ANALYSES

5	A١	NALYSES									
	1.	Central bank liquidity management: underwriting stability in a challenging environment Abstract									
		1. Introduction									
		2. Conventional monetary policy implementation pre-crisis:									
		Striving for a lean balance sheet									
		3. Crisis-induced operational adjustments on the Eurosystem's balance sheet									
		4. Challenges, going forward									
	2.	An MVAR Framework to Capture Extreme Events in Macro-prudential Stress Tests									
		1. Introduction									
		2. The MVAR model: A tool to capture extreme events									
		3. Simulation and Calculation of Capital Requirements									
		4. Conclusion									
		References									
	3.	An Early-warning and Dynamic Forecasting Framework of Default Probabilities									
		for the Macroprudential Policy Indicators Arsenal									
		Abstract									
		1. Motivation									
		2. The modeling framework									
		2.1 Selected models to estimate default probabilities									
		2.2 The Generalized Dynamic Factor Model									
		2.3 A Dynamic Forecasting Framework									
		3. Data									
		 Empirical Results Asset-weighted PDs 									
		4.1 Asset-weighted FDS4.2 Early-warning Features of Single-bank PDs and Weighted Indexes of PDs									
		4.2 Early-warning reactives of Single-bank FDs and weighted indexes of FDs 4.2.1 Granger causality tests									
		4.2.2 Frequency-domain analysis									
		4.3 Out-of-sample Forecasting									
		5. Conclusions and macroprudential policy implications									
		References									
	4.	Comparing the link between macroeconomic conditions and leverage of monetary									
		financial institutions in European countries and Luxembourg									
		1. Introduction									
		2. Theoretical background									
		3. Results of the study									
		4. Conclusion									
		5. References									

1. CENTRAL BANK LIQUIDITY MANAGEMENT: UNDERWRITING STABILITY IN A CHALLENGING ENVIRONMENT

By Hans-Helmut Kotz⁺, Joachim Nagel* and Jürgen Schaaf*⁺

ABSTRACT

Providing central bank money against good collateral has been understood as the operational – mechanical – part of monetary policy. Its purpose was to engineer effectively the policy rate which was deemed most appropriate to achieve the ultimate target of the central bank, in the case of the ECB: an inflation rate below but close to two percent. With interbank money markets becoming dysfunctional a second task came to the forefront: stabilizing highly vulnerable financial markets and containing possibly grave negative externalities. Over the course of the crisis this has led to substantial changes in the size as well as the composition of central bank balance sheets. Unconventional means had to be deployed and non-standard risks were run. Being extraordinary, these measures obviously have to be unwound, the challenge being that – under a strict inflation control constraint – financial stability is preserved.

1. INTRODUCTION

Modern central banks have a clear mandate and pursue a well-defined target: inflation control. Hence they are mainly, at least in the textbooks, institutions of macroeconomic policymaking. The objective of these institutions is the so-called policy rate, which, as a rule, translates into controlling a very short-term (overnight) interest rate. This operational target signals the course pursued in order to achieve the ultimate objective, thereby anchoring inflation expectations and, ultimately, inflation itself. The mechanics of engineering the policy rate close to a very short term market rate have been largely taken for granted, left to specialists in implementing policies through managing central bank balance sheets. In the ordinary course of business this became the dominant approach since it has proven to be successful in delivering what (macro-) monetary policy is assumed to provide: preserving the purchasing power of money. In the case of the ECB, the rate on its main refinancing operation serves as policy rate. And, though not officially endorsed, the stabilization of EONIA, an unsecured interbank market rate, around this policy rate is the implicitly acknowledged operational target. The procedures of liquidity provision, the operational framework, are conceived to keep this spread within in a fairly narrow band. In normal times, when markets work appropriately, i.e. policy impulses are translated smoothly through arbitrage along the yield curve, this is very much akin an engineering task, best left to technicians.

But, as the financial crisis erupting in the summer of 2007 has again demonstrated, markets do not always work seamlessly. For a host of reasons, they are prone to become dysfunctional at times. Hence, there is a second dimension to stability – the resilience, or lack thereof, of the financial system. This, of course, could not come as a surprise. There had been too many crises of a systemic dimension even during the last quarter of a century and even in OECD economies to ignore. In fact, their frequency as well as severity even increased.¹ Nonetheless, the current crisis, which was until the Lehman

Here we exclusively express our personal views, in particular, they should not be attributed to the Deutsche Bundesbank or the Banque centrale du Luxembourg. We would like to thank Marc Resinek and Franziska Schobert from the Markets Department of Deutsche Bundesbank for suggestions and research assistance.

^{*} Deutsche Bundesbank

⁺ Center for Financial Studies, Goethe-University

^{*†} Banque centrale du Luxembourg

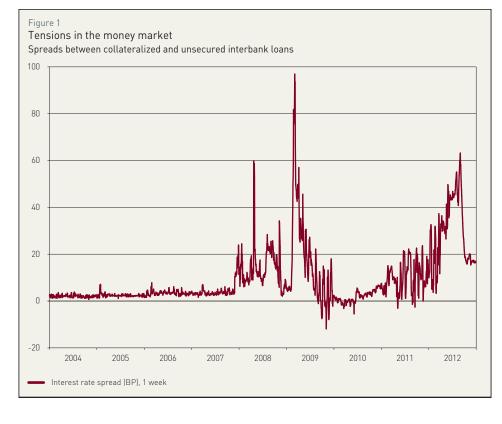
¹ See for example Luc Laeven and Fabian Valencia (2008): Systemic banking crises: A new database, IMF Working paper 08/224.

moment read as an ephemeral turbulence, deemed to fade away, is exceptional in its geographical perimeter as well as its far reaching consequences. It implied very significant social opportunity costs. To highlight but one effect: Still today, most economies concerned are below, often substantially, their output peak of half a decade ago. Indeed, in a number of economies output is still shrinking.

All of this bears witness to the fact why underwriting financial stability is so crucial. As a consequence, numerous efforts have been invested in the regulatory and supervisory domain to safeguard the financial system against future shocks. They are ongoing and entail institutional innovations, including, in the micro domain, the European Supervisory Authorities, as well as, acknowledging the macro dimension, the European Systemic Risk Board. Moreover, financial institutions will be, going forward, obliged to satisfy stricter capital as well as, for a first time, liquidity requirements, reducing maturity transformation.

This is all about future crisis prevention. It is an open issue whether these initiatives suffice. One is, for example, entitled to raise questions whether in Europe we do have a level of coordination amongst supervisors commensurate with the integration of our financial, in particular, banking markets. This leads to thorny, complex and highly politicized issues. Is there, for example, the need of a European bank resolution scheme? Does an integrated market imply a redesign of deposit insurance schemes? The prevailing coordination amongst supervisors, as it was conceived before the crisis, had shown, in any case, substantial room for improvement.

In this article we will however focus on the preceding phase, the crisis containment task - still ongoing. In doing this, we will sketch how the Eurosystem contributed to managing the crisis, as it unfolded, by using its balance sheet as a device to handle and absorb shocks. Initially, these dislocations became manifest in dysfunctional interbank money markets. Volumes were low and spreads between collateralized and unsecured interbank loans (the by far prevailing venue for liquidity management before the crisis) reached unprecedented levels. Over the course of time, the Eurosystem was obliged to engage in an ever larger intermediary role in the reallocation of funds between banks, a function which under standard conditions of course would be discharged in the interbank market. But this market never completely recovered. Against the background of an evol-



ving substantial sovereign debt problem in a number of Euro Area countries and in view of a very significant roll-over risk in the first quarter of 2012 the ECB ultimately decided to launch two 3-year, long-term refinancing operations. Moreover, it felt obliged to further reduce the eligibility criteria for collateral it accepts in exchange for base money. Otherwise, the access to credit by households and firms would have been severely impeded in a number of Euro Area countries. ANALYSES

These measures buy time to face up to the underlying root causes of imbalances in public-sector budgets as well as regional current account imbalances. But adjustment is unavoidable and it cannot be monetary. Quite obviously, these crisis containment measures come at a price. At the margin, they blur the distinction between technocratic (and therefore justifiably independent) monetary policy and democratically legitimized fiscal policies. They also run the risk that adjustment is delayed. As always, options have to be judged in view of next best available alternatives. In any case, the room for maneuver – for buying time – is diminishing.

2. CONVENTIONAL MONETARY POLICY IMPLEMENTATION PRE-CRISIS: STRIVING FOR A LEAN BALANCE SHEET

In response to the financial crisis the Eurosystem had to embark on a wide range of non-standard monetary policy measures. Otherwise financial intermediation in the euro area, access of firms and households to credit as well as, particularly important for monetary policy, the transmission mechanism of its impulses would have been impeded.² As a consequence, the composition and size of the Eurosystem's balance sheet changed considerably. Extraordinary times justify non-conventional steps. At the same time, larger balance sheets, almost as a logical corollary, imply higher financial risks which, in the case of the Eurosystem are (in principle) jointly shared amongst participating central banks.

All of this leads away from what (some) central banks optimally pursue: a balance sheet with a minimal size, as directly as possible derived only from its core function, the provision of central bank balances. Such a lean balance sheet thus follows a double minimalist ideal: one would like to have a minimalefficient size as well as lowest-possible risk balance sheet. On the liability side, this translates into just serving the banking system's structural and aggregate need for central bank liquidity, i.e. reserves. Thus, a lean central bank balance sheet mainly consists of banknotes in circulation and minimum reserve requirements (or working balances for interbank settlement).³ On the asset side, lean would imply domestic or foreign assets, exclusively reflecting monetary policy operations, the latter as they result from managing foreign reserves in pursuing monetary policy purposes. Thus, in normal times a central bank balance sheet would qualify as lean when banknotes in circulation largely determine the balance sheet total. A central bank's own funds, i.e. capital, reserves and provisions, should not significantly increase the balance sheet total.⁴ Such a balance sheet is directly (and exclusively) derived from the primary (macro-) monetary policy objective: maintaining price stability. On the asset side lean would thus translate into mainly monetary policy operations, extending net credit to the banking system.

However, in reality, the balance sheet structure of most central banks is obviously quite different. This testifies to the fact that central banks, as a rule, perform (or had performed) various additional tasks. Indeed, historically, the remit of central banks, without any exception, always included a "second (micro-economic) function, of providing support (e.g., via Lender of Last Resort assistance) and regulatory and supervisory services to maintain the health of the banking system".⁵ This required a potentially wider intervention capacity and thus broader refinancing options (in terms of counterparties as well as eligible collateral). In the same vein and responding to a variety of financial background conditions, in the case of the Eurosystem there is a substantial amount of legacy assets, outright investments which arose out of monetary or currency arrangements previous to EMU.

² ECB Monthly Bulletin, September 2011, p. 41

³ In the case of the Eurosystem, minimum reserve requirements amount to only some 25% of banknotes in circulation.

⁴ Daniel Gros and Franziska Schobert (1999) Excess Foreign Exchange Reserves and Overcapitalisation in the Eurosystem (CEPS Working Document No. 128), Brussels, Centre for European Policy Studies.

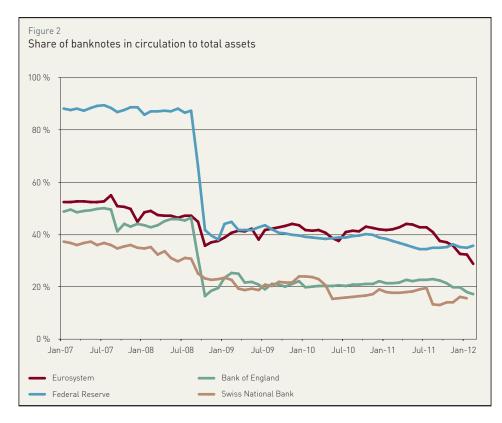
⁵ Charles Goodhart (1989): Why do Banks need a Central Bank?, in: Money, Information and Uncertainty, Oxford, 1989, p. 176. In addition, central banks frequently have been involved in payments and settlements systems, also a business line which could be performed by a separate institution. Usually, they are not, given the joint product (with issuance of money) and (to a degree) public good dimension of these lines of activities.

Obviously, there is also a revenue or income dimension involved in the size as well as the structure of central bank balance sheets. Banknotes are an unremunerated (non-interest bearing) liability. They provide, joint with the decision about the structure of the asset side, for seigniorage, that is, a central bank's net revenues resulting from its monopoly in issuing base money.⁶ Maximizing seigniorage revenues is clearly not the objective of a central bank, however, a reliable stream of income is crucial for underwriting its financial independence. By force of accounting mechanics, larger refinancing operations compress the room for outright or non-monetary policy portfolios.

Amongst prospective Eurosystem members, before 1999, the balance sheet of the Bundesbank was closest to a lean central bank balance sheet (also accounting for the dollar position which arose out of monetary policy intervention obligations). This did not hold true for most of the other prospective members. And it was largely a consequence of the prevailing European exchange rate arrangement, the EMS. In order to defend the peg these central banks had to accumulate foreign reserves which exceeded banknotes in circulation by far. After joining the European Monetary Union, national central banks did not divest these assets, but held them as outright, non-monetary policy portfolios partly denominated in foreign currencies, partly in euro. Thus, the volume and composition of these portfolios are largely the upshot of a preceding monetary regime, in which national central banks intervened in the foreign exchange market or, infrequently, settled international transactions in gold.⁷

The consolidated financial statement of the Eurosystem bears witness to this historical trajectory. It accounts for the assets and liabilities held by the Eurosystem on the balance sheets of the 17 euro area

national central banks (NCBs) as well as the ECB. Gross claims and liabilities between the NCBs and the ECB (intra-Eurosystem claims and liabilities) net out. Since the start of EMU the holdings of foreign reserve assets have slightly decreased over time. This trend, however, has been clearly overcompensated by large valuation gains (mainly on gold holdings), so that the value of foreign reserves recorded in the Eurosystem balance sheet has significantly increased. Prior to the crisis Eurosystem monetary policy operations exclusively consisted of so-called repurchase transactions, i.e. temporary (self-liquidating) Eurosystem credit operations against eligible assets as collateral. Around two thirds of the volume of monetary policy operations was thus made up by the appropriately named main refinancing operations (MROs). These were



6 Base money consists of banknotes and reserves of banks held on accounts at the central bank. In the Eurosystem minimum reserves are fully remunerated and excess reserves can be transferred to the remunerated deposit facility. Thus, only banknotes in circulation are the unremunerated part of base money.

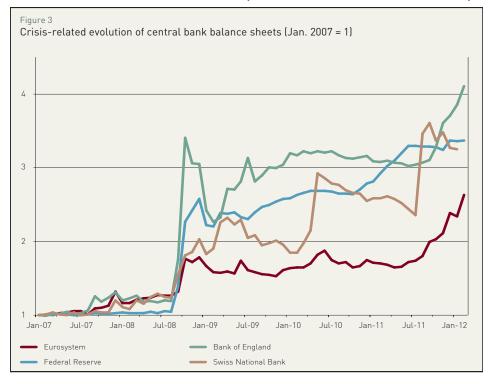
7 Germany's reserve assets, for example, were predominantly the result of intervention duties arising during the period of the Bretton Woods system with its obligation to dollar purchases when the anchor currency was weak. Deutsche Bundesbank (2003) Reserve assets: their development and importance in monetary union, Monthly Report, January, p. 18. ANALYSES

(are) operations with a one week maturity, while the remainder consisted of longer-term refinancing operations (LTROs) with a three-month maturity. Standing facilities, with which the Eurosystem offers to provide or absorb liquidity overnight at the initiative of counterparties, played a minor role on the balance sheet. But they are of course essential for the corridor-approach to managing a short-term market interest rate.

The share of banknotes in circulation to total assets might serve as an indicator of the degree of leanness. Chart 1 compares the Eurosystem's balance sheet to the Federal Reserve System, the Bank of England and the Swiss National Bank. In the Eurosystem banknotes comprised about half of the liability side of the balance sheet at the beginning of 2007, a similar share as for the Bank of England, though much less than in the balance sheet of the Federal Reserve Bank.⁸ The balance sheet of the Swiss National Bank had by far the lowest share of banknotes to total assets due to its high foreign reserve holdings. According to the statutes of the Eurosystem and the Swiss National Bank, the central bank manages foreign reserves, while in the United Kingdom and the United States it is a shared task between the respective Treasuries and the central banks. At all four central banks the crisis led to a steep decline of the share of banknotes to total assets – mirrowing the heightened importance of the financial stability role assumed.

3. CRISIS-INDUCED OPERATIONAL ADJUSTMENTS ON THE EUROSYSTEM'S BALANCE SHEET

When financial turbulences erupted in early August 2007, in the wake of the unfolding US subprime crisis, tensions were primarily the result of a lack of confidence among market participants in interbank money markets as well as uncertainty about the financial soundness and liquidity of counterparties. This was reflected in a decline of lending activity in the secured interbank (term) but in particular in unsecured money markets. In order to reduce uncertainty about access to central bank balances,



the Eurosystem initially responded by satisfying all existing demand at the policy rate, basically making quantity within the maintenance period endogenous. Concurrently, again to enhance certainty about the capacity of honoring requirements over the course of the maintenance period, liquidity provision was frontloaded. With the crisis evolving and the short-term yield curve becoming ever more fragile, the duration of liquidity-providing monetary policy operations was lengthened.⁹ Still, aggregate liquidity provision through monetary policy operations, the size of the balance sheet, remained unchanged on average.¹⁰ Moreover, in view of the tensions in short-term US dollar funding markets and on the

3 The relatively low share of banknotes in the case of the Bank of England is the upshot of a voluntary reserves averaging scheme which has fostered fairly large holdings of banks' reserves.

9 This could be interpreted, given the shallowness of funding markets with longer tenor, reflecting the run of wholesale market on itself, as an attempt to establish focal points on a short-term yield curve where standard arbitrage did not hold anymore; see Hans-Helmut Kotz (2008): Finanzmarktkrise – eine Notenbanksicht, in: Wirtschaftsdienst, 5/2008, pp. 291-296.

10 See Deutsche Bundesbank (2009), Interaction between the Eurosystem's non-standard monetary policy measures and activity in the interbank money market during the crisis, in: Financial Stability Review 2009, pp. 87-99.

basis of a swap agreement with the Federal Reserve System, in December 2007 the ECB also began to provide US dollar liquidity to Eurosystem counterparties against euro denominated collateral. This, however, only became important in size after the collapse of Lehman Brothers and the near-failure of AIG in mid-September 2008. Subsequently, the financial turmoil turned into a global financial crisis.

From October 2008 until early-2010 – "Collateralized lending". In the post-Lehman environment, characterized by unprecedented uncertainty, distrust and funding constraints in the interbank market, euro area banks heavily used the enhanced provision of liquidity offered by the Eurosystem at rapidly decreasing policy rates. Therefore, the size of the Eurosystem balance sheet increased substantially in October 2008. The increase, however, was dwarfed by the rising size of the Federal Reserve System's as well as the Bank of England's balance sheets. The stronger increase of the Swiss National Bank's balance sheet took place more gradually and later.

The Eurosystem's non-standard measures implemented between October 2008 and early-2010, coming under the heading of "enhanced credit support", included three key measures: First, ever since October 2008 the Eurosystem applied a "fixed rate full allotment" tender procedure in all refinancing operations, ensuring the provision of unlimited central bank liquidity to eligible euro area banks at the main refinancing rate and against adequate collateral. Second, the list of assets accepted as eligible collateral for refinancing operations was extended in order to further ease access to Eurosystem operations in an attempt to reduce asset-side constraints on banks' balance sheets. The Eurosystem, for example, expanded the list of eligible collateral to assets denominated in the USD, GBP and JPY issued in the euro area, it reduced the credit quality threshold to "BBB-" from "A-", while simultaneously augmenting haircuts to be applied.¹¹ Third, the Eurosystem conducted additional longer-term refinancing operations with a maturity of up to one year. The main aim of these operations was to promote the decline in money market term rates and to ease liquidity and funding conditions for banks. The longer maturities of liquidity provision enabled banks to reduce the duration gap between the investment side and the funding side of their balance sheet.¹² It implied a further enhancing of the intermediation role taken by the ECB.

The Federal Reserve and the Bank of England also provided central bank balances to banks on longer terms and against a wider collateral base after the collapse of Lehman Brothers.¹³ At the Federal Reserve, the Term Auction Facility (TAF), established in late 2007, became the most important instrument. The TAF allowed for a wider range of counterparties while also accounting, through the tender procedure, for the perceived stigma of borrowing at the discount window. At the Bank of England, the 3-month lending operations provided liquidity on a large scale and substituted the regular 1-week lending operations.¹⁴ At the Swiss National Bank the most important lending operation after the collapse of Lehman Brothers was in USD, which was also provided on the basis of a swap agreement with the Federal Reserve System.

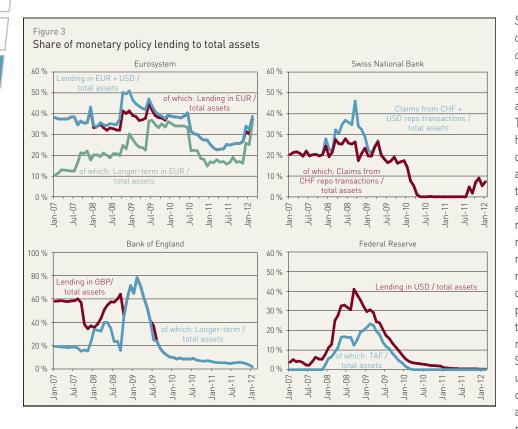
With the inception of the Covered Bond Purchase Programme (CBPP) on 6 July 2009, the Eurosystem for the first time deployed outright monetary policy transactions – in addition to its full allotment monetary policy reverse transactions. The aim of the CBPP was to revitalize the primary euro area covered bond market, where issuing activity had basically ceased, and at the same time to reduce spreads in the secondary market, which were seen as excessive relative to normal (fundamentally justifiable) conditions. The CBPP was clearly communicated to be terminated after one year and had a total nominal amount of \notin 60 billion. A second CBPP, with a planned volume of \notin 40 billion, was started in November 2011. **ANALYSES**

¹¹ While the ECB Governing Council decided to continue applying the reduced credit rating threshold of "BBB-", the use of foreign currency denominated assets was phased out by 31 December 2010.

¹² ECB Monthly Bulletin Oct. 2010: The ECB's response to the Financial Crisis, p. 66.

¹³ See for a concise overview Marlene Amstad and Antoine Martin (2011): Monetary policy implementation: Common goals but different practices, Fed New York: Current Issues, vol. 17, no. 7.

¹⁴ In 2007/2008, liquidity support for individual institutions partly substituted short-term monetary policy lending operations.



Since the start of the sovereign debt crisis in the euro area - "Outright purchases". In early-2010 tensions reemerged in some financial market segments, in particular in the euro area government bond markets. The financial crisis, not at all without precedent, morphed in some of the countries concerned into a sovereign crisis. Spreads between ten-year government bonds of some euro area countries relative to German public sector bonds started to rise, mainly as a result of increasing market concerns about the sustainability of public finances in view of rising government deficits and potentially unsustainable debt positions. On May 10, 2010 the ECB announced the launch of its so-called Securities Markets Program (SMP), under which the Eurosystem can carry out interventions in the euro area public and private debt securities markets to ensure depth and

liquidity in dysfunctional market segments with an eye on ensuring the proper functioning of the monetary policy transmission mechanism. Furthermore, in May 2010 the ECB Governing Council also decided to suspend the application of the minimum credit rating threshold for marketable debt instruments issued or guaranteed by the Greek government for the purposes of Eurosystem credit operations. It did so also with regard to Irish sovereign debt in March 2011 as well as Portuguese sovereign debt in July 2011.

Moreover, on December 8, 2011 the ECB Governing Council decided on additional enhanced credit support measures. These included the conduct of two longer-term refinancing operations with a maturity of three years with full allotment procedures.¹⁵ These operations met unprecedented demand from banks, taking the amount of outstanding monetary policy lending to a record high of some €1 trillion. Moreover, in order to increase collateral availability, the criteria for ABS backed by pools of residential mortgages or loans to small and medium-sized enterprises were relaxed¹⁶ and NCBs were individually given some discretion to accept additional performing credit claims. Any losses from the acceptance of such credit claims would need to be borne by the respective NCB, hence without the feature of standard programs, i.e. loss sharing. This was, of course, a procedure applied during the first years of EMU, before the introduction of the so-called single list in 2007.

In the course of the crisis both the Fed and the Bank of England started large scale asset purchase programs. The outright portfolios are significantly larger than in the Eurosystem, they are partly coordinated with the government and most importantly, there is only one government to coordinate with. The BoE established the Asset Purchase Facility Fund under the remit from the Chancellor of the

¹⁵ The rate will be fixed at the average rate of the main refinancing operations over the life of the respective operation.

¹⁶ The cash flow generating assets backing the ABS must belong to the same asset class and they cannot be non-performing or structured, syndicated or leveraged. The counterparty or any third party to which it has close links cannot act as an interest rate swap provider in relation to the ABS and the transaction documents must contain servicing continuity provisions.

Exchequer in January 2009 with the initial intention of improving the liquidity of the corporate credit market. In March 2009 the remit was extended to allow purchases of assets (actually mainly gilt-edged securities) in pursuit of monetary policy aims. The Fund is indemnified against losses by the Government and its accounts are not consolidated with those of the BoE. However, the BoE finances the Fund with loans reported on its balance sheet. Since March 2009, the loans have found an expression in increased reserves on the BoE's balance sheet.¹⁷

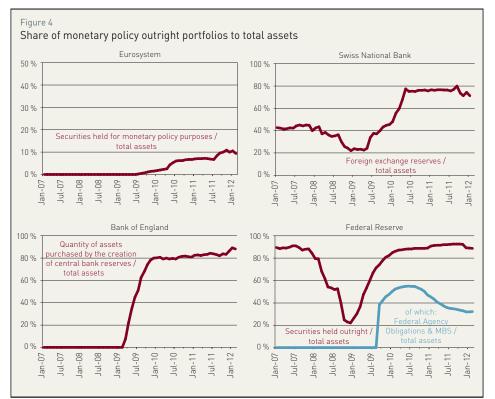
Outright purchases or sales of securities for the System Open Market Account (SOMA), the Federal Reserve's portfolio, obviously are a traditional or conventional monetary policy instrument of the Fed through which it provides the major share of liquidity. During the crisis, however, the composition of this portfolio changed substantially as did its size. It has become a crucial instrument in crisis containment, in particular by engineering credit easing, that is, accepting more risk on the balance sheet of the Fed. Specifically, in November 2008 the Fed announced to purchase agency mortgage backed securities as well as agency debt in order to improve conditions in private credit markets. On March 18, 2009, the FOMC launched a longer-dated Treasury purchase program again with the operating goal, to help, via portfolio effects, improving conditions in private credit markets. On November 3, 2010, the FOMC decided further expanding the Federal Reserve's holdings of securities in order to promote a stronger pace of economic recovery and to help ensure that inflation, over time, is at levels consistent with its mandate (in other words, to contain a potential deflation threat). As announced in June 2011 the reinvestment of maturing funds (as well as proceeds) should continue as Federal Reserve's holdings of domestic securities should be maintained at approximately \$2.6 trillion.¹⁸

At the Swiss National Bank foreign exchange interventions became the dominating instrument with which it pursued monetary policy. It is reflected in the very substantial increase of foreign exchange re-

serves with which the central bank tries to control the exchange rate of the Swiss franc against the euro in order to avoid deflationary pressures and to support the domestic economy. On September 6, 2011 the SNB officially announced a minimum exchange rate of 1.20 CHF/ EUR, buttressed with unconditional intervention intentions.

4. CHALLENGES, GOING FORWARD

Some argue that the very substantial increase of central bank balance sheets, as produced by "quantitative easing" (QE) policies, implies by necessity commensurate inflationary risks. The term 'quantitative easing' is understood in a number of ways, reflecting the diverse backgrounds, and hence differing justifications,



17 Paul Fisher [2009]: The Bank of England's Balance Sheet: Monetary Policy and Liquidity Provision During the Financial Crsisis,

ANALYSES

speech, http://www.bankofengland.co.uk/publications/speeches/2009/speech413.pdf.

¹⁸ http://www.federalreserve.gov/monetarypolicy/bst_openmarketops.htm.

against which these policies have been adopted across central banks. The Bank of Japan's quantitative easing policy, as conducted between 2001 and 2006, set a target for the banks' current account balances (that is: reserves), thus it referred to the liability side of its balance sheet. By contrast, the Bank of England rather focuses its justification on the asset side. In its (large scale) purchase program it buys gilts in secondary markets from private investors and, in banking on a portfolio-effect, expects that the net injection of liquidity (i.e. the quantitative easing) will, by force of arbitrage, make other assets, such as corporate bonds and shares, comparatively more attractive. This should, concurrently, lower longer-term borrowing costs and thus encourage the issuance of new equities and bonds.¹⁹ Common to both understandings of QE policies is the intended expansion of the central banks' balance sheet. But whilst using as point of impact different sides of the balance sheet differential effects are attempted. The BoJ approach was about re-starting credit intermediation through the bank-credit channel whereas the BoE targeted funding conditions more generally. In the reading of the Fed, and this is the third perspective, also focusing on the asset side, the easing crucially comes about through taking on more credit exposure. In essence, the Fed swaps with the private sector riskier assets, which it deems underpriced, against less risky assets.

Borio and Disyatat (2009) use the more general term "balance sheet policies".²⁰ To repeat, during normal times most central banks, of course including the Eurosystem, signal their monetary policy stance by deciding on the so-called policy rate. And they communicate their intents by controlling a short-term market rate. During the course of the crisis, however, in particular since the fall of 2008, operational targets undershot policy rates. This slippage was allowed on purpose. In the case of the Eurosystem it meant waiving the separation principle which, under normal circumstances implies a clear hierarchy: The thrust of monetary policy, defined to achieve the inflation objective, is defined by policymakers. And, taking its directive from there, it is the role of liquidity managers, the desk, to implement these instructions by engineering the appropriate quantity of central bank balances. Circumstance were however not normal: Given the high level of stress, as it transpired for example in spreads between secured (credit riskless) and unsecured funds, additional liquidity was urgently needed – to support a second function: safeguarding financial stability. Moreover, in a number of jurisdictions, in order contain negative externalities, additional measures were deemed unavoidable to support lending to non-banks, to contain risk spreads in specific markets or to limit appreciation pressure on the exchange rate. While the first three objectives for "balance sheet policies" were (and are) valid in the case of the Eurosystem, the Swiss National Bank or many central banks in emerging market countries are typical cases for the latter one.

It is true, in rather simple (and mechanical) textbook interpretations of central bank balances and the money multiplier large reserves (or central balances) signal imminent inflationary risks down the road. But, quite obviously, the multiplier is endogenous. Banks respond to an expected risk-return profile in their lending decisions. Hence, they do not mechanically translate more liquidity into more credit. This is accounted for in the Eurosystem's policy framework. In line with other central banks, the Eurosystem processes information with regard to future risks to price stability from a wide range of economic, financial and monetary indicators. In other word, in case the medium-run outlook for inflation deteriorated, i.e. inflationary risks emerged, it would be perfectly capable – indeed it would – to react by increasing its policy rate. This would increase the marginal opportunity cost of banks' reserve holdings. Since a loan or other investments of banks are made, at the margin, only when and if its expected return exceeds marginal cost, banks consequently will slow down business activities.²¹ Under normal (conventional) condi-

¹⁹ Shigenori Shiratsuka [2010]: Japan's Experience of the Quantitative Easing Policy: Re-examination from the Viewpoint of the Size and Composition of the Central Bank Balance Sheet, Policy Research Institute, Ministry of Finance, Japan, Vol. 99.

²⁰ Claudio Borio and Piti Disyatat (2009): Unconventional monetary policies: an appraisal, BIS Working papers, No. 292; see also Stephen Cecchetti and Piti Disyatat (2010): Central bank tools and liquidity shortages, in: Fed New York, Economic Policy, Review, August, pp. 29-42.

²¹ Martin, McAndrews, Skeie (2011) A Note on Bank Lending in Times of Large Bank Reserves, Federal Reserve Bank of New York Staff Reports, No. 497, May.

tions, when such a situation will arise, the policy rate (as well as the operational target rate) can be set independently of the amount of bank reserves in the system, the separation principle holds.²² Thus, even when large bank reserves have emerged as a consequence of facing other tasks, the central bank can control short-term rates in line with its operational framework. The Fed or the Bank of England might, for example, fully remunerate excess reserves. Others such, as the Eurosystem, may offer a deposit facility.

Table 1

Bank reserves held at major central banks (end of period)

	EUROSYSTEM*	FEDERAL RESERVE	BANK OF ENGLAND	SNB
Jan 2007	EUR 176 bn	USD 27 bn	GBP 17 bn	CHF 5 bn
Feb 2012	EUR 912 bn	USD 1,607 bn	GBP 196 bn	CHF 220 bn

* Includes recourse to the deposit facility; Eurosystem data as of 2 March 2012.

Finally, it should be mentioned that central banks dispose of various instruments to effectively absorb surplus liquidity/reserves, if necessary. Depending on their operational framework they can conduct reverse repos, collect fixed term deposits, raise minimum reserve requirements, issue central bank debt certificates/bills or possibly even sell monetary policy outright holdings. All of the central banks presented in this article currently provide significant amounts of surplus liquidity, for financial stability reasons. When the crisis subsides at some point in the future and the non-standard intermediation role is no longer required, central banks will start to make active use of such liquidity-absorbing instruments. The length of this transition to a post-crisis monetary policy implementation will depend on the maturity of refinancing operations as well as the time to maturity of the crisis-related monetary policy outright portfolio holdings.

Balance sheet policies which go beyond the engineering of the policy rate but in addition try to underwrite financial market stability do accept potentially significant financial risks. Moreover, they do not necessarily have to be conducted by the central bank. Governments, for example, could by themselves purchase impaired assets or issue other forms of public debt, which then substitute part of the large bank reserves.²³ In the euro area, coordinating responsibilities with governments and banking communities across 17 jurisdictions is obviously far more challenging (see for example the debate about the European facilities: EFSF/ESM).

When conducting liquidity-providing monetary policy operations, central banks by necessity assume some (controlled) financial risk. And, rather evidently, such risks substantially increase in times of financial crises. This is justified from a policymaker's perspective by the potential for greater risks to monetary and financial stability were the central bank to remain inactive. Staying on the sideline would come at potentially prohibitive social costs.

Given the balance sheet developments resulting from the described array of non-standard monetary policy measures taken since October 2008, the risk exposure of the Eurosystem has considerably increased. This is, on the one hand, immediately related to the significant lengthening of the balance sheet, commensurate with the increased scale and maturity of monetary policy refinancing operations. On the other hand, this is also an inevitable and accepted consequence of the above mentioned effective relaxation of collateral requirements for monetary policy purposes. In fact, the amount of marketable **ANALYSES**

²² See, from a US perspective, Todd Keister et al. (2008): Divorcing money from monetary policy, in Fed New York, Economic Policy Review, September, pp. 41-56.

²³ Indeed, the German experience after World War II provides an example in which neither central bank nor government purchases of impaired assets were used, but equalization claim to banks holding these assets were offered; see Pontzen, Schobert (2007) Episodes in German monetary history – Lessons for Transition Countries? The Experience of Exchange Rate Regimes in Southeastern Europe in a Historical and Comparative Perspective, Proceedings of OENB Workshops, Oesterreichische Nationalbank.

eligible collateral for Eurosystem credit operations increased from below $\in 10$ trillion in 2007 to almost $\in 14$ trillion in 2009, and has since decreased to some $\in 13$ trillion at the end of 2011, after the phasingout of some non-standard collateral measures introduced in 2008. These developments, i.e. the greater volume of monetary policy lending and the lowering of the collateral requirements, thus entail both, more and higher risks for the Eurosystem.

This risk is, however, strictly monitored and managed, in particular by applying liquidity and credit-risk dependent haircuts. Nevertheless, from a risk management perspective, lower risks with smaller haircuts evidently would be preferable. Still it should be noted that for the Eurosystem to experience a loss, a default of both the counterparty and the deposited collateral at the same time is required (a doubledefault). If the underlying security, but not the counterparty, defaults, the Eurosystem can call for additional margins or - if required - unwind a credit operation. In case the counterparty defaults, the collateral can be sold into the market. As central banks do not face liquidity constraints, the Eurosystem could hold out until market conditions have been improving (normalizing) enough to avoid losses which would result from fire-sales. Thus what matters is not only the risk of a counterparty default and the risk of a collateral default, but the risk of these events occurring jointly and the correlation between them. Clearly, times of financial distress by definition are characterized by higher risk, currently especially concentrated in certain banking systems. Part of the correlation risk is addressed by prohibiting the counterparty from submitting collateral issued by an issuer to whom it has "close-links".²⁴ In sum, even if the risk exposure of the Eurosystem from monetary policy lending has increased since October 2008, stricter risk control measures applied and the fact that double-default has to take place for financial losses to effectively materialize offer the Eurosystem a high degree of risk protection.

However, the situation is different with respect to outright holdings incurred in the implementation of the monetary policy. They result in the context of the SMP and, to a lesser extent, through the implementation of the CBPP.²⁵ Here the Eurosystem is clearly exposed to higher risk. This is due to the fact that by purchasing securities and holding them on its balance sheet, the Eurosystem fully bears the default risk of the issuer without protection. Since the Eurosystem intends to hold all securities purchased to maturity, market, interest and liquidity rate risk does not apply. In fact, the Eurosystem will, in case credit risk does not materialize, realize significant profits on its securities holdings over time. Still the large amount (around €220 billion) of purchases of long-term sovereign bonds issued by euro area countries facing high debt burdens may require Eurosystem central banks to make adequate provisions in order to take into account potential default risk in line with prudent accounting principles. This implies that Eurosystem central bank profits transferred to euro area governments may be significantly lower for an extended period of time. In fact, this can be considered as a risk protection measure: By holding back the distribution of potential profits the Eurosystem can effectively provide for the higher credit risk it is exposed to due to the crisis-related monetary policy outright purchases.

So what does this mean for central bank capital? The assets that were purchased outright by the Eurosystem during the euro area sovereign debt crisis reflect a transfer of risk from the private sector to the public sector. The accumulation of foreign reserves, as is for example the case for the Swiss National Bank, also entails such transfer of risk, here arising from interventions to prevent a further appreciating of a currency. Such a response is, however, regularly interpreted as a signal of strength. Hence, write-downs and resulting central bank capital erosion, reflecting an appreciating (home) currency, can be communicated

²⁴ A close-link is defined as either the counterparty or the collateral issuer having a stake of at least 20% in the other or a third party holding at least 20% of both. The Eurosystem furthermore sets proportional limits within the collateral pools of its counterparties for the amount of uncovered bank bonds issued by banking groups.

²⁵ The risk exposure is lower on the CBPP holdings as Eurosystem covered bond purchases are very diversified covering all covered bond markets in the euro area, and because covered bonds are based on a cover pool of assets which serves as protection in case the issuer default. However, the legal frameworks for covered bonds and the implied protection for investors significantly vary among jurisdictions in the euro area.

more easily. In fact, both at the Deutsche Bundesbank in the 1970s as well as recently at the Czech National Bank, such losses ultimately depleted central bank capital, leading to a significantly negative capital position. However, in both cases, the central bank did not need to ask the government for recapitalization, but decided instead to wait for future net revenues to eventually cover the loss carry-forward. Unlike a private company, a central bank can in principle (almost) never become illiquid and hence bankrupt in a technical sense (again, barring the extreme case of hyperinflation in which such a central bank's money loses all its functions). Therefore, assets bought outright can be held to maturity. Thus, the central bank is exposed to credit risk only, but not to liquidity or interest rate risk. Losses, however, can have a negative effect on a central bank's reputation, which is of course crucial for achieving its ultimate target(s). In some cases they entail unpleasant discussions with the Ministry of Finance on missing profit transfers, which do harm independence - they imply fiscal dominance in a very concrete sense. Therefore, own funds of a central bank are essentially a signalling device for political independence, reputation and credibility with respect to monetary policy implementation, rather than an absorber of potential financial shocks. Eventually, in case of losses, credible communication (in view of the ultimate target) is what matters in order to safequard the public's confidence in a central bank's willingness and ability to perform its primary monetary policy task to maintain price stability, whilst accounting for financial stability – a necessary condition.

Concerning its mechanics or engineering side, from here a number of important questions about monetary policy implementation arise. They are in fact old ones and have to deal with how central banks should account for changing background conditions, again, with an eye on how to most effectively achieve their objective(s). This is obviously reasoning from a functional perspective, as most clearly exposed by James Tobin.²⁶ Insofar as non-bank banks or near-bank banks (i.e. what we recently have become used to call shadow banks) discharge functions which were traditionally deemed to be banks' exclusive remit (frequently of course enforced by law), they possibly might be addressed by monetary policy tools directly. Given, for example, the importance of repurchase markets in an environment where intermediation has become more broadly based institutionally.²⁷ this entails for instance the question of whether the repo rate should be an operational target of monetary policy implementation. The more transaction-driven, market-based the management of risk (credit, liquidity) becomes – and this is the way banking and its functional substitutes have moved for more than a quarter of a century²⁸ –, the more reliant intermediation (performed under whatever institutional guise) becomes on liquidity management. The adage – what credit risk, it's ultimately liquidity risk – is emblematic of this environment.

In brief and to conclude, in a crisis environment, central bank balance sheet management is by necessity (has historically as a rule been) about underwriting financial stability. This is crucial since it highlights, given the joint-product dimension of liquidity management and financial stability, the role central banks rather naturally play in containing systemic risk. Liquidity management under unconventional circumstances therefore has to be conducted in light of containing systemic risks. Thus, risk management in central banks cannot focus on minimizing its "private" risk. It is, instead, about providing a public good. But this can only go so far. As John Hicks famously remarked: "The social function of liquidity is that it gives time...". Ultimately, real solutions have to be found.

ANALYSES

²⁶ See in particular James Tobin and William Brainard (1963): Financial intermediaries and the effectiveness of monetary controls, in: American Economic Review, vol. 53, no. 2 (PaP), pp. 383-400.

²⁷ See in particular Gary Gorton and Andrew Metrick (2011): Securitized banking and the run on repo, in: Journal of Financial Economics, March, see also the recent work of the CGFS, in particular CGFS (2010): The role of margin requirements and haircuts in procyclicality, CGFS Paper No. 36.

²⁸ On this has insisted for example and for a long while Anthony Saunders (1997): Financial institutions management. A risk management approach, New York: Mc Graw Hill. The point was also made early on and forcefully by Alfred Steinherr (1998): Derivatives. The wild beast of finance, Chichester: John Wiley.

2. AN MVAR FRAMEWORK TO CAPTURE EXTREME EVENTS IN MACRO-PRUDENTIAL STRESS TESTS

By Paolo Guarda⁺, Abdelaziz Rouabah^{*}, and John Theal^{*}

1. INTRODUCTION

In the period following the financial crisis, the use of stress testing to assess the effect of adverse economic shocks on bank capitalization levels has become widespread. These tests have become a permanent fixture in the toolbox of regulatory authorities. However, reduced form implementations of these tests tend to be based on the underlying assumption that the residuals behave according to a univariate Gaussian distribution. Indeed, many of these models are formulated within the context of a classical vector autoregressive (VAR) framework. Although this assumption renders the model tractable, it fails to capture the observed frequency of distant tail events that represent the hallmark of systemic financial stress. Consequently, it seems apparent that these kinds of macro models tend to underestimate the actual level of credit risk. The omission of tail events also leads to an inaccurate assessment of the degree of systemic risk inherent in the financial sector. Clearly this may have significant implications for macro-prudential policy makers. One possible way to overcome such a limitation is to introduce a mixture of distributions model in order to better capture the potential for extreme events.

Based on the methodology developed by Fong, Li, Yau and Wong (2007), we have incorporated a macroeconomic model based on a mixture vector autoregression (MVAR) into the stress testing framework of Rouabah and Theal (2010) that is used at the Banque centrale du Luxembourg. This allows the counterparty credit risk model to better capture extreme tail events in comparison to models based on assuming normality of the distributions underlying the macro models. We believe this approach facilitates a more accurate assessment of credit risk.

The financial crisis that began in 2008 highlighted not only the poor risk-management practices implemented by the financial sector, it also illustrated weaknesses in financial regulatory and oversight frameworks. In particular, three major post-crisis lessons emerged. First, analysing financial stability requires a system-wide perspective rather than a strict micro-prudential approach. Second, there is an important link between macroeconomic conditions and financial stability that, prior to the crisis, was poorly understood and inadequately monitored. Third, statistical models of the linkages between the financial system and the real economy may break down in the face of extreme events. To address these three challenges, this paper applies a mixture vector autoregression (MVAR) in the context of macroeconomic stress tests in an attempt to illustrate the inadequacy of commonly employed VAR models. In forward-looking simulations, the MVAR model can provide multi-modal distributions for counterparty risk in the banking sector, reflecting the possible asymmetries and non-linearities that may manifest in the linkages between macroeconomic developments and financial stability.

In this study, we use the MVAR framework to extend previous work by Rouabah and Theal (2010) evaluating aggregate credit risk for Luxembourg's banking sector. We compare stress-test results based on a mixture of normals (MVAR) model to those obtained with a standard linear VAR. We also calculate Basel II tier 1 capital ratios under the MVAR framework and compare these to the values obtained from the standard linear VAR model.

⁺ Banque centrale du Luxembourg, Department of Economics and Research.

^{*} Banque centrale du Luxembourg, Financial Stability Department.

2. THE MVAR MODEL: A TOOL TO CAPTURE EXTREME EVENTS

Fong et al. (2007) develop the MVAR model as a multivariate extension of the mixture autoregression model in Wong and Li (2000). An $MVAR(n,K;p_k)$ model with K components for an observed n -dimensional vector Y_t takes the following form:

$$F(y_t | \mathfrak{S}_{t-1}) = \sum_{k=1}^{N} \alpha_k \Phi \left(\Omega_k^{-1/2} \left(Y_t - \Theta_{k0} - \Theta_{k1} Y_{t-1} - \Theta_{k2} Y_{t-2} - \dots - \Theta_{k1p} Y_{t-p_k} \right) \right)$$
(1)

Where y_t is the conditional expectation of Y_t , p_k is the autoregressive lag order of the k^{th} component, \mathfrak{T}_{t-1} is the available information set up to time t-1, $\Phi(\cdot)$ is the cumulative distribution function of the multivariate Gaussian distribution, α_k is the mixing weight of the k^{th} component distribution, Θ_{k0} is an n-dimensional vector of constant coefficients and $\mathfrak{D}_{k1}, \ldots, \mathfrak{O}_{kp_k}$ are the $n \times n$ autoregressive coefficient matrices of the k^{th} component distribution. Lastly, Ω_k is the $n \times n$ variance-covariance matrix of the k^{th} component distribution. One convenient characteristic of the MVAR is that individual components of the MVAR can be non-stationary while the entire MVAR model remains stationary.

It is possible to estimate the parameters of the MVAR using the expectation-maximization (EM) algorithm of Dempster et al. (1977). This assumes a vector of (generally) unobserved variables $Z_t = (Z_{t,1}, \dots, Z_{t,K})^T$ defined as:

$$Z_{t,i} = \begin{cases} 1 & \text{if } Y_t \text{ comes from the } i^{\text{th}} \text{ component}; \quad 1 \le i \le K, \\ 0 & \text{otherwise} \end{cases}$$

$$\tag{2}$$

Where the conditional expectation of the binary indicator $Z_{t,i}$ gives the probability that an observation originates (or does not originate) from the i^{th} component of the mixture. As shown by Fong et al. (2007), the conditional log-likelihood function of the MVAR model can subsequently be written as follows:

$$l = \sum_{t=p+1}^{T} \left\{ \sum_{k=1}^{K} Z_{t,k} \log(\alpha_{k}) - \frac{1}{2} \sum_{k=1}^{K} Z_{t,k} \log|\Omega_{k}| - \frac{1}{2} \sum_{k=1}^{K} Z_{t,k} \left(e_{kt}^{T} \Omega_{k}^{-1} e_{kt}\right) \right\}$$
(3)

Where the following variable definitions apply:

$$e_{kt} = Y_t - \Theta_{k0} - \Theta_{k1}Y_{t-1} - \Theta_{k2}Y_{t-2} - \dots - \Theta_{kp_k}Y_{t-p_k}$$

$$= Y_t - \tilde{\Theta}_k X_{kt}$$

$$\tilde{\Theta}_k = \left[\Theta_{k0}, \Theta_{k1}, \dots, \Theta_{kp_k}\right]$$

$$X_{kt} = \left(1, Y_{t-1}^{\mathrm{T}}, Y_{t-2}^{\mathrm{T}}, \dots, Y_{t-p_k}^{\mathrm{T}}\right)^{\mathrm{T}}$$
(4)

A number of model parameters need to be estimated. The parameter vector of the MVAR model is, in this case, $\Psi(\hat{\alpha}_k, \tilde{\Theta}_k^{\mathrm{T}}, \hat{\Omega}_k)$. Here $\hat{\alpha}_k$ are the estimated mixing weights of the K component distributions, $\tilde{\Theta}_k^{\mathrm{T}}$ are the estimated $n \times n$ autoregressive coefficient matrices and $\hat{\Omega}_k$ are estimates of the K $n \times n$ variance covariance matrices. As discussed in Fong et al. (2007), for the purpose of identification, it is assumed that $\alpha_1 \ge \alpha_2 \ge \cdots \ge \alpha_K \ge 0$ and $\sum_k \alpha_k = 1$. In the vector X_{kt} , the first element (i.e. the 1) is a scalar quantity.

As shown in Fong et al. (2007), the equations for the expectation and maximization steps can be written as follows. In the expectation step, the missing data Z are replaced by their expectation conditional on

ANALYSES

the parameters $\tilde{\Theta}$ and on the observed data $Y_1 \dots Y_T$. If the conditional expectation of the k^{th} component of Z_t is denoted $\tau_{t,k}$ then the expectation step is calculated according to equation (5):

Expectation Step:

$$\tau_{t,k} = \frac{\alpha_k \left| \Omega_k \right|^{-\frac{1}{2}} \exp\left(-\frac{1}{2} e_{kt}^{\mathrm{T}} \Omega_k^{-1} e_{kt} \right)}{\sum_{k=1}^{K} \alpha_k \left| \Omega_k \right|^{-\frac{1}{2}} \exp\left(-\frac{1}{2} e_{kt}^{\mathrm{T}} \Omega_k^{-1} e_{kt} \right)}, \quad k = 1, \dots, K$$
⁽⁵⁾

Following the expectation step, the maximization step can then be used to estimate the parameter vector $\tilde{\Theta}$. The M-step equations are defined in Fong et al. (2007) as:

Maximization Step:

$$\hat{\alpha}_{k} = \frac{1}{T - p} \sum_{t=p+1}^{T} \tau_{t,k},$$

$$\hat{\tilde{\Theta}}_{k}^{\mathrm{T}} = \left(\sum_{t=p+1}^{T} \tau_{t,k} X_{tk} X_{tk}^{\mathrm{T}}\right)^{-1} \left(\sum_{t=p+1}^{T} \tau_{t,k} X_{tk} Y_{t}^{\mathrm{T}}\right),$$

$$\hat{\Omega}_{k} = \frac{\sum_{t=p+1}^{T} \tau_{t,k} \hat{e}_{kt} \hat{e}_{kt}^{\mathrm{T}}}{\sum_{t=p+1}^{T} \tau_{t,k}}$$
(6)

where $1, \ldots, K$. The model parameters are obtained by maximizing the log-likelihood function given in equation (3).

In addition to the MVAR, a VAR(2) model is also estimated. After estimating the models, it is possible to subject them to exogenous, pre-specified adverse macroeconomic shocks. This provides an empirical measure of 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. Through recursion of the respective VAR or MVAR model equations, 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.

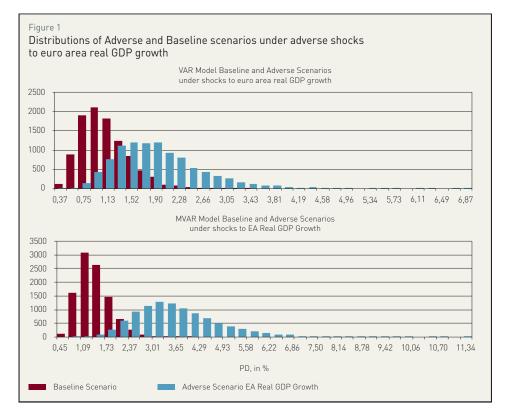
The adverse scenario is constructed in a similar manner, except that at various periods throughout the simulation horizon exogenous shocks are applied to the individual macroeconomic variable equations. Consequently, conditional on the shocks, the distribution of the adverse scenario probability of default 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

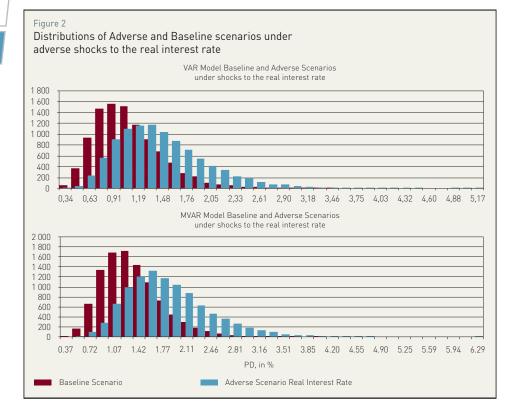
of the probability of default distribution to specific adverse macroeconomic developments. Under this type of deterministic approach, the response of the distribution can be evaluated for more complex macroeconomic scenarios. In any case, comparing the distributions provides information on the probable 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 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.

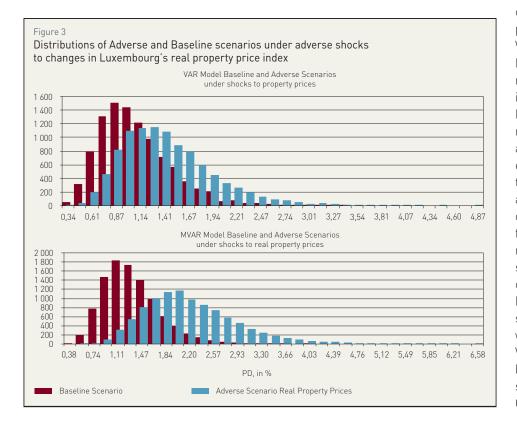
Three different stressed scenarios were employed with shocks being applied individually to the selected macroeconomic variables. The scenarios were chosen in order to focus on the various aspects of the transmission mechanism between the macroeconomic environment and the counterparty credit risk of the Luxembourg banking sector. The three specific scenarios include both domestic and EU level effects and are taken over a horizon of 10 quarters starting in 2011 Q3 and with the simulation ending in 2013 Q4. The scenarios are comprised of the following macroeconomic conditions:

- 1. A decrease in Euro area real GDP growth of magnitude -0.025 in the first quarter of 2012, followed by successive shocks of -0.028, 0.0 and 0.01 in the subsequent quarters
- 2. An increase in real interest rates of 100 basis points beginning in the first quarter of 2012 and a further increase of 100 basis points in 2012 Q3
- 3. A reduction in real property prices of magnitude 4% in 2012 Q1 and subsequent losses of 4% over the remaining quarters of 2012

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 guarterto-quarter basis over the separate scenarios. For both the baseline and adverse scenarios we performed 5000 Monte Carlo simulations of the model and used the 5000 simulated probabilities of default in the last quarter of 2013 to construct the histograms. The actual simulation results for the four scenarios are displayed in figures 1 through 3.







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 euro area real GDP growth, in the VAR case, the mean probability of default increases from approximately 1.09% to 1.70% under the adverse scenario. The corresponding change for the MVAR estimation is from 1.09% to 3.2%. For the remaining scenarios the increase is from 1.05% to 1.42% for the VAR and 1.24% to 1.59% for the MVAR under the real interest rate scenario. For the property price shocks, the VAR distribution increases from 0.9% to 1.27% while the MVAR increases from 1.17% to 2.02%. Tail probabilities under the stressed VAR scenario do not exceed their MVAR counterparts and no scenario displays probabilities of default in excess of approximately 8.14%. 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, except in the MVAR euro area real GDP growth and property price scenarios. For instance, the largest change in average counterparty PDs occurs for the MVAR under shocks to euro area GDP growth with a change of 2.11%. Under the VAR scenarios, the largest change between the adverse and baseline scenario also occurs under the GDP scenario, but the magnitude of the change is only 0.61%. The MVAR increase is more than 3.4 times larger than that observed for the VAR model.

3. SIMULATION AND CALCULATION OF CAPITAL REQUIREMENTS

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 (7) and (8) 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.

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

$$(7)$$

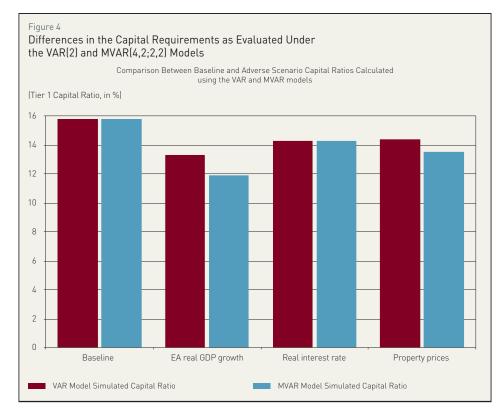
$$capital \ ratio = \frac{K+11}{RWA - 12.5E^{c} \left(k_{c} - k_{c}^{*}\right)}$$
[8]

In equation (7), 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 (8), K denotes tier 1 capital, Π and RWA denote profit and risk weighted assets, respectively, and E^c represents corporate exposures.

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 probability of default values obtained from the Monte Carlo simulation is used during the calculation of the Basel II correlation and capital requirements.

Figure 4 presents a bar chart showing the banking sector capital ratios under the four stressed scenarios in comparison to the baseline scenario. There are some noticeable differences between the capital requirements calculation for the VAR and MVAR models. Empirically the difference is 1.37%, suggesting that the VAR(2) model underestimates the required amount of capital in face of exogenous shocks to euro area real GDP



growth. Similar, although less dramatic, results can be observed for the other variables. For the real interest rate the magnitude of the difference is 0.10% while for property prices the difference is approximately equal to 0.88%.

4. CONCLUSION

According to the empirical results in this paper, the VAR model consistently underestimates counterparty credit risk. In a simulation that applies adverse macroeconomic shocks to the econometric model, it is found that the level of Tier 1 capital required to withstand these shocks is underestimated by the VAR model. For shocks to euro area real GDP growth the magnitude of this underestimation is approximately 1.4% of Tier 1 capital. Financially, for some banks, this may represent a significant amount of capital. The underestimation of capital requirements in the case of the univariate model may demonstrate that there is an information gain provided by the MVAR model which is not present in the VAR framework. Indeed, the difference between the calculated values has its origins in the distributional assumptions underlying the VAR and MVAR models. In the context of the MVAR, the model is capturing a significant amount of the tail effects that, being based on the assumption of univariate normality, the VAR model does not capture. However, at this time there is no statistical test that we can apply to these results in order to empirically evaluate their significance.

In this study we have shown that, compared to a framework with a unimodal distribution, using the MVAR model to assess counterparty risk provides a more accurate representation of the true risk by better capturing the more extreme movements observed in empirical measures of credit risk. The estimations of Tier 1 capital performed using univariate VAR models consistently underestimate the required amount of Tier 1 capital needed to withstand adverse macroeconomic shocks. These differences need to be taken into account since they have significant consequences from a regulatory perspective.

REFERENCES

Dempster, A.P., N.M. Laird and D.B. Rubin. (1977). "Maximum Likelihood from Incomplete Data via the EM Algorithm," *Journal of the Royal Statistical Society. Series B (Methodological)*, Vol. 39, No. 1. pp. 1-38.

Fong, P.W., W.K. Li, C.W. Yau and C.S. Wong. (2007). "On a mixture vector autoregressive model", *The Canadian Journal of Statistics*, Vol. 35, No. 1, pp. 135-150.

Rouabah, A. and J. Theal. (2010). "Stress Testing: The Impact of Shocks on the Capital Needs of the Luxembourg Banking Sector", *Banque centrale du Luxembourg*, Working Paper No. 47.

Wong, C.S. and W.K. Li. (2000). "On a mixture autoregressive model," *Journal of the Royal Statistical Society. Series B (Statistical Methodology)*, Vol. 62, No. 1, pp. 95-115.

3. AN EARLY-WARNING AND DYNAMIC FORECASTING FRAMEWORK OF DEFAULT PROBABILITIES FOR THE MACROPRUDENTIAL POLICY INDICATORS ARSENAL

By Xisong Jin* and Francisco Nadal De Simone⁺

ABSTRACT

The estimation of banks' marginal probabilities of default using structural credit risk models can be enriched incorporating macro-financial variables readily available to economic agents. By combining Delianedis and Geske's model with a Generalized Dynamic Factor Model into a dynamic t-copula as a mechanism for obtaining banks' dependence, this paper develops a framework that generates an early warning indicator and robust out-of-sample forecasts of banks' probabilities of default. The database comprises both a set of Luxembourg banks and the European banking groups to which they belong. The main results of this study are, first, that the common component of the forward probability of banks' defaulting on their long-term debt, conditional on not defaulting on their short-term debt, contains a significant early warning feature of interest for an operational macroprudential framework. Second, incorporating the common and the idiosyncratic components of macro-financial variables improves the analytical features and the out-of-sample forecasting performance of the framework proposed.

We thank the FNR for its financial support.

1. MOTIVATION

A relatively broad characterization of the objective of macroprudential policy is to limit systemic risk so as to minimize the costs of financial instability on the economy (ECB, June 2010). The literature on financial system risk has made a distinction between three different sources of systemic risk (ECB, December 2009): first, the exposure of all financial institutions to common, simultaneous macro-financial shocks; second, the sequential contagion from an idiosyncratic shock affecting a financial institution that spreads to other financial institutions and eventually to the real sector of the economy and; third, financial imbalances that build up over time and may unravel in a disorderly manner. Limiting financial systemic risk requires having indicators that provide a measure, albeit "fuzzy", of financial stability, and a set of instruments to maintain and restore financial stability, when it is perturbed (Borio and Drehmann, 2009). Like the sources of systemic risk, indicators of systemic risk cover the cross-sectional dimension of systemic risk (e.g., Segoviano and Goodhart, 2009) and the time-dimension of systemic risk (e.g., Borio and Lowe, 2002). This paper contributes to several strands of the literature on both dimensions of systemic risk. Its objective is to develop a framework that identifies an early warning indicator of systemic risk that detects as early as possible the build up of endogenous imbalances; that recognizes exogenous shocks timely; that factors in some manner contagion among financial institutions and; that provides robust out-of-sample forecasts of probabilities of default.¹

One of the biggest challenges for credit risk models is modelling dependence between credit quality changes and between default events. Dependence modelling is necessary to understand the risk of simultaneous defaults, the ensuing distribution of losses and their effects on financial stability. Failing

^{*} Luxembourg School of Finance

⁺ Banque centrale du Luxembourg, Financial Stability Department

¹ The issue of financial institutions' contributions to systemic risk is not addressed in this paper, but in an accompanying study.

to account for dependence, therefore, underestimates potential losses (Lando, 2004). This is crucial for meaningful stress-testing exercises, for instance, as well as more generally, for the development of measures of systemic risk. To incorporate dependence, there are basically three broad approaches or mixtures of them: (1) to let probabilities of default be affected by common underlying observable variables; (2) to let probabilities of default be affected by underlying latent variables and; (3) to let direct contagion from a default event affect other firms. However, whether by using a mixture of distributions to model dependence or by using copula or network analysis, models require the estimation of marginal default probabilities as a first step. This study uses two of the structural credit risk models studied in Jin and Nadal De Simone (2011a) and Jin et al (2011b), i.e., Merton (1974) model and Delianedis and Geske (2003) model, to estimate implied neutral probabilities of default. To model dependence among financial institutions' default probabilities, this paper uses the Generalized Dynamic Factor Model (GDFM) of Forni et al (2005), which has been used extensively to exploit the information from a large dataset and also for forecasting (e.g., D'Agostino et al, 2011). However, as that Forni et al (2003) forecasting method is not easily applicable to a large number of underlying assets, and does not generate the distributions of forecasts, this paper introduces a novel approach that combines the GDFM with a dynamic t-copula to improve the GDFM forecasting capacity.

Copula theory provides an easy way to deal with (otherwise) complex multivariate modeling (Jin and Lehnert, 2011). The advantage of the copula approach is its flexibility, because the dependence structure between marginal components can be modeled in a second stage after the univariate distributions have been calibrated. The conditional dynamic t-copula is relatively easy to construct and simulate from multivariate distributions built on marginal probabilities and dependence structure. In fine, the GARCH-like dynamics in the copula variance and rank correlation offers multi-step-ahead predictions of the estimated GDFM common and idiosyncratic components simultaneously.

This study, therefore, shares the core features suggested for an appropriate measure of systemic risk according to Schwaab *et al* (2010): a broad definition of systemic risk such as the ECB's, an international focus, the incorporation of macroeconomic and financial conditions, unobserved factors, and the calculation of probabilities of defaults.

The main results and contributions of this paper to the time-dimension of systemic risk are, first, to show that the common component of the forward probability of banks' defaulting on their long-term debt, conditional on not defaulting on their short-term debt, contains a significant early warning feature of interest for an operational macroprudential framework. This is in the in the tradition recently surveyed by Frankel and Saravelos, 2010. Second, that incorporating the common and the idiosyncratic components of macro-financial variables improves the analytical features of the framework proposed, in agreement with recent work by Koopman *et al* (2010) and Schwaab *et al* (2010). Finally, and a novel contribution, the paper's framework produces robust out-of-sample forecasting of systemic risk, especially at the individual bank level.

The remainder of the study is organized as follows. Next section presents the modelling framework. Section III discusses the data, and section IV examines the empirical results. Section V concludes.

2. THE MODELING FRAMEWORK

2.1 SELECTED MODELS TO ESTIMATE DEFAULT PROBABILITIES

In order to develop tools to measure and assess financial stability it is necessary to characterize instability. The approach taken in this paper is to apply contingent claim analysis to the measurement of credit risk. Structural credit risk models attempt to assess the creditworthiness of a firm by modeling the evolution of the firm's asset values as a stochastic process, and by viewing bankruptcy as an endogenous random event linked to the value of the firm's assets. In this study, Merton model (Merton 1974) is used to compute benchmark default probabilities (PDs) and distance-to-default (DD)², while Delianedis and Geske model (Delianedis and Geske 2003)³ is used to compute the term structure of short- and long-run PDs for a set of Luxembourg and European banks.

For quoted financial institutions, those models are estimated by a two-step iterative algorithm similar to Moody's KMV iterative procedure⁴. Regarding the maturity of the debt value, this study takes all short term obligations due in one year as a one-year maturity debt, and all long-term debt as a ten-year maturity debt. For the Merton model, as in Moody's KMV, debt value equals debt due in one year plus half of long-term debt.

Given that Luxembourg bank subsidiaries are not publicly quoted, an alternative approach to calculate PDs has to be followed. In an application to Brazilian and Mexican banks, Souto *et al* (2009) and Blavy and Souto (2009), respectively, show that the book-based Merton's credit risk measures are highly correlated with market-based Merton's credit risk measures suggesting that banks' financial statements are a crucial piece of information when forming market expectations about the probability of banks' default.⁵ Regarding the estimation of volatility, although a dynamic volatility model is preferred in order to track risks more timely, most of those models require more data points than are available for Luxembourg banks. Alternatively, the RiskMetrics (RM) filter/model assumes a very tight parametric specification. The book value asset RM variance can be defined as: $h^{B}_{t+1} = (1 - \zeta)(\ln(V_{t}^{B} / V_{t-1}^{B}))^{2} + \zeta h^{B}_{t}$, where the variance forecast h^{B}_{t+1} for period *t+1* is constructed at the end of period *t* using the square of the return observed at the end of period *t* as well as the variance on period *t*, and V^{B} is assets' book value. To avoid calibration difficulties due to the limited sample, ζ is assumed to be same for all banks and estimated by numerically optimizing the composite likelihoods (Varin *et al*, 2011). The book-value risk neutral PDs of the Merton model and the Delianedis and Geske model can then be estimated.

2.2 THE GENERALIZED DYNAMIC FACTOR MODEL

The GDFM assumes that each time series in a large data set is composed of two sets of unobserved components: first, the common component, which is driven by a small number of shocks that are common to the entire panel—each time series has its own loading associated with the shocks; second, the idiosyncratic component, which is specific to a particular series and orthogonal with the past, present, and future values of the common component. The common component of PDs is, therefore, best viewed as the result of the underlying unobserved systemic risk process, which is expected to be relatively persistent. The idiosyncratic component instead reflects local aspects of credit risk that while far from negligible, especially in the short term, are transient. Thus, the GDFM model applied to a large macro-financial dataset extracts the common components of marginal PDs of group banks and Luxembourg banks showing how a set of systemic factors affects both of them simultaneously, albeit with different weights. The GDFM model is estimated using the one-sided estimator proposed by Forni *et al* (2005).

ANALYSES

² DD is simply the number of standard deviations that the firm is away from default.

For a bank that has long term debt which matures at date T₂, and short term debt which matures at date T₁, the model allows to calculate the following risk neutral PDs: (1) the joint probability of defaulting at either date T₁ or date T₂; (2) the short-run probability of defaulting on the short-term debt at date T₁; (3) the forward probability held today of defaulting on the long-term debt at date T₂; (2) the short-term debt at date T₁.

⁴ Duan et al, (2004) show that the KMV estimates are identical to maximum likelihood estimates (MLE).

⁵ See also Gray and Jones, 2006, for an early application of this idea.

In this study, the data sets, beside PDs or DDs, includes market indexes and macroeconomic variables for the euro area, Belgium, Canada, Denmark, France, Germany, Greece, Japan, Netherlands, Italy, Spain, Sweden, Switzerland, United Kingdom, United States, and Luxembourg.

2.3 A DYNAMIC FORECASTING FRAMEWORK

Forni *et al* (2005) provide a good framework for multi-step-ahead predictions of the common component of credit risk. Nevertheless, the idiosyncratic (credit risk) component also plays an important role for financial instability, which cannot be neglected (see Schwaab *et al*, 2010). Forni *et al* (2003) construct a linear forecasting model with the contemporaneous common component and the lagged idiosyncratic component. However, their forecasting method is not easily applied to a large number of underlying assets simultaneously, and also does not generate the distribution of these forecasts. This study introduces a novel approach to combine the GDFM with a dynamic copula. Formally, the dynamic forecasting model becomes:

$$\begin{split} X_{t+1}^{F} &= X_{t+1}^{CC_{-F}} + X_{t+1}^{IC_{-F}} \\ X_{t+1}^{CC_{-F}} &= X_{t+1}^{GDF_{-F}} + \sigma_{t+1}^{CC} \varepsilon_{t+1}^{CC} \\ X_{t+1}^{IC_{-F}} &= \sum_{i=1}^{p} X_{t+1-i}^{IC} + \sigma_{t+1}^{IC} \varepsilon_{t+1}^{IC} \\ \sigma_{t+1}^{2} &= \alpha_{0} + \alpha (\sigma_{t} \varepsilon_{t})^{2} + \beta \sigma_{t}^{2} \\ \varepsilon_{t+1} &\sim iid(0,1) \\ F(\varepsilon_{t+1}^{1}, \varepsilon_{t+1}^{2}, ..., \varepsilon_{t+1}^{2n}) = C_{T} (F_{1}(\varepsilon_{t+1}^{1}), F_{2}(\varepsilon_{t+1}^{2}), ..., F_{3}(\varepsilon_{t+1}^{2n}); R_{t}, v_{t}), \end{split}$$

where the forecast X_{t+1}^F of the marginal credit risk is the sum of its forecasted common component $X_{t+1}^{CC}F$ and idiosyncratic component $X_{t+1}^{IC}F$; X_t^{CC} is the common component, and X_t^{IC} is the idiosyncratic component. Both common and idiosyncratic components are assumed to follow a GARCH [1,1] process. The mean of $X_{t+1}^{CC}F$ is the prediction of the common component $X_{t+1}^{GDF}F$ by the GDFM as in Forni *et al* (2005), whereas the mean of $X_{t+1}^{IC}F$ is an autoregressive process of order p, AR (p). The multivariate distribution is $F(\varepsilon_{t+1}^1, \varepsilon_{t+1}^2, ..., \varepsilon_{t+1}^{2n})$ for i=1,2,...,2n, which includes standardized residuals from both common and idiosyncratic components and has a time-varying t-copula.⁶ Using the conditional dynamic copula, it is relatively easy to construct and simulate from multivariate distributions built on marginal distributions and dependence structure⁷. Drawing on Jin and Nadal De Simone (2011a), a PD index of systemic risk is built aggregating the individual banks' PD estimates weighted by their respective implied asset values.⁸

3. DATA

This study is applied to 32 major European banking groups, to their respective 37 subsidiaries active in Luxembourg, and to two 100%-Luxembourg banks. Market data used for estimating marginal PDs of the major European banking groups include government bond yields, the number of outstanding shares, and book value data. The macrofinancial database used for the GDFM model comprises also industrial production, employment, GPD, consumer prices, stock indices, housing prices, exchange rates, credit data. Sources are Bloomberg, DataStream, BIS, Eurostat. The market data start in May 2000 and finish in September 2011.

- 6 See Patton (2006) for the definition of a general conditional copula.
- 7 See Jin and Lehnert (2011) for the dynamic conditional t-copula and forward simulation.
- 8 Weights other than asset values are used and discussed below.

All the Luxembourg banks are unlisted, so quarterly book value data from the BCL database going back to 2003Q1 are used. The 37 subsidiaries registered in Luxembourg represent about 63 percent of the total assets of the Luxembourg banking industry. When the two 100% Luxembourg banks are added to the list, the database represents nearly 70 percent of the total assets of the industry. For all the selected Luxembourg banks, short term debt includes demand and time deposits of up to one-year maturity, short-term funding, and repos, while long term debt includes time deposits of over one-year maturity and other long-term funding.

4. EMPIRICAL RESULTS

This study estimates DDs and risk-neutral marginal PDs from two structural credit risk models, Merton (1974) model and Delianedis and Geske (2003) model, and given its objective of accounting for systemic risk, it incorporates dependence among banks' PDs by using the GDFM Model (Forni et al, 2005) with a dataset including macroeconomic and financial variables. It identifies an indicator of systemic risk that recognizes exogenous shocks timely and spots the build up of endogenous imbalances; in addition, it improves on the GDFM forecasting capacity by combining it with a dynamic t-copula.

This section discusses first the Kendall correlation of asset-weighted PDs between European banking groups and their Luxembourg affiliates. It then addresses the early-warning capabilities of the framework both at the level of banks' individual PDs and DDs, and at the level of indexes of banks' PDs and DDs. Finally, it reports results on the out-of-sample forecasting capabilities of the framework for individual PDs and for total asset-weighted PDs.

4.1 ASSET-WEIGHTED PDS 9

As expected, there is a high degree of correlation (Kendall correlation) among European banking groups and Luxembourg banks PDs (Table 1). However, these correlations vary over time and also in sign depending on whether the short term (ST) or the long term (LT) components of PDs are considered, and on whether the common or the idiosyncratic components of PDs are considered.

During the whole sample period, correlation of PDs between both set of banks are highly significant for the whole time structure of PDs and for the common components. Interestingly, correlations are negative when the idiosyncratic components are involved, especially those of the banking groups' PDs. These results suggest that the parent banks and their affiliates are subject to bank specific factors that may diverge at a given point in time. Finding the causes of this behavior is certainly beyond the scope of this study. Nevertheless, it is possible to conjecture that this may be the result of the different business models of Luxemburg affiliates which overwhelmingly are net suppliers of liquidity to parent banks. This working hypothesis seems reasonable when the same analysis is applied to the pre-crisis period, 2004-07, the crisis period, 2008-09, and the post-crisis period, 2010-2011. It seems that it is the LT idiosyncratic components of PDs that are mostly significant and move in the opposite direction between group banks and Luxembourg affiliates during the pre-crisis period. During the crisis period, as expected, correlations increase—banks' interdependence increases (also seen in the increase of the number of significant correlations).

Finally, in the post-crisis period, there is again an increase in the importance of the idiosyncratic components which move in disparate directions at the parent and at the affiliate banks. This is more the ANALYSES

⁹ The Kendall correlation of asset-weighted DDs between European banking groups and their Luxembourg affiliates provides the similar results as PDs.

case with respect to the ST PDs than with respect to the LT PDs, however, which is an important difference with the pre-crisis period and possibly a reminder of the persistence of short-term solvency issues across some banking groups in Europe.

4.2 EARLY-WARNING FEATURES OF SINGLE-BANK PDS AND WEIGHTED INDEXES OF PDS

As stated above, a macroprudential policymaker is interested not only in the timeliness of measures of credit risk, but ideally would like to have some indication of the buildup of vulnerabilities in the financial system as early as possible. To assess the strength of the framework proposed in this study to that end, two approaches are followed. First, a set of Granger causality tests is performed between the common component of the estimated PDs/the macrofinancial factors and estimated PDs.¹⁰ Second, the degree of commovement and leads and lags between the common components and estimated PDs is studied using spectral methods.

4.2.1 Granger causality tests

Table 2 summarizes the results of the Granger causality tests applied to each bank's estimated PDs. Table 2 reports ratios, which are the percentage of cases when X Granger causes Y, and Y does not Granger cause X at p-values of 1%, 5% and 10%. The ratios under common component mean that the common component Granger causes DPs and DPs do not Granger cause the common component; similarly, for DPs.¹¹ At the p-value of 1%, for example, the common component of the estimated DPs Granger causes banking groups Geske All PDs and DDs in 31% and 25% of the cases, respectively. It also Granger causes Luxembourg banks' PDs in 26% and DDs in 36% of the cases. The opposite is much less frequent. Importantly, the common component has a clearer anticipatory feature with respect to DDs than PDs for both banking groups and for Luxembourg banks.

The framework's best performance is with respect to the LT PDs of Luxembourg banks, i.e. the ratio is 50%. This feature is likely due to the use of book-value data for estimating Luxembourg banks' PDs, which is less timely than the information contained in share prices used for estimating banking groups' PDs. This leading information in the common component of PDs is a particularly useful feature of the proposed methodology for Luxembourg banks given that they are not quoted.

The same analysis is done for indexes of PDs weighted using proxies of some of the indicators of banks' systemic importance suggested in the literature, respectively (e.g. BCBS, 2011, and Drehmann and Tarashev, 2011). Those proxies are total assets—a proxy for *size*—and interbank lending and interbank borrowing—proxies for *interconnectedness*. Individual bank data on interbank lending and borrowing at quarterly frequency are available for Luxembourg banks only.¹² In general, the common component does not Granger cause the PDs or DDs indexes (the results are not shown to conserve space). The use of weighting schemes without dependent structure seems to hide information embedded in the common components and loadings making it more difficult to draw conclusive evidence using Granger causality tests. These weights do not seem useful to construct indices of PDs (or DDs) that could provide a meaningful early warning signal of the buildup of vulnerabilities.

- 11 Only standardized measures are displayed; non-standardized measures provide broadly the same results.
- 12 Drehmann and Tarshev (2011) propose three measures for determining banks' systemic importance. Two measures are top down: the participation approach (i.e., expected losses incurred by a given bank' non-bank creditors) and the contribution approach (i.e. expected losses from a bank's exposure to exogenous shocks, from its contribution to losses via propagation and from its idiosyncratic exposure to shocks). Another measure is bottom up, i.e. the expected losses of the whole banking system conditional on a given bank being in default. The authors show that size is a good proxy of all measures, that interbank lending proxies well the participation and the contribution approaches.

¹⁰ Jin et al (2011b) studied lead-lag relationships across models' PDs predictions, but had no reference to macrofinancial conditions.

However, the nonlinearities and feedback between PDs or DDs and their common components, make it advisable to look at matters in more detail. The leading features of the common component for Luxembourg banks' PDs can be visualized in the set of figures 1a to 1d which show asset-weighted PDs. What is of interest here is the leading behavior of the common component with respect to Luxembourg banks' estimated LT PDs. Starting in 2005 (Figure 1b) for banking groups, and in early 2006 (for Luxembourg banks), there is a clear, persistent increase in LT PDs. This suggests a buildup of credit risk long-term vulnerabilities—a fact also documented in Koopman *et al* (2010).

4.2.2 Frequency-domain analysis

The test in the previous section clearly suffers from the averaging across periods typical of time-domain time series analysis, which in the presence of nonlinearities and feedback effects may mask the lead/lag relationships between common components and estimated PDs. To take that into account, this section briefly looks at the comovement between PDs and its common components using spectral methods. In particular, the coherence (squared) and the phase angle are estimated.¹³ Figures 2a to 2d display the estimated coherences and phase angles between the common components and Geske ST and LT PDs for banking groups and Luxembourg banks. The complicated interrelations and feedback effects between the common components and measures of PDs evince clearly.

In general, the common components lag estimated ST PDs for banking groups only at periodicities between 1 and 2 years. Instead, the common components lead ST PDs in cycles between 2.5 years and 8 years, that is to say, roughly during the *minor* (2 to 4 years) and the *major* (4 to 8 years) business cycles' durations (NBER terminology). The common components lead LT PD during cycles of between 1.5 and 2 years and cycles of between 3 to 5 years, i.e., during most of the minor cycle and the first part of the major cycle.

In the case of Luxembourg banks, the common components lag estimated ST and LT PDs around periodicities of 1 year, and between 1.5 and 2.5 years for ST PDs and about 2 years for LT PDs. Otherwise, the common components lead ST and LT PDs at periodicities of about 3 quarters and in the longer run, at periodicities ranging between 3 and (over) 8 years for the ST PDs, and between 4 and (over) 8 years for the LT PDs.

Summarizing, the results support the leading features of information embedded in the common components at relatively high frequency (i.e., roughly 3 quarters) and at relatively lower frequency (i.e., between around 3 years and 8 years).

4.3 OUT-OF-SAMPLE FORECASTING¹⁴

The short number of data points available constrains a full-fledged, standard evaluation of the outof-sample forecasting capabilities of the framework. Table 3 reports the coverage ratios, root-mean squared errors, as well as the bias, the variance and the covariance of Theil's inequality coefficient from 2010 to 2011 across all estimated Geske's PDs for banking groups and Luxembourg banks. The coverage ratio is the share of banks whose empirical simulated cdf at each of the estimated PDs is within the range of the respective quartiles. Under the null hypothesis that this forecasting framework correctly estimates the dynamics of PDs, the coverage ratio should approximate the range of quartiles if ANALYSES

¹³ Coherence (squared) is the proportion of the variance of a series which can be explained by the other series, period (or frequency) by period (by frequency). The phase lead is the fraction of a cycle by which one series leads (lags) the other at each period or frequency. The phase lead is significant only at the periods (or frequencies) at which the coherence is significant.

¹⁴ The evaluation of the out-of-sample forecasting of DDs provides the similar results as PDs.

the number of underlying banks were large enough. For example, during the first month out-of-sample forecasts, 77% of bank PDs forecasted using only the common component are within quartiles 5%-95% of the forecasted cdf of PDs. It falls to 70% at month six. When not only the common but also the idio-syncratic components are forecasted, 86% percent of the forecasted PDs fall in the quartiles 5%-95% and increases to about 88% at month six. Decomposing Theil's inequality coefficient, it seems that the improvement in forecasting ability by adding the idiosyncratic component results from an improvement in the model's capacity to replicate the degree of variance in PDs (column "Variance Proportion") and from reducing unsystematic error (column "covariance Proportion").

5. CONCLUSIONS AND MACROPRUDENTIAL POLICY IMPLICATIONS

This study develops a framework that recognizes exogenous shocks timely and identifies an early warning indicator of systemic risk that spots the build up of endogenous imbalances in advance. In addition, it provides robust out-of-sample forecasts of PDs.

It uses a two-step approach to proxy banks' default dependency. First, marginal PDs are estimated using Merton and Delianedis and Geske compound option models, the latter of which solves for the time structure of PDs. Second, the generalized dynamic factor model is applied to a large macrofinancial dataset to extract the common component of banks' marginal PDs at the banking group and at the subsidiary levels. This shows how a set of common systemic factors affect both of them simultaneously, albeit with different weights. The same framework also identifies the idiosyncratic component of banks' PDs. This two-step approach tracks in advance over a couple-of-year time span a persistent increase in credit risk for the banking system in the tradition of early warning indicators. This rise in credit risk can be interpreted as an increase in the vulnerability of the financial system.

By separating the role of system developments from individual banks' idiosyncratic features, this study is an important step toward building macro-financial models of systemic risk that contain early-warning features with a realistic characterization of episodes of financial instability. This work contributes to the systemic risk literature incorporating the externalities that financial intermediaries exert on the rest of the financial system and on the economy in general by signaling out the role of common systemic forces affecting all banks and also by showing the buildup of credit risk or widespread imbalances over time, another interpretation of systemic risk. This study also contributes to the macroprudential literature with a method for monitoring systemic risk.

Finally, this research contributes to the macroprudential literature by suggesting a framework to forecast changes in the common and the idiosyncratic components of a large database via using a dynamic conditional t-copula. This remediates the well known feature that simply aggregating banks' marginal PDs provides a downward-biased measure of banking systemic risk. By incorporating the common and the idiosyncratic components of a broad set of macro-financial variables, the framework improves the analytical features and the out-of-sample forecasting performance of the model.

REFERENCES

Basel Committee on Banking Supervision, 2011, "Globally Systemically Important Banks: Assessment Methodology and the Additional Loss Absorbency Requirement", *Bank for International Settlements*.

Blavy, R., and M. Souto, 2009, "Estimating Default Frequencies and Macrofinancial Linkages in the Mexican Banking Sector", *IMF Working Paper*, WP/09/109.

Borio, C. and P. W. Lowe, 2002, "Asset Prices, Financial and Monetary Stability: Exploring the Nexus", Working Paper No. 114, *Bank for International Settlements*.

Borio, C. and M. Drehmann, 2009, "Towards an Operational Framework for Financial Stability: "Fuzzy" Measurement and its Consequences", Working Paper No. 218, *Bank for International Settlements*.

D'Agostino, A. & McQuinn, Kieran & O'Brien, Derry, 2011. "NowCasting Irish GDP", MPRA Paper 32941, University Library of Munich, Germany.

Delianedis, G., and R. Geske, 2003, "Credit Risk and Risk Neutral Default Probabilities: Information about Rating Migrations and Default", Working Paper, University of California at Los Angeles.

Drehmann, M. and N. Tarashev, 2011, "Systemic Importance: some Simple Indicators", *BIS Quarterly Review*, March, Bank for International Settlements.

Duan, J.C., G. Gauthier, J-G Simonato, 2004, "On the Equivalence of KMV and Maximum Likelihood Methods for Structural Credit Risk Models", Working Paper.

European Central Bank, "The Concept of Systemic Risk", *Financial Stability Review*, pp. 134-142, December 2009.

European Central Bank, June 2010, "Macro-prudential Policy Objectives and Tools", *Financial Stability Review*, pp. 129-137.

European Central Bank, December 2010, "Analytical Models and Tools for the Identification and Assessment of Systemic Risk", *Financial Stability Review*, pp. 38-146.

Forni M., Hallin M., Lippi M. and Reichlin L., 2003, "Do Financial Variables Help Forecasting Inflation and Real Activity in the EURO Area?", Journal of Monetary Economics 50, pp. 1243-55.

Forni, M., M. Hallin, M. Lippi, and L. Reichlin, 2005, "The Generalized Dynamic Factor Model Onesided Estimation and Forecasting", *Journal of the American Statistical Association* Vol. 100, No. 471, pp. 830-840.

Frankel, J. and G. Saravelos, 2010, "Are Leading Indicators of Financial Srises Useful for Assessing Country Vulnerability? Evidence from the 2008-09 Global Crisis", *NBER Working Paper 16047*.

Gray, D. and M. Jones, 2006, "Indonesia: Selected Issues Paper, "Measuring Sovereign and Banking Risk in Indonesia: An Application of the Contingent Claims Approach", IMF Country Report No. 06/318, *International Monetary Fund*.

Jin, X. and F. Nadal De Simone, 2011a, "Market- and Book-based Models of Probability of Default for Developing Macroprudential Policy Tools", Working Paper No. 65, *Banque centrale du Luxembourg*.

Jin, X., T. Lehnert, and F. Nadal De Simone, 2011b, "Does the GARCH Structural Credit Risk Model Make a Difference?", Research Working Paper Series No. 11-06, *Luxembourg School of Finance*, University of Luxembourg.

ANALYSES

Jin, X., T. Lehnert, 2011, «Large Portfolio Risk Management and Optimal Portfolio Allocation with Dynamic Copulas», Research Working Paper Series No. 11-10, Luxembourg School of Finance, University of Luxembourg.

Koopman, S. J., A. Lucas and B. Schwaab, 2010, "Macro, Industry and Frailty Effects in Defaults: The 2008 Credit Crisis in Perspective", *Tinbergen Institute Discussion Paper*, TI 2010-004/2.

Lando, D., 2004, Credit Risk Modeling. Theory and Applications, Princeton.

Merton, R., 1974, "On the Pricing of Corporate Debt: The Risk Structure of Interest Rates", *Journal of Finance* 29, pp. 449-470.

Patton, J., 2006, "Modelling Asymmetric Exchange Rate Dependence", *International Economic Review*, 47, 527-556.

Scwaab, B., A. Lucas and S. J. Koopman, 2010, "Systemic Risk Diagnostics", *Duisimberg School of Finance and Tinbergen Institute Discussion Paper*, TI 10-104/DSF 2.

Segoviano, M. and C. Goodhart, 2009, "Banking Stability Measures", *IMF Working Paper WP/09/04*, International Monetary Fund.

Souto, M., Tabak, B., and F. Vazquez, 2009, "Linking Financial and Macroeconomic Factors to Credit Risk Indicators of Brazilian Banks", *Banco Central do Brasil*, Working Paper No. 189.

Varin, C., Reid, N., and D. Firth, 2011, "An Overview of Composite Likelihood Methods", Statistica Sinica 21.

Table 1

Total Asset Value Weighted PDs and PDs' Component Rank Correlation between Banking Groups and Luxembourg Banks

	Lux Geske Total	Lux Geske ST	Lux Geske LT	Lux Accu- mulated Common Compo- nent Total	Lux Accu- mulated Common Compo- nent ST	Lux Accu- mulated Common Compo- nent LT	Lux Accu- mulated Idiosyn- cratic Compo- nent Total	Lux Accu- mulated Idiosyn- cratic Compo- nent ST	Lux Accu- mulated Idiosyn- cratic Compo- nent LT
			20	004-2011					
Group Geske Total	<u>0,51</u>	0,50	<u>0,45</u>	<u>0,47</u>	0,45	0,66	<u>-0,17</u>	<u>-0,19</u>	-0,12
Group Geske ST	<u>0,52</u>	<u>0,50</u>	<u>0,47</u>	<u>0,46</u>	<u>0,43</u>	<u>0,66</u>	<u>-0,15</u>	<u>-0,18</u>	-0,10
Group Geske LT	<u>0,35</u>	<u>0,36</u>	<u>0,25</u>	<u>0,49</u>	<u>0,51</u>	<u>0,51</u>	<u>-0,28</u>	<u>-0,30</u>	<u>-0,24</u>
Group Accumulated Common Component Total	<u>0,62</u>	<u>0,60</u>	<u>0,57</u>	<u>0,34</u>	<u>0,31</u>	<u>0,54</u>	-0,03	-0,06	0,03
Group Accumulated Common Component ST	<u>0,54</u>	<u>0,53</u>	<u>0,49</u>	<u>0,44</u>	<u>0,41</u>	<u>0,62</u>	-0,14	<u>-0,16</u>	-0,05
Group Accumulated Common Component LT	<u>0,50</u>	<u>0,50</u>	<u>0,42</u>	<u>0,17</u>	<u>0,19</u>	<u>0,35</u>	0,12	0,09	0,12
Group Accumulated Idiosyncratic Component Total	<u>-0,57</u>	<u>-0,57</u>	<u>-0,47</u>	<u>-0,28</u>	<u>-0,30</u>	<u>-0,41</u>	-0,02	0,01	-0,05
Group Accumulated Idiosyncratic Component ST	<u>-0,46</u>	<u>-0,46</u>	<u>-0,36</u>	<u>-0,42</u>	<u>-0,44</u>	<u>-0,47</u>	0,13	<u>0,16</u>	0,06
Group Accumulated Idiosyncratic Component LT	<u>-0,51</u>	<u>-0,49</u>	<u>-0,43</u>	<u>-0,15</u>	<u>-0,15</u>	<u>-0,34</u>	<u>-0,19</u>	<u>-0,18</u>	<u>-0,15</u>

	Lux Geske Total	Lux Geske ST	Lux Geske LT	Lux Accu- mulated Common Compo- nent Total	Lux Accu- mulated Common Compo- nent ST	Lux Accu- mulated Common Compo- nent LT	Lux Accu- mulated Idiosyn- cratic Compo- nent Total	Lux Accu- mulated Idiosyn- cratic Compo- nent ST	Lux Accu- mulated Idiosyn- cratic Compo- nent LT		
2004-2007											
Group Geske Total	-0,04	-0,04	0,10	0,09	0,01	0,60	-0,14	-0,08	<u>-0,38</u>		
Group Geske ST	0,00	-0,01	0,14	0,06	-0,02	<u>0,57</u>	-0,09	-0,04	<u>-0,32</u>		
Group Geske LT	<u>-0,46</u>	<u>-0,41</u>	<u>-0,37</u>	<u>0,38</u>	<u>0,32</u>	<u>0,30</u>	<u>-0,59</u>	<u>-0,55</u>	<u>-0,60</u>		
Group Accumulated Common Component Total	<u>0,38</u>	<u>0,35</u>	<u>0,50</u>	<u>-0,38</u>	<u>-0,47</u>	0,09	0,28	<u>0,33</u>	0,18		
Group Accumulated Common Component ST	0,09	0,07	0,19	-0,01	-0,10	<u>0,40</u>	-0,07	-0,04	-0,13		
Group Accumulated Common Component LT	<u>0,36</u>	<u>0,34</u>	<u>0,43</u>	<u>-0,46</u>	<u>-0,47</u>	-0,12	<u>0,42</u>	<u>0,44</u>	<u>0,38</u>		
Group Accumulated Idiosyncratic Component Total	<u>-0,25</u>	<u>-0,27</u>	<u>-0,25</u>	<u>0,43</u>	<u>0,41</u>	<u>0,26</u>	<u>-0,20</u>	<u>-0,21</u>	<u>-0,36</u>		
Group Accumulated Idiosyncratic Component ST	0,17	0,14	0,19	-0,09	-0,12	0,05	<u>0,26</u>	<u>0,28</u>	0,07		
Group Accumulated Idiosyncratic Component LT	<u>-0,37</u>	<u>-0,35</u>	<u>-0,38</u>	<u>0,53</u>	<u>0,53</u>	<u>0,20</u>	<u>-0,52</u>	<u>-0,54</u>	<u>-0,47</u>		
			20	008-2009							
Group Geske Total	<u>0,42</u>	<u>0,38</u>	0,17	<u>0,51</u>	<u>0,38</u>	0,07	-0,20	<u>-0,30</u>	<u>0,31</u>		
Group Geske ST	0,44	<u>0,36</u>	0,20	<u>0,53</u>	<u>0,36</u>	0,09	-0,21	-0,28	<u>0,34</u>		
Group Geske LT	<u>0,37</u>	0,48	-0,13	<u>0,32</u>	<u>0,53</u>	-0,23	-0,10	-0,20	0,16		
Group Accumulated Common Component Total	<u>0,45</u>	<u>0,40</u>	0,16	<u>0,52</u>	<u>0,40</u>	0,06	-0,17	-0,28	<u>0,30</u>		
Group Accumulated Common Component ST	<u>0,46</u>	<u>0,39</u>	0,20	<u>0,55</u>	<u>0,38</u>	0,10	-0,19	-0,26	<u>0,35</u>		
Group Accumulated Common Component LT	<u>0,41</u>	<u>0,53</u>	-0,14	<u>0,36</u>	<u>0,58</u>	-0,24	-0,07	-0,15	0,15		
Group Accumulated Idiosyncratic Component Total	<u>-0,69</u>	<u>-0,78</u>	0,08	<u>-0,45</u>	<u>-0,59</u>	0,19	<u>-0,32</u>	-0,20	-0,03		
Group Accumulated Idiosyncratic Component ST	<u>-0,38</u>	<u>-0,49</u>	0,18	-0,20	<u>-0,39</u>	0,27	-0,25	-0,17	-0,01		
Group Accumulated Idiosyncratic Component LT	<u>-0,55</u>	<u>-0,49</u>	-0,17	<u>-0,54</u>	<u>-0,36</u>	-0,03	-0,20	-0,17	-0,22		
			20	010-2011							
Group Geske Total	<u>0,61</u>	<u>0,61</u>	<u>0,54</u>	<u>0,42</u>	<u>0,37</u>	<u>0,49</u>	<u>0,35</u>	<u>0,35</u>	0,07		
Group Geske ST	<u>0,60</u>	<u>0,60</u>	<u>0,53</u>	0,42	<u>0,37</u>	<u>0,45</u>	0,35	<u>0,35</u>	0,10		
Group Geske LT	0,42	<u>0,42</u>	0,33	0,05	0,00	<u>0,42</u>	<u>0,48</u>	<u>0,50</u>	-0,15		
Group Accumulated Common Component Total	<u>0,70</u>	<u>0,70</u>	<u>0,61</u>	0,27	0,22	<u>0,54</u>	<u>0,54</u>	<u>0,54</u>	0,05		
Group Accumulated Common Component ST	<u>0,67</u>	<u>0,67</u>	<u>0,62</u>	<u>0,33</u>	0,27	<u>0,59</u>	<u>0,46</u>	<u>0,46</u>	0,02		
Group Accumulated Common Component LT	<u>0,41</u>	<u>0,41</u>	0,32	-0,18	-0,23	<u>0,48</u>	<u>0,65</u>	<u>0,70</u>	-0,17		
Group Accumulated Idiosyncratic Component Total	<u>-0,43</u>	<u>-0,43</u>	<u>-0,34</u>	0,12	0,15	<u>-0,50</u>	<u>-0,61</u>	<u>-0,67</u>	0,19		
Group Accumulated Idiosyncratic Component ST	<u>-0,48</u>	<u>-0,48</u>	<u>-0,41</u>	0,05	0,08	<u>-0,51</u>	<u>-0,57</u>	<u>-0,63</u>	0,11		
Group Accumulated Idiosyncratic Component LT	<u>-0,44</u>	<u>-0,44</u>	-0,29	0,19	0,24	<u>-0,45</u>	<u>-0,66</u>	<u>-0,71</u>	0,14		

ANALYSES

The table reports the Kendall correlation matrix of the monthly PDs and their components between banking groups and Luxembourg banks. For Luxembourg banks, monthly PDs are assumed to be same within each quarter. A bold value with underscore indicates significance at the 95% level, whereas a bold value indicates significance at the 90% level.

Table 2

Granger Causality Test between Common Components and DPs for Each Banks

	AT P-VAL	UE 0F 1%	AT P-VAL	UE OF 5%	AT P-VALUE OF 10%		
	COMMON COMPONENT	PDS	COMMON COMPONENT	PDS	COMMON COMPONENT	PDS	
Group Geske All	0,31	0,13	0,41	0,13	0,44	0,13	
Group Geske ST	0,28	0,19	0,28	0,16	0,34	0,16	
Group Geske LT	0,28	0,21	0,28	0,21	0,34	0,21	
Group DD	0,25	0,00	0,41	0,00	0,56	0,00	
Lux Geske All	0,26	0,08	0,28	0,05	0,31	0,05	
Lux Geske ST	0,21	0,08	0,28	0,05	0,28	0,05	
Lux Geske LT	0,50	0,03	0,42	0,08	0,44	0,06	
Lux DD	0,36	0,00	0,41	0,00	0,44	0,00	

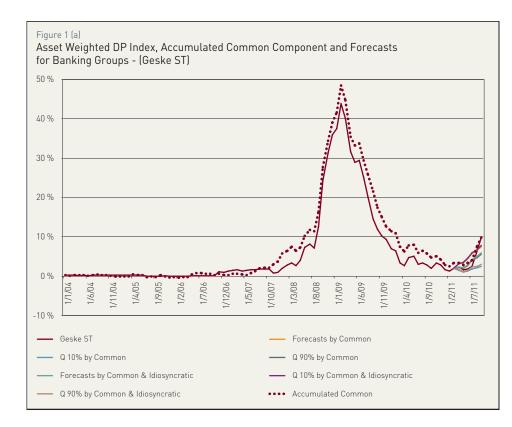
This table reports the ratios according to Granger Causality test at the p-values of 1%, 5% and 10% respectively. The measures are ranked by calculating the ratio of the times X Granger causes another measure Y and Y does not Granger causes X to the number of the available banks for banking groups and Luxembourg banks. The ratios under Common Component mean that the Common Component Granger causes PDs and PDs does not Granger causes the Common Component; similarly, for PDs. The standardized measure is constructed by (x-mean(x))/std(x).

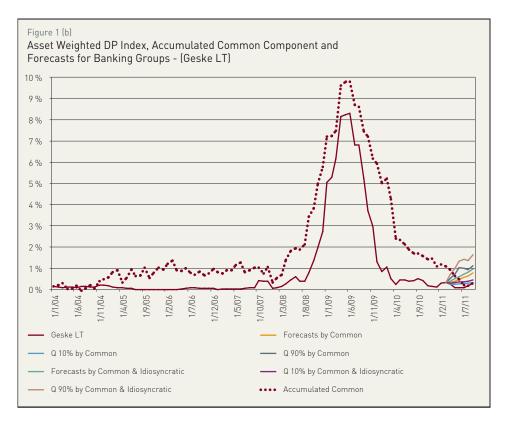
Table 3

Geske DP Forecast Evaluation for Banking Groups and Luxembourg Banks

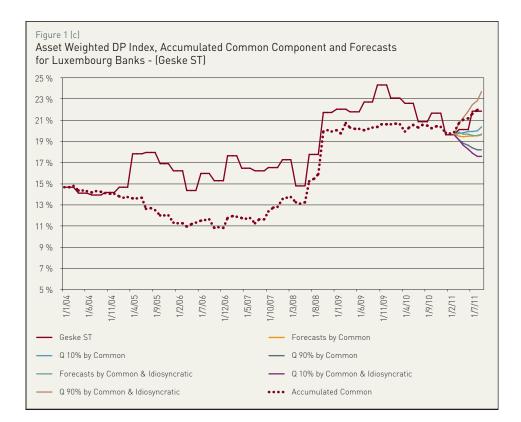
		Coverage Ratio								Bias	Variance	Coviance	
	Q 5%- 95%	Q 10%- 90%	Q 15%- 85%	Q 20%- 80%	Q 25%- 75%	Q 30%- 70%	Q 35%- 65%	Q 40%- 60%	Q 45%- 55%	RMS Error	Propor- tion	Propor- tion	Propor- tion
					(Common	Compon	ent					
1th Month	0,770	0,659	0,566	0,482	0,401	0,324	0,246	0,165	0,085	0,027	0,004	0,015	0,981
2nd Month	0,724	0,607	0,501	0,412	0,342	0,271	0,200	0,133	0,067	0,038	0,004	0,019	0,977
3rd Month	0,709	0,566	0,462	0,376	0,316	0,246	0,187	0,119	0,060	0,044	0,010	0,025	0,965
4th Month	0,705	0,559	0,457	0,383	0,314	0,242	0,181	0,124	0,063	0,051	0,016	0,028	0,956
5th Month	0,707	0,555	0,461	0,379	0,310	0,238	0,180	0,122	0,059	0,057	0,015	0,027	0,958
6th Month	0,704	0,563	0,456	0,381	0,316	0,251	0,186	0,125	0,065	0,063	0,014	0,026	0,960
					Commo	n & Idios	yncratic (Compone	ent				
1th Month	0,857	0,773	0,689	0,596	0,503	0,404	0,310	0,220	0,115	0,031	0,004	0,014	0,981
2nd Month	0,854	0,747	0,649	0,568	0,475	0,381	0,300	0,207	0,108	0,042	0,005	0,015	0,980
3rd Month	0,864	0,748	0,649	0,554	0,467	0,369	0,274	0,184	0,093	0,047	0,010	0,016	0,974
4th Month	0,870	0,751	0,649	0,555	0,469	0,377	0,282	0,188	0,105	0,055	0,015	0,018	0,967
5th Month	0,874	0,753	0,647	0,556	0,475	0,382	0,288	0,190	0,095	0,061	0,012	0,014	0,973
6th Month	0,875	0,759	0,648	0,549	0,463	0,374	0,284	0,191	0,095	0,066	0,011	0,012	0,977

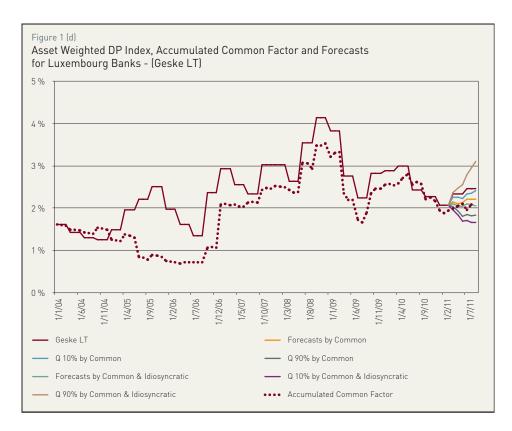
The table reports the coverage ratios, root mean square erros, and the proportions of bias, variance, and covariance respectively from 2010 to 2011 across all Gesk's DPs for both banking groups and luxembourg banks. The coverage ratio is the proportion of banks whose empirical cdf (simulated) at each of the observed DPs are within the range of quantiles.

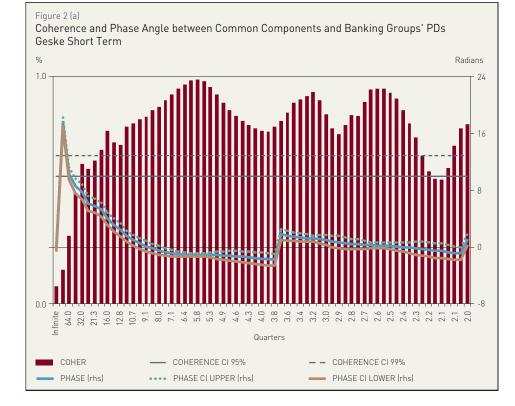


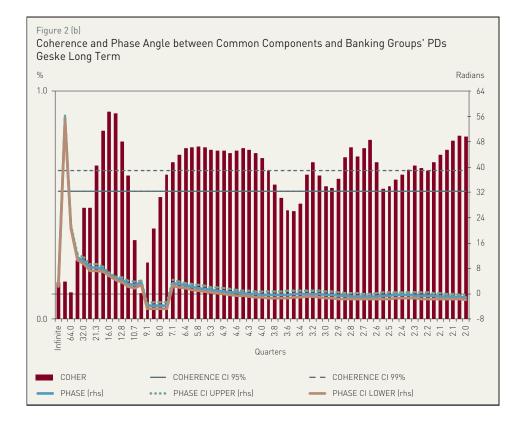


ANALYSES





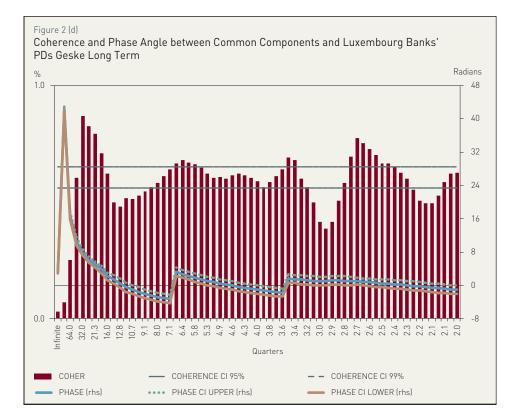




ANALYSES



Figure 2 (c) Coherence and Phase Angle between Common Components and Luxembourg Banks' PDs



4. COMPARING THE LINK BETWEEN MACROECONOMIC CONDITIONS AND LEVERAGE OF MONETARY FINANCIAL INSTITUTIONS IN EUROPEAN COUNTRIES AND LUXEMBOURG

ANALYSES

By Gaston Giordana* and Ingmar Schumacher⁺

1. INTRODUCTION

In this contribution we discuss the relationship between macroeconomic conditions and leverage of monetary financial institutions (MFIs). Our focus will be on evaluating and contrasting the results for a set of European countries with those for Luxembourg.

The current state-of-the art in the literature suggests that favorable economic conditions induce MFIs to expand their balance sheets and leverage, while negative outlooks lead to contractions of balance sheets and deleveraging. This may trigger distressed selling followed by feedbacks in the form of asset price and collateral value reductions, subsequently leading to liquidity and solvency problems. These, then, in turn feed back into the cycle and worsen the previous outlook.

Though there exist many theoretical studies that investigate the links between macroeconomic variables (Bernanke and Blinder, 1992; Brunnermeier, 2009; Krishnamurthy, 2010; Shleifer and Vishny, 2010; Stein, 2011), in a general equilibrium framework it is difficult to precisely know which ones are endogenous and which ones are exogenous. Thus, in order to be able to empirically investigate these dynamic interactions between real, financial and expectational variables we rely on an approach that is specifically designed for this purpose, namely Vector Autoregressive modeling.

We collected country-aggregated, monthly data for European countries, ranging from January 2003 to June 2011. Our variables are country-specific indexes of industrial production, consumer sentiment and stock prices, as well as real interest rates and MFI sector's leverage. With these variables we cover the real and financial sector, both in terms of their actual situation and expectations. Industrial production reflects the economic activity of the real sector, while our confidence indicators reflect the expectation of the real sector. The stock market indexes give information on the valuation of companies active in a country as a whole, and include both information on their real value as well as investors' expectations on their potential value. Thus, while industrial production provides details on the economic activity of a country, the stock indexes give information on the financial valuation of the economy in that country. Finally, the real interest rate summarizes the response, in real terms, to monetary policy. It also provides information on the ability of the financial sector to raise short-term funding.

From an econometric perspective, we shall contrast results from a Panel Vector Autoregressive (PVAR) model for the European countries with results from a VAR model for Luxembourg. By exploiting the panel structure we are able to improve the efficiency of the estimates as we have more data points, less collinearity and control for unobserved individual fixed effects.

We study four models which distinguish themselves by sub-period and variables used. The sub-periods are the pre-crisis period, January 2003 to August 2008, and the crisis period, September 2008 to June 2011. For both sub-periods we investigate a model with leverage, dubbed the "leverage model", and one that contains both components of leverage, the "component model". Additionally, we compare the results for Luxembourg with our sample of European countries.

^{*} Banque centrale du Luxembourg, Financial Stability Department.

t Professor in Economics, IPAG Business School, Paris.

2. THEORETICAL BACKGROUND

Between the years 2003 and 2008, European countries saw a steady improvement in the underlying fundamentals for investment. There was a substantial increase in industrial production, consumer confidence and stock prices. This environment was, until 2007, supported by a stable real interest rate. We also saw important trends in the financial sector. Financial innovations (like securitization and increased use of repos) allowed MFIs to extend their balance sheets at little extra cost. Banks increasingly adopted the new "originate-and-distribute" model, with a significant off-loading of risk and shortening of funding maturities (Brunnermeier, 2009; Pozsar, 2010). This period, dubbed the Great Moderation, allowed MFIs to level up their balance sheets with little concern from investors. In 2007 we witnessed the first turbulences in the financial sector, and the failures of AIG and Lehman Brothers in September 2008 are generally perceived to be the tipping point of the financial crisis. The leverage ratio started to be at the center of investors' attention thereafter. Investors worried about the elevated leverage ratios and started to withdraw their funds. This reduction in funding liquidity required MFIs to adjust their balance sheets, with subsequent impacts on prices and re-sell values. This led to fire sales and thus diminished market liquidity. At the same time, MFIs were faced with large haircuts when trying to shed assets. The losses sustained then led to additional feedback rounds that worsened the previous balance sheet positions.

The theoretical literature tried to pinpoint the underlying mechanisms of the recent crisis. One can broadly distinguish between the following approaches.

In one approach, macroeconomic variables like expectations, industrial production, monetary policy or stock prices work as a positive amplification mechanism and drive MFIs' leverage decisions. This line of causality has been studied extensively. Indeed, theoretical works tend to point towards a positive co-movement between leverage and macroeconomic variables. For example, increasing industrial production induces rises in firms' valuations. This, in turn, leads to heightened expectations in MFIs due to lower expected counter-party default rates or higher collateral values (Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997; Krishnamurthy, 2010), inclining them to expand their balance sheets. Thus, theory tends to predict a positive feedback loop between asset prices, sentiment and leverage. Most empirical research in this respect has been undertaken to study the impact of monetary policy. For example, Friedman and Schwartz (1963), Sims (1990), Christiano and Ljungqvist (1988) as well as Bernanke and Blinder (1992) show how monetary policy affects industrial production and GDP, with Bernanke and Gertler (1995) as well as Cecchetti (1995) illustrating how the banking sector functions as a vehicle for the transmission of monetary policy.

Empirical evidence by Jokipii and Milne (2008) suggests that capital buffers of EU15 banks have a negative co-movement with real GDP growth. Similarly, Jimenez et al. (2010) observe that worse economic conditions reduce loan supply from banks with lower capital or liquidity ratios. Additionally, expectations have been tied to stock returns (Jansen and Nahuis, 2003), while it has been shown that confidence positively co-moves with the real economic cycle (Taylor and McNabb, 2007).

Another approach looks more closely at the feedback loops in order to explain the recent crisis period. For example, theoretical models of fire-sales in financial assets provide the missing ingredients in order to account for the loss-spirals (Brunnermeier, 2009) and the uncertainty that can bring a market to collapse (Shleifer and Vishny, 1992, 1997; Gromb, 2010). More precisely, Stein (2011) describes the role of the bank lending channel in the reduction of real investment which followed the 2007-2008 liquidity crisis. The determinants and consequences of banks' liquidity hoarding behavior are studied, among others, by Caballero and Smisek (2009), Shleifer and Vishny (2010), and Brunnermeir and Sannikov (2011). Caballero and Smisek (2009) characterize a "complexity externality", pointing out the role of the interbank market as fueling the complexity in a highly interconnected financial market. The enhanced payoff uncertainty in such

an environment makes financial institutions prone to hold cash as a flight-to-quality effect. Brunnermeier and Sannikov (2011) considered the interaction of exogenous risk (which is driven by the fundamental determinants of assets' payoffs) and the endogenous risk which is linked to the endogenously determined level of leverage. They describe the "volatility paradox" as a situation where low levels of exogenous risk (or fundamental volatility) results in a higher payoff of levering-up which exposes banks to higher endogenous risk. While cash hoarding is still a flight-to-quality effect, it results from a speculative behavior as, in periods of dampening expected assets prices, it is more profitable to hold on and buy at depressed prices. Likewise, in Shleifer and Vishny (2010) the cash hoarding effect also comes as a consequence of the higher expected payoff of low asset prices. In order to explain the build-up of leverage and the subsequent credit crunch, they focus on investors' sentiments, which are channeled to banks through securitisation practices.

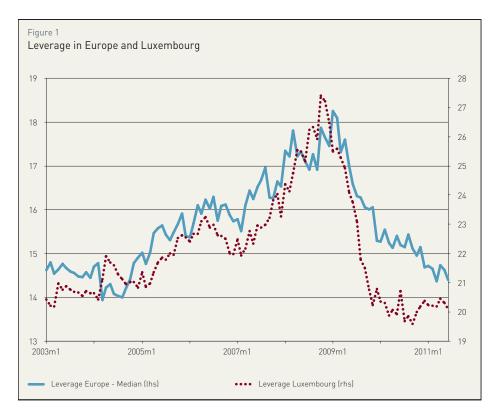
3. RESULTS OF THE STUDY

In Figure 1 we present the evolution of MFI leverage in our sample of European countries and Luxembourg. One can see that both MFI leverage in Europe and Luxembourg follow approximately the same evolution. We observe increasing MFI leverage from 2003 until its peak in late 2008, followed by a subsequent decrease to the levels seen in 2003. MFI leverage in Luxembourg is, on average, six to ten points higher than in Europe.

In Figure 2 we show that leverage in Europe's and Luxembourg's MFIs was procyclical during the last decade. Procyclicality is defined as a positive and significant correlation between the growth of assets and the growth of leverage. Thus, a balance sheet expansion is financed through increasing debt rather than equity. A similar result has been shown by Adrian and Shin (2010), but only for US investment banks, while they found that US commercial banks target a constant leverage.

We now present the results of the econometric estimations of the PVAR model for Europe and the VAR model for Luxembourg. In order to illustrate some results, a subset of the impulse response functions is plotted in Figure 3.

We find weak evidence for a relationship between macroeconomic variables and leverage in the pre-crisis period, with only real interest rates having a negative short-term impact on leverage growth. In contrast to this, we identify positive feedback loops between sentiment and stock prices as well as MFI assets in the pre-crisis period. This supports the theoretical models where heightened expectations due to lower expected counterparty default rates or higher collateral values drive balance sheet expansions (Bernanke, 1989; Kiyotaki and Moore, 1997; Krishnamurthy, 2010).



In addition, we find a positive impact of real interest rate changes on equity and asset growth. Thus, in an environment of low funding costs due to financial innovations (Brunnermeier, 2009), increasing real interest rates allowed MFIs to profit from higher spreads. This stands in contrast to the standard results of trans-

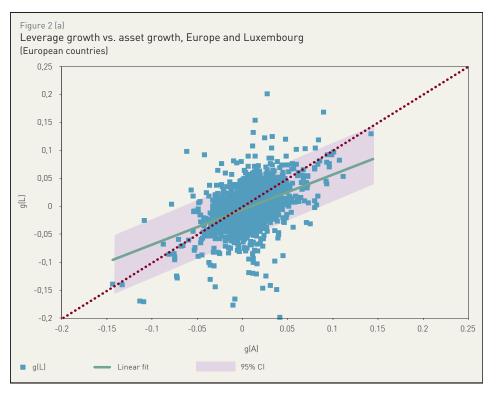
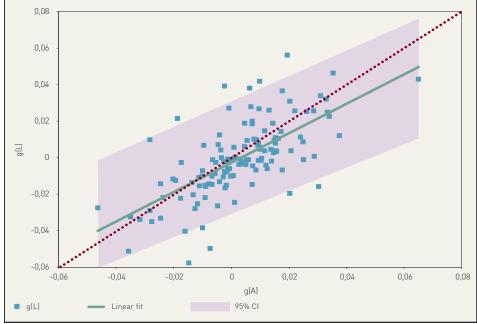


Figure 2 (b)

Leverage growth vs. asset growth, Europe and Luxembourg (Luxemboura)



mission channels of monetary policy, where increasing interest rates reduce MFIs' funding (Bernanke and Gertler, 1995; Cecchetti, 1995). However, studies on monetary policy transmission in Europe are more in line with our results. They show that financial innovations seemed to have reduced the sensitivity of bank lending to interest rate shocks (Altunbas et al. 2009). The differences in results comes about since we focus on the total asset side instead of only on subcomponents of the loan portfolios; we investigate MFIs, which includes both banks and money market funds, while the literature up to now focused mainly on banks; and we use higher frequency data (monthly compared to annually).

During the financial crisis, we observe a counter-cyclical impact from leverage on sentiment and stock prices, while sentiment and stock prices bear a pro-cyclical impact on leverage. We conclude that leverage drives expectations of financial instability (via e.g. default expectations), while sentiment and stock prices drive financial institutions' investment decisions (via e.g. collateral value effects). This is supported by our results that, during the pre-crisis period, asset growth both drove sentiment and stock prices, while, during the crisis, equity growth affected sentiment positively.

Our econometric results for Luxembourg indicate a weak relationship between the macroeconomic variables and leverage during the pre-crisis period, while we find a stronger interaction in the crisis period. This basically conforms to our results on the European sub-sample. However, while we observe a statistically significant, two-way relationship between stock prices and assets for the European sample, we do not find the same results for Luxembourg. Instead, we can only find a one-way

Figure 3

0.4

0,3

0.2

0,1

-0,1

-0.2

-0.3

0.006

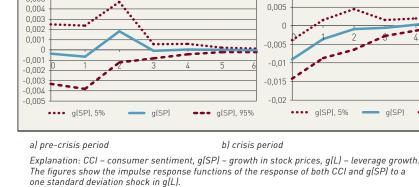
0,005

•••• CCI. 5%

relationship from macroeconomic variables on leverage and asset growth during the crisis period in Luxembourg. This is consistent with the international orientation of Luxembourgish MFIs. Additionally, in comparison to the European sample, we find a stronger reaction of Luxembourg's MFIs leverage when stock prices change. We suggest that this is due to the relatively higher share of securities on MFI's portfolios in Luxembourg.

4. CONCLUSION

We conclude that leverage growth was not a concern (for investors) in the pre-crisis period, while it significantly drove investors' decisions during the crisis. The large impact of equity growth on sentiments during the crisis period is especially noteworthy here, since we did not find a significant impact from equity on sentiment during the pre-crisis period.



Pre-crisis vs crisis impulse response results, results for Europe

resp. of CCI to g(L)

3

CCI

resp. of g(SP) to g(L)

2

What we thus find is evidence that investors, in bull times, base their decisions to a lesser extent on fundamental indicators of financial health. In contrast, during a bear period, we find evidence for what one may dub pessimism, with investors being completely focused on default and financial stability, and where higher leverage reduces consumer sentiment and stock prices.

Our results are, therefore, more indicative of feedbacks between leverage and expectations during downturns, while we find that both lenders and borrowers are not concerned about leverage during upturning. We find, therefore, a stronger support for models that rely on an expectation-leverage feedback (like Kiyotaki and Moore, 1997; Brunnermeier and Sannikov, 2011) rather than on other channels.

5. REFERENCES

Adrian, T. and H.S. Shin, "Liquidity and leverage," Journal of Financial Intermediation, 2010, 19 (3), 418–437.

Altunbas, Y., L. Gambacorta, and D. Marques-Ibanez, "Securitisation and the bank lending channel," European Economic Review, 2009, 53 (8), 996–1009. ANALYSES

CCL 95%

••• g(SP), 95%

resp. of CCI to g(L)

CCI

resp. of a(SP) to a(L)

0.2

-0.2

-0.4

-0,6

-0,8

-1.2

-1.4

-1,6

-1,8

-2

0,01

•••• CCL 5%

5

• CCI, 95%

Bernanke, B.S. and A.S. Blinder, "The Federal Funds Rate and the Channels of Monetary Transmission," The American Economic Review, 1992, pp. 901–921.

Bernanke, B. and M. Gertler, "Agency costs, net worth, and business fluctuations," The American Economic Review, 1989, 79 (1), 14–31.

Bernanke, B. and M. Gertler, "Inside the black box: the credit channel of monetary policy transmission," Journal of Economic Perspectives, 1995, 9 (4), 27–48.

Brunnermeier, M. and Y. Sannikov, "A macroeconomic model with a financial sector," Department of Economics, Princeton University, 2011.

Caballero, R.J. and A. Simsek, "Fire sales in a model of complexity," Technical Report, National Bureau of Economic Research 2011.

Cecchetti, S.G., "Distinguishing theories of the monetary transmission mechanism," Review-Federal Reserve Bank of Saint Louis, 1995, 77, 83–83.

Christiano, L.J. and L. Ljungqvist, "Money does Granger-cause output in the bivariate money-output relation* 1," Journal of Monetary Economics, 1988, 22 (2), 217–235.

Jansen, W.J. and N.J. Nahuis, "The stock market and consumer confidence: European evidence," Economics Letters, 2003, 79 (1), 89–98.

Jimenez, G., S. Ongena, J.L. Peydro, and J. Saurina, "Credit supply: Identifying balance sheet channels with loan applications and granted loans," ECB Working Paper Series, 2010.

Jokipii, T. and A. Milne, "The cyclical behaviour of European bank capital buffers," Journal of Banking & Finance, 2008, 32 (8), 1440–1451.

Kiyotaki, N. and J. Moore, "Credit cycles," Journal of Political Economy, 1997, 105 (2), 211-248.

Krishnamurthy, A., "Amplification Mechanisms in Liquidity Crises," American Economic Journal: Macroeconomics, 2010, 2 (3), 1–30.

Shleifer, A. and R.W. Vishny, "Liquidation values and debt capacity: A market equilibrium approach," Journal of Finance, 1992, pp. 1343–1366.

Shleifer, A. and R.W. Vishny, "Unstable banking," Journal of Financial Economics, 2010, 97 (3), 306-318.

Sims, C.A., J.H. Stock, and M.W. Watson, "Inference in linear time series models with some unit roots," Econometrica, 1990, pp. 113–144.

Stein, J.C., "Monetary policy as financial-stability regulation," Technical Report, National Bureau of Economic Research 2011.

Taylor, K. and R. McNabb, "Business Cycles and the Role of Confidence: Evidence for Europe," Oxford Bulletin