Macroeconomic dynamics, nonlinearities and universal banking†

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Abstract
We analyze the impact of universal banking on the real economy, by comparing the performance of a benchmark linear VAR model with a nonlinear projection process (Jordà, 2005) which tracks shocks asymmetries. We divide bank shocks in two categories—i.e., credit and fee-based shocks—and show that, based on U.S. data, fee-based shocks seem to have a significant feedback effect on real GDP and on the stock market. We corroborate the view that the uncertainty associated with GDP growth explains the bulk of the feedback effects of bank fee-based shocks on economic activity during crises. Although credit shocks produce a significant feedback effect, our sample seems to suggest that it is weaker. More importantly, our results indicate that in normal times, even if nonlinearities are less at play, the feedback effects remain significant, especially since the 1997 regulation changes.

Keywords: Universal banking; Asymmetric effects; Linear VAR; Non-linear local projection process; Feedback effects; Procyclicality.

JEL classification: C32; G20; G21.

Dynamique macroéconomique, non-linéarités et banking universel

Mots-clés : Banking universel; effets asymétriques; VAR linéaire; processus de projection locale; effets de rétroaction (cliquet); procyclicalité.
Classification JEL : C32; G20; G21.
1. Introduction

Despite the risk-mitigating measures put in place in the aftermath of the subprime crisis, bank fee-based activities remain inherently more volatile than lending (Stiroh, 2004; Stiroh and Rumble, 2006; Geyfman and Yeager, 2009; Calmès and Théoret, 2010; 2014). Considering their current weight in bank financial results, it is thus important to examine the impact of universal banking on the real economy. In this paper, we study the interaction between banking activities and some key macroeconomic variables, such as GDP and interest rates, in order to determine whether universal banking produces a feedback effect on macroeconomic dynamics—not just during financial crises, but also during normal times. For instance, if we were to find that the elasticity of fee-based activities to the interest rate is positive, it could suggest that these activities may reduce the impact of monetary policy shocks. On the other hand, it is equally possible that fee-based activities lead to a significant feedback effect, either impacting economic growth or the stock market.

The literature establishes that credit is cyclical—i.e., bank lending is responsive to GDP growth. There is also some evidence that traditional banking might be “procyclical”, in the sense that bank business lines impact the real sector as well—especially during crises. In theory, this feedback effect could be associated with most transmission mechanisms—e.g., the credit channel, the lending channel, the balance sheet channel and the risk channel (Bernanke, 1986; Bernanke and Gertler, 1989; Bernanke and Gertler, 1995; Bernanke and Gertler, 1996; Bernanke and Lown, 1991; Gertler and Kiyotaki, 2010; Borio and Zhu, 2012). However, empirical studies on the feedback effect of bank lending are rarely conclusive enough to support these theories for normal times—with the noticeable exception of the literature on the impact of banking during extreme events. In any case, we know a lot about how credit shocks and the real economy interact, but very little about how fee-based shocks might affect macroeconomic dynamics.

On the methodological front, most studies of interest analyze the interaction between one banking quality indicator—like loan write-offs, loans in default, the level of bank capital or return on equity—, and some macroeconomic variables relying on (i) a linear VAR (e.g., Hoggarth et al., 2005); (ii) an augmented linear VAR which introduces non-linearities (e.g., Marcucci and Quagliariello, 2006); or (iii) a non-linear VAR (Dovern et al., 2010; Puddu, 2012). Although some authors seem to capture significant effects during downturns (Marcucci and Quagliariello, 2006), other results suggest that the neglect of the nonlinear nature of the relationships between banking activities and macroeconomic variables may explain why a significant feedback effect is generally hard to detect robustly enough (Puddu, 2012). More to the point, to our knowledge, almost no study that we are aware of seems to really go beyond examining the impact of lending, de facto overlooking a very substantial portion of the

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1 For instance, the financial accelerator is associated with an increase in the firms’ external finance premium resulting from a contractionary monetary policy. This increase in the cost of external funds leads firms to cut their investments, which produces a negative feedback effect on economic activity. In the balance sheet channel, the impact of a contractionary monetary policy is transmitted to firms or banks via a decrease in asset prices which reduces firms’ net worth and bank capital. Once more, firms reduce their investments and banks decrease their supply of credit, which leads to a negative feedback effect on economic activity. In the risk-taking channel, the feedback effect is associated with an increase in the willingness of banks to take more risk following a loosening of monetary policy. In search for higher yields, banks bear more risk, which eventually leads to a credit crunch, thus again giving rise to a negative feedback effect on economic activity (Borio and Zhu, 2012; Maddaloni and Peydró, 2011).

2 As in using a classical linear VAR setting.
contemporary banking business. Accordingly, the aim of this paper is to analyze the potential feedback effect stemming from bank fee-based activities, within an empirical framework specifically designed to account for nonlinearities.

On this research avenue, most authors examine the feedback effect of a few specific bank off-balance sheet activities, like securitization or loan commitments, during extreme events (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), and the results seem ambiguous, depending on the business lines considered, the degree of substitution between bank securities and market securities, the informational content of securities issued by banks, or the tail risk associated with bank nontraditional activities (Gorton, 2010; Gorton and Metrick, 2010; Shleifer and Vishny, 2010; Gennaioli et al., 2013; Calmès and Théoret, 2014). More recently however, some authors have identified an indirect “waterbed effect”, whereby securitization might mitigate the impact of restrictive monetary policy shocks (Nelson et al., 2015; Beck et al., 2016).

Compared to Nelson et al. (2015), and Beck et al. (2016), we use a nonlinear approach to study commercial banks, and retain fee-based income and loans as our exogenous bank shocks. Considering past results, in particular those of Puddu (2012) and Nelson et al. (2015), it seems absolutely crucial to choose a nonlinear approach in order to detect any significant feedback effect. Since this effect works predominantly during downturns, it is indeed imperative to distinguish regimes. In order to do so, our VAR model includes the squared lagged variables and we rely on a local projection approach to estimate the resulting quadratic VAR model (Jordà, 2004, 2005). We include the volatility of the explanatory variables to account for the impact of nonlinearity on the impulse response functions of the structural shocks considered (Puddu, 2012). Hence, in contrast to previous studies, credit shocks and fee-based shocks are analyzed simultaneously here, bearing in mind that loans may migrate quickly from on to off-balance sheet (Pescatori and Solé, 2016).

Based on U.S. data, we find that a fee-based shock indeed leads to a significant feedback effect on GDP growth. This effect is more important after 1997, a structural break being observed in the U.S. banking time series around this date (Calmès and Théoret, 2010, 2014). Furthermore, compared to the feedback effect computed with a classical linear VAR, the feedback effect of our model is more important and persistent when using the non-linear local projection approach, especially during episodes of crises. For example, over the period covering the subprime crisis, when we simulate local projections with negative shocks, the results confirm that the feedback effect of fee-based activities is asymmetrically more important during bad times. Interestingly, in contrast to Nelson et al. (2015) and Beck et al. (2016), our results seem to suggest that there is a negative co-movement between bank fee-based activities—i.e., non-

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3 In this respect, Kashyap et al. (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 stands as evidence for the bank lending channel. See also Black and Rosen (2007).

4 Especially for Canadian banks which got more involved in securitization after 1997 while US banks have been involved in securitization since the end of the 1970s.
interest income growth—and interest rate hikes. While the classical linear VAR tends to signal that fee-based activities are not much sensitive to an interest rate shock, accounting for nonlinearities in a rigorous manner actually leads to a negative co-movement. Hence, fee-based activities might not counteract the negative effects of a restrictive monetary policy on the supply of credit, and this fact, ceteris paribus, gives more weight to the risk channel theory than to the waterbed effect hypothesis.

Our paper is organized as follows. Section 2 presents our methodology—especially the nonlinear local projection approach we adopt in this paper. Section 3 describes our database. Section 4 reports the empirical results while Section 5 focuses on robustness checks—especially by transposing our models to the Canadian banking system. Section 6 concludes and provides the policy implications related to our study.

2. Methodology

2.1 The non-linear local projection approach

We rely on a nonlinear local projection algorithm to document the interactions between business cycles and financial fluctuations on the one hand, and bank variables on the other hand. Shocks related to macroeconomic and financial variables may be regarded as “external” shocks to the banking sector, while shocks related to banks’ variables can be referred to as “internal” shocks. The credit shock related to bank traditional activities is measured by the innovation in the equation of the change in the logarithm of the aggregate of loans. However, we have no direct measure of banks non-traditional activities. In line with many other studies (e.g., Stiroh, 2004; Stiroh and Rumble, 2006; Calmès and Théoret, 2010, 2014), we gauge them by the level of bank non-interest income. The fee-based shock is thus measured by the innovation in the equation of the change in the logarithm of bank non-interest income.

2.1.1 The linear local projection method to compute the impulse response functions (IRFs)

In the linear local projection method, the coefficients are not computed recursively, as in the standard linear VAR. They are rather based on the following expression of an optimal forecast (Jordà, 2004, 2005; Misina and Tessier, 2008; Tessier, 2015) which, incidentally, corresponds to the general definition of an impulse response (Hamilton, 1994):

\[
IR(t, s, d_i) = E\left( y_{t+s} | y_t = d_i ; X_t \right) - E\left( y_{t+s} | \theta ; X_t \right) \quad s = 0, 1, 2, \ldots
\]

where \( IR \) is the impulse response at time \( t+s \); \( E(\cdot) \) denotes the best mean-squared error predictor; \( y_t \) is the \( k \times 1 \) vector of endogenous variables; \( X_t = (y_{t-1}, y_{t-2}, \ldots)' \); \( \theta \) is of dimension \( k \times 1 \); \( v_t \) is the \( k \times 1 \) vector of...
reduced-form disturbances, and $\mathbf{d}_t$ is the vector of the experimental shocks. An impulse response is thus a difference between two forecasts: (i) the forecast of $y_t$ when the instantaneous structural shocks are equal to $\mathbf{d}_t$; (ii) the forecast of $y_t$ when the structural shocks are equal to $\mathbf{0}$.

In order to compute the IRFs associated with the local projection approach, we must retain the last $s+1$ observations of the sample as dependent variables of the local projection—i.e., from $y_t$ to $y_{t+s}$. We regress sequentially these vectors on the same set of lagged variables—i.e., $(y_{t-1}, y_{t-2}, \ldots, y_{t-p})$. We thus obtain the following sequence of regressions (Jordà, 2004, 2005; Kilian and Kim, 2011):

$$
y_{t+s} = F_1^h y_{t-1} + F_2^h y_{t-2} + \ldots + F_p^h y_{t-p} + \mu_{t+s} \quad h = 0, \ldots, H
$$

(2)

The corresponding structural impulse responses are:

$$
\Omega_h = \varphi_h P^{-1} = F_1^h P^{-1} \quad h = 0, \ldots, H
$$

(3)

where $P^{-1}$ is the Cholesky triangular matrix used to retrieve the structural shocks. Note that the impulse response coefficients involve the terms $y_{t-1}$ only. Hence, they are not computed recursively, as in the classical linear VAR model. According to Jordà (2004, 2005), they are more robust to misspecifications of the data generating process, thereby avoiding escalation of the misspecification error through the nonlinear calculation of the standard VAR technique as the forecast horizon increases.

2.1.2 The nonlinear local projection method to compute IRFs

The non-linear local projection method we use is based on the following transformation of the local projection model (Jordà, 2004, 2005):

$$
y_{t+s} = B_1^{\epsilon+t} y_{t-1} + B_2^{\epsilon+t} y_{t-2} + \ldots + B_p^{\epsilon+t} y_{t-p} + Q_t^{\epsilon+t} y_{t-1}^2 + \xi_{t+s} \quad s = 0, 1, 2, \ldots, h
$$

(4)

where the observations from $t$ to $t+h$ of our time series are used to compute the IRFs. We thus introduce a quadratic term on the first lag of $y_{t-1}$ to account for the possible nonlinearities linking the endogenous variables.

Adding quadratic terms in the local projection model allows accounting for the conditional volatility of the endogenous variables. To see this, assume that the time series $z_t$ is a pure random variable—i.e., $z_t = \epsilon_t$, and that the conditional variance ($\sigma_t^2$) of $\epsilon_t$ follows an ARCH(1) process:

$$
\sigma_t^2 = \alpha + \beta z_{t-1}^2 = \alpha + \beta z_{t-1}^2.
$$

This simple example shows the close link between the conditional variance of $z_t$ and $z_{t-1}^2$.

The IRFs associated with equation (4) are easily computed as follows:

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8 To obtain the structural impulse response, we must post-multiply equation (1) by the Cholesky triangular matrix $P^{-1}$. See the appendix for detail.

9 We neglect the constant term in this equation.


11 See the Appendix for more detail on this matrix.

12 Note that we can add quadratic terms on lagged values of higher order and also introduce cubic terms in equation (4). However, the formulation given by equation (4) performs the best in the context of our study. Moreover, as noted by Jordà (2004, 2005), since the impulse response coefficients involve only the terms $y_{t-1}$ in the local projection technique, it seems parsimonious to restrict nonlinearities to the first lag alone.
\[ \text{IR}(t, s, d_1) = \hat{B}_i^s d_i + \hat{Q}_i^s \left(2\gamma_{t,1}^s d_1 + d_i^2 \right) \quad s = 0, 1, 2, ..., h \]

Equation (5) thus becomes:

\[ \text{IR}(t, s, d_1) = \hat{B}_i^s d_i + \hat{Q}_i^s \left(2\gamma_{t,1}^s d_1 + d_i^2 \right) \quad s = 0, 1, 2, ..., h \]

As usual, the reduced-form shocks have to be orthogonalised before plotting the IRFs of the endogenous variables.

The confidence interval (CI) of the IRFs computed for non-linear local projections is easily obtained. The \((1 - \alpha)\%\) confidence interval of the IRF is equal to:

\[ CI = IR \pm \left[ z_{1-\alpha/2} \times (w_i \Sigma c_i w_i) \right] \]

where \( w_i = (d_i, 2\gamma_{t,1} d_1 + d_i^2) \), \( \Sigma c_i \) is the HAC variance-covariance matrix of the coefficients, and \( z_{1-\alpha/2} \) denotes the \((1 - \alpha/2)\)-quantile of the \( N(0,1) \) distribution.

The non-linear local projection model presents many advantages over the classical linear VAR procedure (Jordà, 2004, 2005). For instance, in the linear VAR model, shocks are symmetric when they change sign, in the sense that responses to positive and negative shocks are mirror images of each other. By contrast in the non-linear local projection model, the impact of a shock depends on its sign: two shocks of equal amplitude have not necessarily the same impact in absolute value if their sign differs. This is a great improvement over the linear VAR model since it is well-known that the behavior of economic time series is asymmetric—i.e., these series react more to negative than to positive shocks. Moreover, the IRFs resulting from the linear VAR model are not state dependent. This is not the case for the non-linear local projection model as evidenced by equation (5).

### 2.2 The models

We compare two impulse response functions: the benchmark impulse response associated with the canonical linear VAR model (Sims, 1980), and the one computed with the non-linear local projection model. The linear VAR model is described in the Appendix, and the nonlinear projection model is represented by equation (4). Our goal is to investigate the differential impact of the introduction of nonlinearities in the VAR model. We expect that the introduction of squared endogenous variables will give rise to impulse responses of greater magnitude, and more persistent than the classical linear VAR—especially in times of crisis.

To identify structural shocks, 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. After many experiments on
different orderings involving the classical information criteria to select a VAR model—i.e., the AIC, AICc\(^{13}\) and SIC—we order the variables of our setting in the following way:

\[ \text{loans growth} \rightarrow \text{non-interest income growth} \rightarrow \text{GDP growth} \rightarrow \text{interest rate} \rightarrow \text{stock market return} \]

The banking variables are thus placed at the beginning of our ordering. This is consistent with many other studies which position the variables representing banking quality—i.e., loan write-offs, credit losses provisions or bank probability of default—at the start of the ordering (e.g., Hoggarth et al., 2002; Marcucci and Quagliariello, 2006; Puddu, 2012). The ordering of the macroeconomic and financial variables is also consistent with other VAR studies, the financial variables being placed after GDP growth. We therefore postulate that, at the shock impact, the banking variables do not react to macroeconomic and financial shocks.

In our local projection model, the vector of dependent variables, is defined as:

\[
y_t = \left[ d\ln(\text{loans}), d\ln(\text{noi}), d\ln(\text{gdp}), dr, \text{stock}_\text{ret} \right]'
\]

and includes the quarterly growth of total on-balance-sheet loans, the quarterly growth of non-interest income associated with bank non-traditional activities, the quarterly growth of real GDP, the change in the three-month T-bills rate\(^{14}\), and the return of the stock market portfolio\(^{15}\), respectively. Our nonlinear-vector takes the following quadratic form:

\[
y^2_{t-1} = \left[ d\ln(\text{loans})_{t-1}^2, d\ln(\text{noi})_{t-1}^2, d\ln(\text{gdp})_{t-1}^2, dr_{t-1}^2, \text{stock}_\text{ret}^2_{t-1} \right]
\]

### 3. Data and descriptive statistics

#### 3.1. Data

To estimate our VAR model, we rely on two samples, a U.S. sample comprising all commercial banks, and a control sample of all Canadian banks which is used for robustness check. The U.S. banks’ data span the period ranging from the first quarter of 1985 to the fourth quarter of 2013. Bank statistics are provided by the Federal Deposit Insurance Corporation (FDIC). U.S. macroeconomic and financial time series—i.e., GDP, the three-month T-bills rate and the rate of return on the S&P500—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—i.e., GDP, the three-month T-bills rate and the rate of return on the S&P/T SX— are drawn from CANSIM (from Statistics Canada).

\[\text{Insert Table 1 here}\]

\(^{13}\) The AICc is a corrected version of the AIC criterion proposed by Hurvich and Tsay (1993) and specifically designed for VARs. See also Jordà (2005).

\(^{14}\) Since the time series on interest rate is not stationary over our sample period, we express it in first-differences.

\(^{15}\) i.e., the return on the S&P/T SX index for Canada and the return on S&P500 index for the U.S.
3.2 Descriptive statistics

Table 1 provides the descriptive statistics of the time series used in this paper over our sample. To build growth rates, we rely on the following formula: $\log\left(\frac{y_t}{y_{t-1}}\right) \times 100$, where $y_t$ is one of the time series, like GDP. To compute stock returns, we sum monthly returns computed with a similar formula over quarters — i.e., the S&P500 return for the U.S. and the S&P/TSX return for Canada. Not surprisingly, the statistics associated with U.S. and Canadian macroeconomic and financial time series are quite similar. In this respect, from 1985 to 2013, the mean annualized real GDP growth rate has been equal to 2.66% in the U.S. versus 2.54% in Canada and the volatility of the growth rate has been somewhat higher in Canada (2.04%) than in the U.S. (1.76%). Furthermore, the average three-month Treasury bills rate has been higher in Canada (5.31%) than in the U.S. (3.82%) (the Bank of Canada following an official anti-inflationary policy since 1991). This explains partly why the stock market return has been higher in the U.S. (7.89%) than in Canada (6.64%). However, the volatility of the stock return is about equal to 16.5% at an annualized rate in both countries.

Turning to bank data, note that loans growth is higher in Canada than in the U.S. over our sample period, the growth rates being equal to 8.05% and 4.48%, respectively, and that their standard deviations are practically equal (Table 1). However, the U.S. and Canadian banking systems differ more as regards to non-interest income growth. Over the sample period, the mean growth rate was much higher in Canada (10.61%) than in the U.S. (6.72%). Moreover, the standard deviation of this measure of the growth of bank non-traditional activities is also much higher in Canada (16.36%) than in the U.S. (8.37%). Actually, the weight of market-related business lines— e.g., trading and investment banking— is higher in Canadian bank non-traditional activities. Yet, the income stemming from these business lines is more volatile than services fees or fiduciary fees, which represent a greater proportion of U.S. bank non-interest income. Finally, the average share of non-interest income in bank net operating income— i.e., the sum of net interest income and non-interest income— is higher in Canada (41.04%) than in the U.S. (35.61%) over the sample period. This share has peaked to nearly 60% in Canada just before the subprime crisis, while the peak stands below 45% in the U.S. Canadian banks thus focus more on non-traditional business lines than their U.S. counterparts. However, in both countries, the share of non-interest income has regressed markedly since the subprime crisis.

Figure 1 shows the plots of loans growth for U.S. and Canadian banks compared to the behavior of the output gap. In both countries, loans growth is clearly procyclical. For instance, loans growth tends to decrease markedly during recessions. However, the drops are more important in the U.S., the lows of loans growth remaining close to 0 during recessions in Canada. Figure 1 also shows that non-interest income growth is much more volatile in Canada than in the U.S. However, the co-movements between the

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16 Remind that returns computed using logarithms are additive over time.
17 However, note that securitization is more developed in the U.S. than in Canada.
U.S. and Canadian series have been very close since 2002. Finally, Figure 2 plots the respective behavior of the share of bank non-interest income in Canada and in the U.S. Note that the behavior of this share is quite comparable in Canada and in the U.S. over the sample period, and that the share of non-interest income displays procyclicality—especially after the 1997 structural break in bank time series (Calmès and Théoret, 2010, 2014).

4. Empirical results

We compute the impulse response functions of our models with three lagged values for our $y_t$ vector (equation (8)), on the basis of the usual information criteria—i.e., the AIC, AIC$_c$ and SIC criteria. We select only one lag for our $y_{t-1}$ vector (equation (9)) since only the first lags of the endogenous variables enter in the computation of the IRFs when using the local projection method (LP)$.^{18}$ Given the restricted dimension of our sample, we do not resort to $y_{t-1}^3$ (cubic) factors in our regressions. Finally, note that our shocks are equal to one standard error innovation associated with the equations of the endogenous variables$.^{19}$

4.1. IRFs over the whole sample period

4.1.1 Direct effects of the real economy on banking

Figure 3 provides the IRFs of U.S. banks over an horizon of 20 quarters ($h = 20$ in equation (4)) for the whole sample period, while Figure 4 delivers the same information for an horizon of 12 quarters ($h = 12$). We first resort to an horizon of 20 quarters since the VAR process may take a long time before converging (Calmès and Théoret, 2016). Additionally, the confidence intervals of the IRFs associated with the LP processes correspond to an alpha of 10% rather than the conventional 5%. Indeed, the bank times series used in this study, and especially non-interest income growth, are quite volatile (Table 1). Since these variables are squared in the LP estimations, they introduce much noise in the computations, so we need to enlarge confidence intervals for the evaluation of the IRFs.

Figure 3 shows that the IRFs corresponding to the own shocks of the endogenous variables may differ substantially, depending on the process used to compute them. The convergence of the shocks related to the linear VAR is always smooth and usually U-shaped. In contrast, the IRFs obtained with the non-linear LP process may display a cyclical pattern which is quite apparent for some volatile variables—as for the S&P500 return and non-interest income growth. This cyclical behaviour may produce instability in the IRFs of the off-diagonal plots. The shocks are also more persistent with the LP process.

$^{18}$ We experimented with two lags for the quadratic term but the results were essentially the same.

$^{19}$ Judge et al. (1988) refer to these shocks as “surprise innovations in the endogenous variables”. The shocks should thus be unexpected.
The IRFs properties related to the own shocks should result in different shapes for the other IRFs, depending on the estimation method—VAR or non-linear LP.

Not surprisingly, loans growth increases significantly following a GDP (positive) shock. However, it does not respond as significantly to an interest rate shock, as usually mentioned in the literature on the lending channel of monetary policy (e.g., Black and Rosen, 2007). This result does not necessarily invalidate the existence of a lending channel at disaggregate levels20.

Non-interest income growth also increases substantially following a GDP shock (with LP), the upward cycle lasting about ten quarters—whereas the reaction delivered by the benchmark VAR is quasi-inexistent. The procyclicality we can detect in the nonlinear setup may be explained by the product-mix of U.S. banks’ non-traditional activities, in which fees that co-move with GDP growth—especially services fees and fiduciary fees—have an important weight (Calmès and Théoret, 2015). Contrary to loans growth, non-interest income growth also decreases significantly following an interest rate shock, albeit with delay. In other words, our experiments do not seem to suggest the presence of any waterbed effect—once nonlinearities are properly factored in21. Indeed, our results might rather suggest that the negative impact of the interest rate on bank non-interest income growth stems from the interest rate volatility, a dimension not captured within the framework of Nelson et al. (2015), and Beck et al. (2016).

This procyclicality of non-interest income growth is in line with the results of Stiroh (2004), but contradicts the findings of Albertazzi and Gambacorta (2009). For Albertazzi and Gambacorta (2009), revenue diversification should contribute to the stabilization of bank profitability. However, this argument is at odds with most existing studies, especially the works of Boyd and Gertler (1994), Stiroh (2004), Stiroh and Rumble (2006), Geyfman and Yeager (2009), Wagner (2010) and Calmès and Théoret (2010, 2014)22 which instead point to increased risk-taking rather than just more flexible risk management. Moreover, Albertazzi and Gambacorta (2009) do not find any significant relationship between non-interest income and the interest rate either. As in other instances, the results obtained by these authors are likely due to the fact that they do not consider any role for nonlinearity in their models—whilst the procyclicality of non-interest income growth and its dependence to the interest rate are mainly driven by nonlinearities.

4.1.2 The feedback effects of banking on macroeconomic dynamics

Turning to the feedback (indirect) effects of bank internal shocks on the real economy, our primary focus, first note that, consistent with Marucci and Quagliariello (2006), and Puddu (2012), we find that a credit shock has a surprisingly significant positive feedback effect on GDP growth when computed with LP, while it is quite weak when using the benchmark linear VAR model (Figure 3). An additional novelty is the the positive feedback effect of a fee-based shock on GDP growth. This new result obtains regardless

20 In this respect, Black and Rosen (2007) find that a restrictive monetary policy does not impact the aggregate of bank loans. However, during periods of tight credit, banks reallocate their loan supply from long-term to short-term loans, which is consistent with the lending channel.

21 Bear in mind that we focus on commercial banks, a sample which differs from Nelson et al. (2015). The waterbed effect might still be present for non-bank financial intermediaries.

22 According to Alessandri and Nelson (2015), the structural decline in interest rates has depressed the net interest margins of banks, which prompted them to diversify their operations in activities which offer a higher yield, and thus embed more risk.
of the method employed, whether VAR or LP. As a matter of fact, the fee-based feedback effect is even significant at the 5% level. Importantly, note that the similarity of the results derived from the VAR and LP suggests, in contrast to Puddu (2012), that the feedback effect of a fee-based shock does not seem to stem from nonlinearity, at least over the whole sample period. Differences are more noticeable with the stock market, where the fee-based impact is cyclical and more persistent with LP, while it converges quickly without displaying fluctuations with the VAR.

Finally, when we estimate our reduced form model over a shorter horizon—twelve quarters corresponding to the expansion period 2011-2013—the impact of external shocks on bank data remain similar, but the feedback effects of credit and fee-based shocks are even more significant with $h=12$ (despite the fact that this subsample excludes the subprime crisis, Figure 4). Importantly, the feedback effect of a fee-based shock on real GDP growth remains significant at the 5% level, and similarly to the feedback effect of a credit shock, it is significant regardless of the method of estimation used.

### 4.2 IRFs after the 1997 structural break

Under very general conditions, stationary processes may be approximated by VAR processes (Judge et al., 1988). But many types of nonstationarities—like a structural break—cannot be captured by a classical VAR model. Nonstationarity can lead to biased IRFs since the parameters of the VAR, which are used to simulate the IRFs, are estimated using OLS. Incidentally, Calmès and Théoret (2010, 2014) have identified a structural break in U.S. and Canadian time series around 1997. In this Section, we thus re-compute our IRFs over the period spanning from 1997 to 2013, and make a local projection over three years of economic expansion ($h=12$). This experiment provides quite similar results for U.S. banks (Figure 5). Our results thus seem to be robust to this structural break. In particular, the feedback effect of a fee-based shock on GDP growth retains its high degree of significance, while the feedback effect of a credit shock on GDP growth is even higher over this subsample (when using LP).

Summing up our experiments using positive shocks, we find that asymmetries are less important during normal times, but still play a role in shaping the series pattern. In particular, consistent with Puddu (2012), we find that two impulse responses depend crucially on non-linearities: the impulse response of non-interest income growth to an interest rate shock, and the feedback effect of a credit shock on real GDP growth. Finally, in expansion, the feedback effect of a fee-based shock on real GDP growth is positive, even when computed with the benchmark linear VAR.

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23 In this respect, even if the Gramm-Leach-Bliley Act (GLBA)—which authorized U.S. commercial banks to get involved in investment banking—was only passed in 1999, it may be considered as a “rubber stamp” endorsing an already common practice (Yeager et al., 2007; Leach, 2008; Geyfman and Yeager, 2009).
4.3 Simulating with negative shocks over the subprime crisis period

In linear VAR models, the impact of positive and negative shocks is symmetric, in the sense that a negative shock is the mirror image of a positive one (Jordà 2004, 2005). However, it is well-known that the impact of negative shocks can be greater, in absolute value, than the one of positive shocks. Actually, financial institutions are confronted to many frictions during crises or recessions—like financial constraints or asymmetric information and agency problems—which push them to deleverage. In this respect, recent models of shadow banking predict a greater deleveraging process in universal banking, leading to fire sales of assets and concomitant spillover effects of banking shocks on the economy (Shleifer and Vishny, 2010; Gennaioli et al., 2013; Meeks, 2014; Santos and Veronesi, 2016). The nonlinear LP process is particularly well-suited to study this kind of asymmetric behavior. We thus investigate the impact of negative shocks over three periods in order to better qualify our results, and for the sake of robustness checks. We first consider the whole sample period (1985-2013), in order to analyze the asymmetry of negative and positive shocks. We next consider the 1985-2010 period with $h=12$, which corresponds to a forecast over the subprime crisis. We include the year 2007 in our information set because the first signs of the crisis actually appeared in June 2007, with the problems of Bear Sterns. We thus introduce all the year 2007 in our information set for this set to include some prior information on the subprime crisis. We also include the year 2010 in our forecast since the crisis had persistent effects over this year. Finally, we replicate the same simulation over the period 1997-2010—i.e., after the structural break.

Insert Figure 6 here

Over the period 1985-2013—the horizon of the projection being twelve quarters—we note two important features. First, the positive impact of a negative interest rate shock on non-interest income growth becomes significant only after a long lag (eight quarters). This represents an obvious asymmetry with respect to a positive interest rate shock, for which the reaction is quicker (Figure 4). Second, as expected, the feedback effect of a credit shock or of a fee-based shock is more important (in absolute value) than with positive shocks, as nonlinear or asymmetric effects are more at play with negative shocks. For instance, the feedback effect of a (negative) fee-based shock on real GDP growth is now significant at the 1% level, and is more important and more persistent with LP than with the VAR. In this respect, after four quarters, the decrease in real GDP growth is equal to 1% with LP, and to 0.5% with the VAR. The negative feedback effect of a fee-based shock on the stock market is also greater and more significant with negative than with positive shocks. Turning to the feedback effect of a credit shock, note that, after four quarters, there is a 0.4% decrease in real GDP growth with LP and 0.2% with the VAR. The results do not differ markedly when simulating over the period 1985-2010 (Figure 7).

Insert Figures 7 and 8 here

24 For the sequence of the subprime crisis, see Veronesi (2010).
25 In this section, we also envision negative shocks for interest rates since they tend to decrease during crises.
Simulating over the 1997-2010 period (Figure 8) rather than over the 1985-2010 one (Figure 7)—i.e., after the structural break—provides several additional results. First, the negative impact of a GDP shock to loans growth is more important and lasts longer—especially with LP. Second, when computed with LP—the IRF obtained with the VAR being not conclusive—the response of loans growth to a (negative) interest rate shock is significantly negative at impact, and significantly positive after a long lag (seven quarters)—this latter effect being more important and lasting longer than the former one. Our interpretation of this phenomenon is that the supply of loans might react at impact to an interest rate shock, then followed by a strengthening of the demand for loans. The lending channel thus seems to be at play during the subprime crisis. The positive response of non-interest income growth to an interest rate shock is also greater after the structural break, as it is the case for its response to a GDP shock (negative and cyclical). Third, the feedback effect of a credit shock on real GDP growth seems to weaken after the structural break, while the corresponding feedback effect of a fee-based shock is obviously stronger. (The results are similar regarding the feedback effect of a fee-based shock on the stock market.)

Summarizing, the effects of shocks are clearly asymmetric, depending on the phase of the business cycle, and most results regarding the feedback effects of banking seem to hold even further when considering negative shocks. Indeed, our simulations confirm that nonlinearities are more at play during crises, likely because the volatility of the endogenous variables—i.e., a measure of uncertainty—impacts more the behavior of the IRFs during these periods. In this respect, the feedback effect of a fee-based shock on real GDP growth is more important after the structural break of 1997, but also when (i) uncertainty increases during crises, which gives rise to an IRF of a greater amplitude with LP; (ii) shocks are negative, which results in a much significant feedback effect. Our main point is thus reinforced, as we find that bank fee-based activities are more sensitive to external shocks than bank traditional ones, and more importantly that they are also responsible for most of the feedback effects from the banking sector to the real economy. Overall, these results support the idea that the consolidation of U.S. universal banking system begun in the late 90s seems to increase banking procyclicality, especially during crises.

5. Robustness checks

In this Section, we perform two robustness checks. First, we apply our models to the Canadian banking system. Second, we investigate if the feedback effect from a fee-based shock on the real sector remains significant when abstracting from extreme events such as the subprime crisis. Ideally, these episodes should strengthen results, not drive them.

5.1 Feedback effects in the Canadian banking system

Over the whole sample period (1985-2013) and with h=12—i.e, when simulating over the expansion period 2011-2013—the results of the IRFs are less significant for Canadian than for U.S. banks (Figure 9). We attribute this divergence to a greater structural break in the Canadian banks' time series.
which—in line with U.S. banks—occurred around 1997 (Calmès and Théoret, 2010, 2014). Regarding the significant IRFs, we note, as expected, that loans growth reacts positively to a GDP shock, the results being similar with the VAR and LP. Not surprisingly, non-interest income growth co-moves negatively with an interest rate shock and positively with a shock on the TSX return. Similarly to the U.S., we also note that a fee-based shock impacts GDP growth positively. However, in contrast to U.S. banks, the impact is more persistent with LP. Another significant difference between the Canadian and U.S. banking systems lies in the feedback effect of a credit shock on real GDP growth, which is significantly negative in Canada—although after a long lag. This link may be related to the depressing impact of loan defaults which may gain strength after a positive loans shock. It can also be due to the impact of the increase in the short-term interest rate which accompanies the increase in GDP. According to Alessandri and Nelson (2015), this increase prompts banks to rise their net interest margin, which co-moves negatively with the level of bank assets. Finally, in line with U.S. banks, a fee-based shock impacts positively the TSX return, the impacts computed with the VAR and LP being similar.

We now examine how asymmetries in the impulse response functions evolve during the subprime crisis and how the 1997 structural break impacts the dynamics. We thus first simulate negative shocks during the subprime crisis (h=12) over the period 1985-2010 (Figure 10) and then over the period 1997-2010—i.e., in the aftermath of the structural break (Figure 11). In line with U.S. banks, the IRFs computed with LP are more significant when simulating negative shocks. However, when we compare the projections performed over the period 1985-2010 to the period 1997-2010, we note that the impact of the structural break was greater for Canadian than for U.S. banks, in the sense that the IRFs display a higher amplitude and are more significant after the structural break, so we discuss only the results obtained after the break. Nonetheless, the IRFs computed over the period 1985-2010 are in the same direction as the ones obtained over the period 1997-2010.

The impact of a negative GDP shock on loans growth is significantly negative at the impact but it reverses quickly and becomes significantly positive after four quarters, a dynamics not observed with the VAR (Figure 11). In contrast, non-interest income growth decreases by 10% after four quarters following a negative GDP shock with LP while the impact is negligible with the VAR. When accounting for nonlinearities, non-interest income growth is thus quite procyclical. The uncertainty (volatility) related to GDP growth is a major factor explaining the procyclicality of non-interest income growth. Non-interest income growth is also very sensitive to an interest rate shock during the subprime crisis, a negative interest rate shock in the order of 30 basis points leading to a 7% increase in non-interest income growth during the crisis, while this impact is negligible when relying on the VAR. The greater response of Canadian banks’ fee-based activities to a negative interest rate shock may be explained by the higher...
weight of market-based claims in Canadian banks' non-traditional activities compared to U.S. banks (Calmès and Théoret, 2015). Similarly, non-interest income growth decreases more with LP following a negative stock market shock and the corresponding IRF displays cycles, which is not the case with the VAR.

Turning to the feedback effects of banking shocks, consistent with our analysis over the period 1985-2013, a negative loans shock impacts positively GDP growth after six quarters. However, this impact is quite moderate. More importantly, we note that a negative fee-based shock has a very significant adverse impact on GDP growth after six quarters when using LP, which is the triple of the impact associated with the VAR. The impact is very persistent with LP while it dies off quickly with the VAR. The interest rate tends to decrease after 6 quarters following a negative fee-based shock, this impact being much lower with the VAR. The stock market return also tends to decrease substantially following a negative fee-based shock when relying on LP, this impact being negligible with the VAR. Finally, the interest rate is very sensitive to a negative GDP shock during the crisis. Following the shock, it decreases quickly and the impact is almost double with LP than with the VAR.

Summing up, excepting credit shocks, we note similar feedback effects in both U.S. and Canadian banking systems. Moreover, the asymmetries related to negative shocks are more important when simulating over the period 1997-2010 than over the period 1985-2010, which indicates the influence of the 1997 structural break on Canadian banks' time series.

5.2 Simulating before the subprime crisis

Figure 12 reports the simulations before the subprime crisis (1985-2006) for U.S. banks while Figure 13 provides the same plots for Canadian banks. Our results are essentially unchanged. More precisely, a fee-based shock impacts positively and significantly real GDP growth in both banking systems. In other respects, the credit shocks retain their power in both countries albeit, consistent with our previous results, they operate in opposite directions. Finally, non-interest income growth reacts negatively to a positive interest rate in both countries, although a significant response is observed after a quite long delay.

6. Conclusion

The three main scenarios we investigate are simulations over a recent expansion period, during the subprime crisis, and around the 1997 structural break. Not surprisingly, asymmetries—as given by the differences in the IRFs computed with our non-linear LP versus the linear case—seem to be more at play during downturns. During normal times however, even if nonlinearities disturb less the dynamics of the IRFs, we find that they still remain significant. Our conclusion is that the IRFs usually computed with the linear VAR model are roughly consistent with the ones obtained with a LP process in most
simulations, but yet differ in amplitude, cyclicalit\textsuperscript{27}y, and explanatory power. In this framework, our main contribution is to show that there are significant feedback effects associated with bank fee-based shocks on the stock market, and especially on real GDP growth. For instance, we find that the IRFs of a bank fee-based shock on GDP growth are significant and quite similar when using VAR or LP during the expansion period analyzed (2011-2013), whereas the forecast over the subprime crisis with adverse shocks reveals that the amplitude of the IRFs is more than double when computed with LP, and, more importantly, that they display a higher degree of persistence.

Our results suggest that a credit shock has also a significant feedback effect on real GDP and, consistent with Puddu (2012), this impact depends crucially on nonlinearities. However, more controversially, our main result suggests that bank non-interest income growth is procyclical in normal times and in downturns, and this procyclicality is mainly related to nonlinearities. Hence, in contrast to Albertazzi and Gambacorta (2009), ceteris paribus, diversification in non-traditional business lines does not contribute to stabilize bank profits (Stiroh, 2004; Stiroh and Rumble, 2006; Calmès and Théoret, 2010, 2014). Once nonlinearities are rigorously accounted for, non-interest income growth decreases significantly following a positive interest rate shock, so that the direct effect, mainly due to the interest rate volatility, does not seem to neither support the so called “waterbed effect” hypothesis (Nelson et al., 2015; Beck et al., 2016).

These findings have important policy implications. Inasmuch as bank non-traditional activities generate a significant feedback effect on real GDP and the stock market, and to the extent that this impact seems to be more important than the feedback effect of traditional activities—especially during crises—regulatory authorities should obviously monitor these activities more closely than they do. This monitoring is all the more important since our findings suggest that the procyclicality of non-interest income growth has increased since the last banking crisis. Central banks should also focus more on the risk channel transmission of monetary shocks, because non-interest income growth is surprisingly more sensitive to changes in interest rates than loans growth itself.

\textsuperscript{27}In this respect, remind that the linear VAR model can only lead to symmetric shocks while the non-linear LP process embeds asymmetric shocks.
Appendix

The linear VAR model

To get a better grasp on an IRF computed with the nonlinear local projection procedure, we
show how it is computed with the classical linear VAR model since local projection is a kind of VAR.
Assume the following k-dimensional structural VAR (Sims, 1980):
\[ Py_t = A_1 y_{t-1} + A_2 y_{t-2} + \ldots + A_p y_{t-p} + \varepsilon_t \]  
(10)
where \( y_t = (y_{t1}, \ldots, y_{tk})' \), \( P \) is of dimension \( k \times k \) and \( E(\varepsilon_t, \varepsilon_t') = \Sigma_e \). To reduced form of equation (10) is obtained by multiplying it by \( P^{-1} \), i.e.,
\[ y_t = P^{-1} A_1 y_{t-1} + P^{-1} A_2 y_{t-2} + \ldots + P^{-1} A_p y_{t-p} + P^{-1} \varepsilon_t = B_1 y_{t-1} + B_2 y_{t-2} + \ldots + B_p y_{t-p} + \mu_t \]  
(11)
where \( E(\mu_t, \mu_t') = \Sigma_\mu \).
The structural shocks \( \varepsilon_t \) may thus be retrieved from reduced form shocks \( \mu_t \) by resorting to: \( P^{-1} \mu_t = \varepsilon_t \).
The matrix \( P \)—which makes the shocks orthogonal—is obtained using the following Cholesky factorization (Judge et al., 1988): \( P \Sigma_p P' = I \) —i.e., \( \Sigma_p = (P')^{-1} \). However, the matrix \( P \) is not unique; it depends on the ordering of shocks. Shocks must be ordered from the most exogenous to the most endogenous. After the ordering of the shocks, we obtain a lower triangular matrix \( P \). At the top of this matrix we find the shock which react only to its own shocks at the impact. Conversely, at the bottom of this matrix, we find the shock which reacts, at the impact, to its own shocks and to the shocks of all endogenous variables. In our setting, the principal diagonal of \( P^{-1} \) is equal to one-standard deviation of the shocks ordered from the most exogenous to the most endogenous.

The coefficients of the IRF function over the horizon \( \{1, \ldots, h\} \) can be computed recursively, the recursive equation to compute the IRF coefficients being (Kilian and Kim, 2011):
\[ \theta_h = \Phi_h P^{-1} = \sum_{s=1}^{h} \Phi_s B_s P^{-1} \]
(12)
with \( \Phi_0 = I_k \). For instance, \( \theta_1 = B_1 P^{-1} \), \( \theta_2 = (B_1^2 + B_2) P^{-1} \), \( \theta_3 = (B_1^3 + B_1 B_2 + B_2 B_1 + B_3) P^{-1} \), and so on.

If the VAR includes only one lag for each endogenous variable—i.e., if \( p = 1 \)—we then have: \( \theta_1 = B_1 P^{-1} \), \( \theta_2 = (B_1^2) P^{-1} \), \( \theta_3 = (B_1^3) P^{-1} \), and so on. In this case, the coefficients of the IRF can be viewed as multipliers of the individual structural shocks.\(^{28}\)

\(^{28}\) Actually, in the classical linear VAR, we often view the coefficients of the IRF as multipliers even if \( p > 1 \).
References


Pescatori, A., Solé, Juan. 2016. Credit, securitization and monetary policy: Watch out for unintended consequences. Working paper, IMF.


**Tables**

**Table 1** Descriptive statistics

<table>
<thead>
<tr>
<th></th>
<th>GDP growth</th>
<th>3-month T-Bills</th>
<th>Stock market return</th>
<th>Loans growth</th>
<th>Non-interest income growth</th>
<th>Share of non-interest income</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>US</td>
<td>Canada</td>
<td>US</td>
<td>Canada</td>
<td>US</td>
<td>Canada</td>
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<tr>
<td>mean</td>
<td>2.66</td>
<td>2.54</td>
<td>3.82</td>
<td>5.31</td>
<td>7.89</td>
<td>6.64</td>
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<tr>
<td>standard deviation</td>
<td>1.76</td>
<td>2.04</td>
<td>2.47</td>
<td>3.55</td>
<td>16.30</td>
<td>16.56</td>
</tr>
<tr>
<td>minimum</td>
<td>-4.77</td>
<td>-3.75</td>
<td>-0.01</td>
<td>0.19</td>
<td>-51.18</td>
<td>-45.08</td>
</tr>
<tr>
<td>maximum</td>
<td>5.14</td>
<td>6.34</td>
<td>8.54</td>
<td>13.54</td>
<td>34.21</td>
<td>48.49</td>
</tr>
</tbody>
</table>

Sources: FDIC; Federal Reserve Bank of St-Louis (FRED); Bank of Canada; Canadian Bankers Association; Statistics Canada (CANSIM).
Figures

Figure 1 U.S. and Canadian banks’ loans growth and non-interest income growth

Loans growth

U.S.

Non-interest income growth

Canada

Notes: 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. Shaded areas correspond to recessions.

Sources: FDIC; Federal Reserve Bank of St-Louis (FRED); Bank of Canada; Canadian Bankers Association; Statistics Canada (CANSIM).
**Figure 2** Shares of non-interest income: U.S. and Canadian banks

Notes: 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. Shaded areas correspond to recessions.

Sources: FDIC; Federal Reserve Bank of St-Louis (FRED); Bank of Canada; Canadian Bankers Association; Statistics Canada (CANSIM).
**Figure 3** U.S. banks’ impulse response functions computed with linear VAR and local projection over the period 1985-2013 with $h=20$

<table>
<thead>
<tr>
<th>Shocks ↓</th>
<th>GDP growth shock</th>
<th>interest rate shock</th>
<th>stock market shock</th>
<th>credit shock</th>
<th>fee-based shock</th>
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</thead>
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<td>GDP growth</td>
<td>GDP growth shock</td>
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<td>US GDP to RSP500 shock</td>
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<tr>
<td>TB3 to RSP500 shock</td>
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<tr>
<td>TB3 to Loans growth</td>
<td>TB3 to Loans growth</td>
<td>TB3 to Loans growth</td>
<td>TB3 to Loans growth</td>
<td>TB3 to Loans growth</td>
<td>TB3 to Loans growth</td>
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<tr>
<td>US GDP to non-interest income growth</td>
<td>US GDP to non-interest income growth</td>
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Notes: These plots represent the impulse responses of the endogenous variables to their own shocks (on the diagonal) and to shocks of the other variables. The outer dotted lines embed the 90% confidence interval associated with local projection. The inner dotted line is the impulse response function related to the non-linear local projection while the solid line is the impulse response function related to the conventional linear VAR model. $h$ denotes the horizon of the impulse response.

**Figure 4** U.S. banks’ impulse response functions computed with linear VAR and local projection over the period 1985-2013 with $h=12$
Notes: These plots represent the impulse responses of the endogenous variables to their own shocks (on the diagonal) and to shocks of the other variables. The outer dotted lines embed the 90% confidence interval associated with local projection. The inner dotted line is the impulse response function related to the nonlinear local projection while the solid line is the impulse response function related to the conventional linear VAR model. h denotes the horizon of the impulse response.
**Figure 5** U.S. banks’ impulse response functions computed with linear VAR and local projection over the period 1997-2013 with $h=12$

Notes: These plots represent the impulse responses of the endogenous variables to their own shocks (on the diagonal) and to shocks of the other variables. The outer dotted lines embed the 90% confidence interval associated with local projection. The inner dotted line is the impulse response function related to the nonlinear local projection while the solid line is the impulse response function related to the conventional linear VAR model. $h$ denotes the horizon of the impulse response.

**Figure 6** U.S. banks’ impulse response functions computed with linear VAR and local projection over the period 1985-2013 with $h=12$: Negative shocks.
Notes: These plots represent the impulse responses of the endogenous variables to their own shocks (on the diagonal) and to shocks of the other variables. The outer dotted lines embed the 90% confidence interval associated with local projection. The inner dotted line is the impulse response function related to the nonlinear local projection while the solid line is the impulse response function related to the conventional linear VAR model. \( h \) denotes the horizon of the impulse response.

Figure 7 U.S. banks’ impulse response functions computed with linear VAR and local projection over the period 1985-2010 with \( h=12 \): Negative shocks.
Notes: These plots represent the impulse responses of the endogenous variables to their own shocks (on the diagonal) and to shocks of the other variables. The outer dotted lines embed the 90% confidence interval associated with local projection. The inner dotted line is the impulse response function related to the nonlinear local projection while the solid line is the impulse response function related to the conventional linear VAR model. \( h \) denotes the horizon of the impulse response.

Figure 8 U.S. banks’ impulse response functions computed with linear VAR and local projection over the period 1997-2010 with \( h=12 \): Negative shocks.
Notes: These plots represent the impulse responses of the endogenous variables to their own shocks (on the diagonal) and to shocks of the other variables. The outer dotted lines embed the 90% confidence interval associated with local projection. The inner dotted line is the impulse response function related to the nonlinear local projection while the solid line is the impulse response function related to the conventional linear VAR model. \( h \) denotes the horizon of the impulse response.

**Figure 9** Canadian banks’ impulse response functions computed with linear VAR and local projection over the period 1985-2013 with \( h=12 \)
Notes: These plots represent the impulse responses of the endogenous variables to their own shocks (on the diagonal) and to shocks of the other variables. The outer dotted lines embed the 90% confidence interval associated with the local projection. The inner dotted line is the impulse response function related to the nonlinear local projection, while the solid line is the impulse response function related to the conventional linear VAR model. \( h \) denotes the horizon of the impulse response.

**Figure 10** Canadian banks' impulse response functions computed with linear VAR and local projection over the period 1985-2010 with \( h=12 \): Negative shocks.
Notes: These plots represent the impulse responses of the endogenous variables to their own shocks (on the diagonal) and to shocks of the other variables. The outer dotted lines embed the 90% confidence interval associated with local projection. The inner dotted line is the impulse response function related to the nonlinear local projection, while the solid line is the impulse response function related to the conventional linear VAR model. $h$ denotes the horizon of the impulse response.

Figure 11 Canadian banks’ impulse response functions computed with linear VAR and local projection over the period 1997-2010 with $h=12$: Negative shocks.
Notes: These plots represent the impulse responses of the endogenous variables to their own shocks (on the diagonal) and to shocks of the other variables. The outer dotted lines embed the 90% confidence interval associated with local projection. The inner dotted line is the impulse response function related to the nonlinear local projection while the solid line is the impulse response function related to the conventional linear VAR model. \( h \) denotes the horizon of the impulse response.

**Figure 12** U.S. banks’ impulse response functions computed with linear VAR and local projection over the period 1985-2006 with \( h=12 \).
Notes: These plots represent the impulse responses of the endogenous variables to their own shocks (on the diagonal) and to shocks of the other variables. The outer dotted lines embed the 90% confidence interval associated with local projection. The inner dotted line is the impulse response function related to the nonlinear local projection while the solid line is the impulse response function related to the conventional linear VAR model. h denotes the horizon of the impulse response.

Figure 13 Canadian banks’ impulse response functions computed with linear VAR and local projection over the period 1985-2006 with h=12.
Notes: These plots represent the impulse responses of the endogenous variables to their own shocks (on the diagonal) and to shocks of the other variables. The outer dotted lines embed the 90% confidence interval associated with local projection. The inner dotted line is the impulse response function related to the nonlinear local projection while the solid line is the impulse response function related to the conventional linear VAR model. \( h \) denotes the horizon of the impulse response.