



**Bank systemic risk and the business cycle:  
Canadian and U.S. evidence†**

Christian Calmès<sup>a,\*</sup>, Raymond Théoret<sup>b</sup>

<sup>a</sup> *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*

<sup>b</sup> *Université du Québec (Montréal), École des sciences de la gestion, 315 est Ste-Catherine, Montréal, Québec; Université du Québec (Outaouais); Chaire d'information financière et organisationnelle, ESG-UQAM,*

*(This version: April 27<sup>th</sup> 2012)*

---

\* Corresponding author. Tel: +1 819 595 3000 1893; fax: +1 819 773 1747  
E-mail addresses: [christian.calmes@uqo.ca](mailto:christian.calmes@uqo.ca) (C. Calmès), [raymond.theoret@uqam.ca](mailto:raymond.theoret@uqam.ca) (R. Théoret).

† We thank the Managing Editor Ike Mathur, Kevin Stiroh, Christian Zimmermann, Céline Gauthier, Étienne Bordeleau and the seminar participants of the 2011 Annual Conference of the Société Canadienne de sciences économiques for their helpful suggestions.

## **Bank systemic risk and the business cycle: Canadian and U.S. evidence**

### **Abstract**

This paper investigates how banks, as a group, react to macroeconomic risk and uncertainty, and more specifically the way bank systemic risk evolves over the business cycle. Adopting the methodology of Beaudry *et al.* (2001), our results suggest that the dispersion across banks' traditional portfolios has 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. In particular, 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. More importantly however, our results also suggest that the cross-sectional dispersion of market-oriented activities is both more volatile and sensitive to the business cycle than the dispersion of bank traditional activities.

*JEL classification:* C32; G20; G21.

*Keywords:* Banking stability; Herding; Macroeconomic uncertainty; Macroprudential policy; Markov switching regime; EGARCH.

## **Risque bancaire systémique et cycles économiques: L'expérience canadienne et américaine**

### **Résumé**

Cet article examine comment les banques réagissent collectivement au risque et à l'incertitude macroéconomiques, et se penche plus spécifiquement sur l'évolution du risque bancaire systémique au cours du cycle économique. À l'aide d'une méthodologie empruntée à Beaudry et al. (2001), nos résultats suggèrent que la dispersion en coupe instantanée des portefeuilles bancaires traditionnels s'est accrue dans le temps. Nous introduisons une procédure d'estimation basée sur la méthode EGARCH et généralisons l'approche proposée par Baum et al. (2002, 2004, 2009) et Quagliariello (2007, 2009) pour analyser la question dans le nouvel environnement bancaire (« shadow banking »). En conformité avec la théorie financière, nous confirmons d'abord que les banques tendent à se comporter de façon homogène en périodes d'incertitude macroéconomique. Plus spécifiquement, nous trouvons que les dispersions en coupe instantanée du ratio des prêts aux actifs, de même que celles des activités non traditionnelles diminuent essentiellement au cours des cycles baissiers, alors que la résilience du système bancaire est à son plus bas. Plus fondamentalement cependant, nos résultats suggèrent également que la dispersion en coupe instantanée des activités bancaires axées sur les marchés financiers est à la fois plus volatile et plus sensible au cycle économique que la dispersion des activités traditionnelles.

*Classification JEL :* C32, G20, G21.

*Mots-clefs :* Stabilité bancaire; Mimétisme; Incertitude macroéconomique; Politique macroprudentielle; Changement de régimes markovien; EGARCH.

## 1. Introduction

Banks' individual response to external shocks can lead to common patterns increasing systemic risk – especially when disaster myopia is at work (Jain and Gupta 1987, Pecchino 1990, Hutchinson 2002, Borio *et al.* 2001, Hyytinen *et al.* 2003). 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, the growth in securitization, trading and cross-selling of the largest U.S. banks holdings fed a systemic risk bubble up to its breaking point (Loutskina 2011<sup>1</sup>).

Whilst regulation keeps focusing on the tightening of capital standards and liquidity requirements, financial institutions have shifted their business model towards market-oriented activities – i.e. shadow banking (Shin 2009). Most authors argue that the business homogenization entailed by this diversification in non-traditional operations reduces banking stability (e.g., Wagner 2007, Calmès and Théoret 2010, De Jonghe 2010)<sup>2</sup>. The new business environment the financial industry is facing indeed motivates the analysis of the link between market-oriented banking and bank systemic risk (Haiss 2005<sup>3</sup>, Loutskina 2011). Given the “procyclicality”<sup>4</sup> of shadow banking, this question is particularly relevant for the conduct of macroprudential policy<sup>5</sup> and the monitoring of systemic risk buildups. In line with this problematic, the motivation of our research is to investigate whether the changes in the banking

---

<sup>1</sup> 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).

<sup>2</sup> 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).

<sup>3</sup> Haiss (2005) provides an extensive literature review on the subject.

<sup>4</sup> 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.

<sup>5</sup> Macroprudential policy aims at monitoring the systemic risk generated by bank risk-taking externalities.

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 differ depending on the type of diversification strategy examined (Jain and Gupta 1987). Besides, this methodology might be appropriate to depict cascade-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 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 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 bank herd-like behaviour in terms of loans portfolios cross-sectional dispersion. In particular, based on U.S. data, 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 regulatory changes<sup>6</sup>.

In this paper we work along these lines, but we analyze the pattern in the context of shadow banking. To better assess bank systemic risk, we enlarge the investigation scope and include all banking business activities, not only considering loans, but also bank off-balance-sheet (OBS) lines of business, and more precisely the share of noninterest income (*snoin*) generated by OBS activities<sup>7</sup>.

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. In this regard, one contribution of this paper is to introduce 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 framework, based on an EGARCH approach (Nelson 1991), provides a more precise account of the relative impact of macroeconomic risk (the first moment), and uncertainty (the second moment).

Consistent with previous studies, Canadian and U.S. data confirm 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 bank behaviour is more homogenous in downturns. In particular, we find that the volatilities of the innovations of the cross-sectional dispersions are lower in

---

<sup>6</sup> Baum *et al.* (2009) find that regulatory changes, more precisely the Basel Accords, seemed to have had a tendency to increase herding.

<sup>7</sup> Note that *snoin* is only a proxy for OBS activities as some *snoin* related items are actually accounted on balance sheet.

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 with Bikker and Hu (2002)<sup>8</sup>, our results would better accord with the balance sheet channel than with the traditional credit channel (Bernanke and Gertler 1995, Kashyap and Stein 2000).

The rise of shadow banking notwithstanding, bank 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 cyclical nature of bank systemic risk is quite substantial, and that the fluctuations of non-traditional activities are large, especially so during recessions – as obviously evidenced by the 2007-2009 crisis. These results hold for both Canada and the U.S. and seem even stronger in the latter case.

This paper is organized as follows. Section 2 presents the theoretical intuition supporting the herd-like hypothesis, i.e., the link between macroeconomic uncertainty and the cross-sectional dispersion of bank risky assets (on-balance sheet and off-balance-sheet related items). The section also exposes the empirical framework and the EGARCH procedure we introduce in the 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.

---

<sup>8</sup> We try several financial variables to represent the supply and demand sides of risky assets like return on assets, 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 bank herd-like hypothesis

Many studies document the influence of the first moments of macroeconomic aggregates, i.e., macroeconomic risk, on systemic risk (e.g. Barth *et al.* 1999, Borio *et al.* 2001, Bikker and Hu 2002, Bikker and Metzmakers 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 are susceptible to influence bank systemic behaviour, so far only few authors looked at the role played by 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 bank risky assets, i.e. a decrease in the aggregate dispersion of banks' portfolios. Our primary 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 bank 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<sup>9</sup>.

In this paper we aim at empirically testing this conjecture – i.e., the banks herd-like hypothesis – with a particular focus on non-traditional business lines. To do so, we introduce a new empirical framework linking bank 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. In this study, 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:

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

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;  $\sigma_{c,mv,t}^2$  is the corresponding conditional variance of the macroeconomic variable<sup>10</sup> (i.e. the second moment measuring macroeconomic uncertainty), and  $\xi_t$  is the innovation. For instance, the first moment of a macroeconomic variable may be GDP growth and its second 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

---

<sup>9</sup> 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.

<sup>10</sup> For the constructs of the conditional variance series proxying macroeconomic uncertainty, see Appendix 2.



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 is that we suspect the first moments of the macroeconomic variables to have a great impact on non-traditional banking activities, whereas the second moments should mainly 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 banking, are designed to manage volatility – the *raison d'être* of derivatives – and to improve financial markets risk-sharing. On the other hand however, given their high degree of liquidity, we also conjecture that OBS activities are relatively more sensitive to the business cycle, so that the cyclicity 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). Indeed, 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:

$$disp(lta)_i = \beta_0 + \beta_1 cv\_gdp_i + \beta_2 d \ln(gdp)_i + \beta_3 output\_gap_i + \beta_4 dtl_i + \beta_5 disp(lta)_{i-1} + \varepsilon_i \quad (2)$$

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 ag-

gregate measure of the degree of total leverage<sup>11</sup>. According to the theory, we expect the sign of  $\beta_1$  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 ( $dttl$ )<sup>12</sup>. 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. For example, contrary to most standard measures, the  $dttl$  suggests that embedded leverage was increasing during the 2002-2007 period, while financial institutions were expanding their OBS activities, and indicates a deleveraging process after 2007, as banks were decreasing their risk to recover<sup>13</sup>. *Ceteris paribus*, to the extent that the herd-like hypothesis has some support,  $\beta_5$ , the coefficient of  $dttl$  should be negative, banks adopting a more homogenous behaviour in times of increasing bank 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 ( $cv\_gdp\_w$ ), whereas, in the third version of the model, the dispersion of  $lta$  is

---

<sup>11</sup> 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.

<sup>12</sup> For the construction of this variable – a measure of banks time-varying leverage obtained with the Kalman filter –, see Calmès and Théoret (2011a).

<sup>13</sup> 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).

expressed in terms of inflation uncertainty and reads as follows:

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

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  $\gamma_1$ , the coefficient associated with inflation uncertainty. We also expect the coefficient associated with the inflation rate,  $\gamma_4$ , 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 *snoin*, 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<sup>14</sup> 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. As a matter of fact, relying on OLS delivers mild results, especially regarding the impact of the first moments of the macroeconomic variables<sup>15</sup>. 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). Hence, imposing a symmetry constraint on the conditional variance of

<sup>14</sup> The EGARCH estimation method is summarized in Appendix 3.

<sup>15</sup> OLS results are reported in Appendix 4.

past innovations might be too restrictive.

We estimate the model versions for *lta* and *snoin* using this EGARCH procedure, but we also rely on EGARCH with instruments since the conditional variances of our macroeconomic variables and the *dil* 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), on 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 *dil* are explicitly considered endogenous.

### **3. Data and some key stylized facts**

Since we focus on the reaction of the banking system to regular macroeconomic fluctuations, 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 banks' non-

traditional activities have indeed some influence on banks' 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<sup>16</sup>.

Accordingly, the first 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.

As a robustness check, we also estimate our models on U.S. bank quarterly data over the same period. Our second sample includes the U.S. banks which are the most similar to the Canadian ones in terms of assets. At the end of 2011, the twenty largest U.S. banks we consider accounted for more than 50 percent of the U.S. bank assets aggregate (computed over 1675 U.S. banks<sup>17</sup>). In the first sample, Canadian bank assets range from \$156 to \$751 billion, while in the second sample, U.S. bank assets range from \$88 to \$1811 billion<sup>18</sup>. In the U.S., only four banks have a total of assets exceeding those of the Royal Bank of Canada (the largest Canadian bank). The next four largest Canadian banks are bigger than the fifth largest U.S. bank. Overall, the Canadian and U.S. samples we use are thus quite comparable in terms

---

<sup>16</sup> Our results on U.S. bank data also support this conjecture. See Section 5.

<sup>17</sup> Source: *Federal Reserve Bulletin*, December 2011.

<sup>18</sup> There was exchange rate parity at the time of bank statistics release.

of assets. The U.S. bank dataset is based on statistics provided by the Federal Reserve Bank of Chicago and the Federal Deposit Insurance Corporation (FDIC), and the U.S. macroeconomic time series come from FRED, a database managed by the Federal Reserve Bank of St-Louis.

Insert Figure 1 and Figure 2 here

Regarding the basic statistics, first note that the Canadian bank 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). Opposite to the *lta* pattern, *snoin*, our proxy for OBS activities, has a tendency to increase over this 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 banking regime 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)<sup>19</sup>. 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). More precisely, authors find that non-traditional business lines have spurred the volatility of bank income over the last decades. 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 bank 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

---

<sup>19</sup> For Canadian evidence see also Calmès (2004).

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 ( $snonin$ ) 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 steadily reverses after 2002 (Figure 3). Surprisingly, this  $disp(lta)$  upward trend actually 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 respects, a first glance at the series also reveals that the cross-sectional dispersion of  $lta$  might be quite 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 anecdotal since this kind of pattern is much susceptible to increase banking procyclicality (Figure 3).

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). Importantly, note that, *prima facie*, 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 much credit commitments were exercised. This kind of response suggests that banks' OBS activities might contract more than traditional business lines during bad times.

Insert Figure 4 here

To better capture the regime changes, we can assume that the endogenous variables are subjected to two Markovian states  $S_t$  (state 0, a regime of low volatility and state 1, a regime of high volatility). Expressing these variables as

$$y_t = \alpha_{S_t} + \varepsilon_t, \quad t = 0, \dots, T, \quad S_t = 0, 1 \quad (4)$$

where  $\alpha_{S_t} = \alpha_0(1 - S_t) + \alpha_1 S_t$ ,  $\varepsilon_t \sim NID(0, \sigma_{S_t}^2)$ ,  $\sigma_{S_t}^2 = \sigma_0^2(1 - S_t) + \sigma_1^2 S_t$ , and  $\sigma_1^2 > \sigma_0^2$ . The regimes being unobservable, we must compute the transition probability  $p_{ij}$  of switching from one regime to the next as:

$$p_{ij} = P(S_t = j | S_{t-1} = i), \quad i, j = 0, 1 \quad (5)$$

Estimating this Markov switching model in the mean and variance with the maximum likelihood method, we can see that *disp(lta)* moves progressively from a high volatility regime at the start of the 2000s to a low volatility regime persisting even during the 2007 credit crisis (Figure 4). This fact confirms that banks' lending behaviour has become less homogeneous since the beginning of the second millennium. By contrast, the changes in the regimes of *disp(snonin)* are essentially conditioned by the phase of the business cycle, high volatility regimes being associated with economic downturns, and low volatility regimes, with expansions.

## 4. Main 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 an 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)), suggesting a delay in the adjustment of  $disp(lta)$ .

Note that the level of economic growth also increases  $disp(lta)$ , confirming that bank 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 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 homoskedasticity 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,  $dlt$ . As expected, column (1) of Table 1 shows that an increase in  $dlt$  decreases  $disp(lta)$ , the estimated coefficient being equal to -5.10 and significant at the 1% level. This result corroborates the view that bank 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  $disp(lta)$ <sup>20</sup>. 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)<sup>21</sup>.

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 expect 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. Weighting the conditional variance of GDP growth delivers similar results, the estimated coefficient of  $cv\_gdp\_w$  being equal to -2.07 (column (2)). Relatedly, when  $cv\_gdp$  is used as the uncertainty proxy, the estimated coefficient of the lagged dependent variable is equal to

---

<sup>20</sup> If, instead of  $dlt$ , 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.

<sup>21</sup> 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.

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 fluctuations. This dynamic property is also consistent with both the relative volatility of  $snonin$  cross-sectional dispersion and the greater liquidity of non-traditional activities.

Note that  $disp(snonin)$  appears more sensitive to inflation uncertainty than  $disp(lta)$ . 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<sup>22</sup> (column (3)). More importantly, 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)).

For all the exogenous variable considered, both those related to risk and to uncertainty, the results largely corroborate our stylized facts. In particular, 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 estimations clearly reveal that, while banks seem better 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<sup>23</sup>.

As a final remark, note that the behaviours of  $disp(lta)$  and  $disp(snonin)$  also differ with respect to  $dtt$ , our control variable for bank risk. Contrary to the  $disp(lta)$  results, an increase in  $dtt$  leads to a corresponding increase in  $disp(snonin)$ . The estimated coefficient of  $dtt$  is positive and significant at the 1% level, regardless of the way we proxy for macroeconomic

---

<sup>22</sup> 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.

<sup>23</sup> 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).

uncertainty. For instance, it is equal to 18.86 when  $cv\_gdp$  is used to measure uncertainty, and to 23.82 with  $cv\_inf$ . This result relates to the fact that when  $dlt$  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  $dlt$  increases, i.e. bank risk rises, banks are induced to off-load risk from on-balance-sheet to off-balance-sheet in order to generate new capital or additional liquidities<sup>24</sup>. *Ceteris paribus*, this transfer tends to decrease  $disp(lta)$  and  $lta$ , and to increase  $disp(snonin)$  and  $snonin$ .

Insert Table 2 about here

#### 4.2. The relative explanatory power of the exogenous variables

To compare more precisely the relative power of our exogenous factors, Table 2 reports the estimated short-term and long-term elasticities of  $disp(lta)$  and  $disp(snonin)$ <sup>25</sup>. 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

<sup>24</sup> For instance, some loans in the balance sheet may be securitized.

<sup>25</sup> 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  $X$  and  $Y$ , computed over the sample period. The long-term elasticity is computed by multiplying the short-term elasticity by  $\frac{1}{1-\lambda}$ , where  $\lambda$  is the coefficient of the lagged dependent variable.

latter should be relatively more immune to uncertainty than risk since the volatility of OBS activities is, by definition, easier to hedge.

More importantly, 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. In this respect, 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).

Finally, note that the long-run elasticity of  $disp(lta)$  with respect to  $dil$ , at -1.12, is higher than 1 in absolute value, whereas the long-run elasticity of  $disp(snoin)$  with respect to  $dil$  is also quite high, at 0.87, but with the opposite sign. This finding suggests that the positive impact of a 1% increase of  $dil$  on  $disp(snoin)$  is mostly counterbalanced by the negative influence of this increase on  $disp(lta)$ . In other words, RCA unlikely exerts a meaningful influence on banks clustering in the long-run.

#### 4.3. *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. 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<sup>26</sup>. The omission of the residuals specification in the experiments based on OLS 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).

---

<sup>26</sup> The OLS estimations are discussed in Appendix 4.

Regarding the results, first note that, for  $disp(lta)$ , the estimated asymmetry coefficient  $\theta_1$  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<sup>27</sup> have indeed 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  $disp(snonin)$ . Hence, 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.

Finally note that, in economic downturns, the volatilities of  $disp(lta)$  and  $disp(snonin)$  shrink *pari passu* with the dispersions. These results suggest that the procyclicality of  $disp(lta)$  and  $disp(snonin)$  might actually be greater than previously reported.

## 5. Robustness checks

### 5.1. The IV-EGARCH estimation results

In our framework, we introduce as generated or endogenous variables a measure of bank risk,  $dtt$ , 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 also regress each of them on instruments before applying the EGARCH to the models. 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).

Furthermore, 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

---

<sup>27</sup> 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.

$disp(snonin)$  decreases 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 risk is the assets cross-sectional *covariance* (Adrian 2007). This financial indicator is defined as:

$$cov(X_{i,j}) = \frac{1}{N^2 - N} \sum_{i=1}^N \sum_{j=1, j \neq i}^N (X_i - \bar{X})(X_j - \bar{X}),$$

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 5 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 (Figure 5). The negative colinearity between  $disp(lta)$  and  $cov(lta)$  appears quite high and, for  $snonin$ , the observation dots relating the cross-sectional covariances to the cross-sectional dispersions are even more aligned with the regression line (Figure 5). *Ceteris paribus*, we can suspect that if a cross-sectional covariance diverges from its associ-

ated cross-sectional dispersion, it might signal a stronger banking resilience. In this respect, one way to interpret the *snoin* 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. In other words, this result is consistent with the view that, in the new banking era, systemic risk likely stem more from market-oriented activities than from traditional business lines.

Insert Figure 6 here

### 5.3. The U.S. experience

The same kind of results should *a fortiori* hold for bank systems which are less immune to external shocks. As a last robustness check, we thus examine the U.S. experience. Figure 6 plots the *lta* and *snoin* ratios for the twenty largest U.S. banks over the period 1997-2010. Not surprisingly, the respective profiles of these variables are very similar to those of the Canadian banks (Boyd and Gertler 1994). For example, the U.S. banks' *lta* ratio displays a tendency to decrease over the sampling period, although the fall starts later than in Canada. The behaviour of the U.S. *snoin* is also very similar to its Canadian counterpart. In particular, it is more cyclical than the corresponding *lta* series. The levels of the series are also comparable across countries.

Insert Figure 7 here

In other respects, the U.S. cross-sectional dispersion of *lta* shows a clear tendency to increase as in the Canadian sample (Figure 7). This stylized fact corroborates the idea that, in terms of lending, bank herding tends to decrease over time. As a matter of fact, this trend begins sooner in the U.S.. Moreover, the U.S. cross-sectional dispersion of *lta* seems even less responsive to the business cycle than its Canadian counterpart.

By contrast, the U.S. cross-sectional dispersion of *snoin* is sensitive to the business cycle, and once again this phenomenon seems more pronounced than in Canada. For example, since



U.S. banks were severely hit by the 2007 credit crisis, the decrease in the cross-sectional dispersion of *snonin* is much larger than for Canadian banks.

Insert Table 4 here

Consistent with our previous results, the macroeconomic uncertainty related to GDP impacts U.S. *disp(lta)* and *disp(snonin)* negatively (Table 4). The estimated coefficients for *cv\_gdp* are quite comparable for *disp(lta)* and *disp(snonin)*, being -14.28 and -15.99 respectively, both significant at the 99% confidence level. For the output gap variable there is also a clear difference in the estimation of the *disp(lta)* and *disp(snonin)*. However, the coefficient associated with the output gap is not only lower for *disp(lta)*, but it actually turns negative, at -739.69 compared to 637.02 for *disp(snonin)*. Another interesting result is that *disp(lta)* reacts quite negatively to bank risk as measured by *drl*. Compared to Canadian banks, the U.S. banks tend to reduce lending in a more homogenous way when bank risk increases. Note that, *ceteris paribus*, this phenomenon is symptomatic of a more fragile banking system.

U.S. banks also appear more sensitive to macroeconomic uncertainty, both for *disp(lta)* and *disp(snonin)*<sup>28</sup>. For instance, the sensitivity of *disp(snonin)* to *cv\_gdp* is greater in the U.S. than in Canada<sup>29</sup>. Note that the U.S. *disp(snonin)* is also more sensitive to the output gap than its Canadian counterpart, the coefficients being respectively 637.02 and 287.26. Finally, remark that the sensitivity of the U.S. banks' *disp(lta)* and *disp(snonin)* to *cv\_inf* is less pronounced than in the Canadian banking system. This might relate to the explicit inflation targeting rule followed by the Canadian central bank since the 1990s.

Overall, these results provide additional support for the relative stability of the two banking systems. Both in Canada and the United States, non-traditional bank activities have progressively become a major determinant of bank risk. On the one hand, bank herd-like behaviour in terms of loans seems to vanish, especially in the U.S.. On the other hand, in both coun-

---

<sup>28</sup> In terms of elasticities, the U.S. results are qualitatively similar to the Canadian ones. Since the cross-sectional dispersions of *lta* and *snonin* are much higher for the U.S. banks, the constant captures a great deal of the difference.

<sup>29</sup> Comparing the relative risk of Canadian and U.S. banks, Calmès and Liu (2009) find that noninterest income contributes more to the variance of bank operating income in the U.S. than in Canada.

tries, herding cyclicalities seem more prevalent for non-traditional activities. In this respect, the procyclicality of  $disp(snonin)$  seems more pronounced in the U.S. than in Canada, which likely weights in the relative stability of the two banking systems.

## 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<sup>30</sup>. We show that this pattern also obtains for assets whose cash-flows are noninterest income. Furthermore, our results suggest 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. 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  $snonin$ .

More importantly, a comparison of  $lta$  and  $snonin$  statistics 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 sup-

---

<sup>30</sup> 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.

port the view that 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 *snoin* 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' *snoin* tend to converge rapidly during contractions, which indeed implies major banks' portfolios reshufflings.

The strong sensitivity to the business cycle phase of the cross-sectional dispersion of *snoin* could relate to first-order demand-side effects generated by the buyers of the short-term debts financing the securitized assets, from the lenders of the repo market<sup>31</sup>, 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. 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 (Vives 2010, Gennaioli *et al.* 2011).

These demand-side effects must be distinguished from the impact of macroeconomic uncertainty (the second moment) on bank systemic behaviour. We find that banks' dispersion of *snoin* seems relatively less sensitive to macroeconomic uncertainty, as measured by the conditional variance of GDP growth, than the dispersion of *lta*. In this respect, while many studies indicate that the rising share of OBS activities in bank 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

---

<sup>31</sup> 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. This market-based financing shrinks heavily during contractions, and especially during liquidity crises, a phenomenon indirectly captured in our framework by the cross-sectional dispersion of *snoin*.

OBS activities might also help banks hedge and better allocate their risks in the long-run (Stiroh 2004).

The estimations based on U.S. bank data support the Canadian results: an increasing resilience of lending activities to business conditions and a significant bank herd-like behaviour in contraction for the non-traditional activities. These findings are actually stronger for the U.S., which suggests the presence of riskier or more speculative off-balance-sheet assets in banks' portfolios.

The main macroprudential policy implication we can derive from this study is that the cyclicity of OBS activities should be closely monitored by the regulatory agencies in charge of financial stability. The traditional role of banks (providing liquidities *sur demande*) is obviously challenged by the development of banks' non-traditional activities. However, macroprudential policy-makers face a delicate conundrum, as the increase in bank aggregate risk, one of the most singular characteristics of the new banking environment<sup>32</sup>, 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 Basel III proposed mandatory leverage ratio, we would strongly advocate 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.

---

<sup>32</sup> Houston and Stiroh (2006) and Gennaioli *et al.* (2011) find that bank systemic risk increases with the development of shadow banking, while idiosyncratic risk decreases thanks to the greater diversification enabled by OBS activities.

## Appendix 1

### The banks portfolio model

The returns on the two categories of assets which compose the representative bank's portfolio are given by the following equations:

$$\forall i, \quad \forall t, \quad r_{i,t}^S = r_f \quad (6)$$

$$\forall i, \quad \forall t, \quad r_{i,t}^{ra} = r_f + \rho + \varepsilon_{i,t} \quad (7)$$

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 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  $\rho$  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 (7)). 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  $\varepsilon_{i,t}$ :  $S_{i,t} = \varepsilon_{i,t} + \nu_t$ , with  $\nu_t \sim N(0, \sigma_{\nu,t}^2)$  and  $E(\varepsilon_{i,t}, \nu_t) = 0$ <sup>33</sup>. The assumption of orthogonality between  $\varepsilon_{i,t}$  and  $\nu_t$  may be justified by considering  $\nu_t$  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  $\nu_t$  whose intensity  $\sigma_{\nu,t}^2$  is time varying. Assume that  $\sigma_{\nu,t}^2$  is driven by macroeconomic uncertainty so that when uncertainty rises, the noise incorporated in the signal rises with  $\sigma_{\nu,t}^2$  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  $E[\varepsilon_{i,t} | S_{i,t}]$ , the expected value of the idiosyncratic noise conditional on the signal. Even if  $E(\varepsilon_{i,t})$ , 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  $\lambda_t$  of the signal:

$$\forall i, \quad \forall t, \quad E[\varepsilon_{i,t} | S_{i,t}] = \lambda_t [\varepsilon_{i,t} + \nu_t] \quad (8)$$

with

---

<sup>33</sup> For a canonical form of this banking theory see Rajan (1994). Rajan relates the signal to the publication of banks earnings rather than to macroeconomic variables, but there is a close link between bank earnings and macroeconomic aggregates (Bikker and Hu 2002, Quagliariello 2008).

$$\forall t, \lambda_t = \frac{\sigma_{\varepsilon,t}^2}{\sigma_{\varepsilon,t}^2 + \sigma_{v,t}^2} \quad (9)$$

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

$$\forall i, \forall t, E[\tilde{R}_{i,t} | S_{i,t}] = w_{i,t}(r_f + \rho + \lambda_t S_{i,t}) + (1 - w_{i,t})r_f \quad (10)$$

and the conditional variance of the portfolio is:

$$\forall i, \forall t, Var[\tilde{R}_{i,t} | S_{i,t}] = \lambda_t \sigma_{v,t}^2 w_{i,t}^2 \quad (11)$$

According to this model, the portfolio variance is simply an increasing function of macroeconomic uncertainty  $\sigma_{v,t}^2$ . 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,

$$\forall i, \forall t, \arg \max_{w_{i,t}} E[\tilde{V}_{i,t} | S_{i,t}] = E[\tilde{R}_{i,t} | S_{i,t}] - \frac{1}{2} \varphi Var[\tilde{R}_{i,t} | S_{i,t}] \quad (12)$$

where  $\varphi$  is the bank degree of risk aversion. Equating the derivative of Equation (12) with respect to  $w_{i,t}$  to 0, we obtain the optimal value of the share of the risky asset in the bank portfolio,

$$\forall i, \forall t, w_{i,t} = \frac{\rho + \lambda_t S_{i,t}}{\varphi \lambda_t \sigma_{v,t}^2} \quad (13)$$

Combining Equations (13) and (9) we can finally compute the variance of the cross-sectional dispersion of the risky asset as follows:

$$\forall i, \forall t, Var(w_{i,t}) = \frac{\sigma_{\varepsilon,t}^2 + \sigma_{v,t}^2}{\varphi^2 \sigma_{v,t}^4} \quad (14)$$

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

$$\forall i, \forall t, \frac{\partial Var(w_{i,t})}{\partial \sigma_{v,t}^2} = -\frac{1}{\varphi^2} \left[ \frac{2\sigma_{\varepsilon,t}^2}{\sigma_{v,t}^6} + \frac{1}{\sigma_{v,t}^4} \right] < 0 \quad (15)$$

Equation (15) 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 using GARCH ( $p,q$ ) specifications (Bollerslev 1986). However, contrary to these authors, we also introduce EGARCH specifications (Nelson 1991). Assume a simple general econometric model written as:

$$Y_t = X_t\beta + \varepsilon_t \quad (16)$$

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

$$\sigma_t^2 = \alpha + \beta\varepsilon_{t-1}^2 + \varphi\sigma_{t-1}^2 \quad (17)$$

which can be generalized to a GARCH ( $p,q$ ) process by adding  $p$  lags to  $\varepsilon_t$  and  $q$  lags to  $\sigma_t^2$ . Equations (16) and (17) are estimated simultaneously using the maximum likelihood estimator.

Then, to build the conditional variances of our two proxies of macroeconomic uncertainty, we first transform the variables in growth rates so that we can work with stationary time series. 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) specification to compute the associated conditional variance of GDP growth after experimenting with several GARCH processes<sup>34</sup>. The estimated coefficient of asymmetry 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)<sup>35</sup> (integrated GARCH) resulting from an AR(1) estimation.

---

<sup>34</sup> For the tests related to the selection of a GARCH process, see Franses and van Dijk (2000).

<sup>35</sup> In an IGARCH process the sum of the  $\beta$  and  $\varphi$  coefficients in equation (17) is close to 1.

### Appendix 3

#### The EGARCH estimation method

To account for the asymmetric impact of good news and bad news on the conditional volatility of the cross-sectional dispersion innovations, we follow Nelson (1991) and introduce a model such that:

$$\log(\sigma_t^2) = \theta_0 + \theta_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \theta_2 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \theta_3 \log(\sigma_{t-1}^2) \quad (18)$$

which can be generalized to an EGARCH( $p, q$ ) process by adding  $p$  lags to  $\frac{\varepsilon_t}{\sigma_t}$  and  $q$  lags to  $\log(\sigma_t^2)$ . 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  $\theta_1$  coefficient. There is asym-

metry if  $\theta_1$  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<sup>36</sup>. This EGARCH model al-

lows good news and bad news to have a different impact on volatility, and important news to have a proportionally greater impact than the standard GARCH model (Engle and Ng 1993).

---

<sup>36</sup> By contrast, in the threshold ARCH (i.e. TAR) model, an alternative way to account for the asymmetric properties of the conditional volatility, this effect is assumed to be quadratic.



#### Appendix 4

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

Table A4 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). The results associated with the OLS estimation of *disp(lta)* are particularly unsatisfactory. 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 not significant. The output gap has a sign opposite to its EGARCH estimate, although not significant. The *dtt* variable has the same sign as in the EGARCH estimation but is also not significant.

Insert Table A4 here

The results obtained with the OLS estimation of *disp(snonin)* are more in line with those resulting from the 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)*, *dtt* 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. These results constitute an additional evidence that banks' market-oriented business lines are quite sensitive to the business cycle.

## 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 asymmetric 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., Metzmakers, 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*.
- 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.
- 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.
- 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.
- 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., 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 Finance* 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

	<i>disp(lta)</i>			<i>disp(snonin)</i>		
	(1)	(2)	(3)	(1)	(2)	(3)
<i>constant</i>	38.43 <i>0.000</i>	41.09 <i>0.000</i>	28.41 <i>0.000</i>	5.11 <i>0.000</i>	4.48 <i>0.010</i>	-2.67 <i>0.665</i>
<i>cv_gdp</i>	-0.790 <i>0.005</i>			-1.090 <i>0.000</i>		
<i>cv_gdp_w</i>		-2.65 <i>0.023</i>			-2.07 <i>0.077</i>	
<i>cv_inf</i>			-10.97 <i>0.020</i>			-49.20 <i>0.000</i>
<i>dln(gdp)</i>	0.83 <i>0.079</i>	0.86 <i>0.059</i>	1.65 <i>0.000</i>			
<i>output_gap</i>	91.73 <i>0.000</i>	50.05 <i>0.099</i>	60.40 <i>0.006</i>	287.26 <i>0.000</i>	295.33 <i>0.000</i>	306.92 <i>0.000</i>
<i>inf</i>			-1.27 <i>0.050</i>			-0.46 <i>0.890</i>
<i>dlt</i>	-5.10 <i>0.000</i>	-5.37 <i>0.000</i>	-2.01 <i>0.065</i>	18.86 <i>0.000</i>	19.39 <i>0.000</i>	23.82 <i>0.000</i>
<i>y<sub>t-1</sub></i>	0.59 <i>0.000</i>	0.60 <i>0.000</i>	0.43 <i>0.000</i>	0.18 <i>0.000</i>	0.18 <i>0.000</i>	- <i>-</i>
EGARCH						
$\theta_1$ (assym.)	1.00 <i>0.006</i>	0.85 <i>0.085</i>	0.99 <i>0.001</i>	0.99 <i>0.000</i>	1.05 <i>0.000</i>	0.73 <i>0.014</i>
$\theta_2$	-0.52 <i>0.180</i>	-0.55 <i>0.188</i>	-0.81 <i>0.072</i>	-2.16 <i>0.000</i>	-2.23 <i>0.000</i>	-1.76 <i>0.000</i>
$\theta_3$	0.60 <i>0.000</i>	0.62 <i>0.000</i>	0.67 <i>0.000</i>	0.13 <i>0.181</i>	0.13 <i>0.416</i>	0.14 <i>0.000</i>
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, columns (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; *dlt*: degree of total leverage. Outliers are controlled with dummies not reported in the table for the sake of clarity. The construction of the *cv\_gdp* and *cv\_inf* variables is explained in Appendix 2 while the computation of the *dlt* variable is explained in Calmès and Théoret (2011a). The equations for *disp(lta)* and *disp(snonin)* are estimated by the EGARCH (1,1) method which is explained in Appendix 3. Coefficient *p*-values are reported in italics.

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

	<i>cv gdp</i>	<i>cv gdp w</i>	<i>cv inf</i>	<i>dil</i>	<i>dln(gdp)</i>	<i>inf</i>
<i>disp(lta)</i>						
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
<i>disp(snonin)</i>						
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  $\lambda$  is the coefficient of the lagged dependent variable in the respective equations.

**Table 3** IV-EGARCH(1,1) estimations

	<i>disp(lta)</i>			<i>disp(snonin)</i>		
	(1)	(2)	(3)	(1)	(2)	(3)
<i>constant</i>	34.41 <i>0.000</i>	35.65 <i>0.000</i>	29.32 <i>0.000</i>	4.73 <i>0.048</i>	2.92 <i>0.699</i>	-2.40 <i>0.131</i>
$\hat{c}v\_gdp$	-0.67 <i>0.000</i>			-2.90 <i>0.009</i>		
$\hat{c}v\_gdp\_w$		-2.26 <i>0.000</i>			-2.42 <i>0.425</i>	
$\hat{c}v\_inf$			-3.55 <i>0.600</i>			-27.44 <i>0.040</i>
<i>dln(gdp)</i>	0.85 <i>0.000</i>	0.79 <i>0.053</i>	1.75 <i>0.000</i>			
<i>output_gap</i>	85.95 <i>0.000</i>	76.71 <i>0.024</i>	82.34 <i>0.010</i>	318.9 <i>0.000</i>	288.17 <i>0.000</i>	214.84 <i>0.000</i>
<i>inf</i>			-1.93 <i>0.038</i>			7.39 <i>0.000</i>
$\hat{d}tl$	-3.83 <i>0.000</i>	-3.61 <i>0.070</i>	-2.36 <i>0.05</i>	19.33 <i>0.000</i>	20.15 <i>0.000</i>	21.44 <i>0.000</i>
$y_{t-1}$	0.60 <i>0.000</i>	0.59 <i>0.000</i>	0.51 <i>0.000</i>	0.20 <i>0.000</i>	0.20 <i>0.000</i>	- <i>-</i>
EGARCH						
$\theta_1$ (asymmetry coef.)	1.08 <i>0.000</i>	0.82 <i>0.000</i>	1.23 <i>0.000</i>	1.13 <i>0.000</i>	0.79 <i>0.031</i>	0.54 <i>0.000</i>
$\theta_2$	-0.70 <i>0.013</i>	-0.55 <i>0.023</i>	-1.18 <i>0.000</i>	-2.77 <i>0.000</i>	-1.60 <i>0.004</i>	-1.85 <i>0.000</i>
$\theta_3$	0.56 <i>0.000</i>	0.53 <i>0.000</i>	0.52 <i>0.000</i>	-0.26 <i>0.283</i>	0.14 <i>0.654</i>	0.35 <i>0.000</i>
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, columns (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; *dil*: degree of total leverage. The construction of the *cv\_gdp* and *cv\_inf* variables is explained in Appendix 2 while the computation of the *dil* variable is explained in Calmès and Théoret (2011a). The equations for *disp(lta)* and *disp(snonin)* are estimated by the EGARCH (1,1) method which is explained in Appendix 3. 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 4** EGARCH (1,1) estimations of the two basic macroeconomic uncertainty models for Canadian and U.S. banks, 1997-2010.

	<i>disp(lta)</i>		<i>disp(snonin)</i>	
	Canada	U.S	Canada	U.S
<b>Model 1:</b>				
<b>Uncertainty related to GDP</b>				
<i>c</i>	38.43	292.53	5.11	312.06
	0.000	0.000	0.000	0.000
<i>cv_gdp</i>	-0.79	-14.28	-1.09	-15.99
	0.005	0.000	0.000	0.000
<i>dln(gdp)</i>	0.83	-0.09	—	7.00
	0.079	0.971	—	0.000
<i>output_gap</i>	91.73	-739.69	287.26	637.02
	0.000	0.000	0.000	0.000
<i>dlt</i>	-5.10	-58.90	18.86	-20.24
	0.000	0.000	0.000	0.000
Adjusted R <sup>2</sup>	0.28	0.74	0.64	0.37
<b>Model 2:</b>				
<b>Uncertainty related to inflation</b>				
<i>c</i>	28.41	315.90	-2.67	302.86
	0.000	0.000	0.665	0.000
<i>cv_inf</i>	-10.97	-9.31	-49.20	-30.18
	0.020	0.000	0.000	0.000
<i>output_gap</i>	60.40	-908.62	306.92	226.92
	0.006	0.000	0.000	0.003
<i>inf</i>	-1.27	5.85	-0.46	-0.75
	0.050	0.000	0.890	0.408
<i>dlt</i>	-2.01	-68.99	23.82	-10.81
	0.065	0.000	0.000	0.000
Adjusted R <sup>2</sup>	0.19	0.71	0.61	0.73

Note. The variables notation reads as follows: *cv\_gdp*, conditional variance of GDP; *cv\_inf*, conditional variance of inflation; *dlt*: degree of total leverage computed on aggregate bank data. The construction of the *cv\_gdp* and *cv\_inf* variables is explained in Appendix 2 while the computation of the *dlt* variable is explained in Calmès and Théoret (2011a). The equations for *disp(lta)* and *disp(snonin)* are estimated by the EGARCH (1,1) method which is detailed in Appendix 3. Since the US series *disp(lta)* presents an upward trend, a deterministic trend was added in its regressions.

**Table A2** Conditional variances of GDP growth and inflation

<b>GDP growth</b>			<b>inflation</b>		
Variable	Coefficient	p-value	Variable	Coefficient	p-value
<i>C</i>	1.31	0.000	<i>C</i>	1.87	0.000
<i>AR(1)</i>	0.75	0.001	<i>AR(1)</i>	0.74	0.000
<i>AR(2)</i>	-0.49	0.000	IGARCH equation		
<i>MA(1)</i>	-0.21	0.396	RESID <sub>1</sub> <sup>2</sup>	0.22	0.060
<i>MA(2)</i>	0.34	0.005	GARCH <sub>1</sub>	0.78	0.000
EGARCH equation			R-squared		
$\theta_1$ (asymmetry coef.)	-0.19	0.273	Adjusted R-squared	0.42	
$\theta_2$	0.59	0.000	Durbin-Watson	1.76	
$\theta_3$	-0.82	0.000			
R-squared	0.33				
Adjusted R-squared	0.28				
Durbin-Watson	1.57				

*Note:* The EGARCH equation is estimated using specification (18), and the IGARCH, equation (17).

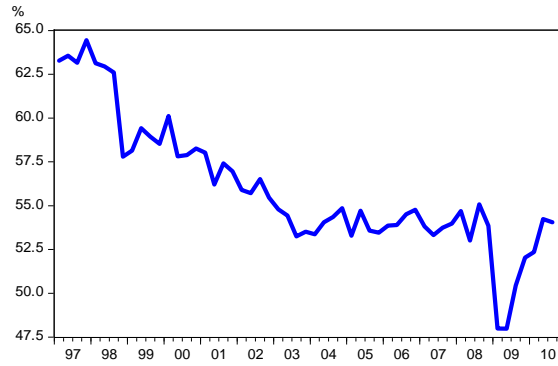
**Table A4** Standard OLS estimations

	<i>disp(lta)</i>			<i>disp(snonin)</i>		
	(1)	(2)	(3)	(1)	(2)	(3)
<i>constant</i>	33.59 <i>0.000</i>	33.86 <i>0.000</i>	31.76 <i>0.000</i>	14.80 <i>0.274</i>	14.00 <i>0.288</i>	3.57 <i>0.746</i>
<i>cv_gdp</i>	1.000 <i>0.378</i>			-2.971 <i>0.056</i>		
<i>cv_gdp_w</i>		-1.17 <i>0.634</i>			-3.22 <i>0.584</i>	
<i>cv_inf</i>			7.84 <i>0.803</i>			-62.09 <i>0.037</i>
<i>dln(gdp)</i>	2.45 <i>0.001</i>	2.42 <i>0.001</i>	2.32 <i>0.001</i>			
<i>output_gap</i>	-3.69 <i>0.955</i>	-9.27 <i>0.886</i>	3.54 <i>0.955</i>	292.51 <i>0.062</i>	288.01 <i>0.102</i>	230.23 <i>0.093</i>
<i>inf</i>			-1.39 <i>0.445</i>			-0.46 <i>0.890</i>
<i>dtil</i>	-3.98 <i>0.223</i>	-3.78 <i>0.257</i>	-3.89 <i>0.244</i>	17.62 <i>0.002</i>	17.98 <i>0.002</i>	-1.41 <i>0.844</i>
<i>y<sub>t-1</sub></i>	0.67 <i>0.000</i>	0.67 <i>0.000</i>	0.61 <i>0.000</i>	0.14 <i>0.149</i>	0.13 <i>0.190</i>	- -
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, Columns (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; *dtil*: degree of total leverage. Outliers are controlled with dummies not reported in the table for the sake of clarity. The construction of the *cv\_gdp* and *cv\_inf* variables is explained in Appendix 2 while the computation of the *dtil* variable is explained in Calmès and Théoret (2011a). The equations for *disp(lta)* and *disp(snonin)* are estimated by the EGARCH (1,1) method which is explained in Appendix 3. Coefficient *p*-values are reported in italics. The *p*-values are adjusted for heteroskedasticity with the HAC matrix.

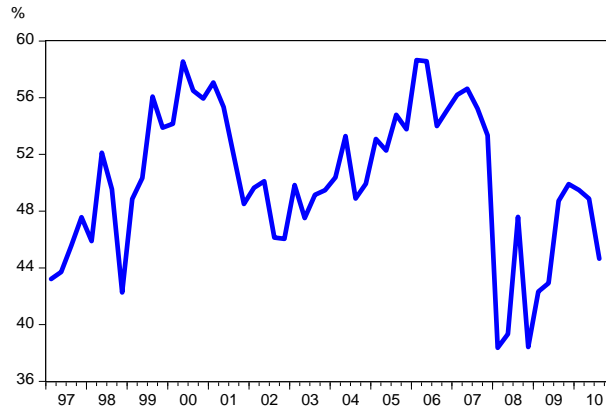
## FIGURES

**Figure 1** Canadian banks' loans-to-assets ratio



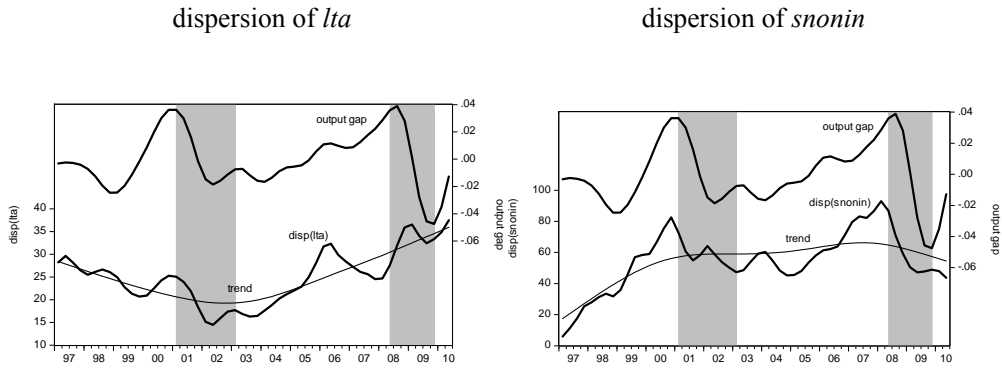
Source: Canadian Bankers Association.

**Figure 2** Canadian banks' share of noninterest income in operating revenue



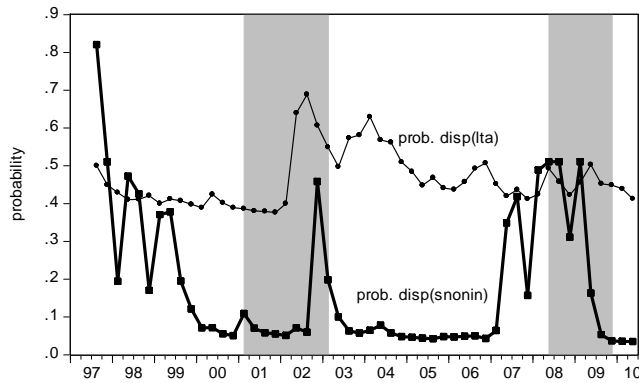
Source: Canadian Bankers Association.

**Figure 3** Canadian banks' cross-sectional dispersion of *lta* and *snonin* v/s the output gap



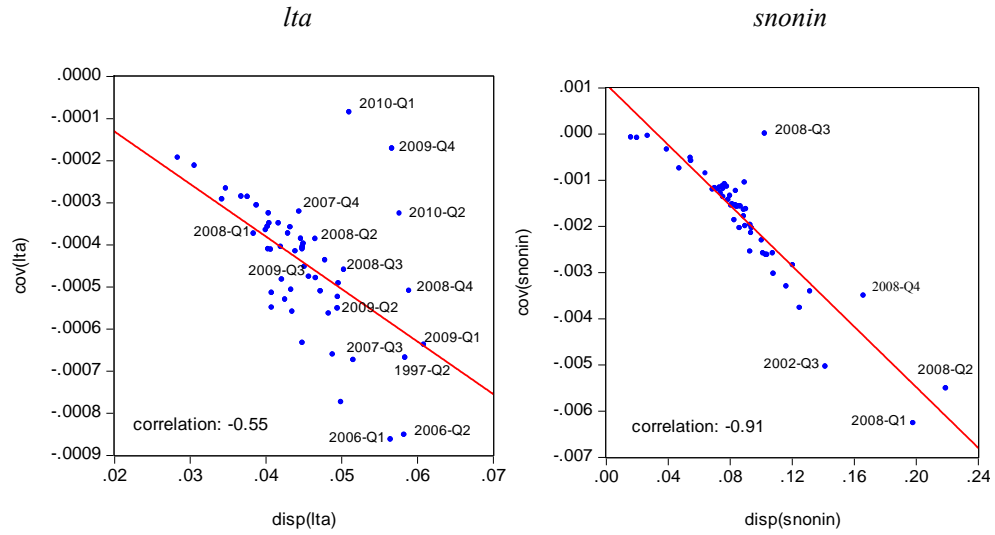
*Note:* Shaded areas correspond to periods of contractions or marked economic slowdown. The trends of the cross-sectional dispersions are computed with the Hodrick-Prescott filter.

**Figure 4** Markov switching probabilities of Canadian banks' *disp(lta)* and *disp(snonin)*

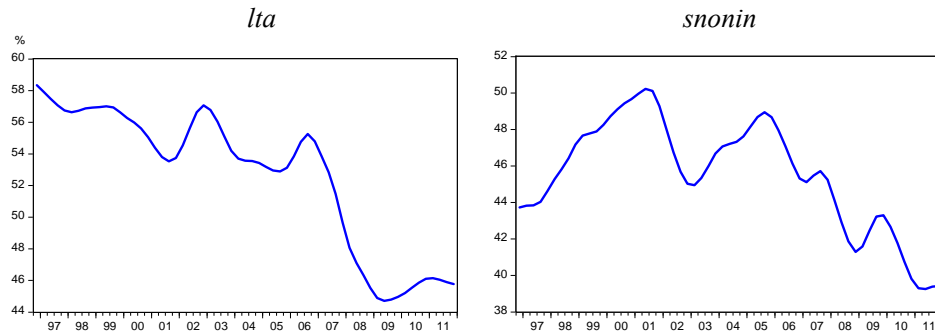


*Note:* Shaded areas correspond to periods of contractions or marked economic slowdown.

**Figure 5** Scatter diagrams of cross-sectional dispersions of *lta* and *snonin* with their respective cross-sectional covariance

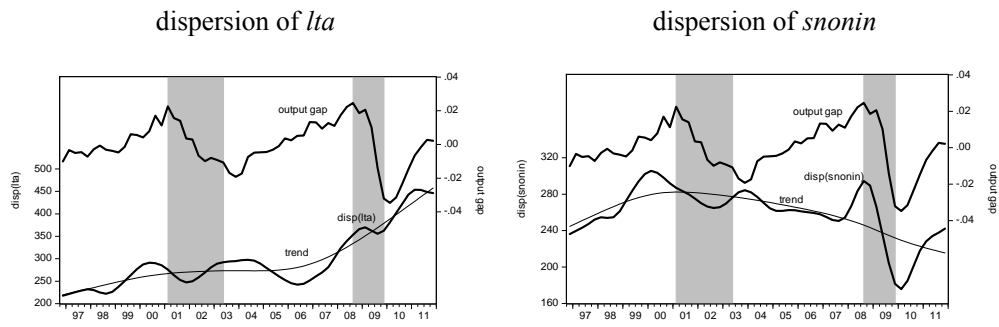


**Figure 6** U.S. banks' *lta* and *snonin*



Sources: FDIC and Federal Reserve Bank of Chicago.

**Figure 7** U.S. banks' cross-sectional dispersions of *lta* and *snonin*



Sources: Federal Reserve Bank of St-Louis, Federal Reserve Bank of Chicago and FDIC.