University of Groningen

Loan loss provisioning, bank credit and the real economy

Pool, Sebastiaan; de Haan, Leo; Jacobs, Jan P. A. M.

Published in:
Journal of Macroeconomics

DOI:
[10.1016/j.jmacro.2015.04.006](https://doi.org/10.1016/j.jmacro.2015.04.006)

IMPORTANT NOTE: You are advised to consult the publisher's version (publisher's PDF) if you wish to cite from it. Please check the document version below.

Document Version
Publisher's PDF, also known as Version of record

Publication date:
2015

[Link to publication in University of Groningen/UMCG research database](#)

Citation for published version (APA):

Pool, S., de Haan, L., & Jacobs, J. P. A. M. (2015). Loan loss provisioning, bank credit and the real economy. *Journal of Macroeconomics*, 45, 124-136. <https://doi.org/10.1016/j.jmacro.2015.04.006>

Copyright

Other than for strictly personal use, it is not permitted to download or to forward/distribute the text or part of it without the consent of the author(s) and/or copyright holder(s), unless the work is under an open content license (like Creative Commons).

The publication may also be distributed here under the terms of Article 25fa of the Dutch Copyright Act, indicated by the "Taverne" license. More information can be found on the University of Groningen website: <https://www.rug.nl/library/open-access/self-archiving-pure/taverne-amendment>.

Take-down policy

If you believe that this document breaches copyright please contact us providing details, and we will remove access to the work immediately and investigate your claim.

Downloaded from the University of Groningen/UMCG research database (Pure): <http://www.rug.nl/research/portal>. For technical reasons the number of authors shown on this cover page is limited to 10 maximum.

Loan loss provisioning, bank credit and the real economy[☆]

Sebastiaan Pool^{a,b,*}, Leo de Haan^b, Jan P.A.M. Jacobs^{a,c}

^a University of Groningen, The Netherlands

^b De Nederlandsche Bank, The Netherlands

^c University of Tasmania, CAMA and CIRANO, Australia

ARTICLE INFO

Article history:

Received 16 October 2014

Accepted 15 April 2015

Available online 28 April 2015

JEL classification:

E32

E44

G21

Keywords:

Loan loss provisioning

Bank lending

Business cycle

ABSTRACT

This paper examines how credit risk affects bank lending and the business cycle. We estimate a panel Vector Autoregression model for an unbalanced sample of 12 OECD countries over the past two to three decades, consisting of the output gap, inflation, the short-term interest rate, bank lending, as well as loan loss provisioning by banks (as proxy for credit risk). Our main findings are that: (i) bank lending and loan loss provisioning are important drivers of business cycle fluctuations, (ii) loan loss provisioning decreases in relative terms as bank lending increases, and (iii) bank lending is primarily affected by output fluctuations.

© 2015 Elsevier Inc. All rights reserved.

1. Introduction

The recent financial crisis has shown that bank credit is an important determinant of business cycle fluctuations. Before the crisis, bank credit was abundant (Adrian and Shin, 2009), boosting economic growth. During the crisis, credit default risk, i.e., the risk that a borrower is unable to pay back a bank loan, increased, restraining the issuance of new bank loans.

In this paper we examine how credit default risk affects bank lending and the business cycle. As a measure of credit default risk, we use loan loss provisioning by banks. While most of the literature on loan loss provisioning examines its determinants, we are especially interested in how loan loss provisioning affects credit and the real economy. Until now the effect of loan loss provisioning on the real economy only received limited attention in the literature. Furthermore, most previous studies use bank-level data instead of macro data.

Bank loan loss provisioning may be either procyclical or countercyclical, depending on whether provisioning is backward-looking (sometimes called ‘non-discretionary’) or forward-looking (‘discretionary’). Backward-looking provisioning relates provisioning to the occurrence of problem loans. This has as potential drawback that expected credit losses are underprovisioned during upswings, when few problem loans are identified and hence the level of provisioning is low. Conversely, during downturns provisioning increases because credit defaults are high. As a result, backward-looking

[☆] Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank. The authors would like to thank the Editor and two anonymous referees, as well as Jan Marc Berk, Jakob de Haan and seminar participants at DNB for comments, and Martin Admiraal for his assistance with the data.

* Corresponding author at: University of Groningen, The Netherlands.

E-mail address: s.pool@rug.nl (S. Pool).

provisioning is procyclical.¹ In contrast, forward-looking provisioning is countercyclical. Banks estimate their expected credit losses over the business cycle and build up provisions during upswings and draw down on them during downturns.

Accounting rules contribute to backward looking provisioning, as they tend to allow provisions based on past events, not on expectations (Borio and Lowe, 2001). International Financial Reporting Standards (IFRS) utilize a so-called ‘incurred loss model’ where loan losses are recognized only after loss events have occurred prior to the reporting date that are likely to result in future non-payment of loans. This is the so-called International Accounting Standard (IAS) 39 rule under IFRS. This rule does not allow for consideration of future expected losses based on trends suggestive of additional future losses (Bushman and Williams, 2012).

Most of the empirical finance literature confirms backward-looking provisioning. Bikker and Metzmakers (2005) find evidence of a negative relation between GDP growth and provisioning for 29 OECD countries, implying backward looking practices. This procyclicality is mitigated partly by the positive relation between banks’ earnings and provisions, which might be due to either income smoothing or forward looking provisioning. Laeven and Majnoni (2003) also find evidence that banks around the world are less prudent during periods of rapid credit growth, in the sense that under favorable conditions banks postpone provisioning until unfavorable conditions set in. Bouvatier and Lepetit (2008) examine the impact of loan loss provisions on bank lending using a sample of 186 European banks for the period 1992–2004. They find that backward looking provisioning amplifies credit fluctuations, while forward looking provisioning or income smoothing does not. Empirical work by Jiménez et al. (2012), examining the impact of countercyclical capital buffers on credit supply using countercyclical ‘dynamic’ provisioning experiments in Spain, find that countercyclical capital buffers help smooth credit supply cycles.

The usefulness of loan loss provisioning for macroprudential regulation has recently also received attention in the theoretical literature. Bouvatier and Lepetit (2012), in a partial equilibrium framework, show that forward-looking provisions can eliminate procyclicality in lending standards induced by backward-looking provisions. Agénor and Zilberman (2013), in a calibrated DSGE model, show that forward-looking loan loss provisions can reduce volatility in financial and real variables by mitigating the changes in the stock of loan-loss reserves over the course of the business cycle. Zilberman and Tayler (2014) examine the interaction between loan loss provisioning rules, business cycle fluctuations and monetary policy in a DSGE model with endogenous credit risk. These authors highlight the importance of forward-looking provisions in mitigating welfare losses, as well as how accounting rules with respect to loan loss provisions alter the transmission mechanism of monetary policy.

For our analysis we set up a macroeconomic framework including a banking sector and credit default risk. The aim of our paper is not to establish a new theoretical framework, but to underpin our empirical panel VAR model with a theoretical framework. Therefore, we simplify an established theoretical framework to bring the model to the data. To keep the number of variables tractable, we use an industrial organization approach to model the banking sector (Freixas and Rochet, 2008). The representative bank maximizes its expected profits anticipating that a fraction of credit will default in the future (Greenbaum et al., 1989). We implicitly solve for the optimal levels of credit and the lending rate (i.e., the price of credit), given the short-term interest rate (the cost of credit) and credit default risk. The equilibrium conditions for credit and the lending rate are embedded in a standard closed-economy macroeconomic framework, as often used to analyze the monetary transmission mechanism (see e.g., Svensson, 1997 and Clarida et al., 1999). Hence, instead of assuming a perfect interest rate pass-through, credit risk and market power in the banking sector determine the interest rate spread (in line with Christiano et al. (2014) for the former and Berger et al. (2004) for the latter). The representative bank is exposed to credit risk which imposes a potential cost for the bank. Consequently, an increase in credit default risk increases the lending rate and decreases bank lending.

In order to assess whether the data support our theoretical model, we estimate a panel VAR for an unbalanced sample of 12 OECD countries over the last two or three decades (1980/1990–2008/9); the sample is determined by the availability of macroeconomic provisioning data.² Panel VARs can be used to uncover the dynamic relationships that are common to all cross-sectional units.³

Our panel VAR impulse response functions (IRFs) are generally in line with our theoretical model. First, the results suggest that credit risk (measured by provisioning by the banking sector) is one of the drivers of business cycle fluctuations. Specifically, an increase in provisioning decreases bank lending and economic activity. Second, it appears that banks decrease provisioning as a percentage of total bank assets when bank lending increases and vice versa. Hence, during upswings banks take on more risk by building up relatively low provisions while in downswings, banks build up loan loss provisions. These results confirm backward-looking provisioning. Third, output is an important determinant of bank lending, more so than other factors such as interest rates.

The remainder of the paper is structured as follows. Section 2 describes the theoretical model, Section 3 the data and Section 4 presents the results. Section 5 concludes.

¹ Bolt et al. (2012), using aggregate bank data for an unbalanced set of 17 countries over the period 1979–2007, find that loan losses are the main driver of the negative impact of recessions on bank profits.

² After 2009 the OECD discontinued the publication of the Bank Profitability Statistics from which the macroeconomic provisioning data are taken.

³ For example, Love and Zicchino (2006) study the impact of financial factors on firm investment and De Haan and Van den End (2013) examine banks’ responses to market funding shocks. See Canova and Ciccirelli (2013) for a survey of the panel VAR literature.

2. The model

This section presents the macroeconomic framework, discusses the model predictions of a loan loss provisioning shock and describes the empirical set-up.

2.1. Macroeconomic framework

Our framework is closely related to DSGE models that examine the transmission of credit risk to business cycles, see e.g., [Bernanke et al. \(1999\)](#), [Cúrdia and Woodford \(2010\)](#) and [Christiano et al. \(2014\)](#). As mentioned in the Introduction, the aim of our paper is not to establish a new theoretical framework, but to underpin our empirical panel VAR model with a theoretical framework.

The banking sector acts as an intermediary sector which lends to the real economy at lending rate i_t^l and funds itself by short-term debt with a (risk-free) short-term interest rate i_t^s ; see [Freixas and Rochet \(2008\)](#). The difference between the short-term interest rate and the lending rate consists of the term spread and a credit risk premium. We follow the conventional approach by assuming that the term spread is constant over time (e.g., [Woodford and Walsh, 2005](#)). [Bouvatier and Lepetit \(2012\)](#) show theoretically that credit risk (accounted for via backward-looking loan loss provisioning) affects the loan rate through at least two specific channels. If the realized number of credit defaults is higher than anticipated, the loan rate increases because (i) expected future interest earnings decrease and (ii) the unanticipated loss deteriorates their capital. The first effect works directly through the risk premium. Banks update their beliefs about future defaults and increase loan loss provisioning. The second effect works via the bank's balance sheet. Banks increase their loan loss provisioning to cover unanticipated losses. The decrease in the bank's capital position increases the lending rate. In this paper we focus on the credit risk premium channel and not on the balance sheet channel. We leave the latter channel to future research as it is notoriously hard to establish a reliable bank capital measure at the macro-level.

Imagine a representative bank which maximizes profits from lending activities:

$$j_t = (i_t^l \vartheta_t - i_t^s) c_t^n, \quad (1)$$

where j_t represents bank profits, ϑ_t the expected credit repayment rate, and c_t^n denotes new credit and subscripts denote the time index.⁴ The difference between the short-term interest rate i_t^s (the cost price for the bank) and the risk adjusted lending rate $i_t^l \vartheta_t$ is determined by the credit spread.

The credit demand curve is constructed as follows. First, we assume that demand for new credit c_t^n depends negatively on the price of credit, i.e., the lending rate. Second, demand for new credit depends positively on the business cycle as measured by the output gap y_t . Third, demand for new credit depends positively on the price level p_t , since a high inflation rate reduces the real interest rate *ceteris paribus*.⁵ Taking the inverse of this (by assumption invertible) relationship with respect to the lending rate i_t^l , we obtain the following relation denoted by $f(\cdot)$:

$$i_t^l = f(c_{t-k}^n, y_{t-k}, p_{t-k}), \quad k = 0, 1, \dots, q, \quad (2)$$

where q denotes the number of lags we consider. Substituting the expression for the lending rate (Eq. (2)) into Eq. (1) and maximizing with respect to new credit, yields (see [Appendix A](#)):

$$f(c_{t-k}^n, y_{t-k}, p_{t-k}) = \frac{i_t^s}{\vartheta_t} - f'_{c^n}(c_{t-k}^n, y_{t-k}, p_{t-k}) c_t^n, \quad (3)$$

where $f'_{c^n}(\cdot)$ denotes the derivative of $f(\cdot)$ with respect to c_t^n . Eq. (3) gives the relation between the short-term interest rate and the real economy. It follows from Eqs. (1) and (2) that the lending rate depends positively on the short-term interest rate, $\frac{\partial i_t^l}{\partial i_t^s} > 0$, negatively on the expected credit repayment rate, $\frac{\partial i_t^l}{\partial \vartheta_t} < 0$, and negatively on the amount of new credit, $\frac{\partial i_t^l}{\partial c_t^n} < 0$.

For ϑ_t , the expected credit repayment rate (Eq. (1)), we assume that banks expect the payback rate in the next period to be equal to the payback rate observed in the current period. This assumption of static expectations formation is consistent with the empirical evidence of backward looking provisioning behavior found by [Laeven and Majnoni \(2003\)](#) and [Bikker and Metzmakers \(2005\)](#). The expected credit repayment rate is therefore:

$$\vartheta_t = \frac{c_t - E_t\{d_{t+1}\}}{c_t} = \frac{c_t - d_t}{c_t}, \quad (4)$$

where c_t denotes total credit, d_t denotes credit defaults, and $E_t\{\cdot\}$ is the expectation operator. Substituting Eq. (4) into Eq. (3) yields:

$$f(c_{t-k}^n, y_{t-k}, p_{t-k}) = i_t^s \frac{c_t}{c_t - d_t} - f'_{c^n}(c_{t-k}^n, y_{t-k}, p_{t-k}) c_t^n. \quad (5)$$

⁴ We assume financing costs to be independent from the risk level of the banks' existing balance sheet. Our representative bank can always finance itself by borrowing from the central bank at rate i_t^s .

⁵ Demand for new credit may also depend on other variables not endogenously determined in the model. We do not consider exogenous variables in our framework.

Since Eq. (5) is an implicit function for new credit, we can only implicitly solve it for new credit and substitute the solution into the lending rate function, Eq. (2). Hence, we replace c_t^n in Eq. (2) by the solution of Eq. (5) and find that the lending rate is defined as a function $g(\cdot)$ of the following variables, see Appendix A:

$$\hat{i}_t^l = g(d_{t-k}, y_{t-k}, p_{t-k}, \hat{i}_{t-k}^s, c_{t-k}). \quad (6)$$

We assume that the law of motion for credit, c_t , equals new credit minus credit defaults plus the share of credit that does not mature, λ :

$$c_t = \lambda c_{t-1} - d_t + c_t^n, \quad 0 < \lambda < 1, \quad (7)$$

where the credit shock ε_t^c is incorporated in c_t^n ; see Eq. (A8) in Appendix A.⁶ We assume that the credit default variable, d_t , follows a stationary AR(1) process that returns to its equilibrium value, a percentage δ of total credit:

$$d_t = (1 - \rho)\delta c_{t-1} + \rho d_{t-1} + \varepsilon_t^p, \quad 0 < \rho < 1. \quad (8)$$

Eq. (8) states that credit defaults is a fraction of total credit in the previous period, $(1 - \rho)\delta$, and a fraction ρ of the amount of credit defaults in the previous period. Hence, ρ captures the persistence of credit defaults, and $(1 - \rho)$ determines how fast the number of credit defaults returns to the average default rate δ after a shock, denoted by ε_t^p . The shock ε_t^p is labeled as a provisioning shock, since we use bad loan provisioning data to proxy credit default risk.

Using the solution of Eqs. 5–8 we can solve the equation for total credit, see Appendix A. The model tries to estimate the effects of credit risk on economic activity. The risk premium is linked to the degree of credit risk and the risk-free part of the lending rate is captured by the short-term interest rate. The term premium is kept constant, as mentioned above. We log-linearize the lending rate function (Eq. (6)), the Equation for total credit (Eq. (7)) and credit defaults (Eq. (8)). Throughout this paper, variable symbols with a hat represent log-linearized variables, except for the interest rates $\hat{i}_t^s$ and $\hat{i}_t^l$. For $\hat{i}_t^s$ and $\hat{i}_t^l$, we use the following convention. Log-linearization of an interest rate under the assumption that its steady state equals zero ($i = 0$), yields: $\frac{(1+\hat{i})-(1+i)}{1+i} = \hat{i}_t$, which we denote by $\hat{i}_t$.

The log-linearized solutions to the lending rate function, total credit and credit defaults are embedded in a standard closed economy macroeconomic framework, complemented by generalized versions of the aggregate demand curve (Eq. (9)), the Philips curve (Eq. (10)) and the Taylor rule (Eq. (11)):

$$\hat{y}_t = \Phi_1(L)\hat{y}_t + \Phi_2(L)(\hat{i}_t^l - \hat{\pi}_t) + \varepsilon_t^a, \quad (9)$$

$$\hat{\pi}_t = \Phi_3(L)\hat{\pi}_t + \Phi_4(L)\hat{y}_t + \varepsilon_t^s, \quad (10)$$

$$\hat{i}_t^s = \gamma \hat{y}_t + \varphi \hat{\pi}_t + \varepsilon_t^m, \quad (11)$$

where $\hat{\pi}_t$ denotes the inflation rate, and $\Phi_j(L)$ is a lag polynomial $\Phi_j(L) \equiv \Phi_{j,1}L^1 + \dots + \Phi_{j,q}L^q$ for $j = 1, 3$ and $\Phi_j(L) \equiv \Phi_{j,0} + \Phi_{j,1}L^1 + \dots + \Phi_{j,q}L^q$ for $j = 2, 4$ where q denotes the number of lags we consider. The shocks, ε_t^a , ε_t^s , ε_t^m are labeled Aggregate Demand (AD) shock, Cost Push (CP) shock, and Monetary Policy (MP) shock, respectively. The aggregate demand curve (9) describes the relationship between the output gap and the real lending rate, $\hat{i}_t^l - \hat{\pi}_t$, the Philips curve (10) the relationship between the inflation rate and the output gap, and the Taylor rule (11) the relationship between the short-term interest rate and the inflation rate and the output gap.

Using Eq. (6) to substitute out the lending rate variable and imposing restrictions on the contemporaneousness of shocks and responses (see below), we summarize the model as a structural Vector Auto Regressive (VAR) system:

$$\mathbf{A}(L)\mathbf{Z}_t = \varepsilon_t, \quad (12)$$

where we assume that ε_t is $iid \sim (0, \Sigma_\varepsilon)$, $\Sigma_\varepsilon = E\{\varepsilon_t \varepsilon_t'\}$, and $\mathbf{A}(L)$ is a lag polynomial of the form $\mathbf{A}(L) = \mathbf{A}_0 - \mathbf{A}_1L - \dots - \mathbf{A}_pL^p$, in which $\mathbf{A}_k$, $k = 1, \dots, p$, are coefficient matrices. We rewrite Eq. (12) into a reduced form:

$$\mathbf{Z}_t = \mathbf{B}_1\mathbf{Z}_{t-1} + \mathbf{B}_2\mathbf{Z}_{t-2} + \dots + \mathbf{B}_p\mathbf{Z}_{t-p} + \mathbf{v}_t, \quad (13)$$

where $\mathbf{B}_k \equiv \mathbf{A}_0^{-1}\mathbf{A}_k$, $\mathbf{v}_t \equiv \mathbf{A}_0^{-1}\varepsilon_t$, and $\mathbf{v}_t$ is $iid \sim (0, \Sigma_v)$, $\Sigma_v = E\{\mathbf{v}_t \mathbf{v}_t'\}$. We define the vectors as follows:

$$\mathbf{Z}_t = [\hat{d}_t \quad \hat{y}_t \quad \hat{\pi}_t \quad \hat{i}_t^s \quad \hat{c}_t]' \text{ and } \varepsilon_t = [\varepsilon_t^p \quad \varepsilon_t^a \quad \varepsilon_t^s \quad \varepsilon_t^m \quad \varepsilon_t^c]'$$

where we use the same convention as with respect to interest rates: $\frac{p_t - p}{p} \equiv \pi_t$ which we denote as $\hat{\pi}_t$.

As the reduced form disturbances, $\mathbf{v}_t$, represent the effect of all structural shocks in the economy, it is not possible to ascribe a particular structural shock in ε_t , for example a MP shock, to $\mathbf{v}_t$ (Christiano et al., 1999). Therefore, for identification of the structural shocks it is common practice to assume, first, that the structural shocks are orthogonal, i.e., Σ_ε is a diagonal matrix with the standard deviations on the diagonal. Second, one has to make identification assumptions to identify the

⁶ Our representation of the banking sector is short-term oriented. We do not take into account, for example, that prudential provisioning might increase credit in the long-term.

relationship between the reduced form VAR disturbances, $\mathbf{v}_t$, and the structural shocks, $\mathbf{e}_t$. We use Eq. (13) to identify this relationship, i.e., $\mathbf{e}_t = \mathbf{A}_0 \mathbf{v}_t \sim (0, \Sigma_e = \mathbf{A}_0 \Sigma_v \mathbf{A}_0')$, where $\mathbf{A}_0$ is the invertible square matrix in Eq. (12). Since $\mathbf{A}_0$ is a lower triangular matrix, the structural shocks in Eq. (13) are identified by assuming a recursive system which imposes zero restrictions on all elements of $\mathbf{A}_0$ above the diagonal, which is also known as a Cholesky Decomposition.

In particular, our model assumes a number of restrictions with respect to the contemporaneous shocks and responses. The output gap, $\hat{y}_t$, is only contemporaneously affected by provisioning and AD shocks. There is indeed considerable consensus in the literature that the output gap is only modestly affected by shocks in other variables (e.g., Bernanke and Gertler, 1995 and Christiano et al., 1999).

Inflation, $\hat{\pi}_t$, is assumed to be only contemporaneously affected by provisioning, AD and CP shocks. The literature often assumes that prices respond very sluggishly to shocks in other variables (for example, Bernanke and Gertler (1995) and Christiano et al. (1999)).

The short-term interest rate, $\hat{i}_t^s$, is assumed to be contemporaneously affected by provisioning, AD, CP and MP shocks.

Credit, $\hat{c}_t$, is contemporaneously affected by provisioning, AD, CP, MP and credit shocks since new credit, $\hat{c}_t^n$, contains the contemporaneous variable $\hat{i}_t^c$. Banks assess the most recent data available to determine credit.

Credit defaults, $\hat{d}_t$, are only contemporaneously affected by provisioning shocks; other shocks have an impact after one period. This assumption reflects backward-looking provisioning behavior, as empirically confirmed by e.g., Laeven and Majnoni (2003) and Bikker and Metzmakers (2005).

2.2. What does a provisioning shock do?

This section discusses the predicted effects of an unanticipated change in loan loss provisioning. The model presented in this section contains reduced form equations and implicit functional forms. We cannot use structural parameters to calculate reduced form coefficients and generate theoretical impulse response functions. Instead we describe the comparative statics of the credit market after a provisioning shock in Fig. 1.

Loan loss provisioning increases because banks expect a lower repayment rate. Therefore, banks will try to compensate the expected loss by decreasing credit supply, see Eq. (6). As a consequence, credit decreases after a positive provisioning shock, see Eq. (7). This is represented by a movement of the credit supply curve in Fig. 1 from c_0^s to c_1^s . The increase in the lending rate decreases the output gap via the aggregate demand curve which causes the inflation rate to decrease via the Philips curve. The drop in the output gap and the inflation rate causes the credit demand curve in Fig. 1 to shift from c_0^d to c_1^d . As a consequence, the economy moves from $(\bar{c}_0; \bar{l}_0)$ to $(\bar{c}_1; \bar{l}_1)$. Note that the total amount of credit in the economy falls unambiguously, whereas the lending rate can either increase or decrease depending on the elasticities of the credit demand and credit supply curve.

The short-term interest rate is expected to decrease after a provisioning shock, see Eq. (11). According to the Taylor rule, lower output and lower inflation leads to a cut of the short-term interest rate. This reverses all the effects described above: banks face a lower short-term interest rate which allows them to increase credit supply, see Eq. (6). As a consequence the credit supply curve in Fig. 1 shifts from c_1^s to c_2^s . These effects will increase credit, see Eq. (7). The decline in the lending rate causes the output gap and the inflation rate to increase again. As a consequence the credit demand curve in Fig. 1 shifts back from c_1^d to c_2^d and the economy returns to point $(\bar{c}_2; \bar{l}_2)$.

2.3. Empirical setup

To bring the model to the data, we estimate a reduced form panel VAR system adding country specific fixed effects:

$$\mathbf{Z}_{i,t} = \mathbf{u}_i + \mathbf{B}(L)\mathbf{Z}_{i,t-1} + \mathbf{v}_{i,t}, \quad (14)$$

where $\mathbf{Z}_{i,t}$ is a vector of endogenous variables, $i = 1, 2, \dots, 12$ denotes the country index, $\mathbf{u}_i$ is a vector of country-specific fixed effects, $\mathbf{B}(L)$ is a lag polynomial $\mathbf{B}(L) \equiv \mathbf{B}_0 + \mathbf{B}_1 L^1 + \dots + \mathbf{B}_p L^p$, and $\mathbf{v}_{i,t}$ is a vector of stacked reduced form residuals. The vector $\mathbf{Z}_{i,t}$ consists of the endogenous variables introduced in Section 2.1 stacked per country, $\mathbf{Z}_{i,t} = [\hat{d}_{i,t}, \hat{y}_{i,t}, \hat{\pi}_{i,t}, \hat{i}_{i,t}^s, \hat{c}_{i,t}]'$.

The main advantage of using a panel approach is the increased efficiency of statistical inference. High-frequency macroeconomic provisioning data are not available and thus the number of observations is relatively small. In VAR models the number of coefficients increases with the number of parameters squared. Estimating a 5-variable VAR lacks degrees-of-freedom if time series have low frequency. To overcome the degrees-of-freedom issue, we use a panel VAR approach. The panel VAR approach implicitly imposes the same underlying structure to each country in the panel. Cross-country heterogeneity is allowed for by adding individual fixed effects. As mentioned in the Introduction, our model is macro-oriented and our focus is not on the determinants of loan loss provisioning or income smoothing, but on the effect of loan loss provisioning on the macro-economy.⁷

⁷ For example, we assume that institutional differences between countries are time-invariant. Other, micro-oriented studies focus more on the determinants of loan loss provisioning. For example, Fonseca and González (2008), using micro-data for 3221 bank-year observations from 40 countries, present evidence that income smoothing by managing loan loss provisions depends on investor protection, disclosure, regulation and supervision, financial structure, and financial development.

Fig. 1. Static representation of an increase in provisioning. *Note:* the lending rate is depicted on the vertical axis and credit is depicted on the horizontal axis. c_t^d and c_t^s denote the credit demand and credit supply curve at point $\tau = 0, 1, 2$ in time, respectively.

We estimate Eq. (14) using the Generalized Method of Moments (GMM). The fixed effects are eliminated by expressing all variables as deviation from their means. Since the fixed effects are correlated with the regressors as a result of the inclusion of lags of the dependent variables, ordinary mean-differencing (i.e., expressing all variables as deviations from their full sample period's means) as commonly used to eliminate fixed effects would create biased coefficients. To avoid this problem, forward mean-differencing, also known as 'Helmert' transformation', is used instead (cf. Arellano and Bover, 1995). This procedure removes only the forward mean, i.e., the mean of all future observations available in the sample and preserves the orthogonality between transformed variables and lagged regressors, so that the lagged regressors can be used as valid instruments for estimating the coefficients by system GMM.⁸

3. Data

Our sample includes 12 OECD countries: Austria, Belgium, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Spain, Sweden, and the United States. We selected developed western economies with a relatively high degree of homogeneity, for which data availability, notably with respect to loan loss provisions, was no problem. We use annual time series of the OECD for the output gap, inflation, the short-term interest rate, outstanding bank loans to the private sector and loan loss provisions. For details, see Table B.1 in Appendix B.

Expectations with respect to credit defaults is a latent variable, which we proxy by banks' loan loss provisioning. The provisions data series starts, depending on the country, between 1979 and 1988 and ends either in 2008 or 2009. In order to make country comparison feasible we transform this variable by taking the percentage of loan loss provisioning to the total bank balance sheet. Table 1 reports the descriptive statistics of loan loss provisioning as percentage of total bank assets. The provisions series of France does not start before 1988, while those of several other countries start in 1979. Provisioning is only a small percentage of the total balance sheet. Fig. 2 shows that especially during the years before the global financial crisis of 2008, provisioning levels were historically low for most countries while during the global financial crisis provisioning levels started to rise sharply.⁹ Table 2 shows the summary statistics for all transformed variables. The dimensions of the variables are: first difference of loan loss provisions as percentage of total bank assets, output gap as percentage deviation of its trend, inflation rate in percentages (delta logs of the price level multiplied by 100%), short-term interest rate in levels, and credit in percentage changes (delta logs of total credit multiplied by 100%).

To test whether the series contain unit roots, we performed Levin–Lin–Chu (LLC) (2002) panel data unit root tests after conversion into balanced panels. We do this for the series suppressing panel-specific means, as our panel VAR model assumes fixed country effects so that the relevant variables to look at are the variables after removing the panel means. The results show that all series are stationary, see Table 3.¹⁰

⁸ For more details about the estimation procedure we refer to Love and Zicchino (2006), whose Stata code we gratefully use for our estimation.

⁹ Fig. 1 shows that, during the late 1980s and early 1990s, loan loss provisioning in Sweden, experiencing a banking crisis during the time, declines sharply. Because of this peculiarity, Bolt et al. (2012) drop Sweden from their sample. Results, which are not presented here but are available on request, show that our main findings do not change significantly when Sweden is omitted from the sample.

¹⁰ Alternatively, Im–Pesaran–Shin (2003) tests for unbalanced panels confirm stationarity of all model variables.

Table 1

Summary statistics for loan loss provisions, per country.

Countries	Years	Mean	Standard deviation	Median
Austria	1989–2008	0.031	0.223	−0.024
Belgium	1981–2009	−0.008	0.133	0.000
Denmark	1979–2009	−0.003	0.322	−0.001
Finland	1979–2009	−0.012	0.122	−0.005
France	1988–2009	0.000	0.122	0.017
Germany	1979–2009	0.007	0.113	−0.001
Italy	1984–2009	−0.008	0.127	−0.026
Japan	1989–2008	0.009	0.299	0.003
Netherlands	1979–2009	−0.012	0.129	−0.009
Spain	1979–2009	0.012	0.212	0.002
Sweden	1979–2009	−0.028	0.912	0.033
United States	1980–2009	0.057	0.252	0.009

Note: First difference of loan loss provisions as percentage of total bank assets.

Fig. 2. Loan loss provisions as a percentage of the total balance sheet of the banking sector, annual by country.**Table 2**

Summary statistics for the model variables.

Variables	Obs.	Mean	Standard deviation	Median
$\hat{d}_t$	321	0.010	0.332	0.002
$\hat{y}_t$	329	−0.104	2.411	0.029
$\hat{\pi}_t$	527	−0.004	2.095	0.000
$\hat{i}_t$	552	6.241	4.773	5.278
$\hat{c}_t$	492	8.645	6.196	8.693

Note: First difference of loan loss provisions as percentage of total bank assets; output gap as percentage deviation of its trend; inflation rate in percentages (Δ logs of the price level multiplied by 100%); short-term interest rate in levels; credit in percentage change (Δ logs of total credit multiplied by 100%).

Table 3
Levin–Lin–Chu (2002) unit-root test.

Variable	Adjusted <i>t</i>	<i>p</i> -Value
$\hat{y}_t$	−10.97	0.00
$\hat{\pi}_t$	−6.71	0.00
$\hat{c}_t$	−4.84	0.00
$\hat{i}_t^s$	−5.68	0.00
$\hat{d}_t$	−10.50	0.00

Note: H_0 : Panels contain unit roots. H_a : Panels are stationary.
ADF regression: 4 lags, AR parameter: common.
LR variance: Bartlett kernel.
Panel means not included.

4. Results

We present the main results followed by some robustness checks.

4.1. Main results

The panel VAR is estimated including 1 lag in line with the Akaike and Schwarz information criteria for the individual time series. Estimation results, which for reasons of space are not presented but are available on request, prove to be robust to different lag length specifications. Instead, as is the convention for VAR models, impulse-response functions (IRFs) are presented.

All shocks are labeled as specified in Section 2. Following Jacobs and Wallis (2005) we apply directly interpretable impulse magnitudes instead of the conventional one standard deviation shocks, which depend on the fit of the equations of the VAR model. The IRFs presented show the first 6 periods after the shock with 90% confidence intervals generated by Monte-Carlo with 1000 iterations.¹¹

This section discusses the main responses of an output gap shock (hereafter: Aggregate Demand (AD) shock) represented by a 1 percentage point increase in the output gap, a credit shock represented by a 5 percentage point increase in the credit growth rate, and a provisioning shock set equal to an increase in the change in provisioning as percentage of total bank assets by 0.2 percentage point. Fig. 2 shows that many countries experienced an increase in provisioning close to 0.2 percentage point during the beginning of the global financial crisis. In addition, Table 1 shows that for many countries the standard deviation of provisioning to total credit is close to 0.2. For these reasons the provisioning shock is set to a 0.2 percentage point increase.

The main consequences of a positive provisioning shock represented in Fig. 3 are a decrease of the output gap and credit (see panels B1 and C1, respectively). The output gap declines for more than three years suggesting that provisioning shocks drive business cycle fluctuations. Specifically, a 0.2 percentage point increase in provisioning decreases the output gap by approximately 0.25 percentage point suggesting a significant decline in economic activity. The effect on credit becomes insignificant after the first period. Hence, the effect of a provisioning shock on credit has no long-lasting effects.¹²

Provisioning itself appears to decrease slightly three years after an AD shock, but decreases strongly after a credit shock; see panel A2 and A3, respectively. These results suggest that banks do not use economic outlook measures to determine loan loss provisioning. The model suggests, by construction, that provisioning increases after a positive credit shock because banks provision a fixed percentage of credit ($\delta > 0$). Our finding is in line with the empirical evidence in the literature. Cavallo and Majnoni (2001) find for non-G10 countries a negative correlation between pre-provisioning income and provisioning. Laeven and Majnoni (2003) present evidence that banks delay provisioning in good times. As a consequence, provisioning levels are too low during bad times.

The main consequence of an AD shock represented in Fig. 3 is an increase in credit (panel C2). The AD shock raises credit for more than 6 years. The results are in line with our theoretical framework which predicts an increase in credit during periods of high economic activity. In addition, the results suggest that an increase in the output gap has long-lasting effects on credit. The economic impact of the AD shock on credit is large: a 1 percentage point increase in the output gap increases credit growth by 1.5 percentage point on impact.

The main consequence of a positive credit shock, represented by a 5 percentage point increase in credit, is a persistent increase in the output gap up to 1.5 percentage point (panel B3). An increase in credit supply, making more funds available for the purchase of goods, increases aggregate demand. It appears that credit is an important determinant of economic activity.

¹¹ We experimented with a larger number of iterations and obtained similar results.

¹² The IRFs of a panel-VAR excluding the provisioning variable are almost identical for the core model variables (output gap, inflation, short-term interest rate and credit). Hence, the destabilizing effect credit risk has on the business cycle comes from credit risk shocks, i.e., provisioning shocks, itself, and does not affect the dynamic relations between the other variables.

Fig. 3. Impulse response functions for provisioning, Aggregate Demand (AD) and credit shocks, annual data. Note: 90% confidence intervals generated by 1000 Monte-Carlo iterations; periods in years on the horizontal axis.

To determine which variables drive credit supply, we also investigate the consequences of a CP shock (1 percentage point increase in the inflation rate) and a MP shock (100 basis point increase in the short-term interest rate) on credit supply. The results presented in Fig. 4 show that credit is unaffected by CP and MP shocks (panels C1 and C2, respectively). The results in Figs. 3 and 4 suggest that credit is mainly affected by an AD shock; hence, it appears that credit is primarily demand-driven.

4.2. Robustness

In this section we show the robustness of our findings for a different definition of the output gap and for the frequency of the observations, respectively.¹³ Output gap measures are controversial because the output gap is hard to estimate. To check for robustness, we replace the OECD output gap by an output gap measure that we derived by application of the Hodrick–Prescott (HP) filter on real annual GDP as a measure of potential output. Fig. C.1 in Appendix C shows the same IRFs using this output gap measure which can be compared with Fig. 3. The main results remain intact. However, while the response of the output gap to a provisioning shock is stronger, the response of the output gap to a credit shock becomes insignificant. Specifically, the decline in the output gap after a positive provisioning shock is four times as large as the corresponding decline in Fig. 3, but lasts only two years (compare panels B1).

The number of observations is relatively small as we use annual time series. The reason for this is that the provisions variable – our chief variable of interest – is only available at an annual frequency. Fig. C.2 in Appendix C shows results from a panel VAR with four lags estimated on quarterly data, where we interpolated the provisions series using the quadratic match average conversion method and the HP output gap derived from quarterly real GDP data.

The IRFs show that the main results remain intact. However, there are some differences with respect to the magnitude. First, the output gap increases after a positive credit shock; however, the increase is smaller than the corresponding increase in Fig. 3 (panel B3). Second, the decrease in provisioning after a credit shock is smaller (panel A1). This could be due to the fact that data interpolation does not sufficiently take into account the volatility of provisions within the year as it smoothens the series between two observed annual data points.

¹³ We also tested the robustness for different selections of countries in our sample and for sub-sample periods. Results, which are not presented for reasons of space but are available on request, show that the main conclusions remain the same.

Fig. 4. Impulse response functions for Cost Push (CP) and Monetary Policy (MP) shocks, annual data. *Note:* 90% confidence intervals generated by 1000 Monte-Carlo iterations; periods in years on the horizontal axis.

5. Conclusion

In this paper we have set up a macroeconomic framework including a banking sector and credit default risk. The banking sector maximizes profits from lending activities anticipating that a fraction of credit will default in the future. The solution to the banks' optimization problem is embedded in a macroeconomic framework. We estimated the model using a panel VAR for 12 OECD countries over the last two or three decades to assess the importance of credit default risk. Thereby we used aggregate loan loss provisioning as a proxy for credit default risk in the banking sector.

Overall, the empirical results are in line with the predictions of the theoretical model. First, the results suggest that credit risk (as measured by loan loss provisioning by the banking sector) is one of the main drivers of business cycle fluctuations. Specifically, an increase in provisioning decreases bank lending and economic activity. Second, it appears that banks decrease provisioning as a percentage of total bank assets as bank lending increases and vice versa. Hence, during upswings banks take on more risk by building up relatively low provisions while in a downswing banks build up more loan loss provisions. Third, output is an important determinant of bank lending, more so than other factors such as interest rates.

The sensitivity analysis shows that our main results remain intact although the magnitude is sometimes weaker when using a different definition for the output gap or when interpolating annual provisions data into quarterly data for quarterly estimation.

Our macroeconomic model predictions and empirical findings confirm the evidence found in the empirical finance literature that loan loss provisions are mostly pro-cyclical and backward-looking. Whereas the literature found that backward-looking provisioning amplifies credit fluctuations, our macroeconomic modeling approach links provisioning behavior to the business cycle. Our finding that loan loss provisioning has a negative impact on bank lending and amplifies business cycle volatility, is consistent with the findings of existing micro-oriented empirical literature, such as [Bikker and Metzmakers \(2005\)](#) and [Laeven and Majnoni \(2003\)](#). Specifically, the incurred loss model, as implemented under International Accounting Standards (IAS) 39, has been viewed as recognizing impairment losses "too little and too late" and promoting cyclicity.

One of the policy implications of our findings is that a forward-looking loan loss provisioning practice rather than a backward-looking one is called for to avoid pro-cyclicality. Indeed, after the global financial crisis, and suggested by the Financial Stability Board, the G-20 and the Basel Committee on Banking Supervision initiated a project to replace the

incurred loss model with the expected loss model. This has resulted into the change-over from the incurred loss model under IAS 39 toward the expected loss model under International Financial Reporting Standards (IFRS) 9, scheduled to become effective in 2018 (e.g., [Gaston and Song, 2014](#)). Under IFRS 9, banks will have to provision not only for credit losses that have already occurred but also for losses that are expected in the future. Our findings suggest that under this new regime, the degree of pro-cyclicality induced by loan loss provisioning will be considerably mitigated or may even disappear.

Appendix A

The inverse demand function is represented by the following relationship:

$$i_t^l = f(c_{t-k}^n, y_{t-k}, p_{t-k}). \quad (\text{A1})$$

The profit function of banks is denoted as follows:

$$j_t = (i_t^l \vartheta_t - i_t^s) c_t^n. \quad (\text{A2})$$

Substituting Eq. (A1) into Eq. (A2) gives:

$$j_t = [f(c_{t-k}^n, y_{t-k}, p_{t-k}) \vartheta_t - i_t^s] c_t^n. \quad (\text{A3})$$

We assume that banks maximize their profits, Eq. (A3), with respect to new credit c_t^n :

$$\frac{\partial j_t}{\partial c_t^n} = 0 \leftrightarrow f(c_{t-k}^n, y_{t-k}, p_{t-k}) \vartheta_t - i_t^s + f'(c_{t-k}^n, y_{t-k}, p_{t-k}) c_t^n = 0, \quad (\text{A4})$$

$$f(c_{t-k}^n, y_{t-k}, p_{t-k}) = \frac{i_t^s}{\vartheta_t} - f'(c_{t-k}^n, y_{t-k}, p_{t-k}) c_t^n. \quad (\text{A5})$$

Eq. (A5) is Eq. (3) in the main text. The credit payback probability is modeled according the following equation:

$$\vartheta_t = \frac{c_t - E_t\{d_{t+1}\}}{c_t} = \frac{c_t - d_t}{c_t}. \quad (\text{A6})$$

Substituting Eq. (A6) into Eq. (A5) gives Eq. (5) in the main text:

$$f(c_{t-k}^n, y_{t-k}, p_{t-k}) = i_t^s \frac{c_t}{c_t - d_t} - f'(c_{t-k}^n, y_{t-k}, p_{t-k}) c_t^n. \quad (\text{A7})$$

We can solve Eq. (5) for new credit in period t :

$$c_t^n = - \frac{f(c_{t-k}^n, y_{t-k}, p_{t-k}) - i_t^s \frac{c_t}{c_t - d_t}}{f'(c_{t-k}^n, y_{t-k}, p_{t-k})} + \varepsilon_t^c. \quad (\text{A8})$$

where ε_t^c denotes a credit shock. Notice, however, that c_{t-k}^n also contains the term c_t^n for $k = 0$. Since we do implicitly assume a functional form for the loan demand function, we cannot solve for c_t^n explicitly. Nevertheless, we can postulate that, disregarding the credit shock term for the moment:

$$c_t^n = x_1(d_{t-k}, y_{t-k}, p_{t-k}, i_{t-k}^s, c_{t-k}, c_{t-k-1}^n), \quad (\text{A9})$$

where $x_1(\cdot)$ is a function operator. We also know that:

$$c_{t-k-1}^n = x_2(d_{t-k-1}, y_{t-k-1}, p_{t-k-1}, i_{t-k-1}^s, c_{t-k-1}, c_{t-k-2}^n). \quad (\text{A10})$$

where $x_2(\cdot)$ is a function operator. Hence, we can substitute out all c_{t-k}^n and denote c_t^n as a function $x_3(\cdot)$ of the following variables:

$$c_t^n = x_3(d_{t-k}, y_{t-k}, p_{t-k}, i_{t-k}^s, c_{t-k}). \quad (\text{A11})$$

Substituting Eq. (A11) into Eq. (A1) gives:

$$i_t^l = g(d_{t-k}, y_{t-k}, p_{t-k}, i_{t-k}^s, c_{t-k}). \quad (\text{A12})$$

For convenience we reproduce Eqs. (7) and (8) from the main text, respectively:

$$c_t = \lambda c_{t-1} - d_t + c_t^n, \quad 0 < \lambda_E < 1, \quad (\text{A13})$$

$$d_t = (1 - \rho) \delta c_{t-1} + \rho d_{t-1} + \varepsilon_t^p, \quad 0 < \rho < 1. \quad (\text{A14})$$

Substituting Eqs. (A11) and (A14) in Eq. (A13) gives:

$$c_t = \lambda c_{t-1} - (1 - \rho) \delta c_{t-1} - \rho d_{t-1} - \varepsilon_t^p + x_3(d_{t-k}, y_{t-k}, p_{t-k}, i_{t-k}^s, c_{t-k}) + \varepsilon_t^c. \quad (\text{A15})$$

We rewrite Eq. (A15) as an implicit function of credit:

$$c_t = h(d_{t-k}, y_{t-k}, p_{t-k}, i_{t-k}^s, l_{t-k}). \quad (\text{A16})$$

where $h(\cdot)$ is a function operator. We assume that the credit equation is additively separable. Using all the contemporaneous restrictions imposed, the model can be represented by Eq. (12).

Appendix B

See Table B.1.

Appendix C

See Figs. C.1 and C.2.

Table B.1

Variable names and definitions.

Variable	Notation	Source	Definition
Inflation	$\hat{\pi}_t$	OECD National Accounts	Δ log of price deflator of private consumption (1990 = 100) multiplied by 100%
Short-term interest rate	$\hat{i}_t^s$	IMF International Financial Statistics (IFS)	Three-month money market interest rate (%)
Credit	$\hat{c}_t$	IMF International Financial Statistics (IFS)	Δ log of bank credit to the private sector, deflated by the price deflator of private consumption multiplied by 100%
Provisions	$\hat{d}_t$	OECD Bank Profitability Statistics, discontinued since 2009	First difference of net provisions, i.e., expense set aside as allowance for bad loans, minus releases, Percentages of total bank assets
OECD output gap	$\hat{y}_t$	OECD Economic Outlook	Deviation of actual real GDP from potential real GDP as a percentage of potential real GDP
HP output gap	$\hat{y}_t$	Own calculations	Deviation of actual real GDP from potential real GDP as a percentage of potential real GDP. Potential output calculated using the Hodrick-Prescott filter on actual output

Fig. C.1. Impulse response functions for provisioning, Aggregate Demand (AD) and credit shocks: annual data. HP output gap instead of OECD output gap. Note: 90% confidence intervals generated by 1000 Monte-Carlo iterations; periods in years on the horizontal axis.

Fig. C.2. Impulse response functions for Cost Push (CP) and Monetary Policy (MP) shocks, quarterly data. Note: 90% confidence intervals generated by 1000 Monte-Carlo iterations; periods in quarters on the horizontal axis.

References

- Adrian, T., Shin, H.S., 2009. Money, liquidity, and monetary policy. *Am. Econ. Rev.* 99 (2), 600–605.
- Agénor, P.R., Zilberman, R., 2013. Loan loss provisioning rules, procyclicality, and financial volatility. Working Paper No. 184, Centre for Growth and Business Cycle Research, University of Manchester.
- Arellano, M., Bover, O., 1995. Another look at the instrumental variable estimation of error-components models. *J. Econom.* 68 (1), 29–51.
- Berger, A.N., Demirgüç, A., Levine, R., Haubrich, J.G., 2004. Bank concentration and competition: an evolution in the making. *J. Money Credit Banking* 36 (3), 433–451.
- Bernanke, B.S., Gertler, M., 1995. Inside the black box: the credit channel of monetary policy transmission. *J. Econ. Perspect.* 9 (2), 27–48.
- Bernanke, B.S., Gertler, M., Gilchrist, S., 1999. The financial accelerator in a quantitative business cycle framework. In: Taylor, J.B., Woodford, M. (Eds.), *Handbook of Macroeconomics*, vol. 1. Elsevier, pp. 1341–1393 (Chapter 21).
- Bikker, J.A., Metzmakers, P.A., 2005. Bank provisioning behaviour and procyclicality. *J. Int. Financ. Markets Inst. Money* 15 (2), 141–157.
- Bolt, W., de Haan, L., Hoeberichts, M., Oordt, M.R., Swank, J., 2012. Bank profitability during recessions. *J. Bank. Finance* 36 (9), 2552–2564.
- Bouvatier, V., Lepetit, L., 2008. Banks' procyclical behavior: does provisioning matter? *J. Int. Financ. Markets Inst. Money* 18 (5), 513–526.
- Bouvatier, V., Lepetit, L., 2012. Provisioning rules and bank lending: a theoretical model. *J. Financ. Stab.* 8, 25–31.
- Borio, C., Lowe, P., 2001. To provision or not to provision. *BIS Q. Rev.* 9.
- Bushman, R.M., Williams, C.D., 2012. Accounting discretion, loan loss provisioning, and discipline of banks' risk-taking. *J. Account. Econ.* 54 (1), 1–18.
- Canova, F., Ciccarelli, M., 2013. Panel Vector Autoregressive Models: A Survey. ECB Working Paper series 1507.
- Cavallo, M., Majnoni, G., 2001. Do Banks Provision for Bad Loans in Good Times? The World Bank Policy Research Paper 2619.
- Christiano, L.J., Eichenbaum, M., Evans, C.L., 1999. Monetary policy shocks: what have we learned and to what end? In: Taylor, J.B., Woodford, M. (Eds.), *Handbook of Macroeconomics*, vol. 1. Elsevier, pp. 65–148 (Chapter 2).
- Christiano, L., Motto, R., Rostagno, M., 2014. Risk shocks. *Am. Econ. Rev.* 104 (1), 27–65.
- Clarida, R., Galí, J., Gertler, M., 1999. The science of monetary policy: a new Keynesian perspective. *J. Econ. Lit.* 37, 1661–1707.
- Cúrdia, V., Woodford, M., 2010. Credit spreads and monetary policy. *J. Money Credit Banking* 42 (s1), 3–35.
- de Haan, L., van den End, J., 2013. Banks' responses to funding liquidity shocks: lending adjustments, liquidity hoarding and fire sales. *J. Int. Financ. Markets Inst. Money* 26, 152–174.
- Fonseca, A.R., González, F., 2008. Cross-country determinants of bank income smoothing by managing loan-loss provisions. *J. Bank. Finance* 32, 217–228.
- Freixas, X., Rochet, J.-C., 2008. *Microeconomics of Banking*, second ed., vol. 1. The MIT Press, Massachusetts.
- Gaston, E., Song, I.W., 2014. Supervisory Roles in Loan Loss Provisioning in Countries Implementing IFRS. IMF Working Paper WP/14/170.
- Greenbaum, S.I., Kanatas, G., Venezia, I., 1989. Equilibrium loan pricing under the bank-client relationship. *J. Bank. Finance* 13 (2), 221–235.
- Im, K.S., Pesaran, M.H., Shin, Y., 2003. Testing for unit roots in heterogeneous panels. *J. Econom.* 115, 53–74.
- Jacobs, J.P.A.M., Wallis, K.F., 2005. Comparing SVARs and SEMs: two models of the UK economy. *J. Appl. Econom.* 20 (2), 209–228.
- Jiménez, G., Ongena, S., Peydro, J.-L., Saurina, J., 2012. Macropprudential Policy, Countercyclical Bank Capital Buffers and Credit Supply: Evidence from the Spanish Dynamic Provisioning Experiments. European Banking Center Discussion Paper No. 2012-011.
- Laeven, L., Majnoni, G., 2003. Loan loss provisioning and economic slowdowns: too much, too late? *J. Financ. Intermed.* 12 (2), 178–179.
- Levin, A., Lin, C.-F., Chu, C.-S.J., 2002. Unit root tests in panel data: asymptotic and finite-sample properties. *J. Econom.* 108 (1), 1–24.
- Love, I., Zicchino, L., 2006. Financial development and dynamic investment behavior: evidence from panel VAR. *Q. Rev. Econ. Finance* 46 (2), 190–210.
- Svensson, L.E., 1997. Inflation forecast targeting: implementing and monitoring inflation targets. *Eur. Econ. Rev.* 41 (6), 1111–1146.
- Woodford, M., Walsh, C., 2005. *Interest and Prices: Foundations of a Theory of Monetary Policy*. Cambridge University Press, Cambridge.
- Zilberman, R., Tayler, W.J., 2014. Financial Shocks, Loan Loss Provisions and Macropprudential Stability. Economics Working Paper Series No. 23, Lancaster University.