ESG UQÀM

Cahier de recherche

2011-09

Chaire d'information financière et organisationnelle

Bank systemic risk and the business cycle:
An empirical investigation using Canadian data

Christian Calmès[a,*], Raymond Théoret[b]

[a] *Chaire d'information financière et organisationnelle, ESG-UQAM; Laboratory for Research in Statistics and Probability, LRSP; Université du Québec (Outaouais), 101 St. Jean Bosco, Gatineau, Québec, Canada, J8X 3X7*

[b] *Université du Québec (Montréal), 315 Ste. Catherine est, Montréal, Québec, Canada, H2X 3X2 ; Chaire d'information financière et organisationnelle, ESG-UQAM; Université du Québec (Outaouais)*

This version: November 25th 2011

Abstract

Since financial institutions are subjected to increasingly tighter requirements regarding the way they conduct their loan business, we could assume that built-in regulatory pressures induce them to adopt collective business strategies, with the unintended consequence of persistently weakening the banking system ability to cope with external shocks. Surprisingly, we find rather the opposite. This paper documents how banks, as a group, react to macroeconomic risk and uncertainty, and more specifically the way banks systemic behaviour evolves over the business cycle. Adopting the methodology of Beaudry *et al*. (2001), our results clearly indicate that the dispersion across banks traditional portfolios has actually increased through time. We introduce an estimation procedure based on EGARCH and refine Baum *et al*. (2002, 2004, 2009) and Quagliariello (2007, 2009) framework to analyze the question in the new industry context, i.e. shadow banking. Consistent with finance theory, we first confirm that banks tend to behave homogeneously *vis-à-vis* macroeconomic uncertainty. Additionally, we find that the cross-sectional dispersions of loans to assets and non-traditional activities shrink essentially during downturns, when the resilience of the banking system is at its lowest. Our results also indicate that banks herd-like behaviour remains predominantly a cyclical phenomenon, almost unaffected by the new banking environment. Most importantly however, the cross-sectional dispersion of market-oriented activities appears to be both more volatile and sensitive to the business cycle than the dispersion of the traditional banking business lines.

JEL classification: C32; G20; G21.

Keywords: Basel III; Banking stability; Macroprudential policy; Herding; Macroeconomic uncertainty.

Risque systémique bancaire et cycle économique : un exercice empirique sur données canadiennes

Résumé

Puisque les institutions financières sont sujettes à des règles de plus en plus strictes à concernant la façon dont elles gèrent leurs prêts, nous pourrions faire l'hypothèse que les pressions émanant de la réglementation financière les induisent à adopter des stratégies collectives, avec pour conséquence indésirable d'affaiblir de manière persistante la capacité du système financier à gérer les chocs externes. De façon surprenante, nous trouvons plutôt l'opposé. Ce papier documente comment les banques, comme groupe, réagissent au risque et à l'incertitude macroéconomique, et plus spécifiquement comment le risque systémique évolue au cours du cycle économique. En adoptant la méthodologie de Beaudry et al. (2001), nous trouvons que la dispersion en coupe transversale des prêts bancaires a augmenté dans le temps. Nous faisons appel à une méthode d'estimation basée sur le EGARCH et nous élaborons le cadre analytique proposé par Baum et al. (2002, 2004, 2009) et Quagliariello (2007, 2009) pour analyser la question dans le contexte du « shadow banking », la nouvelle structure des banques canadiennes. En conformité avec la théorie financière, nous trouvons d'abord que les banques ont tendance à se comporter de façon homogène vis-à-vis de l'incertitude macroéconomique. Nous trouvons également que la dispersion en coupe transversale des prêts et des activités bancaires non-traditionnelles a tendance à surtout diminuer en récession, alors que la résilience du système bancaire est à son plus bas. Nos résultats montrent que le comportement mimétique des banques demeure principalement un phénomène cyclique, pratiquement indépendant du nouvel environnement bancaire. De façon plus importante, la dispersion en coupe transversale des activités bancaires non-traditionnelles semble plus volatile et plus sensible au cycle économique que celle des activités de prêts.

Classification JEL: C32; G20; G21.

Mots-clefs: Bâle III; Stabilité bancaire; Politique macroprudentielle; Mimétisme; Incertitude macroéconomique.

---

* Corresponding author. Tel: +1 819 595 3000 1893.
E-mail addresses: **christian.calmes@uqo.ca** (Christian Calmès), **raymond.theoret@uqam.ca** (Raymond Théoret).

1. Introduction

The 1982 international sovereign debt crisis, the late 1980s Japanese crisis, the Finland and Scandinavian banking crisis of 1987-1997, the 1997-1998 Asian crisis, and actually most financial crises are partly attributable to bank herding (Jain and Gupta 1987, Hutchinson 2000, Hyytilen *et al*. 2003). Whether rational or behavioural, banks individual optimal response to external shocks can lead to aggregate patterns (Pecchino 1990), which, in some cases, increase both systemic risk and failure rates – especially when disaster myopia is at work (Borio *et al*. 2001). For example, it is now widely admitted that the 2007 credit crisis has been severely accentuated by banking strategic complementarities, in the face of regulatory constraints (Wagner 2007, Adrian and Brunnermeier 2008, Farhi and Tirole 2009, Gauthier *et al*. 2010, Wagner 2010). Indeed, there is often a trade-off between regulation benefits and the costs it entails, and legal limitations can put extra pressure on banks decision space (Vives 1996, Llwellyn 2002, Hirshleifer and Teoh 2003). In this respect, within the current, market-oriented banking environment, the new restrictions on capital and liquidity introduced in Basle III might induce banks to get further involved in regulatory capital arbitrage (Jones 2000, Calomiris and Mason 2004, Ambrose *et al*. 2005, Kling 2009, Brunnermeier 2009, Cardone *et al*. 2010, Martin and Parigi, 2011). As they repeatedly did in the past, in this kind of situations banks engage in similar products innovation, financial engineering and organizational restructuring to dodge regulatory requirements (Kane 1981, Barth *et al*. 1999, Vives 2010, Blundell-Wignall and Atkinson 2010). This regulatee avoidance generally translates into excessive risk-taking through product substitution and portfolios risk repackaging (e.g. Calmès and Théoret 2010, Wagner 2010). One particularly dramatic example of this kind of feedback effect is the growth in securitization of the largest US banks holdings preceding the 2007 credit crisis (Loutskina 2011[1]), with trading and cross-selling feeding a systemic risk bubble, up to its breaking point.

Whilst regulators tend to focus on the tightening of capital standards and liquidity requirements, financial institutions are shifting their business model towards market-oriented activities – i.e. shadow banking (Shin 2009). However, most authors seem now to agree that the business homogenization entailed by the diversification in non-traditional operations might, in fact, reduce banking stability (e.g. Wagner 2007, Calmès and Théoret 2010, De Jonghe 2010)[2]. Whether true or not, the new business environment the financial industry is facing motivates the analysis of the kind of impact market-oriented banking can have on bank risk (Haiss 2005[3], Loutskina 2011). Indeed, given the "procyclicality"[4] of shadow banking, this question is particularly crucial for the monitoring of systemic risk buildups and for the conduct of macroprudential policy. In line with this problematic, the motivation of our research is to investigate whether the changes in the banking business have persistently affected the way in which financial institutions collectively respond to macroeconomic shocks.

To support the "herding" theoretical concept introduced by Diamond and Dybvig (1983), many empirical studies try to identify leader banks. However, in practice, this approach suffers from several limitations. In particular, in most cases the leader banks actually differ depending on the type of diversification strategy examined (Jain and Gupta 1987). Besides, this methodology might be appropriate to depict cascade-

[1] According to Loutskina (2011), 40% of total loans outstanding were securitized at the end of 2007 in the United-States (versus 2.2% in 1976).

[2] For example, the probability of bank failure seems to be positively correlated to the ratio of non-traditional to traditional activities (Barrell *et al*. 2010).

[3] Haiss (2005) provides an extensive literature review on the subject.

[4] In the literature banks are generally considered as "special" vis-à-vis the real economy. Authors usually refer to procyclicality as the phenomenon by which banking shocks are propagated to the economy, or as banks feedback effect to macroeconomic shocks, i.e. shocks amplifiers. Note that in this study we sometimes simply refer to the macroeconomic concept of procyclicality, i.e. the way a banking variable comoves with output.

herding, i.e. herding *stricto sensus*, but not necessarily herd-like, clustering behaviour, for which *all* banks react almost simultaneously to a common regime change. The focus of this paper concerns the latter situation, a case where the banking industry systematically allocates assets in the same way. *Ceteris paribus*, the more it is the case, the more likely the banking system lacks resilience, and, consequently, the more financial stability is at risk. To analyze bank systemic risk defined in this narrow, synthetic sense, as the extent to which the banking system is immune to external shocks, we need to rely on a different research methodology. Our theoretical underpinning is based on a signal extraction problem *à la* Lucas, i.e. the simple idea that, in the presence of informational problems, aggregate shocks can disturb the signal quality of prices and distort banks resource allocations in a systematic way (Bernanke and Gertler 1989, Kyotaki and Moore 1997, Beaudry *et al*. 2001, Vives 2010). To explore this kind of conjecture, Baum *et al.* (2002, 2004, 2009) and Quagliariello (2007, 2009) define banks herd-like behaviour in terms of loans portfolios cross-sectional dispersion. In particular, Baum *et al*. (2009) find that an increase in macroeconomic uncertainty, as measured by the conditional variance of industrial production, generates a significant decline in the cross-sectional dispersion of the loans-to-assets ratio after one year. More importantly, the authors argue that this kind of herd-like behaviour is robust to the way dispersion is defined, whether considering total loans, loans to households, or commercial and industrial loans, and even when controlling for monetary regime changes, inflation, leading indicators or, incidentally, regulatory changes[5]. In other words, banks systemic behaviour would be predominantly a cyclical phenomenon.

In this paper we work along these lines, but we analyze the pattern in the context of shadow banking. To better assess banks true systemic risk, we enlarge the investiga-

[5] As a matter of fact, Baum *et al*. (2009) find that regulatory changes, more precisely the Basel Accords, seemed to have had a tendency to increase herding.

tion scope and include all banking business activities, not only considering loans, i.e. banks traditional activities, but also banks off-balance-sheet (OBS) lines of business, and more precisely the share of noninterest income (*snonin*) generated by OBS activities[6]. We know that informational problems and agency costs are generally more severe during business cycle downturns, when banks are the most exposed to moral hazard and adverse selection. The banking business is typically riskier during contraction episodes, because collateral value falls. One important contribution of this paper is then to propose a new methodology specifically designed to detect this kind of asymmetric impact macroeconomic shocks can have on bank systemic risk. Compared to Baum *et al*. (2002, 2004, 2009), our new framework, based on an EGARCH approach (Nelson 1991), also provides a more precise account of the relative impact of macroeconomic risk (the first moment), and uncertainty (the second moment).

Consistent with previous studies, the dataset we use confirms that banks display a herd-like behaviour during times of heightened macroeconomic uncertainty, as measured with the conditional variances of standard series such as GDP and consumer price index. However, one advantage of the generalized framework we propose is that it helps better identify the phase of the business cycle when the dispersion is at its lowest. On this dimension, the dynamics of both the loans-to-assets ratio (*lta*) and noninterest income cross-sectional dispersions suggests that banks behaviour is more homogenous in downturns. In particular, we find that the volatilities of the innovations of the cross-sectional dispersions are lower in downturns, an asymmetric pattern unexplored in previous studies. Interestingly, we also find that the loans dispersion seems to be relatively more influenced by credit variables (as proxied by macroeconomic conditions), rather than supply factors such as the return on assets (*ROA*), so that, consistent

[6] Note that *snonin* is only a proxy for OBS activities as some *snonin* related items are actually accounted on balance sheet.

with Bikker and Hu (2002)[7], our results would better accord with the balance sheet channel than with the traditional credit channel (Bernanke and Gertler 1995, Kashyap and Stein 2000).

A surprising result of our study suggests that, the rise of shadow banking notwithstanding, banks herd-like behaviour measured with *lta* cross-sectional dispersion has actually diminished – and even so during the subprime crisis. However, we cannot be so conclusive about non-traditional activities. Data indicate no clear increase in *snonin* banks cross-sectional dispersion. In fact, our main findings support the idea that the cyclicality of bank systemic risk is quite substantial, and that the fluctuations of non-traditional activities are large during recessions, as obviously evidenced by the 2007-2009 crisis, when banks collectively put a brake on their OBS activities. In other words, the new set of results we provide suggests that, while, on the one hand, banks seem more able to deal with aggregate shocks, on the other hand it might be at the cost of more severe income volatility episodes, a trade-off worth monitoring more closely in the macroprudential analyses of bank systemic risk.

This paper is organized as follows. Section 2 presents the theoretical intuition supporting our hypothesis about the link between macroeconomic uncertainty and the cross-sectional dispersion of banks risky assets (on-balance sheet and off-balance-sheet related items) and exposes our empirical framework and the EGARCH procedure we introduce in our experiments. Section 3 discusses data and basic stylized facts related to the cross-sectional dispersions of *lta* and *snonin*. In section 4 we report our main results, and in section 5 we perform robustness checks and provide complementary results before concluding in section 6.

---

[7] We try several financial variables to represent the supply and demand sides of risky assets like return on asset, short term interest rates, and term structure variables such as the spread between long-term and short-term interest rates, and also credit spreads like the difference between the yields on *BBB* and *AAA* bonds and stock index returns. These variables are usually not significant, so we eliminate them from our analysis. This observation is in line with Bikker and Hu (2002) findings that financial variables such as money supply and interest rates do not seem to explain bank profitability.

2. Empirical framework

2.1 Risk, uncertainty and the banks herd-like hypothesis

Many studies document the influence of the first moments of macroeconomic aggregates, i.e., macroeconomic risk, on bank systemic risk (e.g. Barth *et al*. 1999, Borio *et al* 2001, Bikker and Hu 2002, Bikker and Metzemakers 2005, Baele *et al*. 2007, Wagner 2007, Somoye and Ilo 2009, and Nijskens and Wagner 2011). However, even though all moments of the key macroeconomic factors (e.g. GDP growth and inflation) are susceptible to influence bank systemic behaviour, so far only few authors looked at the role played by their higher moments – i.e., macroeconomic uncertainty. For example, we should expect that, in absolute terms, the homogeneity of banks portfolios increases with macroeconomic risk and uncertainty, as both should lead to a decrease in the cross-sectional distribution of banks risky assets, i.e. a decrease in the aggregate dispersion of banks portfolios. Our first goal is to show that risk and uncertainty have precisely this kind of impact in the current market-oriented banking context. To study the degree of banks business homogeneity when they adjust to macroeconomic shocks, we adopt a research strategy based on the island paradigm developed in Lucas (1973). This kind of approach has been successfully applied in many studies, including the analyses of the cross-sectional dispersion of firms investments, the financial markets, and the banking industry (Beaudry *et al.* (2001), Baum *et al*. 2002, 2004, Hwang and Salmon 2004, Quagliariello 2007, Vives 2010). It has also been specifically used to study how macroeconomic uncertainty affects banks signal about expected returns (e.g. Baum *et al*. 2009 and Quagliariello 2009). In this literature, the main theoretical predicament is that greater economic uncertainty hinders banks' ability to foresee investment opportunities. The testable prediction which derives from this theory is that deteriorating information quality should lead to a narrowing of the cross-sectional dispersion of banks portfolios, as banks allocate assets in their portfolio more homogenously when macroeconomic uncertainty increases[8]. In this paper we aim at empirically testing this conjecture – i.e., the banks herd-like hypothesis – to show that banks diversification in non-traditional business lines has changed the way in which the banking system reacts to external shocks. To do so, we introduce a new empirical framework linking banks systemic behaviour to the first and second moments of proxies of risk and uncertainty, as described below.

2.2 The model

In the new banking environment, macroeconomic shocks can distort the allocation of funds to on-balance-sheet items, but to OBS activities as well, and this constitutes a new area of potential inefficiency worth investigating. In this paper, we follow Baum *et al*. (2009), and our bank portfolio includes two kinds of assets, a risk-free asset (a security) and a risky one. However here, risky assets comprise both loans and off-balance sheet (OBS) investments. More precisely, to test the herd-like behaviour hypothesis we consider the following reduced-form equation model:

$$disp_{j,t} = \beta_0 + \beta_1 \mu_{mv,t} + \beta_2 \sigma^2_{c,mv,t} + \beta_3 disp_{j,t-1} + \xi_t \qquad (1)$$

where $disp_{j,t}$ is a variance measure of the cross-sectional dispersion of a risky asset *j* at time *t*; $\mu_{mv,t}$ is the first moment of a macroeconomic variable proxying for risk; $\sigma^2_{c,mv,t}$ is the corresponding conditional variance of the macroeconomic variable[9], i.e. the second moment measuring macroeconomic uncertainty; and ξ_t is the innovation. For instance, the first moment of a macroeconomic variable may be GDP growth and its sec-

[8] The standard portfolio model used to derive this hypothesis and to establish the relationship between the cross-sectional dispersion of a risky asset and macroeconomic uncertainty is discussed in Appendix 1.
[9] For the construct of the conditional variance series proxying macroeconomic uncertainty, see Appendix 2.

ond moment the conditional variance of GDP growth. The model includes the lagged dependent variable to control for residuals autocorrelation and account for the adjustment delay of the observed $disp_{j,t}$ to its target level.

Importantly, note that our model makes an explicit distinction between macroeconomic risk and uncertainty, macroeconomic risk relating to the phase of the business cycle and macroeconomic uncertainty to its volatility. The first reason explaining this choice relates to the main argument of our paper. We strongly suspect that the first moments of the macroeconomic variables have a great impact on non-traditional banking activities, whereas the second moments manly influence traditional business lines. On the one hand, we can hypothesize that OBS activities are relatively more immune to macroeconomic *uncertainty* than loans because they are more easily hedged. Indeed, financial structured products, which weigh heavily in OBS activities, are designed to manage volatility – the *raison d'être* of derivatives – and to improve financial markets risk-sharing. On the other hand however, and quite importantly, given their high degree of liquidity we conjecture that OBS activities are relatively more sensitive to the business cycle, so that the cyclicality of bank systemic risk is actually quite substantial (Lucas and Stokey 2011).

A second, more technical motivation for including both the first and second moments in equation (1) is that, from an econometric perspective, the first moment of a variable used to define macroeconomic uncertainty must also be included for the sake of robustness (Huizinga 1993, Quagliariello, 2007, 2009). As a matter of fact, excluding the first moment might wrongfully lead the researcher to attribute to the second moment an impact which is actually explained by the first one.

In line with previous studies, we analyze the impact of one macroeconomic factor at a time. For example, for the dispersion of *lta* in terms of *GDP* uncertainty, our model can be expressed as follows:

$$disp(lta)_t = \beta_0 + \beta_1 cv\_gdp_t + \beta_3 d\,ln\left(gdp\right)_t + \beta_4 output\_gap_t + \beta_5 dtl_t + \beta_6 disp(lta)_{t-1} + \varepsilon_t \quad (2)$$

where *disp(lta)* is the cross-sectional dispersion of *lta*, *cv_gdp*, the conditional variance of GDP growth, *dln(gdp)*, the rate of growth of GDP, *output_gap* is the output gap measured as the deviation of the logarithm of real GDP from its Hodrick-Prescott trend, and *dtl* is an aggregate measure of the degree of total leverage[10]. According to the theory, we expect the sign of β_1 to be negative: an increase in macroeconomic uncertainty measured by the conditional variance of GDP growth should decrease *disp(lta)*, and thus increase herding. The next two variables appearing in Equation (2) are two first moments associated with the conditional variance: the GDP growth and the output gap. The former is a measure of the strength of economic growth, while the latter is a measure of the business cycle. We expect the signs of the coefficients of these variables to be both positive. Indeed, when macroeconomic risk increases, i.e. when GDP growth and output gap decrease, banks should behave more homogeneously, as they do in the case of increased macroeconomic uncertainty. In this model version, we also introduce a variable to control for the risk of the banking industry, namely the degree of total leverage (*dtl*)[11]. Our experiments show that this elasticity measure of leverage is more representative of bank risk than the standard accounting leverage measures such as the ratio of assets to equity or the mandatory leverage recommended in Basel I and II[12]. For example, contrary to most standard measures, the *dtl* suggests that embedded bank leverage was increasing during the 2002-2007 period, while financial institution were expanding their OBS activities, and indicates a deleveraging process

[10] Note that we also examined other macroeconomic and financial variables but these factors do not improve the fit of the model. For example, authors often rely on the conditional variance of industrial production to model macroeconomic uncertainty but in our set-up this variable performs badly relative to GDP. Other "indirect" macroeconomic variables like firms' inventories, unemployment rate, leading indicators and the rate of industrial capacity are also found weakly significant in our framework.

[11] For the construction of this variable (a measure of banks time-varying leverage obtained with the Kalman filter) see Calmès and Théoret (2011a).

[12] Note that the additional leverage measure proposed in Basel III remains close to the conventional ratio of assets to equity, a measure which, like the existing mandatory indicators does not track bank risk effectively (Calmès and Théoret 2011a).

after 2007, as banks were decreasing their risk to recover. *Ceteris paribus*, to the extent that the herd-like hypothesis has some support, β_5, the coefficient of *dtl* should be negative, banks adopting a more homogenous behaviour in times of increasing risk.

In order to estimate *disp(lta)* with a smoothed version of the conditional variance of the GDP growth, we also run Equation (2) using the weighted conditional variance measure of GDP growth (*cv_gdp_w*)[13], whereas, in the third version of our model, the dispersion of *lta* is expressed in terms of inflation uncertainty and reads as follows:

$$disp(lta)_t = \gamma_0 + \gamma_1 cv\_inf_t + \gamma_2 d\,ln\left(gdp\right)_t + \gamma_3 output\_gap_t + \gamma_4\, inf_t + \gamma_5 dtl_t + \gamma_6 disp(lta)_{t-1} + \varepsilon_t \quad (3)$$

where *cv_inf* is the conditional variance of inflation and *inf*, the inflation rate, is the first moment associated with the conditional variance of inflation. Similar to the case of the conditional variance of GDP growth, we expect a negative sign for γ_1, the coefficient associated with inflation uncertainty. We also expect the coefficient associated with the inflation rate, γ_4, to be negative since inflation distorts the signal given by-relative prices (Beaudry *et al*. 2001).

We then perform the same three estimations for the cross-sectional dispersion of *snonin*, i.e. the cross-sectional dispersion of the risky assets associated with OBS activities.

2.3. The *EGARCH estimation methods*

To estimate the three versions of our canonical model, we choose to rely on an EGARCH approach using standard tests (Franses and Van Dijk 2000) because, as the literature suggests, the standard OLS estimation method does not properly treat the innovation conditional heteroskedasticity. Relatedly, relying on OLS delivers mild results, especially regarding the impact of the first moments of the macroeconomic vari-

[13] See Appendix 2 for more details on the conditional variance constructs.

ables[14]. The choice of this EGARCH methodology is also motivated by the fact that the standard GARCH (*p,q*) does not rigorously account for the asymmetries encountered in many times series. For instance, bad news ($\varepsilon_{t-i} < 0$) have generally a bigger impact (i.e. a leverage effect) on financial returns volatility than good news ($\varepsilon_{t-i} > 0$), and an unexpected drop in returns (bad news) tend to increase the volatility more than an unexpected rise in returns (good news) of a similar magnitude (Black 1976). In this respect, we suspect that imposing a symmetry constraint on the conditional variance of past innovations might be too restrictive, and actually inappropriate. Consequently, to account for the likely asymmetric impact of good news and bad news on the conditional volatility of the cross-sectional dispersion innovations, we follow Nelson (1991) and introduce an equation such that:

$$log\left(\sigma_t^2\right) = \theta_0 + \theta_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \theta_2 \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \theta_3\, log\left(\sigma_{t-1}^2\right) \qquad (4)$$

which can be generalized to an EGARCH(*p,q*) process by adding *p* lags to $\frac{\varepsilon_t}{\sigma_t}$ and *q* lags to $log\left(\sigma_t^2\right)$. In this equation, good news, $\varepsilon_{t-i} > 0$, and bad news, $\varepsilon_{t-i} < 0$, can have differential effects on the conditional variance. The EGARCH model is asymmetric because the level of $\frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ is included with a θ_1 coefficient. There is asymmetry if θ_1 is significantly different from 0. In particular, bad news have a leverage effect on the volatility if $\theta_1 < 0$, and this effect is exponential since the variance is estimated in logarithm[15]. To summarize, our EGARCH approach differs from a regular GARCH set-up in two main respects: (i) the EGARCH model allows good news and bad news to have a different impact on volatility, and (ii) the EGARCH model allows important news to

[14] OLS results are reported in Appendix 3.

[15] By contrast, in the threshold ARCH (i.e. TARCH) model, an alternative way to account for the asymmetric properties of the conditional volatility, this effect is assumed to be quadratic.

have a proportionally greater impact than the standard GARCH model (Engle and Ng 1993).

We estimate the model versions for *lta* and *snonin* using this EGARCH procedure, but we also rely on EGARCH with instruments since the conditional variances of our macroeconomic variables and the *dtl* series are generated variables, i.e. potentially noisy proxies of their associated unobservable regressors (Pagan 1984, 1986). Indeed, even if relying on OLS or simple maximum likelihood in the presence of generated variables does not lead to inconsistency in the estimation procedure, the *t* tests associated with the estimated coefficients are however invalid (the *F* tests or Wald tests on groups of coefficients still remaining valid, Pagan 1984, 1986). This issue is mentioned in previous studies (e.g. Beaudry *et al*. 2001, Baum *et al*. 2002, 2004, 2009, Quagliariello 2007, 2009) but, to our knowledge, it has not been fully addressed before. Accordingly, we adopt a comprehensive approach by first regressing the generated variables on instruments, including the predetermined variables, and also, as suggested by Fuller (1987) and Lewbel (1997), the higher moments of the models explanatory variables. The second estimation method we use is thus a standard EGARCH with instruments, or an IV-EGARCH, in which the generated variables *cv_gdp*, *cv_gdp_w*, *cv_inf* and *dtl* are explicitly considered endogenous.

3. Data and some key stylized facts

In this paper we are not interested by extreme events such as liquidity crises. To analyse crises episodes and the complete disruption of the banking system, authors usually investigate the testable implications of the contagion theory, whereby a signal triggers a bank run, in a cascade-herding traditional sense (Morris and Shin 2000, Lucas and Stokey 2011). Since we focus instead on the regular reaction of the banking system to the business cycle, it is desirable to rely on a dataset in which crises have a relatively mild impact. In this respect, a Canadian sample appears to be one of the best choices available. Indeed, as Bordo *et al.* (2011) argue, thanks to its domestic regulation design, the Canadian banking system has been relatively immune to the subprime crisis and to the former financial turmoils as well. Consequently, to better isolate the impact of market-oriented banking on systemic risk, it is particularly instructive to look at Canadian data. If we find that the changes in the banking environment have indeed some influence on banks usual response to macroeconomic shocks, then we should expect that market-oriented banking has *a fortiori* significantly changed bank risk in other countries, especially those which were the most hit by the recent crisis.

Accordingly, the sample we chose is derived from Canadian data and runs from the first fiscal quarter of 1997 to the second fiscal quarter of 2010. We study the cross-sectional dispersion of the risky assets of the six major Canadian banks on quarterly data so that we have fifty-four observations, a reasonable number to perform standard time series analysis. Our dataset is based on statistics provided by the Canadian Bankers Association, the Office of the Superintendent of Financial Institutions, and the Bank of Canada; and the macroeconomic time series come from CANSIM, a database managed by Statistics Canada. Taken together, the six major domestic banks account for about 90 percent of the banking business. All the banks we analyze are chartered banks, i.e. commercial banks regulated by the *Bank Act*, running a broad range of activities, from loan business to investment banking, fiduciary services, financial advice, insurance and securitization.

Insert Figure 1 and Figure 2 here

Regarding the basic statistics, first note that the banks aggregate loans-to-assets ratio displays a decreasing trend (Figure 1). In the first quarter of 1997 the *lta* ratio is equal to 63%, but in the first quarter of 2010 it decreases to 54% after a low of 47% in the second quarter of 2009 (at the peak of the subprime crisis). Relatedly, and opposite to the *lta* pattern, *snonin*, our proxy for OBS activities has a tendency to increase over the sample period (Figure 2). The ratio is equal to 43% at the beginning of the period but in the third quarter of 2007 it rises to 55%. This new trend in banking has first been identified by Boyd and Gertler (1994) for the U.S., and then further analyzed for many countries, including in the now famous Rajan's papers (2005, 2006)[16]. The literature suggests that *pari passu* with the development of this market-oriented trend bank risk has increased (e.g., Stiroh 2004, Stiroh and Rumble 2006, Baele *et al*. 2007, Wagner 2007, 2008 and 2010, Lepetit *et al*. 2008, Shin 2009). More precisely, authors find that non-traditional business lines have spurred the volatility of bank income over the last decades. Relatedly, it is also widely believed that bank risk is increasingly associated with the growth in off-balance-sheet activities, (Adrian and Shin 2009, Calmès and Théoret 2010, Cardone *et al*. 2010, Nijkens and Wagner 2011).

Insert Figure 3 here

In this context, the question is then to assess the kind of impact this change in banking has on systemic behaviour. In this respect, Figure 3 provides a first evidence, showing the behaviour of the cross-sectional dispersions of the loans-to-assets ratio, *disp*(*lta*), and of the share of noninterest income in operating revenues, *disp*(*snonin*), from the first fiscal quarter of 1997 to the second fiscal quarter of 2010. The time series are obtained by computing the cross-sectional variances of the loans-to-assets ratio (*lta*) and of the share of noninterest income (*snonin*) over the six banks for every quarter. According to the evolution of the cross-sectional dispersion of *lta*, banks seem to display an increase in herd-like behaviour over the period 1997-2002, but the trend steadely reverses after 2002 (Figure 3). Surprisingly, this *disp(lta)* upward trend actu-

[16] For Canadian evidence see also Calmès (2004).

ally persists, even during the last crisis. This constitutes preliminary evidence that the banks traditional business has in fact become increasingly resilient, i.e. better immune to external shocks. On other respect, a first glance at the series also reveals that the cross-sectional dispersion of *lta* might be sensitive to the output gap. More precisely, the cross-sectional dispersion of *lta* seems positively correlated with the output gap, and this could suggest *a priori* more herd-like behaviour in bad times than in good times. Note that this observation is not merely anecdotical since this kind of pattern is much susceptible to increase banking procyclicality (Figure 3).

More importantly, note that, compared to what obtains with *lta*, the trend of the cross-sectional dispersion of *snonin* is less pronounced over the whole sample period, and strikingly drops after 2007, suggesting more herd-like behaviour in terms of non-traditional activities. This volatility pattern is consistent with the studies arguing that financial innovations tend to increase herding (e.g. Heiss 2005, Wagner 2008, Nakagawa and Uchida 2011). Relatedly, the cross-sectional dispersion of *snonin* appears to be both more volatile and sensitive to the business cycle than the dispersion of *lta*, especially during recessions, when the banking system is the least resilient. For example, during the last subprime crisis, a significant portion of securitized assets flowed back on balance sheets and most of the credit commitments were also exercised. This kind of response suggests that banks OBS activities might contract more than traditional business lines during bad times. Finally, one curious pattern which seems to emerge from Figure 3 is that the drops in the cross-sectional dispersion of *snonin* could predate economic downturns[17].

Insert Figure 4 and Figure 5 here

Another way of directly detecting herd-like behaviour is to examine the cyclical

[17] That might be due to the fact that noninterest income is much related to stock market indices, which lead economic activity (Calmès and Théoret 2011b).

profile of the variance of the banking variables at stake. If we find that the variances move procyclically, this could constitute an additional evidence of a cyclical convergence in banking practices. Figures 4 and 5 provide the moving average variances of the level and logarithm of banks loans and noninterest income, respectively. In these figures we also plot as a benchmark the variances of the unscaled loans and noninterest income variables. Captured this way, herding appears to be predominantly a cyclical phenomenon, as there seems to be a regular decrease in the rolling variances of loans and noninterest income, either prior or during contractions. Moreover, note that consistent with the findings of Calmès and Liu (2009) and Calmès and Théoret (2010, 2011b), we can detect a regime change in loans and non-interest income volatility after 1996. Insofar as the variances of loans and noninterest income may be used as indicators of banks systemic behaviour, data indicate a decrease in herding after 1997, the volatilities of loans and noninterest income being much more pronounced after this date. Actually, consistent with what Figure 3 suggests, since that date, economic downturns seem to be preceded by variances surge.

4. Results

Table 1 provides the estimation results for the model versions based on the EGARCH estimation without instruments. Columns (1) to (3) report the results of the model estimation for the two dependent variables, the cross-sectional dispersions of *lta* and *snonin*.

Insert Table 1 here

4.1. The lta and snonin cross-sectional dispersions

Column (1) of Table 1 displays the estimation results for Equation (2) and confirms that the increase in macroeconomic uncertainty lowers the cross-sectional dispersion of the loans-to-assets ratio, *disp(lta)*. The estimated coefficient of *cv_gdp* is equal to -0.79 and significant at the 1% level, and the coefficient of the weighted conditional variance of GDP growth, *cv_gdp_w*, is even greater in absolute value, at -2.65, and significant at the 5% level (Column (2)), a result which suggests a delay in the adjustement of *disp(lta)* to macroeconomic uncertainty.

Note that the level of economic growth also increases *disp(lta)*, confirming that banks systemic behaviour is more homogenous in economic downturns. Furthermore, the estimated coefficient of *dln(gdp)* is equal to 0.83 and significant at the 10% level, while the coefficient of *output_gap* is equal to 91.73 and significant at the 1% level. According to these results, the first moments seem to play a greater role on herding than reported in previous studies. Indeed, Quagliariello (2009) finds that the control variables accounting for aggregate economic activity or inflation (i.e. first moments) do not have a significant impact on the cross-sectional variability of the share that banks invest in risky loans. Similarly, in Baum *et al*. (2002, 2004), the control variables also play a minor role in the OLS estimations. In this respect, the new results we derive from our framework differ. One plausible reason explaining why the first moments are more significant in our case relates to the homoskedaticy hypothesis embedded in previous studies. Indeed, to our knowledge, the conditional variance of the equation innovations has never been explicitly specified before.

Equation (2) also delivers interesting results on clustering patterns when considering bank risk, as measured with our indicator of bank degree of total leverage, *dtl*. As expected, column (1) of Table 1 shows that an increase in *dtl* decreases *disp(lta)*, the estimated coefficient being equal to -5.10 and significant at the 1% level. This result supports the view that banks behaviour is more homogenous when bank risk increases, and it is also broadly consistent with the impact of increases in macroeconomic risk and uncertainty on *disp(lta)*[18]. With a coefficient of the lagged dependent variable at 0.59, and significant at the 1% level, column (1) also reveals that herd-like behaviour is a persistent phenomenon (Haiss 2005, Nakagawa and Uchida 2011). One explanation sometimes evoked in the literature relates to the Abilene paradox (Harvey 1974), a kind of "mimetic isomorphism", i.e. groupthink strategy characterized by copycat banking practices.

Column (3) of Table 1 reports the corresponding results for Equation (3), the model including inflation as the proxy for macroeconomic uncertainty. Consistent with our hypothesis of a negative link between the dispersion of the risky assets and uncertainty, the estimated coefficient of *cv_inf* is negative, at -10.97 and significant at the 1% level. Inflation has also the expected negative impact on *disp(lta),* its estimated coefficient being equal to -1.27 and significant at the 5% level. These results support the argument of Beaudry *et al*. (2001) and the idea that inflation generates noisy market signals and increases clustering. In other respects, considering inflation instead of GDP growth does not qualitatively alter the role played by economic growth. In particular, the coefficient of *dln(gdp)* nearly doubles from 0.83 to 1.65 between the two specifications, and the coefficient of the output gap is also positive, at 60.40, and significant at the 1% level.

Regarding market-oriented activities, given that they also relate to risky investments, we should anticipate that banks behave *vis-à-vis snonin* in the same way they do with traditional activities. Table 1 largely qualifies this expectation. In particular, economic uncertainty, as measured with the conditional variance of GDP (or inflation) decreases *disp(snonin)*. For example, the coefficient of *cv_gdp* is estimated at -1.09 and significant at the 1% level. More importantly, note that weighting the conditional

[18] If, instead of *dtl*, we use a conventional measure of leverage like the ratio of assets to equity, the estimated coefficient is also negative, although not significant at the usual thresholds.

variance of GDP growth does not improve the results in this case, the estimated coefficient of *cv_gdp_w* being equal to -2.07, but only significant at the 10% level (column(2)). Relatedly, when *cv_gdp* is used as the uncertainty proxy, the estimated coefficient of the lagged dependent variable is equal to 0.18, a lower level than the corresponding 0.59 obtained for *disp(lta)*. This set of results suggests that *disp(snonin)* is less persistent than *disp(lta)*, a phenomenon which can be explained by the faster reaction of OBS activities to economic activity and macroeconomic uncertainty. This dynamic property is consistent with both the relative volatility of *snonin* cross-sectional dispersion, and the greater liquidity of non-traditional activities. For instance, loans which are securitized generally display a high degree of liquidity, and their adjustment to the desired value is thus arguably faster than for their on-balance-sheet counterparts.

Quite strikingly, note that *disp(snonin)* appears much more sensitive to inflation uncertainty than *lta*. As a matter of fact, the coefficient of *cv_inf* is estimated at -49.20 and significant at the 1% level, while the corresponding coefficient for *disp(lta)* is equal to -10.97 and significant at the 5% level[19] (column (3)). Furthermore, and, again, much more so than for *disp(lta)*, economic growth significantly increases *disp(snonin)*, regardless of the macroeconomic factor proxying for uncertainty. For instance, with the conditional variance of GDP growth, the estimated coefficient of the output gap is equal to 287.26 and significant at the 1% level, whereas the corresponding coefficient for *disp(lta)*, at 91.73, is much lower (column(1)). In fact, for all the exogenous variable considered, both those related to risk and to uncertainty, the results confirm our stylized facts, namely the fact that the herding associated with non-traditional activities appears more sensitive to macroeconomic shocks than it is the case for *disp(lta)*. Remark that these findings cannot obtain with the usual OLS approach, but our EGARCH

[19] Note that the coefficients of the *disp(lta)* and *disp(snonin)* equations are directly comparable for a given explanatory variable since the ratios used to compute the cross-sectional dispersions are both defined on the [0,1] interval.

estimations clearly reveal that, while banks seem able to deal with the external shocks hitting their loan business, at the same time, their non-traditional activities appear to be both quite volatile and sensitive to the business cycle[20].

Interestingly, the behaviours of *disp(lta)* and *disp(snonin)* also differ with respect to *dtl*, our control variable for bank risk. Contrary to the *disp(lta)* results, an increase in *dtl* leads to a corresponding *increase* in *disp(snonin)*. The estimated coefficient of *dtl* is positive and significant at the 1% level, regardless of the way we proxy for macroeconomic uncertainty. For instance, it is equal to 18.86 when *cv_gdp* is used to measure uncertainty, and to 23.82 with *cv_inf*. Relatedly, *dtl* and *snonin* positively comove and an increase in *snonin* corresponds to an increase in risk as measured by *dtl* (Calmès and Théoret 2011a). Furthermore, according to the data, when *snonin* increases, *disp(snonin)* also tends to increase. This might actually explain the positive comovement observed between *dtl* and *disp(snonin)*. When *dtl* increases, banks have a tendency to decrease their *lta* ratio, but not necessarily their OBS activities. Authors usually resort to a regulatory capital arbitrage (RCA) argument to explain this opposite reaction to leverage (Jones 2000, Calomiris and Mason 2004, Ambrose *et al*. 2005, Kling 2009, Brunnermeier 2009, Cardone *et al*. 2010, Blundell-Wignall and Atkinson, Vives 2010). When *dtl* increases, i.e. bank risk rises, it may be due to an increase in *snonin* or a decrease in bank liquidity ratio but, in any case, banks are induced to off-load risk from on-balance-sheet to off-balance-sheet in order to generate new capital or additional liquidities[21]. *Ceteris paribus*, this transfer tends to decrease *disp(lta)* and *lta*, and to increase *disp(snonin)* and *snonin*.

Insert Table 2 about here

To compare more precisely the relative power of our exogenous factors, Table 2

[20] This observation nicely complements the seminal view that advances in risk management have essentially led to greater credit availability rather than reduced banking riskiness (Cebenoyan and Strahan 2004, Instefjord 2005).

[21] For instance, some loans in the balance sheet may be securitized.

reports the estimated short-term and long-term elasticities of *disp(lta)* and *disp(snonin)*[22]. When using *cv_gdp_w* as the uncertainty proxy, the elasticity of *disp(lta)* is equal to -0.12 in the short-run, but more than doubles in the long-run, at -0.29, a result in line with other studies (Baum *et al*. 2002, 2004, 2009). This confirms that even if banks can adopt different strategies in the way they manage their traditional portfolio, they consistently tend to follow the same kind of adjustment to deal with macroeconomic shocks. By comparison, the elasticity of *disp(snonin)* to GDP uncertainty is lower, at -0.04 in the short-run and -0.05 in the long-run. This result suggests that, as expected, banks herd-like behaviour is relatively more sensitive to uncertainty when monitored with loans than with OBS activities. Indeed, as mentioned earlier, the latter should be relatively more immune to uncertainty than risk since the volatility of OBS activities is, by definition, easier to hedge. More importantly however, these elasticities also confirm that market-oriented banking is particularly sensitive to macroeconomic risk relative to traditional banking, a phenomenon which should deserve serious attention in the conduct of macroprudential policy.

Relatedly, our elasticity computations suggest that, consistent with Beaudry *et al*. (2001) intuition, market-oriented activities are much influenced by inflation uncertainty, likely because of the close negative link between inflation and stock markets performance (Calmès and Théoret 2011b). In other words, *ceteris paribus*, when faced with heightened inflation uncertainty, banks also tend to herd more in terms of non-traditional business lines than with their loan portfolios. Note also that the long-run elasticity of *disp(lta)* with respect to *dtl*, at -1.12, is higher than 1 in absolute value, whereas the long-run elasticity of *disp(snonin)* with respect to *dtl* is also quite high, at

[22] The elasticity of *Y vis-à-vis X* is computed using the following formula: $coef \times \frac{\bar{X}}{\bar{Y}}$, where *coef* is the estimated coefficient of *X*, and $\bar{X}$ and $\bar{Y}$ are respectively the average of X_t and Y_t computed over the sample period. The long-term elasticity is computed by multiplying the short-term elasticity by $\frac{1}{1-\lambda}$, where λ is the coefficient of the lagged dependent variable.

0.87, but with the opposite sign. This finding clearly confirms that the positive impact of a 1% increase of *dtl* on *disp(snonin)* is in fact mostly counterbalanced by the negative influence of this increase on *disp(lta)*. As a consequence, we should conclude that RCA unlikely exerts a meaningful influence on banks clustering in the long-run, or, to be more exact, that regulatory regime changes have only weakly persistent effects on banks systemic risk.

4.2. The volatility of the cross-sectional dispersions

The bottom of Table 1 reports the estimation results of the EGARCH processes followed by the *residuals* of our dependent variables (Equation(4)). To our knowledge, this modelization is a novelty in the literature. We experimented with several GARCH processes and selected the EGARCH given its superior fit in terms of the usual tests. Globally, our results indicate that omitting to specify the innovation volatility indeed provides weaker fits[23]. The omission of the residuals specification in the studies based on OLS, GARCH and GMM estimations might actually explain why authors often find no significant role for the first moments of the explanatory variables (i.e. macroeconomic risk).

Regarding the results, first note that, for *disp(lta)*, the estimated asymmetry coefficient θ_1 of the EGARCH(1,1) is close to 1 and significant at the usual levels, regardless of the macroeconomic uncertainty factor considered (Table 1). In other words, good news[24] have a positive leverage effect on *disp(lta)* volatility, so the volatility of *disp(lta)* is actually greater when *disp(lta)* increases. We observe the same phenomenon with *disp(snonin)*. In fact, the asymmetry coefficient is close to one for all the un-

[23] The OLS estimations are discussed in Appendix 3.

[24] Note that news are considered good or bad according to the sign of the innovation. We refer to good news when the innovation of *disp(lta)* is positive and to bad news when the innovation is negative. Indeed, our results indicate that *disp(lta)* increases with good news, as measured by the output gap or the GDP rate of growth.

certainty factors we consider. In this sense, our results are coherent in terms of the estimated volatilities of *disp(lta)* and *disp(snonin)*. There is a significant asymmetry in the volatility processes of these two variables, this asymmetry is both positive and high, and it is robust to the various exogenous factors examined. Note that, since in economic downturns, the volatilities of *disp(lta*) and *disp(snonin)* shrink *pari passu* with the dispersions, these results lead us to conclude that the procyclicality of *disp(lta)* and *disp(snonin)* might actually be greater than previously reported.

5. Robustness checks and complementary results

5.1. The IV-EGARCH estimation results

In our framework, we introduce as generated or endogenous variables a measure of bank risk, *dtl*, and the conditional variances of the two macroeconomic variables we use to define macroeconomic uncertainty. To tackle the econometric difficulty posed by this kind of generated variables, we regress each of them on instruments before applying the EGARCH to the models. However doing so leaves our results essentially unchanged. In particular, the results of the IV-EGARCH estimations show that, in the regressions with *disp(lta)* as the dependent variable, the impact of *cd_gdp* and *cv_gdp_w* decreases somewhat but remains significant at the 1% level (Table 3). However, the sensitivity of *disp(lta)* to *cv_inf*, even if it remains negative, is no longer significant when using instruments. Without instruments, the coefficient of *cv_inf* is equal to -10.97 and significant at the 5% level, while with the IV-EGARCH the coefficient is equal to -3.55 and is no longer significant at the usual thresholds. This suggests that, for *disp(lta)*, the macroeconomic uncertainty measured with the growth of GDP might be a more appropriate variable than the inflation proxy[25].

[25] This might also relate to the stabilization role played by the explicit inflation target adopted by the Canadian central bank.

By contrast, consistent with Beaudry *et al*. (2001) argument, the IV-EGARCH confirms that *disp(snonin)* is quite sensitive to inflation uncertainty. Indeed, the impact of *cv_inf* on *disp(snonin)* decreases somewhat from -49.20 to -27.44 with the IV-EGARCH, but it remains significant at the 5% level, contrary to what obtains with *disp(lta)* (Table 3).

Insert Table 3 about here

5.2. The cross-sectional covariances

Previous studies often consider that the risky assets cross-sectional dispersions completely characterize banks comovements. Authors also assume that when dispersion decreases, banks herd-like behaviour necessarily accentuates. However, in some situations this hypothesis might be misleading, and it could be necessary to look at complementary statistics. In this respect, one additional indicator useful to monitor bank systemic patterns is the assets cross-sectional *covariance* (Adrian 2007). This financial indicator is defined as: $cov(X_{i,j}) = \frac{1}{N^2 - N}\sum_{i=1}^{N}\sum_{j=1,\, j\neq i}^{N}\left(X_i - \bar{X}\right)\left(X_j - \bar{X}\right)$, where N is the number of banks analyzed, X_i is the risky asset to total assets ratio (*lta* or *snonin*) of bank *i,* and $\bar{X}$ is the cross-sectional mean of X computed over the banks. This statistics indicates the extent to which the (X_i, X_j) pairs comove in each time period.

Insert Figure 6 here

Data show that, over the whole 1997-2010 period, the correlation between *disp(lta)* and *cov(lta)* is equal to -0.55, and the correlation between *disp(snonin)* and *cov(snonin)* is higher, at -0.91. Both statistics are significant at the 1% level. The cross-sectional dispersions of *lta* and *snonin* thus seem *a priori* to be both coherent indicators of the *lta* and *snonin* respective covariances (comovements). To illustrate the relationship between the cross-sectional dispersions and covariances, Figure 6 provides the scatter diagrams of *disp(lta)* and *disp(snonin)* with their respective cross-sectional covariance. The negative colinearity between *disp(lta)* and *cov(lta)* appears quite high, except for high values of *disp(lta)* for which the relationship deteriorates. According to the dated dots of the scatter diagram, these extreme values are mostly associated with the subprime crisis of 2007-2009 and its aftermath. The cross-sectional covariance of *lta* increases from the third quarter of 2009 to the second quarter of 2010, while the corresponding cross-sectional dispersion is at historical highs. This suggests that the cross-sectional dispersion is actually an incomplete indicator of the comovement of banks *lta* ratios during this kind of extreme episodes. Consistent with the correlations, for *snonin* the observation dots relating the cross-sectional covariances to the cross-sectional dispersions are more aligned with the regression line. However, there is also a deterioration in the year 2008, and a closer look at the scatter diagram reveals that the relationship between *disp(snonin)* and *cov(snonin)* might have shifted somewhat during the crisis, as the comovements are accompanied by larger dispersions. Summarizing, the cross-sectional dispersions of *lta* and *snonin* are generally realiable indicators, but they may nevertheless be insufficient when the cross-sectional covariances are ignored, especially so for contraction episodes.

Since herd-like behaviour is arguably more pronounced in downturns, the additional information conveyed by these cross-sectional covariances can prove to be a useful complement to track bank systemic patterns. In particular, we can suspect that if a cross-sectional covariance diverges from its associated cross-sectional dispersion, this might signal a stronger banking resilience. In this respect, one way to interpret the *snonin* scatter diagram, considering the strong alignment of the cross-sectional dispersion and covariance of the series, is that, on this dimension, the pattern again suggests more herding *vis-à-vis* non-traditional activities. This final result is consistent with the view that, in the new banking era, systemic risk might stem more from market-oriented activities than from traditional business lines.

6. Conclusion

Previous studies on bank risk have focused on traditional activities, essentially lending. In this article we enlarge the analysis by integrating market-oriented banking activities, which have now become a major source of bank income. The results we obtain are robust to the addition of banks new business lines. In particular, when confronted to increased macroeconomic uncertainty, banks adopt a more homogenous behaviour vis-à-vis both their traditional and market-oriented activities. Baum *et al*. (2002, 2004) show that banks collective behaviour with respect to their risky assets is robust to the composition of loans portfolios, and not a result specific to aggregate loans[26]. We show that this pattern also obtains for assets whose cash-flows are noninterest income. What we find is that banks herd-like behaviour is mostly observed in contraction periods for both risky assets. In these episodes, the first and second moments associated with GDP growth play a similar role, and accentuate banks collective appetite, away from risky assets, i.e. loans and OBS activities, and towards liquidity. More precisely, in contractions, the output gap (i.e. first moment) decreases, the volatility of GDP growth (second moment) increases, and both variables decrease the cross-sectional dispersions of *lta* and *snonin.*

[26] Baum *et al*. (2002, 2004) analyze aggregate loans and their components, i.e. three types of risky assets, namely real estate loans, household loans, and commercial and industrial loans. The authors find that bank clustering prevails not only for aggregate loans but also for these components. Their results are particularly prevalent for real estate loans, whose cross-sectional dispersion increases sharply over the period they analyze.

However, a comparison of *lta* and *snonin* statistics also reveals that herding might be more prevalent for non-traditional activities, and thus that, *ceteris paribus*, banking fragility could increasingly stem from market-oriented banking. In this respect, our main results support the view that, in the new banking era, banking stability and systemic risk are more related to OBS activities than to the traditional loan business lines. In particular, in the context of shadow banking, the fact that the cross-sectional dispersion of *snonin* appears quite sensitive to economic downturns might be a new source of concern for policy-makers. The assets involved in OBS activities, like securitized assets, are more liquid than loans, and can flow back quickly on balance sheet, precipitating the decrease in these activities during contractions. We find that banks' *snonin* actually tend to converge rapidly during contractions, which indeed implies major banks portfolios reshufflings. The strong sensitivity to the business cycle phase (first moment) of the cross-sectional dispersion of *snonin* likely relates to first-order demand-side effects emanating from the buyers of the short-term debts financing the securitized assets, from the lenders of the repo market[27], and from firms exercising massively their credit commitments during contractions. For example, the buyers of the special investment vehicles (SIV) short-term debt can provoke a technical run in time of liquidity shortage simply by not rolling over their investments (Vives 2010, Gennaioli *et al*. 2011). The sponsor banks are then simultaneously forced to recuperate the SIV's assets on their balance sheets, and securitization thus creates a strong correlation in the returns of intermediaries in bad times. In the same vein, there can be a surge in firms' bank credit commitments during expansions, but they have to be eventually followed by a massive commitments exercise during contractions, a boomerang effect amplifying the cyclicality of *snonin* cross-sectional dispersion.

[27] The repo market induces banks to reshuffle their OBS activities in periods of contractions or liquidity shortages. According to Lucas and Stokey (2011), the repo market pools cash reserves, like other forms of fractional reserve banking. A pillar of market-based financing, this market shrinks heavily during contractions, and especially during liquidity crises, a phenomenon indirectly captured in our framework by the major decrease in the cross-sectional dispersion of *snonin* observed during financial turmoils.

These demand-side effects must be distinguished from the impact of macroeconomic uncertainty (the second moment) on banks systemic behaviour. We find that the dispersion of *snonin* seems relatively less sensitive to macroeconomic uncertainty than the dispersion of *lta*. In this respect, while many studies indicate that the rising share of OBS activities in banks total operations is associated with an increase in the volatility of bank performance (Calmès and Théoret 2010, Uhde and Michalak 2010, Nijskens and Wagner 2011, Sanya and Wolfe 2011), our results suggest that OBS activities might also help banks hedge and better allocate their risks in the long-run (Stiroh 2004).

To the extent that the cyclical aspects of banks collective behaviour are related to the efficiency and stability of the financial system, an important contribution of our study is first to show that, despite the change in the banking landscape, banks herd-like behaviour remains predominantly a cyclical phenomenon at long horizons, particularly at play during economic contractions; and second that, nevertheless, shadow banking might have changed the way banks manage risks. On the one hand, in the traditional Baumol sense, market-oriented banking offers a more efficient management of liquidity. With the development of shadow banking, liquidity management is more in sink with leverage fluctuations, conventional liquidity ratios are strikingly lower, the ratio of loans loss provisions seems also lower, while, concomitantly, banks effective leverage can increase. On the other hand however, this new banking landscape is also accompanied by increased strategic complementarities, higher risk and higher probabilities of insolvency. In this respect, our study suggests that, far from having reduced banking cyclicality, despite the greater risk-sharing embodied in non-traditional activities, the new business lines could actually increase the volatility of banks assets.

The main macroprudential policy implication we can derive from this study is that the cyclicality of OBS activities should be closely monitored by the regulatory agencies in charge of financial stability. The traditional role of banks, which consists in providing liquidities *sur demande* to the economic system is obviously challenged by the development of banks non-traditional activities, which melt conventional and investment banking. In particular, our study shows that, in this dimension, the banking system is both volatile and exposed to the business cycle. Macroprudential policymakers face a delicate conundrum, as the increase in banking aggregate risk (relative to idiosyncratic risk), one of the most singular characteristics of the new banking environment[28], is accompanied by a new concept of liquidity, not yet fully understood (Lucas and Stokey 2011, Loutskina 2011). For example, when it comes to the Basle III proposed mandatory leverage ratio, we would strongly advocate to envisage broader definitions of leverage to fully capture the new liquidity management practices associated with market-oriented activities (Calmès and Théoret 2011a). This is left for future work.

Appendix 1

The banks portfolio model

As usually assumed in the literature, the returns on the two categories of assets which compose the representative bank portfolio are given by the following equations:

$$\forall i, \quad \forall t, \quad r_{i,t}^{S} = r_f \qquad (5)$$

$$\forall i, \quad \forall t, \quad r_{i,t}^{ra} = r_f + \rho + \varepsilon_{i,t} \qquad (6)$$

where $r_{i,t}^{S}$ is the return on the security for bank i at time t; r_f is the return on a risk-free

[28] Houston and Stiroh (2006) and Gennaioli *et al*. (2011) find that bank systemic risk increased with the development of shadow banking, while idiosyncratic risk decreased thanks to the greater diversification enabled by OBS activities.

asset and $r_{i,t}^{ra}$ is the return on the risky asset. The expected return on the risky asset is equal to $r_f + \rho$, where ρ is the expected risk premium assumed to be fixed. The idiosyncratic risk is represented by the random variable $\varepsilon_{i,t} \sim N(0, \sigma_{\varepsilon,t}^2)$. At time *t*, when bank *i* determines the optimal allocation of its portfolio between the security and the risky asset, it is confronted to uncertainty, $\varepsilon_{i,t}$ (Equation (6)). Assume that at time *t* each bank *i* observes an imperfect signal $S_{i,t}$ which enables the bank to formulate a prediction on the value of $\varepsilon_{i,t} : S_{i,t} = \varepsilon_{i,t} + \upsilon_t$, with $\upsilon_t \sim N(0, \sigma_{\upsilon,t}^2)$ and $E(\varepsilon_{it}, \upsilon_t) = 0$ [29]. The assumption of orthogonality between ε_{it} and υ_t may be justified by considering υ_t as an aggregate shock uncorrelated to the idiosyncratic shock. At time *t*, each bank *i* observes a different signal $S_{i,t}$ comprising an heterogeneous shock $\varepsilon_{i,t}$ and a homogenous noise υ_t whose intensity $\sigma_{\upsilon,t}^2$ is time varying. We assume that $\sigma_{\upsilon,t}^2$ is driven by macroeconomic uncertainty so that when uncertainty rises, the noise incorporated in the signal rises with $\sigma_{\upsilon,t}^2$, and it becomes increasingly difficult to determine the true value of $\varepsilon_{i,t}$ and the optimal return on loans. The best way to predict the return on the risky asset is then to estimate $E\left[\varepsilon_{i,t} \mid S_{i,t}\right]$, the expected value of the idiosyncratic noise conditional on the signal. Even if $E\left(\varepsilon_{i,t}\right)$, the unconditional expectation of the idiosyncratic noise, is equal to 0, this is not the case for its conditional counterpart. Consistent with Baum *et al*. (2002, 2004) we thus assume that the conditional expectation of $\varepsilon_{i,t}$ is equal to a proportion λ_t of the signal:

$$\forall i, \quad \forall t, \quad E\left[\varepsilon_{i,t} \mid S_{i,t}\right] = \lambda_t \left[\varepsilon_{i,t} + \upsilon_t\right] \qquad (7)$$

with

[29] For a canonical form of this banking theory based on signal extraction see Rajan (1994). Rajan relates the signal to the publication of banks earnings rather than macroeconomic time series, but there is obviously a close link between bank earnings and macroeconomic aggregates (Bikker and Hu 2002, Quagliariello 2008).

$$\forall t, \quad \lambda_t = \frac{\sigma_{\varepsilon,t}^2}{\sigma_{\varepsilon,t}^2 + \sigma_{\upsilon,t}^2} \qquad (8)$$

We then compute w_{it}, the optimal share of the risky asset in the bank portfolio. The expected return of the portfolio conditional on the signal is equal to:

$$\forall i, \quad \forall t, \quad E\left[\tilde{R}_{i,t} \mid S_{i,t}\right] = w_{i,t}\left(r_f + \rho + \lambda_t S_{i,t}\right) + \left(1 - w_{i,t}\right) r_f \qquad (9)$$

and the conditional variance of the portfolio is:

$$\forall i, \quad \forall t, \quad Var\left[\tilde{R}_{i,t} \mid S_{i,t}\right] = \lambda_t \sigma_{\upsilon,t}^2 w_{i,t}^2 \qquad (10)$$

According to this straightforward model, the portfolio variance is simply an increasing function of macroeconomic uncertainty $\sigma_{\upsilon,t}^2$. Banks maximize a standard utility function $\tilde{V}_{i,t}$ which depends positively on the expected return of the portfolio, and negatively on risk as measured by its variance,

$$\forall i, \quad \forall t, \quad \underset{w_{i,t}}{arg\,max}\, E\left[\tilde{V}_{i,t} \mid S_{i,t}\right] = E\left[\tilde{R}_{i,t} \mid S_{i,t}\right] - \frac{1}{2}\varphi Var\left[\tilde{R}_{i,t} \mid S_{i,t}\right] \qquad (11)$$

where φ is the bank degree of risk aversion. Equating the derivative of Equation (11) with respect to $w_{i,t}$ to 0, we obtain the optimal value of the share of the risky asset in the bank portfolio,

$$\forall i, \quad \forall t, \quad w_{i,t} = \frac{\rho + \lambda_t S_{i,t}}{\varphi \lambda_t \sigma_{\upsilon,t}^2} \qquad (12)$$

Combining Equations (12) and (8) we can finally compute the variance of the cross-sectional dispersion of the risky asset as follows:

$$\forall i, \quad \forall t, \quad Var\left(w_{i,t}\right) = \frac{\sigma_{\varepsilon,t}^2 + \sigma_{\upsilon,t}^2}{\varphi^2 \sigma_{\upsilon,t}^4} \qquad (13)$$

Its derivative with respect to macroeconomic uncertainty $\sigma_{\upsilon,t}^2$ is thus:

$$\forall i, \quad \forall t, \quad \frac{\partial Var\left(w_{i,t}\right)}{\partial \sigma_{\upsilon,t}^2} = -\frac{1}{\varphi^2}\left[\frac{2\sigma_{\varepsilon,t}^2}{\sigma_{\upsilon,t}^6} + \frac{1}{\sigma_{\upsilon,t}^4}\right] < 0 \qquad (14)$$

Equation (14) is the herd-like hypothesis we examine in this study.

Appendix 2

The conditional variance constructs

In line with Baum *et al*. (2002, 2004, 2009) and Quagliariello (2007, 2009) we model our conditional variances, i.e. the indicators of macroeconomic uncertainty, using GARCH (*p*,*q*) specifications (Bollerslev 1986). However, contrary to these authors, we also introduce EGARCH specifications (Nelson 1991) to model macroeconomic uncertainty and test the herd-like hypothesis. Assume a simple general econometric model written as:

$$Y_t = X_t\beta + \varepsilon_t \qquad (15)$$

with Y_t the vector of the dependent variable, X_t the matrix of the explanatory variables, $\varepsilon_t \sim iid\left(\sigma_t^2, 0\right)$ the innovation, and σ_t^2 the conditional variance of the innovation. This conditional variance follows a GARCH (1,1) process if it can be written as follows:

$$\sigma_t^2 = \alpha + \beta\varepsilon_{t-1}^2 + \varphi\sigma_{t-1}^2 \qquad (16)$$

which can be generalized to a GARCH (*p*,*q*) process by adding *p* lags to ε_t and *q* lags to σ_t^2. Equations (15) and (16) are estimated simultaneously using the maximum likelihood estimator.

Then, to build the conditional variances of our two proxies of macroeconomic uncertainty, respectively based on the GDP and the consumer price index, we first transform these variables in growth rates so that we can work with stationary time series. Otherwise, if the series were not transformed in quarterly percentage rate of changes, the resulting conditional variances would be dominated by the trend of these variables. Transforming the series this way enables us to capture the cyclical fluctuations of the proxies.

Insert Table A2 here

The computations related to the conditional variables are provided in Table A2. To construct the conditional variance of GDP growth, the measure of macroeconomic uncertainty related to this variable, we first rely on an ARMA (2,2) specification to estimate the GDP growth expected mean, selected on the basis of the usual Akaike and Schwartz criteria. We then use an EGARCH (1,1) to compute the associated conditional variance of GDP growth after experimenting with several GARCH processes[30]. The estimations results are provided in Table A2. The estimated coefficient of asymmetry θ_1 (Equation (4)) is negative, so bad news indeed seem to have a leverage effect on the volatility of GDP growth. Since the resulting profile of the conditional volatility of GDP growth is somewhat unstable, we also use a weighted variance of the current and last three quarters' conditional variances (*cv_gdp_w*), with arithmetic weights 0.4, 0.3, 0.2 and 0.1. Similarly, the conditional variance of inflation is computed with an IGARCH(1,1)[31] (integrated GARCH) resulting from an AR(1) estimation. The conditional variance seems very persistent, the coefficient of σ_{t-1}^2 being estimated at 0.78.

[30] For the tests related to the selection of a GARCH process, see Franses and van Dijk (2000).
[31] In an IGARCH process the sum of the β and φ coefficients in equation (16) is close to 1.

Appendix 3

OLS estimations of the cross-sectional dispersions of *lta* and *snonin*

Table A3 provides the OLS estimations of the cross-sectional dispersions of *lta* and *snonin* over the period 1997-2010, the model specifications being the same as those used for the EGARCH estimations (Table 1). As mentioned, the results are poor compared to those obtained with our EGARCH procedure. In particular, the results associated with the OLS estimation of *disp(lta)* are clearly unsatisfactory. Indeed, the only variable which is significant at the 5% level across all the model specifications is the rate of growth of GDP, which displays the same sign as in the EGARCH estimation. The conditional variance of GDP (*cv_gdp*) has the expected negative sign but is not significant, while the conditional variance of inflation (*cv_inf*) has the wrong sign, also insignificant. Moreover, the output gap has a sign opposite to its EGARCH estimate, although insignificant. The *dtl* variable has the same sign as in the EGARCH estimation but is also not significant.

Insert Table A3 here

The results obtained with the OLS estimation of *disp(snonin)* are more in line with those resulting from our EGARCH estimation. The variable *cv_gdp* has the expected sign and is significant at the 10% level, while *cv_inf* has also the right sign and is significant at the 5% level. Similarly, for *disp(snonin)*, the variable *dtl* has the same sign as in the EGARCH estimation in the model featuring *cv_gdp* as the indicator of macroeconomic uncertainty, and is significant at the 10% level. Overall, the OLS estimations confirm that the EGARCH results found for *disp(snonin)* are particularly robust since they remain the same with a linear approach. In this case, the OLS results constitute an additional evidence that banks market-oriented business lines are quite sensitive to the business cycle. This observation suggests that herding seems indeed to be more severe for market-oriented activities than for loans, a finding which underlines the fragility to which new business lines expose the banking system.

Finally, note that the OLS estimations do not deliver significant results regarding the impact of the marcoeconomic first moments. In this respect, the results we obtain when modelling the innovation volatility are superior for both *disp(lta)* and *disp(snonin)*. In this respect, it appears quite important to model the conditional volatility of the innovations of the cross-sectional dispersion equations as we do.

References

Adrian, T., 2007. Measuring risk in the hedge fund sector. Current issues in Economics and Finance 13, 1-7.

Adrian, T., Brunnermeier, M.K., 2008. CoVaR. Staff Report, Federal Reserve Bank of New York.

Adrian, T, Shin, H.S., 2009. The shadow banking system: Implications for financial regulation. Staff Report, Federal Reserve Bank of New York.

Ambrose, B.W., Lacour-Little, M, Sanders, A.B., 2005. Does regulatory capital arbitrage, reputation or asymetric information drive securitization? Journal of Financial Services Research 28, 113-133.

Baele, L., DeJonghe, O., Vennet, R.V., 2007. Does the stock market value bank diversification. Journal of Banking and Finance 31, 1999-2023.

Barrell, R., Davis, E.P., Karim D., Liadzze, I., 2010. Evaluating Off-balance sheet exposures in banking crisis determination models. Working paper, Brunel University.

Barth, J., R., Caprio, G., Levine, R., 1999. Financial regulation and performance: Cross-country evidence. Working paper 2037, World Bank.

Baum, C. F., Caglayan, M., Ozkan, N., 2002. The impact of macroeconomic uncertainty on bank lending behavior. Working Paper, University of Liverpool.

Baum, C. F., Caglayan, M., Ozkan, N., 2004. The second moment matters: the response of bank lending behavior to macroeconomic uncertainty. Working Paper, Boston College.

Baum, C. F., Caglayan, M., Ozkan, N., 2009. The second moment matters: the impact of macroeconomic uncertainty on the allocation of loanable funds. Economics Letters 102, 87-89.

Beaudry, P., Caglayan, M., Schiantarelli, F., 2001. Monetary instability, the predictability of prices, and the allocation of investment: An empirical investigation using panel data. American Economic Review 91, 648-662.

Bernanke, B, .S., Gertler, N., 1989. Agency cost, net worth, and business fluctuations. American Economic Review 79, 14-31.

Bernanke, B., S., Gertler, N., 1995. Inside the black box: the credit channel of monetary policy transmission. Journal of Economic Perspectives 9, 27-48.

Bikker, J.A., Hu, H. 2002. Cyclical patterns in profits, provisioning, and lending of banks and procyclicality of the new Basel capital requirements. Banca Nazionale del Lavoro Quarterly Review 55, 143-175.

Bikker, J.A., Metzemakers, P., A., J., 2005. Bank provisioning behavior and procyclicality. Journal of International financial Markets, Institutions and Money 15, 141-157.

Black, F., 1976. Studies of stock price volatility of changes. American Statistical Association Journal, 177-181.

Blundell-Wignall, A., Atkinson, P., 2010. Thinking beyond Basle III: Necessary solutions for capital and liquidity. Financial Markets Trends 20, 1-23.

Bollerslev, T., 1986. Generalized autoregressive conditional heteroskedasticity. Journal of Econometrics 31, 307-328.

Bordo, M.D., Redish, A., Rockoff, H., 2011. Why didn’t Canada have a banking crisis in 2008 (or in 1930, or 1907, or...)? Working Paper, NBER.

Borio, C. Furfine, C., Lowe, P., 2001. Procyclicality of the financial system and financial stability: issues and policy options. BIS paper 1-2001.

Boyd, J.H., Gertler, M., 1994. Are banks dead? Or are the reports greatly exaggerated? Federal Reserve Bank of Minneapolis Quarterly Review 18, 1-27.

Brunnermeier, M.K., 2009. Deciphering the liquidity and credit crunch 2007-2008. Journal of Economic Perspectives 23, 77–100.

Calmès, C., 2004. Regulatory changes and financial structure: The case of Canada. Swiss Journal of Economics and Statistics 140, 1-35.

Calmès, C., Liu, Y., 2009. Financial structure change and banking income: A Canada-U.S. comparison. Journal of International Financial Markets, Institutions and Money 19, 128-139.

Calmès, C., Théoret, R., 2010. The impact of off-balance-sheet activities on banks returns: An application of the ARCH-M to Canadian data. Journal of Banking and Finance 34(7), 1719-1728.

Calmès, C., Théoret, R., 2011a. Shadow banking and leverage: an application of the Kalman filter to time-varying cyclical leverage measures. Chaire d'information financière et organisationnelle ESG-UQAM Working paper 2011-01.

Calmès, C., Théoret, R., 2011b. The rise of shadow banking and the hidden benefits of diversification. Chaire d'information financière et organisationnelle ESG-UQAM Working paper 2011-02.

Calomiris, C.W., Mason, J.R., 2004. Credit card securitization and regulatory arbitrage. Journal of Financial Services Research 26, 5-27.

Cardone Riportella, C, Samaniego Medina, R., Tujilo Ponce, A., 2010. What drives bank securitization? The Spanish experience. Journal of Banking and Finance, 34, 2639-2651.

Cebenoyan, A.S., Strahan, P.E., 2004. Risk management, capital structure and lending at banks. Journal of Banking and Finance 28, 19-43.

De Jonghe, O.G., 2010. Back to the basics in banking? A micro-analysis of banking system stability. Journal of Financial Intermediation 19, 387-417.

Diamond, D., Dybvig, P., 1983. Bank runs, deposit insurance, and liquidity. Journal of Political Economy 91, 401-419.

Engle, R.F., Ng, V.K., 1993. Measuring and testing the impact of news on volatility. Journal of Finance 48, 1749-1778.

Farhi, E., Tirole, J., 2009. Collective moral hazard, maturity mismatch and systemic bailouts. Working paper, NBER.

Franses, P.H., van Dijk, D., 2000. Non-Linear Time Series Models in Empirical Finance. Cambridge University Press: Cambridge.

Fuller, W.A., 1987. Error Models, John Wiley & Sons.

Gauthier, C., Lehar, A., and Souissi, M., 2010. Macroprudential Regulation and Systemic Capital Requirements, Working Paper 2010-4, Bank of Canada.

Gennaioli, N., Shleifer, A., Vishny, R.W., 2011. A model of shadow banking. Working paper, NBER.

Haiss, P. R., 2005. Banks, herding and regulation: A review and synthesis. Working paper, Europe Institute.

Harvey, J., 1974. The Abilene paradox: the management of agreement. Organizational Dynamics.

Hirshleifer, D., Teoh, S., H., 2003. Herd behavior and cascading in capital markets: a review and synthesis. European Financial Management 9, 25-66.

Houston, J.F., and Stiroh, K.J., 2006. Three decades of financial sector risk. Staff Report, Federal Reserve Bank of New York.

Huizinga, J., 1993. Inflation, uncertainty, relative price uncertainty, and investment in U.S. manufacturing. Journal of Money, Credit and Banking, 25 3, 521-549.

Hutchison, M., N., 2002. European banking distress and EMU: institutional and macroeconomic risk. Scandinavian Journal of Economics 104, 365-389.

Hyytinen, A., Kuosa, I., Takalo, T., 2003. Law or finance: evidence from Finland. European Journal of Law and Economics 16, 59-89.

Hwang, S., Salmon, M., 2004. Market stress and herding. Journal of Empirical Finance 11, 585-616.

Instefjord, N., 2005. Risk and herding: Do credit derivatives increase bank risk? Journal of Banking and Finance 29, 333-345.

Jain, A. K., Gupta, S., 1987. Some evidence on "herding" behavior of U.S. banks. Journal of Money Credit and Banking 19, 78-89.

Jones, D., 2000. Emerging problems with the Basel Capital Accords: Regulatory capital arbitrage and related issues. Journal of Banking Finance 24, 35-58.

Kane, E., 1981. Impact of regulation on economic behavior: accelerating inflation, technological innovation, and the decreasing effectiveness of banking regulation. Journal of Finance 36, 355-367.

Kashyap, A.K., Stein, J.C., 2000. What do a million observations on banks say about the transmission of monetary policy. American Economic Review 90, 407-428.

Kling, A., 2009. Not what they had in mind: A history of policies that produced the financial crisis of 2008. Working paper, Mercatus Center, George Mason University.

Kyotaki, N., Moore, J., 1997. Credit cycles. Journal of Political Economy 105, 211-248.

Lepetit, L., Nys, E., Rous, P., Tazari, A., 2008. Bank income structure and risk : An empirical analysis of European banks. Journal of Banking and Finance 32, 1452-1467.

Lewbel A., 1997. Constructing instruments for regressions with measurement error when no additional data are available, with an application to patents and R&D. Econometrica 65, 1201-1213.

Llewellyn, D., 2002. An analysis of the causes of recent banking crises. European Journal of Finance 8, 152-175.

Loutskina, E., 2011. The role of securitization in bank liquidity and funding management. Journal of Financial Economics 100, 663-684.

Lucas, R. E. Jr., 1973. Some international evidence on output-inflation trade-offs. American Economic Review 63, 326-334.

Lucas, R.E. Jr., Stokey, N.L., 2011. Liquidity crises, understanding sources and limiting consequences: A theoretical framework. The Region, Federal Reserve Bank of Minneapolis, 1-11.

Martin, A., Parigi, B.M., 2011. Bank capital regulation and structured finance. Working paper. Federal Reserve Bank of New York.

Morris, S., Shin, H.S., (2000). Rethinking multiple equilibria in macroeconomic modelling. NBER Macroeconomics Annual 15, 139-161.

Nakagawa, R., Uchida, H., 2011. Herd behaviour of Japanese banks after financial deregulation. Economica (forthcoming).

Nelson, D.B., 1991. Conditional heteroskedasticity in asset returns: A new approach. Econometrica 59, 347-370.

Nijskens, R, Wagner, W., 2011. Credit risk transfer activities and systemic risk: How banks became less risky individually but posed greater risks to the financial system at the same time. Journal of Banking and Finance 35, 1391-1398.

Pagan, A.R., 1984. Econometric issues in the analysis of regressions with generated regressors. International Economic Review 25, 221-247.

Pagan, A.R., 1986. Two stage and related estimators and their applications. Review of

Economic Studies 53, 517-538.

Pecchino, R., 1998. Risk averse bank managers: exogenous shocks, portfolio reallocations and market spillovers. Journal of Banking and Finance 22, 161-174.

Quagliariello, M., 2007. Macroeconomic uncertainty and banks' lending decisions: The case of Italy. Working paper 615, Banca d'Italia.

Quagliariello, M., 2008. Does macroeconomy affect bank stability? A review of the empirical evidence. Journal of Banking Regulation 9, 102-115.

Quagliariello, M., 2009. Macroeconomic uncertainty and banks' lending decisions: The case of Italy. Applied Economics 41, 323-336.

Rajan, R.G., 1994. Why bank credit policies fluctuate: A theory and some evidence. Quarterly Journal of Economics 109, 399-441.

Rajan, R.G., 2005. Has financial developments made the world riskier?, Working paper, NBER.

Rajan, R.G., 2006. Has financial developments made the world riskier? European Financial Management, 12, 499-533.

Sanya, S., Wolfe, S., 2011. Ownership structure, revenue diversification and risk insolvency in European banks. Working paper, IMF.

Shin, H.S., 2009. Securitization and financial stability. Economic Journal 119, 309-332.

Somoye, R. O. C., Ilo, B.M., 2009. The impact of macroeconomic instability on the banking sector lending behavior in Nigeria. Journal of Money, Investment and Banking 7, 88-100.

Stiroh, K.J., 2004. Diversification in banking: is noninterest income the answer? Journal of Money, Credit and Banking 36(5), 853-882.

Stiroh, K.J., Rumble, A., 2006. The dark side of diversification: The case of US financial holding companies. Journal of Banking and Finance 30, 2131- 2161.

Uhde, A., Michalak, T.C., 2010. Securitization and systematic risk in european banking : Empirical evidence, Journal of Banking and Finance 34, 3061-3077.

Vives, X., 1996. Social learning and rational expectations. European Economic Review 40, 589-601.

Vives, X., 2010. Strategic complementarity, fragility, and regulation. Working paper. IESE Business School.

Wagner, W., 2007. The liquidity of bank assets and banking stability. Journal of Banking and Fiannce 31, 121-139.

Wagner, W., 2008. The homogenization of the financial system and financial crises. Journal of Financial Intermediation 17, 330-356.

Wagner, W., 2010. Diversification at financial institutions and systemic crises. Journal of Financial Intermediation 19, 373-386.

TABLES

Table 1 EGARCH(1,1) estimations without instruments

	disp(lta)			*disp(snonin)*		
	(1)	(2)	(3)	(1)	(2)	(3)
constant	38.43	41.09	28.41	5.11	4.48	-2.67
	0.000	*0.000*	*0.000*	*0.000*	*0.010*	*0.665*
cv_gdp	-0.790			-1.090		
	0.005			*0.000*		
cv_gdp_w		-2.65			-2.07	
		0.023			*0.077*	
cv_inf			-10.97			-49.20
			0.020			*0.000*
dln(gdp)	0.83	0.86	1.65			
	0.079	*0.059*	*0.000*			
output_gap	91.73	50.05	60.40	287.26	295.33	306.92
	0.000	*0.099*	*0.006*	*0.000*	*0.000*	*0.000*
inf			-1.27			-0.46
			0.050			*0.890*
dtl	-5.10	-5.37	-2.01	18.86	19.39	23.82
	0.000	*0.000*	*0.065*	*0.000*	*0.000*	*0.000*
y_{t-1}	0.59	0.60	0.43	0.18	0.18	-
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	-
EGARCH						
θ_1 (assym.)	1.00	0.85	0.99	0.99	1.05	0.73
	0.006	*0.085*	*0.001*	*0.000*	*0.000*	*0.014*
θ_2	-0.52	-0.55	-0.81	-2.16	-2.23	-1.76
	0.180	*0.188*	*0.072*	*0.000*	*0.000*	*0.000*
θ_3	0.60	0.62	0.67	0.13	0.13	0.14
	0.000	*0.000*	*0.000*	*0.181*	*0.416*	*0.000*
R-squared	0.35	0.35	0.28	0.64	0.64	0.61
Adj. R-squared	0.28	0.28	0.19	0.60	0.60	0.57
DW	2.02	2.04	1.59	1.97	1.99	1.62

Notes: For each dependent variable, colums (1) and (3) are the models with, respectively, the conditional variances of GDP and inflation as the factors of macroeconomic uncertainty. Column (2) reproduces column (1) specification except that the factor of macroeconomic uncertainty is the weighted conditional variance of GDP instead of its punctual value. The variables notation reads as follows: *disp(lta)*: cross-sectional dispersion of loans-to-assets ratio; *disp(snonin)*: cross-sectional dispersion of *snonin*; *cv_gdp*: conditional variance of gdp growth; *cv_gdp_w*: weighted conditional variance of gdp growth; *cv_inf*: conditional variance of inflation; *dln(gdp)*: gdp growth rate computed as the first difference of the logarithm of GDP; *output_gap*: deviation of log(gdp) from its Hodrick-Prescott trend; *inf*: inflation rate; *dtl*: degree of total leverage. Outliers are controlled with dummies not reported in the table for the sake of clarity. Coefficient *p*-values are reported in italics.

Table 2 Short-run and long-run elasticities of the cross-sectional dispersions with respect to leverage and macroeconomic indicators

	cv_gdp	*cv_gdp_w*	*cv_inf*	*dtl*	*dln(gdp)*	*inf*
disp(lta)						
short-term	-0.03	-0.12	-0.07	-0.45	0.04	-0.02
long-term	-0.08	-0.29	-0.14	-1.12	0.11	-0.04
disp(snonin)						
short-term	-0.02	-0.04	-0.14	0.72	-	-0.01
long-term	-0.03	-0.05	-0.14	0.87	-	-0.01

Note: The long-run elasticity is computed by multiplying the short-run elasticity by $\frac{1}{1-\lambda}$,
where λ is the coefficient of the lagged dependent variable in the respective equations.

Table 3 IV-EGARCH(1,1) estimations

	disp(lta)			*disp(snonin)*		
	(1)	(2)	(3)	(1)	(2)	(3)
constant	34.41	35.65	29.32	4.73	2.92	-2.40
	0.000	*0.000*	*0.000*	*0.048*	*0.699*	*0.131*
$\hat{cv}\_gdp$	-0.67			-2.90		
	0.000			*0.009*		
$\hat{cv}\_gdp\_w$		-2.26			-2.42	
		0.000			*0.425*	
$\hat{cv}\_inf$			-3.55			-27.44
			0.600			*0.040*
$\hat{cv}\_exch\_w$	0.85	0.79	1.75			
	0.000	*0.053*	*0.000*			
output_gap	85.95	76.71	82.34	318.90	288.17	214.84
	0.000	*0.024*	*0.010*	*0.000*	*0.000*	*0.000*
inf			-1.93			7.39
			0.038			*0.000*
$d\hat{t}l$	-3.83	-3.61	-2.36	19.33	20.15	21.44
	0.000	*0.070*	*0.050*	*0.000*	*0.000*	*0.000*
y_{t-1}	0.60	0.59	0.51	0.20	0.20	-
	0.000	*0.000*	*0.000*	*0.000*	*0.000*	-
EGARCH						
θ_1 (assym.)	1.08	0.82	1.23	1.13	0.79	0.54
	0.000	*0.000*	*0.000*	*0.000*	*0.031*	*0.000*
θ_2	-0.70	-0.55	-1.18	-2.77	-1.60	-1.85
	0.013	*0.023*	*0.000*	*0.000*	*0.004*	*0.000*
θ_3	0.56	0.53	0.52	-0.26	0.14	0.35
	0.000	*0.000*	*0.000*	*0.283*	*0.654*	*0.000*
R-squared	0.31	0.33	0.33	0.64	0.64	0.62
Adj. R-squared	0.24	0.26	0.24	0.60	0.60	0.57
DW	2.11	2.06	1.88	1.92	1.99	1.66

Notes: For each dependent variable, colums (1) and (3) are the models with, respectively, the conditional variances of GDP and inflation as the factors of macroeconomic uncertainty. Column (2) reproduces column (1) specification except that the factor of macroeconomic uncertainty is the weighted conditional variance of GDP instead of its punctual value. The variables notation reads as follows: *disp(lta)*: cross-sectional dispersion of loans-to-assets ratio; *disp(snonin)*: cross-sectional dispersion of *snonin*; *cv_gdp_w*: weighted conditional variance of gdp growth; *cv_inf*: conditional variance of inflation; *dln(gdp)*: gdp growth rate computed as the first difference of the logarithm of GDP ; *output_gap*: deviation of *log(gdp)* from its Hodrick-Prescott trend; *inf*: inflation rate; *dtl*: degree of total leverage. Hatted variables are computed using predetermined values of the explanatory variables and their higher moments as instruments. Outliers are controlled with dummies not reported in the table for the sake of clarity. Coefficient *p*-values are reported in italics.

Table A2 Conditional variances of GDP growth and inflation

GDP growth

Variable	Coefficient	p-value
C	1.31	0.000
AR(1)	0.75	0.001
AR(2)	-0.49	0.000
MA(1)	-0.21	0.396
MA(2)	0.34	0.005
EGARCH equation		
θ_1 (assymmetry coef.)	-0.19	0.273
θ_2	0.59	0.000
θ_3	-0.82	0.000
R-squared	0.33	
Adjusted R-squared	0.28	
Durbin-Watson	1.57	

inflation

Variable	Coefficient	p-value
C	1.87	0.000
AR(1)	0.74	0.000
IGARCH equation		
$RESID_{-1}^2$	0.22	0.060
$GARCH_{-1}$	0.78	0.000
R-squared	0.43	
Adjusted R-squared	0.42	
Durbin-Watson	1.76	

Note: The EGARCH equation is estimated using specification (4), and the IGARCH, equation (16).

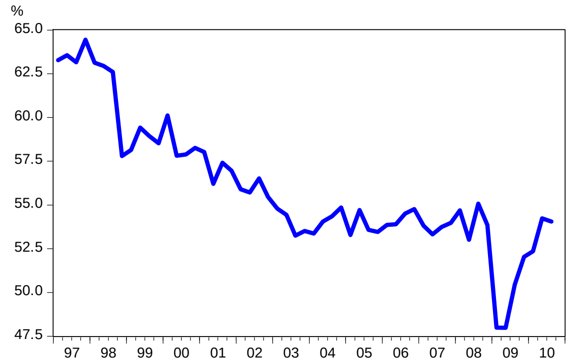
Table A3 Standard OLS estimations

	disp(lta)			*disp(snonin)*		
	(1)	(2)	(3)	(1)	(2)	(3)
constant	33.59	33.86	31.76	14.80	14.00	3.57
	0.000	*0.000*	*0.000*	*0.274*	*0.288*	*0.746*
cv_gdp	1.000			-2.971		
	0.378			*0.056*		
cv_gdp_w		-1.17			-3.22	
		0.634			*0.584*	
cv_inf			7.84			-62.09
			0.803			*0.037*
dln(gdp)	2.45	2.42	2.32			
	0.001	*0.001*	*0.001*			
output_gap	-3.69	-9.27	3.54	292.51	288.01	230.23
	0.955	*0.886*	*0.955*	*0.062*	*0.102*	*0.093*
inf			-1.39			-0.46
			0.445			*0.890*
dtl	-3.98	-3.78	-3.89	17.62	17.98	-1.41
	0.223	*0.257*	*0.244*	*0.002*	*0.002*	*0.844*
y_{t-1}	0.67	0.67	0.61	0.14	0.13	-
	0.000	*0.000*	*0.000*	*0.149*	*0.190*	-
R-squared	0.40	0.39	0.38	0.66	0.65	0.66
Adj. R-squared	0.34	0.33	0.29	0.62	0.62	0.62
DW	2.22	2.24	2.20	1.95	1.97	1.79

Notes: For each dependent variable, Colums (1) and (3) are the models with, respectively, the conditional variances of GDP and inflation as the factors for macroeconomic uncertainty. Column (2) reproduces column (1) specification except that the factor of macroeconomic uncertainty is the weighted conditional variance of GDP instead of its ponctual value. The variables notation reads as follows: *disp(lta)*: cross-sectional dispersion of loans-to-assets ratio; *disp(snonin)*: cross-sectional dispersion of *snonin*; *cv_gdp*: conditional variance of gdp growth; *cv_gdp_w*: weighted conditional variance of gdp growth; *cv_inf*: conditional variance of inflation; *dln(gdp)*: gdp growth rate computed as the first difference of the logarithm of GDP; *output_gap*: deviation of log(gdp) from its Hodrick-Prescott trend; *inf*: inflation rate; *dtl*: degree of total leverage. Outliers are controlled with dummies not reported in the table for the sake of clarity. Coefficient *p*-values are reported in italics. The *p*-values are adjusted for heteroskedacticity with the HAC matrix.

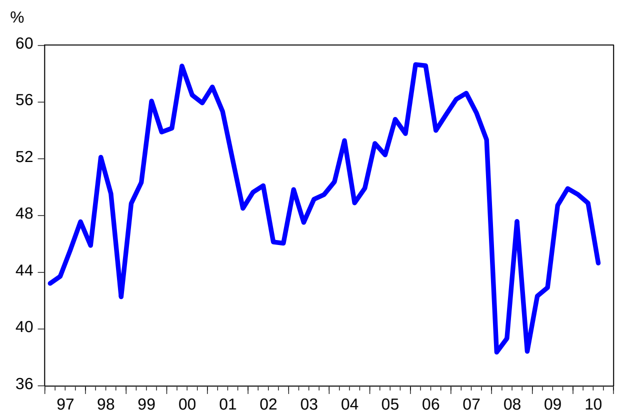
FIGURES

Figure 1 Canadian banks loans-to-assets ratio



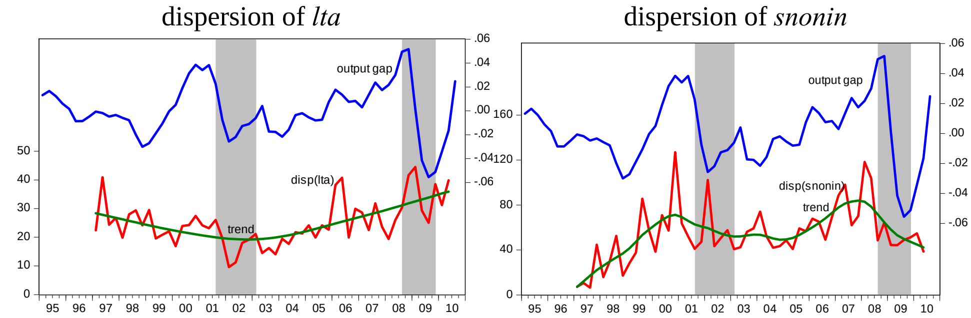
Source: Canadian Bankers Association.

Figure 2 Canadian banks share of noninterest income in operating revenue



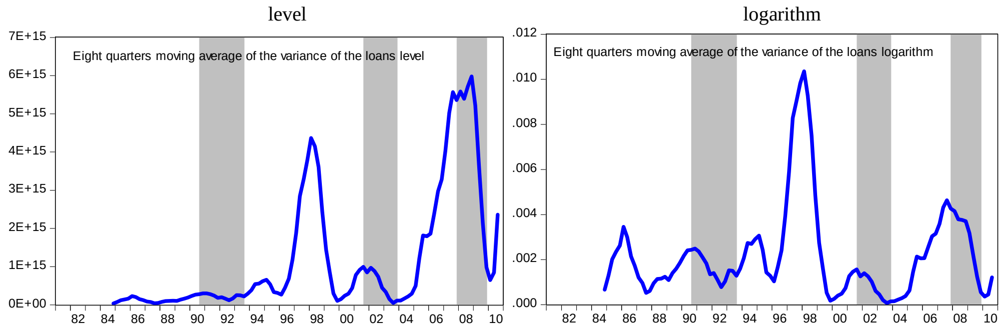
Source: Canadian Bankers Association.

Figure 3 Cross-sectional dispersion of *lta* and *snonin* v/s the output gap



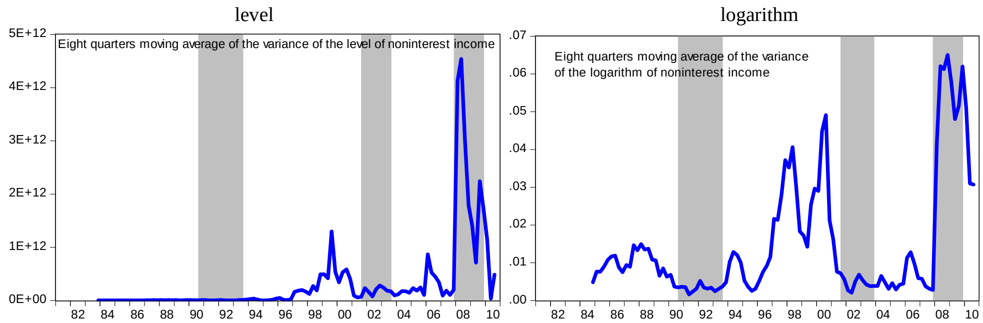
Note: Shaded areas correspond to periods of contractions or marked economic slowdown. The trends of the cross-sectional dispersions are computed with the Hodrick-Prescott filter.

Figure 4 Moving average variance of the level and logarithms of banks loans



Note: Shaded areas correspond to periods of contractions or marked economic slowdown.
Source: Bank of Canada.

Figure 5 Moving average variance of the level and logarithms of banks noninterest income



Note: Shaded areas correspond to periods of contractions or marked economic slowdown.
Source: Bank of Canada.

Figure 6 Scatter diagrams of the cross-sectional dispersions of *lta* and *snonin* with their respective cross-sectional covariance