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Credit Risk in a DSGE Model

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Abstract
This paper develops an open-economy model with banks operating under monopolistic competition, two types of credit subject to credit risk—corporate and mortgage—and Basel-type capital requirements. The model is calibrated and estimated using Bayesian methods and Peruvian data. The estimated model is then used for historical shock decompositions, variance decompositions, and impulse response analysis following monetary and fiscal shocks. It also serves to evaluate the effects of regulatory frameworks such as the IRB approaches under Basel II and III.

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1. Introduction

The Global Financial Crisis (GFC) led governments and international organizations to adopt policy tools that extend beyond conventional monetary policy and place greater emphasis on financial stability (Ben-Gad et al., 2022).[1] Quint and Rabanal (2013) argue that a growing consensus has emerged around the view that the best way to prevent a severe future recession is to reduce the volatility of credit cycles and their broader macroeconomic effects. Rubio and Carrasco-Gallego (2014) also point to a consensus among academics and policymakers that "the ultimate objective of macroprudential policy is to contribute to safeguarding the stability of the financial system as a whole" (European Systemic Risk Board, 2013). Commercial banks determine their capital requirements on the basis of risk-weighted assets. Under Basel I (Basel Committee on Banking Supervision, 1988), risk weights were initially set at 1 and 0.5 for corporate and mortgage loans, respectively. Under Basel II (Basel Committee on Banking Supervision, 2004), banks were allowed to use their own estimates of Probability of Default (PD) and Loss Given Default (LGD) under the IRB approach. Basel III (Basel Committee on Banking Supervision, 2017) retained the risk-weight formulas. The impact of the Foundation IRB approach has also been examined in DSGE models. Darracq Pariès et al. (2011, hereafter DKR), for example, find that it increases the volatility of output growth and inflation by 5 % and 4 %, respectively. Hodbod et al. (2016) find that the Advanced IRB approach amplifies both the expansionary and contractionary phases of the financial cycle. However, these models focus on the euro area and on a closed economy, leaving only limited evidence on the macro-financial effects of IRB methodologies in small open economies.

Motivated by this literature and the limited evidence for small open economies, this paper develops and estimates a small open economy DSGE model with financial frictions to assess the impact of the Foundation and Advanced IRB approaches on the volatility of macroeconomic and financial variables. It addresses two research questions. First, it examines whether the extended DSGE model, which incorporates a banking sector with endogenous credit risk and risk-sensitive prudential regulation, preserves the core dynamic properties documented in the benchmark literature, such as impulse response functions, variance decompositions, and historical shock decompositions. Second, it quantifies the impact of adopting credit risk-sensitive capital requirement frameworks on the dynamics and volatility of macroeconomic and financial variables.

A key distinction in the design of banking regulation is whether capital requirements respond to the riskiness of assets. Under risk-insensitive frameworks, such as those inherited from Basel I, risk weights are fixed by type of exposure, for example, 100 % for corporate credit and 50 % for mortgages, regardless of the borrower's credit quality or prevailing macroeconomic conditions. This approach has the advantage of simplicity and predictability, but it overlooks meaningful differences in risk and provides limited incentives for active risk management.

By contrast, risk-sensitive regulation, introduced under Basel II, allows capital requirements to depend explicitly on estimates of PD and LGD. Under these frameworks, risk-weighted assets

[1] This study expands and updates the preliminary version published as a working paper (Rodríguez, 2020).

adjust endogenously to changes in perceived risk, bringing regulatory capital into closer alignment with the risk profile of banks' portfolios.

From a microprudential perspective, this design improves capital allocation and strengthens incentives for sound risk measurement. From a macro-financial perspective, however, risk sensitivity introduces a potentially procyclical mechanism. During economic expansions, declines in PD and LGD reduce capital requirements and support faster credit growth. In recessions, rising risk increases regulatory requirements precisely when bank capital is already under pressure, encouraging credit contractions that further amplify the downturn.

This distinction is critical for understanding its implications for macroeconomic and financial volatility. While risk-insensitive frameworks tend to generate more stable credit dynamics, they are less efficient from the standpoint of risk allocation. Risk-sensitive frameworks, by contrast, can amplify financial cycles through spreads, credit supply, and bank balance sheet channels. In the presence of feedback effects between credit, asset prices, and real activity, this procyclicality may translate into greater volatility in output, inflation, and financial variables.

The paper's main contribution is to evaluate IRB methods in a small open economy DSGE framework. To do so, it develops and estimates a model that combines elements from Christiano et al. (2011) and Darracq Pariès et al. (2011) and features a monopolistically competitive banking sector, incomplete pass-through of the policy rate, and two types of loans—corporate and mortgage—that account for 70 % of Peruvian banks' credit portfolios and are subject to Basel-type prudential regulation. For Peru, Céspedes Reynaga and Orrego (2014) estimate the Panzar-Rosse H-statistic for the banking sector and find evidence of a monopolistically competitive market structure. The model is estimated using Bayesian methods with Peruvian data and used to examine impulse response functions, variance decompositions, and historical shock decompositions. It also evaluates the volatility of the main macro-financial variables under the Foundation and Advanced IRB methodologies, with PD and LGD determined endogenously within the model. This sets it apart from models that assume exogenous relationships between capital requirements and measures of economic activity. Finally, the paper conducts a counterfactual exercise to evaluate the adoption of these IRB methods and estimate credit risk weights consistent with the observed macro-financial dynamics.

The analysis begins from the baseline estimated model, which assumes fixed capital requirements of 100 % and 50 % for corporate and mortgage lending, respectively, in line with Basel I. It then replaces these requirements with the Foundation and Advanced IRB frameworks to assess their impact on the volatility and dynamics of the main macro-financial variables.

The main findings are as follows. First, the extended model preserves the impulse response properties of benchmark models in response to monetary and fiscal shocks. Second, for core macroeconomic variables in the Peruvian economy—output, inflation, consumption, investment, employment, wages, the policy rate, and the real exchange rate—volatility under the Foundation and Advanced IRB frameworks remains broadly unchanged relative to the baseline. For banking sector variables, volatility is marginally lower.

In 2004, the Basel Committee issued the International Convergence of Capital Measurement and Capital Standards (Basel II) (Basel Committee on Banking Supervision, 2004), incorporating advances in risk measurement and management for banks adopting the IRB approach. Under this framework, financial institutions are allowed to use their own estimates of key credit risk parameters as inputs for capital calculations, subject to supervisory approval and specific eligibility criteria. The regulatory framework allows banks adopting the Foundation IRB approach to estimate PD, while those adopting the Advanced IRB approach may also rely on their own estimates of LGD. These measures are translated into risk weights for capital requirement calculations using formulas specified by the Basel Committee. Basel III (Basel Committee on Banking Supervision, 2017) retains the core structure of these formulas. The Basel II and Basel III frameworks incorporate variables such as PD and LGD into the determination of capital requirements (Basel Committee on Banking Supervision, 2004, 2017). Several studies—including Clerc et al. (2015), Mendicino et al. (2017, 2018), Hodbod et al. (2016), Darracq Pariès et al. (2011), Aguiar and Drumond (2007), and Covas and Fujita (2010)—model default risk explicitly using the framework of Bernanke et al. (1999). More recently, Darracq Pariès et al. (2015, 2016, 2018, 2019) develop richer open economy structures with detailed modeling of credit risk, sovereign risk, and banking sector fragility.

DSGE models are widely used by major policy institutions, including the Federal Reserve, the European Central Bank, and the International Monetary Fund, and are expected to remain central to how macroeconomists think about aggregate phenomena and policy (Christiano et al., 2018). In Latin America, the central banks of Peru, Brazil, Colombia, and Chile have also developed their own DSGE models (Castillo et al., 2009; De Castro et al., 2011; González et al., 2011; Medina and Soto, 2006). These models share a common structure rooted in Christiano et al. (2005) and Smets and Wouters (2003, 2007). Sergi (2017) argues that the adoption of DSGE models was not significantly disrupted by the GFC. The study documents 39 models developed by policy institutions both before and after 2008, of which 22 were developed after the GFC, including models for Asian economies such as India, Japan, and Thailand. Binder et al. (2017) present an additional set of 19 DSGE models with financial frictions used by international organizations and central banks. Recent work has focused on incorporating financial factors into DSGE models. A prominent example is the Sveriges Riksbank's RAMSES II model developed by Christiano et al. (2011), which incorporates a credit market following Bernanke et al. (1999). Coenen et al. (2018) extend the euro area model used by the European Central Bank by incorporating financial intermediaries. These developments were partly motivated by the GFC, which underscored the importance of financial market dynamics in shaping macroeconomic outcomes. Galí (2009) and Vega (2013) identify as a key challenge the need to incorporate a more detailed treatment of the financial sector in macroeconomic modeling. Lindé (2018) argues that enhanced DSGE models—modified to incorporate the lessons of the recent crisis—will remain a workhorse tool in many policy institutions for a long time. DSGE models offer several advantages. They provide a flexible framework for policy analysis, allowing the evaluation of the response of key variables to monetary, fiscal, and other shocks, as well as comparisons in terms of welfare and volatility under alternative policy rules. They also allow the contribution of shocks to the evolution of key variables to be decomposed. In addition, DSGE models support the construction of internally consistent projections that capture dynamic interactions across variables (Brázdik et al., 2012). Del Negro et al. (2016) note that extending the Smets and Wouters (2007) model to incorporate financial frictions following Bernanke et al. (1999) substantially improves its ability to account for the dynamics of real GDP growth and inflation following the collapse of Lehman Brothers (Del Negro and Schorfheide, 2013, Figure 1).

These features also make DSGE models particularly well suited for assessing the impact of banking regulation frameworks, such as the use of internal ratings-based methods by commercial banks to meet credit risk-sensitive capital requirements, macroprudential policy measures, and stress tests.

This paper is closest to Angelini et al. (2012, 2014), where credit risk weights are cyclical, varying with output growth, and the baseline specification follows Gerali et al. (2010a). The analysis explicitly incorporates credit risk weights in line with the regulatory framework for capital requirements under Basel II (Basel Committee on Banking Supervision, 2004; Superintendencia de Banca, Seguros y AFP, 2009). This approach has also been used in Aguiar and Drumond (2007) and Darracq Pariès et al. (2011), where the LGD component of risk weights is set exogenously at 0.35 and 0.45 for mortgage and corporate lending, respectively, under the Foundation IRB approach. In contrast to these studies, LGD is endogenized, consistent with the Advanced IRB approach. The specification derives LGD equations similar to those in Hodbod et al. (2016) and Mendicino et al. (2017). It also follows Christiano et al. (2011) in modeling a small open economy.

These results are relevant for supervisory authorities when evaluating the adoption of IRB methodologies in emerging economies, where the implementation of Basel II and Basel III raises challenges related to credit procyclicality and financial stability. IRB methodologies alter the amount of capital banks are required to hold, thereby affecting credit supply and the volatility of macro-financial variables. The paper therefore assesses whether IRB methods amplify or dampen business cycle fluctuations. The analysis is particularly relevant for emerging economies, where the banking system plays a central role in the transmission of shocks and where empirical evidence on IRB remains limited. The proposed framework also provides a structural tool to evaluate regulatory reforms, conduct macro-financially consistent counterfactual exercises, perform stress tests, and generate both conditional and unconditional projections. It further presents the effects of monetary and fiscal policy through impulse response functions for key banking sector variables, along with historical shock decompositions and variance decompositions.

The remainder of the paper is organized as follows. Section 2 briefly describes the model (details are available upon request in an unpublished section). Section 3 outlines the Bayesian estimation method and the data. Section 4 presents the main results, including a discussion of the estimated parameters and model fit. The estimation results also include historical shock decompositions, variance decompositions, and impulse response functions to monetary and fiscal shocks. Section 5 reports the behavior of volatility under the adoption of IRB methods. Section 6 presents the results of a counterfactual exercise, providing estimated trajectories for the main variables under the Foundation and Advanced IRB frameworks. Finally, Section 7 concludes and offers final remarks.

2. Model specification

Following Smets and Wouters (2003, 2007) and Christiano et al. (2005), later DSGE models incorporated open economy features. One of the earliest contributions in this direction is Adolfson et al. (2007), later adopted by the Sveriges Riksbank as RAMSES. Christoffel et al. (2008) subsequently developed a similar model for the euro area (NAWM), which also served as the basis for RAMSES II.

Gerali et al. (2010b,a, hereafter GNSS) show that the degree of competition among banks is correlated with interest rates and access to credit. Their model features four key elements. First, it includes two types of loans—corporate and mortgage—and banks set different interest rates for each type with some degree of market power, generating spreads over the policy rate under monopolistic competition. Second, nominal rigidities in interest rate setting, driven by adjustment costs, result in incomplete pass-through of financial conditions. Third, banks accumulate capital through retained earnings and target a capital-to-assets ratio set by the regulator, subject to Basel-type capital requirements. The balance sheet identity equates assets, loans to firms and households, with liabilities, household deposits, plus bank capital. Fourth, households and firms face borrowing constraints linked to the value of collateral—housing in the case of households and physical capital in the case of firms.

GNSS does not incorporate an explicit treatment of default. Darracq Pariès et al. (2011, hereafter DKR) address this gap by combining the GNSS framework with that of Bernanke et al. (1999), in which borrowers' collateral is affected by risk shocks and default occurs when asset values fall below outstanding debt. This results in a structure in which firms and households face financial constraints in their consumption and investment decisions. Firms and households use profits and capital as collateral, and housing or a portion of labor income, respectively. The framework, however, is set in a closed economy.

The model combines RAMSES II with the DKR framework. The resulting specification represents a small open economy with a banking sector operating under monopolistic competition and subject to Basel-type capital requirements. It includes two types of loans exposed to default risk. This setup is similar to Coenen et al. (2018), who extend the NAWM model by incorporating a financial block with wholesale banks facing funding constraints and retail banks operating under monopolistic competition. Figure 1 summarizes the main model components.

For Peru, Céspedes Reynaga and Orrego (2014) and Huayta et al. (2018) estimate the Panzar-Rosse H-statistic for the banking and microfinance sectors, respectively, and find evidence consistent with monopolistic competition. Céspedes Reynaga (2017) estimates the elasticity of credit demand with respect to interest rates and finds it to be lower than in studies based on comparable administrative data, consistent with a relatively inelastic credit market and limited competition. The study also notes that the literature generally associates competitive credit markets with higher demand elasticities. Lahura (2017) finds that the pass-through of policy interest rates is incomplete and heterogeneous across lending and deposit operations.

The real and banking sectors follow DKR, while the external sector follows CTW.

Domestic sector: key assumptions

The model builds on the DKR framework:

1. The economy consists of two sectors: residential and non-residential goods.
2. There are two types of households: savers and borrowers. Households derive utility from consumption of residential and non-residential goods and incur disutility from labor.
3. Consumption of non-residential goods is a composite of domestic and imported goods.
4. Borrower households face borrowing constraints linked to the value of their collateral. They use housing as collateral in credit markets. Default occurs when the value of collateral falls below outstanding debt.
5. Firms are also financially constrained by the value of their collateral. They use capital as collateral in credit markets. Default occurs when the value of collateral falls below outstanding debt.
6. The banking sector collects deposits from saver households and provides loans to borrowing households and firms.
7. Wholesale banks maximize profits subject to a capital-to-assets ratio set exogenously, as in Basel-type frameworks, and accumulate capital through retained earnings derived from the spread between lending and deposit rates.
8. Retail banks face nominal rigidities, which result in incomplete pass-through of the policy rate to deposit and lending rates.
9. Firms produce domestic intermediate goods—both residential and non-residential—under financing constraints. Borrowing is limited by the value of collateral, the capital stock, which is subject to risk shocks that may trigger default.
10. Non-residential goods are produced using capital and labor.
11. Residential goods are produced using capital, labor, and land.
12. Retailers purchase and differentiate intermediate goods produced by firms, operate under monopolistic competition, and set prices in a staggered manner. They sell to distributors operating under perfect competition, who aggregate differentiated goods.
13. These goods serve as final non-residential consumption goods and are also used by capital and housing producers.
14. Market prices of capital and housing stocks determine the value of collateral for firms and borrower households. These prices enter their budget constraints, affect lending decisions, and influence default outcomes.
15. There are two types of capital: for non-residential and residential production.

    Capital producers combine non-residential goods, investment, and depreciated capital and, subject to adjustment costs, produce new capital to be sold to firms.

16. There are two types of housing stock: for saver and borrower households.

    Housing producers combine residential goods, residential investment, and depreciated housing stock and, subject to adjustment costs, produce new housing to be sold to households.

External sector: key assumptions

The model follows CTW:

1. Patient households can hold both domestic and foreign assets. Foreign assets are traded in international markets, implying an interest rate parity condition.

2. Consumption, investment, and export goods are produced using both domestic goods and imported inputs.

3. There are three types of importing firms, depending on whether goods are used for consumption, investment, or exports.

4. Nominal rigidities give rise to incomplete exchange rate pass-through in both import and export sectors.

5. Firms finance a fraction of their working capital with debt, generating a working capital channel. Changes in interest rates directly affect the marginal costs of exporters and importers.

6. Export demand depends on foreign output and on the relative price of exports with respect to foreign goods.

Monetary and fiscal policy

Monetary policy follows a Taylor rule, in which the policy rate responds to its own lag, lagged inflation, lagged output, and the first differences of inflation and output. Government spending enters the aggregate demand equation and follows an exogenous AR(1) process. The government finances spending through lump-sum transfers drawn from the budget constraints of households and firms. Section 4.6 provides further discussion of this assumption.

3. Estimation

Estimation follows Schorfheide (2000) and An and Schorfheide (2007). The objective is to estimate the joint posterior distribution of the model parameters based on its linear state-space representation.

Bayesian methods allow prior information to be incorporated into the estimation of DSGE models, which is particularly useful when the sample period is short. In practice, Bayesian inference helps mitigate the difficulties associated with highly nonlinear estimation problems (Christoffel et al., 2008). It can also improve identification of parameters and shocks when the likelihood function is relatively flat in key dimensions (Smets et al., 2010).

The model is estimated using Dynare 6.2 (Adjemian et al., 2024). The estimation relies on 200,000 draws from a Random Walk Metropolis-Hastings algorithm. Appendix E provides a description of the RWMH algorithm. The treatment of local variables and steady-state dependence on parameters follows Pfeifer (2024).

3.1 Calibration

Calibration draws heavily on DKR and CTW. On the preference side, the intertemporal elasticity of substitution for both household types is set at $\sigma_X = 0.70$. For entrepreneurs, σ_{CE} is set at 0.999. The intratemporal elasticity of substitution, η_D, is also set at 0.999. The habit parameter h is assumed to be the same across all agents and is set at 0.52, following DKR, close to the value of 0.65 in CTW and 0.75 in Castillo et al. (2006, 2009). The discount factors are calibrated at $\beta_s = 0.995$ for patient households and $\beta_b = \beta_E = 0.96$ for impatient households and entrepreneurs. The share of residential goods in the utility function, ω_D, is set at 0.2 for both household types.

On the production side, the depreciation rate of housing, δ, is set at 0.005, corresponding to an annual depreciation rate of 2 %, while the depreciation rate of capital, δ_K, is set at 0.025, corresponding to an annual depreciation rate of 10 %. In the non-residential goods sector, the share of capital inputs, α_C, is set at 0.3, with labor accounting for 0.7. In the residential sector, the share of land, α_L, is set at 0.1, while the share of capital, α_D, is reduced to 0.2. As a broad calibration target, the government spending-to-output ratio is set at 18 %, close to its historical average of 15 %, including both public consumption and public investment.

Markups in sector j are denoted by λ_j. The markups λ and λ_D are set at 1.3 in the markets for non-residential and residential goods, respectively. In the labor market, $\lambda_w = 1.5$. Markups for exporters and importers, λ_i with $i \in \{(x, m), (c, m), (i, m)\}$, are set at 1.2, following the calibration in CTW.

In the external sector, the shares of imported goods in consumption, investment, and exports—ω_c, ω_i, and ω_x—are set as in CTW at 0.25, 0.43, and 0.35, respectively. The elasticities of substitution for consumption, investment, and exports are set at $\eta_j = 1.5$ for $j \in \{c, i, x\}$, following the prior distributions in Christiano et al. (2011). The parameter $\tilde{\phi}_a$ is set at 0.01, as in Christiano et al. (2011), to ensure a unique steady state for net foreign asset positions.

In the banking sector, deposit and lending markups are calibrated to match an annual spread of 100 basis points between the policy rate and deposit rates, and spreads of 200 and 120 basis points for household and corporate lending rates, respectively.

Monitoring costs are set at $\mu_E = 0.2$ for firms and $\mu_{HH} = 0.15$ for households, following Darracq Pariès et al. (2011). Carlstrom and Fuerst (1997) suggest a range of 0.20–0.36 as empirically relevant. Bernanke et al. (1999) assume a value of 0.12, while Christiano et al. (2003, 2010, 2011, 2014) report values of 0.12, 0.94, 0.52, and 0.27. Forlati and Lambertini (2011) calibrate a value of 0.12. Clerc et al. (2015) assume 0.30, Lambertini et al. (2017); Lambertini and Wu (2020) assume 0.12, and Mendicino et al. (2017, 2018) calibrate 0.30.

Loan-to-value (LTV) ratios are set at 0.4 and 0.8, corresponding to $\chi_E = 0.6$ and $\chi_{HH} = 0.2$. Gerali et al. (2010b,a) assume LTV ratios of 0.35 and 0.70 for firms and households, respectively.

The target loan-to-capital ratio for banks is set at 0.09, in line with regulatory requirements. In the baseline specification, this calculation assumes fixed risk weights of 1 and 0.5 for corporate and household lending, respectively; the same values are used in Darracq Pariès et al. (2011, 2015). By contrast, Gerali et al. (2010b,a) assume a value of 1 for both types of credit.

Appendix 10 describes the calibration of $\bar{\omega}_j$ and σ_j based on non-performing loan ratios of 2.5 % and 2.08 % for corporate and mortgage credit, respectively, historical averages.

Saavedra García and Saavedra García (2010) summarize the credit risk weights under the 1988 Basel I framework (Basel Committee on Banking Supervision, 1988) as 50 % and 100 % for residential mortgage and corporate exposures, respectively. Held (2007) reports similar weights under Basel I and Basel II, with floors of 35 % and 75 % under Basel II.

3.2 Prior distributions

The prior distributions are based on DKR and CTW. Symmetry is imposed across agents and sectors to limit the number of parameters.

The adjustment cost parameter for non-residential investment, ϕ_K, is assumed to be the same for investment in capital used in the production of non-residential goods, K_t^C, and in residential goods, K_t^D. Similarly, the adjustment cost parameter for residential investment, ϕ_D, is assumed to be the same for borrower households, $\tilde{D}_t$, and saver households, D_t. The parameter governing capital utilization adjustment costs, φ, is also assumed to be identical across sectors, u_t^C and u_t^D.

On the preference side, the labor supply elasticity is assumed to be the same for both types of households, $\sigma_{LC} = \sigma_{LD} = \sigma_L$.

The parameter ξ_j denotes the Calvo parameter governing price setting in sector j, capturing the fraction of firms that do not reoptimize prices, or the corresponding probability. Firms that do not reoptimize update prices based on past sectoral inflation and the inflation target, according to $P_{j,t} = (\Pi_{j,t-1})^{\gamma_j}(\overline{\Pi})^{1-\gamma_j}P_{j,t-1}$. The parameter γ_j governs the degree of indexation to past sectoral inflation. Wage indexation is tied to non-residential inflation, Π_{t-1}. In the banking sector, there is no indexation to inflation; banks that do not reoptimize keep interest rates constant, $R_{j,t} = R_{j,t-1}$.

The Calvo parameter for non-residential price setting, ξ_C, and the associated indexation parameter, γ_C, are estimated. In the residential sector, the Calvo parameter ξ_D is estimated, while the indexation parameter γ_D is set to zero. Wage-setting Calvo rigidities in the non-residential sector are assumed to be identical across household types, $\xi_{w,CB} = \xi_{w,CS} = \xi_{wC}$. In the residential sector, wage rigidities are also assumed to be the same across households, $\xi_{wDB} = \xi_{wDS} = \xi_{wD}$. The wage indexation parameter is assumed to be identical across household types and sectors, $\gamma_w^{i,j} = \gamma_w$, with $i \in \{C, D\}$ and $j \in \{S, B\}$. Calvo rigidities and indexation are also estimated for exports and imports, ξ_j and γ_j, with $j \in \{(x,m),(c,m),(i,m)\}$. To capture imperfect interest rate pass-through, Calvo parameters are estimated for lending and deposit rates. The adjustment cost of bank capital, χ_{wb}, is also estimated.

The fraction of borrower households, ϱ, is estimated. The prior for the share of working capital financed with credit is assumed to be the same for exporters and importers, $\nu^x = \nu^* = \nu$.

The price elasticity of export demand, η_f, and the country risk adjustment parameter, $\tilde{\phi}_S$, are also estimated. The prior for the foreign VAR is constructed using moments from the posterior distribution reported in CTW.

The parameters of the Taylor rule—ρ, r_π, r_y, $r_{\Delta\pi}$, and $r_{\Delta y}$—are estimated.

3.3 Data

The selection of observable variables follows Adolfson et al. (2007), Christoffel et al. (2008), Christiano et al. (2011), Gerali et al. (2010b,a), and Darracq Pariès et al. (2011). The model is estimated using Peruvian data over the period 2002Q1–2019Q4. The dataset includes 22 series: corporate and mortgage credit together with their corresponding interest rates; deposits and the corresponding interest rate; consumption, investment, output, exports, and imports; the CPI consumption deflator, the investment deflator, and the output deflator; the policy rate; the real exchange rate; house prices; employment; and wages. The foreign block includes U.S. output, inflation, and the interest rate. Data are obtained from the Central Reserve Bank of Peru, the Superintendency of Banking, Insurance and Pension Funds, and the Federal Reserve Bank of St. Louis (FRED). Appendix A describes the data treatment in detail.

Measurement errors are assumed to account for 10 % of the variance of output, consumption, investment, exports, imports, the real exchange rate, employment, wages, and corporate credit, following Adolfson et al. (2007) and Christiano et al. (2011). Measurement errors are also assumed to account for 25 % of the variance of the investment, consumption, and output deflators, as well as house prices.

4. Estimation results

4.1 Posterior distributions

The adjustment cost parameter for non-residential investment, $\phi_K = 2.73$, is roughly half the value reported in Darracq Pariès et al. (2011), 7.72. By contrast, the adjustment cost parameter for residential investment, $\phi_D = 5.89$, exceeds the estimate in Darracq Pariès et al. (2011), 0.23. The comparison between ϕ_K and ϕ_D indicates that investment adjustment is more rigid in the residential sector.

The capital utilization adjustment cost parameter, $\varphi = 0.90$, is close to the estimate in Darracq Pariès et al. (2011), 0.75.

The inverse Frisch elasticity of labor supply, $\sigma_L = 2.49$, lies very close to the center of the prior distribution. This estimate is close to that in Castillo et al. (2009), 2, and to the value of 1.32 reported in Darracq Pariès et al. (2011), but substantially below the estimate of 7.77 in Christiano et al. (2011). Castillo et al. (2006) report estimates between 2 and 6 across different models and note that "this value lies within the range reported by studies using microeconomic data for advanced economies."

Nominal rigidities differ across sectors: the non-residential sector is more rigid, with $\xi_C = 0.90$ and $\xi_D = 0.48$. This pattern is qualitatively similar to that reported in Darracq Pariès et al. (2011), who estimate 0.83 and 0.81, respectively.

Consistent with Christiano et al. (2011), the consumption goods sector exhibits lower indexation to past sectoral inflation than wages, with $\gamma_C = 0.52$ and $\gamma_w = 0.70$. Their corresponding estimates are 0.14 and 0.43. This contrasts with Darracq Pariès et al. (2011), who report 0.58 and 0.24, respectively.

Wage rigidities exceed price rigidities in the residential sector, with $\xi_{wC} = 0.61$ and $\xi_{wD} = 0.94$, compared with $\xi_D = 0.48$.

The Calvo parameters for exporters and importers are also close to those reported in Christiano et al. (2011), where the corresponding value is 0.80: $\xi_x = 0.87$, $\xi_{mc} = 0.85$, $\xi_{mi} = 0.80$, and $\xi_{mx} = 0.67$. The indexation parameter in the export sector is $\gamma_x = 0.37$. For imports, the estimates are close to 0.80: $\gamma_{mc} = 0.85$, $\gamma_{mi} = 0.83$, and $\gamma_{mx} = 0.82$.

The degree of nominal rigidity in non-residential price setting and residential wage setting, captured by ξ_C and ξ_{wD}, implies average price and wage contract durations of $1/(1-0.90) = 10$ and $1/(1-0.94) = 16$ quarters, respectively. These values are high relative to the estimates reported by Christiano et al. (2005), at 2 and 3 quarters. The degree of price rigidity also exceeds the calibrated value of 0.75 reported by Castillo et al. (2009), which implies a duration of 4 quarters.

We find greater rigidity in the setting of corporate lending rates, with $\xi_E^R = 0.83$, than in deposit rates, $\xi_D^R = 0.40$, and mortgage lending rates, $\xi_{HH}^R = 0.23$. The relatively low rigidity of mortgage lending rates contrasts with the results in Gerali et al. (2010b,a) and Darracq Pariès et al. (2011). In particular, Darracq Pariès et al. (2011) report values of 0.92 for mortgage loans, 0.76 for corporate loans, and 0.32 for deposits. The adjustment cost parameter governing banks' capital structure, $\chi_{wb} = 19.06$, remains close to the center of its prior distribution, 20, and is quantitatively similar to the estimate in Darracq Pariès et al. (2011), 18.58.

The persistence parameter in the Taylor rule, $\rho = 0.86$, is close to the estimates in Christiano et al. (2011), 0.81, and Darracq Pariès et al. (2011), 0.84. The response to inflation, $r_\pi = 2.63$, is higher than the corresponding estimates reported there, 1.90 and 2.37, respectively. The response to output, $r_y = 0.009$, is lower than the corresponding values of 0.02 and 0.03. The response to changes in inflation, $r_{\Delta\pi} = 0.43$, is larger than the estimate in Darracq Pariès et al. (2011), 0.24. Finally, the response to output growth, $r_{\Delta y} = 0.03$, is lower than the corresponding estimate there, 0.07.

We also estimate the share of borrowing households at $\varrho = 0.19$, close to the calibrated value of 0.25 in Darracq Pariès et al. (2011).

The share of working capital that must be financed through loans, $\nu = 0.01$, is substantially lower than the estimate of 0.46 in Christiano et al. (2011).

As for the export demand elasticity, $\eta_f = 1.41$ is close to the value of 1.63 reported by Christiano et al. (2011). Finally, we estimate a country risk adjustment coefficient of $\tilde{\phi}_S = 0.91$, which lies within a region whose upper bound exceeds one, specifically 1.02. This is consistent with the evidence in Christiano et al. (2011) on uncovered interest parity and the hump-shaped response of output to a monetary policy shock.

4.2 Model fit: risk measures

Figure 2 shows the evolution of delinquency and default probabilities for firms and households generated by the model. In the corporate sector, the two variables display a strong comovement, along with a marked increase in credit risk during the GFC. Similar evidence for the corporate sector is reported by Christiano et al. (2010, 2014),Adolfson et al. (2013), and Copaciu et al. (2016) for the United States, the euro area, Sweden, and Romania. The corresponding result for the mortgage sector appears to be novel in this context. Extending the model to incorporate direct multiplicative shocks to labor income, as in De Carvalho et al. (2014); De Carvalho and Castro (2015, 2017), could improve the fit of mortgage credit risk.

Table 2 reports the standard deviations in the data and those implied by the estimated model. A notable discrepancy emerges for the mortgage interest rate, whose standard deviation is 9.28 in the model and 0.40 in the data (computed as deviations from a linear trend), reaching 1.02 when the series is considered in levels. This result suggests that the modeling of the mortgage sector, the data treatment, or the estimation approach may warrant further investigation.

4.3 Historical decomposition of unobserved variables: default probabilities

Figures 3 and 4 report the historical PD decompositions by stochastic shocks. This exercise follows Algorithm 8 in Del Negro and Schorfheide (2013). To this end, the exogenous stochastic shocks are grouped as follows:

- Technology shocks ($\epsilon_{A,t}, \epsilon_{A_D,t}$)
- Investment shock ($\epsilon_{I,t}$)
- Preference shocks ($\epsilon_{B,t}, \epsilon_{D,t}, \epsilon_{L,t}$)
- Firm markup shocks ($\epsilon_{P,t}$)
- Fiscal shock ($\epsilon_{G,t}$)
- Monetary policy shock ($\epsilon_{R,t}$)
- Risk shocks ($\epsilon_{\sigma,t}, \epsilon_{\sigma_{HH},t}$)
- Bank markup shocks ($\epsilon_{R_L,t}, \epsilon_{R_{L_E},t}, \epsilon_{R_D,t}$)
- Bank capital shock ($\epsilon_{Bankcap,t}$)
- Exporter and importer markup shocks ($\epsilon_{\tau^x,t}, \epsilon_{\tau^{mc},t}, \epsilon_{\tau^{mi},t}, \epsilon_{\tau^{mx},t}$)
- External shocks ($\epsilon_{R^\star,t}, \epsilon_{y^\star,t}, \epsilon_{\pi^\star,t}, \epsilon_{\tilde{\phi},t}$)
- Measurement errors ($\epsilon_{\mu,t}$)

Corporate and household PD are estimated at around 2.5 % and 2.08 %, respectively, consistent with the steady-state values used in the model calibration. LGD estimates are approximately 38 % for firms and 29 % for households (Appendix 11.2). These values are close to the benchmark regulatory parameters under the Foundation IRB approach, namely 45 % and 35 %, respectively.

For firms, investment, risk, fiscal, and external shocks contribute significantly to credit risk dynamics. For households, risk, external, and fiscal shocks account for a large share of default probability dynamics.

During the GFC in 2009, quarterly output growth fell below its average level by 0.64 %, 1.43 %, 1.27 %, and 0.54 % over the four quarters. Shock decomposition shows that the adverse effects of external shocks were partially offset by the expansionary monetary policy implemented by the BCRP. In particular, in the second and third quarters of 2009, monetary policy increased quarterly output growth by 0.52 % and 0.41 %, respectively (Appendix 11.3).

Figure 18 shows that fiscal policy contributed negatively during this period, consistent with the historical decompositions reported by Jiménez and Rodríguez (2020, Figure 10), Meléndez Holguín and Rodríguez (2023, Figure 7), and Rodríguez and Santisteban (2024, Figure 5). These studies show that shocks to current expenditure growth had a slightly negative effect on output growth, whereas shocks to capital expenditure had a larger and positive effect. This reflects the fact that the fiscal shock in the model is closer to a public consumption shock—reflected in current expenditure—than to a public investment shock. After the GFC, from the first quarter of 2010 onward, fiscal policy played an important role in supporting the recovery of output growth.

Fiscal and monetary policy jointly mitigated the rise in credit risk during the GFC. In the absence of these measures, firms' default probability would have reached 3.9 % in the second quarter of 2009; policy interventions reduced it by 0.3 percentage points. A similar effect is observed for households: default probability would have risen to 8.3 % in the first quarter of 2009 but declined to 7.17 % with policy support, a reduction of 1.13 percentage points. In subsequent quarters, the effect remained close to 1.5 %, with fiscal policy playing a particularly important role in this sector (Table 3; Figures 3 and 4).

4.4 Variance decomposition

Table 4 reports forecast error variance decompositions for the Peruvian economy, including the results obtained in this study. Table 5 presents the results of this study with a more detailed breakdown of shocks and variables, while Table 6 further disaggregates external and financial shocks.

A forecast error variance decomposition for the variables included in the estimation, as well as for additional variables such as bank capital, default probabilities, LGD, and bank leverage, over an eight-quarter business cycle horizon, shows that fiscal and external shocks account for a large share of output growth fluctuations (i.e., unexpected fluctuations eight quarters after the shocks occur), with contributions of 41.2 % and 39.8 %, respectively. By contrast, financial shocks account for only 1 % (Table 5).

Early variance decomposition results appear in Castillo et al. (2006, 2013), who find that external shocks explain about 35 % of the forecast error variance of output. They also document a substantial role for permanent technology shocks (48 %), a feature not included in this study.

The decomposition of output variance is consistent with the evidence in Guevara et al. (2024), who note that "in Peru, the consensus among most authors is that external shocks are the main drivers of economic fluctuations" (Table 4, column 2).

Dancourt (2009) argues that "the recessions in the Peruvian economy over the past fifty years have been associated with declines in the terms of trade." Nolazco et al. (2016) find that external sources account for more than 50 % of economic growth in some periods.

Castillo and Salas (2012) report results for a similar eight-quarter horizon and find that external shocks, through the terms of trade, explain 69 %, 68 %, and 78 % of the variability of output, consumption, and investment, respectively.

Fiscal shocks are also important, accounting for 41.2 % of output variance, in line with the estimates reported by Mendoza and Collantes Goicochea (2017), Jiménez and Rodríguez (2020), Chávez and Rodríguez (2022), Meléndez Holguín and Rodríguez (2023), and Rodríguez and Santisteban (2024) (Table 4, column 3).

Jiménez and Rodríguez (2020) note that "it is clear that Peru's economic growth depends on the international environment, with the most important shock occurring around the GFC. However, domestic factors such as aggregate demand shocks, current expenditure shocks, and capital expenditure shocks, fiscal shocks, are also key determinants of GDP fluctuations, and are as important as external shocks in the post-crisis period."

Mendoza and Collantes Goicochea (2017) report closely related results. They find that external factors explain 67 % of output variability. Among domestic factors, public investment stands out, accounting for 15 % of that variability, a result that "also suggests that the most effective macroeconomic policy instrument for affecting economic activity is public investment."

Florián et al. (2018) also argue that "although the terms of trade may explain a large share of the variation in Peruvian GDP, it should be emphasized that around 50 % of GDP variability depends on other factors, such as domestic conditions, which may limit or amplify the positive effect of the terms of trade. Therefore, internal variables should not be disregarded by policymakers."

The variance decomposition of inflation shows that 16.6 %, 14.7 %, and 4.8 % of its variability are explained by external, fiscal, and monetary shocks, respectively. This pattern suggests that both fiscal and monetary policy retain scope for stabilization in Peru, consistent with Lavanda and Rodríguez (2011). Preference shocks and firm markup shocks are also important, contributing 22.9 % and 20.3 %, respectively.

Preference, external, fiscal, and monetary shocks explain a large share of policy rate variance, at 27.7 %, 23.8 %, 22.6 %, and 9.1 %, respectively.

The variability of the GDP and investment deflators is driven primarily by external shocks (36.7 % and 53.7 %, respectively), followed by firm markup shocks (23.1 % for the GDP deflator) and preference shocks (11.5 % and 11.8 % for the GDP and consumption deflators, respectively).

A large share of consumption variance is explained by preference shocks (42.8 %), followed by external, fiscal, technological, and monetary shocks, with contributions of 13.3 %, 10.4 %, 9.8 %, and 9.0 %, respectively.

Investment is driven mainly by investment efficiency shocks (32.1 %), followed by financial shocks (18.8 %) and technology shocks (10.8 %).

Exports, imports, and the real exchange rate are driven primarily by external shocks, which account for 96.1 %, 75.2 %, and 73.9 % of their variance, respectively.

Wage variability is driven primarily by preference shocks (30.2 %), external shocks (27.0 %), firm markup shocks (14.4 %), and fiscal shocks (12.4 %). Employment fluctuations are mainly explained by fiscal shocks, which account for 37.0 % of its variance, followed by external shocks (26.3 %) and technology shocks (22.1 %).

House price variability is driven primarily by technology shocks (52.4 %) and preference shocks (26.0 %).

The variance of the corporate lending rate is explained to a large extent by financial shocks, which account for 58.2 % of the total. Within this group, the main drivers are risk shocks (40.9 %), bank markup shocks (12.7 %), and bank capital shocks (4.5 %) (Table 6). Investment shocks also contribute materially, accounting for 19.6 % of the variance.

The variance of the mortgage lending rate is likewise dominated by financial shocks, which explain 57.6 % of the total. Within this group, the main contributors are risk shocks (31.3 %), bank markup shocks (25.4 %), and, to a lesser extent, bank capital shocks (0.9 %) (Table 6). They are followed by preference shocks (19.1 %), fiscal shocks (10.0 %), and external shocks (8.9 %).

The deposit rate is driven by factors broadly similar to those affecting the policy rate. One difference is the role of financial shocks, which account for 9.6 % of its variance and arise almost entirely from bank markup shocks (9.5 %) (Table 6).

Corporate credit is driven by factors similar to those affecting investment, with a large contribution from investment efficiency shocks (47.1 %). Financial shocks account for 18.8 %, mainly through risk shocks (13.7 %) and bank markup shocks (3.2 %), with a smaller contribution from bank capital shocks (1.8 %). External shocks are also relevant, accounting for 7.2 % of the variance.

The variability of mortgage credit is explained by preference shocks (33.1 %), external shocks (19.9 %), fiscal shocks (18.4 %), and financial shocks (16.8 %). Within the latter group, bank markup shocks stand out, contributing 15.2 %.

Deposits are driven mainly by financial shocks, which account for 21.9 %, particularly bank capital shocks (14.4 %). Preference shocks (21.4 %) and external shocks (20.7 %) also make substantial contributions.

Bank capital variance is explained almost entirely by bank markup shocks and shocks to the exogenous component of bank capital, which account for 36.3 % and 61.7 %, respectively.

Corporate credit risk, measured by PD, is driven primarily by financial shocks (62.5 %) and investment shocks (29.5 %). Within the financial sector, risk shocks account for most of the contribution (61.0 %). LGD follows a qualitatively similar pattern.

Household PD is driven mainly by financial and preference shocks, which account for 62.8 % and 27.6 % of its variance, respectively. Within the financial sector, risk shocks again dominate, contributing 60.3 %. LGD follows a similar pattern.

Bank leverage variability is explained by shocks to the exogenous component of bank capital and by bank markup shocks, with contributions of 55.5 % and 31.3 %, respectively.

Table 5, column 8, highlights the importance of external shocks in driving the variability of macroeconomic variables, as well as deposits, the deposit rate, and mortgage credit.

Column 9 shows that financial shocks play a limited role in explaining fluctuations in macroeconomic variables, except for investment (18.8 %). By contrast, they are important for banking sector variables, including interest rates, credit, deposits, capital, credit risk, and leverage.

4.5 Impulse responses to a monetary policy shock

Consistent with Darracq Pariès et al. (2011), an increase in the policy rate leads to a contraction in consumption and investment. The decline in domestic demand raises net exports, as in

Christiano et al. (2011), but this effect does not offset the drop in consumption and investment, so output falls by about 0.4 %, in line with Castillo et al. (2006) and Sánchez León (2016). In line with output dynamics, employment and domestic inflation also decline, with inflation falling by 35 basis points (0.35 %), close to the 0.20 % reported by Castillo et al. (2006). Overall, the responses of output and inflation are similar to those reported by Lahura (2012, Table 1).

The impulse responses in Figure 5 highlight the relationship between credit and interest rates. The credit channel, as discussed by Dancourt (2012), refers to the effect of monetary policy instruments on lending volumes and the interest rates charged by banks.

Early evidence in Rossini and Vega (2007), based on a survey of empirical studies on the monetary transmission mechanism in Peru, finds that the credit channel was not significant for monetary policy, although the ongoing process of de-dollarization could strengthen it over time. More recent studies provide stronger evidence of its activation and increasing relevance (Table 7).

The policy rate declines monotonically from an initial increase equal to the size of the shock, $4 \times 100 \times 0.25 = 100$ basis points. This contrasts with corporate lending and deposit rates, which display hump-shaped responses and increase by less than the policy rate, reaching peak increases of 10 and 30 basis points, respectively. On impact, the corporate lending rate falls by 10 basis points. The mortgage rate declines by 40 basis points on impact and subsequently rises to a peak increase of 50 basis points.

Corporate credit declines following the shock, reaching a maximum contraction of 0.4 % in the fifth quarter, in line with the increase in the corresponding lending rate. This result is consistent with Sánchez León (2016), who reports a similar decline of 0.4 %. Gerali et al. (2010b,a) also find a decline of 0.3 % following a peak increase of 25 basis points in the corporate lending rate.

For mortgage credit, Sánchez León (2016) reports an increase in mortgage rates in foreign currency (FC) and a corresponding decline in credit volumes, consistent with standard theoretical predictions. In local currency (LC), however, the response differs: mortgage rates fall on impact and credit volumes increase.

The results reported here are closer to the LC case. Mortgage rates increase by about 50 basis points on impact and then decline by up to 30 basis points. Sánchez León (2016) reports an initial increase of 60 basis points followed by a decline of up to 80 basis points. For credit volumes, they find an initial decline of 1 %, followed by an increase of up to 2 % in subsequent quarters. In this study, the peak increase is about 0.8 % (Figure 6).

Darracq Pariès et al. (2011) attribute this puzzle to the limited pass-through of a temporary monetary policy shock to lending rates, as banks set rates based on expected future yield curve conditions. As a result, a temporary increase in short-term policy rates has only a limited effect on lending rates, which depend more on the long end of the yield curve, as in the case of mortgage loans. Christiano et al. (2010, Figure 14) report similar evidence for private sector credit in the euro area. Céspedes Reynaga (2017) also finds that the elasticity of mortgage credit demand is close to zero (Table 7).

The contraction in demand, employment, and wages increases aggregate risk. Corporate and household PD rise by about 5 and 15 basis points, respectively, in line with results from benchmark models.

Table 7 also reports evidence on interest rate pass-through. Lahura (2017) finds stronger pass-through to lending rates than to deposit rates. In contrast, the results here show a stronger response of deposit rates than of corporate lending rates. Mortgage rates, after the initial impact, rise more than deposit rates up to the fifth quarter; thereafter, their decline and subsequent adjustment are larger. Overall, mortgage rates exhibit overshooting relative to both deposit and corporate lending rates (Figure 6).

4.6 Impulse responses to a fiscal shock

Coenen et al. (2012) assess whether fiscal expansion can mitigate the depth and duration of the 2007–2009 recession. The project includes six policy institutions and seven structural DSGE models: the Bank of Canada (BoC-GEM), the Federal Reserve System (FRB-US and SIGMA), the European Central Bank (NAWM), the European Commission (QUEST), the IMF (GIMF), and the OECD (OECD Fiscal).

Four of these models are global (BoC-GEM, GIMF, QUEST, and SIGMA). NAWM is a two-region model for the United States and Europe, FRB-US focuses on the United States, and OECD Fiscal focuses on Europe. The results from policy models are compared with those from two widely used DSGE models—Christiano et al. (2005) and Smets and Wouters (2007)—and show "considerable agreement across models on the absolute and relative sizes of different fiscal multipliers."

This result reflects the fact that policy models incorporate empirically relevant transmission channels. For example, instead of assuming that all households are Ricardian forward-looking agents, they typically allow for a significant share of liquidity-constrained or rule-of-thumb households. By contrast, in Christiano et al. (2005) and Smets and Wouters (2007), government spending enters as a component of aggregate demand and follows an exogenous AR(1) process.

Fiscal policy in the model follows Christiano et al. (2005) and Smets and Wouters (2007). In the version used by Coenen et al. (2012), steady-state government spending is set at 0.2 of output. Public spending is assumed to be financed through lump-sum transfers drawn from the budget constraints of households and firms.

A 1 % increase in government spending, relative to its steady-state level, raises output by 0.18 % ($= 1\,\% \times 0.18$), where 0.18 is the steady-state share of government spending in output, consistent with Christiano et al. (2011) and Darracq Pariès et al. (2011). Inflation increases by 4 basis points and returns to baseline after about 15 quarters due to the policy rate response. The persistence of the fiscal shock, $\rho_g = 0.919$ (Appendix 11.1), is close to the values reported in Christiano et al. (2011) and Darracq Pariès et al. (2011), 0.90. The responses of output, employment, inflation, and the policy rate are similar to those reported in these studies. Results are also broadly consistent with Sánchez León (2016), who finds an initial increase in output of 0.1 % and a policy rate response of 4 basis points.

Corporate lending rates increase by 2 basis points on impact and reach a peak of 6 basis points in the seventh quarter, in line with Sánchez León (2016), who reports an initial increase of 4 basis points and a peak of 5 basis points.

Mortgage rates reach a peak increase of 20 basis points, close to the estimates in Sánchez León (2016), where LC rates increase by up to 12 basis points and rates in FC by up to 5 basis points. Deposit rates follow a similar path to corporate lending rates, with an initial increase of 2 basis points and a peak of 6 basis points.

Consistent with these interest rate dynamics, corporate credit, mortgage credit, and deposits decline, with peak contractions of 0.1 %, 0.4 %, and 0.25 %, respectively. The response of corporate credit is similar to that reported in Christiano et al. (2011) and Darracq Pariès et al. (2011). The increase in domestic demand also reduces credit risk, with corporate and household PD declining by about 0.8 and 3 basis points, respectively.

5. Volatility under IRB approaches

Aguiar and Drumond (2007) find that the application of capital requirements amplifies the procyclicality of banks, in tension with the Basel II objective of promoting financial stability. Covas and Fujita (2010) show that Basel I and Basel II capital requirements significantly increase output volatility, with a stronger amplification effect under Basel II. DKR find that risk-sensitive capital requirements such as Basel II generate slightly more volatility than a regime with fixed capital requirements such as Basel I.

Under IRB approaches, as specified in Basel Committee on Banking Supervision (2004), the capital ratio is based on risk-weighted assets, where the weights depend on default probabilities. These probabilities are in turn linked to macroeconomic conditions through their effects on borrowers' net worth—via income and housing wealth for households, and through the value of the capital stock for firms.

The Basel framework builds on the Merton (1974) model, in which default occurs when the value of assets falls below the value of debt (Basel Committee on Banking Supervision, 2005). Bernanke et al. (1999) adopt a similar definition of default.

In regulatory practice, default is defined as a payment delay exceeding 90 days, but both measures are closely aligned. Christiano et al. (2014) show for the United States that "the two variables (model-implied default probability and delinquency rate) are reasonably similar" (Figure 8). Christiano et al. (2010) report similar evidence for the euro area and the United States, where model-implied measures track default probabilities constructed using the Moody's KMV methodology (Figure 16). Adolfson et al. (2013) show that the model-implied corporate bankruptcy rate closely matches low-frequency movements in Swedish delinquency data (Figure H). Copaciu et al. (2016, Figure 10) find similar patterns for Romania, with model-implied bankruptcy rates closely tracking observed data.

Corporate and household PD, for $j \in \{E, HH\}$, are defined as

$$\begin{aligned} \text{Probability of Default} = F(\overline{\omega}_{j,t}) &= \int_0^{\overline{\omega}_{j,t}} f(\omega_{j,t}) d\omega_{j,t} \\ &= \left(\frac{\ln(\overline{\omega}_{j,t})}{\sigma_{j,t}} + 0.5 \times \sigma_{j,t} \right), \quad j \in \{E, HH\} \end{aligned} \tag{1}$$

where the default threshold $\overline{\omega}_{j,t}$ is determined in general equilibrium. The term $\sigma_{j,t}$ denotes an exogenous stochastic risk shock, and is the standard normal cumulative distribution function.

The IRB risk weight formula follows the Basel II and Basel III framework (BCBS, 2004, 2017):

$$P_{j,t}(\overline{\omega}_{j,t}) = 10 \times \mathrm{LGD}_{j,t}\left[\left((1-\tau_{j,t})^{-0.5\,-1}(F(\overline{\omega}_{j,t})) + \left(\frac{\tau_{j,t}}{1-\tau_{j,t}}\right)^{0.5}{}^{-1}(0.999)\right) - F(\overline{\omega}_{j,t})\right] \tag{2}$$

The parameter τ equals 0.15 for households. For firms, it follows the specification for non-retail exposures in BCBS (2004):

$$\tau_{E,t} = 0.12\left(\frac{1-\exp(-50 \times F(\overline{\omega}_{E,t}))}{1-\exp(-50)}\right) + 0.24\left(1 - \frac{1-\exp(-50 \times F(\overline{\omega}_{E,t}))}{1-\exp(-50)}\right) \tag{3}$$

Darracq Pariès et al. (2011, 2015, 2016, 2018) use closely related formulations.

The parameter τ captures the correlation between firms' asset returns and common factors that represent systematic risk. The term ${}^{-1}(0.999)$ corresponds to the realization of the common factor at a 99.9 % confidence level. Aas (2005) derives the IRB formulas.

5.1 Fixed LGD

This exercise sets LGD at 0.45 for firms and 0.35 for households, consistent with Darracq Pariès et al. (2011, 2015, 2018).

5.2 Endogenous LGD

Following Hodbod et al. (2016, Equation 5.3), the starting point is the definition of expected loss. The exposure value is assumed to equal the value of assets, including accrued returns, in line with regulatory practice (Basel Committee on Banking Supervision, 2004). The loss measure reflects the difference between exposure at default and collateral value, net of foreclosure costs μ_j.

Let $B_{j,t-1}$ denote real credit to sector $j \in \{E, HH\}$, firms or households, in period $t-1$. In nominal terms, credit equals $B_{j,t-1}P_{t-1}$, where P_{t-1} is the consumption price index. In period t, the nominal value of debt is $(1+R^L_{j,t})B_{j,t-1}P_{t-1}$, where $R^L_{j,t}$ is the lending rate. In real terms, debt is $(1+R^L_{j,t})B_{j,t-1}P_{t-1}/P_t = (1+R^L_{j,t})B_{j,t-1}/(1+\pi_t)$, where $(1+\pi_t) = P_t/P_{t-1}$ and π_t denotes inflation.

As in Bernanke et al. (1999), a multiplicative shock $\omega_{j,t}$ affects the value of assets $\tilde{A}^b_{j,t}$, so that asset value is given by $\omega_{j,t}\tilde{A}^b_{j,t}$. There exists a threshold $\overline{\omega}_{j,t}$ at which the collateral value equals the value of debt, in real terms at time t prices.

When $\omega_{j,t} < \overline{\omega}_{j,t}$, collateral does not cover debt and the borrower defaults. In this case, the bank incurs monitoring costs and seizes the collateral. As in Bernanke et al. (1999), these costs can be interpreted as bankruptcy costs, including auditing, accounting, and legal expenses, as well as losses associated with asset liquidation and business disruption.

These costs are assumed to equal a fraction μ_j of asset value. Net proceeds from collateral seizure are therefore $\omega_{j,t}\tilde{A}^b_{j,t} - \mu_j\omega_{j,t}\tilde{A}^b_{j,t} = (1-\mu_j)\omega_{j,t}\tilde{A}^b_{j,t}$.

Given exposure at default $(1+R^L_{j,t})B_{j,t-1}/(1+\pi_t)$ and collateral value $(1-\mu_j)\omega_{j,t}\tilde{A}^b_{j,t}$, losses equal

$$\frac{(1+R^L_{j,t})}{1+\pi_t}B_{j,t-1}-(1-\mu_j)\omega_{j,t}\tilde{A}^b_{j,t} \tag{4}$$

In default, expected losses are

$$\int_0^{\varpi_{j,t}}\left(\frac{(1+R^L_{j,t})}{1+\pi_t}B_{j,t-1}-(1-\mu_j)\omega_{j,t}\tilde{A}^b_{j,t}\right)dF(\omega_{j,t}) \tag{5}$$

which can be written as

$$\frac{(1+R^L_{j,t})}{1+\pi_t}B_{j,t-1}F(\varpi_{j,t})-(1-\mu_j)\tilde{A}^b_{j,t}\int_0^{\varpi_{j,t}}\omega_{j,t}dF(\omega_{j,t}) \tag{6}$$

Household collateral corresponds to housing, D^b_{t-1}. For firms, collateral consists of capital used in non-residential and residential production, K^C_{t-1} and K^D_{t-1}, respectively. Real prices are $\widetilde{Q}_{D,t}T_{D,t}$ for housing, and Q^C_t and Q^D_t for capital.

Assets depreciate at rate δ for housing and δ_K for capital. LTV limits are $(1-\chi_{HH})$ and $(1-\chi_E)$ for households and firms, respectively.

Collateral values are therefore

$$\tilde{A}^b_{j,t}=(1-\chi_{HH})(1-\delta)\widetilde{Q}_{D,t}T_{D,t}D^b_{t-1} \qquad \text{si} \quad j=HH(1-\chi_E)(1-\delta_K)(Q^C_tK^C_{t-1}+Q^D_tK^D_{t-1}) \qquad \text{si} \quad j=E \tag{7}$$

Expected loss per unit of credit is

$$\text{EL}_{j,t}=(1+R^L_{j,t})1+\pi_tB_{j,t-1}F(\varpi_{j,t})-(1-\mu_j)\tilde{A}^b_{j,t}\int_0^{\varpi_{j,t}}\omega_{j,t}dF(\omega_{j,t})B_{j,t-1} \tag{8}$$

Mendicino et al. (2017, Equation 28) report a related expression for write-offs.

Using $\text{EL}_{j,t}=\text{PD}_{j,t}\times\text{LGD}_{j,t}$, LGD is given by

$$\text{LGD}_{j,t}=\frac{(1+R^L_{j,t})}{1+\pi_t}\left(1-(1-\mu_j)\int_0^{\varpi_{j,t}}\omega_{j,t}f(\omega_{j,t})d\omega_{j,t}\int_0^{\varpi_{j,t}}f(\omega_{j,t})d\omega_{j,t}\tilde{A}^b_{j,t}B_{j,t-1}\right). \tag{9}$$

Define:

$$\begin{aligned} z_{j,t} &= \frac{\ln(\varpi_{j,t})+0.5\sigma^2_{j,t}}{\sigma_{j,t}} \\ F(\varpi_{j,t}) &= (z_{j,t}) = \text{Probability of Default} \\ \Omega(\varpi_{j,t}) &= \int_0^{\varpi_{j,t}}\omega_{j,t}f(\omega_{j,t})d\omega_{j,t}=(z_{j,t}-\sigma_{j,t}) \end{aligned} \tag{10}$$

Then

$$\text{LGD}_{j,t}=\frac{(1+R^L_{j,t})}{1+\pi_t}\left(1-(1-\mu_j)\Omega(\varpi_{j,t})F(\varpi_{j,t})\tilde{A}^b_{j,t}B_{j,t-1}\right) \tag{11}$$

For macro variables—output, inflation, consumption, investment, employment, wages, the policy rate, and the real exchange rate—volatility under both Foundation and Advanced IRB remains broadly unchanged relative to the baseline. This is consistent with DKR, who report modest increases in output and inflation volatility of 5 % and 4 %, respectively. For banking sector variables, volatility is slightly lower.

To benchmark these results, the IRB formulas are also embedded in the model of Darracq Pariès et al. (2011) (Table 9). In this framework, macro volatility remains broadly unchanged, while banking sector volatility increases, particularly for corporate and mortgage lending rates, which rise by between 5 % and 17 %. This suggests that the impact on banking variables depends on country-specific features.

6. Counterfactual exercise: adoption of IRB approaches

Figures 8 and 9 present a counterfactual exercise that simulates the evolution of key variables under both Foundation and Advanced IRB approaches. Given the estimated parameter vector, the model is recast in state-space form under IRB-based risk weight formulas. The state-space system is then driven by the shock paths recovered from the baseline model.

Consistent with the previous section, adopting IRB approaches does not alter the path of macroeconomic variables. In the banking sector, mortgage rates become more volatile and remain below baseline levels over most of the sample. Corporate lending rates are also lower than in the baseline, accompanied by higher credit risk.

Figures 9 reports the implied risk weights. For firms, LGD under Advanced IRB fluctuates around 0.38, about 7 percentage points below the fixed value of 0.45 under Foundation IRB. The baseline LGD is close to the Advanced IRB estimate. The associated risk weights are below the baseline level of 1. Under Foundation IRB, they range between 0.7 and 1; under Advanced IRB, between 0.6 and 0.9.

In the mortgage segment, LGD remains below the Foundation IRB benchmark of 0.35 for most of the sample, fluctuating around 0.3, with a maximum of 1.5 and a minimum close to zero. Risk weights under both IRB approaches remain close to 0.5, consistent with the regulatory benchmark.

7. Conclusions

This paper combines two modeling frameworks: a version of Christiano et al. (2011) and the model of Darracq Pariès et al. (2011). The resulting setup is an open-economy DSGE model with a detailed banking sector operating under monopolistic competition, imperfect policy rate pass-through, and two types of credit—corporate and mortgage—under Basel regulation with endogenous credit risk. The model is estimated using Bayesian methods with Peruvian data and applied to historical shock decompositions, variance decompositions, and impulse response analysis. It evaluates the volatility of key macro-financial variables under IRB approaches for risk-weighted assets and includes a counterfactual exercise on the adoption of these frameworks. The main findings are as follows:

1. Fiscal and monetary policy mitigated the increase in credit risk for both firms and households during the global recession. In the absence of these policies, PD would have been higher by about 0.3 and 1.5 percentage points, respectively.

2. A variance decomposition over an eight-quarter horizon shows that fiscal and external shocks account for a large share of output fluctuations (41.2 % and 39.8 %, respectively). This result aligns with the literature and suggests that fiscal policy can influence economic activity despite external conditions.

3. External shocks dominate the variability of macroeconomic variables, as well as deposits, the deposit rate, and mortgage credit. Financial shocks play a limited role in macro fluctuations—except for investment—but are important for banking sector variables.

4. A 100-basis-point monetary policy shock generates output and inflation responses consistent with benchmark models and the literature on Peru. Corporate credit declines by about 0.2 % on impact and reaches a maximum contraction of 0.4 % in the fifth quarter, in line with the increase in lending rates, peaking at 10 basis points. This provides evidence of an active credit channel in this segment. As demand, employment, and wages decline, credit risk increases, with PD rising by about 5 and 15 basis points for firms and households.

   Mortgage credit exhibits a puzzle: volumes increase despite no clear response in interest rates. This may reflect the stronger link of mortgage rates to the long end of the yield curve.

5. A 1 % increase in government spending raises output by 0.18 % and inflation by 4 basis points, with the latter dissipating after about 15 quarters due to the policy rate response. The responses of output, employment, inflation, and the policy rate are consistent with benchmark models.

   Corporate lending rates increase by 2 basis points on impact and peak at 6 basis points in the seventh quarter. Mortgage rates peak at 20 basis points in the fifth quarter. Deposit rates follow a similar pattern, with an initial increase of 2 and a peak of 6 basis points. Corporate credit, mortgage credit, and deposits decline by up to 0.1 %, 0.4 %, and 0.25 %, respectively. Higher domestic demand reduces credit risk, with PD declining by about 0.8 and 3 basis points for firms and households.

6. For macro variables—output, inflation, consumption, investment, employment, wages, the policy rate, and the real exchange rate—volatility under both Foundation and Advanced IRB remains broadly unchanged relative to the baseline. Banking sector variables exhibit slightly lower volatility.

7. For firms, LGD fluctuates around 0.38. Combined with PD estimates, this implies risk weights below the baseline level of 1. Under Foundation IRB, risk weights range between 0.7 and 1; under Advanced IRB, between 0.6 and 0.9.

   In the mortgage segment, LGD remains below the Foundation IRB benchmark, 0.35, for most of the sample, fluctuating around 0.3, with a maximum of 1.5 and a minimum close to zero. Risk weights under both IRB approaches remain close to 0.5, consistent with regulatory benchmarks.

The model can be extended to assess the impact of regulatory frameworks on banking sector fragility, including the probability of bank failure. Darracq Pariès et al. (2015, 2016, 2018, 2019), Clerc et al. (2015), and Mendicino et al. (2017) provide relevant contributions in this direction.

Since the model generates PD and LGD endogenously—and therefore expected loss (PD × LGD)—it could be extended to incorporate loan loss provisions consistent with accounting treatment in financial statements.

The model could also incorporate direct multiplicative shocks to labor income, as in De Carvalho et al. (2014); De Carvalho and Castro (2015, 2017), to improve the fit in the mortgage segment.

Finally, model estimation could also incorporate micro-based measures of default probabilities. De Carvalho et al. (2014); De Carvalho and Castro (2015, 2017), for example, use loans overdue by more than 90 days as a share of total loans.

8. Tables and Figures

8.1 Tables

Table 1
Metropolis–Hastings estimation results (parameters)

	Prior			Posterior			
	Dist.	Mean	Std. dev.	Mean	Std. dev.	HPD lower	HPD upper
			Adjustment costs				
ϕ_K	norm	4.000	1.5000	2.732	0.5925	1.7715	3.7085
ϕ_D	gamm	1.000	0.5000	5.894	0.9675	4.3351	7.4956
φ	beta	0.500	0.1500	0.900	0.0401	0.8388	0.9690
			Inverse Frisch elasticity of labor supply				
σ_L	gamm	2.500	0.1000	2.494	0.1000	2.3236	2.6508
			Nominal rigidities (prices and wages)				
ξ_C	beta	0.750	0.0500	0.903	0.0157	0.8818	0.9317
ξ_D	beta	0.200	0.1000	0.487	0.0722	0.3751	0.6105
γ_C	beta	0.500	0.1500	0.526	0.1075	0.3547	0.7087
ξ_{wC}	beta	0.850	0.0500	0.619	0.0312	0.5662	0.6676
ξ_{wD}	beta	0.850	0.0500	0.949	0.0200	0.9154	0.9772
γ_w	beta	0.500	0.1500	0.702	0.1187	0.5197	0.9032
ξ_x	beta	0.750	0.0750	0.874	0.0219	0.8410	0.9072
ξ_{mc}	beta	0.750	0.0750	0.856	0.0288	0.8118	0.9005
ξ_{mi}	beta	0.750	0.0750	0.809	0.0352	0.7573	0.8660
ξ_{mx}	beta	0.660	0.1000	0.677	0.0413	0.6150	0.7455
γ_x	beta	0.500	0.1500	0.374	0.1057	0.1998	0.5339

Table 1

Metropolis–Hastings estimation results (parameters) (continued)

	Prior			Posterior			
	Dist.	Mean	Std. dev.	Mean	Std. dev.	HPD lower	HPD upper
γ_{mc}	beta	0.500	0.1500	0.856	0.0566	0.7686	0.9477
γ_{mi}	beta	0.500	0.1500	0.831	0.0639	0.7214	0.9272
γ_{mx}	beta	0.500	0.1500	0.822	0.0711	0.7067	0.9350
Nominal rigidities (banking sector)							
ξ_E^R	beta	0.500	0.2000	0.837	0.0735	0.7317	0.9541
ξ_{HH}^R	beta	0.500	0.2000	0.237	0.0745	0.1226	0.3557
ξ_D^R	beta	0.500	0.2000	0.402	0.0588	0.3061	0.4895
χ_{wb}	gamm	20.000	2.5000	19.060	2.4066	14.9840	22.9532
Taylor rule							
ρ	beta	0.750	0.1000	0.862	0.0232	0.8235	0.8995
r_π	gamm	2.500	0.2500	2.636	0.2225	2.2650	2.9871
$r_{\Delta\pi}$	gamm	0.300	0.1000	0.437	0.0846	0.3024	0.5836
r_y	gamm	0.200	0.1000	0.009	0.0044	0.0021	0.0159
$r_{\Delta y}$	gamm	0.120	0.0500	0.031	0.0099	0.0151	0.0478
Share of borrowing households							
ϱ	beta	0.250	0.1000	0.191	0.0414	0.1232	0.2525
Working capital financing share							
ν	beta	0.500	0.2500	0.014	0.0107	0.0001	0.0283
Export demand elasticity							
η_f	gamm	1.500	0.2500	1.411	0.1641	1.1495	1.6876
Country risk premium adjustment coefficient							
$\tilde{\phi}_S$	gamm	1.250	0.1000	0.915	0.0649	0.8114	1.0235

Table 2
Observed and model-implied volatility

	Volatility		Relative volatility
Variable	Data	Model	Model/Data
Output	0.62	1.51	2.43
Inflation	1.40	2.11	1.50
Consumption	0.57	1.06	1.86
Investment	2.55	2.20	0.86
Employment	0.69	1.66	2.41
Wages	1.09	1.52	1.39
Interbank rate	1.11	3.18	2.88
Real exchange rate	1.95	2.91	1.49
Corporate credit	2.45	2.24	0.91
Mortgage credit	1.71	2.63	1.53
Deposits	1.74	2.09	1.20
Corporate lending rate	1.29	5.10	3.96
Mortgage rate	0.40	9.28	23.02
Deposit rate	0.87	2.07	2.37
Corporate PD	2.23	1.83	0.82
Household PD	1.55	2.16	1.39

Table 3

Historical decomposition of fiscal and monetary shocks

Period	Corporate PD (%)	Fiscal shock	Monetary shock	Fiscal + monetary	Estimated PD without fiscal and monetary policy
2008Q4	2.39	-0.26	-0.09	-0.35	2.74
2009Q1	2.79	-0.23	-0.06	-0.29	3.09
2009Q2	3.65	-0.14	-0.12	-0.26	3.90
2009Q3	3.61	-0.03	-0.10	-0.13	3.73
2009Q4	3.68	0.02	-0.02	0.00	3.68
2010Q1	3.55	-0.04	0.04	0.00	3.55

Period	Household PD (%)	Fiscal shock	Monetary shock	Fiscal + monetary	Estimated PD without fiscal and monetary policy
2008Q4	5.46	-0.76	-0.08	-0.84	6.30
2009Q1	7.17	-1.03	-0.10	-1.13	8.30
2009Q2	5.98	-1.16	-0.40	-1.56	7.54
2009Q3	4.92	-1.12	-0.55	-1.67	6.59
2009Q4	0.85	-0.91	-0.50	-1.41	2.26
2010Q1	-0.45	-0.65	-0.46	-1.11	0.66

Table 4

Variance decomposition: evidence for Peru (%)

Reference	Output			Inflation			Interest rate		
	External	Fiscal	Monetary	External	Fiscal	Monetary	External	Fiscal	Monetary
Castillo et al. (2006)	37		0.29	32		58	87		10
Lavanda and Rodríguez (2011)				50					
Castillo and Salas (2012)*	69–95								
MEF (2014)	55								
Rodríguez et al. (2018)	95								
Mendoza and Collantes Goicochea (2017)	67	15	0.86						
Schmitt-Grohé and Uribe (2018)	19								
Florián et al. (2018)	50								
MEF (2019)	54								
Portilla Goicochea and Rodríguez (2020)	>40		0.7	>40		0.3	>40		11
Jiménez and Rodríguez (2020)	60, 15**	40, 75**							
Rodríguez and Vassallo (2021)	80, 65**								
Ojeda Cunya and Rodríguez (2022)	80			60–100		0.12			
Chávez and Rodríguez (2022)	70		1	80			80		
Chávez and Rodríguez (2022)***	38	60							
Ganiko and Jiménez (2023)	62		2.3	61		3	54		26
Meléndez Holguín and Rodríguez (2023)		68							
Pérez Rojo and Rodríguez (2023)	50								
Guevara et al. (2024)	65			65			67		
Guevara et al. (2024)***	30								
Alvarado Silva et al. (2024)	40–60								<20
Rodríguez and Santisteban (2024)	17	79							
This study	39.8	41.2	1.7	16.6	14.7	4.8	23.8	22.6	9.1

Where available, estimates correspond to inflation targeting regimes.
* Horizon: 8–40 quarters.
** Estimate for the final part of the sample.
*** Robustness: including public investment in the model.

Table 5

Variance decomposition (%)

Shock Description	$\epsilon_{A,t} + \epsilon_{A_{D,t}}$ Technology	$\epsilon_{I,t}$ Investment	$\epsilon_{B,t} + \epsilon_{D,t} + \epsilon_{L,t}$ Preferences	$\epsilon_{G,t}$ Fiscal	$\epsilon_{R,t}$ Monetary	$\epsilon_{P,t}$ Firm markup	External total (1)	Financial total (2)
Output	1.6	0.2	8.0	41.2	1.7	4.6	39.8	1.1
Inflation	7.8	0.4	22.9	14.7	4.8	20.3	16.6	0.9
Interbank rate	8.8	0.4	27.7	22.6	9.1	6.3	23.8	1.3
Output deflator	4.9	0.2	11.5	7.4	2.0	23.1	36.7	0.3
Investment deflator	3.3	0.2	11.8	7.3	2.7	5.0	53.7	0.7
Consumption	9.8	0.4	42.8	10.4	9.0	6.7	13.3	4.6
Investment	10.8	32.1	4.6	6.8	3.2	2.1	6.9	18.8
Exports	0.0	0.0	0.1	0.0	0.0	0.0	96.1	0.0
Imports	0.5	0.6	4.5	0.5	1.4	0.4	75.2	0.7
Real exchange rate	1.6	0.1	9.6	5.4	0.9	0.4	73.9	3.6
Wages	3.0	0.2	30.2	12.4	5.0	14.4	27.0	2.5
Employment	22.1	0.2	7.5	37.0	1.4	3.1	26.3	0.9
House prices	52.4	0.0	26.0	0.5	0.0	0.5	0.6	0.0
Corporate lending rate	4.0	19.6	5.8	6.2	0.1	0.5	5.7	58.2
Mortgage rate	3.3	0.0	19.1	10.0	0.6	0.5	8.9	57.6
Deposit rate	8.8	0.4	27.2	22.1	4.6	4.2	23.0	9.6
Corporate credit	4.9	47.1	3.6	1.5	0.4	1.5	7.2	18.8
Mortgage credit	9.7	0.2	33.1	18.4	0.9	1.0	19.9	16.8
Deposits	4.8	16.6	21.4	13.6	0.0	1.0	20.7	21.9
Bank capital	0.1	0.1	0.5	0.3	0.4	0.2	0.4	98.1
Corporate PD	2.6	29.5	0.9	1.6	0.2	0.1	2.6	62.5
Household PD	1.9	0.0	27.6	3.0	1.1	0.5	3.2	62.8
LGD, firms	0.8	8.5	0.2	0.3	0.1	0.2	0.7	89.3
LGD, households	0.8	0.0	10.7	1.8	0.1	0.2	1.8	84.5
Bank leverage	1.2	0.5	3.8	3.3	0.6	0.4	3.2	86.9

(1) External total: external shocks + exporter and importer markup shocks.
(2) Financial total: risk shocks + bank markup shocks + bank capital shock.
Row sums may differ from 100 because of measurement errors.

Table 6

Variance decomposition: external and financial shocks (%)

	External total		Financial total		
Shock Description	$\epsilon_{j^\star,t} + \epsilon_{\tilde{\phi},t}$ External	$\epsilon_{\tau^k,t}$ Markup Exporters/Importers	$\epsilon_{\sigma,t} + \epsilon_{\sigma_{HH},t}$ Risk	$\epsilon_{R_i,t}$ Markup Banks	$\epsilon_{Bankcap,t}$ Capital Bank capital
Output	4.4	35.4	0.2	0.9	0.1
Inflation	10.5	6.1	0.0	0.8	0.0
Interbank rate	15.0	8.8	0.0	1.2	0.1
Output deflator	2.2	34.5	0.0	0.2	0.0
Investment deflator	14.4	39.4	0.0	0.6	0.0
Consumption	10.9	2.4	0.7	3.5	0.4
Investment	2.7	4.3	13.0	3.9	1.9
Exports	23.9	72.1	0.0	0.0	0.0
Imports	13.3	61.9	0.2	0.3	0.1
Real exchange rate	64.7	9.2	0.0	3.5	0.0
Wages	2.0	24.9	0.3	1.9	0.3
Employment	2.7	23.6	0.1	0.6	0.1
House prices	0.5	0.1	0.0	0.0	0.0
Corporate lending rate	2.6	3.1	40.9	12.7	4.5
Mortgage rate	3.8	5.2	31.3	25.4	0.9
Deposit rate	15.2	7.9	0.0	9.5	0.1
Corporate credit	1.8	5.5	13.7	3.2	1.8
Mortgage credit	5.9	14.0	1.5	15.2	0.1
Deposits	5.7	15.0	5.0	2.4	14.4
Bank capital	0.3	0.1	0.0	36.3	61.7
Corporate PD	0.2	2.4	61.0	1.0	0.5
Household PD	0.6	2.6	60.3	2.2	0.2
LGD, firms	0.0	0.7	88.4	0.6	0.3
LGD, households	0.4	1.4	83.1	1.4	0.1
Bank leverage	1.8	1.4	0.1	31.3	55.5

Table 7

Empirical evidence on the credit channel in Peru (*)

Study	Methodology/Data	Findings
Dancourt and Ganiko (2009)	Panel 2003M1–2010M6	Changes in the policy rate have a negative and significant effect on local-currency lending by banks and municipal savings institutions. The sum of significant coefficients is −0.11. Excluding municipal institutions, the coefficient ranges between −0.11 and −0.0675.
Dancourt (2012)	Panel 2003M1–2011M12	Increases in the policy rate have a negative and significant effect on the growth rate of local-currency bank lending by banks and municipal savings institutions. A 1 p.p. increase reduces average credit growth by 0.551 p.p. after one year. For banks only, the coefficient is −1.11.
Cermeño et al. (2015)	Panel 2003M6–2010M6	An increase in the policy rate has a positive and significant effect on commercial lending rates in LC (0 to 360 days) set by the six largest banks. Long-run elasticities of lending rates with respect to the policy rate are below one, indicating incomplete pass-through.
Carrera (2011)	Panel and VAR 2001–2010	Evidence supports the presence of a credit channel in the Peruvian economy (2002–2010). Credit growth is inversely related to the stance of monetary policy. Results are reported for consumer credit, commercial credit, and their aggregate.
Viladegut and Cabello (2014)	SVAR 2002Q1–2012Q2	The credit channel operates as a transmission mechanism of monetary policy to aggregate activity (credit to the private sector by multiple operations institutions). A 1 % increase in the policy rate reduces credit growth by 0.07 % in the second quarter, with the decline reaching 0.05 % between the fifth and tenth quarters.
Pérez-Forero and Vega (2014)	SVAR 1995M10–2013M12	Policy rate shocks affect credit levels in both LC and FC (bank credit to the private sector). A 0.25 % increase in the policy rate leads to a statistically significant decline in credit within the first year. The peak effect is a reduction of about 0.05 % in both currencies.
Céspedes Reynaga (2017)	Heckman model 2008–2014	Estimated credit demand elasticities at the household level are −0.29. Consumer credit shows higher elasticity (−0.40), mortgage credit is close to zero, and microenterprise credit is −0.06.
Lahura (2017)	Error-correction models 2010M8–2017M5	Pass-through is stronger for lending rates than for deposit rates. It is higher for loans with maturities below one year and approaches one for short-term loans.

Study	Methodology/Data	Findings
Sánchez León (2016)	DSGE 2003Q1–2015Q4	A 100-basis-point policy rate shock increases corporate lending rates by 80 basis points and reduces credit by 0.4 %. For mortgage credit in LC, the rate rises by 60 basis points on impact and then declines from the second quarter, reaching a maximum drop of 80 basis points in the sixth quarter before converging. Credit volumes fall by 1 % on impact and then increase by up to 2 % before converging. For mortgage credit in FC, the rate rises by 80 basis points on impact, while credit falls by 1 % in the first two quarters before converging.
Bustamante et al. (2019)	Panel 2005M1–2017M12	Banks with stronger balance sheets exhibit a smaller contraction in local-currency lending following an increase in the policy rate.

(*) Effects of changes in reserve requirements are also reported in the referenced studies but are not included here.

Table 8

Evaluation of IRB approaches

	Volatility				Relative volatility	
	Data	Base	IRB^0	IRB^1	$\frac{IRB^0}{Base}$	$\frac{IRB^1}{Base}$
	Macroeconomic variables					
Output	0.62	1.51	1.52	1.51	1.01	1.00
Inflation	1.40	2.11	2.12	2.11	1.00	1.00
Consumption	0.57	1.06	1.06	1.06	1.00	1.00
Investment	2.55	2.20	2.20	2.19	1.00	1.00
Employment	0.69	1.66	1.67	1.67	1.00	1.00
Wages	1.09	1.52	1.53	1.53	1.01	1.01
Interbank rate	1.11	3.18	3.19	3.18	1.00	1.00
Real exchange rate	1.95	2.91	2.92	2.91	1.00	1.00
	Banking sector variables					
Corporate credit	2.45	2.24	2.22	2.24	0.99	1.00
Mortgage credit	1.71	2.63	2.54	2.55	0.97	0.97
Deposits	1.74	2.09	1.96	1.93	0.94	0.92
Corporate lending rate	1.29	5.10	4.92	4.95	0.96	0.97
Mortgage rate	0.40	9.28	8.87	8.91	0.96	0.96
Deposit rate	0.87	2.07	2.07	2.07	1.00	1.00
Corporate PD	2.23	1.83	1.78	1.79	0.98	0.98
Household PD	1.55	2.16	2.18	2.18	1.01	1.01

* Not directly observed in the estimation; proxied by the non-performing loan ratio.

Base refers to the model with time-invariant risk weights. IRB^0 denotes Foundation IRB (fixed LGD). IRB^1 denotes Advanced IRB (endogenous LGD).

Table 9
Evaluation of IRB approaches under DKR

	Volatility			Relative volatility	
	Base	IRB^0	IRB^1	$\frac{IRB^0}{Base}$	$\frac{IRB^1}{Base}$
Macroeconomic variables					
Output	0.71	0.71	0.71	1.00	1.00
Inflation	1.94	1.96	1.97	1.01	1.02
Consumption	0.76	0.76	0.76	1.00	1.00
Investment	2.05	2.04	2.06	1.00	1.00
Employment	0.86	0.86	0.87	1.00	1.00
Wages	0.64	0.64	0.64	1.00	1.00
Interbank rate	3.20	3.22	3.22	1.01	1.00
Banking sector variables					
Corporate credit	0.95	0.92	0.95	0.97	1.00
Mortgage credit	0.84	0.90	0.91	1.07	1.08
Deposits	0.84	0.86	0.82	1.02	0.97
Corporate lending rate	2.74	2.87	3.14	1.05	1.15
Mortgage rate	2.96	3.39	3.47	1.14	1.17
Deposit rate	1.97	1.98	1.99	1.01	1.01
Corporate PD	0.97	1.00	0.99	1.03	1.02
Household PD	0.43	0.44	0.44	1.02	1.02

* Not directly observed in the estimation.

Base refers to the model with time-invariant risk weights. IRB^0 denotes Foundation IRB (fixed LGD). IRB^1 denotes Advanced IRB (endogenous LGD).

8.2 Figures

Figure 1. Model structure overview

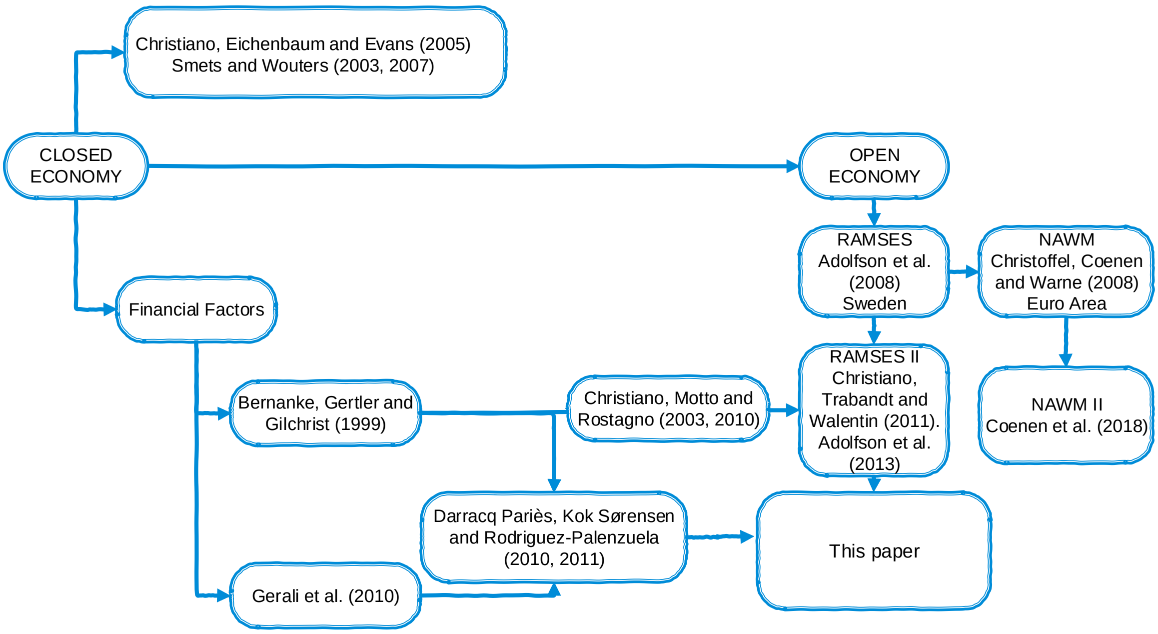
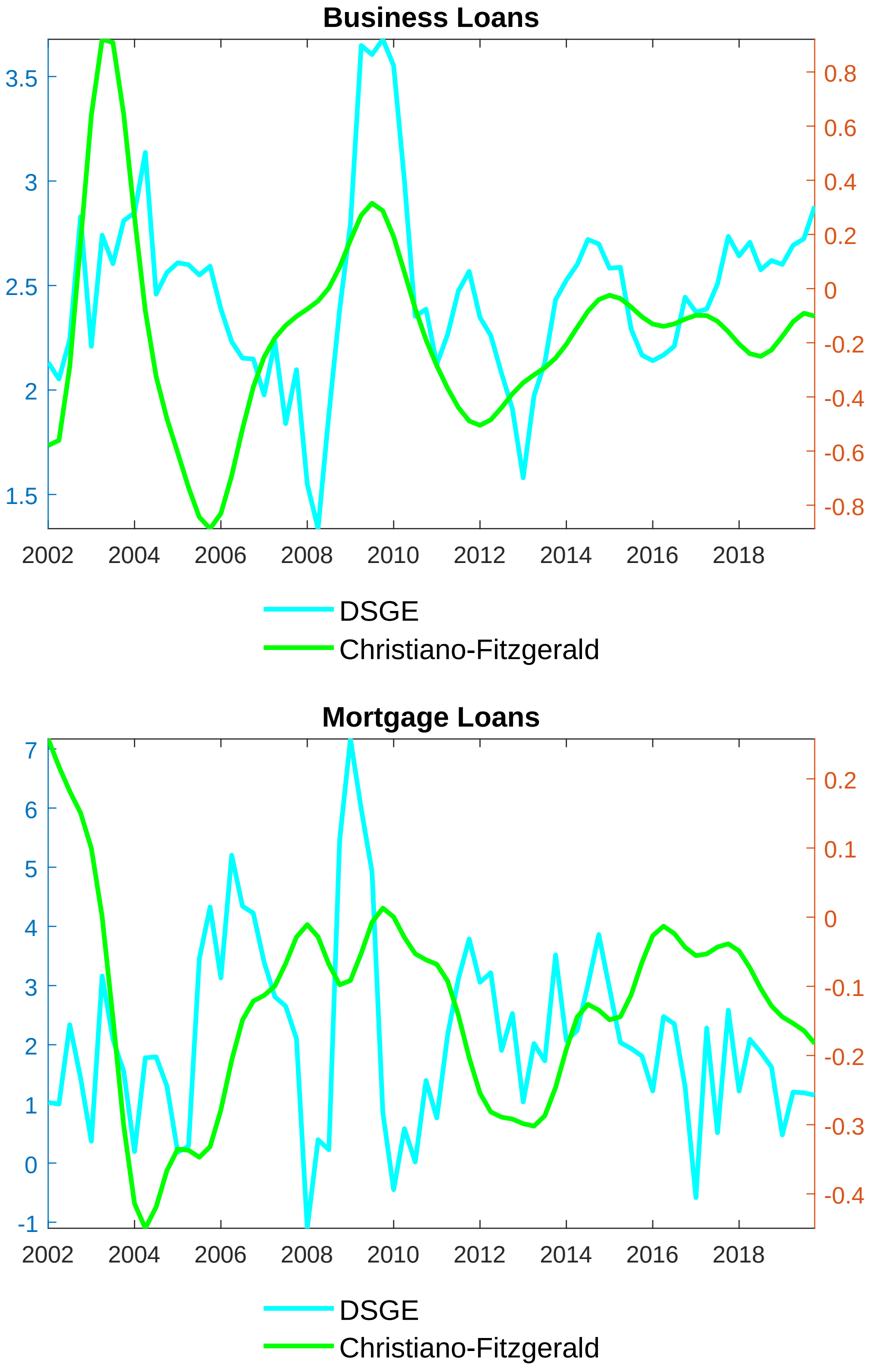


Figure 2. Delinquency (cycle) vs. PD



Christiano–Fitzgerald filter using the code of Kowal (2005).

Figure 3. Corporate PD

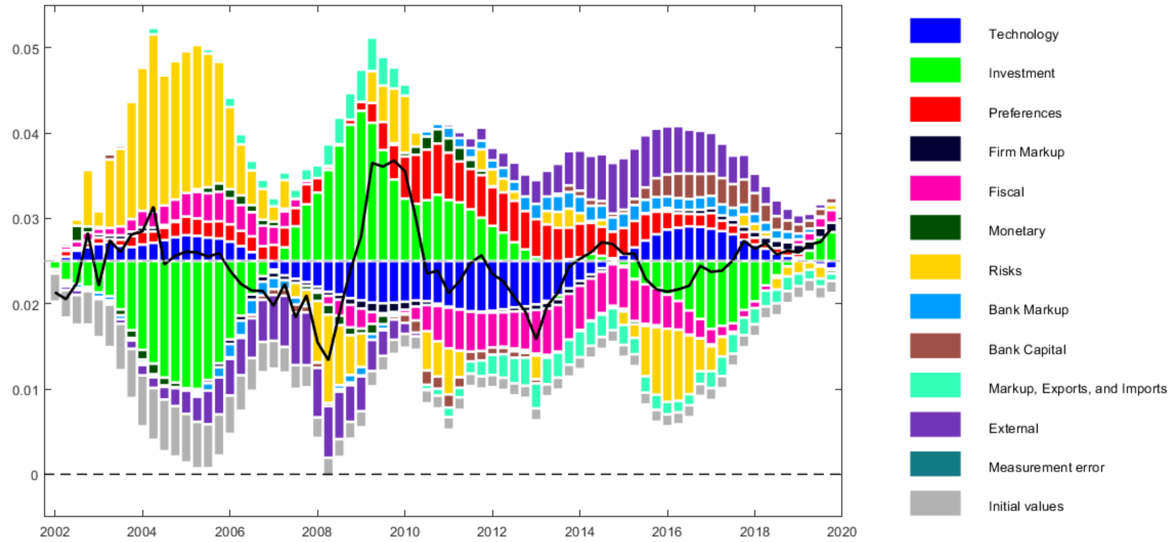


Figure 4. Household PD

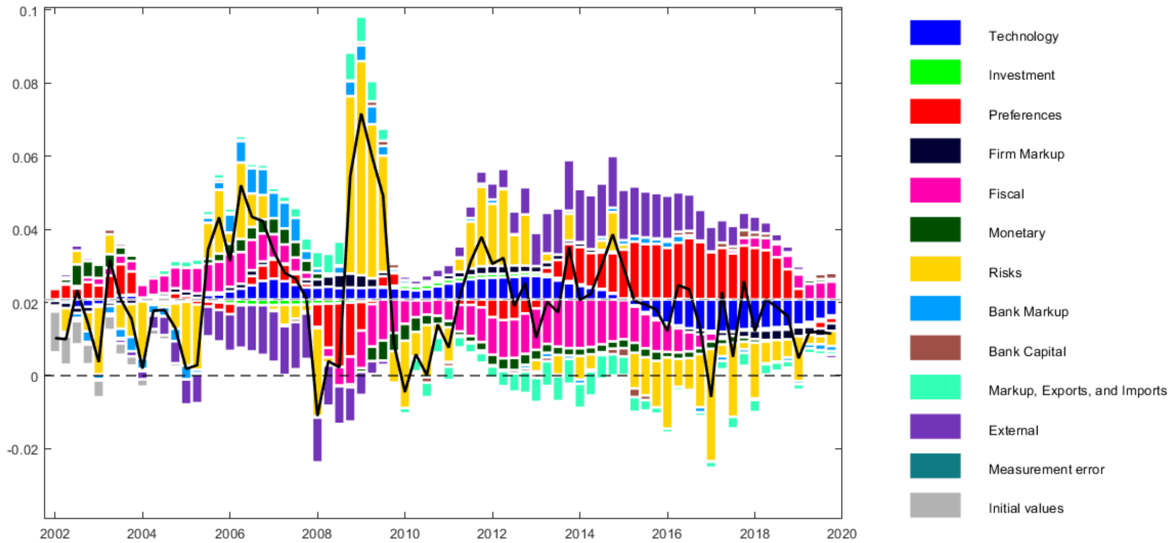
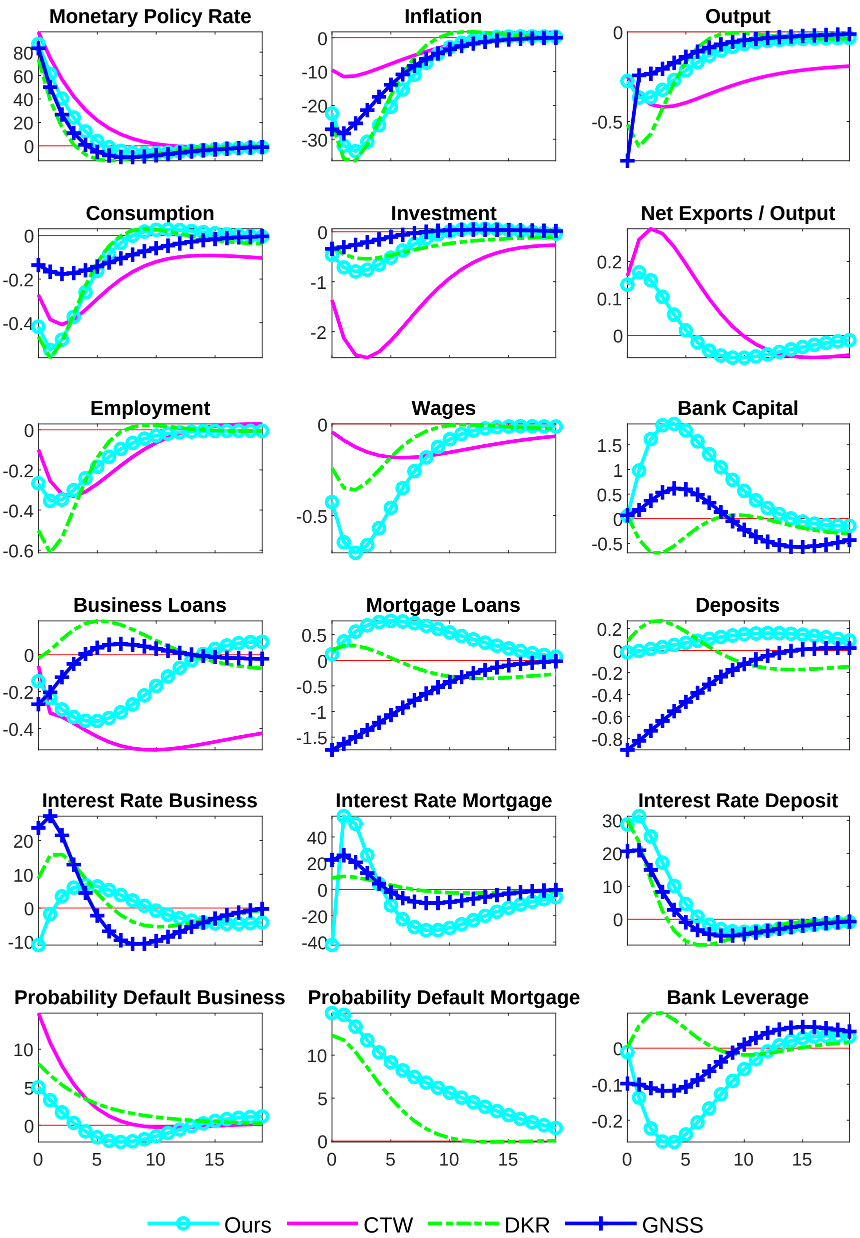
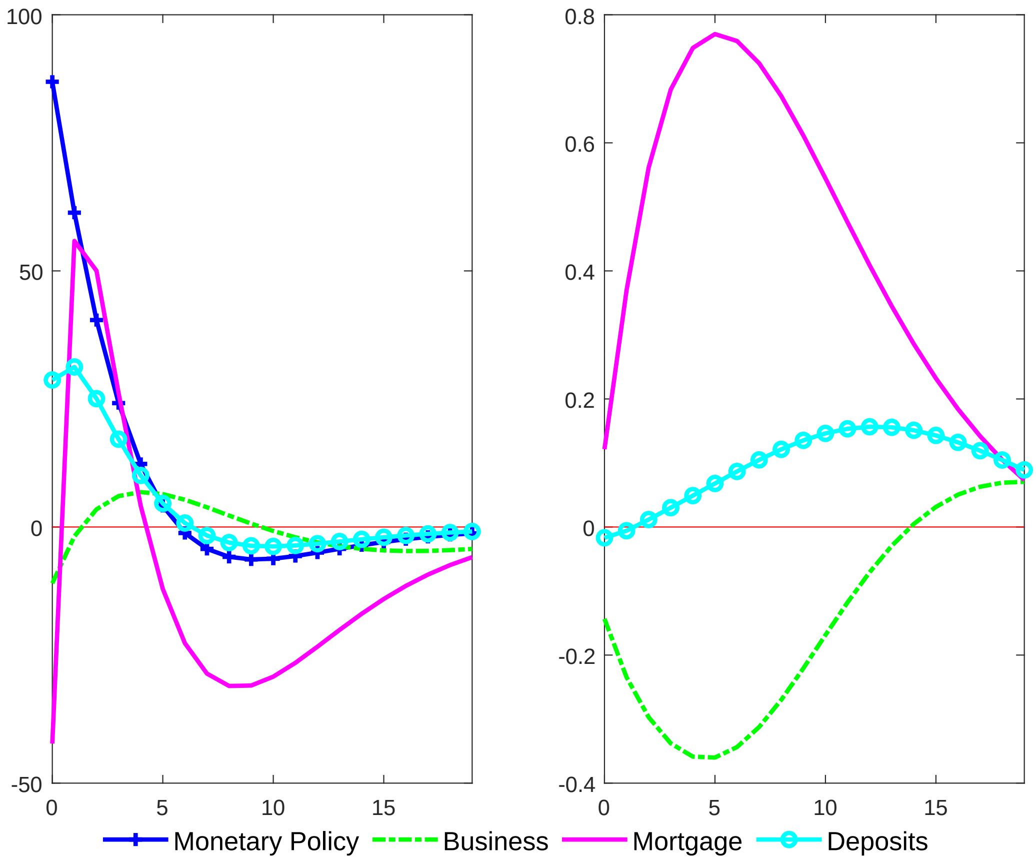


Figure 5. Impulse responses to a 100-basis-point monetary policy shock



Ours refers to the model developed in this paper. CTW is estimated with Swedish data. DKR is estimated with euro area data. GNSS is estimated with euro area data. Interest rates and inflation are reported as annualized deviations from steady state, in basis points. PD is reported as deviations from steady state, in basis points. The ratio NX/Y is expressed in percent. All other variables are reported as percentage deviations from steady state.

Figure 6. Impulse responses to a 100-basis-point monetary policy shock



The right-hand panels report interest rates as deviations from steady state, in basis points. The left-hand panels report corporate credit, mortgage credit, and deposits as percentage deviations from steady state.

Figure 7. Impulse responses to a 1 % fiscal shock

Ours refers to the model developed in this paper. CTW is estimated with Swedish data. DKR is estimated with euro area data. Interest rates and inflation are reported as annualized deviations from steady state, in basis points. PD is reported as deviations from steady state, in basis points. The ratio NX/Y is expressed in percent. All other variables are reported as percentage deviations from steady state.

PUCP

Figure 8. Counterfactuals

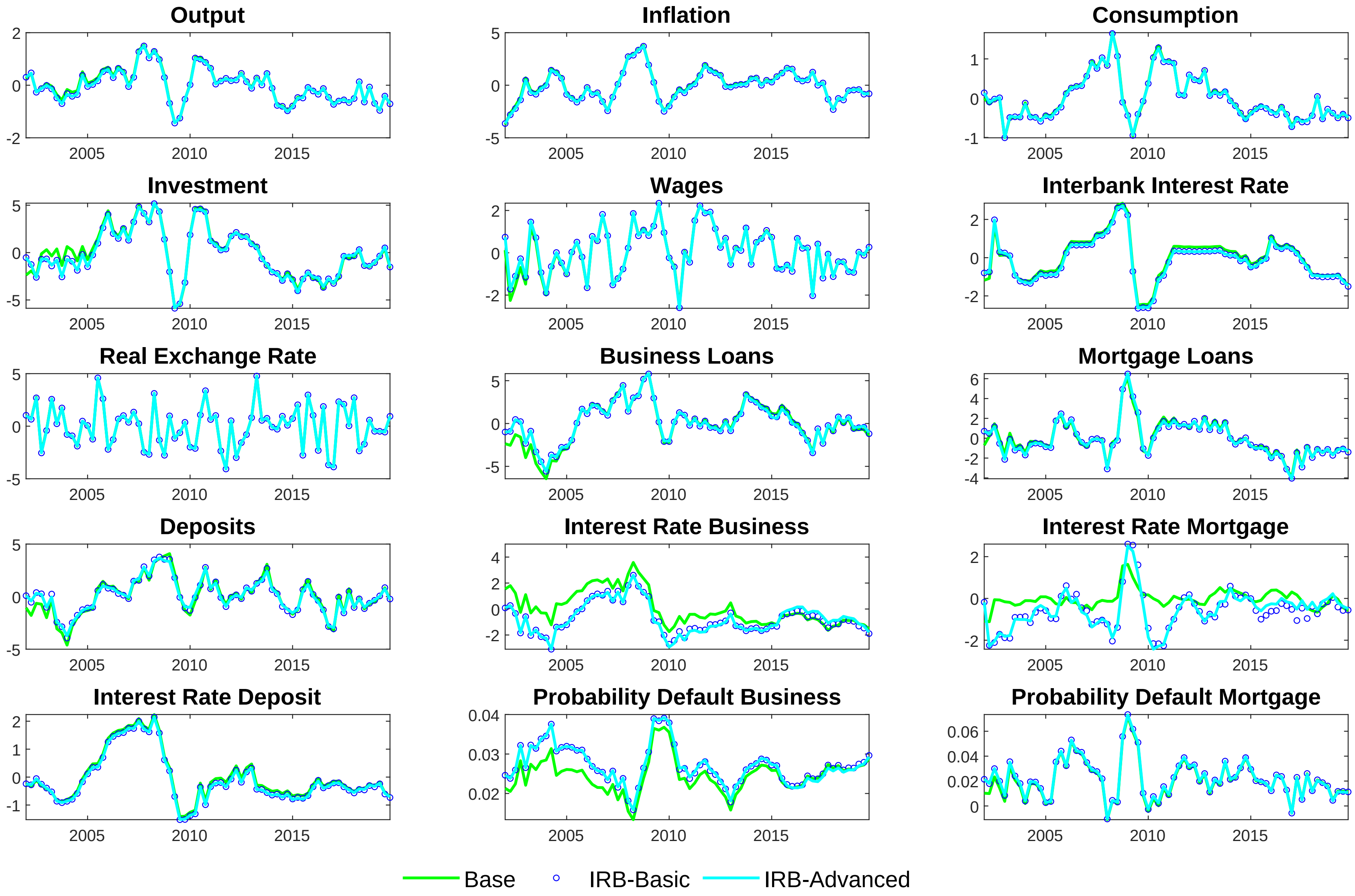
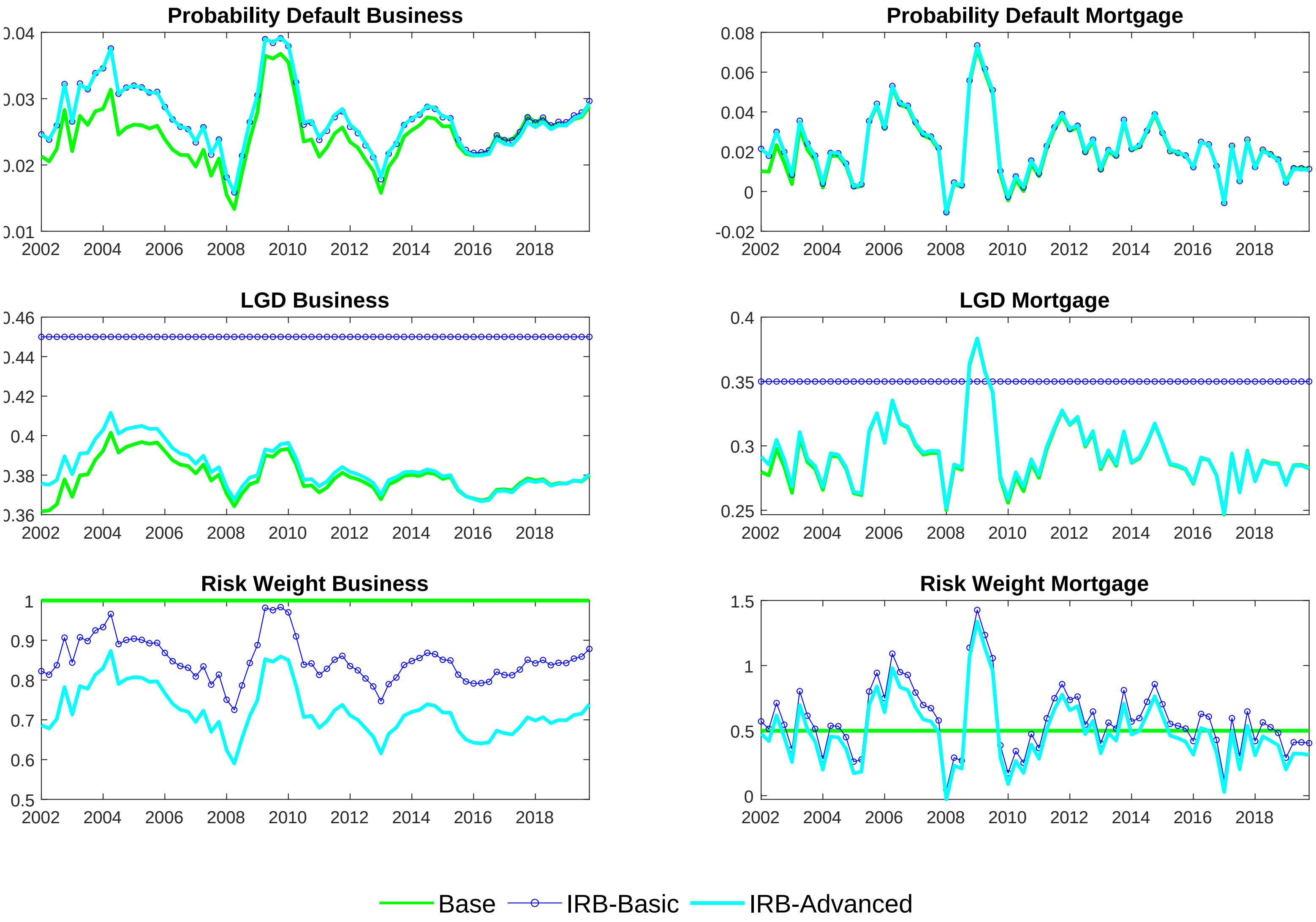


Figure 9. Counterfactuals: risk weights



Appendix

9. Data Description

9.1 Banking sector

- Business loans
- Mortgage loans
- Deposits

End-of-quarter credit and deposit volumes, seasonally adjusted using four-quarter moving averages and deflated by the CPI (to match the real counterpart in the model), expressed in quarter-on-quarter growth rates.

Following the June 2010 loan reclassification, we map commercial loans (under the former classification) into three categories under the new classification: corporate, large firms, and medium-sized firms. SBS (2008, 2009).

Source: Superintendencia de Banca, Seguros y AFP (SBS).

- Interest rate on business loans
- Interest rate on mortgage loans
- Interest rate on deposits

The data from the SBS website include daily information on lending and deposit interest rates, reported by each financial institution in accordance with reporting formats 6-D and 6-E. Until July 2010, total credit was classified into four categories: commercial, microenterprise, consumer, and mortgage. Thereafter, the classification was expanded to include Corporate, Large Firms, Medium-sized Firms, Small Firms, Microenterprises, Consumer, and Mortgage categories. SBS (2008, 2009).

The interest rate on business loans corresponds to the average across individual banks. Maturities of less than 360 days (average of up to 30 days, 31–90 days, 91–180 days, and 181–360 days). As with credit volumes, we match commercial loans (under the former classification) to corporate loans to large and medium-sized firms (average) under the new classification. Weighted average using the corresponding dollarization series. Corresponds to transactions carried out over the previous 30 business days. Expressed as deviations from the historical average. Figures 10 and 11. Source: SBS.

The mortgage interest rate corresponds to the average across individual banks. It is a weighted average using the corresponding dollarization series and refers to transactions conducted over the previous 30 business days. Expressed as deviations from the historical linear trend. Figure 12. Source: SBS.

The deposit interest rate is the weighted average of the FTIPMN and FTIPMEX rates (based on the corresponding dollarization series), which capture the market average of transactions conducted over the previous 30 business days. Expressed as deviations from the historical average. Source: BCRP.

Figure 10. Business interest rates - Domestic currency

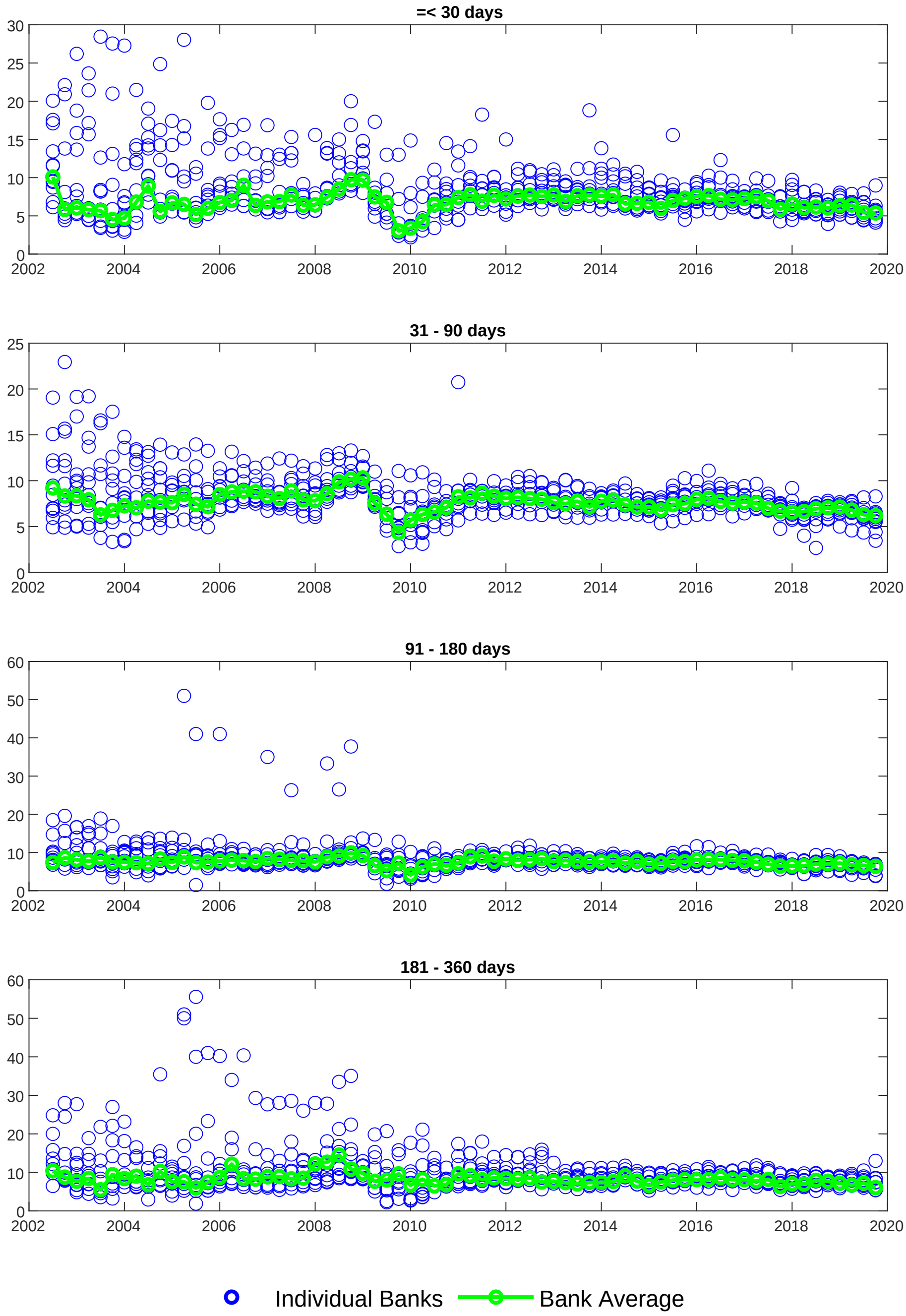


Figure 11. Business interest rates - Foreign currency

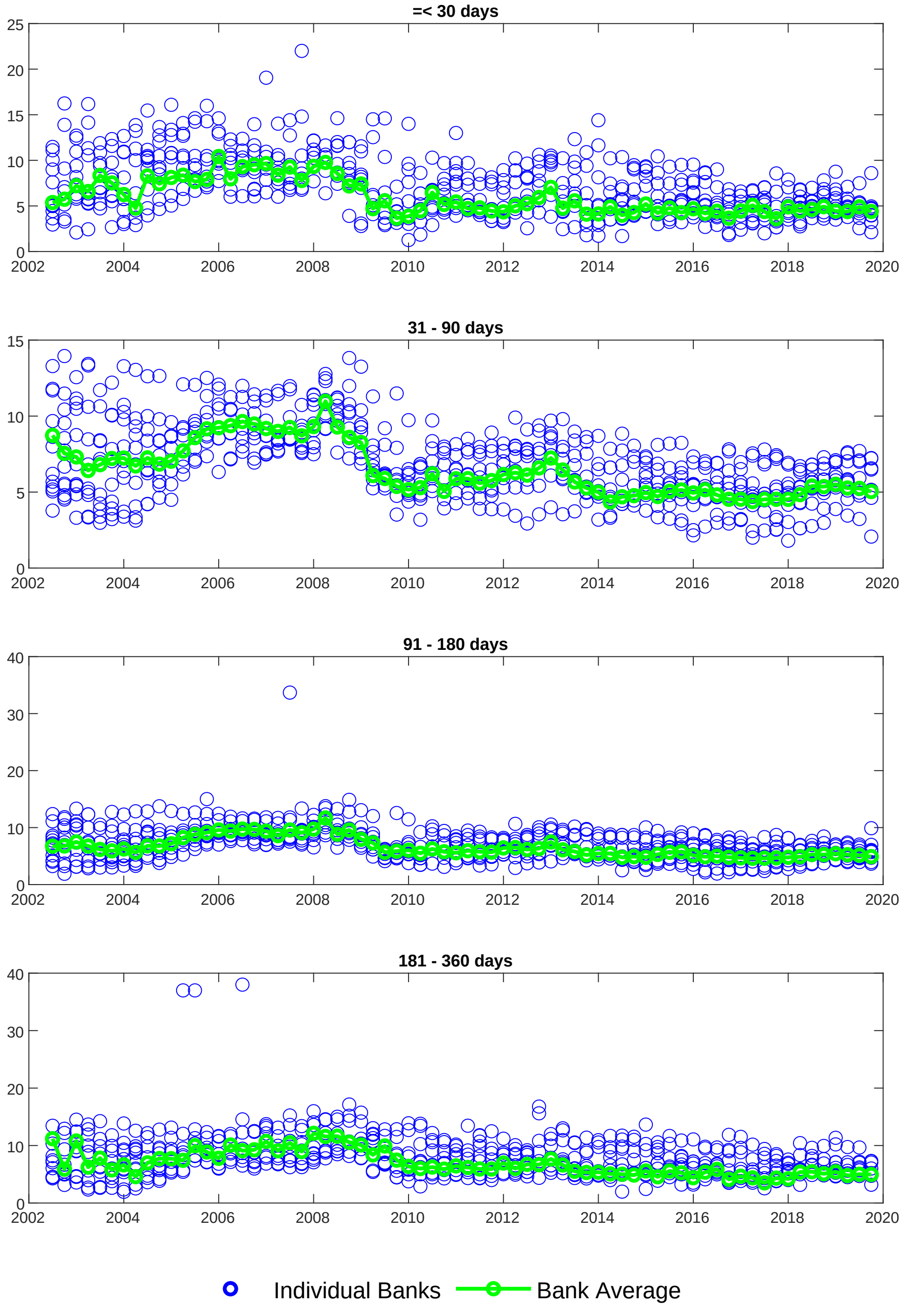
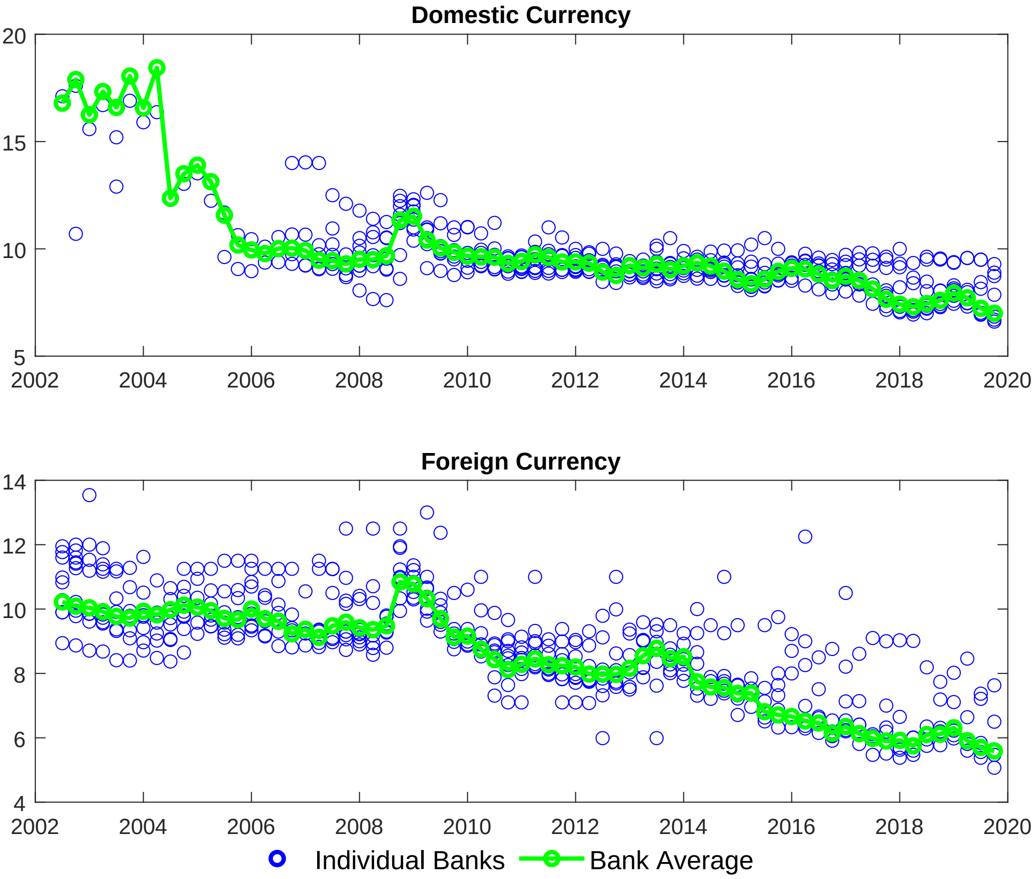


Figure 12. Mortgage interest rates



9.2 Housing prices

Series linking:

2002Q1 - 2018Q4: Apartments (five districts): La Molina, Miraflores, San Borja, San Isidro and Surco - Prices per m2 (2009 constant soles) (discontinued).

2019Q1 - 2019Q4: Apartments (High Sector): Barranco, La Molina, Miraflores, San Borja, San Isidro and Surco - Prices per m2 (2009 constant soles).

Expressed in quarter-on-quarter growth rates.

Source: BCRP.

9.3 Monetary policy interest rate

Interbank rate (MN). In levels. Source: BCRP.

9.4 Output

- GDP
- Private consumption
- Private investment
- Imports
- Exports

Millions of soles at 2007 prices, seasonally adjusted using four-quarter moving averages, and expressed in quarter-on-quarter growth rates.

Similarly, deflators are computed for investment and output (annualized quarter-on-quarter growth rates).

Source: BCRP.

9.5 CPI (Consumer Price Index)

Lima Metropolitan Area Price Index (December 2021 = 100), seasonally adjusted using four-quarter moving averages and in annualized growth rates. Source: BCRP.

9.6 Real exchange rate

Multilateral real exchange rate index (2009 = 100), expressed in quarter-on-quarter growth rates. Source: BCRP.

9.7 Real wages

Monthly income. Employment in Metropolitan Lima – three-month moving average (thousands of persons), seasonally adjusted, deflated by the CPI, and expressed in quarter-on-quarter growth rates. Source: BCRP.

9.8 Employment

Urban total employment index in Peru, smoothed using a four-quarter moving average, and expressed in quarter-on-quarter growth rates. Source: INEI.

9.9 Foreign variables (United States)

- Inflation, measured as the annualized growth rate of the CPI.
- Real GDP, seasonally adjusted and expressed as an annualized quarter-on-quarter growth rate.
- Interest rate.

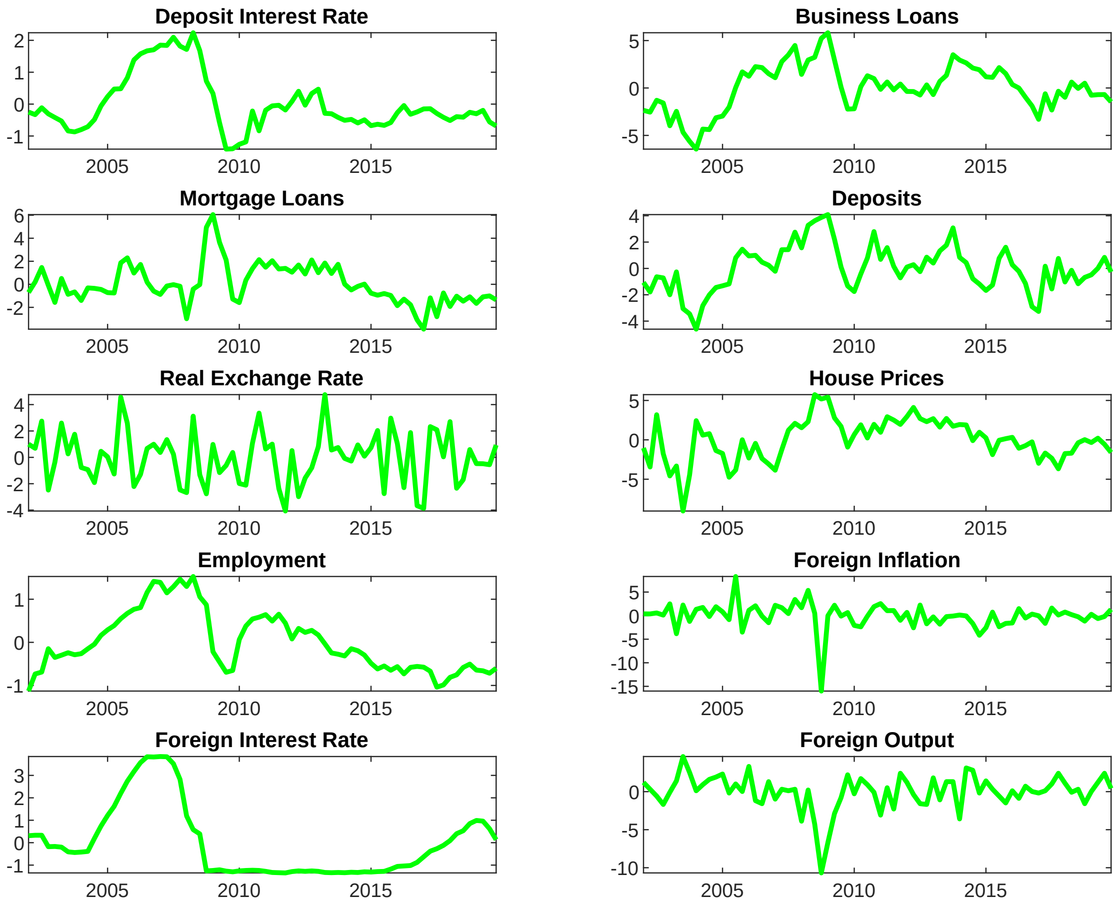
Source: FRED (Federal Reserve Economic Data).

The time series of the variables used in the estimation are presented in the following figures.

PUCP

Figure 13

Figure 14



10. Calibration of $\overline{\omega}$ and σ

$$j \in \{E, HH\} \tag{10.1}$$

We begin with the moments of ω_j

$$\begin{aligned} E(\omega_j) &= 1 \\ Var(\omega_j) &= v_j \end{aligned} \tag{10.2}$$

From which we derive the parameter that appears in a lognormal density

$$\sigma_j = \sqrt{\ln(1 + v_j)} \tag{10.3}$$

We use the modified Euler equations

$$1 = \beta_j(1 + \overline{R_j})\mathcal{Y}_j(\overline{\omega}_j, \sigma_j) \tag{10.4}$$

$$Y_j(\overline{\omega}_j, \sigma_j) = \frac{1 - \left(\dfrac{\ln(\overline{\omega}_j) + 0.5\sigma_j^2}{\sigma_j}\right)}{1 - \left(\dfrac{\ln(\overline{\omega}_j) + 0.5\sigma_j^2}{\sigma_j}\right) - \mu_j\phi\left(\dfrac{\ln(\overline{\omega}_j) + 0.5\sigma_j^2}{\sigma_j} - \sigma j\right)\dfrac{\omega_j}{\sigma j}} \tag{10.5}$$

$$\overline{F_j} = \left(\frac{\ln(\overline{\omega}_j) + 0.5\sigma_j^2}{\sigma_j}\right) \tag{10.6}$$

$\overline{F_j}$ denotes the steady-state default probability. ϕ denotes a standardized normal density and the cumulative standardized normal distribution.

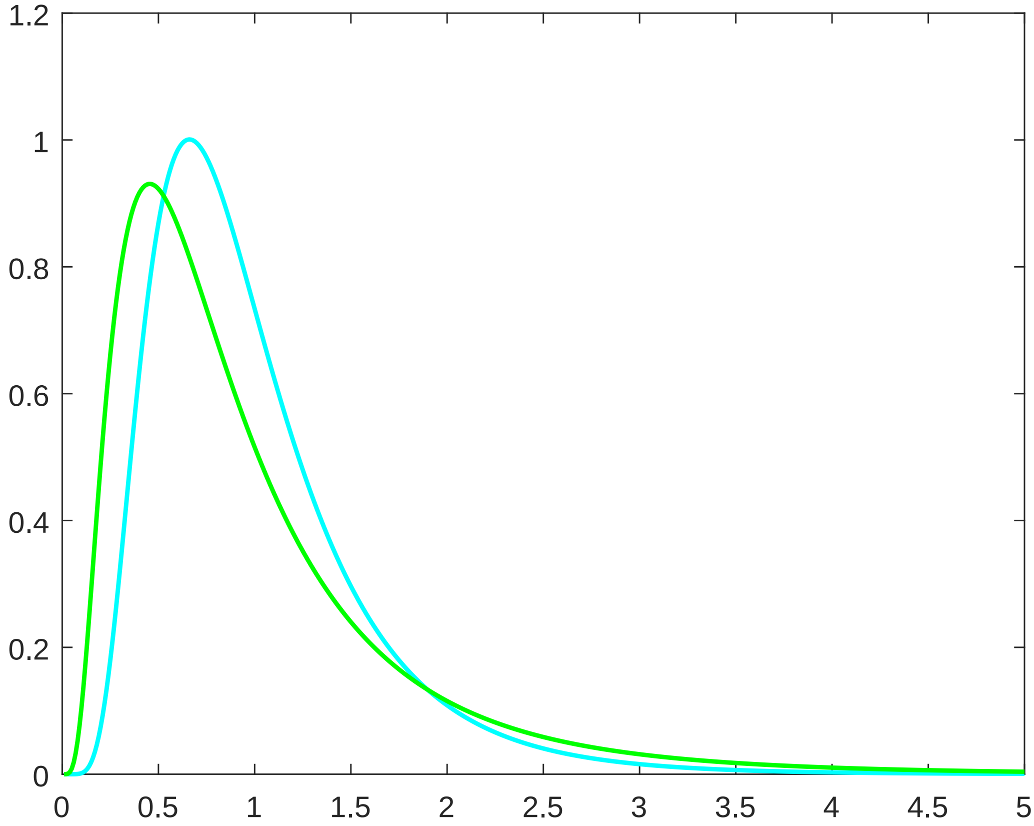
We consider the historical average default rates in the Peruvian banking system, which are 2.5 % and 2.08 % for business and mortgage loans, respectively.

We take as given β_j, $\overline{R_j}$ and μ_j.

With (B.6) and reemplazando (B.5) en (B.4) tenemos dos ecuaciones en dos variables $\overline{\omega}_j$ and σ_j (specifically in v_j). This system is solved using MATLAB's `fsolve`.

In the following figure, we present densities of ω_j.

Figure 15. Density of ω_j ($\sigma_{HH} = 0.5252$, $\sigma_E = 0.7246$)



$\omega$is lognormally distributed with mean $m = 1$ and variance v, from which we obtain $\mu = \ln(m^2/\sqrt{(m^2+v)})$ and $\sigma = \sqrt{\ln(1+v/m^2)}$ which are directly related to the mean and variance of the normal density. $f(\omega_{HH})$ appears in cyan and $f(\omega_E)$ in green.

11. Tables and Figures

11.1 Structural shocks and foreign VAR

Table 10
Results from Metropolis-Hastings (structural shocks)

	Prior			Posterior			
	Dist.	Mean	Stdev.	Mean	Stdev.	HPD inf	HPD sup
ρ_A	beta	0.500	0.2000	0.937	0.0417	0.8679	0.9908
ρ_B	beta	0.500	0.2000	0.821	0.0402	0.7569	0.8846
ρ_G	beta	0.500	0.2000	0.919	0.0163	0.8958	0.9472
ρ_L	beta	0.500	0.2000	0.941	0.0389	0.8800	0.9909
ρ_I	beta	0.500	0.2000	0.703	0.0867	0.5598	0.8401
ρ_{A_D}	beta	0.500	0.2000	0.938	0.0143	0.9164	0.9626
ρ_D	beta	0.500	0.1750	0.999	0.0005	0.9981	0.9993
ρ_{R_L}	beta	0.500	0.2000	0.176	0.0828	0.0400	0.2989
$\rho_{R_L E}$	beta	0.500	0.2000	0.343	0.1828	0.0464	0.6003
ρ_{R_D}	beta	0.500	0.2000	0.661	0.0684	0.5510	0.7742
$\rho_{Bankcap}$	beta	0.500	0.2000	0.400	0.0966	0.2380	0.5485
ρ_σ	beta	0.500	0.2000	0.907	0.0407	0.8427	0.9753
$\rho_{\sigma_{HH}}$	beta	0.500	0.2000	0.321	0.0821	0.1903	0.4580
$\rho_{\tilde{\phi}}$	beta	0.700	0.2000	0.996	0.0036	0.9911	1.0000
ϵ_A	unif	1.250	0.7217	0.509	0.0892	0.3656	0.6658
ϵ_B	invg	2.000	Inf	1.300	0.1633	1.0368	1.5833
ϵ_G	unif	5.000	2.8868	5.700	0.9307	4.3883	7.1635
ϵ_I	invg	0.250	Inf	0.311	0.0569	0.2128	0.3976
ϵ_R	invg	0.250	Inf	0.159	0.0149	0.1362	0.1852
ϵ_{R_L}	invg	0.250	2.0000	4.287	1.2717	2.2068	6.3454
$\epsilon_{R_{L_E}}$	invg	0.250	2.0000	0.082	0.0182	0.0548	0.1109
ϵ_{R_D}	invg	0.100	2.0000	0.142	0.0256	0.1024	0.1844
ϵ_{A_D}	unif	5.000	2.8868	3.337	0.5722	2.4122	4.2186
ϵ_P	unif	5.000	2.8868	0.262	0.0317	0.2120	0.3075
ϵ_L	unif	5.000	2.8868	3.183	0.4398	2.4762	3.8891
ϵ_D	invg	2.000	Inf	4.271	0.7443	3.1566	5.4587
$\epsilon_{Bankcap}$	invg	2.000	Inf	5.180	0.6729	4.1332	6.2643
ϵ_σ	invg	0.250	Inf	0.033	0.0020	0.0294	0.0354
$\epsilon_{\sigma_{HH}}$	unif	1.000	0.5774	0.119	0.0138	0.0945	0.1399
$\epsilon_{R^{star}}$	invg	1.500	Inf	0.820	0.0689	0.7037	0.9323
$\epsilon_{\tilde{\phi}}$	invg	0.150	Inf	0.123	0.0126	0.1021	0.1438
$\epsilon_{y^{star}}$	invg	0.500	Inf	0.586	0.0533	0.4921	0.6649
$\epsilon_{\pi^{star}}$	invg	0.500	0.5000	0.631	0.0355	0.5709	0.6915
ϵ_{τ^x}	invg	0.500	Inf	8.356	2.4666	4.1280	12.0770
$\epsilon_{\tau^{mc}}$	invg	0.500	Inf	3.546	1.3157	1.6538	5.8542
$\epsilon_{\tau^{mi}}$	invg	0.500	Inf	1.780	0.6370	0.7884	2.8228

(Continued on next page)

Table 10
(continued)

	Prior			Posterior			
	Dist.	Mean	Stdev.	Mean	Stdev.	HPD inf	HPD sup
$\epsilon_{\tau^{mx}}$	invg	0.500	Inf	4.428	0.9939	2.7388	5.9502

Table 11
Results from Metropolis-Hastings (parameters)

	Prior			Posterior			
	Dist.	Mean	Stdev.	Mean	Stdev.	HPD inf	HPD sup
a_{11}	norm	0.900	0.0500	0.971	0.0282	0.9276	1.0181
a_{22}	norm	0.100	0.1500	-0.078	0.0868	-0.2185	0.0647
a_{33}	norm	0.900	0.0100	0.900	0.0099	0.8837	0.9158
a_{12}	norm	0.300	0.2500	0.140	0.0887	-0.0165	0.2760
a_{13}	norm	-0.500	0.1500	-0.287	0.1220	-0.4963	-0.0964
a_{21}	norm	0.050	0.0500	0.013	0.0226	-0.0263	0.0490
a_{23}	norm	-0.100	0.1000	-0.126	0.0989	-0.2881	0.0376
a_{31}	norm	0.010	0.0100	0.008	0.0048	-0.0002	0.0152
a_{32}	norm	0.090	0.0500	0.006	0.0170	-0.0236	0.0312
c_{21}	norm	0.150	0.1000	0.294	0.0713	0.1683	0.4025
c_{31}	norm	0.150	0.0500	0.081	0.0139	0.0583	0.1045
c_{32}	norm	0.050	0.0500	0.020	0.0107	0.0018	0.0370

11.2 Estimation of unobservables: LGD

Figure 16. Firms

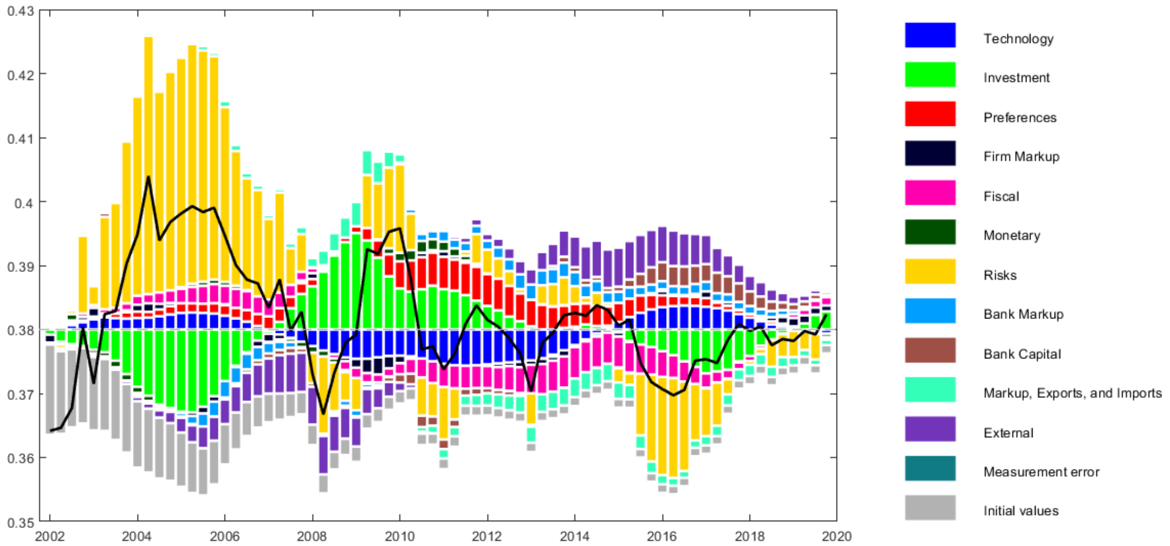
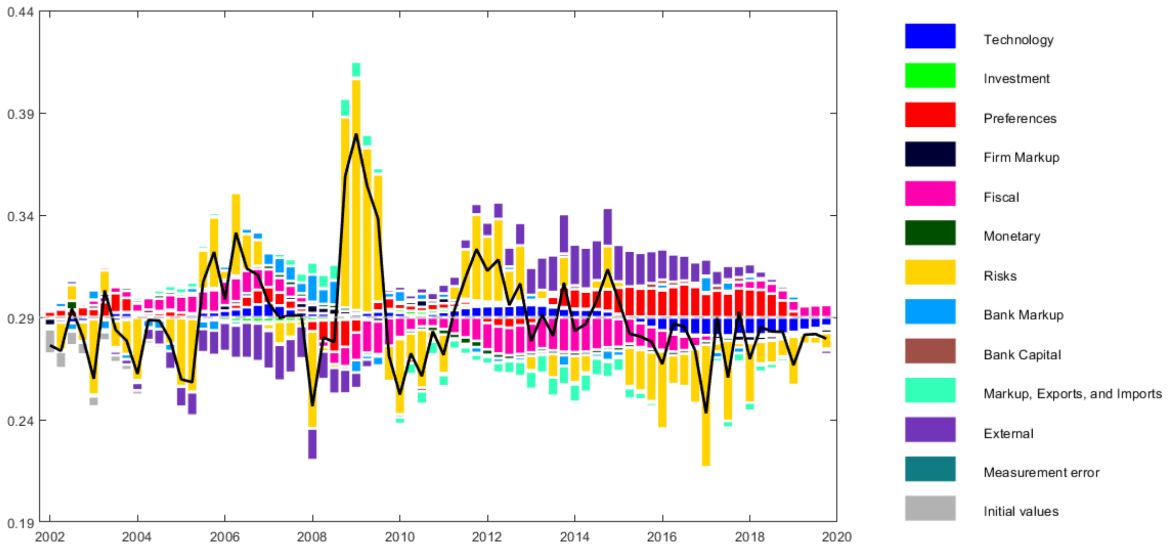


Figure 17. Households

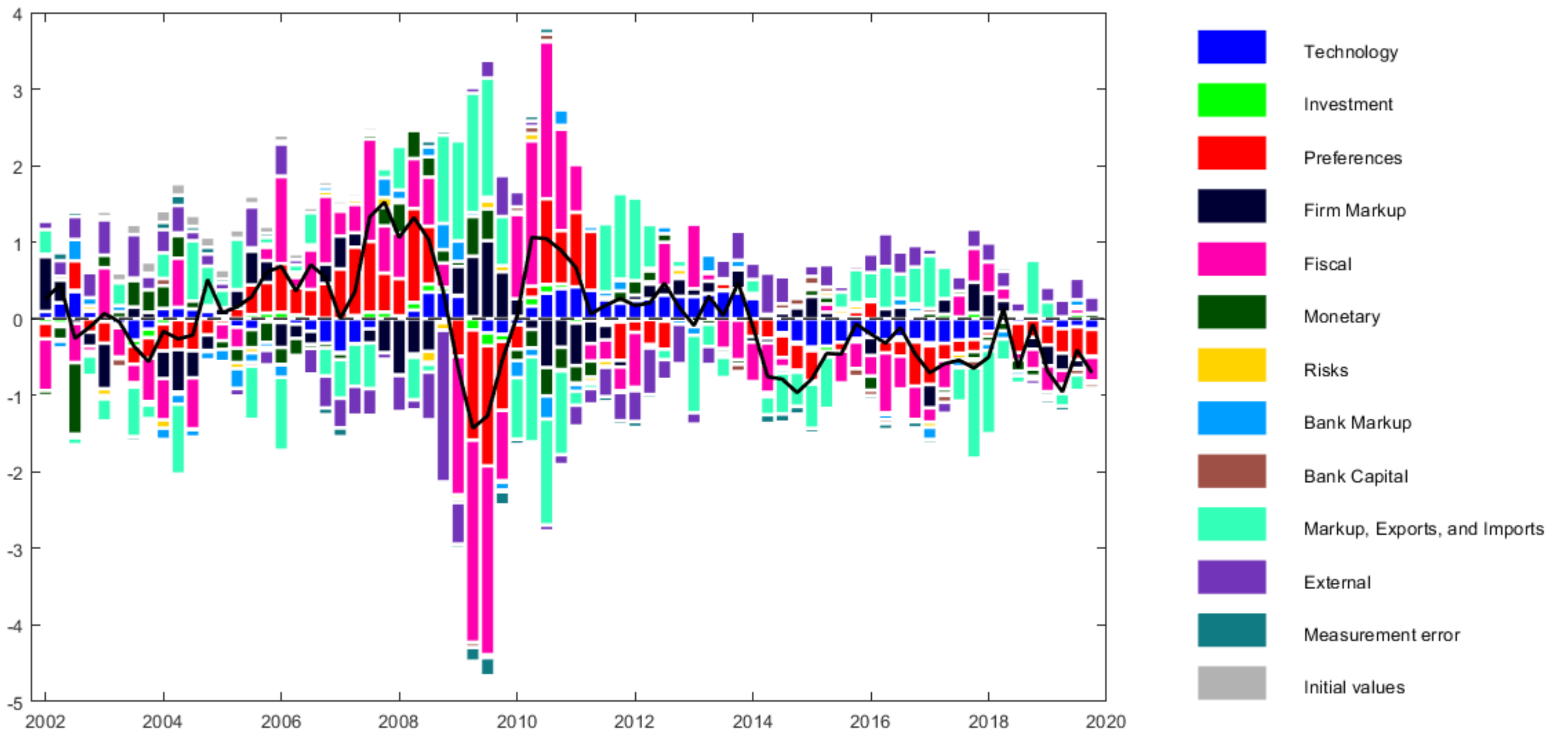


11.3 Historical decomposition of GDP growth

Table 12
Shock decomposition: Output growth

Period	Output growth (%)	Fiscal Shock	Monetary Shock
2008Q4	0.35	0.32	0.17
2009Q1	-0.64	-1.81	0.07
2009Q2	-1.43	-2.64	**0.52**
2009Q3	-1.27	-2.47	**0.41**
2009Q4	-0.54	-0.92	-0.02
2010Q1	0.04	1.10	-0.15

Figure 18. Output Growth (Quarterly): Deviation from the Mean



12. Random Walk Metropolis algorithm

The method of Uhlig (2001) provides the linear approximation of the model and the transition equation; combined with the measurement equation, it yields a state-space representation.

$$s_t = \mathcal{T}(\theta)s_{t-1} + \mathcal{R}(\theta)\epsilon_t \tag{12.1}$$

$$y_t = \mathcal{D}(\theta) + \epsilon_{\mu,t} + \mathcal{Z}(\theta)s_t \tag{12.2}$$

θ is a vector that includes the model parameters, ϵ_t is a vector of structural shocks, and $\epsilon_{\mu,t}$ denotes measurement errors.

The RWM algorithm generates Markov chains whose stationary distributions correspond to the posterior distributions.

1. We begin by maximizing

$$\ln p(\theta|\mathcal{Y}_T) = \ln L(\theta|\mathcal{Y}_T) + \ln p(\theta). \tag{12.3}$$

where $L(\theta|\mathcal{Y}_T)$ denotes the likelihood function evaluated at θ computed via the Kalman filter, $p(\theta)$ is the prior density, and $p(\theta|\mathcal{Y}_T)$ is the posterior density. $\mathcal{Y}_T$ denotes the data. Denotaremos este máximo por $\tilde{\theta}$.

2. $\tilde{\Sigma}$ denotes the negative of the inverse Hessian evaluated at the posterior mode $\tilde{\theta}$

$$\tilde{\Sigma} = \left[-\frac{\partial^2 \ln p(\theta|\mathcal{Y}_T)}{\partial\theta\partial\theta'}\bigg|_{\theta=\tilde{\theta}} \right]^{-1} \tag{12.4}$$

which approximates the covariance matrix under maximum likelihood (Hamilton, 1994), the difference here is that we compute the Hessian of the posterior density. An alternative option to approximate the covariance matrix is to use the outer product of gradients:

$$\tilde{\Sigma} = \left[\sum_{t=1}^{T} [h(\tilde{\theta}, \mathcal{Y}_t)].[h(\tilde{\theta}, \mathcal{Y}_t)]' \right]^{-1} \tag{12.5}$$

where:

$$h(\hat{\theta}, \mathcal{Y}_t) = \frac{\partial \ln p(\theta|\mathcal{Y}_t)}{\partial\theta}\bigg|_{\theta=\tilde{\theta}} \tag{12.6}$$

In the estimation, we use the option, `mode_compute = 5, optim = ('Hessian',2)` by Marco Ratto, which combines both methods, with diagonal elements obtained from second derivatives and correlations derived from the outer product.

3. We draw $\theta^{(0)}$ from $N(\tilde{\theta}, c_0^2\tilde{\Sigma})$.

4. For $s = 1, ..., n_{sim}$, we draw ϑ from the distribution $N(\theta^{(s-1)}, c^2\tilde{\Sigma})$. The jump from $\theta^{(s-1)}$ is accepted ($\theta^{(s)} = \vartheta$) with probability $\min\{1, r(\theta^{(s-1)}, \vartheta|Y)\}$ and rejected ($\theta^{(s)} = \theta^{(s-1)}$) otherwise. Here:

$$r(\theta^{(s-1)}, \vartheta|Y) = \frac{L(\vartheta|Y)p(\vartheta)}{L(\theta^{(s-1)}|Y)p(\theta^{(s-1)})} \tag{12.7}$$

With c close to 0.1, chosen to achieve an acceptance rate of around 23 %, as recommended by Roberts et al. (1997).

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