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The asymmetric impact of bank shocks: U.S. and Canadian evidence

Christian Calmès

Département des sciences administratives, Université du Québec (Outaouais), Campus St. Jérôme, 5 rue St Joseph, St Jérôme, Québec, Canada, J7Z 0B7; Chaire d'information financière et organisationnelle (UQAM). **christian.calmes@uqo.ca**

Raymond Théoret

Université du Québec (Montréal), École des sciences de la gestion, 315 Ste.-Catherine est, R-2915, Montréal, Québec, Canada, H2X 3X2; Chaire d'information financière et organisationnelle (Université du Québec à Montréal), and Université du Québec en Outaouais.
raymond.theoret@uqam.ca

* Corresponding author. Tel: +1 450 530 7616 (1893)

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The asymmetric impact of bank shocks:
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Abstract: *Efficient liquidity matching requires from banks to anticipate GDP growth shocks, stock market shocks and monetary policy shocks, in order to optimally allocate their assets between loans and other business lines. Profit maximizing banks have to rebalance their product-mix in advance to take advantage of these unfolding shocks. In other respects, even though banking is cyclical, and contemporaneously reacts to these shocks, there are thus obviously feedback effects at play, whereby banking changes, in turn, affect economic and financial outcomes. Generalizing Marcucci and Quagliariello (2006, 2009), who find an asymmetric impact of credit shocks on economic and financial time series in recession, we use the same kind of VAR framework to show that a similar feedback effect can be documented for fee-based shocks, and that this effect has actually a more significant impact than credit shocks.*

Keywords: Universal banking; Banking cycle; VAR; feedback effects; procyclicality; Markov regime-switching model.
JEL classification: C32; G20; G21.

L'impact asymétrique des chocs bancaires:
L'expérience canadienne et américaine

Résumé. *L'appariement efficient des liquidités requiert que les banques anticipent les chocs de croissance du PIB, les chocs boursiers et les chocs associés à la politique monétaire, de sorte qu'elles puissent allouer leurs actifs de façon optimale entre les prêts et leurs autres activités. Les banques qui maximisent leurs profits doivent modifier leur product-mix à l'avance de manière à bénéficier des chocs en développement. D'autre part, même si l'industrie bancaire est cyclique, et réagit concomitamment à ces chocs, des effets de chocs en retour sont évidemment en action en vertu desquels des changements d'origine bancaire se répercutent sur les conditions économiques et financières. En généralisant l'approche de Marcucci et Quagliariello (2006, 2009), qui ont détecté un impact asymétrique des chocs de crédit sur les séries économiques et financières en récession, nous utilisons le même cadre d'analyse VAR pour montrer qu'un effet similaire de rétroaction peut être documenté pour les chocs associés aux activités non-traditionnelles des banques, et que cet effet est même plus puissant que celui émanant des chocs de crédit.*

Mots-clefs: Banking universel; cycle bancaire; VAR; effets de rétroaction; procyclicalité; Modèles markoviens de changement de régime.
Classification JEL: C32; G20; G21.

1. Introduction

There is ample evidence that credit and business cycle are linked—i.e., banking is a cyclical industry (e.g., Williamson 1987; Bernanke et al., 1999; Kiyotaki and Moore, 1997). However, most empirical studies are mainly interested in the cyclicality of loans provided by banks, rather than its procyclicality. Indeed, the amplifying feedback effect of bank credit on the business cycle is less documented (Bikker and Hue, 2002; Marcucci and Quagliariello, 2006; Quagliariello, 2008). More precisely, "Most of these analyses tend to assume—rather than document—that procyclicality is the consequence of cyclicality" (Quagliariello, 2008). On the one hand, several theoretical papers take into account bank non-traditional activities and suggest that, in theory, the feedback effect from the banking sector to the real economy might be substantial (Bernanke et al., 1996; Bernanke et al., 1999; Shleifer and Vishny, 2010; Gertler and Kiyotaki, 2011; Gennaioli et al., 2013; Dewatcher and Wouters, 2014).

On the other hand, the empirical literature substantiating the existence of such a feedback effect is still rather scarce. Most articles approach the feedback effect of a bank credit shock in the framework of the transmission channel of monetary policy (Kashyap and Stein, 1993; Bernanke and Gertler, 1995; Black and Rosen, 2007; Disyatat, 2010; Gambacorta and Marquez-Ibanez, 2011). Other models focus on some nontraditional activities, analyzing the feedback effect of *specific* bank off-balance sheet activities like securitization or loan commitments (Sofianos et al., 1987; Morgan, 1998; Estrella, 2002; Kashyap et al., 2002; Smant, 2002; Thakor, 2005; Aysion and Hepp, 2011; Loutskina, 2011; Pennachi, 2011; Peersman and Wagner, 2014), but, in any case, these analyses are generally performed in the framework of the transmission channel of monetary policy, and the results are often found ambiguous, depending on the diversification effect of bank fee-based business lines, on the degree of substitution between bank securities and market securities[1], on the informational content of securities issued by banks, and on the tail risk related to bank nontraditional activities (Gorton, 2010; Gorton and Metrick, 2010; Shleifer and Vishny, 2010; Gennaioli et al., 2013; Calmès and Théoret, 2014).

In one of the rare articles[2] considering the feedback effect of bank credit *independently* of the stance of monetary policy, Marcucci and Quagliariello (2006), using a VAR (vector autoregressive) model, find that measures of bank risk, like borrowers' default rate, may indeed impact GDP growth. They document the presence of a credit feedback effect essentially operating during financial turmoil. Marcucci and Quagliariello (2009) establish that the relationship between the business cycle and credit risk is significantly asymmetric, in the sense that it is more at play during downturns than during normal times. However, no author examines whether the feedback effect might also concern banks' non-traditional activities.

[1] In this respect, Kashyap and Stein (1993) rely on the mix of bank debt and commercial paper to identify the bank lending channel. The authors find that the ratio of bank debt to commercial paper outstanding decreases following a restrictive monetary policy, which is an evidence for the bank lending channel. See also Black and Rosen (2007).
[2] See also Puddu (2010).

In this paper, our main contribution is to complement the work of Marcucci and Quagliariello (2006, 2009), by studying the feedback effect of bank nontraditional activities in addition to the feedback effect of bank credit shocks. In other words, we aim at generalizing the analysis by looking at universal banking—not just traditional banking. To the best of our knowledge, we are the first to analyze the feedback effect of banks' fee-based business lines independently of the stance of monetary policy (with the notable exception of Peersman and Wagner, 2014). Using a VAR model, we distinguish a bank credit shock[3]—related to bank traditional activities—and a fee-based shock[4]—related to bank non-traditional activities. For instance, a credit shock may be due to an increase in loans' default rate or a decrease in bank capital, while a fee-based shock may be related to a collapse of the mortgage-backed securities market as in the recent subprime crisis. In our VAR setting, these two endogenous variables interact with a real GDP shock (technology shock), an interest rate shock (monetary policy shock) and a stock market shock (financial market shock).

Surprisingly, when we apply our models to the U.S. and Canadian banking systems' quarterly data over a period stretching from 1984 to 2014, we find that the feedback effect of a fee-based shock to real GDP and to the stock market is actually quite strong. More importantly, compared to Peersman and Wagner (2014), we also find that the feedback effect from non-traditional activities, to both the real sector and to the stock market, is more significantly at play after 1997. This year corresponds to a structural break in the Canadian and U.S. shares of non-interest income in net operating income, and as suggested by Calmès and Théoret (2010), it coincides with the emergence of universal banking as the prevalent banking business model. Following Marcucci and Quagliariello (2006, 2009), we thus examine the asymmetry related to the feedback effects of bank shocks according to the state of the business cycle. Consistent with the recent literature, we find that most economic variables seem to respond more to shocks in recession while their behavior is much smoother in expansion (Neftci, 1984; Sichel, 1987; Hamilton, 1989, 2005; Bloom, 2009, 2014; Leduc and Liu, 2013; Caggiano et al., 2014; Ferrara and Guérin, 2015). In the spirit of Puddu (2010), we introduce non-linearities in our VAR model to study these asymmetries. More precisely, we run Markov regime-switching regressions on the equations associated with the feedback effect—i.e., the VARs relating economic growth and stock returns to the change in the logarithm of banks' fees (Goldfeld and Quandt, 1973; Hamilton, 1989, 2005). Similarly to the Kalman filter, our switching regressions act as a filter which determines the optimal statistical estimates of the state of the economy in which the feedback effects are the most operative. Generalizing the evidence reported in Marcucci and Quagliariello (2006), we find that this state corresponds to recession or crises for both banking variables (loans and fee-based activities). Finally, our analysis supports the idea that net interest income reacts negatively to the short-term interest rate. In other words, our results suggest that monetary policy continues to impact net interest income in the same way, despite the multiplication of hedging vehicles and the influence of universal banking after 1997.

[3] As measured by the innovation in the equation of bank net interest income growth (change in the logarithm of net interest income).
[4] As measured by the innovation in the equation of bank non-interest income growth (change in the logarithm of non-interest income).

This paper is organized as follows. Section 2 presents our database and the stylized facts related to our time series. Section 3 presents our VAR model and the Markov regime-switching model we use to document the asymmetric impact of bank shocks. Section 4 provides our empirical VAR analysis of U.S. and Canadian bank credit shocks and fee-based shocks. Section 5 documents the structural break in our time series while Section 6 concludes.

2. Data and stylized facts

2.1. Data

To estimate our VAR we rely on two samples, a U.S. sample comprising all commercial banks, and a sample of all Canadian banks. The U.S. banks' data span the period ranging from the first quarter of 1984 to the fourth quarter of 2013. The statistics are provided by the Federal Deposit Insurance Corporation (FDIC). U.S. macroeconomic and financial time series are drawn from FRED, a database managed by the Federal Reserve Bank of St-Louis. The Canadian banks' sample is defined over the same period as the U.S. banks' one, and comes from the Canadian Bankers Association, the Office of Superintendent of Financial Institutions, and the Bank of Canada. Finally, Canadian data on macroeconomic and financial time series are drawn from CANSIM (from Statistics Canada).

Table 1 Granger causality tests: U.S. and Canada

Test		U.S.	Canada
Real GDP growth GC non-interest income growth			
	F-Statistic	2.64	0.67
	p-value	0.04**	0.61
Non-interest income growth GC real GDP growth			
	F-Statistic	3.98	3.47
	p-value	0.01**	0.01**
Real GDP growth GC net interest income growth			
	F-Statistic	1.16	1.01
	p-value	0.33	0.40
Net interest income growth GC real GDP growth			
	F-Statistic	0.93	0.96
	p-value	0.44	0.43
Stock market return GC non-interest income growth			
	F-Statistic	0.98	3.32
	p-value	0.41	0.01**
Non-interest income growth GC stock market return			
	F-Statistic	1.21	2.50
	p-value	0.30	0.04**
Stock market return GC net interest income growth			
	F-Statistic	0.61	3.17
	p-value	0.65	0.02**
Net interest income growth GC stock market return			
	F-Statistic	0.71	1.45
	p-value	0.58	0.22
Change in T-bills rate GC non-interest income growth			
	F-Statistic	1.04	0.54
	p-value	0.38	0.70
Non-interest income growth GC change in T-bills rate			
	F-Statistic	0.82	1.33
	p-value	0.50	0.26
Change in T-bills rate GC net interest income growth			
	F-Statistic	3.77	2.36
	p-value	0.01**	0.05**
Net interest income growth GC change in T-bills rate			
	F-Statistic	1.63	1.07
	p-value	0.17	0.37

Notes: * indicates that the test is significant at the 10% level and ** indicates that the test is significant at the 5% level.

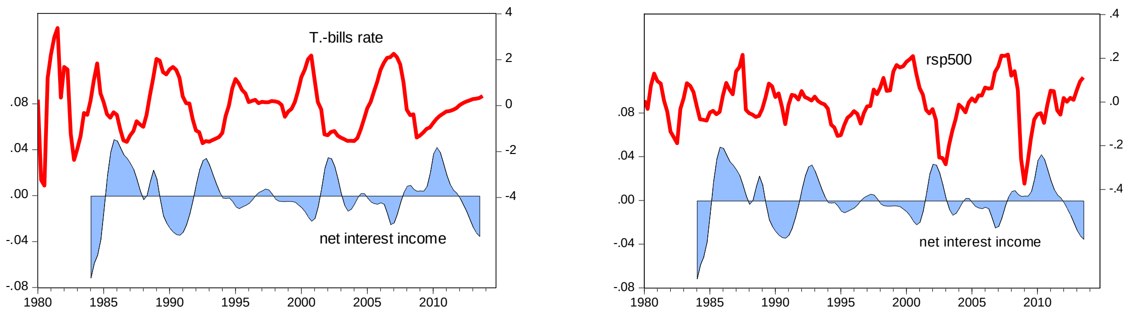
2.2. Stylized facts

2.2.1 Granger causality tests

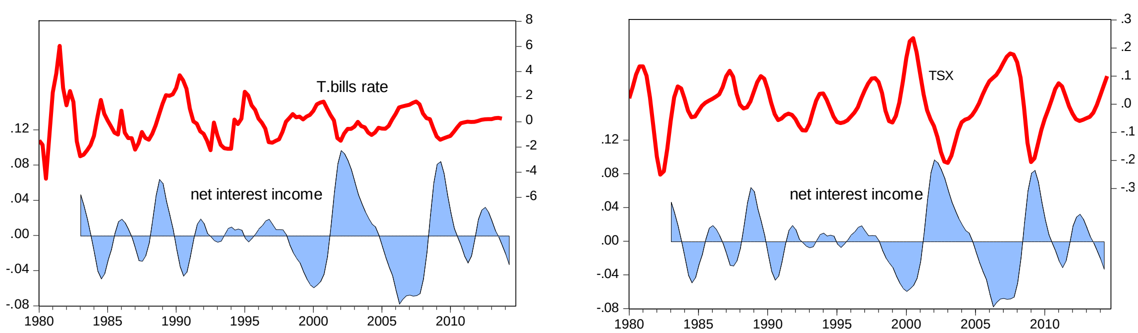
Since VAR embed many interactions, the nature of these links ought to be first captured by Granger causality tests (Table 1). This preliminary experiment aims at indicating the direction of causality, if any—i.e., helps the shocks identification. Our initial tests suggest that GDP growth Granger-causes non-interest income growth only for U.S. banks, but that, more importantly, the reverse might also hold true (in both countries), the tests being significant at the 1% level. More precisely, the growth of non-interest income seems to actually lead GDP growth, a *prima facie* evidence of a feedback effect from the banking sector to the real economy. Moreover, stock market return Granger causes non-interest income growth in Canada, but the reverse also holds true[5]. Finally, Granger causality tests related to the short-term interest rate are not conclusive, suggesting that non-interest income growth is not very sensitive to the changes in the short-term interest rate.

Figure 1 Co-movements between the cycles of bank net interest income, Treasury bills interest rate and stock market index

Panel A: United States



Panel B: Canada



Notes: To compute the cycles of, respectively the logarithm of net interest income, the logarithm of the stock market index and the Treasury bills interest rate, we detrend these series using the Hodrick-Prescott filter. The residuals of this computation constitute the cycles of the respective series.

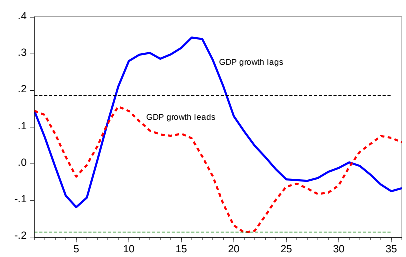
[5] That may explain the cyclicality of non-interest income growth observed in our spectral analysis since GDP growth does not seem to account for the cycles of non-interest income growth in Canada (Appendix 1). However, in the U.S., Granger-causality tests on the stock market return are not conclusive.

Net interest income growth does not seem to lead any of the three selected external shocks and, in this sense, our data only corroborate the common view that (traditional) banking is a very cyclical industry, typically reactive to the changes in business conditions. In both countries, tests are negative when linking net interest income growth to GDP growth. The stock market return Granger causes net interest income growth only in Canada[6]. Finally, as well documented in the literature (e.g., Freixas and Rochet, 2008), a change in the short-term interest rate seems to Granger cause net interest income growth, the test being more conclusive in the U.S. (an increase in interest rate leading to a decrease in net interest income growth). The negative co-movement between net interest income and the interest rate is more pronounced in the U.S. than in Canada—the correlation coefficients being -0.57 and -0.44, respectively (Figure 1).

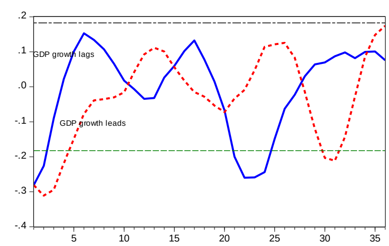
Figure 2 Cross-correlations: U.S. and Canada

Net interest income growth and GDP growth

U.S.

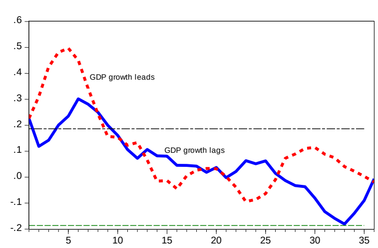


Canada

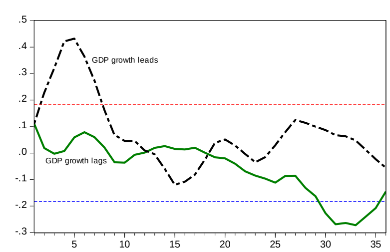


Non-interest income growth and GDP growth

U.S.



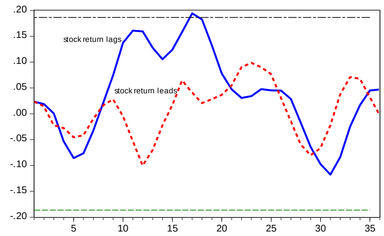
Canada

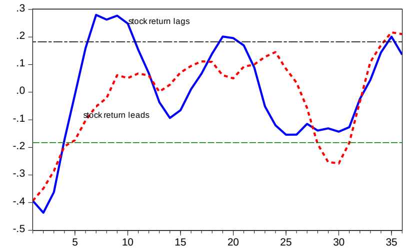


Net interest income growth and stock market return

U.S. **Canada**

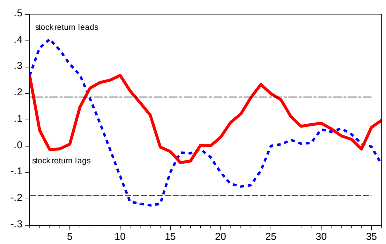
[6] As shown later, there is a negative correlation in Canada between net interest income growth and the lagged values of the stock market return.



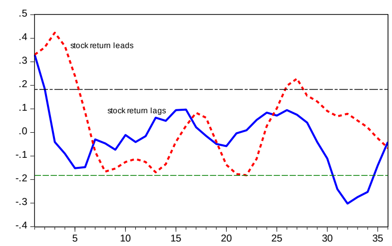


Non-interest income growth and stock market return

U.S.

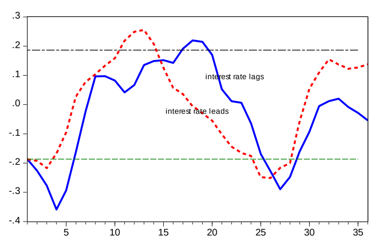


Canada

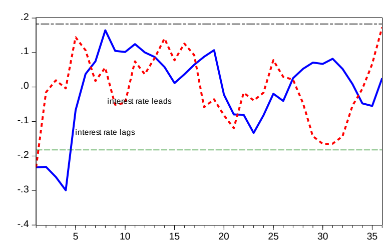


Net interest income growth and change in the T-bill rate

U.S.

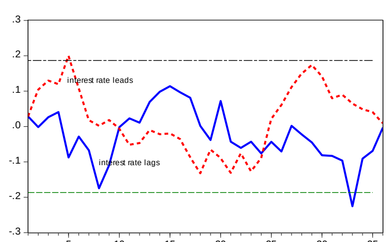


Canada

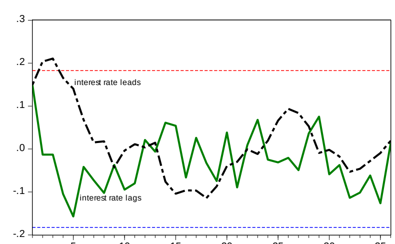


Non-interest income growth and change in the T-bill rate

U.S.



Canada



Notes: In each figure, the two parallel dotted lines enclose the 95% confidence interval. A correlation coefficient is significant at the 5% level if it lies outside the confidence interval.

2.2.2 Cross-correlations

Cross-correlations between bank income flows variables, on the one hand, and the set of macroeconomic and financial variables, on the other hand, are an important input in the preliminary interpretation of our VARs.

As can intuitively be expected, net interest income is correlated positively and significantly with GDP growth in the U.S., and this correlation is quite persistent (Figure 2). In contrast, in Canada, the correlation of net interest income growth is negative at impact. We also observe a significant negative correlation for *leads* $t+1$ to $t+4$. This counterintuitive profile is consistent with the negative correlation between the two components of net operating income in Canada, which reflects a different bank product-mix in the two countries (Calmès and Théoret, 2015). For the same reason, the correlation profile between U.S. net interest income growth and the stock market return is similar to the one of GDP growth, whereas in Canada net interest income growth is correlated negatively with the stock market return over four-quarter lags and leads. Not surprisingly, the correlation is also higher than with GDP growth. Overall, the relationship between net interest income growth and GDP growth is thus more in line with the traditional banking channel in the U.S. than in Canada—an increase in real GDP growth being associated with a rise in lending. More importantly, the feedback effects from net interest income growth to real GDP growth (or the stock market) are generally found weak or non-existent. In other words, as far as traditional banking is concerned, banking is clearly cyclical, as generally agreed in the literature.

In contrast to Canada, non-interest income growth seems positively and significantly correlated with *lags* of GDP growth in the U.S. (Figure 2). However, in both countries, data confirm the presence of a positive correlation with *leads* of GDP growth. These properties are further preliminary evidence that there might indeed exist a feedback effect from bank non-interest income growth to the real economy, and that this phenomenon is country robust. Turning to the stock market return influence, the positive correlation between non-interest income growth and the stock market return leads seems to be a rather robust phenomenon in both the U.S. and Canada. These cross-correlation profiles thus suggest the presence of a well anchored feedback effect from non-interest income growth to the stock market. In other respects, the cross-correlation between non-interest income growth and the short-term interest rate is much lower than with GDP growth or the stock market return. There is a positive feedback effect from non-interest income growth to the short-term interest rate—especially in Canada—but this feedback effect is weaker than in the case of GDP growth or the stock market.

Summarizing, we arrive at a two-part phenomenon: (i) net interest income is influenced by the macroeconomic and financial shocks, but do not lead them; (ii) Non-interest income impacts GDP and especially the stock market, and is not much influenced by the interest rate. These are the two stylized facts motivating the VAR analysis presented in the next sections, where we aim at substantiating these two observations more rigorously.

3. Methodology

3.1 The VAR model

We first rely on a straightforward VAR analysis to document the interactions between business cycles and financial fluctuations on the one hand, and bank income flows on the other hand. To be consistent with the Granger causality tests and cross-correlations, and assuming that banks ought to anticipate the external shocks impacting their profitability, we identify the former set of variables as "external" shocks to the banking sector, while the latter are interpreted as "internal" shocks. The credit shock related to bank traditional activities is thus measured by the innovation in the equation of the change in the logarithm of bank net interest income. The fee-based shock is accordingly measured by the innovation in the equation of the change in the logarithm of bank non-interest income. We compute the impulse response functions (IRF) of these two shocks to the short-term interest rate, GDP growth and the return of the stock market portfolio. An IRF is computed using a reduced-form vector autoregressive system (VAR) defined as follows:

$$\mathbf{Y_t} = \mathbf{A_0} + \sum_{i=1}^{n} \mathbf{A_i} \mathbf{Y_{t\text{-}i}} + \boldsymbol{\varepsilon}_\mathbf{t} \qquad (1)$$

where $\mathbf{Y}_t$ is the vector of endogenous variables included in the VAR. If the matrix of the residuals ($\boldsymbol{\varepsilon}_\mathbf{t}$) is diagonal, the identification of the shocks associated with the variables is straightforward. For instance, if there are two variables, the residuals matrix provides directly the respective shocks related to these variables on its diagonal. However, the residuals are usually correlated so that the residuals matrix is not diagonal. In other words, we need a method to identify the structural shocks related to the variables of the VAR. In a first set of experiments, we follow Sims' (1980) Cholesky decomposition of the reduced form residuals' covariance matrix.

Using this decomposition requires the ordering of the endogenous variables in the VAR, from the most exogenous to the most endogenous. In the first run, we order the variables of our setting in the following way:

GDP growth $\rightarrow$ interest rate $\rightarrow$ stock market return $\rightarrow$ net interest income growth $\rightarrow$ non-interest income growth

We thus assume that GDP growth, being the most exogenous variable in our VAR, is only impacted by itself at time *t*. As it is usually the case in VARs, the financial variables—i.e., the interest rate and the stock market return—are assumed more endogenous than GDP growth. In this setup, we thus interpret banking variables as the most endogenous. The credit shock precedes the fee-based shock, a banking cycle being usually triggered by a credit shock[7].

To build the IRF, we first transform the VAR equation into its infinite moving average representation—i.e., an MA(∞) (Wold, 1938; Hamilton, 1994, p. 318-319). Then, we compute the partial

[7] Some authors, like Marcucci and Quagliariello (2006) and Puddu (2010) rank banking shocks before "external" shocks, arguing that banking variables react to external shocks only after a lag. However, we obtain similar results by adopting this alternative specification of our VAR model. Moreover, interchanging the order of our two banking shocks does not sensitively change the results.

derivative of the MA(∞) as follows: $\frac{\partial Y_t}{\partial \varepsilon_t^{'}} = \Psi_s$, where ε_t is the vector of innovations of the MA(∞) representation. The last step consists in plotting the row *i*, column *j* element of Ψ_s—i.e., the $\frac{\partial Y_{i,\,t+s}}{\partial \varepsilon_{jt}}$. This plot is the IRF.

More specifically, denote by Σ_v the variance-covariance matrix of the innovations of our VAR (5) process. Since this matrix is positive definite, there exists a matrix **P** such that $\mathbf{P\Sigma_v P'} = \mathbf{I}$, where **I** is the identity matrix with dimension 5x5 in our VAR model. (Judge et al., 1988). This Cholesky matrix makes the shocks orthogonal[8]. Following Judge et al. (1988), we can express the impulse response function as follows:

$$Y_t = \mu + \sum_{i=0}^{\infty} \Psi_i w_{t-i} \qquad (2)$$

The components of w_t correspond to unit shocks. In our case, there are five shocks. At time 0, the coefficient matrix of the IRF is equal to $\mathbf{P^{-1}}$ and the IRF is equal to $\mathbf{P^{-1}I}$, **I**—the identity matrix— being of dimension 5x5. The principal diagonal of $\mathbf{P^{-1}}$ is equal to one-standard deviation of the shocks ordered from the most exogenous to the most endogenous shocks. It is a lower triangular matrix which "orthogonalizes" the shocks so we can recover the structural shocks. The other $\mathbf{\Psi_i}$ are computed using the following recursive process (Judge et al., 1988, p. 773):

$$\mathbf{\Psi_i} = \mathbf{M_i P^{-1}} \qquad (3)$$

where $\mathbf{M_i}$ is equal to:

$$\mathbf{M_i} = \sum_{\mathbf{j=1}}^{\mathbf{min(p,i)}} \mathbf{A_j M_{i-j}} \qquad (4)$$

The $\mathbf{A_j}$ are the coefficients of the VAR process and *p* is the order of the VAR. Since at time 0, $\mathbf{M_0} = \mathbf{I}$, at time 1 the corresponding $\mathbf{M_1}$ is equal to:

$$\mathbf{M_1} = \mathbf{A_1 M_0} = \mathbf{A_1} \qquad (5)$$

and the corresponding IRF is :

$$\mathbf{IRF_1} = \mathbf{A_1 P^{-1}} \qquad (6)$$

[8] Note that, even if their presentation of the VAR is one of the best in the econometric literature, Judge et al. (1988) do not make an explicit reference to the ordering of the variables. In their VAR example, y_1 is U.S. consumption and y_2 is U.S. disposable income. They estimate their VAR using the order $y_1 \rightarrow y_2$. Obviously, their P matrix must be upper triangular since y_1—i.e., consumption—must react to y_2 —i.e., income—at the impact. However, they note that there exists another **P** matrix which is lower triangular. They conclude that the interpretation of the multipliers is rendered difficult given this non-uniqueness of the **P** matrix. They do not mention that the choice of the **P** matrix is related to the initial ordering of the variables which compose the VAR. Have they ordered their variables on the other side—i.e., $y_2 \rightarrow y_1$, they would have chosen the **P** matrix which is lower triangular. In this case, at the impact of the two shocks, disposable income does not react to the consumption shock but consumption reacts to the income shock. Yet, the concept of the ordering of variables in the VAR has been previously analyzed by Sims (1980, 1981), references which appear in Judge et al.'s seminal book.

By continuing the recursive process given by Eq. (4), the IRF coefficients at time 2 are equal to:

$$\mathbf{M_2} = \mathbf{A_1 M_1} + \mathbf{A_2 M_0} = \mathbf{A_1 A_1} + \mathbf{A_2} = \mathbf{A_1^2} + \mathbf{A_2} \quad (7)$$

and the corresponding IRF, i.e., IRF[3], is equal to $IRF_2 = (\mathbf{A_1^2} + \mathbf{A_2})\mathbf{P^{-1}}$. At time 3, the recursive process is given by:

$$\mathbf{M_3} = \mathbf{A_1 M_2} + \mathbf{A_2 M_1} + \mathbf{A_3 M_0} = \mathbf{A_1}(\mathbf{A_1^2} + \mathbf{A_2}) + \mathbf{A_2 A_1} + \mathbf{A_3 I} = \mathbf{A_1^3} + \mathbf{A_1 A_2} + \mathbf{A_2 A_1} + \mathbf{A_3} \quad (8)$$

and so on for $t>3$. The coefficient matrices which propagate the shocks are called *multipliers* (Judge et al., 1988). This appellation is quite obvious in the case of a VAR(1), which includes only one time-lag of its variables. The multipliers are then equal to $\mathbf{A}^i$. We rely on the same iterative procedure to compute the variance-covariance matrix of the innovation, which is required to establish the confidence intervals of the IRFs. For instance, assume that the variance-covariance matrix computed at time 0 is equal to $\hat{\Sigma}_{\mathbf{v}}$. At time 1, it is equal to: $\hat{\Sigma}_v + \mathbf{M_1} \hat{\Sigma}_v \mathbf{M_1'}$, and so on.

In our framework each VAR is composed of the two bank income flows expressed in logarithmic first-differences or growth rates, and of the three variables associated with macroeconomic or financial shocks: the rate of growth of GDP, the change in the short-term interest rate[9], and the return on the stock market portfolio. We compute these VAR for the aggregate of U.S. and Canadian banks.

3.2 Markov regime-switching model

To study the asymmetric impact of bank income flows, we rely on a Markov regime-switching model (MRSW)[10]. In the framework of our VAR model, the MRSW model takes the following form:

$$y_t = \begin{cases} \gamma_{01} + \sum_{i=1}^{n} \gamma_{i1} IFG_{t-i} + \varepsilon_{t1} \quad if \ s_t = 1 \\ \gamma_{02} + \sum_{i=1}^{n} \gamma_{i2} IFG_{t-i} + \varepsilon_{t2} \quad if \ s_t = 2 \end{cases} \quad (9)$$

where y_t is GDP growth or stock market return; IFG is growth of the bank net interest income or non-interest income; s_t is one of the two states of the economy—i.e., a low regime and a high regime. For the sake of simplicity, we thus assume that there are only two states of the economy and we discard from the equation other variables which may impact the VAR.

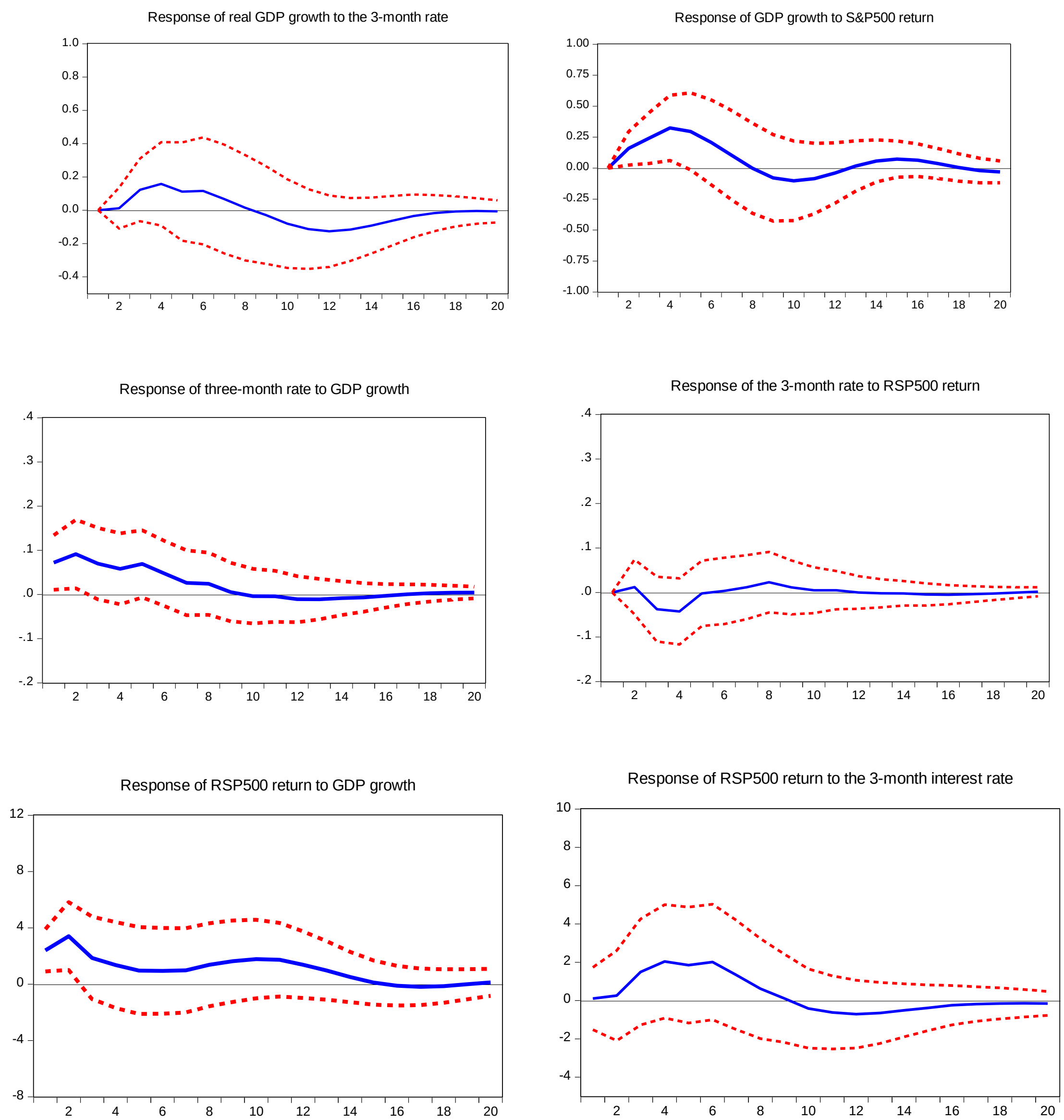
4. VAR analysis

An IRF plots the impact of a one-time shock to one of the innovations of the variables which constitute the VAR system. A shock is equal to one standard deviation of the innovation. As explained earlier, the shocks which constitute our VAR analysis are (i) two internal shocks: a credit shock—as

[9] Since the series related to the short-term interest rate is not stationary, we express it in first differences in the VAR.
[10] The rudiments of this model appear in the Appendix 2.

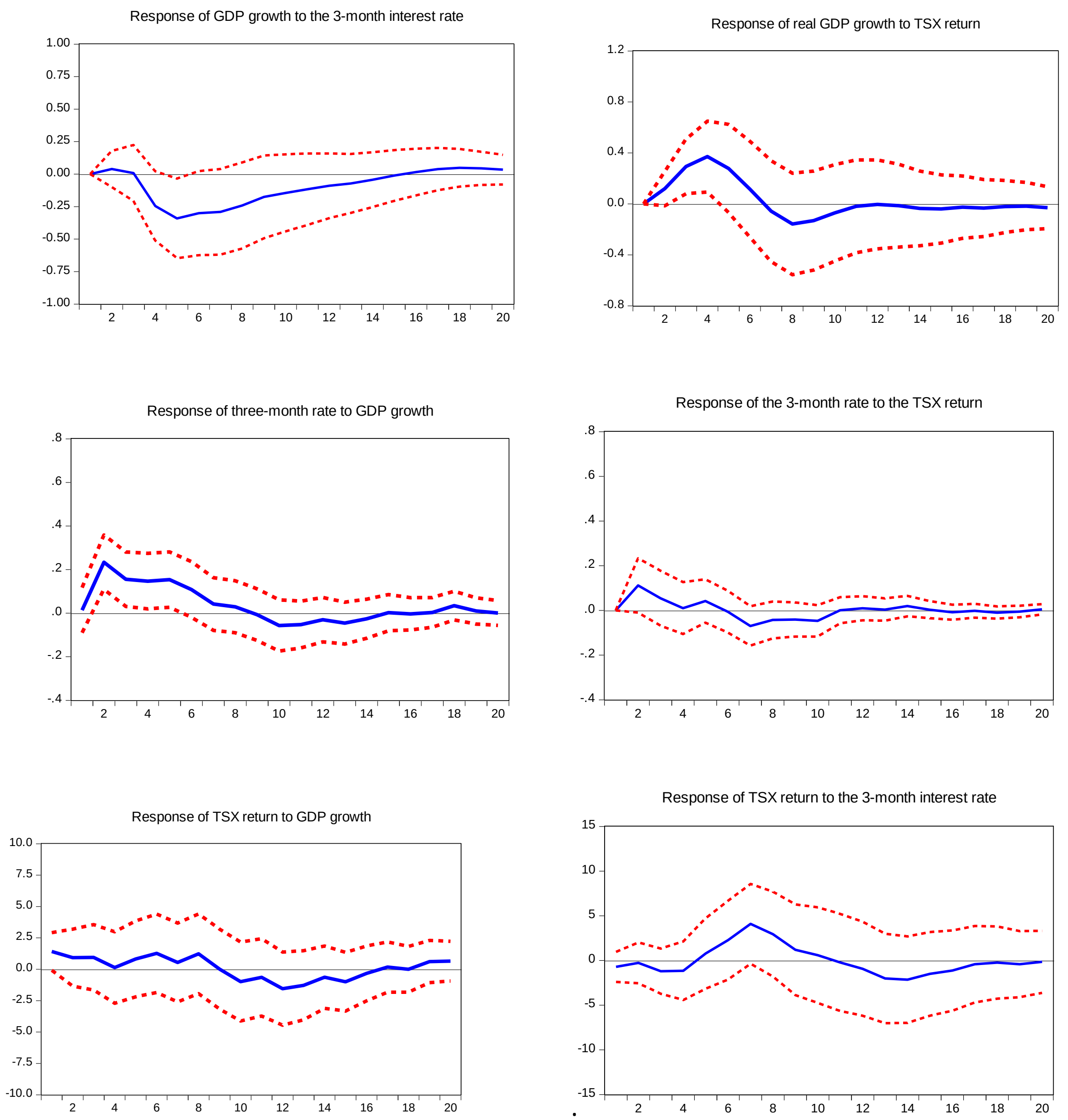
measured by the innovation of the bank net interest income growth equation—, and a fee-based shock—as measured by the innovation of the bank non-interest income growth equation—, and (ii) three external shocks: a real GDP growth shock, a stock market return shock—i.e., the S&P500's in the U.S. and the S&P/TSX in Canada—and a short-term interest rate shock—i.e., the three-month Treasury bills rate.

Figure 3 Interactions between the external shocks: U.S.



Notes: In each figure, the dashed lines enclose the 95% confidence interval. A coefficient is significant at the 5% level if it associated confidence interval lies above or below the zero mark.

Figure 4 Interactions between the external shocks: Canada



Notes: In each figure, the dashed lines enclose the 95% confidence interval. A coefficient is significant at the 5% level if it associated confidence interval lies above or below the zero mark.

4.1 Interactions between the external shocks

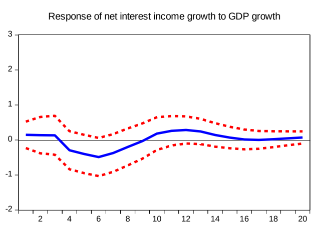
We first examine if external shocks behave "normally" in our very simplified economy. In the U.S., as expected, a GDP shock gives rise to a significant increase in the interest rate and in the stock market return (Figure 3). Conversely, a rise in the stock market return entails a significant increase, albeit smaller, in GDP growth which lasts four quarters—the stock market return being a leading indicator of economic activity. In Canada, we observe the same relationships (Figure 4). In addition, a stock market shock is followed by a significant increase in the short-term interest rate. In the U.S., the interest rate also tends to increase following a positive stock market shock but this effect is not significant.

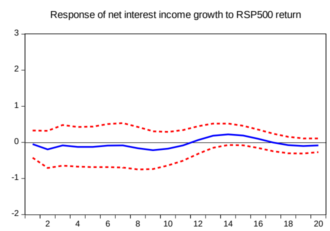
Figure 5 External shocks and credit shock

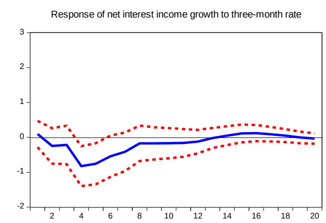
Panel A: U.S. banks

Response of credit to external shocks

GDP shock **stock market shock** **interest rate shock**

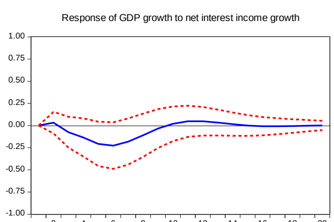


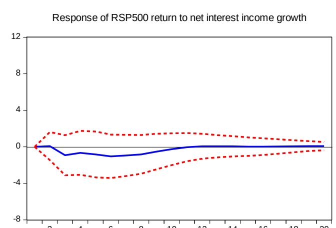


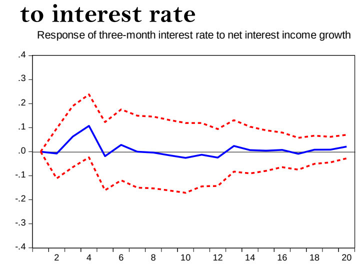


Feedback effect of credit shocks

to GDP growth **to stock market** **to interest rate**



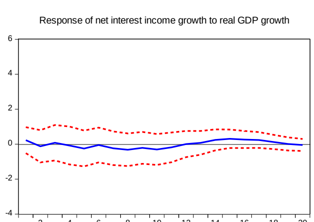


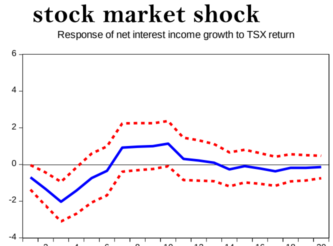


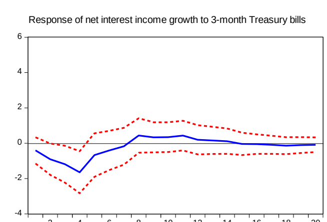
Panel B: Canadian banks

Response of credit to external shocks

GDP shock **stock market shock** **interest rate shock**

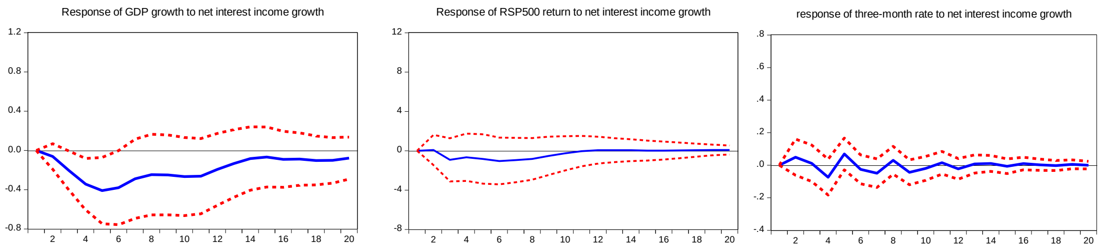






Feedback effect of credit shocks

to GDP growth **to stock market** **to interest rate**



Notes: In each figure, the dashed lines enclose the 95% confidence interval. A coefficient is significant at the 5% level if it associated confidence interval lies above or below the zero mark.

4.2 The direct impact of credit shocks

Figure 5 gives the impulse response functions of bank credit—as measured by net interest income growth—to our three external shocks, and the feedback effects of the credit shock to the three selected external variables. In the U.S., net interest income growth responds positively to a GDP shock, but this effect reverses quickly and turned significantly negative. This effect is not observed in Canada. As documented previously, there is no significant obvious response of U.S. banks' net interest income growth to a stock market shock; however, for Canadian banks, it decreases significantly following such a shock. As expected, an interest rate shock leads to a significant decrease in net interest income growth in both countries, which suggests that the lending channel is generally operative.

Figure 5 conversely shows evidence that a credit shock gives rise to a significant decrease in U.S. and Canadian GDP growth. In other words, credit shocks have a feedback effect on the real economy. Importantly, remember that the result might be driven by an asymmetry in the behavior of the feedback effect, whereby this effect would be more operative in recession than in expansion (Marcucci and Quagliariello, 2006; Puddu, 2010)[11], and this asymmetry may also be strengthened by the bank capital channel (Marcucci and Quagliariello, 2006, 2009; Dewatcher and Wouters, 2014).

To summarize the feedback effects of credit shocks, GDP growth decreases significantly following a credit shock. On the other hand, a credit shock does not impact significantly the financial variables appearing in our VAR system—i.e., the stock market return and the short-term interest rate.

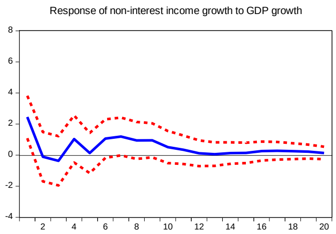
[11] For instance, Marcucci and Quagliariello (2006) note that the feedback effect seems to be due to the fact that the default rate and the credit spread Granger causes the output gap. In the same vein, Puddu (2010) argues that an increase in non-performing loans leads to a decrease in the output gap. We will test more precisely this non-linear relationship in the section devoted to Markov regime-switching models.

Figure 6 External shocks and fee-based shocks

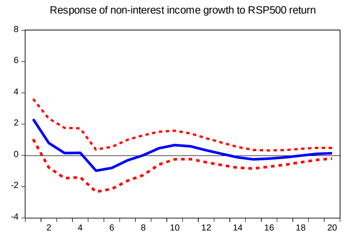
Panel A: U.S. banks

Response of fee-based income growth to external shocks

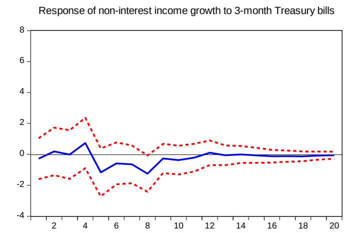
GDP shock



stock market shock

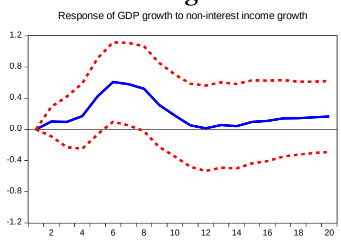


interest rate shock

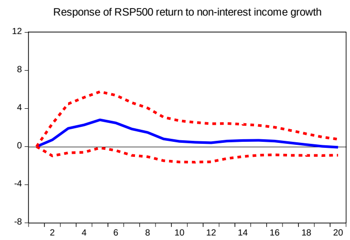


Feedback effect of fee-based shocks

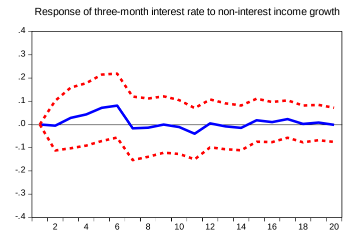
to GDP growth



to stock market



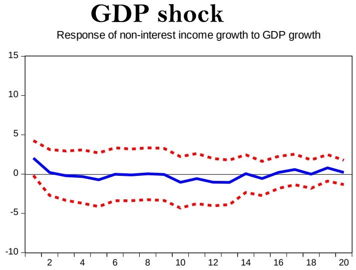
to interest rate



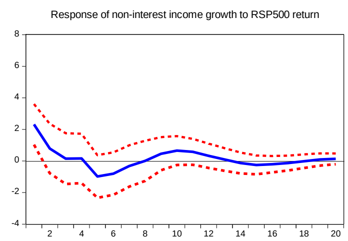
Panel B: Canadian banks

Response of fee-based income to external shocks

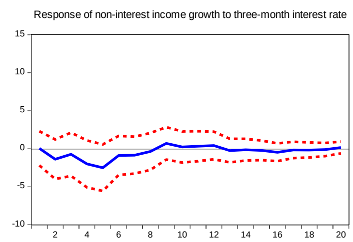
GDP shock



stock market shock

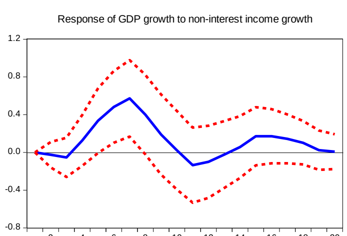


interest rate shock

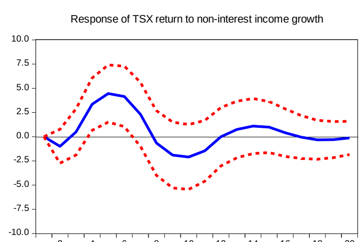


Feedback effect of fee-based shocks

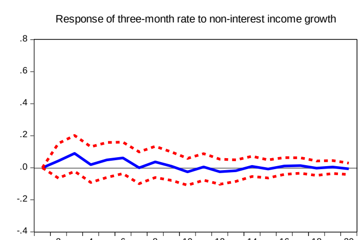
to GDP growth



to stock market



to interest rate



Notes: In each figure, the dashed lines enclose the 95% confidence interval. A coefficient is significant at the 5% level if it associated confidence interval lies above or below the zero mark.

4.3 The direct impact of fee-based shocks

Consistent with our cross-correlation analysis of bank income flows, U.S. bank non-interest income growth reacts positively and significantly to a GDP shock and this impact is quite persistent (Figure 6, Panel A). This may be explained by the product-mix of U.S. banks' non-traditional activities in which products which co-move with GDP have an important weight (Calmès and Théoret, 2015). Not surprisingly, U.S. bank non-interest income growth also reacts positively and significantly to a positive shock emanating from the stock market, market-oriented products being important in banks' non-traditional activities. In contrast, an interest rate shock does not seem to impact significantly bank non-interest income growth.

Conversely however, the response of real GDP growth to a fee-based shock is positive and very significant. U.S. banks' non-traditional activities display a positive feedback effect on GDP. Although less significant, we also observe a positive response of the stock market. Note however that, as in the case of credit, there are reasons to suspect that this feedback effect is stronger when banks are confronted with financial constraints (Marcucci and Quagliariello, 2006, 2009).

In Canada (Figure 6, Panel B), the product-mix of banks' non-traditional activities co-moves less with GDP (Calmès and Théoret, 2015). This may explain why non-interest income growth displays no significant response to a GDP shock. However, since Canadian banks are involved in investment banking, it is normal to observe a positive response of non-interest income growth to a stock market shock. Importantly, the feedback effect of non-interest income growth to GDP is also observed in Canada, and the feedback effect of a fee-based shock to the stock market seems actually stronger (Figure 6, Panel B).

4.4 The asymmetrical impact of bank income flows on GDP and the stock market

It is well-established that the behavior of economic and financial times series is asymmetric according to the state of the economy. In the banking sector, this asymmetry is related to the fact that informational problems and agency costs are more severe during slow growth episodes, when financial institutions are more exposed to moral hazard and adverse selection (Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997; Vennet et al., 2004; Calmès and Théoret, 2014; Dewatcher and Wouters, 2014; Racicot and Théoret, 2016). According to Marcucci and Quagliariello (2009) and Gennaioli et al. (2011), it is when the banks' financial constraints, and especially the capital constraint, are binding that the feedback effects should be stronger. Accordingly, we want to explore the asymmetry of the feedback effects of credit shocks and fee-based shocks to the real economy and to the stock market.

Table 2 Markov switching regression: Feedback effect from net interest income growth to GDP growth

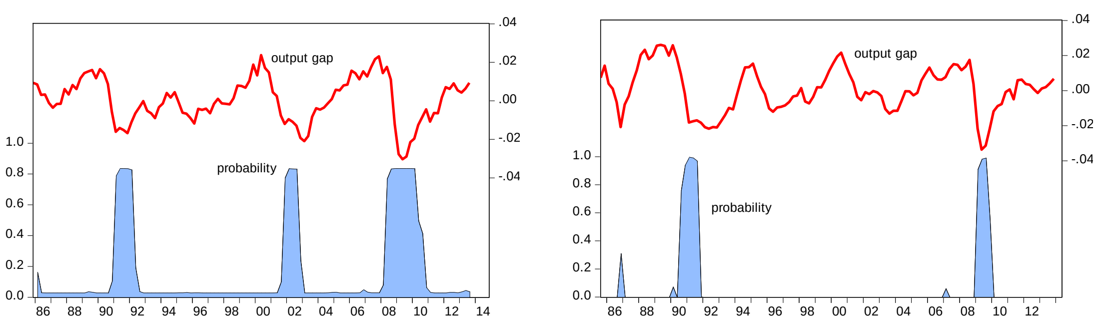
	U.S.		Canada	
	Low regime	**High regime**	**Low regime**	**High regime**
constant	-0.35	3.06	-2.06	3.35
	-0.36	*15.68*	*-4.62*	*13.47*
gnetin(-1)	0.32	0.11	-0.02	-0.02
	2.50	*2.29*	*-0.40*	*-13.54*
gnetin(-2)	-0.04	-0.01	0.02	-0.03
	-0.25	*-0.15*	*0.29*	*-0.82*
gnetin(-3)	-0.10	-0.01	-0.16	-0.01
	-0.62	*-0.15*	*-2.27*	*-0.41*
gnetin(-4)	-0.27	-0.04	0.16	-0.01
	-2.18	*-1.00*	*2.33*	*-0.58*

Notes: The t-statistics are in italics. *gnetin* stands for the growth of net interest income.

Figure 7 Switching regime regression: feedback effect from net interest income growth to real GDP growth

Probability to be in the low regime

U.S. **Canada**



Notes: To compute the quarterly output gap, we first take the log of U.S. real GDP. We then detrend this transformed series with the Hodrick-Prescott filter using a smoothing coefficient (λ) equal to 1600—the trend of the series being a measure of potential output. The resulting residuals are the output gap measure.

4.4.1 The asymmetric feedback effect of credit shocks

Table 2 provides the estimation of system (9) when the income flow is net interest income. Even if we expect the credit shock feedback effect to be weak, there is still a significant (positive) feedback effect from bank net interest income—our measure of bank credit—to GDP growth at lag *t-1* for both regimes in the U.S., this effect being, as expected, stronger in the low regime[12]. Figure 7 plots the unconditional probability to be in the low regime. This probability is clearly associated with the recessions in the U.S. observed since 1990. Consistent with our earlier explanation on bank product-mix and by contrast to the U.S., net interest income growth impacts negatively GDP growth at lag *t-3* in the low regime in Canada, but this effect cancels itself at lag *t-4* (Table 2)[13].

Table 3 Markov switching regression: Feedback effect from net interest income growth to the stock market

	U.S.		**Canada**	
	Low regime	**High regime**	**Low regime**	**High regime**
constant	-0.01	10.99	-10.04	4.10
	-0.09	*6.96*	*-2.48*	*5.03*
gnetin(-1)	-0.56	0.01	-2.54	-0.12
	-0.53	*0.10*	*-4.20*	*-1.21*
gnetin(-2)	0.13	-0.17	1.19	-0.05
	0.09	*-0.43*	*1.84*	*-0.48*
gnetin(-3)	0.93	0.63	0.77	0.24
	0.57	*1.19*	*1.63*	*1.87*
gnetin(-4)	-3.46	0.13	-0.89	-0.23
	-2.95	*0.37*	*-0.89*	*-2.18*

Notes: The t-statistics are in italics. *gnetin* stands for the growth of net interest income.

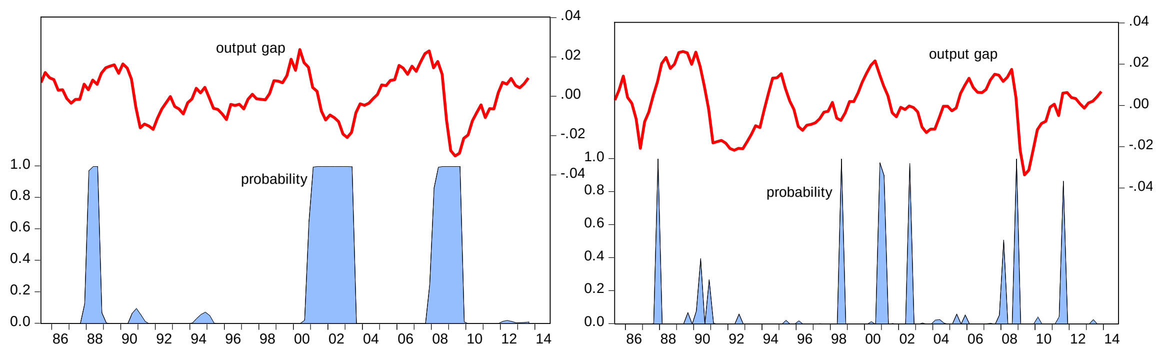
[12] Note that there are two ways to identify the low regime. First, the constant of the regression is usually negative in the low regime and much lower than in the high regime. Second, we can identify *ex post* the state of the periods for which the unconditional probability plot is near 1.

[13] Note that we refrain to compare the estimation coefficients for U.S. and Canadian banks given the complexity of the estimation of the MRSW model.

Figure 8 Switching regime regression: feedback effect from net interest income growth to the stock market return

Probability to be in the low regime

U.S. **Canada**



Notes: To compute the quarterly output gap, we first take the log of U.S. real GDP. We then detrend this transformed series with the Hodrick-Prescott filter using a smoothing coefficient (λ) equal to 1600—the trend of the series being a measure of potential output. The resulting residuals are the output gap measure.

Table 3 repeats the same exercise as in Table 2 for the stock market return. In the U.S., we observe that there is only a significant negative feedback effect of net interest income growth on the S&P500 return in the low regime at lag *t-4*. This confirms the weak feedback effect emanating from credit shocks. Figure 8 shows that the probability to be in the low regime is associated with the last two U.S. recessions and to the big defaults on sovereign debt observed at the end of the 1980s. Once again, the regime switching is clearly associated with credit risk. In Canada, the feedback effect of net interest income growth to the stock market is somewhat more important in the low regime (Table 3). It is observed at lag *t-1* but, as expected, it reverses quickly. At the impact, the feedback effect of net interest income growth on the stock market is thus negative in the low regime, which suggests that net interest income growth acts as a buffer for banks in bad times. Surprisingly, Figure 8 shows that in Canada the negative feedback effect of net interest income growth on the stock market is not only associated with recessions, but also with all the major financial crises which did not lead to recessions: the sovereign debt crisis of emerging countries (1988), the Asian crisis[14] (1998), and the European sovereign debt crisis (2011). Canadian banks thus seem to have a pervasive impact on the domestic stock market.

[14] More precisely, the Asian-Russian-LTCM crisis.

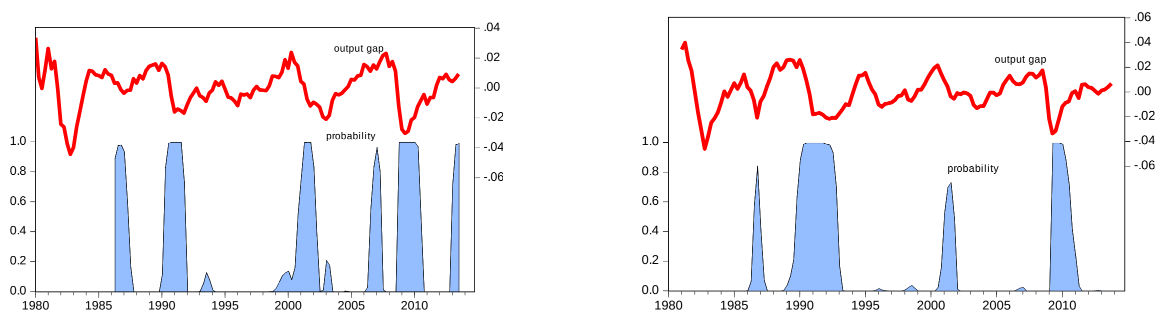
Table 4 Markov switching regression: Feedback effect from non-interest income growth to GDP growth

	U.S.		Canada	
	Low regime	**High regime**	**Low regime**	**High regime**
constant	-1.03	2.21	-1.64	2.18
	-4.30	*14.14*	*-2.69*	*12.10*
gnonin(-1)	0.02	0.02	0.04	0.03
	1.44	*1.38*	*1.17*	*2.84*
gnonin(-2)	0.05	0.04	-0.01	0.01
	3.21	*2.24*	*-0.10*	*1.00*
gnonin(-3)	0.10	0.03	0.04	0.02
	4.78	*2.54*	*2.12*	*2.07*
gnonin(-4)	0.08	0.03	0.04	0.01
	3.51	*2.72*	*2.83*	*0.76*
gnonin(-5)	0.04	0.03	-	-
	1.72	*2.08*	-	-

Notes: The t-statistics are in italics. *gnonin* stands for the growth of non-interest income.

Figure 9 Switching regime regression: feedback effect from non-interest income growth to real GDP growth

U.S. **Canada**
Probability to be in the low regime



Notes: To compute the quarterly output gap, we first take the log of U.S. real GDP. We then detrend this transformed series with the Hodrick-Prescott filter using a smoothing coefficient (λ) equal to 1600—the trend of the series being a measure of potential output. The resulting residuals are the output gap measure.

4.4.2 The asymmetric feedback effect of fee-based shocks

Table 4 plots the feedback effect of non-interest income growth on GDP growth. In both countries, this effect plays in both regimes but it is more pronounced in the low regime. As evidenced by Figure 9, the probability to be in the low regime in the U.S. is close to one in recessions but also in financial crises not associated with recessions. Hence, non-traditional activities of U.S. banks impact GDP growth every time their growth decreases substantially. In Canada, in contrast to the U.S. banking system, the feedback effect is mostly related to domestic recessions (Figure 9). Therefore, the fee-based activities of Canadian banks do not seem to aggravate financial crises not related to recessions. Again, the product-mix of Canadian banks may be a factor explaining this result[15].

Table 5 Markov switching regression: Feedback effect from non-interest income growth to the stock market

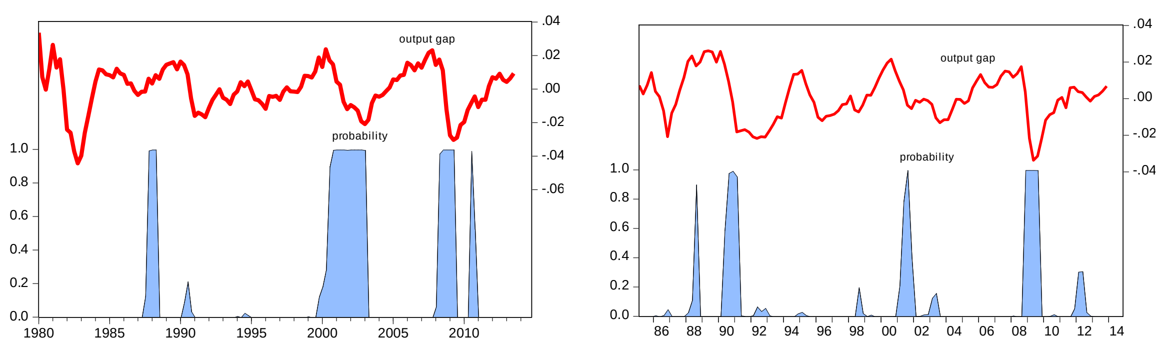
	U.S.		**Canada**	
	Low regime	**High regime**	**Low regime**	**High regime**
constant	-28.09	7.61	-23.90	5.82
	-15.81	*5.12*	*-4.84*	*3.16*
gnonin(-1)	0.25	0.52	0.14	0.24
	1.03	*4.50*	*0.99*	*2.72*
gnonin(-2)	0.23	0.37	0.12	0.24
	1.16	*3.09*	*0.99*	*2.26*
gnonin(-3)	-0.40	0.14	0.10	-0.07
	-1.63	*1.13*	*0.69*	*-0.68*
gnonin(-4)	0.79	-0.35	0.15	-0.08
	6.31	*-2.32*	*1.16*	*-0.94*
gnonin(-5)	1.10	0.11	-	-
	7.24	*0.85*	-	-

Notes: The t-statistics are in italics. *gnonin* stands for the growth of non-interest income.

Figure 10 Switching regime regression: feedback effect from non-interest income growth to the stock market return

U.S. **Canada**

Probability to be in the low regime



[15] In this respect, loans commitments, which weigh heavily in the Canadian banks' off-balance sheet activities, may sustain economic activity in periods of crises.

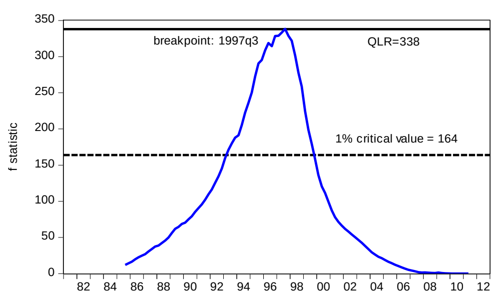
Notes: To compute the quarterly output gap, we first take the log of U.S. real GDP. We then detrend this transformed series with the Hodrick-Prescott filter using a smoothing coefficient (λ) equal to 1600—the trend of the series being a measure of potential output. The resulting residuals are the

Turning to the impact of bank non-traditional activities on the stock market, note that the feedback effect operates quickly and very significantly in the high regime for both countries (Table 5). This result is consistent with what is obtained for the GDP growth feedback effect. In the U.S., the probability to be in the low regime is related to all financial crises, including recessions (Figure 10)[16]. In Canada, the feedback effect from fee-based activities to the stock market is less significantly at play in the low regime. To summarize, the feedback effect of a fee-based shock is generally present, and especially so in low regime.

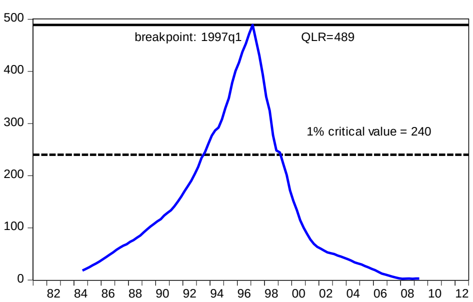
Figure 11 Quandt-Andrews unknown breakpoint test and switching regression on banks' *snonin.*

Quandt-Andrews test

U.S. banks

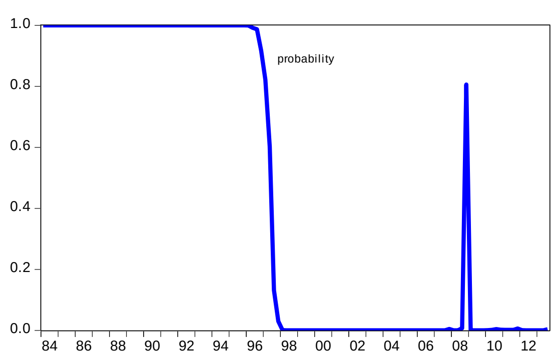


Canadian banks

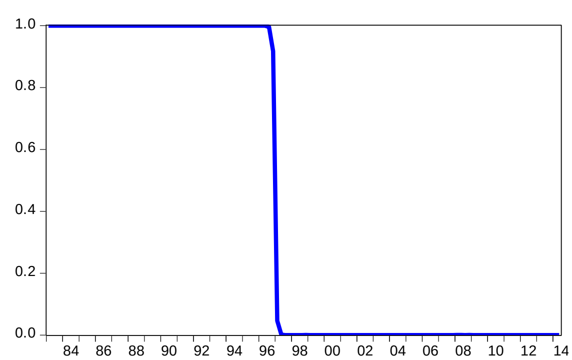


Markov switching regression

U.S. banks



Canadian banks



Notes: For more detail on the Quandt-Andrews test, see Quandt (1960), Andrews (1993, 2003), and Stock and Watson (2003, 2011). According to Stock and Watson (2011, p. 560), the *QLR* (Quandt likelihood ratio) statistic is given by:

[16] A quite sensitive result since the stock market should be in a low regime every time the stock index drops substantially—i.e., in recessions or financial crises.

$QLR = MAX\left[F(\tau_0), F(\tau_0+1), ..., F(\tau_1)\right] \quad \tau_0 \le \tau \le \tau_1$ where *F(.)* refers to the standard *F* statistic evaluated at time τ. In other words, the *QLR* statistic is the maximum *F* statistic computed over a possible set of breakpoints stretched over the sample used.

5. The development of the feedback effect of fee-based activities

5.1 The 1997 structural break and the development of the feedback effect

Figure 11 shows that a structural break occurred in the banks' non-interest income series around 1997, both in the U.S. and in Canada. The Quandt-Andrews unknown breakpoint test[17] reveals that a breakpoint is depicted for the U.S. *snonin* (share of non-interest income in total net operating income) series around the third quarter of 1997, and around the first quarter of 1997 for the Canadian banks' corresponding time series[18]. Figure 11 also shows the unconditional probability of *snonin* to be in regime 1 or 2—obtained with a Markov regime-switching model[19]. Consistent with the Quandt-Andrews test, the switching regression identifies a structural break around 1997 for both banking systems[20]. In this section, we study the incidence of this structural break on our VAR results. Accordingly, we thus recast our analysis over two subperiods: 1984-1996 and 1997-2013. Since the 1997 threshold coincides with the rise of universal banking, we expect an increase in the feedback effects in the last period. Our results largely qualify this intuition.

[17] For more detail on this test, see Quandt (1960), Andrews (1993, 2003), and Stock and Watson (2003, 2011). According to Stock and Watson (2011, p. 560), the *QLR* (Quandt likelihood ratio) statistic is given by:
$QLR = MAX\left[F(\tau_0), F(\tau_0+1), ..., F(\tau_1)\right] \quad \tau_0 \le \tau \le \tau_1$ where *F(.)* refers to the standard *F* statistic evaluated at time τ. In other words, the *QLR* statistic is the maximum *F* statistic computed over a possible set of breakpoints stretched over the sample used. It is thus a generalization of the basic Chow test.

[18] For more detail on this structural break, see Calmès and Théoret (2010, 2014). This break is associated with a consolidation of the growth of non-interest income in Canada and the U.S. It is also related to the adoption of the VaR by banks as a gauge of market rate risk. Finally, a risk premium was added to Canadian bank returns around 1997 which accounts for the greater risk embedded in bank non-traditional business lines (Calmès and Théoret, 2010).

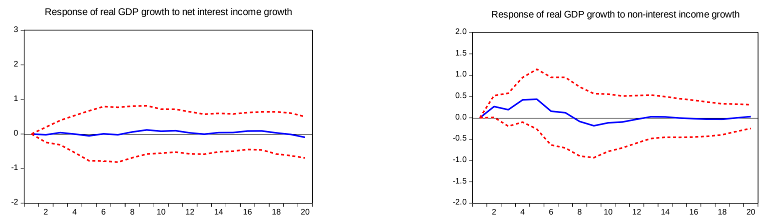
[19] See Appendix 2 for a presentation of this model.

[20] There is also a jump in the probability of being in the low regime during the subprime crisis but it quickly fades away.

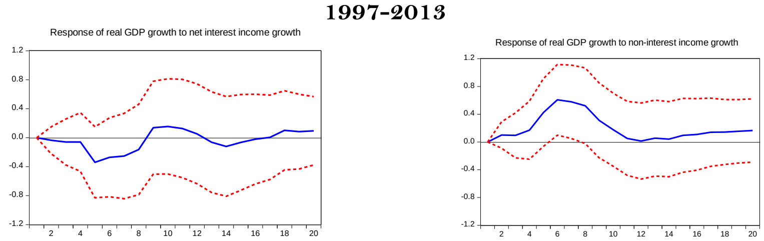
Figure 12 Feedback effect of credit and fee-based shocks to real GDP growth over two subperiods (1984-1996 and 1997-2013)

Panel A: U.S. banks

1984-1996

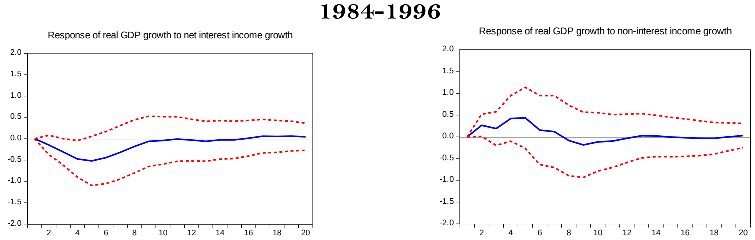


1997-2013

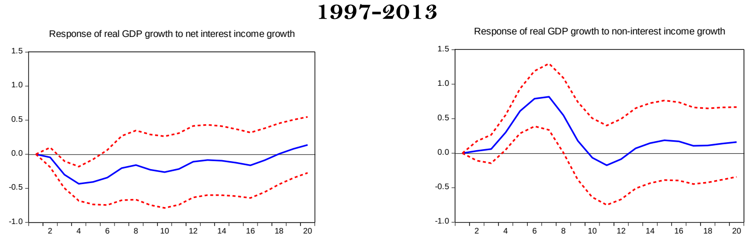


Panel B: Canadian banks

1984-1996



1997-2013



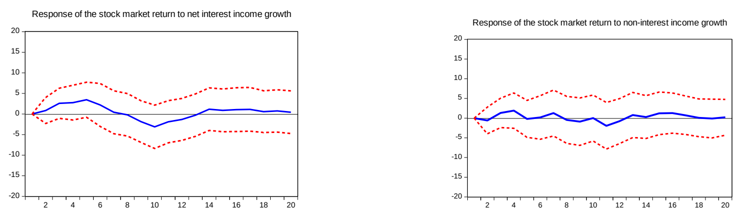
Notes: In each figure, the dashed lines enclose the 95% confidence interval. A coefficient is significant at the 5% level if it associated confidence interval lies above or below the zero mark.

Before 1997, there is actually no significant feedback effect from a fee-based shock to GDP growth in both countries (Figure 12, Panel A). The situation materializes only during the last period

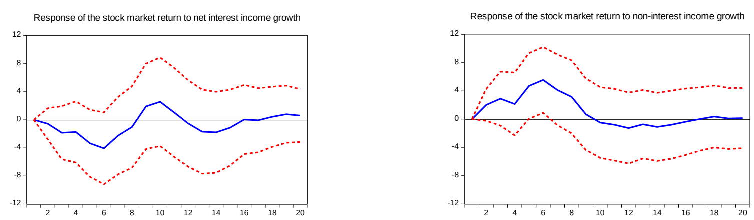
(1997-2013): a significant positive feedback effect from a fee-based shock to GDP growth appears after 1997, and it is even more significant for Canadian banks[21].

Figure 13 Feedback effect from banks' traditional and fee-based activities to the stock market on two subperiods (1984-1996 and 1997-2013): U.S.

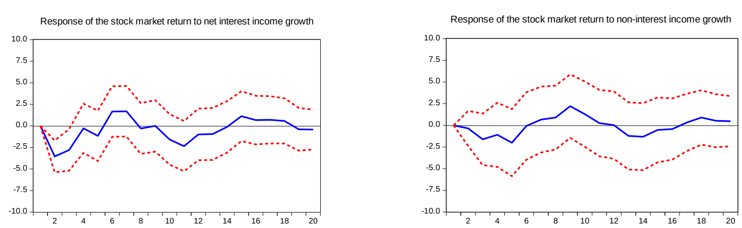
Panel A: U.S. banks
1984-1996



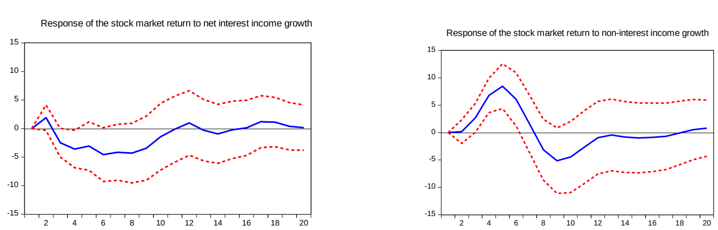
1997-2013



Panel B: Canadian banks
1984-1996



1997-2013



Notes: In each figure, the dashed lines enclose the 95% confidence interval. A coefficient is significant at the 5% level if it associated confidence interval lies above or below the zero mark.

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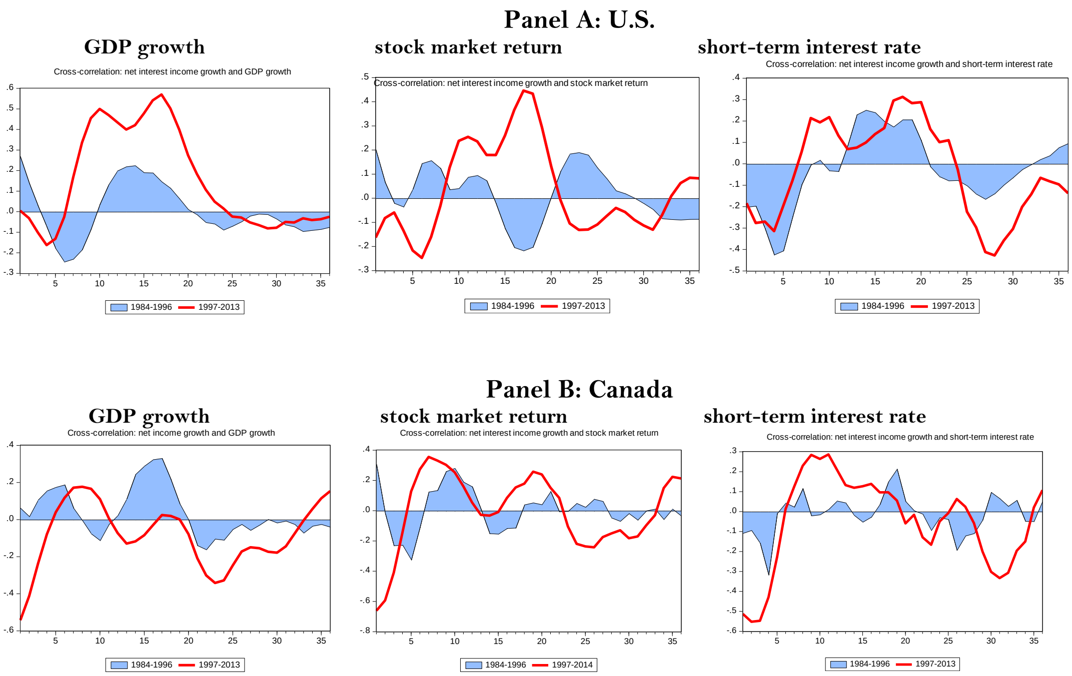
[21] In Canada, there is also a significant negative feedback effect from a credit shock to GDP growth over the period 1984-1996, but it becomes clearly more significant over the second period (1997-2013) (Figure 12, Panel B). No comparable relationship is observed in the U.S. for the credit shock over both subperiods.

The feedback effect from a fee-based shock to the stock market has also a similar pattern in both countries (Figure 13, Panels A and B): a significant positive feedback effect from this kind of shock to the stock market appears over the last period. Consistent with our previous results, there is also a negative feedback effect from a credit shock to the stock market for Canadian banks over both subperiods, and this effect is more persistent in the second subperiod.

Figure 14 Cross-correlations between net interest income growth and the lagged values of macroeconomic and financial shocks over two subperiods: 1984-1996 and 1997-2013



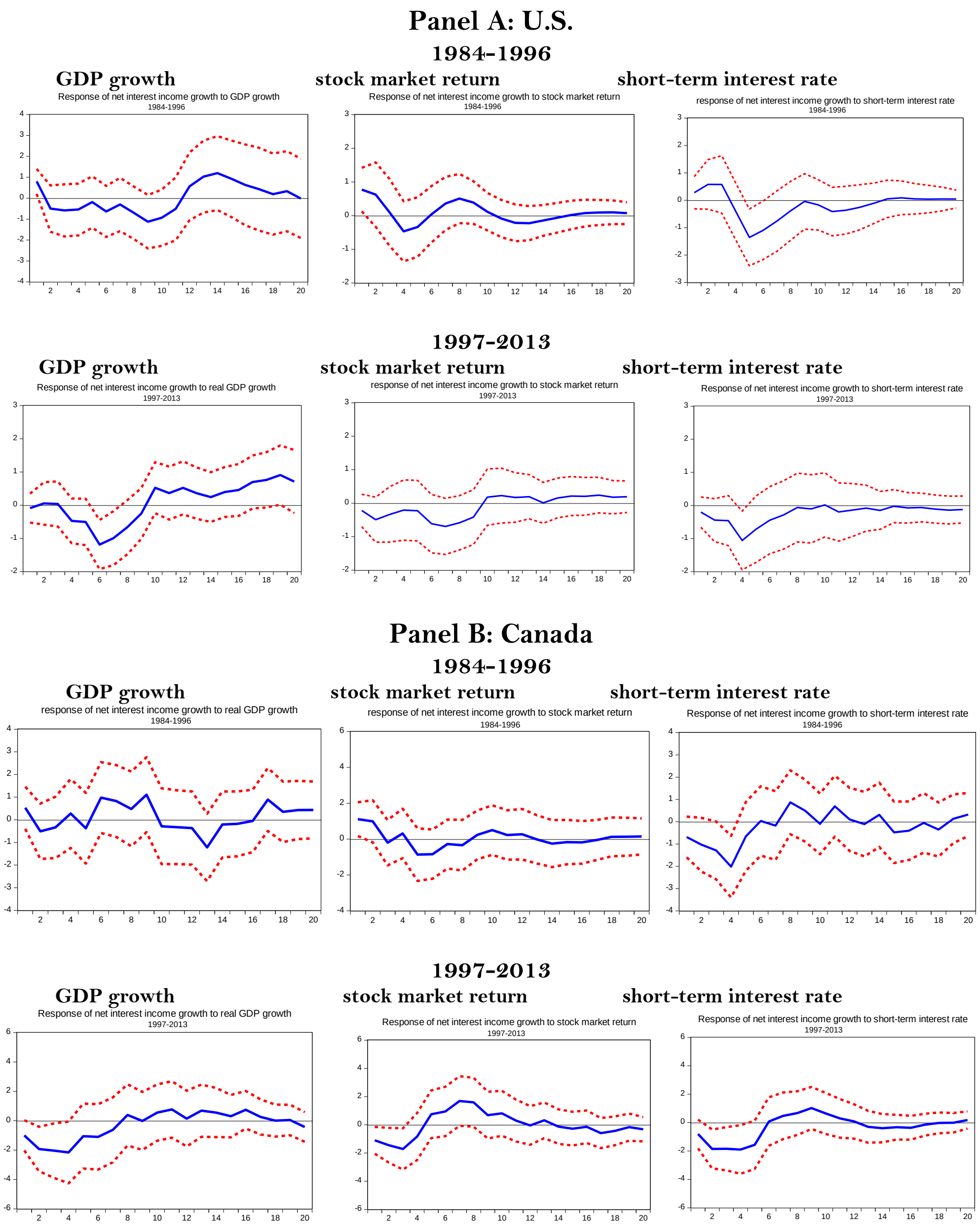
5.2 Monetary policy shocks

Since monetary policy essentially impacts the banking system's performance through net interest income, it is interesting to examine how the behaviour of net interest income growth might have changed before versus after the structural break. Not surprisingly, based on cross-correlation analysis, note that banks' net interest income growth is more responsive to GDP growth and to the stock market after the 1997 structural break (Figure 14)[22]. More importantly however, the sensitivity of banks' net interest income growth to the short-term interest rate does not decrease after the structural break. This result might seem counterintuitive since more financial claims working as insurance vehicles (like credit derivatives) are available during the last period. The fact that banks remain evenly exposed to monetary

[22] This may be attributable to increasing complementarities between bank traditional and non-traditional activities.

shocks despite the availability of these financial instruments is broadly consistent with the argument that financial innovation is mainly used to take more calculated risks rather than to protect the banking system (Demsetz and Strahan, 1995).

Figure 15 IRFs: response of net interest income growth to various shocks over two subperiods: 1984-1996 and 1997-2014



Notes: In each figure, the dashed lines enclose the 95% confidence interval. A coefficient is significant at the 5% level if it associated confidence interval lies above or below the zero mark.

The IRFs of net interest income growth support these preliminary results. The short-term response of net interest income growth to GDP and stock market shocks turns from positive to negative after the structural break (Figure 15). More importantly, the negative short-term impact of a monetary shock on net interest income growth shows no obvious change.

To summarize, bank net interest income growth has become countercyclical, at least in the short-run, both in Canada and in the U.S. After the 1997 structural break, net interest income seems to act as a buffer against fluctuations[23]. A positive shock originating from the stock market also tends to decrease net interest income growth in both countries. This is consistent with the "search-for-yield" of bank depositors, which tends to increase banks' cost of funds and decrease net interest income growth (Gambacorta and Marquez-Ibanez, 2011). Finally, despite the rise of universal banking, monetary policy does not seem to have lost its influence on bank credit and net interest income.

6. Conclusion

Prior to the advent of universal banking, banks were based on the originate-to-hold model, and loan growth was strongly linked to GDP growth. However, more recently, counteracting forces seem to have surfaced. On the one hand, fee-based activities offer greater diversification opportunities. With the accelerated development of derivatives—especially credit derivatives like credit swaps—banks can better manage credit and market fluctuations. On the other hand, diversification in fee-based activities increases the volatility of banks' income flows and, *ceteris paribus*, this factor tends to increase the amplitude of the business cycle. The main contribution of this paper is to show that such a feedback effect is indeed at play in the data.

In the U.S., given banks' product-mix, lagged values of GDP growth still have a significant impact on non-interest income growth. However, non-interest income growth seems to give rise to a significant feedback effect, both on real GDP and on the stock market, a result much in line with Peersman and Wagner (2014). In particular, we show that this feedback effect gains strength after the 1997 structural break in banks' share of non-interest income in net operating income.

Finally, in the universal banking era, even though banks might have a greater impact on economic activity and on the stock market, central banks may nevertheless continue to impact net interest income growth, even if this effect seems to have become shorter-lived. Although the decline in the impact of monetary policy on the lending channel could easily be expected, in practice, financial innovation seems to be mainly used by banks to take more calculated risk rather than to protect themselves and reduce their global level of risk. This finding is consistent with the main argument of Demsetz and Strahan (1995).

[23] As Calmès and Théoret (2014) suggest however, this might be due to a simple risk shifting, as the detrimental impact of OBS activities seem to have increased, at the same time credit risk was becoming more manageable.

Appendix 1

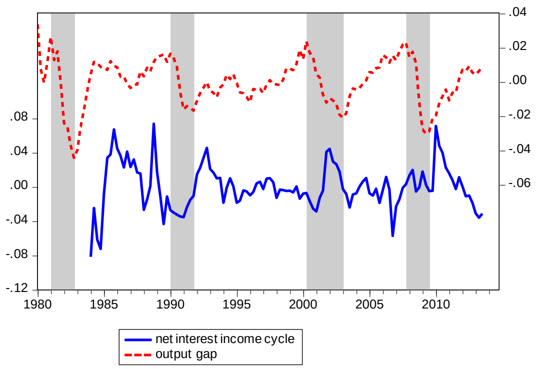
Banking cyclicality

Figure 16 provides the cycles of net interest and non-interest income growth computed with the Hodrick-Prescott filter. U.S. banks show no obvious cycle for net interest income growth while, for Canadian banks, its growth tends to be higher during recessions. In other words, net interest income growth seems to be countercyclical in Canada, acting as a buffer against the fall in banks' profits during bad times. On the other hand, regarding non-interest income growth, the data suggest more procyclicality in the Canadian than in the U.S. series. These two sets of observations are both corroborated by the spectral analysis of the growth of bank income flows (Figure 17). For example, in Canada, net interest income growth shows a moderate peak at business cycle frequency—between 6 and 40 quarters (DeJong and Dave, 2007)—and another one at the quarterly frequency. By contrast, the spectrum of U.S. bank net interest income growth displays no such obvious cycle at business cycle frequency, and rather indicates that the series is persistent. On the other hand, non-interest income growth has a clearer peak at business cycle frequency in Canada, stronger than in the U.S. (according to the ordinate axis of the spectrum).

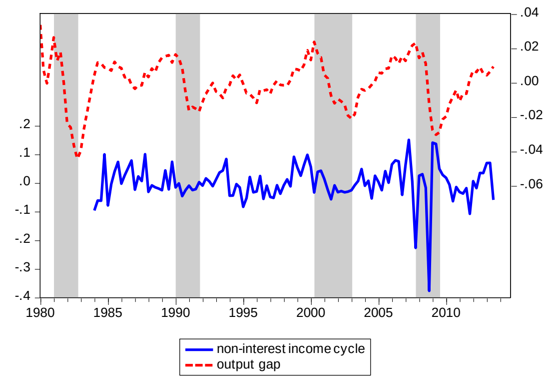
Figure 16 Net interest and non-interest income cycles: U.S. and Canada

Panel A: U.S.

Net interest

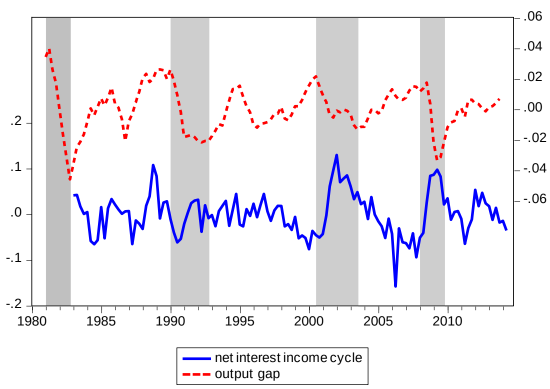


Non-interest

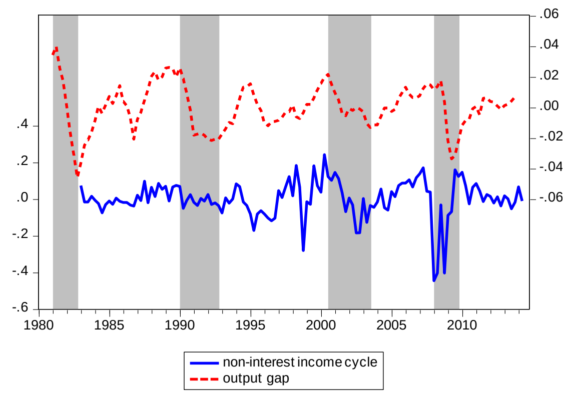


Panel B: Canada

Net interest



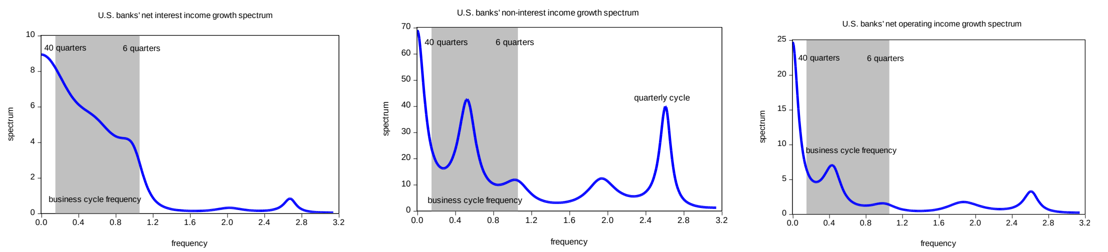
Non-interest



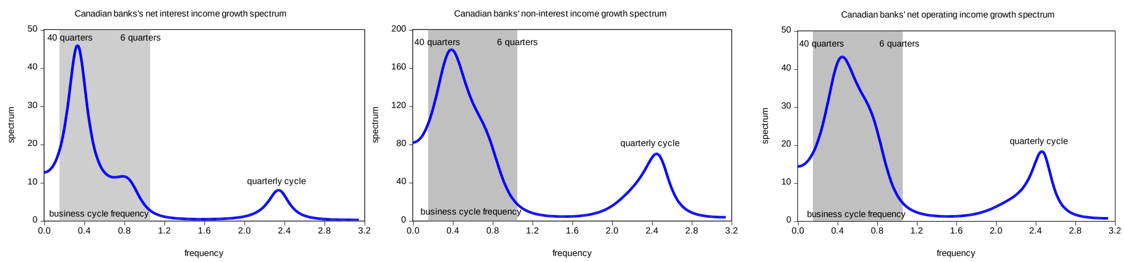
Notes: Shaded areas are associated with periods of economic slowdown. To compute the quarterly output gap, we first take the log of real GDP. We then detrend this transformed series with the Hodrick-Prescott filter using a smoothing coefficient (λ) equal to 1600—the trend of the series being a measure of potential output. The resulting residuals are the output gap measure.

Figure 17 Spectral analysis of bank income components: U.S. and Canadian banks

Panel A: U.S.



Panel B: Canada



Notes: These spectra are built using an AR(p) model. Specifically, the spectrum is a decomposition of the variance of a time series by frequency—the cycle frequency being low near the origin and increasing progressively till π . Comparisons of the height of the spectrum for alternative values of frequency indicate the relative importance of fluctuations at the chosen frequencies in influencing variance of the time series. A spectrum having a peak near the origin indicates that the series is very persistent through time: its autocorrelation function declines very slowly. A spectrum having a peak in the shaded area indicates that this time series has a cycle in the conventional business cycle frequency. A spectrum which shifts to the left through time indicates less volatility for the series, i.e. a more stable series. Shaded areas correspond to the business cycle frequency, which is comprised between 6 and 40 quarters (DeJong and Dave, 2007).

Appendix 2

The Markov regime-switching model[24]

To capture the asymmetries in the behavior of hedge funds according to the state of the business cycle, we rely on a Markov regime-switching model (Goldfeld and Quandt, 1973; Hamilton, 1989, 2005)[25]. There is indeed evidence that the dynamics of financial institutions' behavior in recession—or crisis—differ markedly from the dynamics observed in expansion—i.e., normal times (e.g., Calmès and Théoret, 2014; Racicot and Théoret, 2016).

We assume that a time series y_t is subject to two regimes: a high[26] and a low regime[27]. The regimes, which we denote by s_t, are unobserved. Without loss of generality, y_t follows an *ar(1)* process—

[24] To write this section, we borrow heavily from the presentation of Franses and Van Dijk (2000), chapter 3.
[25] When proposing his Markov switching model, Hamilton (1989) was particularly interested in the asymmetry of the business cycle. He found that the dynamics of recessions are qualitatively distinct from those of normal times. See also: Neftci (1984) and Sichel (1987).
[26] e.g., expansion or normal times.
[27] e.g., recession or crisis.

i.e., an autoregressive process of order 1—and the parameters of this process differs in state 1 ($s_t = 1$) and state 2 ($s_t = 2$), i.e.,

$$y_t = \begin{cases} \delta_{0,1}+\delta_{1,1}y_{t-1}+\varepsilon_{t,1} & \text{if } s_t=1 \\ \delta_{0,2}+\delta_{1,2}y_{t-1}+\varepsilon_{t,2} & \text{if } s_t=2 \end{cases} \qquad (10)$$

Hamilton (1989) assumes that the behavior of the regimes is governed by a Markov process—i.e., the state at time *t* depends only on the state at time *t-1*. At each point of time *t*, the transition and the unconditional probabilities to be in one of the two states must be computed. Denote the transition probability to be in state *j* at time *t* given that state *i* was observed at time *t-1* by: $P(s_t = j \mid s_{t-1} = i) = p_{ji} \quad i = 1,2; j = 1,2$. After having computed these transition probabilities, the unconditional probabilities to be in state 1 or 2 may be easily derived by the following formulas (Hamilton, 1994; Franses and Van Dijk, 2000):

$$P(s_t = 1) = \frac{1 - p_{22}}{2 - p_{11} - p_{22}}$$

$$P(s_t = 2) = \frac{1 - p_{11}}{2 - p_{11} - p_{22}}$$

The parameters embedded in the regime switching model given by equation (10) and the transition probabilities may be estimated using the maximum likelihood method. In addition, the algorithm used must provide an estimate of the probability to be in one of the two regimes at each point of time. To write the likelihood function, we assume that the innovations $\varepsilon_{j,t}$ in the system given by equation (10) are normally distributed. The maximum likelihood density of y_t given by $f(y_t)$ may then be written as (Franses and Van Dijk, 2000):

$$f\left(y_t \mid s_t = j; \Omega_{t-1}; \theta\right) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left[\frac{-\left(y_t - \delta_j' x_t\right)^2}{2\sigma^2}\right] \qquad (11)$$

where Ω_{t-1} is the information set available at time *t-1*; $x_t = \left(1, y_{t-1}\right)'$; $\delta_j = \left(\delta_{0,j}, \delta_{1,j}\right)'$ for *j*=1,2, and θ is a vector containing all the parameters of the regime switching model[28]—i.e., $\theta = \left[\delta_1', \delta_2', p_{11}, p_{22}, \sigma^2\right]'$.

The likelihood function given by equation (11) is calculated using an iterative algorithm which is similar to the Kalman filter algorithm (Hamilton 1989, 2005). In this respect, the process by which the

[28] Note that $p_{12} = 1 - p_{11}$

probabilities are updated is labelled "filtering". Probabilities may be *filtered* or *smoothed.* The filtered probabilities are obtained using only the contemporaneous information set. In contrast, to estimate the smoothed probabilities, we use all the observations till the end of the dataset (Hamilton, 2005)[29]. The smoothed probabilities are thus an improved version of the filtered ones since the Markov process links the likelihood of the data in different periods till the end of the sample.

[29] The algorithm used to compute the smoothed probabilities was developed by Kim (1994). To compute this kind of probability, later information is thus used to identify the probability of being in state 1 or 2 at time *t*.

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