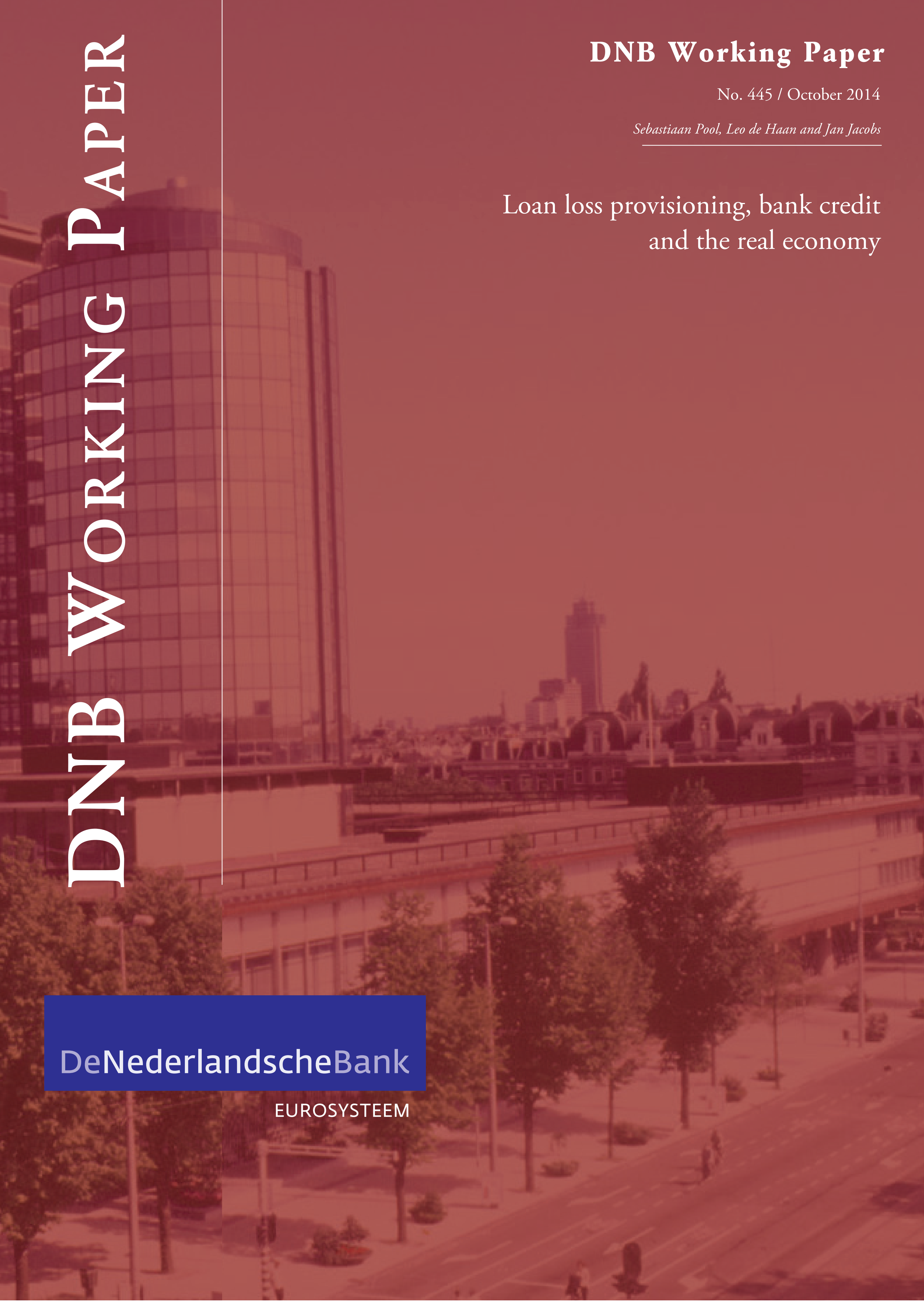

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De Nederlandsche Bank

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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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Loan loss provisioning, bank credit and the real economy*

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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.

Keywords: loan loss provisioning, bank lending, business cycle.
JEL Classifications: E44, G21.

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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. The literature shows that bank loan loss provisioning may have either procyclical or countercyclical effects, 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 an upswing phase, during which 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 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 upswing phases 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 generally 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 Metzemakers (2005) find evidence of a negative relation between GDP growth and provisioning for 29 OECD countries, implying backward looking practices. This procyclical effect is mitigated partly by the positive relation between banks' earnings and provisions, which

[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.

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.

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 this focus has been scarce in the literature. 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. In this paper, we not only examine the impact of provisioning on credit, but also on the real economy. Another difference with the provisioning literature is that we use macroeconomic data.

For our analysis we set up a macroeconomic framework including a banking sector and credit default risk. 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, Kanatas and Venezia, 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 (Svensson, 1997). Hence, instead of assuming a perfect interest rate pass-through, credit risk and market power in the banking sector determine the interest rate spread. 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 countries over the last two or three decades (1980/1990–2008/9); the sample is determined by the availability of macroeconomic provisioning data.[2] The countries are: Austria, Belgium, Denmark, Finland, France, Germany, Italy, Japan, the

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

Netherlands, Spain, Sweden and the United States. Panel VARs can be used to uncover the dynamic relationships that are common to all cross-sectional units.[3]

The panel VAR Impulse Response Functions (IRFs) that we find 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 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 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.

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

The macroeconomic framework that we use is a generalized version of the aggregate demand curve (Equation (1)), the Philips curve (Equation (2)) and the Taylor rule (Equation (3)), as in Svensson (1997):

$$y_t = \Phi_1(L)y_t + \Phi_2(L)\left(i_t^l - \pi_t\right) + \varepsilon_t^a, \tag{1}$$

[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 Ciccarelli (2013) for a survey of the panel VAR literature.

$$\pi_t = \Phi_3(L)\pi_t + \Phi_4(L)y_t + \varepsilon_t^s, \quad (2)$$

$$i_t^s = \gamma y_t + \varphi \pi_t + \varepsilon_t^m, \quad (3)$$

where y_t denotes the output gap, i_t^l the lending rate, i_t^s the short-term interest rate, π_t the inflation rate, and $\Phi_j(L)$ is a lag polynomial $\Phi_j(L) \equiv \Phi_{j,1}L^1 + \cdots + \Phi_{j,p}L^p$ for $j = 1{,}3$ and $\Phi_j(L) \equiv \Phi_{j,0} + \Phi_{j,1}L^1 + \cdots + \Phi_{j,p}L^p$ for $j = 2{,}4$ where p denotes the number of lags we consider. Throughout this paper, lower case letters, except for the interest rates i_t^s and i_t^l, represent log-linearized variables. The shocks, ε_t^a, ε_t^s, ε_t^m are labelled aggregate demand (AD) shock, cost push (CP) shock, and monetary policy (MP) shock, respectively. The aggregate demand curve (1) describes the relationship between the output gap and the real lending rate, $i_t^l - \pi_t$, the Philips curve (2) the relationship between the inflation rate and the output gap, and the Taylor rule (3) the relationship between the short-term interest rate on the one hand and the inflation rate and output gap on the other.

The term structure between the lending rate and short-term interest rate is determined by the banking sector; see Freixas and Rochet (2008). The difference between the short-term interest rate and the lending rate consists of the term spread and a risk premium. We follow the conventional approach by assuming that the term spread is constant over time (e.g., Woodford and Walsh, 2005). Instead, our focus is on the risk premium. Imagine a banking sector which maximizes profits from lending activities:

$$P_t = \left(i_t^l \vartheta_t - i_t^s\right) c_t^n, \quad (4)$$

where P_t represents bank profits, ϑ_t the expected credit repayment rate, and c_t^n denotes new credit.[4] The difference between the short-term interest rate i_t^s 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, which is determined by the lending rate. Second, demand for new credit depends positively on the business cycle as measured by the

[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.

output gap. Third, demand for new credit depends positively on the inflation rate, since a high inflation rate reduces the real interest rate *ceteris paribus*.[5] Taking the inverse of this relationship with respect to the lending rate i_t^l, we obtain the following relation denoted by $f(\cdot)$:

$$i_t^l = f(c_{t-k}^n, y_{t-k}, \pi_{t-k}), \quad k = 0, 1, \dots, p, \tag{5}$$

where subscript $t-k$ denotes the time index. Substituting the expression for the lending rate (Equation (5)) into Equation (4) and maximization with respect to new credit, yields (see Appendix A):

$$f(c_{t-k}^n, y_{t-k}, \pi_{t-k}) = \frac{i_t^s}{\vartheta_t} - f'_{c^n}(c_{t-k}^n, y_{t-k}, \pi_{t-k})c_t^n, \tag{6}$$

where $f'_{c^n}(\cdot)$ denotes the derivative of $f(\cdot)$ with respect to c_t^n. Equation (6) gives the relation between the short-term interest rate and the real economy. It follows from Equations (4) and (5) that the lending rate positively depends 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 (Equation (4)), 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 behaviour found by e.g. Laeven and Majnoni (2003) and Bikker and Metzemakers (2005). The expected credit repayment rate is therefore:

$$\vartheta_t = \frac{c_t - E_t\{d_{t+1}\}}{c_t} = \frac{c_t - d_t}{c_t}, \tag{7}$$

where c_t denotes total credit, d_t denotes credit defaults (both in log-linearized form), and $E_t\{\cdot\}$ is an expectation operator. Substituting Equation (7) into Equation (6) yields:

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

$$f(c_{t-k}^n, y_{t-k}, \pi_{t-k}) = i_t^s \frac{c_t}{c_t - d_t} - f'(c_{t-k}^n, y_{t-k}, \pi_{t-k}) c_t^n. \quad (8)$$

Since Equation (8) 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, Equation (5). Hence, we replace c_t^n in Equation (5) by the solution of Equation (8) and find that the lending rate is defined as a function $g(\cdot)$ of the following variables, see Appendix A:

$$i_t^l = g(d_{t-k}, y_{t-k}, \pi_{t-k}, i_{t-k}^s, c_{t-k}). \quad (9)$$

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:

$$c_t = \lambda c_{t-1} - d_t + c_t^n,\ 0 < \lambda < 1, \quad (10)$$

where the credit shock ε_t^c is incorporated in c_t^n; see Equation (A7) 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:

$$d_t = (1-\rho)\delta c_{t-1} + \rho d_{\mathrm{t}-1} + \varepsilon_t^p, \qquad 0 < \rho < 1. \quad (11)$$

Equation (11) states that the amount of 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.

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

Using the solution of Equation (8) and Equations (9), (10) and (11) 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. Using Equation (9) and imposing restrictions on the contemporaneousness of shocks and responses (see below), we can summarize the model as a structural Vector Auto Regressive (VAR) system:

$$\boldsymbol{A}(L)\boldsymbol{Z}_t = \boldsymbol{\varepsilon}_t, \tag{12}$$

where we assume that $\boldsymbol{\varepsilon}_t$ is $iid{\sim}(0, \boldsymbol{\Sigma}_\varepsilon)$, $\boldsymbol{\Sigma}_\varepsilon = E\{\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}_t'\}$, and $\boldsymbol{A}(L)$ is a lag polynominal of the form $\boldsymbol{A}(L) = \boldsymbol{A}_0 - \boldsymbol{A}_1 L - \cdots - \boldsymbol{A}_p L^p$, in which $\boldsymbol{A}_k$, $k = 1, \dots, p$, are coefficient matrices. We rewrite Equation (12) into a reduced form:

$$\boldsymbol{Z}_t = \boldsymbol{B}_1\boldsymbol{Z}_{t-1} + \boldsymbol{B}_2\boldsymbol{Z}_{t-2} + \cdots + \boldsymbol{B}_p\boldsymbol{Z}_{t-p} + \boldsymbol{v}_t, \tag{13}$$

where $\boldsymbol{B}_k \equiv \boldsymbol{A}_0^{-1}\boldsymbol{A}_\mathrm{k}$, $\boldsymbol{v}_t \equiv \boldsymbol{A}_0^{-1}\boldsymbol{\varepsilon}_t$, and $\boldsymbol{v}_t$ is $iid{\sim}(0, \boldsymbol{\Sigma}_v)$, $\boldsymbol{\Sigma}_v = E\{\boldsymbol{v}_t\boldsymbol{v}_t'\}$.

We define the vectors as follows:

$$\boldsymbol{Z}_t = [d_t \quad y_t \quad \pi_t \quad i_t^s \quad c_t]' \text{ and } \boldsymbol{\varepsilon}_t = \left[\varepsilon_t^p \quad \varepsilon_t^a \quad \varepsilon_t^s \quad \varepsilon_t^m \quad \varepsilon_t^c\right]',$$

As the reduced form disturbances, $\boldsymbol{v}_t$, represent the effect of all structural shocks in the economy, it is not possible to ascribe a particular structural shock in $\boldsymbol{\varepsilon}_t$, for example a MP shock, to $\boldsymbol{v}_t$ (Christiano, Eichenbaum and Evans (1999)). Therefore, for identification of the structural shocks it is common practice to assume, first, that the structural shocks are orthogonal, i.e. $\boldsymbol{\Sigma}_\varepsilon$ is a diagonal matrix with the standard deviations on the diagonal. Second, one has to make identification assumptions to identify the relationship between the reduced form VAR disturbances, $\boldsymbol{v}_t$, and the structural shocks, $\boldsymbol{\varepsilon}_t$. We use Equation (13) to identify this relationship, i.e. $\boldsymbol{\varepsilon}_t = \boldsymbol{A}_0\boldsymbol{v}_t{\sim}(0, \boldsymbol{\Sigma}_\varepsilon = \boldsymbol{A}_0\boldsymbol{\Sigma}_v\boldsymbol{A}_0{}')$, where $\boldsymbol{A}_0$ is the invertible square matrix in Equation (12).

Since $\boldsymbol{A}_0$ is a lower triangular matrix, the structural shocks in Equation (14) are identified by assuming a recursive system which imposes zero restrictions on all elements of $\boldsymbol{A}_0$ 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, y_t, is only contemporaneously affected by a provisioning and AD shock. 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, Eichenbaum and Evans (1999)).

Inflation, π_t, is assumed to be only contemporaneously affected by a provisioning, AD and CP shock. The literature often assumes that prices respond very sluggishly to shocks in other variables (for example, Bernanke and Gertler (1995) and Christiano, Eichenbaum and Evans (1999)).

The short-term interest rate, i_t^s, is assumed to be contemporaneously affected by a provisioning, AD, CP and MP shock.

Credit, c_t, is contemporaneously affected by a provisioning, AD, CP, MP and credit shock since new credit, c_t^n, contains the contemporaneous variable i_t^s. Banks assess the most recent data available to determine credit.

Credit defaults, d_t, are only contemporaneously affected by a provisioning shock; 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 Metzemakers (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 statistics of the credit market after a provisioning shock statically in Figure 1.

Loan loss provisioning increases because banks expect a lower repayment rate. Therefore, banks will try to compensate the expected loss by increasing the lending rate and decreasing credit supply, see Equation (9). As a consequence, credit decreases after a positive provisioning shock, see Equation (10). This is represented by a movement of the credit supply curve in Figure 1 from S_0 to S_1. The increase in the lending rate decreases the output gap via de 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 Figure 1 to shift from D_0 to D_1. As a consequence, the economy moves from E_0 to E_1.

The short-term interest rate is expected to decrease after a provisioning shock, see Equation (3). According to the Taylor rule, lower output and lower inflation is followed by 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 decrease the lending rate and increase credit supply, see Equation (9). As a consequence the credit supply curve in Figure 1 shifts from S_1 to S_0. These effects will increase credit, see Equation (10). 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 Figure 1 shifts back from D_1 to D_0 and the economy returns to point E_0.

2.3 Empirical setup

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

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

where $\boldsymbol{Z}_{i,t}$ is a vector of endogenous variables, $i = 1,2,\dots,12$ denotes the country index, $\boldsymbol{u}_i$ is a vector of country-specific fixed effects, $\mathbf{B}(L)$ is a lag polynomial $\mathbf{B}(L) \equiv \mathbf{B}_0 + \mathbf{B}_1 L^1 + \cdots + \mathbf{B}_p L^p$, and $\boldsymbol{v}_{i,t}$ is a vector of stacked reduced form residuals. The vector $\boldsymbol{Z}_{i,t}$ consists of the endogenous variables introduced in Section 2 stacked per country, $\boldsymbol{Z}_{i,t} = \left[d_{i,t}, y_{i,t}, \pi_{i,t}, i^s_{i,t}, c_{i,t}\right]'$.

The main advantage of using a panel approach is the increased efficiency of the 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.

We estimate Equation (14) using the Generalized Method of Moments (GMM), with one set of instruments to deal with the endogeneity of regressors and another set to deal with the correlation between the lagged dependent variables and the error terms. 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. [7]

3 Data

Our sample includes 12 countries: Austria, Belgium, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Spain, Sweden, and the United States. We use annual time series of the OECD 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. 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. However, as Figure 2 shows, provisioning is highly volatile. Especially during the years before the Global Financial Crisis of 2008, provisioning

[7] For more details about the estimation procure we refer to Love and Zicchino (2006), whose State code we gratefully use for our estimation.

levels were historically low for most countries while during the Global Financial Crisis provisioning levels started to rise sharply.[8] Table 2 shows the summary statistics for all transformed variables.

To test whether the series contain unit roots, we perform the Levin-Lin-Chu (LLC) (2002) panel data unit root test. 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 B.2 in Appendix B. Loan loss provisioning is occasionally negative and non-stationary. 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 B.2 in Appendix B also reports the LLC tests statistics for the percentage of loan loss provisioning to the total balance sheet. Results, which are not presented here but are available on request, show that the main conclusions presented in Section 4 are indifferent to the transformation choice.

4 Results

We present the main results followed by some robustness checks.

4.1 Main results

The panel VAR is estimated including 1 lag which is loosely consistent 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 fairly 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 usual one standard deviation

[8] Figure 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.

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 the 5% and 95% confidence intervals generated by Monte-Carlo with 1000 iterations.[9]

This section discusses the main responses of an output gap shock (hereafter: aggregate demand (AD) shock) represented by a 1 percent point increase in the output gap, a credit shock represented by a 5 percent 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 percent point. Figure 2 shows that many countries experienced an increase in provisioning close to 0.2 percent point during the beginning of the Global Financial Crisis. In addition, Table 1 shows that for many countries the standard deviation of provisioning to the total credit is close to 0.2. For these reasons the provisioning shock is set equal to a 0.2 percent point increase.

The main consequences of a positive provisioning shock represented in Figure 3 are a decrease of the output gap and credit (see panels B1 and C1, respectively). The output gap declines for more than three year suggesting that provisioning shocks drive business cycle fluctuations. Specifically, a 0.2 percent point increase in provisioning decreases the output gap by approximately 0.25 percent 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. These results are consistent with our theoretical model prediction.

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 $\delta > 0$, implying that banks provision a fixed percentage of credit. Our finding is in line with the empirical evidence in the literature. Cavallo and Majnoni (2002) 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 Figure 3 is an increase in credit (panel C2). The AD shock raises credit for more than 6 years and the magnitude of the response

[9] We experimented with a larger number of iterations and obtained similar results.

is similar to the AD shock itself. The results are in line with our theoretical model which predicts an increase in credit during periods of high economic activity. In addition, these results suggest that an increase in the output gap has long-lasting effects on credit. The economic magnitude of the AD shock on credit is large: a 1 percent point increase in the output gap increases credit growth by 1.5 percent point on impact.

The main consequence of a positive credit shock, represented by a 5 percent point increase in credit, is a persistent increase in the output gap up to 1.5 percent point (panel B3).[10] It appears that credit is an important determinant of economic activity.

To determine which variables drive credit supply, we also investigate the consequences of a CP shock (1 percent 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 Figure 4 show that credit is unaffected by CP and MP shocks (panels C1 and C2, respectively). The results in Figure 3 and Figure 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.[11] 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. Figure C.1 in Appendix C shows the same IRFs using this output gap measure which can be compared with Figure 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 Figure 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

[10] A 5 percent point credit shock is not an exceptionally large shock. Table 2 shows that the annual standard deviation is about 6 percent.

[11] 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 hold.

this is that the provisions variable – our chief variable of interest – is only available at an annual frequency. Figure 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 used 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 Figure 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.

5 Conclusion

Overall, the empirical results are in line with the predictions of the theoretical model. First, the results suggest that credit risk (measured by loan loss 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 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 showed that our main results remain intact although the results - are sometimes less strong when using a different definition for the output gap and 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 that literature found that backward-looking provisioning amplifies credit fluctuations, our macroeconomic modeling approach links this provisioning behavior to the business cycle.

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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.

Table 2 - Descriptive Statistics.

Variables	Obs.	Mean	Standard Deviation	Median
d_t	321	0.010	0.332	0.002
y_t	329	-0.104	2.411	0.029
π_t	527	-0.004	2.095	0.000
i_t^s	552	6.241	4.773	5.278
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 (delta logs of the price level multiplied by 100%); short-term interest rate in levels; total credit in percentage change (delta logs of total credit multiplied by 100%)

Figure 1. Representation of an increase in provisioning.

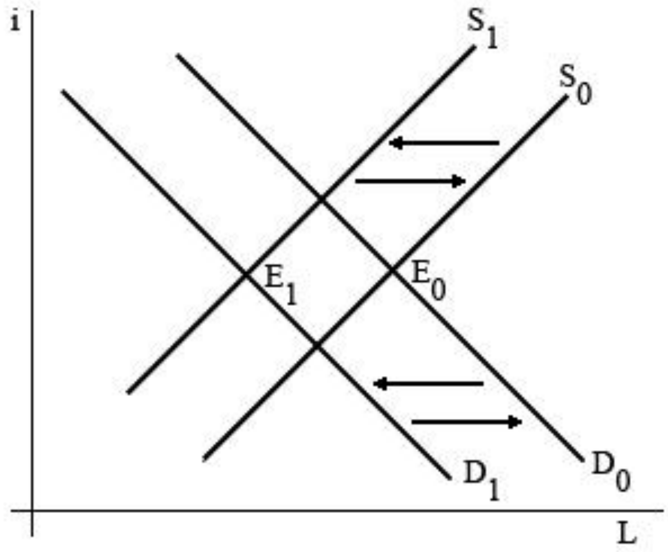


Figure 2. Loan loss provisions as a percentage of the total balance sheet of the banking sector, annual by country.

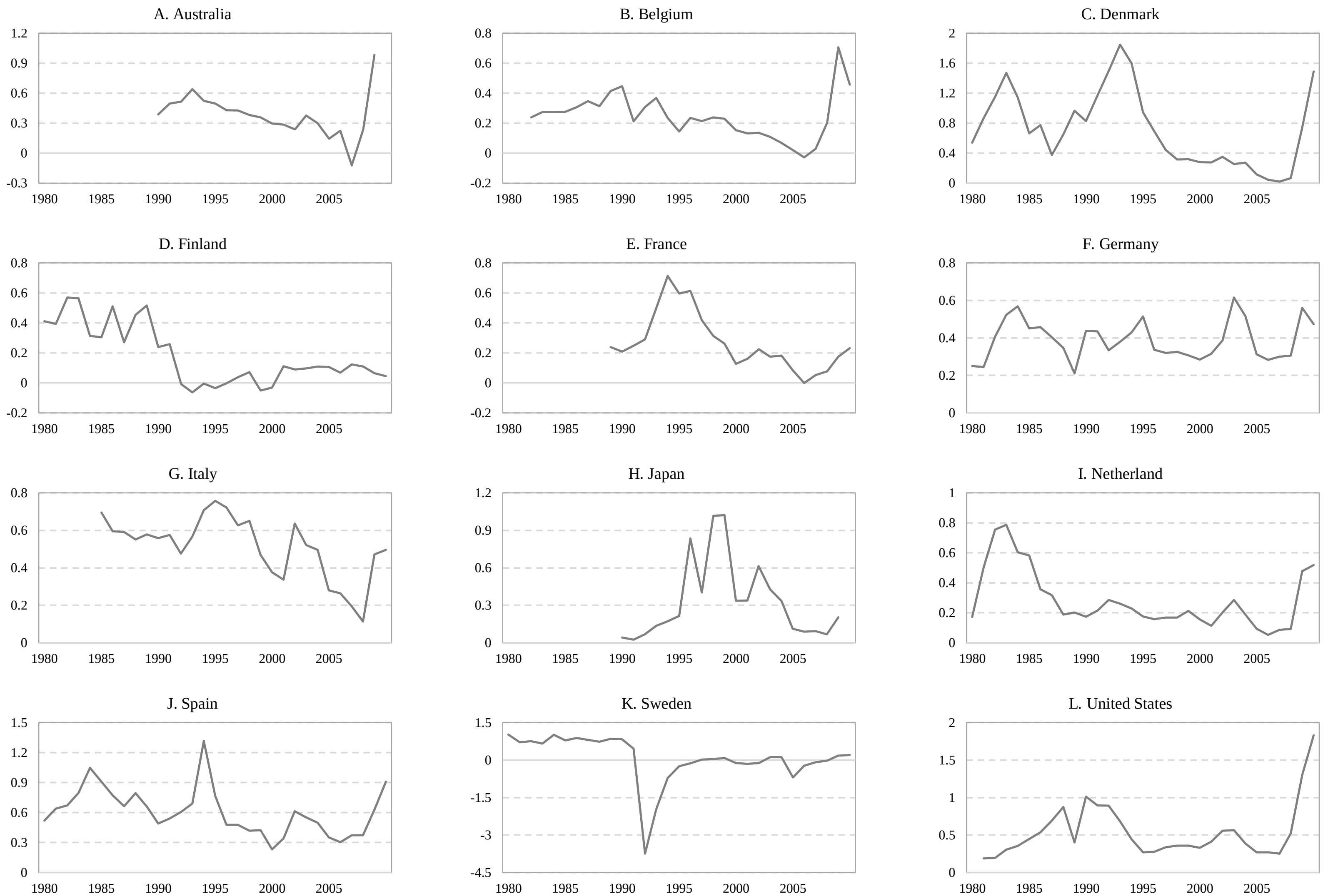
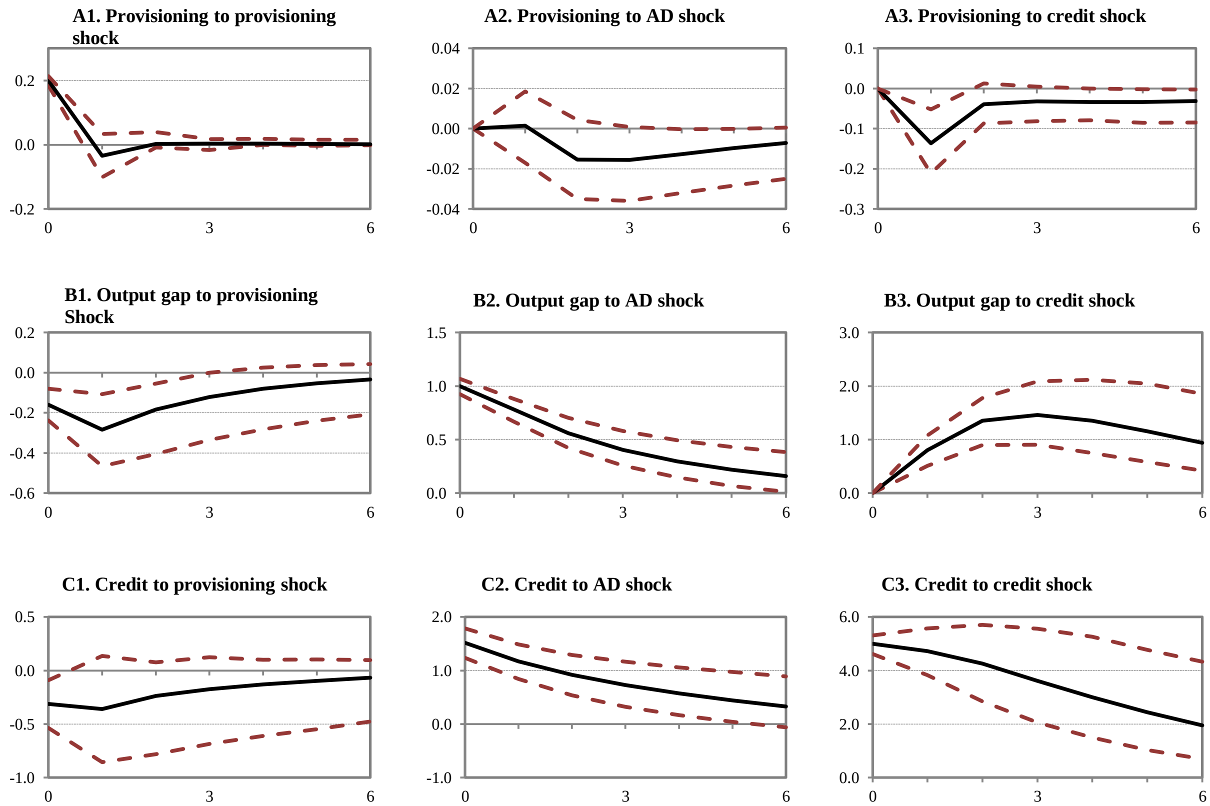
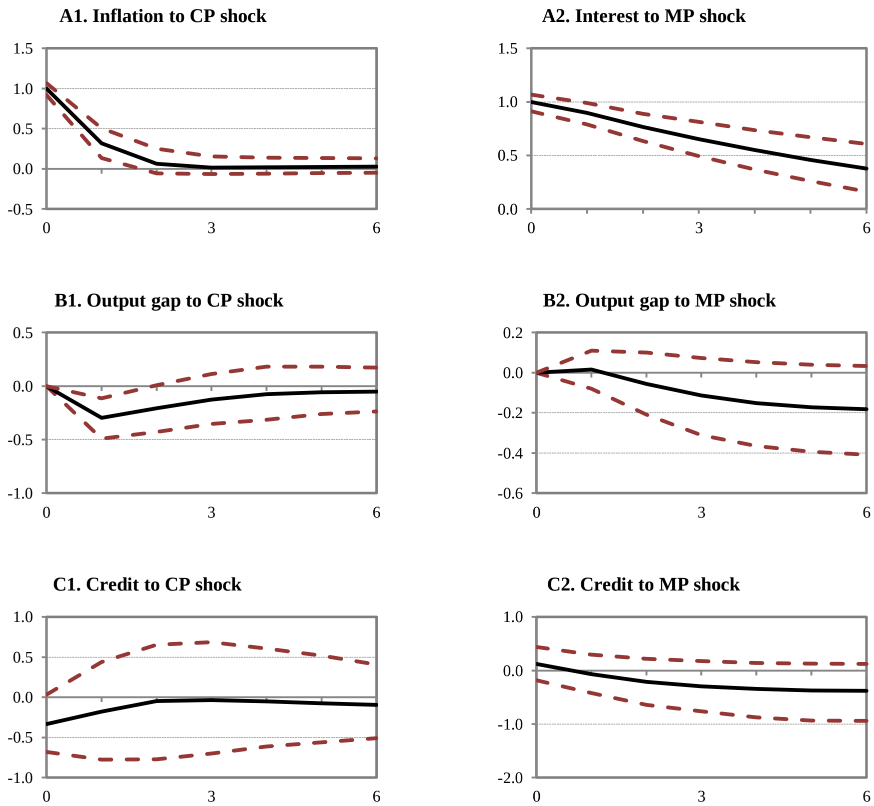


Figure 3. Impulse response functions for provisioning, Aggregate Demand (AD) and credit shocks, annual data



Note: 90% confidence intervals generated by 1000 Monte-Carlo iterations; periods in years on the horizontal axis.

Figure 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.

Appendix A

The inverse demand function is represented by the following relationship:

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

The profit function of banks is denoted as follows:

$$P_t = \left(i_t^l \vartheta_t - i_t^s\right) c_t^n. \tag{A2}$$

Substituting Equation (A1) into Equation (A2) gives:

$$P_t = [f(c_{t-k}^n, y_{t-k}, \pi_{t-k}) \vartheta_t - i_t^s] c_t^n. \tag{A3}$$

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

$$\frac{\partial P_t}{\partial c_t^n} = 0 \leftrightarrow f(c_{t-k}^n, y_{t-k}, \pi_{t-k}) \vartheta_t - i_t^s + f'(c_{t-k}^n, y_{t-k}, \pi_{t-k}) c_t^n = 0$$

$$f(c_{t-k}^n, y_{t-k}, \pi_{t-k}) = \frac{i_t^s}{\vartheta_t} - f'(c_{t-k}^n, y_{t-k}, \pi_{t-k}) c_t^n. \tag{A4}$$

Equation (A4) is Equation (6) in the main text. The credit payback probability is modelled according the following equation:

$$\vartheta_t = \frac{c_t - E_t\{d_{t+1}\}}{c_t} = \frac{c_t - d_t}{c_t}. \tag{A5}$$

Substituting Equation (A5) into Equation (A4) gives Equation (8) in the main text:

$$f(c_{t-k}^n, y_{t-k}, \pi_{t-k}) = i_t^s \frac{c_t}{c_t - d_t} - f'(c_{t-k}^n, y_{t-k}, \pi_{t-k}) c_t^n. \tag{A6}$$

We can solve Equation (8) for new credit in period t:

$$c_t^n = -\frac{f(c_{t-k}^n, y_{t-k}, \pi_{t-k}) - i_t^s \dfrac{c_t}{c_t - d_t}}{f'(c_{t-k}^n, y_{t-k}, \pi_{t-k})} + \varepsilon_t^c. \tag{A7}$$

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:

$$c_t^n = x_1(d_{t-k}, y_{t-k}, \pi_{t-k}, i_{t-k}^s, c_{t-k}, c_{t-k-1}^n), \tag{A8}$$

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

$$c_{t-k-1}^n = x_2(d_{t-k-1}, y_{t-k-1}, \pi_{t-k-1}, i_{t-k-1}^s, c_{t-k-1}, c_{t-k-2}^n). \tag{A9}$$

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:

$$c_t^n = x_3(d_{t-k}, y_{t-k}, \pi_{t-k}, i_{t-k}^s, c_{t-k}). \tag{A10}$$

Substituting Equation (A9) into Equation (A1) gives:

$$i_t^l = g(d_{t-k}, y_{t-k}, \pi_{t-k}, i_{t-k}^s, c_{t-k}). \tag{A11}$$

For convenience we reproduce Equation (10) and Equation (11) from the main text, respectively:

$$c_t = \lambda c_{t-1} - d_t + c_t^n, \qquad 0 < \lambda_E < 1, \tag{A12}$$

$$d_t = (1-\rho)\delta c_{t-1} + \rho d_{\mathrm{t-1}} + \varepsilon_t^p, \qquad 0 < \rho < 1. \tag{A13}$$

Substituting Equation (A10) and Equation (A13) in Equation (A12) gives:

$$c_t = \lambda c_{t-1} - (1-\rho)\delta c_{t-1} - \rho d_{t-1} - \varepsilon_t^p + x_3(d_{t-k}, y_{t-k}, \pi_{t-k}, i_{t-k}^s, c_{t-k}) + \varepsilon_t^c. \quad \text{(A14)}$$

We rewrite Equation (A14) as an implicit function of credit:

$$c_t = h(d_{t-k}, y_{t-k}, \pi_{t-k}, i_{t-k}^s, l_{t-k}). \quad \text{(A15)}$$

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 Equation (12).

Appendix B

Table B.1 - Variable names and definitions

Variable	Notation	Source	Definition
Inflation	π_t	OECD National Accounts	Delta log of price deflator of private consumption (1990=100) multiplied by 100%.
Short-term interest rate	i_t^r	IMF International Financial Statistics (IFS)	Three-month money market interest rate (%).
Credit	c_t	IMF International Financial Statistics (IFS)	Delta log of bank credit to the private sector, deflated by the price deflator of private consumption multiplied by 100%.
Provisions	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	y_t	OECD Economic Outlook	Deviation of actual real GDP from potential real GDP as a per cent of potential real GDP.
HP Output gap	y_t	Own calculations	Deviation of actual real GDP from potential real GDP as a per cent of potential real GDP. Potential output calculated using the Hodrick-Prescott filter on actual output.

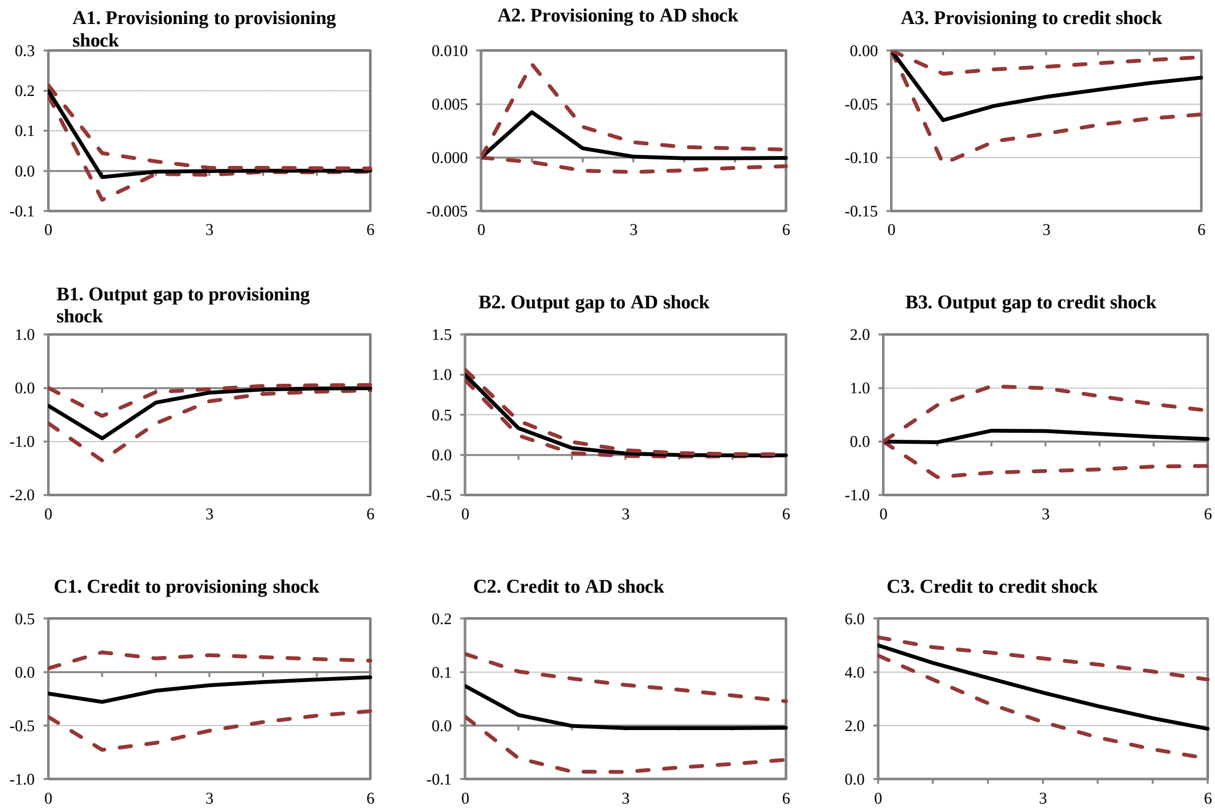
Table B.2 - Levin-Lin-Chu (2002) unit-root test.

Variable	Adjusted t	p-Value
y_t	-10.97	0.00
π_t	-6.71	0.00
c_t	-4.84	0.00
i_t^s	-5.68	0.00
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.

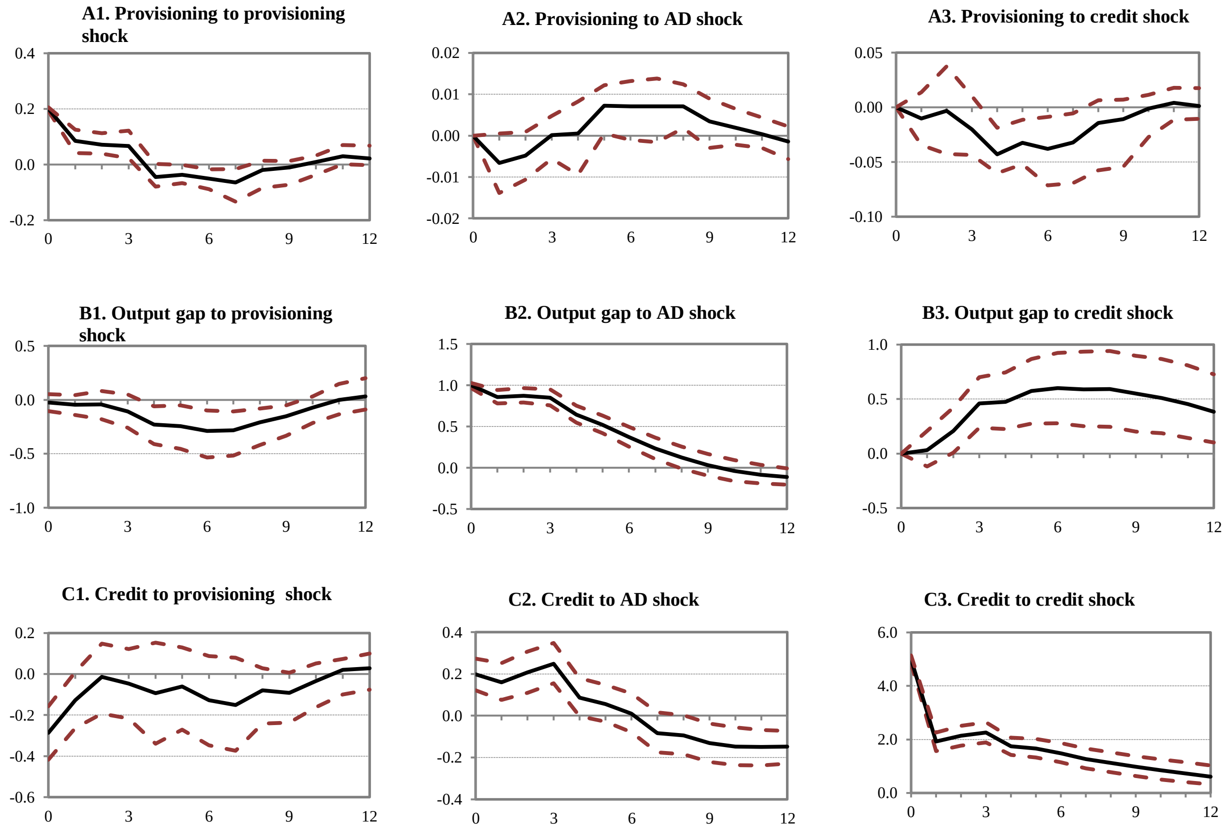
Appendix C

Figure 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.

Figure 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.

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