The leveraged network-based financial accelerator and the real economy: an empirical investigation for Luxembourg

Abstract

The financial sector represents a disproportionate share of the Luxembourgish economy, with 26% of gross value added generated by financial firms. This proportion is much higher than in other European countries, where the average percentage is 5%. The question of whether and how the financial sector and the real economy are interrelated is therefore particularly important for Luxembourg. This paper assesses the role of the financial accelerator in the amplification and propagation of transitory shocks through the financial system. Building on Glocker (2016), it also aims to provide a partial macroeconomic model for Luxembourg. The model builds on the standard financial accelerator framework of Bernanke et al. (1999), to which the network financial accelerator is added as initiated by Delli Gatti et al. (2010) and developed by Riccetti et al. (2016). The model allows for self-reinforcing co-movements between private and non-financial investment in machinery and equipment, credit, spreads and a banking solvency index. Using quarterly data for the period 2000Q1 to 2018Q4, this paper identifies a long-run cointegrating system for those variables. Moreover, the dynamic properties of the model are analysed through impulse-response functions.
The results show that the leveraged network-based financial accelerator can contribute to magnify the shocks on the Luxembourgish economy. In particular, the model allows for self-reinforcing co-movements between the financial sphere and the real activity through these two financial accelerators. The paper illustrates how a 1 percentage point increase in the 3-months money-market interest rate and a negative shock on activity affect the real economy and the financial sphere through macro-financial linkages.

JEL codes: I31; O11; E6; O21; D60.

Keywords (JEL): financial markets and the macroeconomy (E44), time-series models (C32), model construction and estimation (C51), financial risk (G32).
1. Introduction

Increasing interdependence between the financial sector and the real economy has critically affected advanced economies over the past decades, leading the academic community to examine the linkages between the financial sphere and the real economy (e.g., Bernanke and Gertler, 1989; Bernanke et al., 1999; Bond et al., 2003; Sørensen et al., 2009). One remarkable feature of the relationship between credit market imperfections and the degree of shock amplification to the real economy has been the fast-growing interest among academics in the financial accelerator (Assenmacher-Wesche and Pesaran, 2009; Delli Gatti et al., 2010; Riccetti et al., 2016; Glocker, 2016; Adam and Glocker, 2018; Catalân-Herrera et al., 2019). The main idea is that the effect of a temporary real shock affecting firm's or the bank's net worth might generate large, persistent fluctuations in the economy, even if the initiating shock has little or no intrinsic persistence.

In this paper, we focus on two financial accelerators: the leverage financial accelerator initiated by Bernanke and Gertler (1989) and the network financial accelerator developed by Riccetti et al. (2016) and initiated by Delli Gatti et al. (2010). This paper develops a long-run structural cointegrating system of equations that relate the core macroeconomic variables of the Luxemburgish economy to the current and lagged values of four key variables: investment in machinery and equipment\(^1\), credit, spreads and a banking solvency index. The model is estimated using quarterly data over the period 2000Q1 to 2018Q4 to assess the role of the financial accelerator in the amplification and propagation of shocks.

The mechanism behind financial accelerators is based on the idea that there are imperfections in credit markets. The presence of information asymmetries between banks and non-financial corporations (NFCs) in credit market implies that firms' abilities to borrow essentially depend on the market value of their net worth (i.e. their financial health). Bernanke and Gertler (1989), among others, argue that informational asymmetries lead to higher agency costs between banks and NFCs that translate into an "external finance premium\(^2\)." The leverage financial accelerator is essentially based on the assumption that the cost of funds of borrowers depends inversely on

\[1\] It includes private non-residential construction (office buildings, industry halls).
\[2\] The external finance premium corresponds to an extra cost to firms' investment projects financed with external funds. It corresponds to the difference between the cost to a borrower of raising funds externally and the opportunity cost of internal funds.
their creditworthiness, as measured by indicators such as inverse financial leverage\(^3\). Notably, banks can force borrowers to repay their debts because durable assets such as machinery and equipment, land and buildings serve as collateral for loans (Kiyotaki and Moore, 1997). Credit and financial leverage are also interdependent. Accordingly, a negative shock in the economy, such as a productivity shock, would imply a decrease in firms' production and a deterioration of firm's capital stock, all other things being equal. The latter increase financial leverage, which implies a higher premium on external finance and therefore worse financing conditions in the credit markets. Firms would be induced to decrease their investments even after the initial productivity shock had dissipated. The positive shocks cause opposite dynamics.

The existence of the “network financial accelerator” is derived from various imperfections in credit markets. The basic idea is that the banking system plays a role in the amplification and the propagation of shocks in the economy. In theory, a deterioration of the net worth of banks should imply an increase in the lending interest rate to all the borrowers to cover the losses (Stiglitz and Greenwald, 2003; Riccetti et al., 2016; Delli Gatti et al., 2010). However, there is no clear-cut effect of the rise in the interest rate on the profits of banks. In other words, an increase in the interest rate does not necessarily lead banks to cover their losses. Indeed, Stiglitz and Weiss (1981) show that increasing interest rates or increasing collateral requirements could increase the riskiness of the banks' loan portfolio. Notably, this could discourage safer investments or induce borrowers to invest in riskier projects, implying a decrease in banks' profits. Under those circumstances, banks limit the number of credits (credit rationing) rather than limiting the size of each loan to reduce the risk of default. This result is consistent with arguments that banks should maintain proper leverage ratios and fulfill certain minimum capital requirements to cover the credit risk because of the asymmetry of information in the credit market. Accordingly, the implication of Basel I provides a platform of reforms designed to improve the regulation, supervision and risk management within the banking sector\(^4\). As a result, a shock that negatively affects banks' net worth decreases capital and requires banks to cover a lower level of credit risk (credit rationing). The opposite dynamic is observed for positive shocks. Credit granted by credit institutions also positively depends on net worth of banks, implying a credit-banking solvency feedback loop\(^5\). Whereas Riccetti et al. (2016)

\(^3\) The financial leverage corresponds to the share of credits on the net worth of the borrowers.
\(^4\) Basel I is an internationally agreed on set of measures developed by the Basel Committee on Banking Supervision. Basel III has been created in response to the financial crisis of 2007-2009. The measures aim to strengthen the regulation, supervision and risk management of banks.
\(^5\) The banking solvency index is calculated at the macroeconomic level. Thus, the model assumes that all banks have a similar behavior after a shock to their net worth.
suggest that the net worth of banks affects the lending rate, this paper follows Stiglitz and Weiss (1981) and assumes that their net worth has a direct impact on credits. The model developed in this paper is hence a modified version of the network financial accelerator.

The contributions of this paper are twofold. The first contribution is the proposition to include the empirical network financial accelerator of Riccetti et al. (2016) in the leverage financial accelerator model. As such, a new endogenous variable called the "banking solvency index" enables the model to generate a new feedback loop between gross domestic product, the index of the solvency of banks and credit. In this manner, the two financial accelerators are connected in a unique empirical framework, that is, one financial accelerator can influence the outcome of the other. The empirical strategy of this paper is therefore designed to describe and evaluate (i) how a shock affecting the banking system or the financial conditions of the NFCs could affect the real economy and (ii) whether there is a relationship between the two types of financial accelerators and how to measure the strength of the dependence. A detailed analysis of the dynamic properties of the model by means of impulse-response functions (IRF) is provided. Second, so far, the models including the financial accelerator for Luxembourg (Glocker, 2016; Adam and Glocker, 2018) were based on annual data. Here, the model is estimated with quarterly data.

Several reasons explain why quarterly data is more suitable for studying financial accelerators. The larger the sample size of the quarterly data, the greater is the accuracy of the short-run and long-run estimators. Additionally, this allows for more explanatory variables in the regressions because of more degrees of freedom. For instance, compared with Glocker (2016), the investment equation contains additional variables related to some sources of funding, economic and financial uncertainty and economic activity. In addition, studies (Assenmacher-Wesche and Pesaran, 2009; Hammersland and Træe, 2014) have demonstrated that higher-frequency data is more suitable for modelling highly volatile variables in a financial accelerator framework.

This study finds that the leveraged network financial accelerator can contribute to magnifying the effects of shocks to the Luxembourgish economy. In particular, the model allows for self-reinforcing co-movements between the financial sphere and real activity through these two types of financial accelerators. Additionally, whereas the leverage financial accelerator alone matters in the amplification of the business cycle, the network financial accelerator interacts with the other one. In particular, the impact of the leveraged network-based financial accelerator on the real economy radically differs from the leveraged financial accelerator alone, both in its magnitude and in its findings.
The remainder of the paper is organised as follows. Section 2 reviews more broadly some details on the data and the literature for each equation of the model. Section 3 reports and discusses the econometric results and Section 4 analyses the impulse-response functions. Section 5 concludes.
2. Data and literature review

Quarterly data on Luxembourg's economy and financial sector has been collected from 2000Q1 to 2018Q4. The endogenous variables are the Luxemburgish private non-financial investment in machinery and equipment (INVEST), the stock of credit granted by domestic credit institutions to the national NFCs (CRED), the interest rate spread (SPREAD) and the solvency index of the national banks (BNQSOLV). All variables are expressed in real prices (see Table A.2 in Appendix A for more details).

2.1. Drivers of non-financial corporation's investment

Private non-financial investment in machinery and equipment\(^6\) (INVEST) represents on average more than 55\% of total investment in Luxembourg. This variable is very sensitive to the fluctuations of economic developments. What motivates a firm to invest? Building on existing work (Glocker, 2016; Adam and Glocker, 2018) and the literature (Bond et al., 2003; Chirinko, 1993; Tevlin and Whelan, 2003; Lim, 2014; Lee and Rabanal, 2010; Oliner et al., 1995, among others), a set of explanatory variables has been identified. For the sake of clarity, determinants are split into three groups: (i) related to sources of funding, (ii) related to economic and financial uncertainty and (iii) related to economic activity.

First, three types of funding sources have been included in the investment equation: real cash flow of the Luxembourgish NFCs (CASHFLOW), the real stock of credits granted by Luxembourgish credit institutions to the NFCs (CRED) and bond securities in real terms issued by the Luxembourgish NFCs (BOND). A positive effect of these three variables on investment spending is expected. Firms identified as financially constrained (i.e. firms that face constraints in their ability to raise funds externally) show greater sensitivity in investment spending to the availability of cash flow (Fazzari et al., 1988; Mizen and Vermeulen, 2005). The cash flow variable also interacts with a measure of the financial constraint of the NFCs (CONSTFIN) (Barkbu et al., 2015). The interaction effect implies that the relationship between investments and cash flow is weakened or strengthened by the financial constraint variable.

Second, choosing the adequate measure of uncertainty is a more complex topic because it can take several forms. Two measures of uncertainty are considered: (i) the volatility of the Euro Stoxx 50 index (VSTOXX) and (ii) a news-based metric of policy uncertainty (ECONUNC).

\(^6\) It includes private non-residential construction (office buildings, industry halls). See Appendix B for more details.
Because each proxy is related to different components of uncertainty, they may have different impacts on investment. The economic uncertainty variable (ECONUNC) used in this paper has been used in Barkbu et al. (2015) and Lee and Rabanal (2010). These authors have demonstrated a negative and a statistically significant effect of this indicator on investment. The last group of variables comprises measures of economic activity. Real non-financial market gross value added (VABPRVO) and its profit margin (MARKUP) should have a positive impact on investment (Lim, 2014; Bond et al., 2003).

Compared with Glocker (2016) and Adam and Glocker (2018), this paper attempts to explain that Luxembourgh investment spending depends on additional sources of funding (BOND and CASHFLOW), on the performance of the NFCs (MARKUP) and on variables related to economic and financial uncertainty (CONSTFIN, ECONUNC and VSTOXX).

2.2. Drivers of credit to non-financial corporations

To explain the evolution of credit stock granted to NFCs, drivers are divided into three groups of variables: (i) those related to credit demand, (ii) those associated with credit supply and (iii) one variable to measure economic uncertainty.

The first set of variables comprises real private and non-financial capital stock in machinery and equipment (CAP), the real output gap\(^7\) (OUTPUTGAP), the lending rate (TINFC) and the real bonds issued by the NFCs (BOND). The capital stock and the output gap should have positive effects on demand for credits (Glocker, 2016). Bonds should affect credits because loan demand could depend on the relative price of credits compared with other sources of financing\(^8\). Moreover, Sørensen et al. (2009) include GDP into the credit equation and fix the coefficient to unity. In this paper, the output gap is introduced into the equation to consider the pro-cyclical pattern of credit supply. Furthermore, the commercial interest rate charged to NFCs\(^9\) (TINFC) should have a negative impact on credit demand.

Second, variables related to credit supply comprise the profit margin of domestic banks (MARKUPBNQ) and a banking solvency index\(^10\) (BNQSOLV). The latter is the sum of the capital ratio and the return on assets of banks (ROA), divided by the standard deviation of the

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\(^7\) The output gap is the difference between actual GDP and potential GDP.
\(^8\) NFCs have the choice to finance their investments with credits or bonds.
\(^9\) The lending interest rate corresponds to the weighted average of the interest rate with different maturity (less than 1 year, between 1 and 5 years and more than 5 years) and applied to the Luxembourgh non-financial corporations. The weights are calculated with credits with different maturity.
\(^10\) The banking solvency index is calculated from the z-score formula (Giordana and Ingmar, 2012) with macroeconomic data (see Table A.2 in Appendix A for more details).
ROA of banks. The Central Bank of Luxembourg (BCL) calculates this variable by using bank-level data from the bank's statistical reporting and their prudential reporting to the Financial Sector Supervisory Commission (CSSF). The aim of this paper consists in analysing the leveraged network-based financial accelerator at the macroeconomic level. This paper therefore uses country-level data of banks from the BCL website to calculate the banking solvency index. As a consequence, Tier 1 capital of the BCL is a narrower definition of the capital ratio calculated in this paper because it captures the amount of regulatory capital to risk-weighted assets. A positive effect of banking solvency on credit supply is expected because a decrease in this index would lead banks to be more selective in their credit supply to reduce their credit risk, implying a decrease in credit supply (Stiglitz and Weiss, 1981). Notably, banks are required by law to hold an amount of capital requirement to cover credit risks (Basel I). More specifically, the reasoning is as follows: a negative shock on their net worth, corresponding to a decrease in the capital ratio, generates a decrease in the banking solvency index. The decrease in banking solvency should imply a decrease in credit supply. Along the same line, Igani and Pinheiro (2011) find that the distance to the default of banks is positively associated with credit growth. Accordingly, Sivec and Volk (2019) show that capital requirement has a significant and positive impact on credit growth. Third, economic uncertainty should have a negative impact on credit. This variable is proxied by the spread between the weighted average commercial interest rate of the NFCs (TINFC) and the short-term interbank rate in the euro area (SPREAD). Because the 3 month Euribor is considered almost risk free and the interest rate for NFCs not, the difference between both, i.e. "the spread", proxies for the risk premium. A high credit rate and an overall high level of risk dampen credit demand (Glocker, 2016; Sørensen et al., 2009; Adam and Glocker, 2018).

The credit specification can be seen as a complementary approach to Glocker (2016) and Adam and Glocker (2018) which consists in investigating the determinants of credit supply (BNQSOLV and MARKUPBNQ) and in examining the impact of bonds issued by NFCs (BOND).

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11 Regulatory capital differs from capital, but both terms are linked. Capital requirement is the amount of capital a bank or other financial institution has to have as required by its financial regulator. These requirements ensure that banks do not take on excess leverage and thus do not risk becoming insolvent.

12 The short-term interest rate corresponds to the Euro area interbank rates EURIBOR 3 months.
2.3. Drivers of the interest rate spread

Two sets of variables are used to explain the spread between the commercial rate and the risk-free rate: (i) measures of economic and financial uncertainty and (ii) a variable related to economic activity.

The first group of variables comprises financial leverage (LEV), corresponding to the ratio of the stock of credit to the value of the capital stock (loan-to-value ratio). This paper considers the nominal capital stock as collateral (Glocker, 2016; Catalán-Herrera et al., 2019; Kiyotaki and Moore, 1997). The first set of variables also includes the euro area yield curve (YIELDCURVE) and the volatility in the financial market (VSTOXX). A positive impact of these driving factors on the spread is expected. Moreover, the coefficient of the real output gap (OUTPUTGAP) should be negative because the risk premium decreases in a period of higher economic activity. Additionally, according to Bredl (2018), a higher stock of non-performing loans is associated with higher lending rates. Unfortunately, this data is not included in the spread specification because this variable is only available since 2007 in an annual frequency for Luxembourg.

Compared with Glocker (2016), the spread specification includes additional variables of risk (YIELDCURVE, VSTOXX) and a variable of economic activity (OUTPUTGAP).

2.4. Drivers of the banking solvency index

The banking solvency index (BNQSOLV) reflects the aggregate degree of solvency of the Luxembourgish banking system and is calculated as the capital ratio of banks plus the return on assets of banks divided by the standard deviation over time of the return on assets of banks (Giordana and Ingmar, 2012). BNQSOLV also compares the macroeconomic buffers (capitalization and returns) with the volatility of those returns. A higher index points towards a higher degree of solvency of banks in Luxembourg. Building on the literature (Chan-Lau and Sy, 2006; Giordana and Ingmar, 2012; Rouabah, 2007), two sets of explanatory variables are used to explain banking solvency: (i) a measure of financial uncertainty approximated by the volatility in the euro area financial markets (VSTOXX) and (ii) variables related to the revenues of banks. The latter contain the following variables: real gross domestic product of

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13 The capital stock of private and non-financial corporations includes private non-residential construction (office buildings, industry halls). They often serve as collateral for loans.

14 The banking solvency index is based on the calculation of the aggregate zscore (Giordana and Ingmar, 2012). However, this variable is calculated at the macroeconomic level with macroeconomic data because the micro-data are not available on the website of the Central Bank of Luxembourg (BCL).
Luxembourg (GDP), real credits granted by national credit institutions to the domestic NFCs (CRED) and the euro area yield curve\textsuperscript{15} (YIELDCURVE). The main idea is that banks remunerate deposits with the short-term interest rate and grant loans with the long-term rate. The difference between the two interest rates is also an approximation of the interest margin of the Luxembourgish banks in the euro area.

Related to the literature review, we estimate a banking solvency index equation, which enables the model to generate a new feedback loop between GDP, the index of the solvency of banks and credits, called the network-based financial accelerator.

\textsuperscript{15} The degree of competition between banks could affect the solvency of banks (see Lim, 2014, Almarzoqi et al., 2015), but this variable is not available in quarterly frequency.
3. Empirical part and results

Tables C.3 and C.4 in Appendix C show the unit root and cointegration tests with the autoregressive distributed lag (ARDL) bounds testing approach (Pesaran et al., 2001; Narayan, 2005). All estimated models show significantly negative error correction coefficients. Their t-statistics exceed the upper bound in absolute value for all ARDL models. The F statistic always exceeds the upper bound and thus rejects the hypothesis of no level effects in the ARDL specifications. The evidence thus indicates the existence of four long-run relations in the ARDL models. As such, the following sections present the results of the two-step Engle and Granger (1987) error correction models (ECMs). In the first part, the long-term regressions of each equation are analysed and in the second part, the complete ECMs are examined.

3.1. Long-run structural model relations

Because the cointegration relationship has been confirmed, the estimated long-run relations are reported as follows.

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\begin{align*}
\log(\text{INVEST}_t) &= -8.77 + 0.15\log(\text{CRED}_t) + 0.09\log(\text{BOND}_t) + \log(\text{VABPRVO}_t) + 1.29\log(\text{MARKUP}_{t-1}) + \epsilon_{t}^{\text{INVEST}} \\
\log(\text{CRED}_t) &= -5.5 + 1.23\log(\text{CAR}) - 0.23\text{SPREAD}_{t-1} + 0.48\log(\text{BNQSOV}) + \epsilon_{t}^{\text{CRED}} \\
\text{SPREAD}_t &= 2.54 + 0.61\log(\text{LEV}_{t-2}) + \epsilon_{t}^{\text{SPREAD}} \\
\log(\text{BNQSOV}) &= -16.03 + 2.15\log(\text{GDP}_{t-1}) + 0.99\text{YIELDCURV}_{t} + \epsilon_{t}^{\text{BNQSOV}}
\end{align*}
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In the investment equation, the results show that investment spending (INVEST) positively depends on credits (CRED), bonds (BOND), private and non-financial gross value added (VABPRVO) and the profit rate of NFCs (MARKUP). A 1% increase in credits increases investment by 0.15%, all things being equal. This is consistent with Glocker (2016), who finds that an increase of 1% in credits drives investment up by 0.09%.\(^{16}\) Furthermore, an increase of 1% in bonds implies a rise of 0.09% in investment. Bonds and credits are the main sources to finance investment spending in the long term.\(^{17}\) The coefficient of gross value added in the

\(^{16}\) The long run equations of Glocker (2016) are in Table D.5 in Appendix D.

\(^{17}\) Additional regressions show that the equities issued by NFCs do not have a significant impact on investment spending. Thus, this variable is not included in the baseline specification.
investment equation is fixed to unity to respect the value expected from theory. At last, the relationship between the profit rate and investment is positive. A 1% increase in the profit margin of NFCs pushes investment up by 1.3%, keeping other things constant. Investment reacts more than proportionally to a variation of NFCs’ profit margins.

In the credit equation, the endogenous variable (CRED) is linked in the long term to investment (INVEST) through the capital stock variable (CAP). A 1% increase in the stock of capital enhances credits by 1.2%, all other things constant. Glockner (2016) finds a coefficient of 2.2, confirming that credits increase more than proportionally with an increasing capital stock in the two studies. Moreover, a connection is established between the spread (SPREAD) and credits. The cost of funding is of course negatively related to credits. A 1 percentage point increase in the interest rate spread contracts credit by 0.23% in the baseline but by 0.96% in Glockner (2016) (semi-elasticity).

However, the coefficients of this paper are not comparable with the estimators of Glockner (2016) for two reasons. First, estimations go until 2014 in Glockner (2016) but this work extends them until 2018Q4. Second, the two specifications are not exactly identical because an additional explanatory variable (BNQSOLV) has been included in this work. Therefore, an additional robustness check regression has been run with the same specification over the same period as in Glockner (2016). This additional regression allows for a comparison of the two results. The only difference is the number of observations because this paper uses quarterly data and Glockner (2016) uses annual data.

An elasticity of 1.70 is found for the capital stock and -0.12 for the spread. Therefore in Glockner (2016), the estimators from the credit equation could be overestimated due to the relatively small sample size. Fortunately, the coefficients of the baseline are stable over time because, with the same specification as Glockner (2016) but over the period 2000Q1-2018Q4, the elasticities equal -0.14 for the spread (against -0.12) and 1.8 for the capital stock (against 1.70). Results show that the impact of the banking solvency index on credits is positive and significant. They provide evidence that a 1% decrease in the banking solvency index decreases

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18 This assumption has been relaxed in an additional robustness check regression. The estimator equals 0.795 with a standard error of 0.404. A Wald test has been performed, the gross value added elasticity is statistically not different from one (p-value of 0.6140).

19 The literature had indicated that the regressions usually reveal a small, often-insignificant role of the cost of capital (Bond et al., 2003, Chirinko, 1993, Tevlin and Whelan, 2003, Lee and Rabanal, 2010). Additional regressions show that this variable has no significant impact on investment. As such, the baseline regression does not contain this variable.

20 This paper takes the recent version of the national accounts. However, the annual and quarterly databases are consistent; thus, the two sets of data are comparable.
credits by 0.5% in the long term. Thus, banks prefer to limit their volume of loans when a negative shock on their net worth occurs, to minimize the risk of default of NFCs (Stiglitz and Weiss, 1981). Credit rationing makes borrowers incur additional difficulties in financing investments, increasing the weakness of the non-financial sector. Another explanation of this positive impact can reasonably be inferred from the evidence that credit supply depends on banks’ net worth because they should detain capital to cover credit risk. However, changes in capital (capital ratio in the banking solvency index) caused by regulatory capital requirements could influence loans with a delay because of a long revision process (Sivec and Volk, 2019). But banks can anticipate, progressively adjust and smooth their regulatory capital before the time of the regulation, implying that changes in the capital ratio because of regulatory capital requirements can influence loans instantaneously. Regarding non-regulatory capital, the return on assets of banks (ROA in the banking solvency index) should have an immediate impact on credit supply because a high ROA indicates that banks are in a healthy financial situation. Consequently, the banking solvency index could have an instantaneous effect on credits.

As expected, the regression shows a positive relationship between the spread (SPREAD) and financial leverage (LEV). The loan-to-value ratio (LEV) is at the heart of the financial accelerator. Notably, in the presence of information asymmetry in the credit market, banks need guarantees when they grant credits to NFCs. In case of default of an NFC, a bank recovers the initial loan by selling the firm’s capital stock at the market price. Accordingly, financial leverage has a positive impact on interest rates because a firm's ability to borrow depends inversely on its creditworthiness measured by the inverse financial leverage. Leverage that is too high exerts upward pressure on the lending rate because of higher risk. In other words, banks increase their risk premium because of a higher degree of indebtedness, causing an increase in the spread. When the leverage increases by 1%, the spread increases by 0.6 percentage points (semi-elasticity). Glocker (2016) finds a semi-elasticity of 0.15. Considering the same sample size as in Glocker (2016), we find an estimator of 0.6. This result indicates that the long-term coefficient is stable with different sample sizes and that regressions with a relatively small sample size would be accompanied by an underassessment of the impact of leverage on the spread.

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21 An additional robustness check regression shows there is no significant effect of the banking solvency index on the spread, confirming the results of Stiglitz and Weiss (1981).

22 In turn, credits immediately influence the banks’ balance sheet, generating a potential endogeneity issue and a bias on estimators. Nonetheless, the long-run regression in a cointegration analysis should not be considered a causality relationship because the main objective is to test whether the linear combination of non-stationary data is stationary. Traditional endogeneity and weak instruments’ tests cannot be applied when the variables are nonstationary.
From the banking solvency equation, we observe that a boost in economic activity (GDP) definitively improves the banking solvency index (BNQSOLV). A 1% increase in GDP increases the banking solvency index by 2%. Moreover, the relation between the euro area yield curve (YIELDCURVE) and the solvency index is positive and an increase in the yield curve by 1 percentage point improves the banking solvency index by 0.01%.

In a rather sketchy manner, Figure 1 shows the link between the two financial accelerators:

![Figure 1: Leverage and network financial accelerator mechanisms](image)

3.2. **Error correction mechanisms**

Table 1 shows the estimates of the reduced-form error correction equations and some diagnostic statistics. The deviations from the long-run relations enter in all equations with a high level of significance. Results indicate that the lagged error terms of the long run equation are statistically significant at 1% in all equations. Their negative sign shows the speed of adjustment path from the short run toward the long-run equilibrium. The significance of the error correction terms is another proof of an established long-run relationship between endogenous variables and their long-run determinants. In the investment equation, the error correction coefficient is -0.29, which implies that deviations from the long term in investment spending are corrected by 29% every quarter. In other words, 29% of disequilibrium is eliminated before the next quarter, all else remaining constant. Of course, other new shocks may add or subtract from the disequilibrium in the next quarter. Furthermore, the deviation
from the long-run path is corrected every quarter by 22% for the credits, 30.4% for the spread and 20.8% for the banking solvency index.

The adjusted R^2 values of the different equations range from 0.49 (banking solvency equation) to 0.82 (spread equation). The investment and the credit equations fit quite well with the adjusted R^2 values of, respectively, 0.72 and 0.55. The diagnostic statistics indicate no serial correlation in the error terms of all equations. Notably, the p-value of the LM serial correlation test ranges from 0.35 to 0.63. The hypothesis of homoscedasticity of errors cannot be rejected at the 5% level of significance for the spread, investment and credit equations and at the 10% level for the banking solvency equation. Overall, the system seems to perform well. The fit of each specification can be seen graphically in Figures 2a to 2d. As often done in macroeconomic studies, potential endogenous explanatory variables are lagged to mitigate possible endogeneity issues.

Equation 1 in Table 1 shows that an increase in cash flow improves investment spending (INVEST) and that the impact is more important when the financial constraint increases (CASHFLOW*CONSTFIN). As such, a 1% increase in cash flow improves investment spending by 0.04%, everything else remaining constant. This impact is statistically significant at the 5% level. Nevertheless, when the financial constraint increases in the same time by 2%, the impact of cash flow on investment equals 0.08%. This result is consistent with Bond et al. (2003), who find that cash flow appears to have a significant impact on investment spending. Additionally, they suggest that this effect may be relatively important when financial constraints are severe. Notably, the availability of internal finance through profitability and cash flow can be important for investment (e.g., Barkbu et al., 2015). Moreover, weaker cash flow can exacerbate the need for external finance and affect the ability of a firm to borrow and the cost of credit.

Additionally, NFCs' profit rate (MARKUP) has a significant and positive impact on investments, suggesting that the investment opportunities are related to firms' profitability (as in Bond et al., 2003). A 1% expected increase in the profitability rate is associated with a 0.5% increase in investment spending. This impact is relatively large compared with the other coefficients, suggesting that the profit earnings rate is a critical factor for firms to engage in new investment projects.

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23 The time-stability of the estimated coefficients cannot be tested because of a relative short sample size.
Finally, uncertainty in financial markets and in the economy decreases investment spending. Indeed, the implied volatility in the financial markets (VSTOXX) and the economic uncertainty variable (ECONUNC) have negative coefficients but unfortunately, they remain insignificant. Concerning the credit equation (Equation 2 in Table 1), results provide evidence of the relative importance of the effect of the banking profit rate (MARKUPBNQ) and the solvency index of banks (BNQSOLV) on credit supply (CRED). These two variables have positive and significant impacts at the 1% level. The banking solvency coefficient represents the highest impact. A 1% decrease in the solvency index is followed by a 0.4% decrease in aggregate credit growth. Furthermore, a 1% increase in the banking profit rate increases credit supply by 0.2%. Notably, a 1 percentage point increase in the output gap (OUTPUTGAP) implies an increase in credits by 0.01%, suggesting that credit supply depends on economic activity, but with a weak link.

Another noteworthy result is the modest role of credit demand determinants. First, results show that a 1% increase in bonds (BOND) decreases credits by 0.1% because credit and bonds are considered substitutes for financing investments. This variable is statistically significant at the 5% level. Additionally, credits depend positively but not significantly on investment spending (INVEST). Notably, the regression provides no evidence of a significant effect of commercial interest rates on credits (TINFC) in the short term, but this variable is significant in the long term. Finally, there is no evidence of short-term persistence in credits because the lagged dependent variable is not statistically significant.

Results of the spread equation are reported in equation 3 in Table 1. There is a significant impact of economic and financial risk variables on the interest rate spread (SPREAD). The yield curve (YIELDCURVE), volatility in the financial markets (VSTOXX) and financial leverage (LEV) have a positive and significant impact on the spread at least at the 5% level, indicating that the lending rate translates the economic and financial risk in the euro area. A 1% increase in the current yield curve increases the spread by 0.2% at the 1% level of significance. Additionally, the current and lagged output gap (OUTPUTGAP) plays a significant role in explaining the spread. They have a negative and significant impact on the spread at the 1% level. Finally, there is little evidence of persistence with a consistently positive but non-significant coefficient of the lagged dependent variable.

An investigation of the determinants of the banking solvency index (BNQSOLV) is presented in Equation 4 in Table 1. Results suggest that financial uncertainty and variables related to economic activity are critical factors in determining the solvency index of banks. Volatility in financial markets (VSTOXX) has significant and negative effects on banking solvency at the
1% level. A 1% increase in the implied volatility deteriorates the index by 0.07%. Additionally, the positive and significant coefficients of the current and past yield curve (YIELDCURVE) suggest that an expected decrease in the current and lagged yield curve is associated with a decrease in bank earnings. In addition, a 1% increase in lagged credit (CRED) raises the banking solvency index by 0.1%. This coefficient is statistically significant at the 5% level. At last, results suggest persistence, because the second-order lag dependent variable is positive and statistically significant, but any persistence is short lived.
### Table 1: Error-Correction Model for Investments, Credits, Spread ans Banking Solvency Index

<table>
<thead>
<tr>
<th>Equation 1</th>
<th>Equation 2</th>
<th>Equation 3</th>
<th>Equation 4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent Variable = ΔLOG(INVEST_t)</td>
<td>Dependent Variable = ΔLOG(CRED_t)</td>
<td>Dependent Variable = ΔSPREAD_t</td>
<td>Dependent Variable = ΔLOG(BNQSOLV_t)</td>
</tr>
<tr>
<td>Explanatory Variable</td>
<td>Coefficients</td>
<td>Explanatory Variable</td>
<td>Coefficients</td>
</tr>
<tr>
<td>C</td>
<td>-2.525 *** [0.644]</td>
<td>C</td>
<td>-2.057 *** [0.426]</td>
</tr>
<tr>
<td>ΔLOG(CASHFLOW_t) × CONSTFIN_t</td>
<td>0.04 ** [0.017]</td>
<td>ΔLOG(MARKUPBNQ_{-3})</td>
<td>0.216 *** [0.066]</td>
</tr>
<tr>
<td>ΔLOG(MARKUP_{-1})</td>
<td>0.525 * [0.292]</td>
<td>ΔLOG(BNQSOLV_{-3})</td>
<td>0.379 *** [0.126]</td>
</tr>
<tr>
<td>ΔLOG(VSTOXX_{-3})</td>
<td>-0.049</td>
<td>ΔLOG(CRED_{-2})</td>
<td>-0.141 * [0.083]</td>
</tr>
<tr>
<td>ΔLOG(ECONUNG_{-1})</td>
<td>-0.036 [0.034]</td>
<td>ΔLOG(BOND_{-1})</td>
<td>-0.108 ** [0.053]</td>
</tr>
<tr>
<td>EG_{-1}</td>
<td>-0.29 *** [0.073]</td>
<td>ΔLOG(INVEST_{-1})</td>
<td>0.069</td>
</tr>
<tr>
<td>Control variables</td>
<td>YES</td>
<td>Control variables</td>
<td>YES</td>
</tr>
</tbody>
</table>

**Adj R²** | 0.72 | **Adj R²** | 0.55 | **Adj R²** | 0.82 | **Adj R²** | 0.49 |
**Log lik.** | 92.34 | **Log lik.** | 125.01 | **Log lik.** | 63.56 | **Log lik.** | 152.95 |
**DW** | 2.2 | **DW** | 2.19 | **DW** | 1.71 | **DW** | 1.9 |
**Obs.** | 75 | **Obs.** | 75 | **Obs.** | 75 | **Obs.** | 75 |
**S.E. of Reg.** | 0.08 | **S.E. of Reg.** | 0.05 | **S.E. of Reg.** | 0.11 | **S.E. of Reg.** | 0.03 |
**LM Test: (pval)** | 0.35 | **LM Test: (pval)** | 0.63 | **LM Test: (pval)** | 0.4 | **LM Test: (pval)** | 0.39 |
**Heterosk.: (pval)** | 0.52 | **Heterosk.: (pval)** | 0.35 | **Heterosk.: (pval)** | 0.53 | **Heterosk.: (pval)** | 0.07 |

Standard error in parentheses. *p < 0.05, **p < 0.01, ***p < 0.001

Note: The Table reports the estimates of the error correction model for each endogenous variable. Columns 1 and 2 of each regression correspond respectively to the explanatory variables and the short error correction term. The control variables are the following for each equation: Equation 1: Investments in airplane and satellites (ΔAIRSAT_t) and three time dummies (DUM2001Q4, DUM2014Q1, DUM2018Q3); Equation 2: Three time dummies (DUM2002Q2, DUM2008Q3, DUM2015Q2); Equation 3: Three time dummies (DUM2001Q4, DUM2008Q2, DUM2008Q4); Equation 4: Three time dummies (DUM2001Q1, DUM2011Q4, DUM2015Q2).
Figure 2: Actual, predicted and residual values for each equation

(a) Investment equation

(b) Credit equation

(c) Spread equation

(d) Banking solvency equation
4. Impulse-response functions

A standard tool for analyses of interactions and dynamics are impulse response functions (IRF), which show the effects of typical shocks on the time paths of the variables of the model. The model's short- and long-run properties are illustrated by adding a series of shocks. The shocks are established for a period of 12 quarters. Two shocks are conducted: (i) a one-percentage point maintained increase in the 3-months money-market interest rate and (ii) a negative shock of 5% on non-financial private gross value added. To that end, a model is constructed in which the four ECMs (INVEST, CRED, SPREAD and BNQSOLV) and additional accounting identities (GDP\textsuperscript{24}, LEV, OUTPUTGAP, TOTINV\textsuperscript{25}, CAP and YIELDCURVE) are interconnected. The model is solved and shows that the IRFs trace the effects of the selected shocks on the whole endogenous variables. This information is then used to analyse the transmission channels of the two types of financial accelerators.

4.1. A monetary policy shock.

Figure 3 shows the response of a shock to the equations including the short-term interest rate\textsuperscript{26}. By assumption, the short-term interest rate increases by 1 percentage point in this first scenario. The blue line corresponds to the leveraged network-based financial accelerator. It shows the combined two financial accelerators at work in one model. The red line corresponds to the leverage financial accelerator alone. By using a more complete modelling framework (blue line), the impulse-response patterns overall are very much in line with expectations (Adam and Glocke, 2018; Hammersland and Træe, 2014) or what they would be in a dynamic stochastic general equilibrium model (Dib and Ian, 2005).

The short-term interest rate increase is channelled to the real economy through an increase in the banks' lending rate, as well as through a yield curve decrease. Both have a complementary effect on investment spending and economic activity, amplified by the two financial accelerators (blue line). Notably, the lending rate increases and generates a decrease in credits

\textsuperscript{24} Expenditure and production approaches of GDP.

\textsuperscript{25} TOTINV corresponds to total investment. It is the sum of investment in machinery and equipment of the private and non financial sector, investment from the financial and public sectors and the residential investment. A link is established between the expenditure approach of the GDP and the investment in machinery and equipment through the total investment variable.

\textsuperscript{26} For the sake of clarity, most impulse responses for the variables are displayed as deviations from the baseline in percent. Lending and short-term interest rates, the spreads and the yield curve are displayed as deviations in percentage points from the baseline scenario.
in the short term. As such, during the two quarters following the shock, investment spending and GDP decrease. However, at the same time, the lending rate increases but very slowly. Therefore, the spread, corresponding to the difference between the lending and the short-term rates, decreases, causing an increase in credits. As such, this limits the decrease in investment and GDP. Nevertheless, this effect is very short lived because simultaneously, the fall of the yield curve generates a decrease in the banking solvency index. Consequently, the credit supply decreases again during the fourth quarter after the shock and then investment spending and GDP decline too. They become negative compared with the baseline and they continue to decline until the end of the period. Notably, the decrease in GDP generates a new deterioration of the banking solvency index and the output gap, causing a new fall of the credits and a new rise of the spread. The results indicate that the shock is persistent, illustrating very nicely the self-reinforcing co-movements between investment, GDP, credit, leverage, the spread and a banking solvency index.

As aforementioned, the model includes the network financial accelerator mechanism where a shock that affects the banking system transits to the real economy through credit supply. Notably, a decrease in the banking solvency index has a direct impact on credit supply. Besides, the leverage financial accelerator mechanism is at work in the simulations because a shock that affects the borrowing capacity of non-financial enterprises affects the real economy through credit demand. Notably, financial leverage decreases because of a relatively important decrease in credits. This decrease is insufficient to increase credit demand, because of a counterbalanced effect of the network financial accelerator through credit supply.

The difference between the blue and the red line corresponds to the difference between the impact of the leveraged network-based financial accelerators (blue line) and the leverage financial accelerator alone (red line). To make the two models comparable, they maintain the same estimated coefficients, the same trajectory of the banking solvency index when the shock occurs and the same specification except that the banking solvency index becomes exogenous as shown by the red line. Figure 3 shows a stronger decline in GDP when the combination of the two financial accelerators is considered (blue line) compared with the leverage financial accelerator alone (red line). Notably, in the latter case, there are no self-reinforcing co-movements among credits, GDP and the banking solvency index. As such, the decrease in credit is also less important and it recovers its initial value three quarters following the shock.

---

27 This result is not standard. It comes from the negative impact of the spread on credits. More conventional economic behavior is observed afterward.
generating a less-substantial drop in investments and GDP as in Hammersland and Træe (2014).
The difference between the level of GDP in the baseline and the level of GDP in the scenario with a shock is relatively marginal twelve quarters after the shock. However, the size of the impact depends largely on the size of the initial shock. A similar experiment using a larger shock on the monetary policy interest rate leads to a slightly more pronounced decrease in output.

Figure 3: The financial accelerator at work – monetary policy shock

Note: Quarterly data; numbers on the time axis refer to observations for a time period from 1 to 12 quarters. Most impulse responses for the variables in levels are displayed as deviations from the baseline in percent. Lending and short-term interest rates, the spread, and the yield curve are displayed as deviations in % points from the baseline scenario.
Figure 4 shows the response to a permanent negative shock of 5% to market non-financial gross value added\textsuperscript{28}. In the leveraged network-based financial accelerators (blue line), results indicate that a negative gross value-added shock in the model leads to an instantaneous decrease in GDP. This lowers the output gap, triggers an increase in the lending rate and decreases banking solvency. A higher spread (because of the increase in the lending rate) and a lower banking solvency index lead to lower credits and thus lower investment and GDP. Additionally, the decrease in gross value added triggers a decrease in investment spending, accelerating the decrease in GDP. Moreover, a weaker investment decreases capital stock, which contributes to decreasing credits, generating a new decrease in investment spending and GDP. A new cycle starts exactly as aforementioned.

In accordance with financial accelerator theory, this process of subsequent cycles continues until they become so small that they eventually die out. After 12 quarters, the initial negative shock on the market non-financial gross value added continues to decrease GDP and investment in machinery and equipment compared to the baseline, but the amplitude of the effect becomes less and less important. Notably, the slope of the decrease in GDP becomes less and less important.

Both financial accelerators are at work in this simulation. The lower financial leverage, due to a relatively strong decrease in credits, dampens the increase in the lending rate. Notably, the rate with the leveraged network-based financial accelerator (blue line) is below the rate with the leverage financial accelerator alone (red line). This eventually leads to an improvement in credit demand. Nevertheless, combined with the network financial accelerator, this recovery is insufficiently strong to offset the negative impact of the banking solvency index on credit supply. As such, the combined financial accelerators imply a stronger decrease in credits (blue line) than in the leverage financial accelerator alone (red line). The difference between the two models however is more pronounced when the shock occurs in the short-term interest rate, compared with a scenario of a negative shock in gross value added. Notably, interactions between the two financial accelerators are more important when an initial shock occurs in the financial sphere.

\textsuperscript{28} This includes all activities like industry, construction, trade, transport, health, etc. except financial services and non-market (government) services.
Figure 4: The financial accelerator at work – Private and NFC Gross Value Added shock

Note: Quarterly data; the numbers on the time axis refer to observations for a time period from 1 to 12 quarters. Most impulse responses for the variables in levels are displayed as deviations from the baseline in percent. Lending and short-term interest rates, the spread, and the yield curve are displayed as deviations in % points from the baseline scenario.

The banking solvency equation is particularly important because it allows to consider in an indirect means the banking "fire sale" issue. Choi and Cook (2012) show in a theoretical model that a financial shock substantially increases the default risk through an increase in financial leverage of the NFCs. In case of default of NFCs, banks repossess and sell collaterals in the (financial) markets to recover their initial loans. However, in a period of financial turmoil, collaterals are sold below their steady-state value (fire sale). The resulting decrease in collateral prices in the financial market could imply a decrease in the recovery rate of the banks and then a decrease in their net worth, implying a decrease in the banking solvency index.
5. Conclusion

This paper estimates a partial macroeconomic model with macro-financial linkages. It includes a leveraged network-based financial accelerator to mimic the amplification and propagation of shocks to the real economy. To that end, a structural cointegrating system of equations for the Luxemburgish economy has been developed. Four long-run relations are identified between investment in machinery and equipment, credit, spreads and a banking solvency index.

The model developed in this paper hence integrates two financial accelerator mechanisms that are interdependent. The leveraged financial accelerator originates in firms where financial leverage affects borrowing capacity and by so doing the real economy through a variation in real investment. The network financial accelerator originates in banks where banking net worth affects lending capacity. This model builds on the leverage financial accelerator framework of Bernanke et al. (1999), to which the network financial accelerator of Riccetti et al. (2016) is included. A procyclical feedback mechanism is observed among leverage, credit and capital stock on the one hand and between a banking solvency index, credit and GDP on the other hand.

The impulse-response patterns overall are in line with what theory predicts. Two financial accelerators interact in a complex manner and the effect of one may offset or magnify the effect of the other. Empirical results show self-reinforcing co-movements between the financial sphere and real activity: the two financial accelerators contribute to magnifying the effects of shocks to the economy. Notably, a decrease in GDP and the output gap generates a deterioration of the banking solvency index, causing a fall of credits and a rise of the spread. The shock is persistent, illustrating the self-reinforcing co-movements between investment, GDP, credit, leverage, spread and the banking solvency index. In particular, the interactions between the two financial accelerators are more important when an initial shock occurs in the financial sphere.

A weakness of the model is that it provides no analysis at the micro level. Because of data aggregation at the country level, this paper merely relies on the assumption that, on average, credit rationing generates a decrease in investment spending. It provides no analysis of who becomes credit constrained and by which bank.

Potential extensions of this paper are as follows. First, one should check out-of-sample forecasting performance of the endogenous variables included in the model. Second, further research could introduce new endogenous variables to complete the model presented here, such as the link between investments and imports. Third, the fiscal optimization strategy of
multinational firms in Luxembourg could pollute the data. One way to overcome this could be to separate multinational firms from the other enterprises in the database.
References


Table A.2: Database description

<table>
<thead>
<tr>
<th>Variable</th>
<th>Source</th>
<th>Unit</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>CONSTFIN</td>
<td>Business Surveys, Industrial Confidence Indicator</td>
<td>%</td>
<td>Percentage of Luxembourgish firms that consider the financial constraints as the main factor limiting production. Proxy for credit rationing based on a question on financial constraints from the European Commission’s consumer and business survey (see Barkbu et al., 2015).</td>
</tr>
<tr>
<td>BNQSOLVt</td>
<td>BCL</td>
<td>Mio EUR to 1 standard variation</td>
<td>Luxembourgish banking solvency index. Indicator of solvency of the Luxembourgish banks that corresponds to the aggregate return of assets ratio of the national credit institutions plus the aggregate banking capital ratio divided by the standard deviation of the return on assets ratio (Giordana and Ingmar, 2012). The return on asset ratio corresponds to the results before provision of national credit institutions divided by their total asset. The capital ratio corresponds to the capital of the national credit institutions divided by their total assets.</td>
</tr>
<tr>
<td>BONDt</td>
<td>Financial Account of sector 11</td>
<td>Mio EUR</td>
<td>Total real debt securities issued by the Luxembourgish non-financial corporations. Debt securities are all kind of bonds (zero-bonds, covered bonds, etc.). Expressed in volume with the investment deflator.</td>
</tr>
<tr>
<td>CAPI</td>
<td>National Account</td>
<td>Mio EUR</td>
<td>Luxembourgish private and non-financial real stock of capital in machinery and equipment. This variable is obtained by subtracting total stock of capital from the residential capital stock and the stock of capital of public and financial sectors. Expressed in volume with the stock of capital deflator.</td>
</tr>
<tr>
<td>CASHFLOWt</td>
<td>Author calculation</td>
<td>Mio EUR</td>
<td>Real internal financing capacity of the Luxembourgish private non-financial sector. The author subtracts from the gross operating surplus of the private non-financial sector the dividend and the interest rate that the NFCs have to pay. Interest and dividend receivable less interest and dividend payable are available in the national account. The gross operating surplus is calculated from the national accounts database. Expressed in volume with the investment deflator.</td>
</tr>
<tr>
<td>CREDt</td>
<td>BCL</td>
<td>Mio EUR</td>
<td>Total real credit granted by Luxembourgish credit institutions to the national non-financial corporations. Expressed in volume with the investment deflator.</td>
</tr>
<tr>
<td>ECONUNCt</td>
<td>policyuncertainty.com</td>
<td>Index</td>
<td>European Economic Policy Uncertainty: Index based on newspaper articles regarding policy uncertainty. It corresponds to the average number of European newspaper articles that contain a trio of terms pertaining to the economic uncertainty or the policy uncertainty. The index increases when the economic policy uncertainty rises.</td>
</tr>
<tr>
<td>GDPt</td>
<td>National Account</td>
<td>Mio EUR</td>
<td>Real national gross domestic product of Luxembourg.</td>
</tr>
<tr>
<td>INV ESTt</td>
<td>National Account</td>
<td>Mio EUR</td>
<td>Luxembourgish private and non-financial real investments in machinery and equipment. This variable is obtained by subtracting total investment from the residential investment and the investment of the public and financial sectors. Expressed in volume with the investment deflator.</td>
</tr>
<tr>
<td>LEVt</td>
<td>BCL &amp; National account</td>
<td>%</td>
<td>Profit leverage of private and non financial corporations. Share of the credits value to NFCs in the private and non-financial capital stock value in machinery and equipment.</td>
</tr>
<tr>
<td>MARKUPt</td>
<td>National Accounts</td>
<td>%</td>
<td>Profit margin rate of the private and non financial corporations. Indicator of profitability that corresponds to the share of gross operating surplus of NFC in the gross value added of NFC. The gross operating surplus is the surplus generated by operating activities after the labour factor input has been recompensed.</td>
</tr>
<tr>
<td>MARKUPBNQt</td>
<td>National Accounts</td>
<td>%</td>
<td>Profit margin rate of the national banks. This is an indicator of profitability that corresponds to the share of gross operating surplus of national banks in the gross value added of national banks. The gross operating surplus is the surplus generated by operating activities after the labour factor input has been recompensed.</td>
</tr>
<tr>
<td>OUTPUTGAPt</td>
<td>National Account</td>
<td>Mio EUR</td>
<td>Real output gap of the national GDP. It corresponds to the difference between the real national GDP and the real potential GDP. The potential GDP is calculated with the Hodrick-Prescott-Filer. It decomposes a variable into a trend and cycle.</td>
</tr>
<tr>
<td>SPREADt</td>
<td>BCL</td>
<td>% points</td>
<td>The commercial spread is the difference between the weighted average of commercial interest rate with different maturity applied to the Luxembourgish NFCs minus the Euro Area interbank rates EURIBOR 3 months. The weights are calculated with the credits with different maturity.</td>
</tr>
<tr>
<td>TINFCt</td>
<td>BCL</td>
<td>% points</td>
<td>The commercial interest rate is the weighted average of the interest rate with different maturity applied to the Luxembourgish NFCs.</td>
</tr>
<tr>
<td>VABPRVQt</td>
<td>National Accounts</td>
<td>Mio EUR</td>
<td>Real gross value added of private and non-financial corporations. Expressed in volume with the gross value added deflator.</td>
</tr>
<tr>
<td>VSTOXXt</td>
<td>Macrobond</td>
<td>Index in %</td>
<td>VSTOXX, officially Euro Stoxx 50 Volatility Index, is the “Euro area VIX”, i.e. the volatility in the euro area financial market. It measures implied volatility of near term EuroStoxx 50 options, which are traded on the Eurex exchange.</td>
</tr>
<tr>
<td>YIELDCURVQt</td>
<td>BCL</td>
<td>% points</td>
<td>Euro area yield curve. The yield curve is the difference between the long and the short term interest rate in Euro Area.</td>
</tr>
<tr>
<td>AIRSATt</td>
<td>National Account</td>
<td>Mio EUR</td>
<td>Total real amount invested in the airplanes and satellites. Expressed in volume.</td>
</tr>
<tr>
<td>DUMY YYYY QX</td>
<td>Author calculation</td>
<td>Mio EUR</td>
<td>Dummy which takes the value of one in year YYYY and quarter QX and zero otherwise.</td>
</tr>
</tbody>
</table>
Appendix B. The Data

Investments in machinery and equipment exclude residential investments and correspond to the investments in “other buildings and structures,” “total machinery and equipment and weapon system,” “transport equipment,” “ICT equipment,” “other machinery and equipment and weapon systems,” “cultivated biological resources,” and “intellectual property products.”

Appendix C: Unit root and cointegration analysis.

Econometric literature provides several techniques to test for cointegration. The autoregressive distributed lag (ARDL) approach (Pesaran et al., 2001) is used in this paper. Recent studies have shown that the ARDL bounds testing approach to cointegration is preferable to other conventional cointegration approaches such as Engle and Granger (1987) or Hansen (1996). The main strength of the ARDL approach is its flexibility because it can be applied irrespective of whether the underlying regressors are I(0) (purely stationary), I(1) (purely non-stationary), or mutually cointegrated, that is, I(0)/I(1). However, the regressors should not be integrated of order 2. In doing so, the Dickey-Fuller (DF-GLS) unit root test, the augmented Dickey-Fuller (ADF) unit root test and the KPSS stationarity test are applied to make sure that no variable has a 2nd difference order of integration.

C.1. Unit root and stationarity tests

Unit root tests have low power in small samples or when the AR process is close to one but below one. However, the DF-GLS test improves on the power of the ADF test at near stationary autoregressive coefficients when there is a small sample size (Elliott et al., 1996), which is the case in this study. The results of the unit root and stationarity tests are reported in Table C.3. The results show that all the long-term variables are integrated of order one, that is, I(1), except that the interest rate spread (SPREAD) and the yield curve (YIELDCURVE) may be I(0) or I(1). This finding shows that the two latter variables have a mixed order of integration. Interestingly, the statistical tests might have classified some variables that are stationary in theory as being non-stationary, such as the profit margin rate. This result is probably because of the short sample size of 75 observations, implying that there are not enough consecutive cycles because of the crisis. In such a situation, the ARDL bounds testing approach to cointegration is suitable to examine the long-run relationship among the variables. Moreover,
the ARDL technique is more robust and performs better for small size samples than other cointegration techniques (Narayan, 2005).

Table C3: Unit root decision

<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Obs</th>
<th>DFGLS</th>
<th>ADF</th>
<th>KPSS</th>
<th>Conclusion</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>HO: nonstationary</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>level</td>
<td>last diff</td>
<td>level</td>
<td>last diff</td>
</tr>
<tr>
<td>LOG(BNQSOLV)</td>
<td>75</td>
<td>0.50</td>
<td>-4.70***</td>
<td>-0.42</td>
<td>-9.06***</td>
</tr>
<tr>
<td>LOG(BOND)</td>
<td>75</td>
<td>0.08</td>
<td>-5.29***</td>
<td>-1.30</td>
<td>-5.26***</td>
</tr>
<tr>
<td>LOG(CAP)</td>
<td>75</td>
<td>-0.91</td>
<td>-0.61</td>
<td>-1.63</td>
<td>-1.18</td>
</tr>
<tr>
<td>LOG(CRED)</td>
<td>75</td>
<td>1.01</td>
<td>-4.41***</td>
<td>-0.40</td>
<td>-11.08***</td>
</tr>
<tr>
<td>LOG(GDP)</td>
<td>75</td>
<td>1.86*</td>
<td>-2.69</td>
<td>-0.65</td>
<td>-5.57***</td>
</tr>
<tr>
<td>LOG(INVEST)</td>
<td>75</td>
<td>-1.11</td>
<td>-2.05**</td>
<td>-1.75</td>
<td>-12.20***</td>
</tr>
<tr>
<td>LOG(LEV)</td>
<td>75</td>
<td>-0.52</td>
<td>-4.32***</td>
<td>-1.09</td>
<td>-11.07***</td>
</tr>
<tr>
<td>LOG(MARKUP)</td>
<td>75</td>
<td>-1.40</td>
<td>-4.43***</td>
<td>-2.68</td>
<td>-10.65</td>
</tr>
<tr>
<td>LOG(VAPBRVC)</td>
<td>75</td>
<td>1.61</td>
<td>-2.77***</td>
<td>-0.59</td>
<td>-9.60***</td>
</tr>
<tr>
<td>SPREAD</td>
<td>75</td>
<td>-2.66***</td>
<td>-2.57</td>
<td>-3.06**</td>
<td>-4.55</td>
</tr>
<tr>
<td>YIELD CURVE</td>
<td>75</td>
<td>-2.30**</td>
<td>-6.91</td>
<td>-2.41</td>
<td>-6.89***</td>
</tr>
</tbody>
</table>

T-statistics: * p < 0.05, ** p < 0.01, *** p < 0.001

C.2. Cointegration ARDL Bound Testing

The critical values tabulated in Pesaran et al. (2001) provide a lower and an upper bound for the null hypothesis of no cointegration. To investigate the existence of a long-run relation, an ARDL regression in error correction form is estimated. Then, a test is performed to check whether lagged levels of the variables are statistically significant. Alternatively, the significance of the coefficient on the error-correction term can be tested. The test statistics follow a non-standard distribution, irrespective of whether the variables included in the model are I(0) or I(1). Pesaran et al. (2001) provide critical values for an F test of the exclusion of the lagged levels and for a t test of the significance of the error-correction term. Depending on whether the variables are I(0) or I(1), the critical values tabulated in Pesaran et al. (2001) provide a lower and upper bound for the null hypothesis of no cointegration. When the test statistic lies below the lower bound, the null hypothesis cannot be rejected; when it lies above the upper bound, the null is rejected; when it lies between the lower and the upper bound, the result depends on whether the variables are I(0) or I(1). The critical values also depend on the characteristics of the deterministic variables, that is, whether a trend or a constant are included in the model and in case of the F test whether the intercepts or the trend coefficients are restricted. The results of the ARDL regression are shown in Table C.4. Columns two to four of Table C.4 show the error-correction coefficients, their t-ratios and the lower and upper bound critical values of Pesaran et al. (2001). The next three columns present the F statistic for the exclusion of the levels of the variables and the respective upper and lower critical values from
Pesaran et al. (2001) and from Narayan (2005) with 75 observations. All estimated models show a significantly negative error-correction coefficient. The t-statistic exceeds the upper bound in absolute value for all ARDL models. The F statistic always exceeds the upper bound and thus rejects the hypothesis of no level effects in the ARDL specifications. The evidence thus indicates the existence of four stable long-run relations in the ARDL models.

Table C.4: ARDL Bound Testing

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>EC t-stat.</td>
<td>CV Bounds</td>
<td>F-stat.</td>
</tr>
<tr>
<td>LOG(INVEST1)</td>
<td>-0.29</td>
<td>[-2.88; -3.78]</td>
<td>4.19</td>
</tr>
<tr>
<td>LOG(RED1)</td>
<td>-0.21</td>
<td>[-2.88; -3.78]</td>
<td>5.75</td>
</tr>
<tr>
<td>SPREAD1</td>
<td>-0.31</td>
<td>[-2.88; -3.22]</td>
<td>24.52</td>
</tr>
<tr>
<td>LOG(BNQSOLV1)</td>
<td>-0.21</td>
<td>[-2.88; -3.53]</td>
<td>10.08</td>
</tr>
</tbody>
</table>

The first column shows the error correction term from the ARDL regression. The columns 3 to 4 show the error-correction term's t-ratio and the lower and upper bound of the associated critical values at the 5% significance level. The next three columns give the F-statistic for exclusion of the levels variables and the respective upper and lower critical value bounds of Pesaran et al. (2001) and Narayan (2005) with 75 observations at the 5% significance level.

Appendix D: Comparison of the long-term equations with Glocker (2016)

Table D.5: Comparison of long term equations

<table>
<thead>
<tr>
<th>Investment equation</th>
<th>Baseline</th>
<th>Glocker</th>
<th>Credit equation</th>
<th>Baseline</th>
<th>Glocker</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOG(VAE1)</td>
<td>1</td>
<td>1</td>
<td>LOG(CAP1)</td>
<td>1.228</td>
<td>2.21</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[0.293]</td>
<td></td>
<td>[NA]</td>
</tr>
<tr>
<td>LOG(RED1)</td>
<td>0.146</td>
<td>0.50</td>
<td>SPREAD1</td>
<td>-0.226</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>[0.072]</td>
<td>[NA]</td>
<td>[0.042]</td>
<td></td>
<td>-</td>
</tr>
<tr>
<td>LOG(MARKUP1-1)</td>
<td>1.392</td>
<td>-</td>
<td>SPREAD1</td>
<td>-0.96</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>[0.453]</td>
<td></td>
<td>[NA]</td>
<td></td>
<td>-</td>
</tr>
<tr>
<td>LOG(BOND1)</td>
<td>0.092</td>
<td>-</td>
<td>LOG(BNQSOLV1)</td>
<td>0.479</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>[0.026]</td>
<td></td>
<td>[0.233]</td>
<td></td>
<td>-</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Spread equation</th>
<th>Baseline</th>
<th>Glocker</th>
<th>Banking solvency equation</th>
<th>Baseline</th>
<th>Glocker</th>
</tr>
</thead>
<tbody>
<tr>
<td>LOG(LEV1-1)</td>
<td>0.614</td>
<td>0.15</td>
<td>LOG(PB1-1)</td>
<td>2.149</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>[0.279]</td>
<td>[NA]</td>
<td>[0.083]</td>
<td></td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>RISK MKT</td>
<td>0.094</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>[0.012]</td>
<td></td>
<td>-</td>
</tr>
</tbody>
</table>

Standard error in brackets. "Baseline" corresponds to the long-run regression of this paper and "Glocker" refers to the long term equation of Glocker (2016)