic	-0.424	-12.786	-2.391	-12.744
Probability	**0.901**	0.000	**0.383**	0.000
Real mortgage rate, r_t				
Lags	0	0	0	0
Test Statistic	-2.047	-11.429	-3.033	-11.447
Probability	**0.267**	0.000	**0.127**	0.000
Average households, hh_t				
Lags	4	3	4	3
Test Statistic	2.523	-0.868	-1.204	-2.847
Probability	**1.000**	**0.796**	**0.906**	**0.183**
Net migration, m_t				
Lags	1	0	1	0
Test Statistic	-1.566	-6.338	-2.821	-6.315
Probability	**0.497**	0.000	**0.192**	0.000

Source: BCL calculations. Lags represent the optimal lag length according to the Schwarz information criterion. The probability is the p-value associated with the ADF null hypothesis of existence of unit root. Numbers in bold represent the cases where we cannot reject the null.

The finding that housing stock and demographic variables are $I(2)$ is common in the literature and often discarded due to data availability constraints. In this case, alternative measures seem to be a better option: in terms of construction activity, building permits and construction cost are good proxies and stationary in differences; regarding demographic variables, net migration effectively captures the increase in population in Luxembourg and is also $I(1)$. According to Turk (2015), net migration is preferred over other demographic factors, as immigration typically generates more immediate housing needs compared to the natural increase in population. Given these results, we opt for dropping housing stock and the number of households from the analysis. This ensures that all variables included in

Figure 1
Evolution of Main Variables



Source: BCL calculations

the econometric modeling are integrated of order one. Figure 1 displays their time-series, covering the sample period 1980Q1 to 2016Q3.

3 MODEL

3.1 Modeling Housing Prices

In general, the relationship between housing prices and fundamentals can be analyzed under the life-cycle model of housing. We follow Anundsen and Jansen (2013) and augment this model with a term capturing the presence of credit constraints. Market efficiency requires that, in equilibrium, the cost of owning a given dwelling should be equal to the real imputed rental price for housing services, Q_t (i.e. what it would have cost to rent a dwelling of similar quality). It follows that:

$$RHPI_t = \frac{Q_t}{\left[(1-\tau_t)i_t - \pi_t + \delta - \frac{R\dot{H}PI}{RHPI} + \frac{\lambda_t}{\mu_c}\right]} \quad (1)$$

where $RHPI_t$ is the real housing price index, τ_t is the marginal tax deduction rate, i_t is the nominal mortgage rate, π_t is the inflation rate, δ is the housing depreciation rate (which is assumed to be constant), $R\dot{H}PI/RHPI$ is the expected real rate of appreciation for housing prices, λ_t is the shadow price of the credit constraint and μ_c is the marginal utility of consumption. The term in brackets is commonly referred to as the real user cost of housing, in this case augmented with the credit constraint. As Q_t is unobservable, one common approach in the literature is to assume that it is a function of related variables. This paper uses proxies that are related to housing stock and construction activity, as well as demographic variables. In particular, we use building permits BP_t and real construction cost CC_t, as well as net migration, MI_t. Equation (1) can then be written as:

$$RHPI_t = f\,(BP_t,\ CC_t,\ MI_t,\ r_t,\frac{R\dot{H}PI}{RHPI},\frac{\lambda_t}{\mu_c}) \qquad (2)$$

where $r_t = (1 - \tau_t)\, i_t - \pi_t$ is the real after tax interest rate. We follow the literature and model price expectations by allowing lagged real price appreciations in the model dynamics. Finally we use mortgage loans MG_t as a proxy for the credit constraint, in the spirit of Anundsen and Jansen (2013). Then a log-linear approximation of equation (2) yields:

$$rhpi_t \approx \tilde{\beta}_{BP} bp_t + \tilde{\beta}_{CC} cc_t + \tilde{\beta}_{MI} mi_t + \tilde{\beta}_r r_t + \tilde{\beta}_{MG} mg_t \qquad (3)$$

where lower-case letters indicate that the variables are measured in logs and r_t is expressed as per cent p.a. Following Anundsen (2015), the equilibrium correction representation of equation (3) can be expressed as:

$$\Delta rhpi_t = \tilde{\gamma} + \tilde{\alpha}_{rhpi}\left(rhpi_{t-1} - \sum_k \tilde{\beta}_k k_{t-1}\right) + \sum_{i=1}^{p-1} \tilde{\rho}_{rhpi,i} \Delta rhpi_{t-i} + \sum_k \sum_{i=1}^{p-1} \tilde{\rho}_{k,i} \Delta k_{t-i} + \tilde{\epsilon}_t \qquad (4)$$

where $k = \{bp,cc,mi,r,mg\}$ denotes the set of housing market fundamentals used in the analysis and we expect $(rhpi_t - \sum_k \tilde{\beta}_k k_t)$ to be $I(0)$. The adjustment coefficient $\tilde{\alpha}_{rhpi}$ is expected to be negative and statistically significant if housing prices are determined by fundamentals.

3.2 Vector Error Correction Model

To analyze the relationship between residential property prices and housing market fundamentals, we generalize condition (4) above and estimate a multivariate vector error correction model (VECM) of the form:

$$\Delta \mathbf{y}_t = \nu + \Pi \mathbf{y}_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta \mathbf{y}_{t-i} + \epsilon_t \qquad (5)$$

where $\mathbf{y}_t$ is a K × 1 vector of variables, ν is a K × 1 vector of parameters, and ϵ_t is a K × 1 vector of disturbances. ϵ_t has mean $\mathbf{0}$, covariance matrix Σ, and is *i.i.d.* normal over time. The variables in $\mathbf{y}_t$ are the set $\{rhpi,bp,cc,mi,r,mg\}$ so that $K = 6$. If the variables $\mathbf{y}_t$ are stationary in differences, the matrix Π has rank $0 < r < K$, where r is the number of linearly independent cointegrating vectors. Furthermore, if the variables cointegrate, then $0 < r < K$. The tests for cointegration used to determine the rank are based on Johansen's method (see Johansen (1991)).

Given the rank, the matrix Π can be expressed as $\Pi = \alpha\beta'$, where α and β are both $K \times r$ matrices of rank r. Without further restrictions, the cointegrating vectors are not identified; in practice, the VECM estimation requires at least r^2 identification restrictions. The deterministic component can also be expressed as $\nu = \alpha\mu + \gamma$. Equation (5) can therefore be rewritten as:

$$\Delta \mathbf{y}_t = \alpha(\beta' \mathbf{y}_{t-1} + \mu) + \sum_{i=1}^{p-1} \Gamma_i \Delta \mathbf{y}_{t-i} + \gamma + \epsilon_t \qquad (6)$$

Equation (6) allows for a linear time trend in the level variables and restricts the cointegration equations to be stationary around constant means.

4 ESTIMATION

4.1 Cointegration Tests

Table 3 provides the results of Johansen's cointegration tests, where $K = 6$. The results are mixed. At a 5% confidence level, the max-eigenvalue test suggests the existence of two cointegrating relations, whereas the trace test suggests the existence of three cointegrating relations. We analyze the number of cointegrating equations in more detail using recursive cointegration tests. We find that results are time-varying and that, for most of the sample, a rank of two is a better representation of the data. Hence, we estimate a model with two cointegrating relationships and, following the literature (see, for example, Gimeno and Martinez-Carrascal (2010)), we identify them as long-run equilibrium relationships for house prices and mortgage loans.

Table 3:

Johansen Cointegration Tests

NO. OF CE(S)	EIGENVALUE	TRACE STATISTIC			MAX-EIGENVALUE STATISTIC		
		TEST STAT	5% C.V.	1% C.V.	TEST STAT	5% C.V.	1% C.V.
$r = 0$	0.329	147.87	95.75	104.96	57.48	40.08	45.87
$r \leqslant 1$	0.232	90.39	69.82	77.82	38.02	33.88	**39.37**
$r \leqslant 2$	0.166	52.37	47.86	**54.68**	26.08	**27.58**	32.72
$r \leqslant 3$	0.107	26.30	**29.80**	35.46	16.28	21.13	25.86
$r \leqslant 4$	0.049	10.02	15.49	19.94	7.17	14.26	18.52
$r \leqslant 5$	0.020	2.85	3.84	6.63	2.85	3.84	6.63

Source: BCL calculations. The tests allow for two lags in first-differences and the inclusion of a linear deterministic trend. The columns 5% c.v. (1% c.v.) represent the critical values from surface regressions in MacKinnon et al. (1999) at 5% (1%) level. Numbers in bold denote the first hypothesis that is not rejected for each test and significance level.

4.2 Initial VECM Estimation

4.2.1 Identifying Restrictions

The estimation of the VECM parameters requires at least r^2 identification restrictions in the cointegrating vectors, where $r = 2$ in our case. As discussed in the previous section, we identify the two cointegrating equations as long-run equilibria for house prices and mortgage loans. This implies that, in the first equation, we impose a normalization restriction on housing prices (so that $\beta_{rhpi,1} = 1$) and, in the second cointegrating relationship, we impose a normalization restriction on mortgage loans (so that $\beta_{mg,2} = 1$).

For the third identification restriction, we assume that building permits bp_t do not directly affect the amount of mortgage loans in the long-run, i.e. $\beta_{bp,2} = 0$. This is in accordance with e.g. Fitzpatrick and McQuinn (2007), where the housing stock variable is excluded from the long-run equation for credit. It should be noted that there is still a second-round effect, via the impact of construction activity on housing prices and their effect on mortgage credit.

Regarding the last identification condition, we start by restricting the coefficient of the interest rate r_t on the price equation and imposing $\beta_{r,1} = -0.1$.[94] Empirically, the derivative of real house prices with respect to the interest rate is often found to be statistically insignificant (see, for example, Caldera Sanchez and Johansson (2011)). Moreover, as argued by Anundsen and Jansen (2013), its sign is theoretically ambiguous when controlling for disposable income and mortgage loans, as the main effects of a change in the interest rate work through these variables, and the remaining substitution effects may be of either sign. The authors start by estimating long-run equations for housing prices and debt without restricting the interest rate coefficient and find $\beta_{r,1} = -0.13$ (although statistically insignificant). Similarly, Gimeno and Martinez-Carrascal (2010) impose a zero coefficient on interest rates, so that aggregate credit is the variable that captures the impact of financing costs on house prices. In our case, when allowing for one cointegrating equation on housing prices (the only identifying restriction in this case is $\beta_{rhpi,1} = 1$), we obtain a positive effect for the real interest rate. As Fitzpatrick and McQuinn (2007) point out, a possible explanation for the positive sign may be the relatively high correlation with other market interest rates, such as deposit rates. This effect might be particularly important in Luxembourg, where households have high levels of financial assets. Moreover, as shown below, this identifying restriction will be relaxed with very similar results.

4.2.2 Initial VECM Results

Table 4 displays the results of the exactly identified model, using a lag of two periods and a rank of two. Panel A presents the initial estimated cointegrating equations for housing prices (CEq1) and mortgage loans (CEq2), which correspond to the long-run equilibria. Most variables are statistically significant at the 10% confidence level and show the expected signs in both equations (the exceptions are the statistically insignificant net migration, mi_t, in the first relationship, and real construction cost index, cc_t, in the second equation). Our initial results support the hypothesis that housing prices and mortgage credit are mutually dependent. We find that, in the long-run, increases in mortgage credit are associated with increases in real housing prices, which is consistent with a positive effect on housing demand. The number of building permits, a proxy for construction activity and the supply of dwellings, is negatively related with the price level. Similarly, an increase in the construction cost index translates to lower supply and higher housing prices. For the long-run equation on mortgage loans, we find that the positive effect of housing prices is highly statistically significant, confirming the existence of a two-way interaction between prices and credit. Moreover, the real interest rate is negatively related to credit, so that higher financing costs lead to a lower search for house credit by households. Finally, an increase in the number of households caused by net migration to Luxembourg translates to a more significant amount of mortgage loans.

94 The two cointegrating vectors are expressed as $CEqi_t = \sum_y \beta_{y,i} y_t + c_i$, where $y = \{rhpi,bp,cc,mi,r,mg\}$ and $i = \{1,2\}$. Hence, $\beta_{rhpi,1} = 1$ and $\beta_{r,1} = -0.1$ imply a positive long-run relationship between the interest rate and housing prices.

Table 4:

Initial Results: Exactly Identified VECM

PANEL A: COINTEGRATING EQUATIONS							
	$rhpi_t$	mg_t	bp_t	r_t	mi_t	cc_t	c
CEq1	1	-0.996**	1.523**	-0.1	-0.058	-6.277**	21.355
		[-10.801]	[8.198]		[-1.101]	[-4.434]	
CEq2	-1.412**	1	0	0.022**	-0.100**	-0.270	1.472
	[-16.981]			[4.379]	[-4.928]	[-0.512]	

PANEL B: SHORT-TERM DYNAMICS							
	$CEq1_{t-1}$	$CEq2_{t-1}$	$\Delta rhpi_{t-1}$	$\Delta rhpi_{t-2}$	Δmi_{t-1}	c	
$\Delta rhpi_t$	-0.011	0.019	0.243*	0.381**	0.015*	0.003*	R^2 = 0.538
	[-1.756]	[1.122]	[2.575]	[4.255]	[1.976]	[2.557]	Adj. R^2 = 0.488
Δmg_t	-0.093*	-0.361**	-	-	-	0.015	R^2 = 0.174
	[-2.502]	[-3.572]				[1.941]	Adj. R^2 = 0.084

*Source: BCL calculations. Panel A displays the estimated cointegrating equations. Panel B presents the (partial) estimated short-term dynamics for $\Delta rhpi_t$ and Δmg_t. T-statistics are shown in brackets and * (**) represents statistical significance at the 5% (1%) level.*

Panel B of Table 4 presents the estimation output of the short-term equations for $\Delta rhpi_t$ and Δmg_t, where for brevity only adjustment coefficients and coefficients that are statistically significant at a 10% cutoff level are displayed. Regarding the first equation, the error correction term CEq1_{t-1} (i.e. the lagged residuals of the long-run equation for prices) is statistically significant at 10% but the second error correction term for mortgages is not. Our initial results suggest that, if housing prices deviate from their long-run equilibrium, they will revert back to the fundamental value at a very slow pace (i.e. with a correction of 1.1% of the disequilibrium per period) and they do not adjust to a disequilibrium in the mortgage market. Regarding the second equation, both error correction terms are statistically significant and negative. The speed of adjustment of mortgage loans is estimated to be 36.1% per quarter, while a positive deviation of housing prices from their long-run equilibrium leads to a decrease of 9.3% in mortgage loans over the next period.

4.3 Main Results

4.3.1 Weak Exogeneity Tests and Restricted VECM

In this section, we investigate the weak exogeneity of the variables with respect to the long-run coefficients. This amounts to testing if the loadings of both cointegrating vectors with respect to each variable y are zero, i.e. $\alpha_{y,1} = \alpha_{y,2} = 0$ (see Johansen (1992)). The only variable for which we find support for the weak exogeneity hypothesis is the real construction cost index, cc_t. The test statistic for the binding restrictions on cc_t is $X^2(2) = 0.47$ with a p-value of 0.79. To illustrate what this implies in terms of the VECM estimation, it is convenient to partition the vector $\boldsymbol{y}_t$ containing the variables into a vector of endogenous variables, $\boldsymbol{x}_t$, and a vector of weakly exogenous variables, $\boldsymbol{z}_t$. The VECM representation of equation (6) can then be expressed as:

$$\Delta \mathbf{x}_t = \alpha(\beta' \mathbf{y}_{t-1} + \mu) + \sum_{i=1}^{p-1} \Gamma_{x,i} \Delta \mathbf{x}_{t-i} + \sum_{i=0}^{p-1} \Gamma_{z,i} \Delta \mathbf{z}_{t-i} + \gamma + \epsilon_t \tag{7}$$

where $\boldsymbol{y}_t = (\boldsymbol{x}'_t, \boldsymbol{z}'_t)$ (see Anundsen (2015) for details and references therein). According to the results of the weak exogeneity tests, we consider $\boldsymbol{z}_t = cc_t$ and $\boldsymbol{x}_t = [rhpi_t, mg_t, bp_t, r_t, mi_t]'$.

As Table 4 shows, the estimated coefficient of cc_t in the long-run mortgage equation of the exactly identified VECM is statistically insignificant. Given this result, we also test the hypothesis $\beta_{cc,2} = 0$ in addition to the weak exogeneity restrictions $\alpha_{cc,1} = \alpha_{cc,2} = 0$ and find strong empirical support for the joint test. The test statistic for the three binding restrictions is $X^2(3) = 0.48$ with a p-value of 0.92. Finally, as the coefficient of net migration in the first cointegrating equation CEq1 is statistically insignificant, we impose $\beta_{mi,1} = 0$ and instead estimate the coefficient on the real interest rate. Specifically, the second identifying restriction on CEq1 is now given by the zero constraint on the migration coefficient and $\beta_{r,1}$ is estimated freely. This allows us to confirm our conjecture relative to the positive semi-elasticity of housing prices with respect to the real interest rate.

Therefore, the estimation of the restricted VECM described in equation (7) drops mi_t from the cointegration vector for housing prices (CEq1) and drops cc_t from the cointegrating vector for mortgage loans (CEq2). Moreover, insignificant variables in the second part of the VECM estimation output are sequentially deleted (using a 10% cutoff). In particular, we use the results from the first step Johansen's procedure for the restricted cointegrating vectors and estimate the short-term equations for $\Delta\mathbf{x}_t$ using the Seemingly Unrelated Regressions (SUR) approach.[95] This allows us to find a parsimonious model by using a general-to-specific approach and stepwise elimination of insignificant variables in the system. Table 5 presents the main estimation results.

95 For example, Caldera Sanchez and Johansson (2011) use SUR to jointly estimate both long- and short-run systems of equations for housing prices and residential investment. Unlike this paper, they do not consider the Johansen's procedure for the cointegrating vectors in the long-run, and do not allow for interactions of the error correction terms. As our focus is to model the mutual dependence between housing prices and mortgage loans, we use the results of the cointegration long-run analysis and employ SUR to jointly estimate the short-run system.

Table 5:

Main Results: Restricted VECM Estimation

PANEL A: COINTEGRATING EQUATIONS

	$rhpi_t$	mg_t	bp_t	r_t	mi_t	cc_t	c
CEq1	1	-0.872**	0.859**	-0.063**	0	-3.480**	11.691
		[-11.190]	[7.023]	[-6.799]		[-4.344]	
CEq2	-1.410**	1	0	0.022**	-0.115**	0	0.340
	[-21.398]			[4.199]	[-6.559]		

PANEL B: SHORT-TERM DYNAMICS

	$CEq1_{t-1}$	$\Delta rhpi_{t-1}$	$\Delta rhpi_{t-2}$	Δbp_{t-1}	Δmi_{t-1}	Δcc_t	Δcc_{t-1}	c
$\Delta rhpi_t$	-0.023**	0.277**	0.210**	0.041*	0.016**	0.913**	-0.343	0.003**
	[-3.454]	[3.647]	[3.073]	[2.288]	[2.784]	[5.701]	[-1.939]	[3.225]

$R^2 = 0.609$, Adj. $R^2 = 0.589$

	$CEq1_{t-1}$	$CEq2_{t-1}$	Δbp_{t-1}	c
Δmg_t	-0.138**	-0.360**	0.248*	0.015*
	[-2.899]	[-4.464]	[2.325]	[2.572]

$R^2 = 0.118$, Adj. $R^2 = 0.099$

	$CEq1_{t-1}$	Δbp_{t-1}	Δr_{t-1}	Δmi_{t-1}
Δbp_t	-0.088**	0.519**	-0.007	0.050*
	[-3.542]	[7.558]	[-1.829]	[2.171]

$R^2 = 0.358$, Adj. $R^2 = 0.344$

	$CEq1_{t-1}$	$CEq2_{t-1}$	$\Delta rhpi_{t-2}$	Δmg_{t-1}	Δmg_{t-2}	Δmi_{t-1}	Δmi_{t-2}	Δcc_t	Δcc_{t-2}	c
Δr_t	2.950**	-1.712	8.853	2.380*	1.812	1.410**	-1.224**	31.456**	24.405	-0.298**
	[5.232]	[-1.695]	[1.847]	[2.252]	[1.871]	[3.085]	[-2.658]	[2.783]	[1.941]	[-4.014]

$R^2 = 0.332$, Adj. $R^2 = 0.287$

	$CEq1_{t-1}$	$CEq2_{t-1}$	Δr_{t-2}	Δmi_{t-1}	Δmi_{t-2}	Δcc_t	Δcc_{t-2}
Δmi_t	0.230**	0.579**	-0.041**	0.463**	0.138	-3.752*	6.110**
	[2.620]	[4.159]	[-3.995]	[6.420]	[1.907]	[-2.225]	[3.481]

$R^2 = 0.469$, Adj. $R^2 = 0.445$

*Source: BCL calculations. Panel A presents the restricted cointegrating equations. Panel B presents the estimated short-term dynamics, where the equations are estimated by SUR and we sequentially eliminate coefficients that are not statistically significant at the 10% level. T-statistics are shown in brackets and * (**) represents statistical significance at the 5% (1%) level.*

4.3.2 Long-Run Analysis

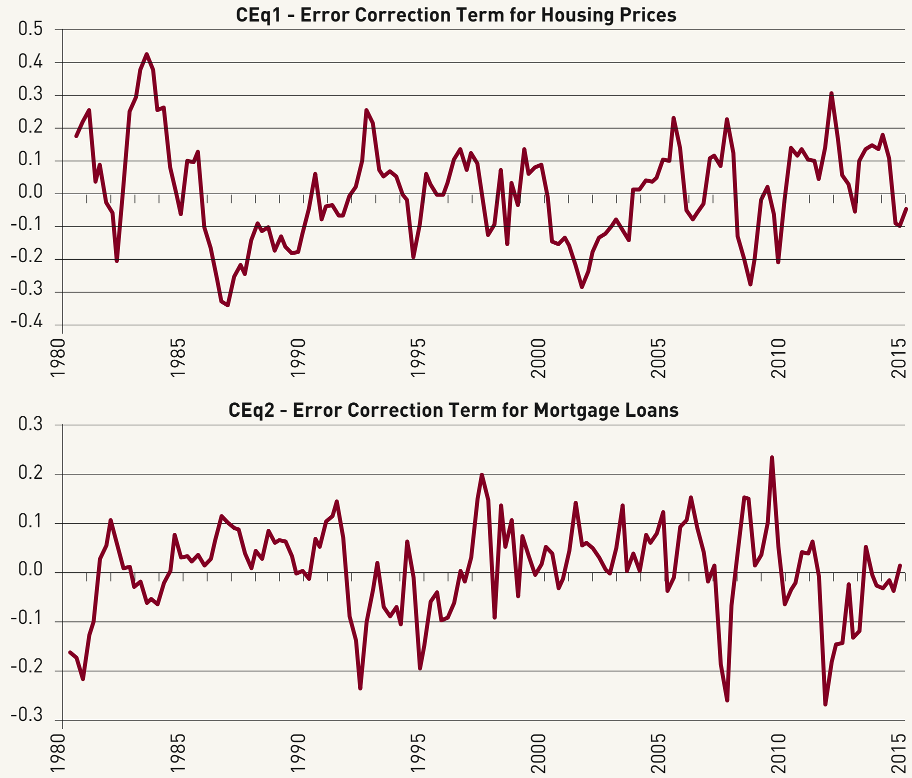
Regarding the cointegrating equations (see Panel A), all variables are highly statistically significant and the results overall confirm the signs and magnitudes of the initial estimation. The results support the hypothesis that housing prices and mortgage credit are mutually dependent. In the long-run, higher housing prices lead to a mortgage credit expansion, which in turn translates to higher housing demand and puts upward pressure on prices.

We report an elasticity of housing prices with respect to mortgage debt of 0.87, similar to the 0.98 documented by Anundsen and Jansen (2013) for Norway. Moreover, the elasticities of prices with respect to housing supply proxies are in line with the literature (respectively, -0.86 for building permits and 3.48 for construction cost). Although not directly comparable, Caldera Sanchez and Johansson (2011) use the stock of dwellings and find high negative elasticity values (i.e. lower than -1) for 15 out of the 21 OECD countries considered. Anundsen and Jansen (2013) estimate an elasticity of housing prices with respect to the stock of dwellings of -3.03 for Norway. Di Filippo (2015a) uses the number of dwellings and estimates a corresponding elasticity value of -4.53 for Luxembourg. Regarding demographics, net migration no longer directly affects the long-run equation for housing prices (recall that, in the initial estimation, the coefficient on net migration was 0.06 but statistically insignificant). For comparison purposes, Turk (2015) documents a corresponding value of 0.07 for Sweden. More importantly, we obtain a positive small effect for the real interest rate on housing prices, supporting the initial identifying restriction on $\beta_{r,1}$. As discussed above, a possible explanation for the sign may be the relatively high correlation with other market interest rates, such as deposit rates. This effect might be particularly important in Luxembourg, where households have high levels of financial assets. In the same line, Arestis and Gonzalez (2013) find a positive and significant long-run effect of mortgage rates on housing prices for Canada, Sweden, and the United Kingdom.

Regarding the long-run equation for credit, the estimated semi-elasticity of mortgage loans with respect to the real interest rate is -0.02, which implies that a 1 percentage point increase in the real interest rate will decrease mortgage borrowing by 0.02% in the long-run. This value is close to the value of -0.04 documented by Brissimis and Vlassopoulos (2009) for Greece. In turn, Fitzpatrick and McQuinn (2007) find a positive but very small effect of interest rates on credit in Ireland. With respect to net migration, there is a positive effect on the volume of new mortgage loans, with an estimated elasticity of 0.12. Finally, we find that housing prices exercise a greater long-run impact on mortgage credit than does mortgage credit on prices; this result is the opposite of that found by Anundsen and Jansen (2013) for total household borrowing, but is in line with the conclusions of Gimeno and Martinez-Carrascal (2010) for house purchase loans. In particular, we estimate that a 1% increase in housing prices increases mortgage loans by 1.41% in the long-run.

The estimated long-run values can be interpreted as the *fundamental values* of housing prices and mortgage loans. The deviations of the actual series from the estimated values are the error correction terms CEq1 and CEq2. Model inference depends crucially on the stationarity of these long run-residuals. Figure 2 plots their time-series and indicates that both series are stationary and roughly between -40% and 40%. Unreported results further confirm that the existence of unit roots for both series is strongly rejected (using individual or group unit root tests).

Figure 2
Long-Run Residuals



Source: BCL calculations. CEq1 and CEq2 are estimated using the first-step Johansen's procedure for the restricted cointegrating vectors as presented in Table 5.

4.3.3 Short-Run Dynamics

Panel B of Table 5 presents the estimation output of the restricted VECM short-term dynamics, where standard Portmanteau tests indicate no serial correlation in the system residuals.

Regarding the $\Delta rhpi_t$ equation, the housing prices' error correction term $CEq1_{t-1}$ is found to be statistically significant. Whereas the estimated coefficient is higher (in absolute terms) in comparison to the exactly identified VECM, the adjustment of housing prices in Luxembourg to deviations from fundamentals is considered slow, with an estimated correction of 2.3% per quarter. Caldera Sanchez and Johansson (2011) show that there are wide differences across countries in the implied speed of price adjustment, estimating quarterly corrections to be between 2.7% (for Japan and Denmark) and 77.6% (for Poland). This is also corroborated by the findings in Arestis and Gonzalez (2013) but neither paper considered the inclusion of a long-run equilibrium equation for mortgage credit. Similarly, the speed of price adjustment estimated here is considerably lower than the value of 7.7% documented for Luxembourg by Di Filippo (2015a), most likely due to the inclusion of mortgage credit in the analysis. In fact, we find that the coefficient on the mortgage error correction term is *positive* but insignificant (and therefore $CEq2_{t-1}$ is dropped from the equation). This result contrasts with the findings of Gimeno and Martinez-Carrascal (2010) and Anundsen and Jansen (2013), who document a negative coefficient for Spain and Norway respectively; nonetheless it is in line with the results of Brissimis and Vlassopoulos (2009), who also show that property prices do not adjust to the disequilibrium in the mortgage lending market in Greece. With respect to other variables, we document a positive effect of lagged house price changes on $\Delta rhpi_t$ (in line with the literature) and similarly for building permits, a positive (negative) contemporaneous (lagged) effect of changes in construction cost, and a positive coefficient for lagged net migration changes. Overall, the fit of the first short-term equation is noticeable, with an adjusted R^2 of 58.9%.

In the Δmg_t equation, both error correction terms are statistically significant and negative. The speed of adjustment of mortgage loans is now estimated to be 36.0% per quarter, while the effect of $CEq1_{t-1}$ is more important in comparison to the unrestricted case. In particular, a positive deviation of housing prices from their long-run equilibrium leads to a decrease of 13.8% in mortgage loans over the next period. It seems therefore that the equilibrium in the mortgage market in Luxembourg is restored faster than for the case of housing prices. For comparison purposes, the same values estimated by Gimeno and Martinez-Carrascal (2010) for Spain are 10.9% and 2.8%, respectively. Anundsen and Jansen (2013) find a lower speed of adjustment for real household debt in Norway (the estimated coefficient is -0.046) and an insignificant effect of the price error correction on the debt equation.

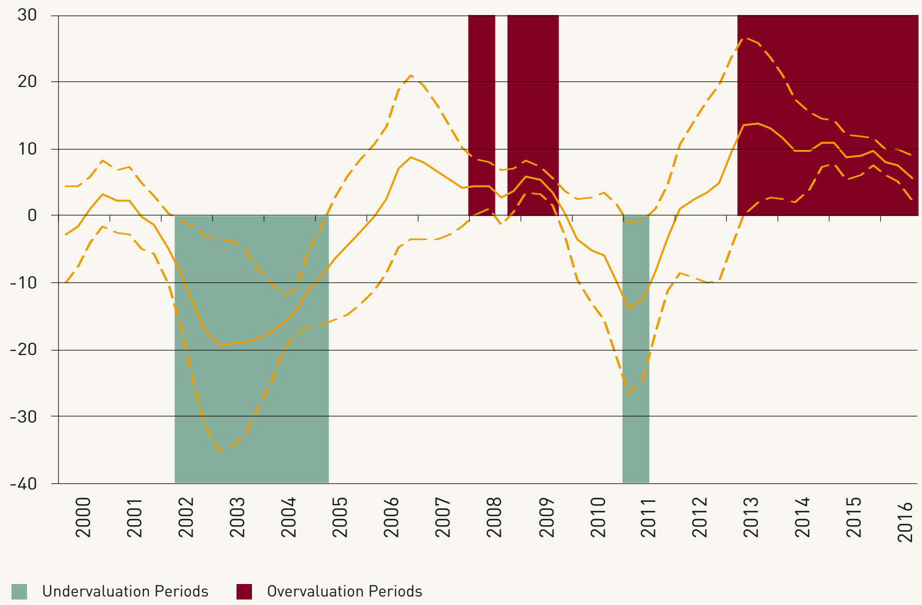
Regarding other interesting short-term effects, we find a negative and significant effect of lagged CEq1 on building permits Δbp_t. This implies that positive housing price deviations from fundamentals contribute, in the short-run, to a decrease in construction activity. These dynamics may contribute to magnify the existing supply constraints on dwelling availability.

4.3.4 Valuation Measure of Residential House Prices

The results suggest an important role for the interaction between residential housing prices and mortgage credit in Luxembourg. While the adjustment of housing prices to long-term deviations from fundamentals is done at a slow pace, property prices do not directly adjust to disequilibria in the mortgage market. Against this background, an important question refers to the degree of overvaluation or undervaluation of housing prices. To investigate this issue, we follow the literature and calculate a valuation measure based on the misalignment of the actual price series from the fundamental values estimated with the restricted cointegrating vectors. In particular, we use smoothed long-run residuals, calculated as a moving average of CEq1 over eight quarters, as our valuation measure. Figure 3 displays the results for the period between 2000Q1 and 2016Q3.

Overall the evidence suggests the existence of an undervaluation period between 2002Q2 and 2005Q1. This is consistent with the observation of a sharp decline in building permits and construction activity in the early 2000's (see Figure 1). The deceleration of construction activity would be reflected in a more limited supply of dwellings and, therefore, a jump in the fundamental value of housing. As the actual prices were growing at a steady rate, the dynamics are consistent with the estimated undervaluation. Furthermore it should be noted that, although net migration to Luxembourg also decreased, this drop was less significant and its long-run effect on housing prices is of a second-round nature (as it acts through a positive impact on mortgage credit).

Figure 3
Housing Prices - Overvaluation and Undervaluation Periods
(in %)



Source: BCL calculations. The solid line represents the smoothed deviations of housing prices from fundamentals. The dotted lines represent a confidence band around the estimated misalignment. Overvaluation (undervaluation) periods are signaled by the shaded red (green) areas.

The model also identifies two major overvaluation periods, the first roughly around 2008-2009 and coinciding with a decline in new mortgage loans after the onset of the financial crisis, and the second since 2013Q2. The analysis of the endogenous variables since 2013Q2 reveals a continuous increase in housing prices, an expansion of mortgage credit, a rise in construction cost, a stabilization of net migration to Luxembourg and some fluctuation in building permits and mortgage rates. Both the expansion of mortgage credit and the rise in construction cost directly contribute to a higher estimated fundamental value of housing prices. At the same time, $rhpi_t$ is increasing at a steady pace. Overall this evolution translates to a moderate overvaluation of housing prices. Over 2015 and the first three quarters of 2016, the average overvaluation in the Luxembourg residential real estate market is estimated to be 8.5%, with a value of 5.7% in 2016Q3. For comparison purposes, Turk (2015) estimates that housing prices were between 5.5% and 12% above the long-run equilibrium in Sweden in 2015Q2 using a similar approach. The analysis therefore confirms that the sustained increase in housing prices in Luxembourg is partially explained by structural factors, such as supply-side constraints (reflected in high construction cost and an insufficient level of building permits) and changes in demographics (with mortgage demand being heavily influenced by net migration to Luxembourg).

5 CONCLUSION

This paper investigates the interaction between housing prices and mortgage loans in Luxembourg. To this end, we estimate a restricted VECM that allows for feedback effects between the two variables. In line with the literature results for other countries, we confirm the existence of such interaction. In the long-run, higher housing prices lead to an expansion of mortgage credit, which in turn puts upward pressure on prices. Our analysis also confirms the importance of structural factors in the Luxembourg housing market: first, construction activity is an important long-run determinant of property prices, reflecting supply-side limitations on dwelling availability; second, demographic factors should be taken into account, as positive net migration to Luxembourg helps sustain the demand for mortgage credit.

While price dynamics are partially explained by these structural factors, we estimate that residential housing prices are currently characterized by a moderate overvaluation with respect to market fundamentals. Our valuation measure is based on the misalignment of the actual price series from the fundamental long-run fitted values. Since the beginning of 2015, the average overvaluation in the Luxembourg residential real estate market is estimated to be 8.5%, with a value of 5.7% in 2016Q3.

In terms of short-term dynamics of housing prices, we find that the adjustment coefficient is 2.3%, which implies that price deviations from fundamentals are corrected at a slow pace when comparing to other countries. This is most likely due to the inclusion of mortgage credit in the analysis. In fact, we find that property prices do not directly adjust to disequilibria in the mortgage market. Therefore, an increase in mortgage credit that is not explained by fundamentals may sustain the already strong housing demand in Luxembourg and contribute to a further short-term increase in housing prices. On the other hand, the speed of adjustment of mortgage loans is estimated to be 36.0% per quarter, while a positive deviation of housing prices from their long-run equilibrium leads to a decrease of 13.8% in mortgage loans over the next period. The results therefore suggest that the equilibrium in the mortgage market is restored faster than for the case of housing prices.

REFERENCES

Anundsen, A. (2015). "Econometric regime shifts and the US subprime bubble", *Journal of Applied Econometrics*, Vol. 30, pp. 145-169.

Anundsen, A., and Jansen, E. (2013). "Self-reinforcing effects between housing prices and credit", *Journal of Housing Economics*, Vol. 22, pp 192-212.

Arestis, P., and Gonzalez, A. (2013). "Modeling the Housing Market in OECD countries", Levy Economics Institute, *Working Paper* No. 764.

Brissimis, S.N., and Vlassopoulos, T. (2009). "The interaction between mortgage financing and housing prices in Greece", *Journal of Real Estate Finance and Economics*, Vol. 39, pp. 146-164.

Caldera Sanchez, A., and Johansson, A. (2011). "The price responsiveness of housing supply in OECD countries", OECD Economics Department, *Working Paper* No. 837.

Di Filippo, G. (2015a). "Residential Property Price Dynamics in Luxembourg: Lessons from ratio-based and model-based analyses", *Working paper.*

Di Filippo, G. (2015b). "An assessment of Luxembourg's Residential Real Estate Market", Central Bank of Luxembourg, *Financial Stability Review*, pp. 112-126.

Fitzpatrick, T., and McQuinn, K. (2007). "House prices and mortgage credit: empirical evidence for Ireland", *The Manchester School*, Vol. 75, pp. 82-103.

Gimeno, R., and Martinez-Carrascal, C. (2010). "The relationship between house prices and house purchase loans: The Spanish case", *Journal of Banking and Finance*, Vol. 34, pp. 1849-1855.

Johansen, S. (1991). "Estimating and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models", *Econometrica*, Vol. 59 (6), pp. 1551-1580.

Johansen, S. (1992). "Cointegration in partial systems and the efficiency of single-equation analysis", *Journal of Econometrics*, Vol. 52, pp. 389-402.

MacKinnon, J., Haug, A., and Michelis, L. (1999). "Numerical Distribution Functions of Likelihood Ratio Tests for Cointegration", *Journal of Applied Econometrics*, Vol. 14 (5), pp. 563-577.

Oikarinen, E. (2009). "Interaction between housing prices and household borrowing: the Finnish case", *Journal of Banking and Finance*, Vol. 33, pp. 747--756.

Peltier, F. (2011). "Projection des ménages privés et des besoins en logements 2010-2030", STATEC *Working Paper*, No. 55.

Turk, R. (2015). "Housing Price and Household Debt Interactions in Sweden", IMF *Working Paper Series*, WP/15/276.