Stress Testing: The Impact of Shocks on the Capital Needs of the Luxembourg Banking Sector

Abdelaziz Rouabah*
John Theal*

ABSTRACT

We use data on loan loss provisions and total loans over the period spanning 1995 until 2009 to estimate a stress testing model for the Luxembourg banking sector. The sample encompasses the recent global crisis and covers a period in which the average probability of default of the Luxembourg banking sector's counterparties is observed to increase significantly. A joint model, consisting of several macroeconomic variables and the logit-transformed probability of default, is specified and estimated via seemingly unrelated regression (SUR). The results suggest that counterparty default rates are significantly affected by the euro area real GDP growth rate, the real interest rate and a domestic property price index. Conversely, changes in the Luxembourg real GDP growth rate have a much smaller effect on counterparty risk. We attribute this to the large number of foreign subsidiaries operating within Luxembourg. The estimated model is then used to simulate values of the probability of default and the macroeconomic variables over a horizon of 10 quarters. This allows us to construct distributions for the probability of default under both baseline and adverse scenarios. From the results of these simulations stressed Basel II tier 1 capital ratios are calculated and compared to their associated unstressed capitalization levels. Our calculations suggest that, under all the given adverse macroeconomic scenarios, the aggregate Luxembourg financial sector remains above the 4% minimum Basel II tier 1 capital requirement. Repeating the exercise on a limited sample of 5 individual banks produces similar results.

JEL classification: C15, E44, G01, G21
Keywords: financial stability; stress testing; Luxembourg banking sector; tier 1 capital ratio; counterparty risk

* Financial Stability Department

I. Introduction

In its broadest sense, macro stress testing refers to a range of techniques employed in generating both baseline and adverse scenarios that can be used to gauge the response of a financial system to "exceptional but plausible" shocks in the prevailing macroeconomic conditions. While stress tests are garnering much attention in the post-crisis period, they are not a recent innovation. The origins of programs directed at monitoring the solidity of the financial system date back to the late 1990's and arose from the IMF and World Bank Financial Sector Assessment Programs, or FSAPs. The FSAP programs were originally orientated towards macro-prudential surveillance, but they also contained elements of micro-financial linkages. These programs contributed to the development of the present financial regulations, supervisory frameworks and payment systems. In effect they were a kind of prototypical macro-prudential surveillance program. Nevertheless, these early supervision frameworks were not without deficiencies. As Blaschke et al. (2001) explain there are weaknesses in many aspects of the stress testing process. One important limitation in the FSAP program was that the adverse scenarios employed in the testing were largely *ad hoc*. This was complicated, in some cases, by a lack of adequate data, time and/or resource constraints and a lack of expertise needed to conduct the tests. Finally, fewer than 50% of the FSAP programs incorporated an analysis of the resistance of the banking sector to liquidity shocks and yet it is known that liquidity crises can cause major disruptions to the stable operation of the financial markets.

Although many authorities adopted stress testing procedures as a result of the implementation of the Financial Sector Assessment Programs, the IMF and World Bank were not the only institutions to advocate stress tests as a technique to assess financial stability. Stress testing for risk management purposes also features prominently as a pillar in the Basel II regulations. Supervisory authorities and central banks increasingly view macroeconomic stress tests as a valuable tool for assessing the vulnerability of the financial system. This is true in the euro area where stress testing exercises have been conducted by the ECB and European supervisory authorities such as the Committee of European Banking Supervisors (CEBS) and many national central banks (NCBs). However, these exercises are not performed solely to evaluate the level of financial robustness; they are also used to identify any potential vulnerability in the financial system. As nowadays the financial system extends globally, stress testing programs and efforts at the international level are being undertaken. Initiatives to try and establish an international agreement on a macro-prudential surveillance framework are ongoing. Nevertheless, there is currently no single internationally accepted standard procedure for stress testing. Currently there is a need for comprehensive and effective stress testing models.

One of the striking aspects of the recent crisis was that it was the regulated financial institutions that turned out to be the source of much of the turmoil. Exacerbating this problem was that excessive supervisory attention was given to firms at the individual level, while the build-up of risks in entire sectors and markets was, for the most part, ignored. As discussed in Borio (2009), it is now recognized that the development of systemic risk at the aggregate level is just as important, if not more so, than the accumulation of risk at the level of the individual institution. The unfortunate oversight of this observation in the period prior to the turmoil underscores the deficiencies that were present in the pre-crisis supervisory framework. In particular, regulators focused on micro-prudential supervision to the detriment of developments at the macro-prudential level. The outcome was that, in the wake of the crisis, significant costs were imposed on both the public sector and the macro economy in order to rescue the banking sector. This resulted in profits being privatized while losses were socialized effectively creating no downside risks for banks. From a stability perspective, it was this lack of a robust regulatory structure that permitted the creation of channels for the transmission of contagion and the correlated, or horizontal, risks that played such a prominent role in the development of the crisis.

In order to rectify these deficiencies, under the mandate of the European Commission, the de Larosière Group (2009) proposed that the ECB should pursue a more prominent role in "*over-seeing the macro-prudential aspects of banking activities*" and subsequently recommended that stress-testing should be performed on a consistent and regular basis[1]. This proposed routine monitoring activity is important because systemic risk arises from the common exposures of many financial institutions to identical risk factors and can accumulate across institutions and through time. As the recent crisis showed, episodes of financial instability can impose large costs on the real economy and disrupt economic growth.

For these reasons, it is imperative that macro-prudential analysis attempts to analyze and detect the risk of common or correlated shocks which could trigger contagion and/or feedback effects. As noted in Borio (2009), it is this failure to account for these common exposures and endogenous risks that may promote financial instability. Since the goal of supervision is to detect problems at an early stage, and thereby avoid crises, stress-testing is one particular tool that supervisory authorities can employ as an early detection mechanism.

[1] The de Larosière Group report, page 20.

II. Stress Testing Methodologies

According to Sorge (2004) there are two main methodological categories of stress testing: the "piecewise approach" and the "integrated approach". The piecewise approach entails evaluating the susceptibility of the financial sector to individual macroeconomic factors. These risk factors are subsequently used to forecast financial soundness indicators (FSIs) under various macroeconomic scenarios. Possible indicators include such variables as non-performing loans, capital ratios and various other risk exposures[2]. The models commonly employed are usually reduced-form or structural in nature and time series or panel data are used for the estimation procedure. In terms of their specification, linear functional forms are commonly utilized. As a result, the piecewise approach has the benefit of a low computational burden along with the ability to provide a broad characterization of the stressed scenario by incorporating financial soundness indicators. Including these soundness indicators in the stress testing model permits a better overall assessment of the vulnerability of the financial sector to exogenous macroeconomic shocks. Studies using the piecewise approach include Hanschel and Monnin (2005), who construct a stress index of the Swiss banking system, and Kalirai and Scheicher (2002) who use loan loss provisions to assess vulnerabilities in the Austrian banking system.

Rather than using individual FSIs, the integrated approach combines both market and credit risk analysis to produce an estimate of a portfolio loss distribution. Models of this class were first explored by Wilson (1997a), (1997b). The benefit of this method is that it is able to capture any non-linear effects that macroeconomic shocks may exert on credit risk. Furthermore, shifts in the loss distribution are driven by the effect of macroeconomic shocks on the individual risk components. However, these models mainly focus on short-horizon credit risks and tend to inadequately capture feedback effects which may result in parameter instabilities over the long-term. Nonetheless, in this work, to evaluate the response of the Luxembourg banking sector to a series of adverse macroeconomic scenarios, the integrated approach is employed. The particular approach used is based upon the stress testing framework published by Wong, Choi and Fong (2008), who implement a SUR system in order to capture correlation in the cross-equation residuals. During the simulation of the adverse scenario, the SUR specification allows them to impose the characteristic historical correlation pattern on the macroeconomic variables and the financial soundness indicator which, in their case, is taken to be the probability of default.

It is worth mentioning that DSGE models have, recently, been increasingly used to study financial fragility. Goodhart et al. (2006), (2009) propose a heterogeneous agent model

[2] See Appendix 1 of Sorge (2004) for an extensive list.

with endogenous default and liquidity. This allows them to capture the short to medium-term effects of endogenous default on the financial sector. Since this amounts to introducing frictions, their model can be used as a tool for studying the effects of monetary, productivity and fiscal policy shocks on the level of financial stability. Dib (2009) uses a micro-founded DSGE framework that incorporates an interbank market. In the context of this approach, bank behaviour is able to influence credit supply conditions and the transmission of shocks. Via the supply and demand sides of credit the model is also able to incorporate frictions. In the presence of these frictions, policy effects on bank capital regulations, endogenous defaults and the degree of leverage in the system can be analyzed using policy simulations. Finally, using a heterogeneous banking sector, de Walque et al. embed an interbank market in a standard RBC model. This allows them to show that liquidity injections act to reduce financial instability. They also are able to confirm the procyclicality of the Basel II regulations.

Empirically based index models such as those of Hanschel and Monnin (2005), Illing and Liu (2006) and Rouabah (2007) have also been proposed. This class of models is generally based on balance sheet and market quantities and provides a measure of stress, or vulnerability, in the form of a composite index. This allows for the identification of periods of increasing or elevated stress in the financial sector. There is, however, some concern as to whether or not these index-based indicators can uniquely capture rising risks in the financial system as they generally consider stress to be a deviation of an indicator variable from its long-run mean. Consequently, uncertainty in the model specification and neglect of the higher moments (i.e. skewness) in the weighting of the index components remain important issues that need to be addressed by future research.

III. The Model

To stress test the Luxembourg banking sector, we implement an integrated model, in the sense of Sorge (2004), and similar in form to that of Wong et al. (2008); but with some key differences. In particular, our specification consists of a joint system of equations that incorporates lagged values of the endogenous variables. This jointly specified system allows us to simultaneously model both default probabilities and macroeconomic variables. The advantage of this is that it is able to account for interactions and feedback effects between the macroeconomic environment and the aggregate probability of default. This further permits us to simulate a distribution of probabilities of default conditional on a given adverse scenario. By including lags of the exogenous variables, this specification also allows us to capture the persistence of shocks to the macroeconomic variables. This is a direct result of the presence of lagged values of the independent variable in the regression equations. The implication is that defaults across different economic sectors can be correlated and macroeconomic variables may become mutually dependent. However, our Monte Carlo simulations diverge from Wong et al. (2008) as we use the simulated adverse scenarios to calculate stressed Basel II tier 1 capital requirements, whereas they estimate credit losses. In this respect we mirror the ECB study on "*The Credit Cycle and its Impact on EU Banking Stability*"[3].

A multivariate macroeconomic model is used to estimate default rates for the counterparties of the Luxembourg banking sector. Within this framework, the model is able to produce an estimate of the likely shift in the distribution of default rates under various adverse macroeconomic scenarios. This is classed as a top-down approach that links changes in the macroeconomic environment to the aggregate counterparty probability of default. The advantage of the top-down stress test over the bottom-up test is that it applies the same testing procedure to all banks rather than testing on a bank by bank basis. Nonetheless, nothing impedes us from applying the method to individual banks and we perform such an exercise in section VI. However, the disadvantage is that the stress test must be based on historical data and, subsequently, historical relationships between the probability of default and macroeconomic conditions. Consequently, we may not capture the complete spectrum of risks facing banks' current portfolios but it nevertheless allows us to simulate the impact of other sectors' defaults on the Luxembourg banking sector. In turn, these results can be used to calculate Basel II tier 1 capital ratios.

Estimation of the model was conducted using a seemingly unrelated regression (SUR) system in order to capture any contemporaneous correlation in the cross-equation residuals. Within this multivariate framework, the model is able to produce an estimate of the likely shift in the distribution of default rates under various adverse macroeconomic scenarios. Since data on the aggregate default rate of Luxembourg banking sector counterparties was unavailable, it was necessary to construct a time series of historical probabilities of default. To estimate the probability of default an aggregate balance sheet was constructed using a ratio of provisions on loans to total loans over all sectors. This ratio was used as an approximation for the aggregate probability of default, thereby providing a metric for assessing the vulnerability of the Luxembourg financial system to various adverse macroeconomic scenarios. Though provisioning provides an estimate of the probability of default, it is important to recognize that loan loss provisions are an imperfect approximation for default rates over the business cycle. Specifically, provisioning is considered tax deductible in some countries and therefore loan loss provisions may only partially reflect credit risk concerns and the

[3] European Central Bank, "*The Credit Cycle and its Impact on EU Banking Stability*", (2009)

true degree of loan impairments. Indeed, loan loss provisions themselves can, in some cases, be used in order to meet regulatory capital requirements. Additionally, both of these series are considered to be backward-looking, so the results of the test should therefore be interpreted with some care. Nonetheless, the default probabilities can be related to a comprehensive and joint system of macroeconomic variables that links the fundamental economic environment to the vulnerability of the banking sector as a whole.

The historical probability of default series consists of quarterly observations over the period from the first quarter of 1995 until the third quarter of 2009 resulting in a total of 59 observations over a 14 year period. Since p_t is a probability, and therefore lies in the fixed interval $[0,1]$, a logit transform, given by equation (1), is applied:

$$y_t = \ln\left(\frac{1-p_t}{p_t}\right) \quad \textbf{(1)}$$

Note that y_t and p_t are inversely related to one another. Equation (1) transforms p_t such that y_t takes on values in the interval $-\infty < y_t < \infty$. We assume that the dynamics of y_t are governed by a set of macroeconomic variables both foreign and domestic in origin. Figure 1 shows the evolution of the counterparty default probability over the period from 1995 until 2009. The increase in counterparty risk corresponding to the crisis period can be clearly seen in the latter half of the chart.

[Figure 1 about here]

In detailed terms, the macroeconomic model consists of a joint system of six linear equations for the probability of default, the growth rate of Luxembourg GDP, the euro area real GDP growth rate, the real interest rate, the change in real property prices, and returns on the SX5E index. This specification allows for feedback effects between the probability of default series and the evolution of the macroeconomic variables. In particular, using one or two lags of the endogenous variables in the regression allows for the persistence and transmission of exogenous shocks through the system. Through the SUR specification, the probability of default can be related to a group of macroeconomic variables thereby linking the fundamental economic environment to the vulnerability of the banking sector as a whole. Any correlation between shocks is captured by the variance covariance matrix of the residual series. This matrix is used to impose the characteristic correlation structure on the macroeconomic variables when conducting the Monte Carlo simulations.

The equations for the probability of default and the macroeconomic variables are given by equations (2) and (3), respectively:

$$\mathbf{y}_t = \mathbf{m} + \mathbf{A}_1\mathbf{x}_t + \ldots + \mathbf{A}_{1+s}\mathbf{x}_{t-s} + \mathbf{\Phi}_1\mathbf{y}_{t-1} + \ldots + \mathbf{\Phi}_k\mathbf{y}_{t-k} + \mathbf{v}_t \quad \textbf{(2)}$$

$$\mathbf{x}_t = \mathbf{n} + \mathbf{B}_1\mathbf{x}_{t-1} + \ldots + \mathbf{B}_p\mathbf{x}_{t-p} + \boldsymbol{\varepsilon}_t \quad \textbf{(3)}$$

In our case, $\mathbf{y}_t$ is 1×1, $\mathbf{x}_t$ is an $M\times1$ vector of M macroeconomic variables, $\mathbf{A}_{1+s}$ is $1\times M$, and $\mathbf{\Phi}_k$, $\mathbf{y}_{t-k}$ and $\mathbf{v}_t$ are scalars. Finally, $\mathbf{B}_p$ is an $M\times M$ coefficient matrix and $\boldsymbol{\varepsilon}_t$ is an $M\times1$ vector of independent and identically normally distributed disturbances. The variance covariance matrix, $\mathbf{E}$, is given by:

$$\mathbf{E} = \begin{pmatrix} \mathbf{v} \\ \boldsymbol{\varepsilon} \end{pmatrix} \sim N(\mathbf{0}, \mathbf{\Sigma}), \quad \mathbf{\Sigma} = \begin{bmatrix} \mathbf{\Sigma}_{\mathbf{v}} & \mathbf{\Sigma}_{\mathbf{v},\boldsymbol{\varepsilon}} \\ \mathbf{\Sigma}_{\mathbf{v},\boldsymbol{\varepsilon}} & \mathbf{\Sigma}_{\boldsymbol{\varepsilon}} \end{bmatrix} \quad \textbf{(4)}$$

This specification allows for feedback effects between the probability of default series and the evolution of the macroeconomic environment thereby making the probability of default dependent on the chosen macroeconomic variables. Incorporating lagged values of the dependent variables allows for the persistence and transmission of exogenous shocks through the system. This approach has some advantages over the standard VAR models as used, for example, in Hoggarth, Sorensen and Zicchino (2004) and Filosa (2007) which ignore the contemporaneous correlation between the residuals. This naïve VAR system may cause the estimated coefficients to be biased in addition to ignoring tail effects. Fong and Wong (2008) have addressed this latter issue by estimating an MVAR model which uses a mixture of Gaussian distributions to better capture tail effects. Notwithstanding these alternative approaches, the SUR estimation allows for the extraction of the variance covariance matrix of the residual series. In turn, this can be used to impose the characteristic correlation structure on the evolution of the macroeconomic variables when conducting the Monte Carlo simulations. In this context, the SUR system provides a parsimonious modeling of the relationship between the counterparties' probability of default and the prevailing macro environment.

IV. Model Estimation

The SUR system is derived from equations (2) and (3) and consists of six equations[4] which are jointly estimated over the sample period. Econometrically, the

[4] In this case there is one equation for the probability of default and five equations for the respective macroeconomic variables.

macroeconomic time series are required to be stationary so the first differences of the log of Euro area and Luxembourg real GDP along with the first differences of the series for real property prices are employed in the estimation. Consequently, the GDP series are expressed in terms of growth rates while the SX5E data is expressed as index returns. The coefficients of the estimated SUR model are presented in Table 1.

[Table 1 about here]

The table reports coefficient estimates, and missing entries in the table signify that these variables were not included in the equation specifications. The signs of the coefficients appear appropriate for the expected dependence of the probability of default on the selected macroeconomic variables. It is clear that increases in the growth rate of both Luxembourg and Euro area GDP result in an increase of y_t, which is inversely related to the probability of default. Correspondingly, within the context of the model, a decrease in Euro area or Luxembourg economic growth could result in a positive increase in the probability of default of the Luxembourg banking sector counterparties. A similar effect can be observed for the property price index, although the regression coefficient shows a considerable amount of uncertainty. Finally, an increase in the real interest rate will negatively impact y_t resulting in a positive increase in the probability of default. Additionally, the lagged probability of default coefficient is positive and significant which suggests that autocorrelation in the probability of default series will result in exogenous shocks persisting for a time horizon exceeding the duration of the shock. The same observation holds for the macroeconomic variable equations. Therefore, the model correctly captures the expected dynamics between the macro-economy and the probability of default.

V. Monte Carlo Simulation and Stress Testing

Once estimated, the model can be used to gauge how the probability of default of counterparties responds to exogenous shocks in the macroeconomic environment. To predict the response of the system, we can use a Monte Carlo simulation to generate both a baseline and a conditional adverse scenario for the probability of default. The baseline scenario is constructed by first drawing a random sample from a standard normal distribution. In order to impose the model-specific correlation pattern on the simulation, this random vector $\boldsymbol{\zeta}_t$ of normal variates and dimension $(M+1)\times 1$ is pre-multiplied by the Cholesky decomposition of the residual variance covariance matrix $\boldsymbol{\Sigma}$, estimated from the SUR system. This gives a matrix $\mathbf{C}$ such that $\Sigma = \mathbf{CC}'$. This procedure produces a pseudo-random vector $\mathbf{r}$ of correlated disturbances which is added to the equations via $\mathbf{v}_t$ and $\boldsymbol{\varepsilon}_t$ defined in the regression model. Effectively, this is given by $\mathbf{r}_t = \mathbf{C}'\boldsymbol{\zeta}_t$. Through recursion of equations (2) and (3) it is therefore possible to generate simulated forward values of both the probability of default and the macroeconomic variables over some finite horizon period. The end result of this process is that a distribution of the probabilities of default can be constructed. The distribution thus generated can subsequently be considered as the baseline scenario.

The adverse scenario is constructed in a similar manner, except that at various periods throughout the simulation horizon exogenous shocks are applied to the individual macroeconomic variable equations. Consequently, the distribution, conditional on the shocks, of the adverse scenario probability of default is governed by the dynamics of the macroeconomic variables in combination with the persistence of the shocks induced by the lagged specification of the model. This ability to generate two separate distributions for the probability of default allows for comparison of the estimated baseline and adverse scenarios when an artificial and exogenous shock is applied to a particular macroeconomic variable. The application of the exogenous shocks to the variables of the model allows us to analyze the sensitivity of the probability of default distribution to specific adverse macroeconomic developments. Thus, under this type of deterministic approach, the response of the distribution can be evaluated for more complex macroeconomic scenarios. In any case, comparing the distributions provides information on the probable impact of macroeconomic shocks on the probability of default and can thus the procedure can be considered as a form of stress test.

In order to perform the actual stress test, we must decide on some exceptional but plausible stressed scenarios. It is the selection of these scenarios that lies at the heart of a stress test. It is critical that the scenarios selected are neither too extreme nor too mild in their impact on the system because if the exogenous shocks are chosen inappropriately then the exercise will provide no relevant insight.

Four different stressed scenarios were employed with shocks being applied individually to the selected macroeconomic variables. The scenarios were chosen in order to focus on the various aspects of the transmission mechanism between the macroeconomic environment and the counterparty credit risk of the Luxembourg banking sector. The four specific scenarios include both domestic and EU level effects and are taken over a horizon of 9 quarters starting in 2009 Q3 and ending in 2011 Q4. The scenarios are comprised of the following:

1. A decrease in Luxembourg's real GDP growth of magnitude 4% starting in 2010 Q1 and ending in 2010 Q4
2. A decrease in Euro area real GDP growth of magnitude 1% for the first two quarters of 2010, magnitude of 0.5% in Q3 and no shocks in the subsequent quarters
3. An increase in real interest rates of 200 basis points in the first quarter of 2010 and a further increase of 100 basis points in 2010 Q3
4. A reduction in real property prices of magnitude 2% in 2010 Q1 and subsequent losses of 2% over the remaining quarters of 2010

Shocks of this magnitude represent particularly severe disturbances. It is important to note that if the shocks are too small, the test will provide no insight into the possible impact on the probability of default. Conversely, if the shocks are too large in magnitude, then the probability of such an event occurring would be too small and the testing exercise risks being uninformative. All shocks are applied on a quarter-to-quarter basis over the separate scenarios. For both the baseline and adverse scenarios we performed 10000 Monte Carlo simulations of the model and used the 10000 simulated probabilities of default in the last quarter of 2011 to construct the histograms. A sample of simulated default paths is shown in figure 2 while the actual simulation results for the four scenarios are displayed in figures 3 through 6.

[Figure 2 about here]

[Figure 3 about here]
[Figure 4 about here]
[Figure 5 about here]
[Figure 6 about here]

For all scenarios, the histograms exhibit a characteristic shift to the right of the stressed distribution, indicating that the average probability of default under the adverse scenario increases relative to the baseline scenario. An associated increase in the standard deviation is also observed along with increased weight in the tails of the distributions. For the shock to Luxembourg real GDP growth, the mean probability of default increases from 1.31% to 1.46% under the adverse scenario. For the remaining scenarios the increase is from 1.31% to 1.62% for Euro area real GDP growth, 1.31% to 1.58% for an increase in the real interest rate and from 1.31% to 1.61% under shocks to Luxembourg real property prices. Tail probabilities under the stressed scenario rarely exceed 3.5% and no scenario displays probabilities of default in excess of 4%. Despite the severity of the scenarios, the results for the selected adverse scenarios suggest that exogenous shocks to fundamental macroeconomic variables have a limited and somewhat mild effect on the average probability of default.

The results of the Monte Carlo simulation can also be used to gain insight into the capitalization level of the entire Luxembourg banking sector. Using equations (5) and (6) for capital requirements for corporate exposures and Basel II tier 1 capital ratios, respectively, it is possible to calculate capital requirements under the adverse scenario.

$$k_c^* = \left(LGD \times N\left[\frac{G(PD)}{\sqrt{(1-R_c)}} + \left(\frac{R_c}{(1-R_c)} \right)^{\frac{1}{2}} \times G(0.999) \right] - PD \times LGD \right) \times \left(\frac{1}{1-1.5b} \right) \quad \textbf{(5)}$$

$$capital\ ratio = \frac{K+\Pi}{RWA - 12.5E^c\left(k_c - k_c^*\right)} \quad \textbf{(6)}$$

In equation (5), $G(PD)$ represents the inverse normal distribution with the probability of default, PD, as its argument. Here $N(\cdot)$ is the cumulative normal distribution, R_c denotes asset correlation and b is the maturity adjustment. The asterisk superscript on k denotes capital requirements under the stressed scenario. In equation (6), K denotes tier 1 capital, Π and RWA denote profit and risk weighted assets, respectively, and E^c represents corporate exposures. In equation (6) we do not specify a profit model; rather we assume that profits remain static.

This is an informative stress test in that it provides information on capitalization ratios under adverse macroeconomic conditions. To calculate the capital ratio, we use data on bank profitability, risk weighted assets, loans and the amount of tier 1 capital held by banks. As the entire sector is studied, it is important to stress these values represent average quantities. Throughout the analysis, the loss given default (LGD) is assumed to be 0.5, or 50%, and a maturity adjustment is used based on the Basel II regulations for risk-weighted assets for corporate, sovereign and bank exposures. The mean value of the 10000 probability of default values obtained from the Monte Carlo simulation is used during the calculation of the Basel II correlation and capital requirements.

Figure 7 presents a bar chart showing the banking sector capital ratios under the four stressed scenarios in comparison to the baseline scenario.

[Figure 7 about here]

The horizontal line in the figure represents the Basel II minimum capital requirement of 4% while the bar on the extreme left shows the capitalization ratio of the baseline scenario. Shocks to Luxembourg real GDP growth evidently have little impact on bank capitalization levels, while shocks to the remaining variables, and especially Euro area real GDP growth, visibly impact capital ratios in comparison to the baseline scenario. Indeed, in the Euro area real GDP case the tier I capitalization ratio decreases from 11.7% to 6.4%.

VI. Study of Five Systemic Luxembourg Banks

In addition to the aggregate results of the Luxembourg banking sector, the simulations were repeated for a study involving the five largest and most systemic banks operating in Luxembourg. These banks were ranked based on total assets. Table 2 shows their tier 1 capital ratios for both the baseline and adverse scenarios under a Basel II regime while figure 8 shows the related histogram for a selected bank. The capital ratios under the adverse scenario are evaluated under conditions in which the four macroeconomic variables of the model are independently subjected to shocks. These stressed scenarios are identical to the scenarios used for the aggregate sector model.

[Table 2 about here]

[Figure 8 about here]

From table (2) it is clear that all 5 banks in the sample are able to retain a tier 1 capital ratio above the minimum accepted level of 4%. However, adverse shocks to the Euro area real GDP growth rate and a decline in the Luxembourg property price index preferentially affect capitalization ratios compared to shocks applied to Luxembourg's GDP growth rate and the real interest rate. Despite the decreases in capital buffers resulting from a decrease in the real GDP growth rate of the Euro area, banks in the sample exhibit capital ratios comfortably above the 4% minimum. Indeed, Banks 1 and 4 appear quite robust under all adverse scenarios considered. Individual bank performance notwithstanding, it is evident that the banks in the sample are most vulnerable to decreases in the euro area GDP growth rate, followed by falls in the property price index. These variations in tier I capital ratios can be attributed primarily to the respective levels of exposure of an individual bank.

VII. Some Remarks on What the Stress Tests Do Not Provide

As mentioned in Jones, Hilbers and Slack (2004), stress tests can "*provide information on how much could be lost under a given scenario, but not how much is likely to be lost*". The results of a stress test then are a numerical estimate of sensitivity conditional on a given set of adverse macroeconomic conditions and allow us to understand the sensitivity of a financial system to various risk factors. In the absence of a formalized selection criterion for the adverse scenario, a series of assumptions and judgments must be made in determining the exceptionality and plausibility of the shocks. Naturally, this introduces a wide margin of error into the testing results and they must consequently be interpreted with care. This is true even more so if the data is aggregated over the entire sector rather than being at the level of an individual bank.

Typically stress testing exercises are performed at the level of a subset of institutions that comprise the financial sector. However, such a specification ignores the complex linkages and feedback mechanisms present in financial systems although some studies on contagion such as Degryse and Nguyen (2004) and Gropp and Vesala (2004) have attempted to fill this gap. Depending on the nature and origins of financial turmoil, this can be a considerable disadvantage as we have seen during the recent crisis that these connections and channels can play a primary role in the unfolding of an episode of financial instability. Additionally, system-focused tests tend to aggregate a number of heterogeneous banks into a single financial system. This is not as robust as a test conducted at the individual level and requires that dissimilar banks are analyzed in an identical manner. For these reasons, system level stress tests are designed to complement individual bank tests rather than to replace them. However, in practice, system level tests are more tractable in both and analytical and computational sense. One advantage is that the result of a system-wide test can convey information regarding possible contagion and the potential effects on stability for the entire financial sector. Nevertheless, it remains that conducting tests at *both* the individual and aggregated level provides the maximum amount of information about the vulnerability of the financial system to economic shocks.

Another limitation of stress tests is that they do not take into account endogenous actions by financial institutions or monetary authorities. While such an assumption may be valid in the short-term, in the long-run this is clearly unrealistic and an oversimplification. When stressed, financial institutions will readjust their balance sheets by selling distressed assets or rebalancing portfolios as part of their normal risk management activities. Additionally, central banks and governments will intervene during crisis either through monetary policy or more exceptional measures as was observed during the most recent period of instability. These effects, of considerable importance to the promotion of financial stability, are not captured by the types of econometric models employed in stress testing. Consequently, the actual response of the financial system to an exogenous shock may be quite different than the outcome predicted by a stress test.

It is possible to apply a formal method for adverse scenario selection such as that discussed in Breuer, Jandačka, Rheinberger and Summer (2009). The authors propose the use of the Mahalanobis distance as a measure of the plausibility of an adverse shock. This metric is given by equation (7):

$$Maha(\mathbf{r}) := \sqrt{(\mathbf{r}-\boldsymbol{\mu})^T \cdot Cov^{-1} \cdot (\mathbf{r}-\boldsymbol{\mu})} \qquad (7)$$

where $\mathbf{r}$ is the test scenario and $\boldsymbol{\mu}$ is the mean or center of mass representing an average scenario. This measure thus represents the number of standard deviations by which $\mathbf{r}$ exceeds $\boldsymbol{\mu}$, taking into account the correlation structure between the risk factors. The interpretation is rather intuitive and suggests that a large Mahalanobis distance represents a low plausibility of the scenario, $\mathbf{r}$. Although we could apply such a formalized method, we choose some plausible scenarios by keeping in mind the limitations of selecting the scenarios in the absence of a formalized method. It is important to note that such an *ad hoc* selection method could result in the omission of some plausible adverse scenarios. The end result is that while we might be selecting an adverse scenario, *it may not be either the most plausible or most plausibly adverse scenario*. Thus, there may be in existence some more plausible and even more harmful scenarios than those selected for this study.

VIII. Conclusion

Despite some heterogeneity amongst the capital ratios computed for the panel study, overall the results suggest that, in the aggregate, Luxembourg banks would possess a tier 1 capital buffer sufficient to absorb the macroeconomic shocks studied in this stress-testing exercise. More specifically, Basel II tier 1 capital ratios would remain comfortably above the current regulatory minimum of 4% under all the adverse macroeconomic scenarios considered. Luxembourg's banking sector therefore appears well positioned to deal with any further adverse macroeconomic developments. However, it should be noted that there are some limitations to this study. First, loan loss provisions are an imperfect proxy for the probability of default. Secondly, we have assumed that banks' balance sheets remain static and do not respond to changes in the macroeconomic conditions. This is obviously unrealistic. Lastly, we lack a suitable profit model for banks and therefore, throughout the simulation horizon, we have assumed that bank profits remain static. These limitations strongly point towards areas of potential future research that could help to improve upon the quality of the model.

References

Basel Committee on Banking Supervision. (2004) "International convergence of Capital Measurement and Capital Standards: A Revised Framework"

Blaschke, Winfrid, Matthew T. Jones, Giovanni Majnoni and Soledad Martinez Peria. (2001). "Stress Testing of Financial Systems: An Overview of Issues, Methodologies, and FSAP Experiences", *IMF Working Paper* 01/88.

Borio, C. (2009). "Implementing the macroprudential approach to financial regulation and supervision.

Breuer, T., Martin Jandačka, Klaus Rheinberger, and Martin Summer. (2009). "How to Find Plausible, Severe, and Useful Stress Scenarios", *International Journal of Central Banking*, Vol. 5, No. 3, September, pp 205-224.

de Walque, G., O. Pierrard and A. Rouabah. (2008). "Financial (In)Stability, Supervision and Liquidity Injections: A Dynamic General Equilibrium Approach", *Banque centrale du Luxembourg*, Working Paper No. 35, October.

Degryse, H. and G. Nguyen. (2004) "Interbank Exposures: An Empirical Examination of Systemic Risk in the Belgian Banking System"

Dib, A. (2009). "Banks, Credit Market Frictions, and Business Cycles", *Bank of Canada Working Paper*.

Filosa, R. (2007). "Stress testing of the stability of the Italian banking system: a VAR approach", *Working Paper*.

Fong, T. P., and C. Wong. (2008). "Stress Testing Banks' Credit Risk Using Mixture Vector Autoregressive Models". *Hong Kong Monetary Authority Working Paper* 13/2008.

Goodhart, C. A. E., C. Osorio and D. P. Tsomocos. (2009). "Analysis of Monetary Policy and Financial Stability: A New Paradigm", *CESIFO Working Paper*, No. 2885, December.

Goodhart, C. A. E, P. Sunirand and D. P. Tsomocos. (2006). "A Model to Analyse Financial Fragility", *Economic Theory*. 27, 107-142.

Gropp, R. and J. Vesala. (2004). “Bank Contagion in Europe”

Hanschel, E. and P. Monnin (2005). “Measuring and forecasting stress in the banking sector: Evidence from Switzerland”, *BIS papers*, No. 22, pp. 131-449, April.

Hoggarth, G., Steffen Sorensen and Lea Zicchino. (2005). “Stress tests of UK banks using a VAR approach”, *Bank of England Working Paper*, November.

Illing, M. and Y. Liu (2006). “Measuring financial stress in a developed country: An application to Canada”, *Journal of Financial Stability*, No. 2, pp. 243-265.

Jones, M. T., Hilbers, P, and Slack, G. (2004). “Stress Testing Financial Systems: What to Do When the Governor Calls”, *IMF Working Paper* 04/127.

Kalirai, H. and M. Scheicher (2002). “Macroeconomic stress testing: preliminary evidence for Austria”, *Financial Stability Report, Austrian National bank*, no. 3

Larosière, J. de. (2009). “The high-level group report on financial supervision in the EU”.

Rouabah, A. (2007). “Mesure de la vulnérabilité du secteur bancaire luxembourgeois”, *Banque centrale du Luxembourg Working Paper*, No. 24, April.

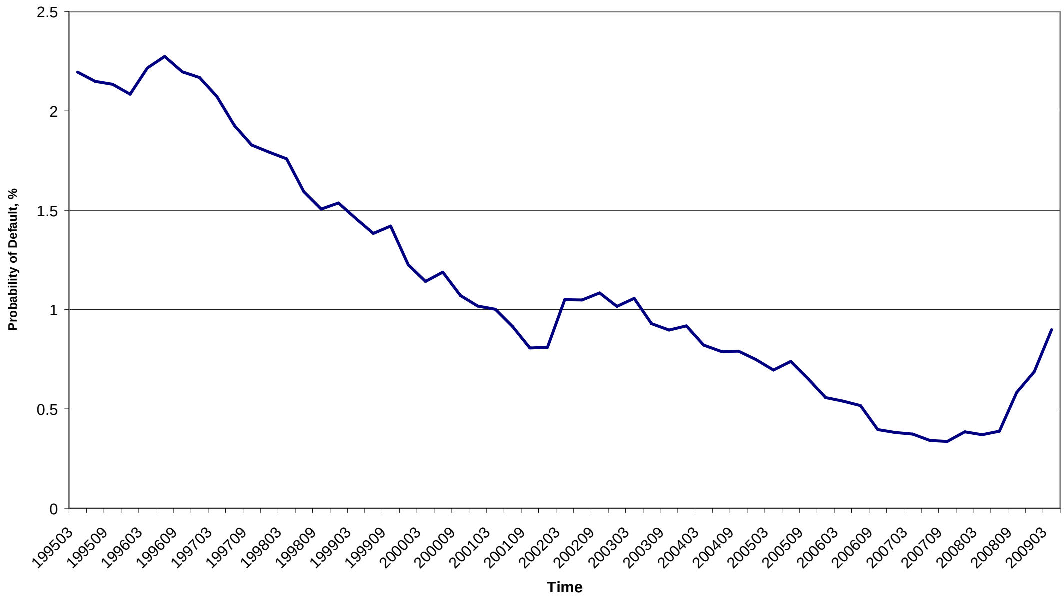
Sorge, M. (2005). “Stress-testing financial systems: an overview of current methodologies”. *Bank of International Settlements Working Paper*. No. 165, December.

Wilson, T. C. (1997a). “Portfolio credit risk (I)”, *Risk*, vol. 10, issue 9, pp 111-17.

Wilson, T. C. (1997b). “Portfolio credit risk (II)”, *Risk*, vol. 10, issue 10, pp 56-61.

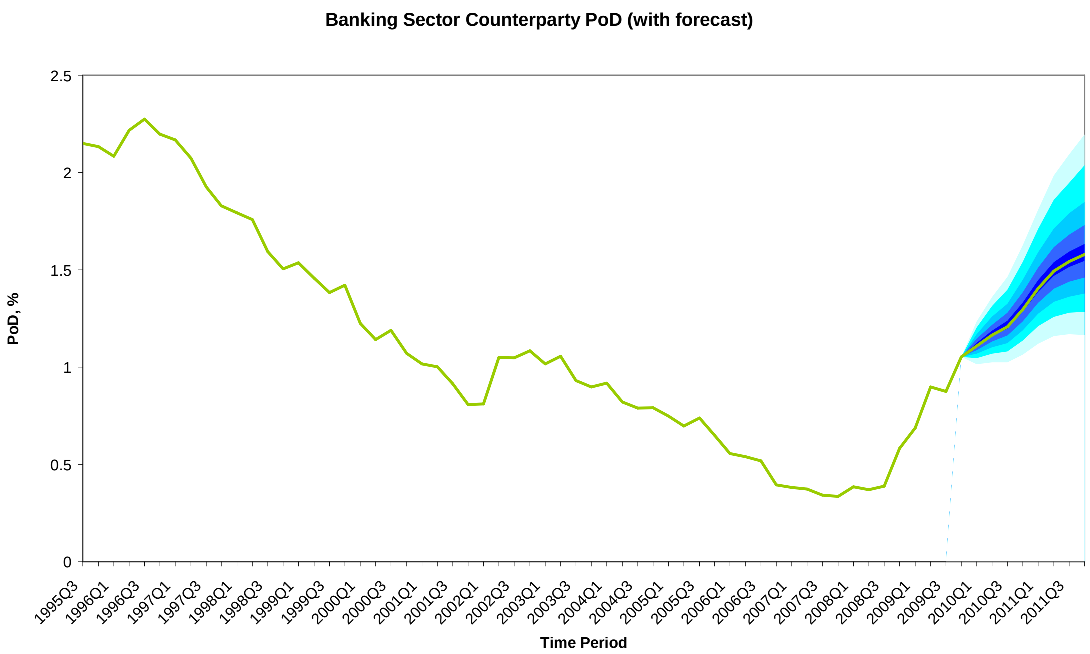
Wong, J., K. Choi and T. Fong. (2008). “A Framework for Stress Testing Banks’ Credit Risk”, *The Journal of Risk Model Validation*, Vol. 2, No. 1, pp. 3-23.

Figure 1:
Probability of Default of the Luxembourg Banking Sector Counterparties



Source: Authors' calculations

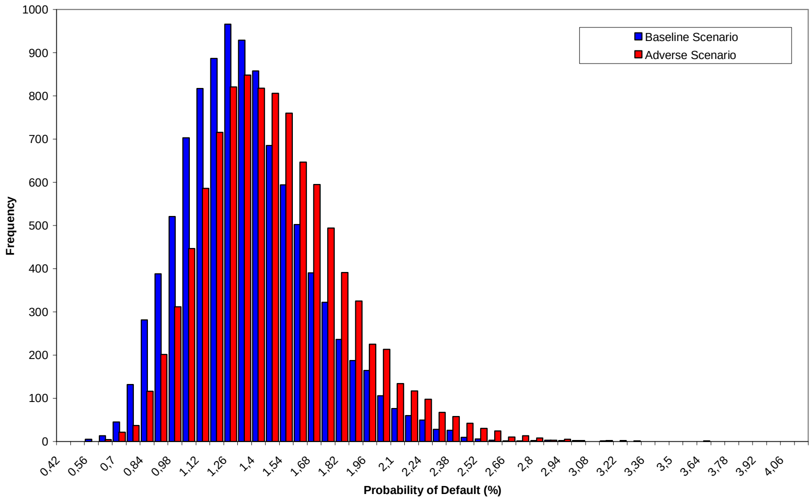
Figure 2:
PD Simulated Sample Path with Confidence Intervals



Source: Authors' calculations

Figure 3:

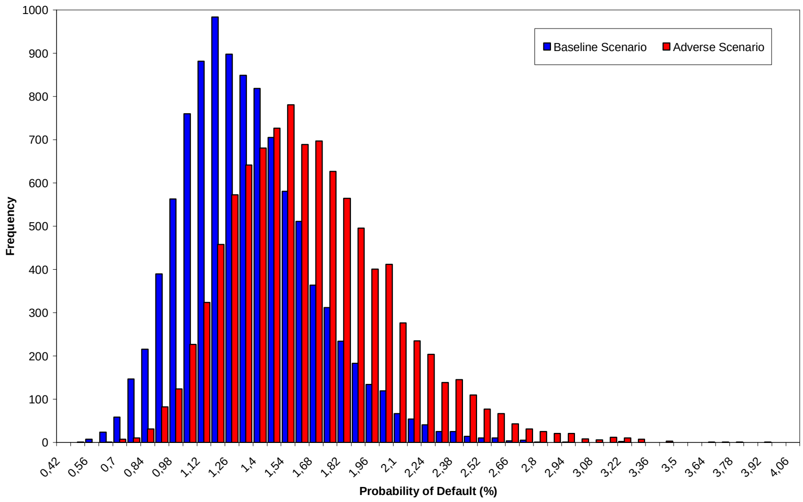
Baseline and adverse scenarios under shocks to Luxembourg real GDP growth



Source: Authors' calculations

Figure 4:

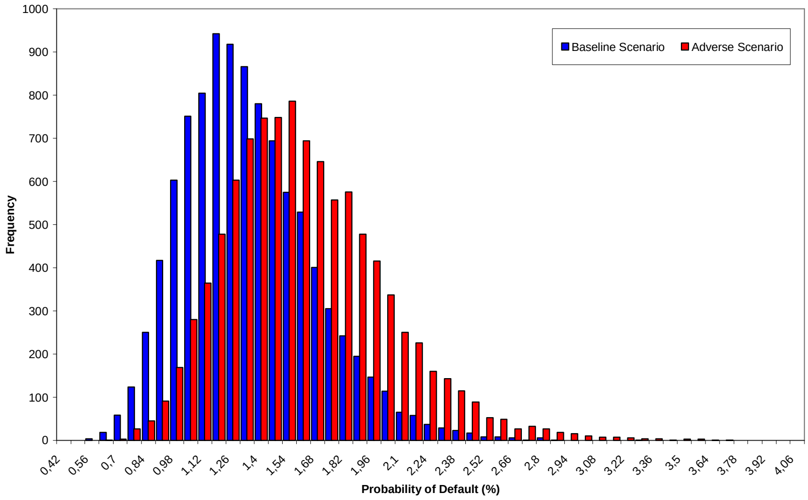
Baseline and adverse scenarios under shocks to Euro area real GDP growth



Source: Authors' calculations

Figure 5:

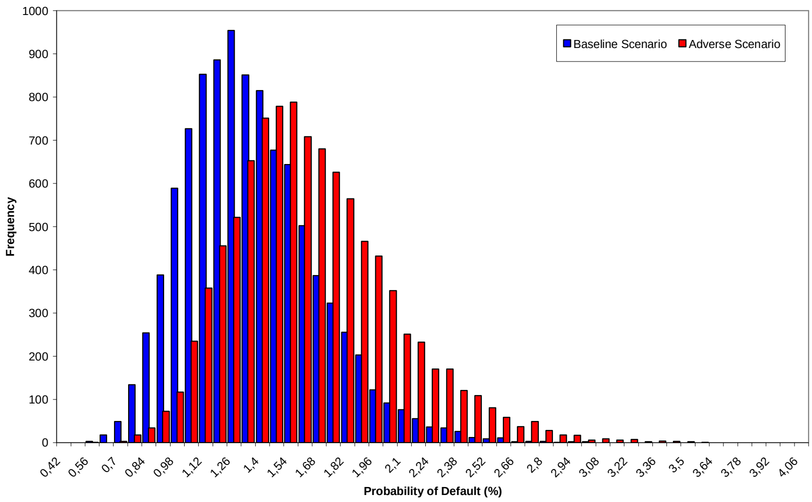
Baseline and adverse scenarios under shocks to the real interest rate



Source: Authors' calculations

Figure 6:

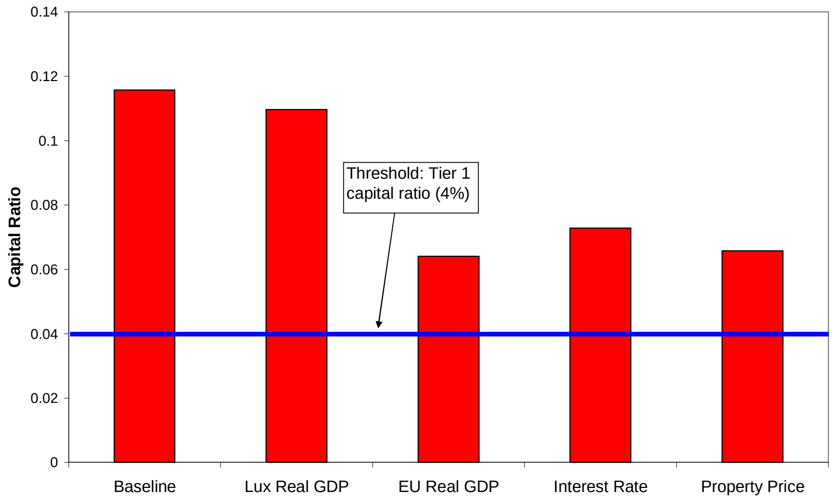
Baseline and adverse scenarios under shocks to real property prices



Source: Authors' calculations

Figure 7:

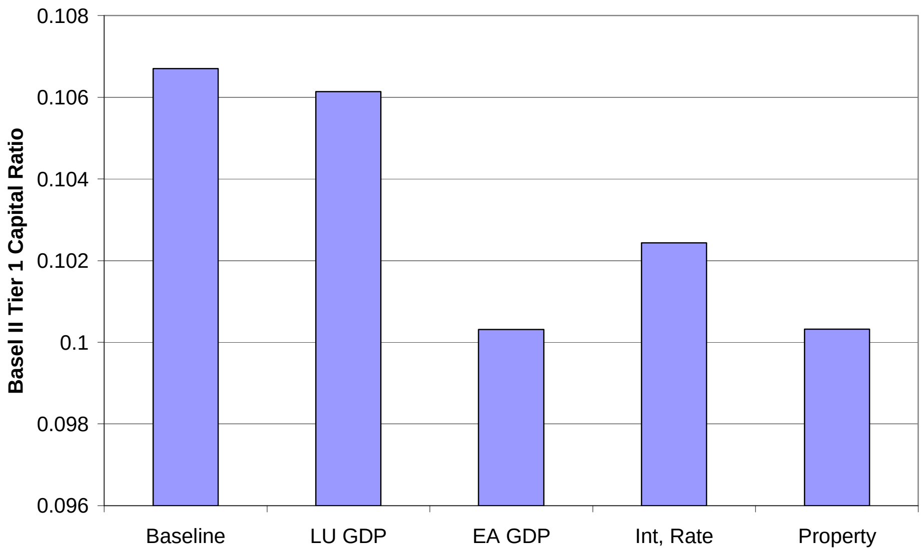
Basel II capital ratios for the Luxembourg banking sector under the four adverse scenarios



Source: Authors' calculations

Figure 8:

Basel II capital ratios for Bank 1 of the Luxembourg banking sector under the four adverse scenarios



Source: Authors' calculations

Table 1:
Results of the SUR system estimation for the period 1995 Q1 to 2009 Q3

	Dependent Variable					
Variable	y_t	$\Delta\ln\left(g_t^{EUR}\right)$	$\Delta\ln\left(g_t^{LUX}\right)$	r_t	$\Delta\ln\left(p_t\right)$	$\Delta\ln\left(sx5e_t\right)$
Intercept	0.162***	0.002*	0.009***	0.001	0.002	0.002
$\Delta\ln\left(g_{t-1}^{EUR}\right)$	4.399***	0.422*	0.120			
$\Delta\ln\left(g_{t-2}^{EUR}\right)$		-0.041			0.398**	
$\Delta\ln\left(g_{t-3}^{EUR}\right)$		0.120				
$\Delta\ln\left(g_t^{LUX}\right)$	0.989**					
$\Delta\ln\left(g_{t-1}^{LUX}\right)$			-0.209			
r_{t-1}	-1.535		0.025	0.890*		
$\Delta\ln\left(p_{t-1}\right)$	0.623				0.933*	
$\Delta\ln\left(sx5e_{t-1}\right)$			0.027**			0.919*
y_{t-1}	0.961*					
R^2	0.985	0.424	0.124	0.843	0.943	0.829
No. of obs.	57	64	58	58	56	58

Notes:

1. In the equations for y_t, $\Delta\ln\left(g_t^{EUR}\right)$ and Δp_t dummy variables have been added in order to control for structural breaks
2. In the table *, ** and *** indicate significance at the 10%, 5% and 1% level, respectively.

Sources: Authors' calculations, CSSF

Table 2:

Comparison of Basel II tier 1 capital ratios for the baseline and stressed scenario for the five largest systemic banks in Luxembourg

Bank		Stressed Scenario			
	Baseline	LU GDP	EA GDP	Int. Rate	Property
Bank 1	**0.107**	0.106	0.100	0.102	0.100
Bank 2	**0.137**	0.127	0.116	0.120	0.116
Bank 3	**0.343**	0.332	0.315	0.321	0.315
Bank 4	**0.162**	0.160	0.154	0.156	0.154
Bank 5	**0.154**	0.151	0.143	0.146	0.143

Source: Authors' calculations