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## Article

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Latin American Journal of Central Banking (LAJCB)

## Provided in Cooperation with:

Center for Latin American Monetary Studies, Mexico City

*Suggested Citation:* Arroyo Marioli, Francisco; Becerra Cartes, Juan Sebastián; Solorza, Matías (2022) : The credit channel in Chile through the lens of a semi-structural model, Latin American Journal of Central Banking (LAJCB), ISSN 2666-1438, Elsevier, Amsterdam, Vol. 3, Iss. 2, pp. 1-18, <https://doi.org/10.1016/j.latcb.2022.100056>

This Version is available at:

<https://hdl.handle.net/10419/336344>

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# The credit channel in Chile through the lens of a semi-structural model

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## A B S T R A C T

In this paper, we estimate a semi-structural model with a banking sector for the Chilean economy. Our innovation consists of incorporating a system of equations that reflects the dynamics of credit, interest rate spreads, and loan-loss provisions to the Central Bank of Chile's semi-structural model (*modelo semi-estructural de proyección*). We estimate the model and analyze the macroeconomic effects of incorporating this sector. We find that the banking sector plays a role in accelerating the business cycle through lower spreads and procyclical credit supply, in contrast to its counter-cyclical role in the COVID-19 crisis. Additionally, we find that credit growth can explain about 0.3 pp of total output gap variation on average. Moreover, we find that in episodes of severe stress, this gap can grow to 1.9 pp, as it did during the COVID-19 pandemic. We also identify a credit multiplier of up to 0.06 pp of GDP for each 1 pp of growth in commercial credit. Our results suggest not only that these nonconventional policies through the credit channel can be useful but also that our model can be used for evaluation purposes.

## 1. Introduction

The global financial crisis of 2008-09 highlighted the serious impact that credit supply disruptions can have on macroeconomic performance. Of course, this is not a new phenomenon, but it attracted renewed attention after this event. Therefore, under certain circumstances, it can be important to understand credit dynamics' role in business cycles and macroeconomic policy. This necessity to understand the role of this part of the economy can increase in times of distress because credit crunches could occur and exacerbate a downfall.

In this document, we present a macroeconomic model that incorporates the dynamics of the banking sector. We part from the semi-structural model (*modelo semi-estructural de proyección*) used at the Central Bank of Chile for macroeconomic projections and incorporate a set of equations that reflect the dynamics of this sector. The semi-structural model consists of a series of general equilibrium equations derived from New Keynesian models, as Arroyo-Marioli et al. (2020) explained. We incorporate a block of interrelated equations for commercial loans, interest rate spreads, and provision of funds for loan defaults. These equations directly affect aggregate demand through loan quantities and affect GDP. Impacts on inflation and exchange rate fluctuations occur indirectly through the original model's channels. We use 2005 to 2019 Chilean data to estimate the model, simulate it, and analyze the results until 2020 to incorporate the model's readings of the crisis caused by COVID-19. We introduce the standard semi-structural model parameter values as priors and then re-estimate them with the new block of banking system equations. We then simulate impulse response functions to contrast the impact of shocks with and without this new mechanism. Finally, we perform a historical decomposition of the Chilean cycle and quantify the role of credit.

We find that the banking sector acts as a relevant part of the cycle, accelerating it in expansion periods and further contracting it in recessions. We also find that this channel is more significant during large events, such as the 2008 financial crisis and the 2020 coronavirus pandemic. The mechanism through which this occurs is one in which a positive demand shock results in higher

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output, which in turn increases credit supply and reduces the bank's default provisions. It then positively affects output, providing an acceleration effect. We find that this channel can accelerate growth by up to 0.13% after a 1% demand shock occurs, within the first year. Additionally, we decompose the effects of this sector's variables in the historical business cycle. We find that credit growth can explain, on average, about 0.3 pp of total output gap variation. Moreover, we find that in episodes of severe stress, this influence on variation can grow to 1.9 pp, as was the case during the 2020 COVID-19 pandemic. This last fact is important because in many cases, monetary policy faces the challenge of implementing nonconventional measures, many of them through the commercial banking sector. This specification allows the model to quantify better the impact of measures that have favored the flow of credit in periods of stress.

We also find that a 1% increase in credit growth can accelerate GDP by 0.06% at best 3 to 5 quarters ahead. We also perform a counterfactual analysis by using the model to read the data. We find that (inferred) autonomous shocks to credit could have contributed 2 pp of GDP during the pandemic in Chile. This increase sets an upper bound on the impact of credit policies enacted in Chile (mainly the Conditional Financing Facility for Increased Loans [FCIC] and Guarantee Fund for Small Entrepreneurs [FOGAPE]). We use these results to estimate the impact of nonconventional credit policies enacted in Chile during the pandemic. These results indicate not only that these policies are relevant to policy making but also that the model can be useful in evaluating them quantitatively.

We contrast our results with those of other countries, finding that this relevant role of the banking sector is similar to what happens in other countries. Some authors suggest that nonlinearities could emerge in the effects of credit, implying that in times of distress, parameters could change and magnify the standard effect. We believe this could be an interesting venue to explore for future versions of this model. We also contrast our results with those of other authors who study the role of credit in Chile. Our empirical results are not far from those of Barajas et al. (2008), who used a VAR approach instead for the same variables, finding that credit follows a procyclical pattern. Soderling (2008) also presented similar results for Chile regarding the credit cycle.

We organize the remainder of the article as follows. Section 2 presents the literature, Section 3 presents the model, Section 4 describes the data used, Section 5 shows the model estimation, Section 6 presents the results, and Section 7 offers our conclusions.

## 2. Literature

A growing body of literature emphasizes the role of macro-financial links in the analysis of monetary policy. Vleck and Roger (2012) compiled a long list of central banks that have models that include either financial frictions or financial intermediation. Most of these models consist of endogenous financial frictions, as in Bernanke et al. (1999) and Iacoviello (2005). In general, these models focus on understanding the factors that affect credit demand and tend to propagate and amplify the transmission of shocks through an accelerator mechanism. Another large group of authors used structural models; this group includes Gerali et al. (2010), Angeloni and Faia (2013), Angelini et al. (2014), Lama and Medina (2020), Basu et al. (2020) or Gertler and Karadi (2011). Many of these models set a theoretical framework for their analysis, usually in the form of dynamic stochastic equilibrium models. In the case of Chile, Medina and Soto (2005) and García-Cicco et al. (2014) studied the role of credit using this approach, although other authors, such as Barajas et al. (2008) and Soderling (2008), used more empirical methodologies. We contribute to this empirical branch of the literature by analyzing the role of credit from the perspective of a semi-structural model that is mainly used for monetary policy in Chile. In particular, we follow the approach used in other central bank papers, such as those by Ehrenbergerová and Malovaná (2019). This approach allows us to contrast our results with those used actively for monetary policy making, providing a better understanding of the monetary role of credit, aside from its macro-prudential aspect. We contribute to the list of central-bank models used in this sector while using Bayesian methods (just as we do in our baseline model).

Finally, it is worth mentioning the vast stream of macroeconomic models that focus on particular features of the credit industry, such as the role of credit supply factors, credit spreads, the structure of the banking system, the role of the bank balance sheet's composition in the transmission of macroeconomic and financial shocks, and the cyclical aspect (Brunnermeier and Sannikov, 2014; Christiano et al., 2014; Curdia and Woodford, 2010; Gertler and Karadi, 2011; Gilchrist and Zakrajšek, 2012; Jermann and Quadrini, 2012). These researchers have analyzed various frictions, shocks, and aspects from the banking sector and their potential implications in the business cycle. Although this paper is less related to this area, it is worth mentioning their contribution to the study of macro-financial links and monetary policy.

## 3. Model

The Central Bank of Chile regularly uses two main models for medium-term forecasting: the XMAS (Extended Model for Analysis and Simulation (García et al., 2019)), a large-scale DSGE model, and the semi-structural model (*Modelo Semi-Estructural de Proyección*), a semi-structural model (Arroyo-Marioli et al., 2020). The semi-structural model is based on the basic structure of New Keynesian (NK) models. The simplest NK model contains four equations: an *IS Curve*, a *Phillips Curve*, an equation for the exchange rate, and the Central Bank's reaction function. We will use the semi-structural model as our baseline model because it makes our results comparable to those regularly used for policy making. With this information in mind, we proceed to construct a model that accounts for the interaction between a standard macroeconomic configuration (a "macroeconomic" block) and key financial variables (a "financial" block). Given that our baseline is the semi-structural model, we use its structure to construct the macroeconomic block and proceed to extend it with

the inclusion of a financial block. Therefore, we extend the base model to account for the main macroeconomic variables' interaction with the financial sector.<sup>1</sup> Specifically, we follow the approach [Arroyo-Marioli et al. \(2011\)](#) and [Carrillo et al. \(2021\)](#) adopted.<sup>2</sup>

Formally, the model consists in four equations for the macroeconomic block and three equations for the financial block. In the macroeconomic block we model an IS curve, Phillips curves for CPI components, an equation for the exchange rate and a Taylor rule. It is important to note that consumers and firms can obtain these equations as log-linear approximations of the first-order conditions based on an optimization problem with monopolistic competition where the price adjustment is slow, as [Aguirre and Blanco \(2015\)](#) suggested. The financial block is the innovation of this paper: it captures the role of the credit sector. We construct it following [Becerra et al. \(2021\)](#) and [Ehrenbergerová and Malovaná \(2019\)](#). The financial block feeds the macroeconomic block through the IS curve. At the same time, the macroeconomic block feeds back into the financial block through income and interest rates, generating an acceleration effect. As is common in these types of specifications, lowercase variables represent gaps (deviations in logarithms) of their respective steady states.

Finally, to capture the risk in the banking sector, we use the relationships [Ehrenbergerová and Malovaná \(2019\)](#) specified. Using a quarterly projection model (QPM, a gap model the Czech National Bank uses), they extended their macroeconomic block by incorporating a financial block with total credit, credit risk, and credit interest rates, highlighting the feedback from both sectors.

### 3.1. Macroeconomic block

The block can be divided into four main parts: the IS curve (economic activity), the Phillips curves (inflation dynamics for major CPI components), the UIP condition (exchange rate), and the monetary policy rule (interest rates). Before explaining each part, it is useful to remind the reader that our model is a gap model and follows the baseline model's structure, as in [Arroyo-Marioli et al. \(2020\)](#). Therefore, we must first explain how we define potential GDP.

The output gap is defined as the difference between the log of non-mining GDP (NMGDP) ( $Y$ ) and the log of potential NMGDP ( $\bar{Y}$ ):

$$y_t = Y_t - \bar{Y}_t \tag{1}$$

Output is determined with the following equations.

#### Quarter on quarter variation of potential NMGDP

$$\Delta \bar{Y}_t = G_t + \xi_t^{\bar{Y}}, \quad \xi_t^{\bar{Y}} \stackrel{iid}{\sim} \mathcal{N}(0, \sigma_{\xi^{\bar{Y}}}^2) \tag{2}$$

#### Potential NMGDP growth ([Blagrove et al., 2015](#))

$$G_t = \theta_G G^{ss} + (1 - \theta_G)G_{t-1} + \xi_t^G, \quad \xi_t^G \stackrel{iid}{\sim} \mathcal{N}(0, \sigma_{\xi^G}^2) \tag{3}$$

Eq. (2) specifies the level of potential output in terms of its growth rate ( $G$ ) and a shock to the level ( $\xi^{\bar{Y}}$ ). In turn, potential growth follows an AR(1) process and converges to a long-run constant rate  $G^{ss}$ .

#### 3.1.1. IS curve

The IS Curve presents the following structure:

$$\begin{aligned} \Delta y_t = & -a_1(y_{t-1} + y_{t-2}) - a_2(y_{t-1} - y_{t-2}) - a_3(r_t - rn_t + r_{t-1} - rn_{t-1}) \\ & + a_4(y_t^{em} + y_{t-1}^{em}) + a_5(y_t^{ad} + y_{t-1}^{ad}) + a_6rer_{t-1} + a_7tot_t + a_8\hat{c}r_t - a_9LLP_t + v_t^y. \end{aligned} \tag{4}$$

#### Demand shock $v^y$

$$v_t^y = \rho^{vy}v_{t-1}^y + \xi_t^y, \quad \xi_t^y \stackrel{iid}{\sim} \mathcal{N}(0, \sigma_{\xi^y}^2) \tag{5}$$

This specification closely follows that of [Blagrove et al. \(2015\)](#) and [Blagrove and Blagrove and Santoro \(2016\)](#) but with an important difference. We do not model the output gap as an AR(1) process but rather as an error correction process, as in the [Central Bank of Chile \(2003\)](#).

A semi-structural IS curve describes the change in the output gap, following an error correction setting, including additional controls. The real interest rate ( $r$ ), net of the neutral level ( $rn$ ), has a negative impact on the output gap ( $y$ ). The emerging and advanced trading partners' output gaps ( $y^{em}$  and  $y^{ad}$ ), as a proxy for the external demand, have a positive effect. The terms of the trade gap ( $tot$ ) and the real exchange rate ( $rer$ ) also capture the link with the rest of the world. Finally, the shock  $v^y$  follows an AR(1) with persistence  $\rho^{vy}$ , and shocks  $\xi^{\bar{Y}}$ ,  $\xi^G$ , and  $\xi^y$  follow an IID process with a mean of zero and constant variance.

In addition to the baseline model, the IS curve contains two elements from the financial block. First, credit growth ( $\hat{c}r_t$ ) positively affects economic activity, and the second element is credit risk ( $LLP_t$ ). We base this specification on [Ehrenbergerová and Malovaná \(2019\)](#) work. The idea behind this specification is to separate credit expansion that comes from an increased demand for credit from a credit expansion that comes from an increased willingness to take more risk from lenders.

<sup>1</sup> The model has limitations. First, its lack of microfundamentals makes the model sensitive to Lucas's criticism and inadequate for welfare analysis. Second, it is based on a representative agent configuration, leaving aside the heterogeneity among the agents.

<sup>2</sup> [Alfaro and Sagner \(2011\)](#), [Becerra et al. \(2017\)](#) and [Becerra et al. \(2021\)](#) proposed a similar idea for the elaboration of stress scenarios. However, their approach is based on VAR-type econometric models, not models with macroeconomic structure.

### 3.1.2. Phillips Curve

Inflationary dynamics are similar to those presented in [Arroyo-Marioli et al. \(2020\)](#) with the innovation of using as core inflation ( $\pi^{Core}$ ) the CPI excluding volatile terms<sup>3</sup>. CPI is split into core and non-core CPI. Core CPI is then split into tradable ( $\pi^T$ ) and non-tradable ( $\pi^{NT}$ ). Each component has its own Phillips curve. Therefore, the model has three separate Phillips curves that we then aggregate into the overall CPI by weights.

#### Core CPI

$$\pi_t^{Core} = \alpha_2 \pi_t^{NT} + (1 - \alpha_2) \pi_t^T, \quad \alpha_2 \in (0, 1) \quad (6)$$

#### Non-tradable Core CPI

$$\pi_t^{NT} = bnt_1 \mathbb{E}_t \left[ \pi_{t+1}^{NT} \right] + bnt_2 (\pi_{t-1}^{NT} - \epsilon_{t-1}^{NT}) + bnt_3 y_t + \epsilon_t^{NT} + v_t^{NT} \quad (7)$$

$$v_t^{NT} = \rho^{vNT} v_{t-1}^{NT} + \xi_t^{NT}, \quad \xi_t^{NT} \stackrel{iid}{\sim} \mathcal{N}(0, \sigma_{\xi^{NT}}^2), \quad \epsilon_t^{NT} \stackrel{iid}{\sim} \mathcal{N}(0, \sigma_{\epsilon^{NT}}^2) \quad (8)$$

#### Tradable Core CPI

$$\pi_t^T = bt_2 (\pi_{t-1}^T - \epsilon_{t-1}^T) + bt_3 y_t + bt_4 (deus_t + deus_{t-1}) + bt_5 rer_{t-1} + \epsilon_t^T + v_t^T, \quad (9)$$

$$v_t^T = \rho^{vT} v_{t-1}^T + \xi_t^T, \quad \xi_t^T \stackrel{iid}{\sim} \mathcal{N}(0, \sigma_{\xi^T}^2), \quad \epsilon_t^T \stackrel{iid}{\sim} \mathcal{N}(0, \sigma_{\epsilon^T}^2) \quad (10)$$

#### Food Non-Core CPI

$$\pi_t^F = \rho^{F1} \pi_{t-1}^F + \rho^{F2} y_t + \xi_t^F, \quad (11)$$

$$v_t^F = \rho^{vF} v_{t-1}^F + \xi_t^F, \quad \xi_t^F \stackrel{iid}{\sim} \mathcal{N}(0, \sigma_{\xi^F}^2) \quad (12)$$

#### Energy Non-Core CPI

$$\pi_t^E = \alpha_3 \text{poil}_t^{MEPCO} + (1 - \alpha_3) v_t^E, \quad (13)$$

$$v_t^E = \rho^{vE} v_{t-1}^E + \xi_t^E, \quad \xi_t^E \stackrel{iid}{\sim} \mathcal{N}(0, \sigma_{\xi^E}^2) \quad (14)$$

#### Rest of Non-Core CPI

$$\pi_t^{nCore} = bv_1 (\pi_{t-1}^{nCore} - \epsilon_{t-1}^{nCore}) + bv_2 deus_t + bv_3 rer_{t-1} + \epsilon_t^{nCore} + v_t^{nCore}, \quad (15)$$

$$v_t^{nCore} = \rho^{vnCore} v_{t-1}^{nCore} + \xi_t^{nCore}, \quad \xi_t^{nCore} \stackrel{iid}{\sim} \mathcal{N}(0, \sigma_{\xi^{nCore}}^2), \quad \epsilon_t^{nCore} \stackrel{iid}{\sim} \mathcal{N}(0, \sigma_{\epsilon^{nCore}}^2) \quad (16)$$

#### Consumer Price Index (CPI)<sup>a</sup>

$$\pi_t^{CPI} = \alpha_4 \pi_t^{Core} + \alpha_5 \pi_t^F + \alpha_6 \pi_t^E + (1 - \alpha_4 - \alpha_5 - \alpha_6) v_t^{nCore}, \quad \alpha_4, \alpha_5, \alpha_6 \in (0, 1) \quad (17)$$

We measure total inflation using the CPI and its sub-components reflected in [Eqs. \(6\)–\(17\)](#). First, we divide total CPI ( $\pi^{CPI}$ ) into food CPI ( $\pi^F$ ), energy CPI ( $\pi^E$ ), rest-volatile CPI ( $\pi^{nCore}$ ) and core CPI ( $\pi^{Core}$ ). The core CPI comprises 65% of total CPI, and the non-core CPI represents 35%. Such separation follows the method of [Carlomagno and Sansone \(2019\)](#), who used econometric tools to isolate the most volatile components of consumer prices. Last, we divide core CPI into tradable (27% of total CPI) and non-tradable (38%) CPI. Tradable prices [\(9\)](#) respond not only to the domestic business cycle but also to exchange rates and quarter-on-quarter nominal depreciation (*deus*). On the other hand, non-tradable prices [\(7\)](#) correlate more with domestic activity, past prices (via indexation), and inflation expectations.

For each core CPI's sub-component, we allow for two kinds of cost-push shocks: temporary and more persistent. Specifically, persistent shocks are the following  $v^{NT}$  and  $v^T$  and one-period-lived shocks are  $\epsilon_t^{NT}$  and  $\epsilon_t^T$ .

[Eq. \(11\)](#) specifies that food inflation depends on its own lag and the output gap. [Eq. \(13\)](#) shows that energy inflation depends on the fuel prices stabilization mechanism (MEPCO)-smoothed price of oil<sup>4</sup> and the quarter-on-quarter nominal depreciation (*deus*). We use the nominal (instead of the real) depreciation because we assume that prices are rigid in the short-term. Finally, [Eq. \(17\)](#) reconstructs total inflation from its sub-components.

<sup>3</sup> For more details see Monetary Policy Report December 2019.

<sup>4</sup> The National Petroleum Enterprise implemented MEPCO as a device designed to smooth oil price variations.

### 3.1.3. UIP condition

The bilateral nominal depreciation of the peso against the dollar,  $deus$ , is not observed by the model, but deduced from the following identity:

#### Nominal depreciation

$$deus_t = rer_t - rer_{t-1} - \pi_t^* + \pi_t^{CPI}. \tag{18}$$

The UIP allows us to deduce the expected bilateral depreciation in the short-run,  $\mathbb{E}_t[deus_{t+1}]$  by equating the yield of domestic risk-free financial assets,  $i_t$ , and the yield of external assets,  $i_t^*$  plus the sovereign risk premium,  $\rho_t^{embi}$ , given foreign inflation,  $\pi_t^*$ . On the other hand, empirical evidence shows that exchange rate expectations depend on fundamentals such as the terms of trade. Therefore, the spot exchange rate depends on the difference between domestic and international interest rates, risk premiums, and the terms of trade. This relation is expressed in Eq. (20):

#### ToT UIP modification

$$\mathbb{E}_t rer_{t+1} = \theta tot_t + v_t^{UIP}, \tag{19}$$

$$rer_t = \mathbb{E}_t rer_{t+1} - \frac{i_t - in_t}{4} + \frac{i_t^*}{4} + \frac{\rho_t^{embi}}{4}, \tag{20}$$

#### AR(1) structure for UIP shock

$$v_t^{UIP} = \rho^{UIP} v_{t-1}^{UIP} + \xi_t^{UIP}, \quad \xi_t^{UIP} \stackrel{iid}{\sim} \mathcal{N}(0, \sigma_{\xi^{UIP}}^2) \tag{21}$$

### 3.1.4. Monetary policy rule

To close the macroeconomic block, the Taylor rule describes the behavior of the Central Bank. This equation includes three terms. First, a persistence term to account for the Central Bank's reaction to changes in its macroeconomic outlook. Then, the expected (core) inflation plays a significant role. Its associated coefficient satisfies the Taylor principle ( $c_2 > 1$ ), implying that the Central Bank moves the nominal interest rate beyond the change in inflation to accommodate the real interest rate, thus stabilizing prices. Finally, this rule also depends on the output gap. It is worth noting that the Taylor rule does not operate on the interest rate directly but on its deviation from the neutral interest rate ( $in$ , Eq. (24)).

#### Taylor rule

$$i_t - in_t = c_1(i_{t-1} - in_{t-1}) + (1 - c_1) \left( c_2 \mathbb{E}_t \left[ \pi_{t+1}^{core,annual} \right] + c_3 y_t \right) + v_t^i \tag{22}$$

$$v_t^i = \rho^{vi} v_{t-1}^i + \xi_t^i, \quad \xi_t^i \stackrel{iid}{\sim} \mathcal{N}(0, \sigma_{\xi^i}^2) \tag{23}$$

The Fisher Eq. (25) establishes the relationship between neutral real ( $rn$ ) and neutral nominal interest rates ( $in$ ).

#### The neutral nominal rate

$$in_t = rn_t + Target \tag{24}$$

#### Fisher Equation

$$r_t - rn_t = i_t - in_t - 4 \mathbb{E}_t \pi_{t+1}^{CPI}. \tag{25}$$

The real neutral interest rate ( $rn$ ) is determined by potential GDP growth according to Eq. (26). This definition follows Laubach and Williams (2016). We calibrate the parameter  $c_{rn\_pot}$  using the long-term growth rate ( $G^{SS}$ ) and the long-term real neutral interest rate ( $rn^{SS}$ ), which we assume as given.

#### The Neutral Real Rate

$$rn_t = c_{rn\_pot} \mathbb{E}_t[G_{t+1}] + \xi_t^{rn}, \quad c_{rn\_pot} = \frac{rn^{SS}}{G^{SS}}, \quad \xi_t^{rn} \stackrel{iid}{\sim} \mathcal{N}(0, \sigma_{\xi^{rn}}^2) \tag{26}$$

We assume that international variables are exogenous. In consequence, we model them as auto-regressive processes as shown in the Appendix.

## 3.2. Financial Block

We add the financial block to the rest of the economy to capture the credit channel in a stylized way. Specifically, we consider a financial sector, characterized by the existence of banks, in charge of the intermediation of resources between borrowers and lenders. This intermediation is carried out at a cost, the spread ( $SPR$ ) between placement rates ( $i_t^{Loan}$ ) and monetary policy rates (MPRs), which is represented by the Eq. (27).<sup>5</sup>

$$SPR_t = i_t^{Loan} - i_t \tag{27}$$

<sup>5</sup> It is important to note that (27) shows the spread between the rate charged for loans and the MPR and not with the rate of deposits as traditionally found in the literature. Empirical evidence shows no significant difference exists between either rates.

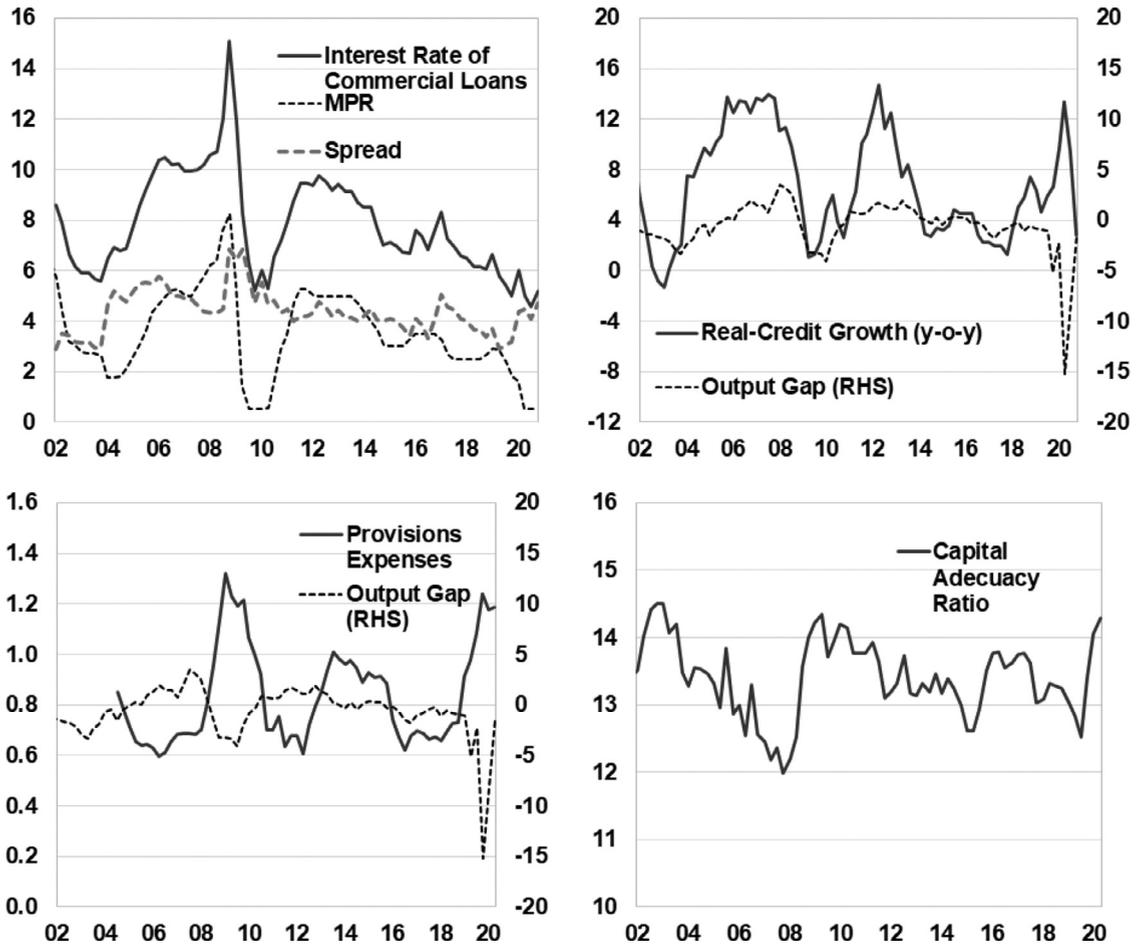


Fig. 1. Observable variables from the financial block and output gap. Note: variables are shown in percentages. All are at level, except for credit growth, which is shown in annual variation.

Curdia and Woodford (2010) argue that given the frictions present in credit demand, it is possible to impose an additional premium on the rate faced by borrowers. Along the same line, Gerali et al. (2010) show that banks devote resources to the management of their balance sheet and/or to cover the costs associated with regulatory requirements. In this paper, we also assume that banks enjoy some market power due to the presence of monopolistic competition that allows them to charge a margin on the policy rate when they grant credit.

Eq. (28) describes the dynamics of the placement rate.

$$i_t^{Loan} = \eta_1(i_t - i_n) + \eta_2LLP_t + \eta_3CAR_t + \epsilon_t^{Loan} \tag{28}$$

The credit rate is affected by the MPR with an effect equal to  $(\eta_1)$  that captures the transfer of the policy rate to the credits. It is also affected by credit risk (LLP). That is, if the banking sector experiences complications in recovering the payment of its credits, the rate at which the new credits will be made will be higher to compensate for losses. On the other hand, if the regulation becomes severer-greater capital requirement on risk-weighted assets (CAR)-the banks will increase the interest rate at which they grant loans<sup>6</sup>.

$$\hat{c}r_t = \theta_1\hat{c}r_{t-1} + \theta_2y - \theta_3SPR_t + \epsilon_t^{\hat{c}r} \tag{29}$$

Credit dynamics are represented in Eq. (29), where  $\hat{c}r_t$  is credit growth.<sup>7</sup> A higher spread reduces the demand for credit, while the term  $\theta_2$  captures the procyclical behavior of credit. Thus, we can capture the accumulation of risks in the financial sector through the evolution of the credit gap, which will be positively related to the economic activity (i.e., credit booms generally begin after periods of rapid economic growth) and negatively related to the spread. This last relationship accounts for the link between financial

<sup>6</sup> Banks will seek to obtain a higher return on their obligation to maintain a higher level of capital, in other words, will keep the return on capital constant.

<sup>7</sup> This is defined as  $\hat{c}r_t = CR_t - \bar{C}R_t$ . The equations make clear that changes in credit growth are a deviation of its trend.

**Table 1**  
Parameters, priors and posterior.

Equation	Parameter	Dist.	Prior		Posterior	
			Media	Std.	Mode	Int. 90 % prob
IS	$\alpha_1$	Beta	0.15	0.04	0.19	0.15 / 0.26
	$\alpha_2$	Beta	0.05	0.03	0.07	0.02 / 0.16
	$\alpha_3$	Beta	0.07	0.02	0.05	0.03 / 0.07
	$\alpha_4$	Beta	0.07	0.02	0.04	0.03 / 0.06
	$\alpha_5$	Beta	0.06	0.02	0.03	0.02 / 0.06
	$\alpha_6$	Beta	0.01	0.005	0.01	0.00 / 0.02
	$\alpha_7$	Beta	0.02	0.005	0.01	0.01 / 0.02
	$\alpha_8$	Beta	0.04	0.01	0.03	0.02 / 0.04
	$\alpha_9$	Beta	0.04	0.01	0.04	0.02 / 0.05
	$bm_1$	Beta	0.20	0.05	0.16	0.10 / 0.23
	$bm_2$	Beta	0.50	0.15	0.53	0.35 / 0.64
	$bm_3$	Beta	0.10	0.03	0.07	0.05 / 0.10
	Phillips's curve	$bt_2$	Beta	0.70	0.08	0.70
$bt_3$		Beta	0.02	0.005	0.02	0.01 / 0.03
$bt_4$		Beta	0.05	0.01	0.03	0.02 / 0.04
$bt_5$		Beta	0.02	0.005	0.02	0.01 / 0.02
$bv_1$		Beta	0.20	0.01	0.20	0.18 / 0.21
$bv_2$		Beta	0.10	0.025	0.10	0.07 / 0.13
ToT UIP	$bv_3$	Beta	0.05	0.01	0.04	0.03 / 0.06
	$\theta$	Beta	0.25	0.07	0.17	0.11 / 0.25
	$c1$	Beta	0.80	0.05	0.81	0.76 / 0.86
Taylor rule	$c2$	Norm	1.70	0.10	1.59	1.42 / 1.76
	$c3$	Gamm	0.20	0.05	0.20	0.12 / 0.30
Lending rate	$\eta_1$	Norm	1.50	0.10	1.26	1.16 / 1.38
	$\eta_2$	Norm	2.50	0.10	2.47	2.31 / 2.63
	$\eta_3$	Beta	0.60	0.02	0.60	0.57 / 0.63
Credit	$\theta_1$	Beta	0.70	0.10	0.56	0.44 / 0.67
	$\theta_2$	Norm	1.50	0.10	1.31	1.17 / 1.48
	$\theta_3$	Beta	0.2	0.05	0.17	0.11 / 0.26
Provision expenses	$\theta_1$	Norm	0.9	0.10	0.81	0.68 / 0.95
	$\theta_2$	Beta	0.20	0.03	0.11	0.08 / 0.14
Capital Adequacy Ratio	$\theta_3$	Beta	0.027	0.01	0.01	0.01 / 0.02
	$\rho_{CAR}$	Beta	0.30	0.10	0.65	0.53 / 0.74

conditions and credit booms. This is in line with [Drehmann and Tsatsaronis \(2014\)](#) who suggest that a strong credit expansion would be an indicator of possible banking problems.

$$LLP_t = \vartheta_1 LLP_{t-1} - \vartheta_2 \left( \frac{\sum_{i=1}^4 y_{t+i}}{4} \right) + \vartheta_3 \hat{c}r_{t-1} + \varepsilon_t^{LLP} \quad (30)$$

The loan-loss provisions ( $LLP$ ) dynamics are described in [Eq. \(30\)](#). We assume that it depends on expected economic activity, credit and some lag. The intuition behind this specification is that periods of expansion in economic activity are accompanied by reductions in delinquency levels because debtors can meet the payment of their obligations. On the other hand, an accelerated expansion of credit, which would be captured by a positive credit gap, could result in vulnerabilities for banks because of the possibility that the new loans are of lower quality due to a relaxation of standards for granting credit during credit booms. This translates into higher provisions.

$$CAR_t = \rho_{CAR} CAR_{t-1} + \varepsilon_t^{CAR} \quad (31)$$

Finally, [Eq. \(31\)](#) describes the evolution of the capital adequacy ratio ( $CAR$ ), which is independent of the central bank and follows its own dynamics.

#### 4. Data

This section describes the data set that we use in the model's estimation. For the macroeconomic block, we use the output gap, inflation, core inflation, the MPR, the real and nominal exchange rates, and several external variables. These come from the Central Bank of Chile, with the exception of inflation, which comes from the National Statistics Institute (INE). External variables are produced internally in the Central Bank of Chile International Analysis Division, which uses data from the Federal Reserve, Bloomberg, and official statistic agencies of Chile's trade partners (weighted by trade participation). For the financial block, we use the interest rate for new commercial loans, the expenditure on provisions for that kind of loan, the commercial credit gap, and the capital adequacy index ( $CAR$ ). These come from the Central Bank of Chile, with the exception of commercial loan provisions and  $CAR$ , which come from the Financial Market Commission. The data are in quarterly frequency with information from the first quarter of 2005 to the first quarter of 2019.

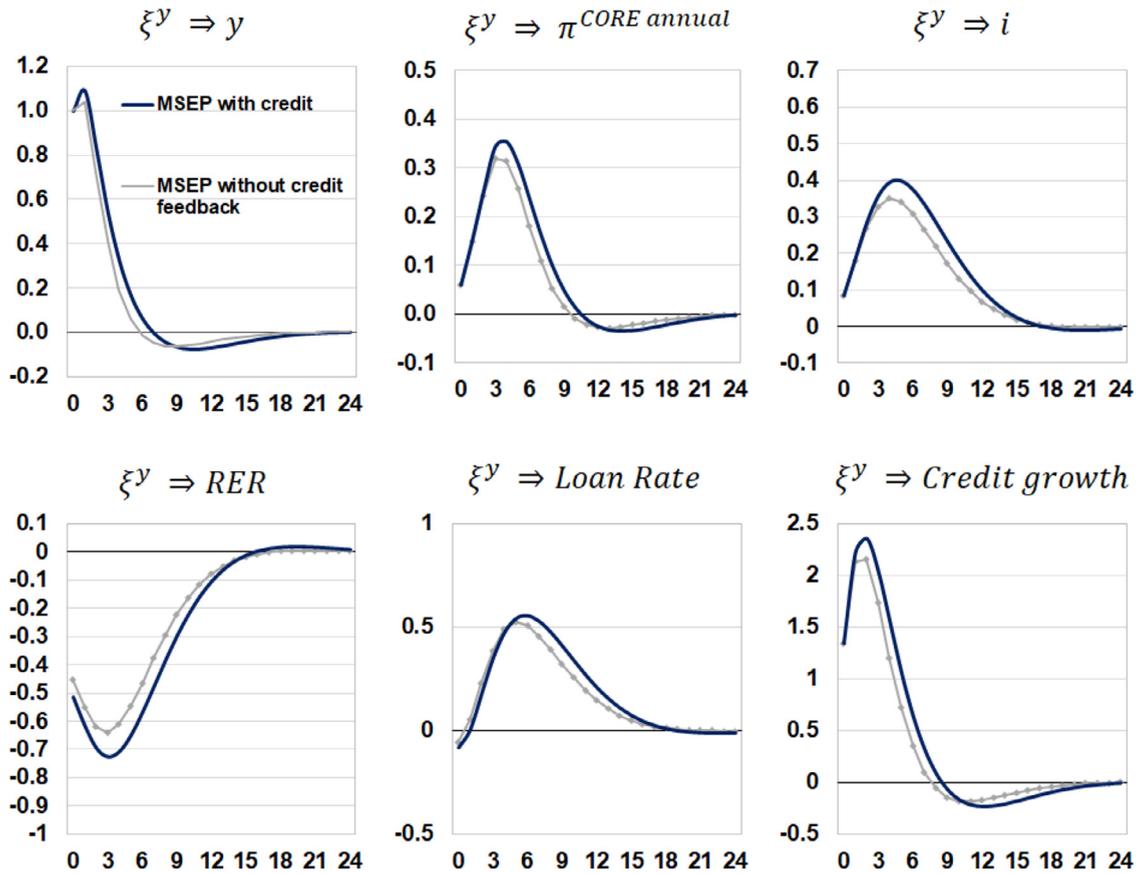


Fig. 2. Activity shock. Note: IRFs use the posterior mode.

We specify the model in terms of gaps and assume that these converge to zero over time. In other words, once the gaps are closed, in the absence of perturbations, the variable dynamics are those of the trend variables. The semi-structural model extended with the banking sector aims to explain the joint dynamics of these variables during the business cycle. Gaps for variables in the macroeconomic block were estimated using the same techniques as in Arroyo-Marioli et al. (2020). We use the Hodrick-Prescott filter to determine the trend of interest rates on commercial loans. For the rest of the variables of the financial block, credit growth, CAR, and credit risk the long trends are modeled as the sample mean.

For the variables of the macroeconomic block, we use the same data as in Arroyo-Marioli et al. (2020). For the financial block, we restricted the analysis to commercial credit because we wanted to study the feedback from the banking sector to economic activity through firms. For the credit gap, we use the annual credit growth of commercial loans. Finally, the provision expense index corresponds to the sum of the commercial provisions plus penalties in the previous 12 months divided by the total commercial credit.

The use of the aforementioned indicator as a measure of credit risk is well-known. Jara et al. (2007) estimate a credit risk model for 16 Chilean banks from 1989 to 2004 and relate the evolution of expenditure in total provisions with variables that characterize the economic cycle, also controlling for the heterogeneity of the banking industry. Alfaro and Sagner (2011) focus on the credit risk of consumer banks and relate spending on consumer provisions during the period 1992 to 2009 with macroeconomic variables such as the GDP gap, the credit rate between 1 to 3 years, and the unemployment rate. Additionally, Jara et al. (2007), Alfaro and Sagner (2011) and Becerra et al. (2017) point out that the Central Bank of Chile uses the provision expense broken down by type of portfolio as a measure of credit risk in preparation of stress tests. Fig. 1 illustrates the variables.

#### 4.1. Observable variables from the financial block and output gap

We transform the variables to feed the gap-model. We specify these transformations below. The model observes: the output gap ( $y$ ), potential GDP ( $\Delta\bar{Y}$ ), total inflation rate, core inflation (tradable y non-tradable), non-core inflation rate, food and energy inflation ( $\pi^{CPI}$ ,  $\pi^{Core}$ ,  $\pi^T$ ,  $\pi^{NT}$ ,  $\pi^{nCore}$ ,  $\pi^F$  and  $\pi^E$  respectively), MPR ( $i$ ), real exchange rate ( $rer$ ), terms of trade ( $toi$ ), the output gap of advanced and emerging trading partners ( $y^{ad}$  and  $y^{em}$  respectively), Chile's Emerging Markets Bonds Index (EMBI;  $\rho^{embi}$ ), external interest rate ( $i^*$ ), oil price ( $poil$ ), copper price ( $pcu$ ), external inflation ( $\pi^*$ ), and the unemployment rate ( $u_t$ ). The variables of the financial block are *detrended*.

We get these variables through the following relationships:

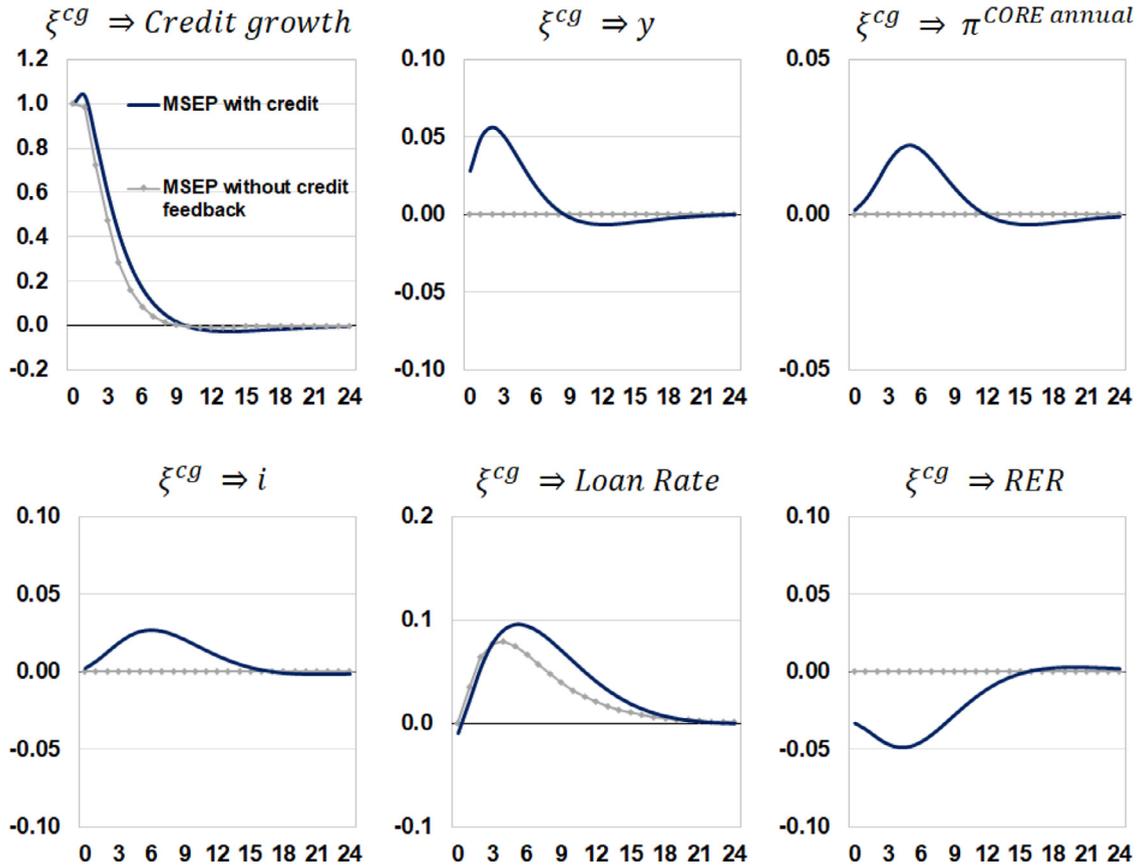


Fig. 3. Credit growth shock.

$\pi_t^{CPI} = \Delta \log (CPI_t^{sa}) - \bar{\pi},$	
$\pi_t^{Core} = \Delta \log (CoreCPI_t^{sa}) - \bar{\pi},$	$\pi_t^{nCore} = \Delta \log (NcoreCPI_t^{sa}) - \bar{\pi},$
$\pi_t^{NT} = \Delta \log (CoreCPI_{NT,t}^{sa}) - \bar{\pi},$	$\pi_t^T = \Delta \log (CoreCPI_{T,t}^{sa}) - \bar{\pi},$
$\pi_t^F = \Delta \log (FCPI_t^{sa}) - \bar{\pi},$	$\pi_t^E = \Delta \log (ECPPI_t^{sa}) - \bar{\pi},$
$y_t = \log \left( \frac{NMGDP_t^{sa}}{NMGDP_t^{pot}} \right),$	$\Delta \bar{Y}_t = \Delta \log (NMGDP_t^{pot}),$
$\Delta Y_t = \Delta \log (NMGDP_t),$	$i_t = MPR_t,$
$rer_t = \log \left( \frac{RER_t}{RER^{eq}} \right),$	$tot_t = \log \left( \frac{ToT_t}{ToT_t^{trend}} \right),$
$y_t^m = \log \left( \frac{EMGDP_t}{EMGDP_t^{trend}} \right),$	$y_t^{ad} = \log \left( \frac{ADGDP_t}{ADGDP_t^{trend}} \right),$
$\rho_{t}^{emb} = \log \left( \frac{EMBI_t}{EMBI^{eq}} \right) / 10000,$	$pcu_t = \log \left( \frac{PCU_t}{PCU_t^{trend}} \right),$
$poil_t = \log \left( \frac{PWTI_t}{PWTI_t^{trend}} \right),$	$\pi_t^* = \Delta \log (FPI_t) - \bar{\pi}^*,$
$u_t = U_t - NAIRU_t,$	$i_t^* = IUS_t - \bar{i}^*,$
$i_t^{loan} = i_t^{loan,obs} - i_t^{loan,trend},$	$\hat{c}r_t = cr_t - cr_t^{trend},$
$LLP_t = LLP_t^{obs} - LLP_t^{trend},$	$CAR_t = capital_t^{obs} - capital_t^{trend},$

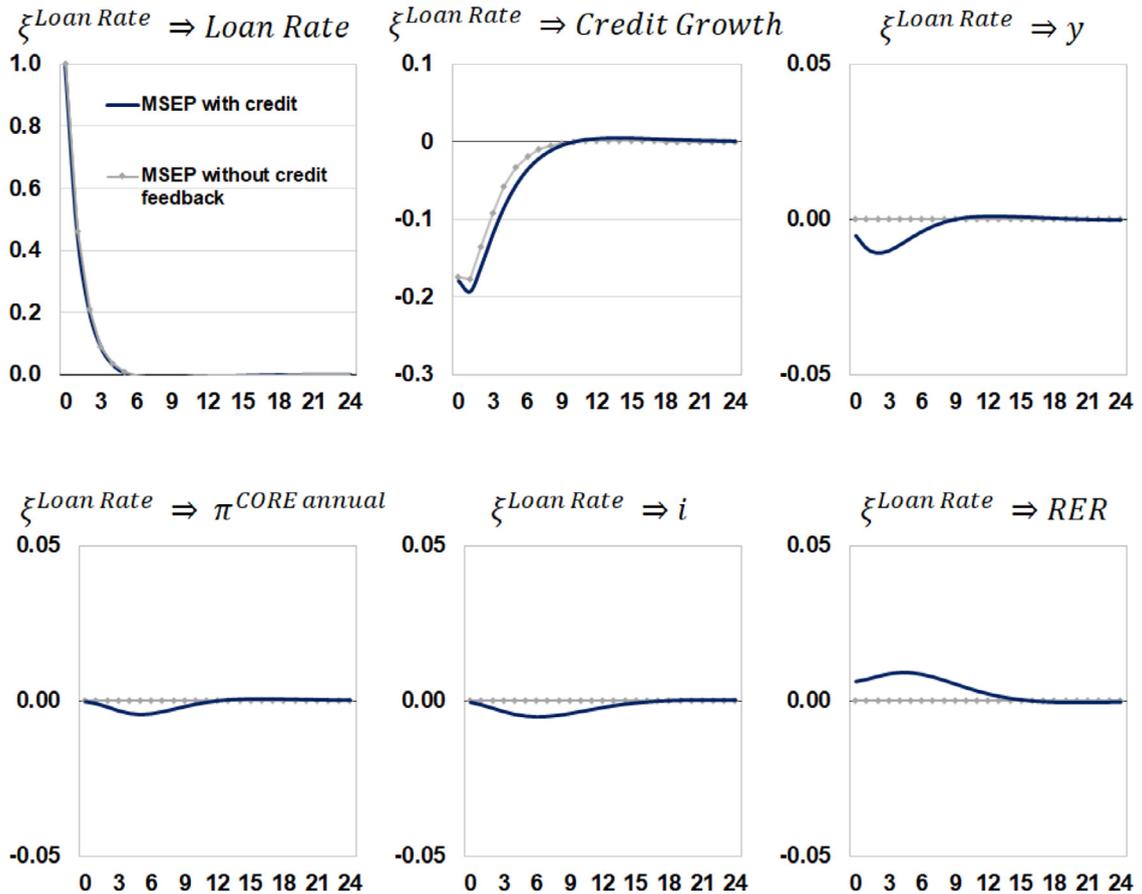


Fig. 4. Loan rate shock.

where  $NMGDP^{Pot}$  denotes potential GDP, estimated via multivariate filters.<sup>8</sup> The following trends:  $EMGDP^{trend}$ ,  $ADGDP^{trend}$ ,  $PWTI^{trend}$ ,  $PCU^{trend}$  and  $ToT^{trend}$  were calculated as in Arroyo-Marioli et al. (2020). While  $i_{trend}^{loan}$  is estimated through Hodrick-Prescott filter and  $c_r^{trend}$ ,  $LLP^{trend}$ , and  $capital^{trend}$  are the means of the data.

## 5. Model estimation

We proceed to estimate the model with a Bayesian approach by taking the baseline values as priors and re-estimating them with Chilean data. We use the following strategy. For the macroeconomic block, we take the prior distributions from Arroyo-Marioli et al. (2020). For the financial block, we obtain prior distributions from univariate regressions using standardized econometric techniques (ordinary least squares and generalized method of moments), as well as priors used in Becerra et al. (2021). The model is then estimated jointly.

Bayesian estimation was performed using *Dynare* software. We performed 200,000 iterations of *Metropolis-Hasting* algorithm to recover key moments of the posterior distribution.<sup>9</sup> The data set goes from 2005Q1 to 2019Q1. This is the starting point for the commercial credit data series.

Table 1 reports assumed priors distribution as well as the mode, mean, the 10th and 90th percentiles of the estimated parameter's posterior distribution. Less relevant parameters are not reported.

## 6. Results

### 6.1. Dynamic of the Chilean economy

Table 1 presents the results for the posterior. We find that the average estimated parameters for the macroeconomic block are in the range of estimates observed in the literature as well as presented in the base-line model in Arroyo-Marioli et al. (2020). Regarding

<sup>8</sup> The Central Bank of Chile periodically updates the potential GDP estimation. For more details see Monetary Policy Report June 2021.

<sup>9</sup> For robustness, we performed simulations with 1,000,000 iterations, obtaining identical results.

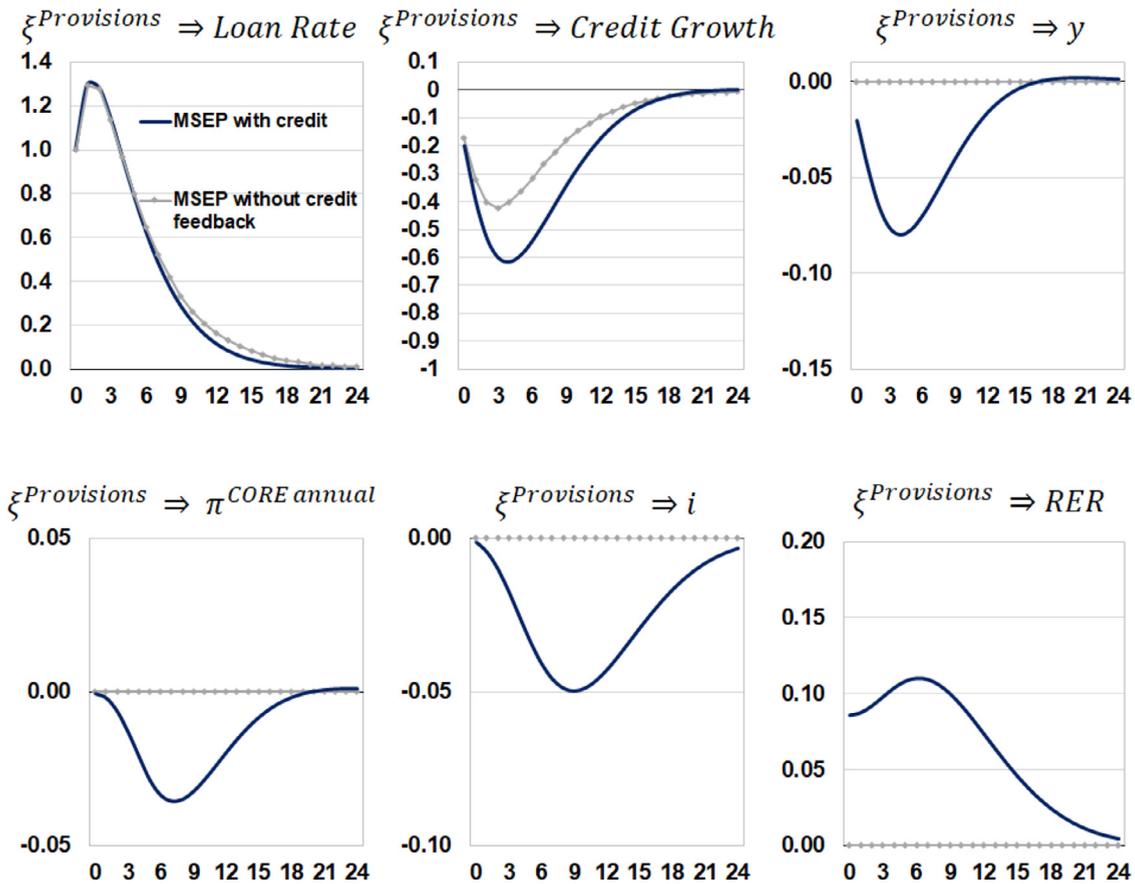


Fig. 5. Provisions expenses shock.

the financial block, as expected from Fig. 1, we find that the MPR is an important factor for the determination of how much Banks will charge to their clients,  $\eta_1$ , followed by the credit risk,  $\eta_2$ , and the capital requirement  $\eta_3$ . Therefore, if the regulatory institutions require banks to have a higher capital level, the cost will be transferred to the users through a higher interest rate. On the credit dynamics side, the parameter ( $\theta_2$ ) reflects its procyclical behavior.

As in Ehrenbergerová and Malovaná (2019), we then analyze the impulse response functions derived from our model to understand its basic dynamics, with emphasis on how the financial block interacts with the rest of the economy. We do this by showing the impulse response both with and without the banking channel. More specifically, the blue lines in Figs. 2–4, 6, and 7 indicate impulse responses of the full model, with all the posterior parameter estimations in Table 1, whereas gray lines show the same model but set the accelerating parameters  $\alpha_8$  and  $\alpha_9$  (the two parameters that represent the feedback between the financial sector and the real economy) to zero. Such parameters are statistically significant, and therefore, the exercise in the figures should not be interpreted as a comparison of two models, but as a visualization of the estimated role of the banking channel.

Fig. 2 shows the model’s dynamics when a domestic demand shock increases the output level by 1% with respect to potential output. In this case, the MPR increases in response to the new level of the output gap and the increase in inflation. The MPR increase translates into an appreciation of the real exchange rate that helps to stabilize the economy. The loan rate increases as a response to a higher cost of funding. That effect dominates the improvement in the banks’ portfolio reflected in the fall in provision expenses. Finally, real-credit growth follows a procyclical behavior increasing around 2% over 1 year. The figure also reflects the accelerating effect of the feedback caused by the increase in credit depicted in both cases with and without feedback to activity through the IS curve. Overall, in the first year, this accelerating effect increases GDP up to 0.13%, inflation by 0.05%, interest rates by 0.04 basis points and appreciated the exchange rate (ER) by an additional 0.1%.

Fig. 3 shows the response of the endogenous variables to an idiosyncratic shock that increases credit by 100 basis points year on year. First, an increase in credit boosts activity and inflation, generating a monetary policy response. Because of the latter, the loan rate increases as well, because the cost of funding dominates. Eventually, the effect on GDP can reach 0.05% or 0.06%. This particular result (the credit multiplier) will be useful when evaluating policies in the following sections.

Fig. 4 illustrates the impulse response function for a higher lending rate. A higher lending rate reduces credit because it is now relatively more expensive to borrow. This result affects activity because worse financial conditions contract product, and therefore inflation decreases. Monetary policy responds by reducing interest rates, which in turn depreciates the currency via the UIP condition.

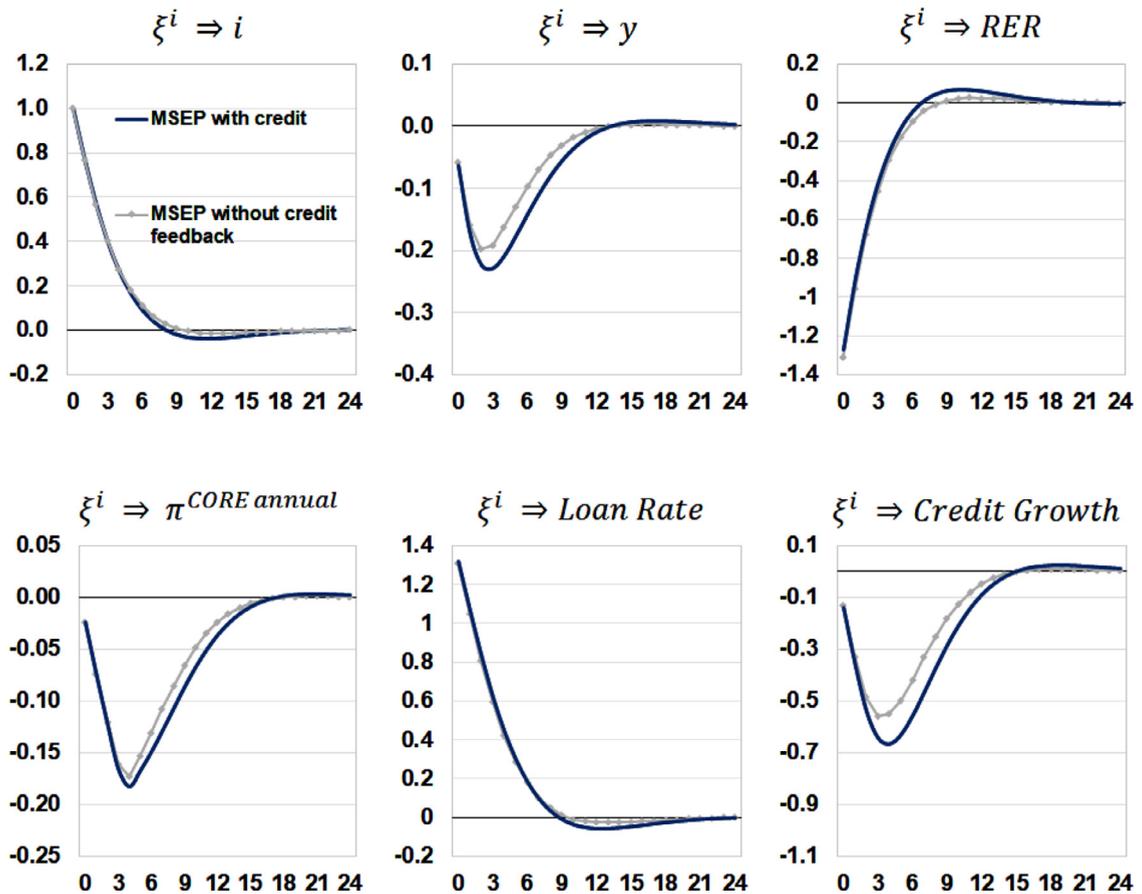


Fig. 6. Monetary policy shock.

The mechanism of a provision expenses shock is similar to the loan rate shock. A higher lending rate reduces credit because it is now relatively more expensive to borrow. An effect on activity also occurs because worse financial conditions reduce GDP. Given this, inflation also decreases. The main difference resides in the fact that the provision expenses shock has a higher impact on activity. The reason is the presence of this term in the IS curve.

Fig. 6 shows the model’s response to a monetary policy shock that increases the MPR by 100 basis points. First, a fall in the output gap is generated as well as an exchange rate appreciation due to domestic-foreign interest rate arbitrage. The combined effect of these last two variables translates into a fall in core inflation. The cumulative effect is a decrease of approximately 0.2% over 1 year. The response of the loan rate is relatively higher than the MPR. The reason is the feedback from activity to the banking block due to provisions, interpreted as an increase in risk. Finally, credit contracts because of the decline in activity and higher loan rates.

Finally, Fig. 7 illustrates the model’s dynamics when a cost-push shock of size 1% hits the economy. First, the output gap becomes positive due to a decrease in the real rate due to Taylor’s rule persistence. However, once it becomes positive, the output gap decreases, and, accompanied by an appreciation in the real exchange rate, inflation finally converges again to the equilibrium level. Communication with the banking block occurs through two channels. The first is the increase in the loan rate following the MPR, and the second is the increase in provisions due to the fall in activity. Both effects go in the same direction.

### 6.2. Variance decomposition

Table 2 shows the unconditional variance decomposition of forecast errors of the main model’s endogenous variables. This measure indicates the contribution of each shock (columns) to the total variance of the forecast error of each variable (rows).

For activity, it is observed that output-gap unconditional forecast error variance is explained in more than 60% by  $\xi^y$  shock, which is interpreted as a demand shock. Then, foreign demand (emerging and advanced business partners) explains almost 16%. The banking channel is not relevant on average.

Regarding core inflation, cost-push shocks explain roughly 70% of the unconditional core inflation forecast error variance, and both the demand (domestic and foreign) and exchange rate channels explain about 10 and 17%, respectively.

When considering the total CPI, the unconditional forecast error variance is 11% explained by energy and food prices shocks and 16% by cost-push shocks. In addition, oil price shock (ToT) affects nearly 19%.

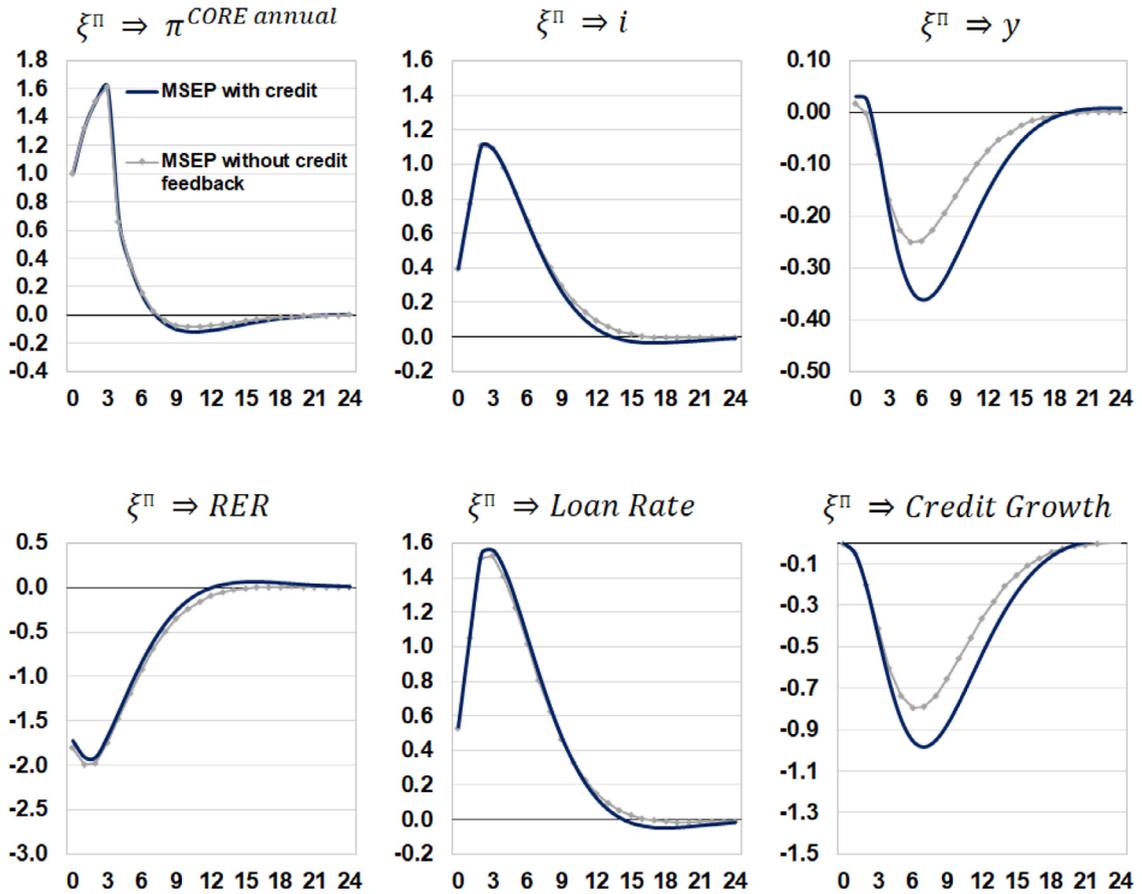


Fig. 7. Cost-push shock.

Table 2  
Forecast error variance decomposition (percentage).

Variable	Shock										Total
	Demand	Cost	Monetary	UIP	F. fin.cond.	F. Demand	ToT	F&E	Banking	Others	
$y$	63.0	3.6	7.3	0.6	0.1	16.2	6.2	0.1	1.9	1.1	100
$\pi^{CORE}$	8.3	67.1	3.9	6.4	1.2	2.4	0.9	0.1	0.3	9.4	100
$\pi^{CPI}$	4.3	35.2	2.3	6.2	1.0	1.2	19.7	11.0	0.2	19.0	100
$i$	12.6	22.1	40.8	4.9	1.5	5.9	1.1	0.1	0.5	10.6	100
$rer$	5.0	8.3	6.8	49.1	9.4	4.7	11.9	0.0	0.2	4.6	100
Credit Growth	32.6	3.2	5.9	0.3	0.1	12.0	4.5	0.1	40.5	0.8	100
$i_{loan}$	10.6	20.9	35.2	3.8	1.1	2.2	0.9	0.1	18.8	6.4	100
$Spread$	6.2	8.1	11.0	1.0	0.2	4.3	1.7	0.0	65.1	2.4	100
$LLP$	8.4	3.8	4.0	0.4	0.1	12.2	3.6	0.0	66.5	1.1	100

In the case of the nominal MPR, domestic demand (12%), cost-push (22%), monetary policy (40%) and foreign demand (6%) shocks explain most of its unconditional forecast error variance. Notice that foreign transitory shocks, such as UIP and oil price shocks, have relatively little impact. Regarding the RER, more than 11% of its unconditional forecast error variance is explained by ToT shocks, especially copper price shocks.

Until here, no major changes with respect to Arroyo-Marioli et al. (2020) have occurred, but now, within the scope of the bank-credit block, when considering credit growth, the unconditional forecast error variance is 41% explained by shocks from the banking sector. In addition, demand shocks explained 33%, depicting the procyclical behavior of credit. The third element is the external sector, which affects credit through aggregate activity.

Regarding the loan rate, monetary policy shocks explain about a third of the variance, followed by cost shocks and shocks from the banking sector, which explain 20% each. The spread, being the difference between the MPR and the loan rate, is mainly explained (around 60%) by elements of the banking sector.

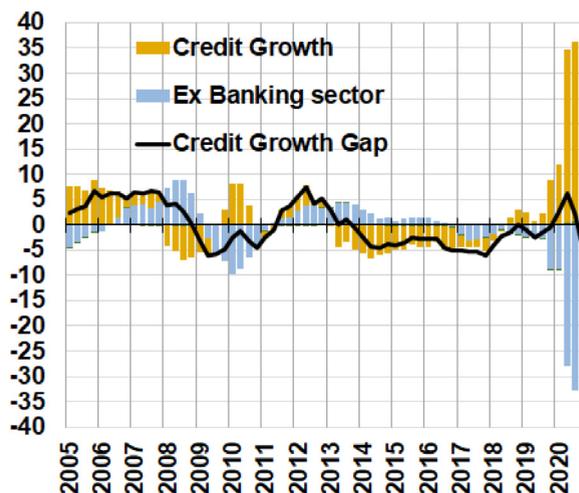


Fig. 8. Credit growth (Annual Var. [%], demeaned).

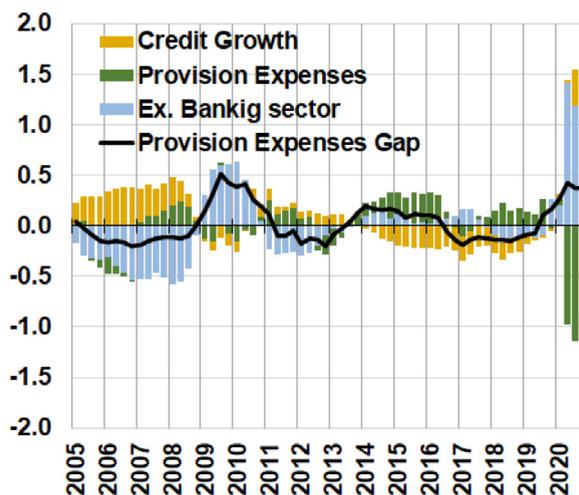


Fig. 9. Provision expenses. (ratio [%], demeaned).

Finally, spending on provisions is explained mostly by elements of the banking sector (about two-thirds of the variance), whereas the second most relevant shocks are demand and external demand shocks, which explain about 10% each.

### 6.3. Historical decomposition

We use the model to decompose historically the behavior of banking variables and their effects in the economy. Fig. 8 shows the behavior of credit allocations from 2005 to 2020. The gray areas indicate endogenous behavior due to the cycle and the yellow the exogenous component. Allocations are clearly procyclical. This makes sense because in the model estimation we find that credit exacerbates the cycle. The innovations in credit during the global recession and, in particular, during the current pandemic, can potentially reflect the role of nonconventional monetary policy, among other innovations. We find this to be a very useful tool in times of distress, because our model allows estimation of the impact of these nonconventional measures.

A similar point can be made for provisions. Fig. 9 shows that the exogenous component of provisions also acted counter-cyclically during the recent pandemic. Given the significant drop in GDP, provisions should have increased significantly. However, they have not. The model reads this as an exogenous impulse towards reducing provisions. This could also be capturing, at least partially, the effect of nonconventional monetary policy.

Finally, and most importantly, we can see the role of these shocks in the cycle in Fig. 10. During regular times, these innovations do not play a significant role. However, during the pandemic, exogenous impulses from the credit sector allowed a counter-cyclical effect on GDP by almost 2 pp. This result highlights the importance of nonconventional measures and provides a tool for policymakers to measure the effects of these types of policies in aggregate terms. In the case of Chile, we interpret this result as the combined effects of FCIC, FOGAPE guarantees, and other measures. Specifically, FCIC (Conditional Financing Facility for Increased Loans) was a

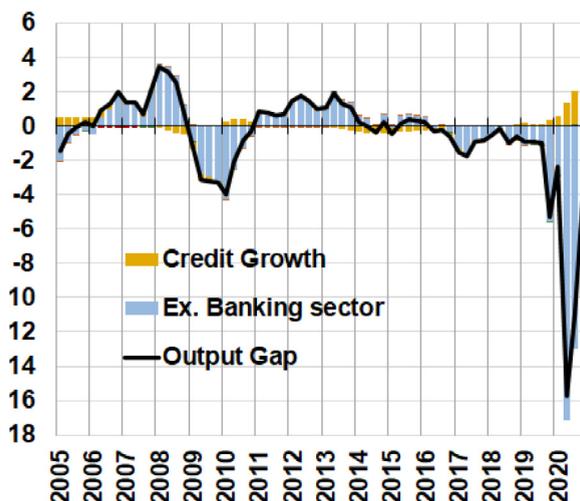


Fig. 10. Output gap. (%)

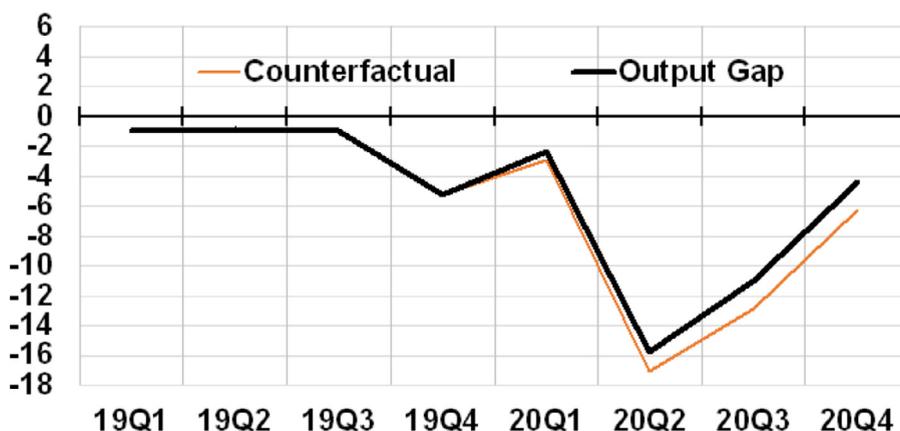


Fig. 11. Counterfactual of the output gap. (%). Note: The counterfactual removes the effects from autonomous commercial credit shocks.

program in which commercial banks had access to special funding in exchange for reassuring that the funds were lent to the public (see Appendix for details).

According to the model’s reading, significant credit-growth shocks have taken place since the beginning of the pandemic. A correct interpretation of these shocks is that they reflect everything that is not associated with the usual credit drivers. In other words, the drivers indicate that by historical standards, credit growth should have followed the significant drop in aggregate demand. However, given this was not the case, the model infers an autonomous shock to credit to match the observable.

Another way of depicting these is through a counterfactual exercise for GDP, which consists of simulating the evolution of the output gap without the contributions from the inferred autonomous credit shocks. This exercise shows an activity gap that is more negative (Fig. 11), indicating that the fall in GDP during the COVID-19 crisis would have been even greater had it not been for the exogenous credit boost. It is possible to hypothesize that this boom is related to policy, especially given the orders of magnitude involved. However, to evaluate the real impact of each specific program properly, further simulations should be performed with alternative identification strategies, because autonomous shocks could also be capturing other measures. It is even possible that the credit shocks were not necessarily induced by policy. Further research is required to reach stronger conclusions.

Finally, it is important to clarify that the exercises performed here are linear. Indeed, under a shock as the one seen during 2020, an implicit fall of 30% of credit (as inferred by the model, Fig. 12) would have most likely implied nonlinear effects, such as the bankruptcy of firms. This would most certainly have generated an even more significant drop in output that is not captured in this exercise. These limitations should be considered when using the model.

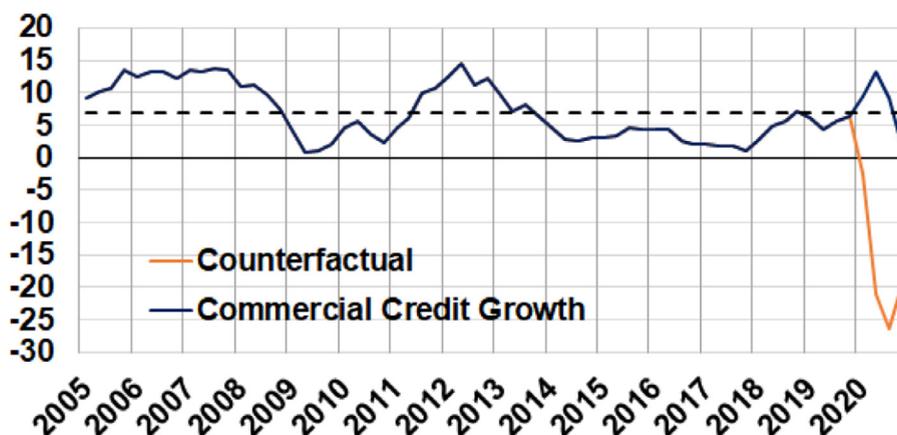


Fig. 12. Counterfactual of the commercial credit growth. (%) Notes: (1) The counterfactual removes the effects from autonomous commercial credit shocks. (2) Dotted line represents average commercial credit growth in the estimation sample.

## 7. Conclusions

In this paper, we incorporate the banking sector into the Central Bank of Chile's semi-structural model. We do this by incorporating a block of equations that describe dynamics for commercial loans, interest rate spreads, and loan-loss provisions. The goal is to understand the role that this sector plays in the macroeconomic cycle, with potential implications for monetary policymaking.

We estimate the model through a Bayesian approach for Chile from 2005 to 2019. We find that the banking sector plays an acceleration role in the business cycle: higher (lower) output gap level increases (reduces) credit loans and reduces (increases) loan-loss provisions. This in turn increases (reduces) aggregate demand, accelerating the initial effect. We find that under a 1% demand shock, this acceleration can add up to an additional 0.13% impulse to GDP and 0.05% to inflation in the first year. It also has a 0.04 bp effect on interest rates in the first year and 0.07 bp effect in the second. The ER appreciates an additional 0.1% in both the first and second year. These latter two effects (interest rates and ER) occur through the Taylor rule and UIP condition.

Additionally, we decompose historically the effects of this sector's variables in the historical business cycle. We find that commercial loans can explain on average about 0.3 pp of total output gap variation. Moreover, we find that in episodes of severe stress, this role can grow to 1.9 pp, as has been the case of the 2020 COVID-19 pandemic. This last fact is important, given that in many cases, monetary policy is faced with the challenge of implementing nonconventional measures, many of them through the commercial banking sector. We also find that a 1% increase in credit increases GDP up to 0.06% within four quarters. Finally, we use the model to perform a historical decomposition of the credit sector and economic activity. We find that autonomous credit shocks could have boosted GDP by up to 2 pp during the pandemic in Chile. This counterfactual exercise sets an upper bound to the impact of major credit programs, such as FOGAPE and FCIC. It provides evidence that the model can be used for policy analysis.

As a conclusion, it is worth mentioning that the goal of this paper is to study the role of the banking sector in the economy by focusing on macro variables. The model was not designed to address the stability of the financial sector, but rather to see its effect in income and inflation. For a macroprudential analysis, please see [Martínez et al. \(2020\)](#).

## Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Acknowledgments

For their suggestions and comments we would like to thank Andrei Zlate, Rodrigo Alfaro, Juan Francisco Martínez, Markus Kirchner, Andrés Sagner, and Jorge Fornero. We also thank the editor and referees. The views and conclusions presented here are exclusively those of the authors and do not necessarily reflect the position of the Central Bank of Chile or its Board members nor the World Bank Group or its Board members.

## Appendix A. Full characterization of the model

We assume that international variables are exogenous. In consequence, we model them as auto-regressive processes as shown in [Eqs. \(A.32\) to \(A.43\)](#). These variables include: the output gaps of emerging and advanced trading partners, the oil price, the copper price, the terms of trade, the external interest rate, external inflation, and the risk premium.

## Emerging trading partners output gap

$$y_t^{em} = \rho^{em} y_{t-1}^{em} + v_t^{em}, \quad (A.32)$$

$$v_t^{em} = \rho^{vem} v_{t-1}^{em} + \xi_t^{em}, \quad \xi_t^{em} \text{ iid } \mathcal{N}(0, \sigma_{\xi^{em}}^2) \quad (A.33)$$

## Advanced trading partners output gap

$$y_t^{ad} = \rho^{ad} y_{t-1}^{ad} + v_t^{ad}, \quad (A.34)$$

$$v_t^{ad} = \rho^{vad} v_{t-1}^{ad} + \xi_t^{ad}, \quad \xi_t^{ad} \text{ iid } \mathcal{N}(0, \sigma_{\xi^{ad}}^2) \quad (A.35)$$

## Domestic oil price

$$poil_t^{mepco} = \alpha_{mepcomepco} poil_{t-1}^{mepco} + (1 - \alpha_{mepco})(deus_t + \pi_t^{exl} + poil_t + poil_{t-1}) + \xi_t^{mepco}, \quad (A.36)$$

$$\xi_t^{mepco} \text{ iid } \mathcal{N}(0, \sigma_{\xi^{mepco}}^2)$$

## ToT

$$tot_t = px_t - pm_t \quad (A.37)$$

## Foreign interest rate

$$i_t^* = \rho^{i^*} i_{t-1}^* + v_t^{i^*}, \quad (A.38)$$

$$v_t^{i^*} = \rho^{vi^*} v_{t-1}^{i^*} + \xi_t^{i^*}, \quad \xi_t^{i^*} \text{ iid } \mathcal{N}(0, \sigma_{\xi^{i^*}}^2) \quad (A.39)$$

## Foreign inflation

$$\pi_t^* = \rho^{\pi^*} \pi_{t-1}^* + v_t^{\pi^*}, \quad (A.40)$$

$$v_t^{\pi^*} = \rho^{v\pi^*} v_{t-1}^{\pi^*} + \xi_t^{\pi^*}, \quad \xi_t^{\pi^*} \text{ iid } \mathcal{N}(0, \sigma_{\xi^{\pi^*}}^2) \quad (A.41)$$

## Risk premium

$$\rho_t^{embi} = \rho^{embi} \rho_{t-1}^{embi} + v_t^{embi}, \quad (A.42)$$

$$v_t^{embi} = \rho^{v\rho^{embi}} v_t^{embi} + \xi_t^{embi}, \quad \xi_t^{embi} \text{ iid } \mathcal{N}(0, \sigma_{\xi^{embi}}^2) \quad (A.43)$$

## Appendix B. Some context on FOGAPE and FCIC

The objective of these programs was to maintain the credit flow to firms in a context where the Central Bank could not reduce interest rates any further.

FOGAPE is an instrument for the funding of SMEs. Its size and scope were broadened significantly during the second quarter of 2020, with guarantees of US\$3 billion that could be levered up to \$24 billion in new credits. This represented a ten-fold increase in the program (reaching 10% of GDP in potential new credits).<sup>10</sup>

The other program is the FCIC. This is a 4-year lending facility at the MPR at its effective lower bound (ELB), which is assessed to be 0.5%. To incentivize uptake even in the case that banks expect the ELB to be revised downward, a clause for automatic refinancing at a lower rate was included. FCIC1 was implemented in March 2020 and saw an uptake in bank funding of close to 10% of GDP. FCIC2 was implemented in June 2020 to boost the credit stock and make adjustments to link the facility more directly to the flow of FOGAPE-COVID loans. The third line (FCIC3) was announced in January 2021. This phase is focused on facilitating the refinancing of loans that are up to date, as well as loans that already have a guarantee through programs such as FOGAPE-COVID.<sup>11</sup>

<sup>10</sup> <https://www.fogape.cl>.

<sup>11</sup> <https://www.bcentral.cl/en/exceptional-measures>.

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