ESSAYS ON UNCERTAINTY AND CREDIT MARKET FRICIONS

A Dissertation
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By

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The dissertation comprises of three chapters. The first chapter studies the role of credit market frictions in transmitting time-varying aggregate uncertainty to economic activity. First, we document that changes in country-specific aggregate volatility are positively correlated with the current account dynamics but negatively correlated with investment, output and credit flows. Then we build an International Real Business Cycle model with credit market frictions that matches these empirical facts. The version of the model with no financial frictions can only account for positive correlation between volatility and current account, but implies counterfactual predictions for the other correlations.

In the second chapter we analyze banking crises and lending of last resort (LOLR) in a quantitative model of financial frictions with bank defaults. We find that the LOLR, even if it induces an increase in banks’ leverage, is beneficial for small open economies. We show that pools of small economies cannot be successful LOLRs for empirically reasonable levels of liquidity support: They need too many uncorrelated countries or large initial levels of reserves to be sustainable. A country with ample reserves like China can be a sustainable international LOLR.

The third chapter analyzes supranational deposit insurance in a quantitative model of financial and sovereign debt crisis. We show that the common deposit insurance fund can bring about sizable economic benefits by weakening an adverse link between domestic banking sector stress and sovereign default risk. The model simulations suggest that the sustainability of such a fund requires a certain number of
participating countries with strong fundamentals, while feasibility calls for risk-based
insurance premiums. These results can inform the design of the common European
deposit insurance fund.

INDEX WORDS: Credit Supply, Uncertainty, Trade Balance, Precautionary
Savings, Banking Crises, China, Financial Frictions, Lender of
Last Resort, Supranational Deposit Insurance, European Union
Dedication

To my parents.
I would like to especially thank my advisor Professor Pedro Gete for his constant support and guidance throughout my Ph.D. career. The first two chapters of this dissertation are based upon joint work with him. Besides my advisor, I would like to thank my committee members, Professors Behzad Diba and Robert Cumby, for their useful feedback on the dissertation. I also thank my parents who, despite being physically far away, were always there for me. Finally, I would like to thank Allie Stashko for always believing in me.
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Chapter 1

Aggregate Volatility and International Dynamics: The Role of Credit Supply

1.1 Introduction

There is increasing evidence that time-varying uncertainty is important for macroeconomic dynamics (see Bloom 2014 for a survey). A new literature studies the international dimensions of uncertainty. For example, Fogli and Perri (2015) and Hoffmann, Krause and Tillmann (2016) document that uncertainty and current account dynamics are positively correlated across countries. Both papers explain the correlation using an International Real Business Cycle model (IRBC) with a precautionary savings channel: when countries become more volatile than their partners, their households save and run a current account surplus.

In this paper we use OECD data from the period 1970q1–2014q4 to document four other international facts: when aggregate uncertainty increases in a country, then investment, credit flows and output fall, while the credit spread increases. An IRBC model with only the precautionary savings channel is unable to simultaneously get right all the previous correlations. In the model, investment and output increase in the more volatile country. The reason is an application of Jensen’s inequality: due to
convex returns from investment, higher volatility leads to higher investment, capital, output and employment.  

We show that an IRBC model correctly predicts all the previous correlations if it is expanded with a credit supply mechanism in which countries have domestic credit markets with default and lenders exposed to aggregate risk. Moreover, with a credit supply channel, the model generates current account dynamics consistent with the data as higher uncertainty induces an investment collapse and a surge of savings. In the IRBC the counterfactual investment boom pushes the current account towards a deficit.

We study a two-country, incomplete markets IRBC model extended with a costly state verification friction à la Bernanke, Gertler and Gilchrist (1999, BGG) between domestic entrepreneurs and domestic lenders. Households deposit with banks that lend to a continuum of entrepreneurs, who use the funds to buy capital that they then rent to the firms. However, a crucial difference from BGG is that in our model lenders are exposed to both aggregate and idiosyncratic credit risk. That is, the lenders’ return is not risk-free. If lenders’ return does not vary with the aggregate state of the economy as in BGG, then the model with financial accelerator generates the same counterfactual predictions as the IRBC model.

Our mechanism works as follows: higher aggregate uncertainty increases the probability of entrepreneurs’ default and, because banks are exposed to aggregate risk, this

\[ \text{Cho, Cooley and Kim (2015) and Lester, Pries and Sims (2014) analyze how higher uncertainty leads to higher investment in the standard real business cycle model with variable productive inputs.} \]

\[ \text{In the BGG framework, borrowers (entrepreneurs) bear the aggregate risk of the financial contract. Lenders obtain a riskless rate of return. Thus, since depositing with lenders is a risk-free investment, higher aggregate uncertainty makes households more willing to supply loanable funds due to a “flight-to-safety” mechanism. As a consequence, in the BGG framework, higher aggregate uncertainty leads to an expansion of credit supply.} \]
leads to a contraction of credit supply even if banks’ cost of funds remains constant. Moreover, when banks’ credit risk increases, the risk of losses on bank deposits also becomes higher and households, who would like to avoid the riskier deposits, require a higher risk premium to finance the banks. The combined effect is that higher aggregate uncertainty induces a large contraction of credit supply, and lending rates to entrepreneurs soar. Since entrepreneurs need credit to finance investment, the credit crunch leads to an investment collapse. Less investment lowers capital, employment and output. Moreover, the current account and the trade balance react strongly and move towards surpluses since the precautionary savings channel is accompanied by an investment collapse.

Quantitative simulations of the model show that the credit channel is consistent with the data. That is, following volatility shocks, the credit crunch dominates the convex returns from investment that lead to the counterfactual predictions of the IRBC model. Moreover, the model with a credit channel is supported by the cross-country evidence on credit flows and spreads that we show in Section 1.3. That is, more volatile countries see a reduction in credit towards the private non-financial sector and an increase in credit spreads.

The credit channel that we analyze in the benchmark economy is mitigated when we study global instead of domestic banks. The reason is that with diversified global banks higher volatility in one country does not alter the ability of the global bank to raise funds. Although, higher uncertainty still contracts credit supply because it increases the likelihood of default and debt contracts imply concave payoffs for the lender. In this regard, the model shows that the retreat of banking globalization

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3In a debt contract, banks’ payoff from holding risky loans is a concave function of the borrowers’ stochastic income. Thus, a mean-preserving spread (i.e. higher uncertainty) to the borrowers’ income reduces lenders’ expected return through Jensen’s inequality effect.
after the 2008 financial crisis (Forbes, Reinhart and Wieladek 2017) may amplify the negative effects of higher uncertainty.

The rest of the paper is organized as follows. Section 1.2 discusses the related literature. Section 1.3 documents the facts. Section 3.3 presents the model. Section 1.5 explains how volatility affects credit supply. Section 1.6 has the core quantitative exercise. Section 1.7 studies the case when banks are global instead of domestic. Section 1.8 compares with the time-varying volatility of interest rates studied by Fernandez-Villaverde et al. (2011). Section 1.9 concludes. The appendix documents the data sources. An online appendix contains the algebra and the robustness exercises.

1.2 Related Literature

Our paper contributes to the literature studying uncertainty in open economies, and to the literature studying uncertainty and credit markets. Since these are large areas here we only review the more related papers.

Fogli and Perri (2015) and Hoffmann, Krause and Tillmann (2016) document that countries which become more volatile have current account surpluses. Both papers use models driven by precautionary savings motives. Clarida (1990) and Chang, Kim and Lee (2013) also study the role of precautionary savings in accounting for current account dynamics.

Our paper complements the previous papers in both the empirical and the theoretical dimensions. On the empirical side, we confirm the link between volatility and current account dynamics and expand it to other key macro variables: investment, output and credit variables. We show that the precautionary savings channel alone can account for the correlation between volatility and current account dynamics. However,

\footnote{We measure uncertainty as the realized stock market returns volatility, which is a standard measure in the literature as discussed in the next section.}
the precautionary savings channel generates counterfactual predictions concerning
the effects of volatility on investment and output. We show how to extend the IRBC
model with a credit sector to be consistent with all the empirical correlations. Our
model gets the current account dynamics right by getting right both the savings and
the investment dynamics. To the best of our knowledge this is the first paper to show
this result.

Carrière-Swallow and Cespedes (2013) estimate vector auto-regressions and show
that there is substantial heterogeneity in the reaction to uncertainty shocks across
countries. They find that in comparison to the U.S. and other developed countries,
emerging economies suffer more severe falls in investment and private consumption.
Their evidence suggests that differences in credit market depth across countries explain
the cross-country heterogeneity. Our theoretical framework rationalizes these facts
by showing that financial intermediation and credit market frictions are key for the
transmission of uncertainty into investment.

In cross-sectional regression analysis on long-run averages, Hoffmann, Krause and
Tillmann (2016) find that investment reacts by less than consumption to long-run
volatility of GDP growth. Our results, although focused on the short-run effects of
uncertainty shocks on real economic activity, provide further evidence that changes in
aggregate uncertainty have strong effects on investment.

Fernandez-Villaverde et al. (2011) show that changes in the volatility of interna-
tional interest rates have significant negative effects on small open economies. We
complement this paper because we show that shocks to interest rate volatility are
isomorphic to shocks to domestic TFP growth volatility. This result suggests that
domestic macroeconomic factors, such as uncertainty about productivity shocks or
default risk, can cause the time-varying volatility of interest rates.
To our knowledge, we are the first to document the cross-country patterns of uncertainty and credit variables with an international focus. Several recent papers have looked at U.S. data. For example, Gilchrist, Sim and Zakrajsek (2014) document that in the U.S. fluctuations in idiosyncratic uncertainty across-firms (measured from high-frequency stock market data) affect credit spreads. Baum, Caglayan and Ozkan (2009) and Bordo, Duca and Koch (2016), using U.S. bank data, show that aggregate uncertainty is a driver of credit supply. Caldara et al. (2016) show that identified uncertainty shocks have a significant negative effect on real economic activity, and that the effect is larger when these shocks are being accompanied by tightening of financial conditions.

The literature that analyzes credit frictions and volatility fluctuations has focused on closed economies and shocks to the cross-sectional dispersion of firms’ productivity. This literature includes, among others, Arellano, Bai and Kehoe (2016), Christiano, Motto and Rostagno (2014), Chugh (2016), Gilchrist, Sim and Zakrajsek (2014), Pesaran and Xu (2016) and Straub and Ulbricht (2015). In this paper we show that aggregate uncertainty shocks with lenders exposed to those shocks generate similar transmission channels.\(^5\) Given the substantial evidence on aggregate uncertainty discussed above there is value in expanding the credit channel to aggregate shocks, which requires to depart from the BGG framework as we show in this paper.

1.3 Facts

In this section we document that, in OECD countries, larger macroeconomic uncertainty leads to a positive trade balance, lower investment, output and credit

\(^5\)Basu and Bundick (2017) and Born and Pfeifer (2014) show that nominal rigidities can help RBC models produce data-consistent comovement between uncertainty and macro aggregates through countercyclical mark-ups.
growth, and larger credit spreads.\textsuperscript{6} We measure uncertainty as the realized volatility of stock market returns, which is the standard measure in the literature (see for example, Bloom 2009, Baker and Bloom 2013, Cesa-Bianchi, Pasaran and Rebuch\textsuperscript{c} 2016 or Gilchrist, Sim and Zakrajsek 2014, among others). This measure has significant variation at the quarterly frequency and can be compared across OECD countries because these economies have developed stock markets with high frequency data.\textsuperscript{7,8}

We focus on the relative volatility of stock market returns, $\Omega_{i,t}^R$. That is, $\Omega_{i,t}^R$ is the domestic volatility $\Omega_{i,t}$ minus the average volatility $\bar{\Omega}_{-i,t}$ in all other countries in our sample, excluding country $i$.\textsuperscript{9}

Formally, volatility $\Omega_{i,t}$ in quarter $t$ for country $i$, is the quarterly standard deviation of daily stock market returns,

$$
\Omega_{i,t} = 100 \sqrt{\frac{1}{d_t} \sum_{d=1}^{d_t} \left( u_{i,t}^d - \bar{u}_{i,t} \right)^2 },
$$

where $u_{i,t}^d$ is the daily stock market return, $d_t$ denotes the number of trading days in the quarter, and $\bar{u}_{i,t}$ is the average daily return in quarter $t$,

$$
\bar{u}_{i,t} = \frac{1}{d_t} \sum_{d=1}^{d_t} u_{i,t}^d.
$$

\textsuperscript{6}Following the IRBC literature, we focus on the trade balance as a measure of a country’s external position. However, all the results of the paper hold for the current account. In our panel of OECD countries, the average correlation between the two series is 0.84.

\textsuperscript{7}Ex-ante uncertainty measures like the VIX index are not available for most countries in our sample. Figure A1 in the online appendix shows that for the U.S. the volatility of stock market returns is highly correlated with the VIX index and with the measure of uncertainty constructed by Ludvigson, Ma and Ng (2017). The correlation coefficients are 0.93 and 0.75 respectively.

\textsuperscript{8}Figure A2 in the online appendix shows that the volatility of stock market returns is strongly correlated with TFP growth volatility. Thus, one can interpret the volatility shocks as capturing changes in uncertainty about economic policy (fiscal, trade, or financial policies), or broadly about future economic conditions.

\textsuperscript{9}Cesa-Bianchi, Pasaran and Rebuch\textsuperscript{c} (2016) find that there is a global common factor driving some of the variation in domestic country volatilities. The relative volatility takes out that global common factor to obtain a country-specific domestic volatility. Table A3 in the online appendix confirms that our facts are robust to using the absolute volatility measure $\Omega_{i,t}$. 

7
The relative volatility $\Omega^R_{i,t}$ in time $t$ for country $i$ is

$$\Omega^R_{i,t} = \Omega_{i,t} - \overline{\Omega}_{-i,t}.$$  \hfill(1.3)

where

$$\overline{\Omega}_{-i,t} \equiv \frac{1}{n-1} \sum_{j \neq i} \Omega_{j,t},$$  \hfill(1.4)

and $n$ is the number of countries.

Table 1.1 and Figure 1.1 show plain-vanilla country-specific pairwise correlations between relative volatility and the trade balance-to-GDP ratio, real quarterly growth rates of output, investment and bank credit, and credit spread.\textsuperscript{10} Aggregate uncertainty positively correlates with the trade balance-to-output ratio and with credit spreads. There is a negative correlation of uncertainty with growth rates of output, investment and bank credit. Figure 1.2 confirms these associations with scatter plots on the entire sample. Each dot groups quarterly observations of volatility and each variable of interest between 1970q1 and 2014q4. For ease of appearance the scatterplots are binned following Jorda, Schularick and Taylor (2016).

Table 1.2 contains a regressions analysis that we interpret as correlations since we lack an identification mechanism to think on causality.\textsuperscript{11} Country and time fixed effects control for country-specific time-invariant characteristics and events common across countries that could drive the correlations. Panel B adds controls for macro variables that proxy for the stance of government policies. We include government consumption growth, CPI inflation, changes in exchange rates, trade openness (measured as imports plus exports to GDP), the Chinn-Ito index of financial openness, and the level of stock market returns. The rationale for including these controls is that government policies could drive macroeconomic volatility and the outcome variables.

\textsuperscript{10}Credit spreads are defined as the difference between the domestic corporate lending rate and long-term U.S. government bond yields.

\textsuperscript{11}All variables are quarterly, non-filtered and stationary. The appendix describes the dataset. It is an unbalanced panel that uses the maximum available data.
The results are robust across panels of Table 1.2. An increase in relative aggregate volatility is associated with an increase in the trade balance-to-output ratio and credit spreads, with a decrease in output, in investment and in credit growth. As the online appendix shows, we obtain similar results if we use the country’s absolute volatility, or alternative measures of a country’s external balance, credit supply and interest spreads like, for example, the current account, total credit to the private non-financial sector, and government bond spreads.

The online appendix redoes Table A2 using multi-year rolling windows standard deviation of quarterly GDP growth as the measure of uncertainty. This is the measure of uncertainty used by Fogli and Perri (2015), although it is not common in the literature. The results are broadly consistent with those discussed above. However, this measure has several drawbacks that lead us to prefer stock market volatility. For example, rolling windows volatility has a strong time-varying trend component and does not fluctuate much at quarterly frequency. In addition, Figures A1 and A3 show that rolling windows volatility measure spikes at different dates than the popular indices of uncertainty of Bloom (2014) and Ludvigson, Ma and Ng (2017).

The online appendix contains additional robustness tests. For example, Table A2 shows that the stylized fact on the association between volatility and credit spreads is robust to controlling for exchange rate risk. First, we control for expected exchange rate dynamics and volatility using 1-year forward exchange rates and daily exchange rate changes like Gadanecz, Miyajima and Shu (2014). Second, we use a sample without exchange rate risk by focusing on EU countries starting from 1999q1, the period when the Euro was introduced. We obtain similar results as in the benchmark regressions.

To sum up, the data suggest that countries with larger macroeconomic volatility run trade surpluses, have less investment and output, with credit being more expensive
and less available. As we will show next, an IRBC model without a credit sector can generate the positive correlation between volatility and the trade balance, but it fails with the other correlations. Adding credit supply with lenders exposed to aggregate volatility can reconcile the model with the data. Moreover, this new theory is consistent with the evidence on credit spreads and volume discussed above.

1.4 Model

We study a two-country model with domestic credit markets subject to costly state verification frictions. The key ingredient is that lenders are exposed to aggregate credit risk. Each country is inhabited by households, entrepreneurs, banks, and firms producing goods and capital. The two countries trade consumption goods and risk-free bonds.

1.4.1 Households and Banks

In each country \((i = 1, 2)\) there is a continuum of homogeneous households who maximize expected utility over consumption \((C_{i,t})\) and hours worked \((H_{i,t})\). Households can invest in risky domestic deposits \((D_{i,t})\), and in riskless international bonds \((B_{i,t})\). The representative household of country \(i\) maximizes

\[
E_0 \sum_{t=0}^{\infty} \beta^t U(C_{i,t}, H_{i,t}),
\]

subject to a sequence of budget constraints,

\[
C_{i,t} + B_{i,t} + D_{i,t} = W_{i,t} H_{i,t} + R^f_{i,t-1} B_{i,t-1} + R^P_{i,t} D_{i,t-1} - \frac{\phi B}{2} Z_{i,t} \left( \frac{B_{i,t}}{Z_{i,t} - \bar{B}} \right)^2 + \Pi_{i,t} + \Pi^c_{i,t} - Z_{i,t} T^E,
\]

where \(W_{i,t}\) is the wage in country \(i\), \(\Pi_{i,t}\) and \(\Pi^c_{i,t}\) are the profits of the producers of goods and capital respectively and \(R^f_{i,t-1}\) is the gross return on last period holdings of
the international bond. $Z_{i,t}T^E$ are lump-sum transfers to domestic entrepreneurs to ensure that entrepreneurs’ equity is never zero.\textsuperscript{12} Like in Rabanal, Rubio-Ramirez and Tuesta (2011), we impose small adjustment costs ($\phi_B$) on international bond holdings that depend on the trending variable $Z_{i,t}$ to ensure a balanced growth path. Also for the same reason, the transfers are scaled up by $Z_{i,t}$.

In each country there is a continuum of perfectly competitive banks who collect deposits from the domestic households and lend these funds to the entrepreneurs. Banks are 100\% deposit financed and make zero profits. Thus, the return on loans equals the return on deposits. The gross return on bank deposits of country $i$ ($R_{i,t}^D$) is risky because banks may suffer credit losses and be unable to repay their borrowings. Therefore, households of country $i$ are exposed to the credit risk of their financial system.

The previous assumption is consistent with the recent experiences of Iceland, Ireland, Portugal and Spain during the 2008 financial crisis. These countries had deposit insurance systems in place, but when their banks suffered major credit losses, the countries were unable to honor all the borrowings of their domestic financial systems (Santos 2014, Zeissler et al. 2015). Households in those countries either suffered losses on their deposits (Iceland), experienced higher taxes, or their government debt increased to fund the bailout of their domestic banks.\textsuperscript{13} Thus, the recent Euro crisis supports the theory that households are exposed to the credit risk of their domestic banks. This is a crucial assumption for our results, as we will discuss later.

\textsuperscript{12}All results hold if we use alternative mechanisms, like giving labor income to the entrepreneurs.

\textsuperscript{13}Moreover, the financial repression which followed the crisis has translated into limits on banking competition and low returns on deposits. Reinhart (2012) refers to this as a partial default on depositors.
Denoting by $U_H$ and $U_C$ the marginal utility of leisure and consumption, the households’ optimality conditions are:

$$\frac{-U_H(C_{i,t}, H_{i,t})}{U_C(C_{i,t}, H_{i,t})} = W_{i,t}, \quad (1.7)$$

$$R_t^f E_t[M_{i,t+1}] = 1 + \phi_B \left( \frac{B_{i,t}}{Z_{i,t}} - \hat{B} \right), \quad (1.8)$$

and

$$E_t[M_{i,t+1}R_{i,t+1}^D] = 1, \quad (1.9)$$

where

$$M_{i,t+1} \equiv \beta \frac{U_C(C_{i,t+1}, H_{i,t+1})}{U_C(C_{i,t}, H_{i,t})} \quad (1.10)$$

is the household’s stochastic discount factor.

### 1.4.2 Entrepreneurs and Financial Contract

In each country there is a continuum of mass one of risk-neutral entrepreneurs. In period $t$, the equity of entrepreneur $j$ in country $i$ is $N_{i,j,t}$. Each entrepreneur borrows $L_{i,j,t}$ from the domestic banks and buys domestic capital at price $Q_{i,t}$,

$$Q_{i,t}K_{i,j,t} = N_{i,j,t} + L_{i,j,t}. \quad (1.11)$$

After purchasing the capital, each entrepreneur experiences an idiosyncratic shock $\omega_j$ such that $K_{i,j,t}$ units of capital generate $\omega_j K_{i,j,t}$ units of effective capital. Next period, the entrepreneur rents her effective capital to domestic firms at the rental rate, $r_{i,t+1}$, and then sells the undepreciated capital, $\omega_j (1 - \delta) K_{i,j,t}$, at price $Q_{i,t+1}$. Thus, an entrepreneur with idiosyncratic productivity $\omega_j$ has a rate of return $\omega_j R_{i,t+1}^K$, where $R_{i,t+1}^K$ is the rate of return on capital in country $i$,

$$R_{i,t+1}^K = \frac{r_{i,t+1} + Q_{i,t+1}(1 - \delta)}{Q_{i,t}}. \quad (1.12)$$
The idiosyncratic productivity shocks $\omega_j$ are not observable when borrowing happens and ex-post create profitable and unprofitable entrepreneurs. These shocks are i.i.d. across both entrepreneurs and time. In both countries, the shocks are drawn from a log-normal distribution with a cumulative density function $F(\omega)$ with mean one and standard deviation $\sigma_\omega$.

At time $t$, the financial contract between a bank and an entrepreneur $j$ specifies a loan amount, $L_{i,j,t}$, and a default threshold for next period $\omega_{i,j,t+1}$ such that if the entrepreneur has idiosyncratic productivity below $\omega_{i,j,t+1}$, then the entrepreneur defaults and her assets are seized by the bank. Default costs are a share $\mu$ of the entrepreneur’s assets and paid by the bank. The state-contingent interest rate $R^L_{i,j,t+1}$ is implicitly defined as

$$R^L_{i,j,t+1} = \omega_{i,j,t+1} R^K_{i,t+1} Q_{i,t} K_{i,j,t}.$$  \hspace{1cm} (1.13)

The lender’s return on deposits is the revenue from those entrepreneurs who repay plus the value of the assets seized from the entrepreneurs who default,

$$R^D_{i,t} L_{i,j,t-1} = \int_{\omega_{i,j,t}}^{\infty} R^L_{i,j,t} L_{i,j,t-1} dF(\omega) + \int_{0}^{\omega_{i,j,t}} (1 - \mu) \omega R^K_{i,t} Q_{i,t-1} K_{i,j,t-1} dF(\omega).$$ \hspace{1cm} (1.14)

To avoid self-financing, entrepreneurs die at the end of each period with an exogenous probability $(1 - \chi)$ and consume their equity, which evolves as

$$N_{i,j,t+1} = \int_{\omega_{i,j,t+1}}^{\infty} [\omega R^K_{i,t+1} Q_{i,t} K_{i,j,t} - R^L_{i,j,t+1} L_{i,j,t}] dF(\omega).$$ \hspace{1cm} (1.15)

Carlstrom, Fuerst and Paustian (2016) show that with forward looking entrepreneurs the optimal contract maximizes expected discounted terminal equity

$$V_{i,j,t} = (1 - \chi) \mathbb{E}_t \sum_{s=0}^{\infty} (\beta \chi)^s N_{i,j,t+s},$$ \hspace{1cm} (1.16)

subject to the lenders’ participation constraint, which is the household’s Euler equation (1.9) with the return on deposits defined in (1.14).\textsuperscript{14}

\textsuperscript{14}All the results of the paper hold when entrepreneurs are one period myopic like in BGG.
Because of constant returns to scale and risk neutrality, the financial contract is linear in entrepreneur’s equity.\textsuperscript{15} This implies that all entrepreneurs have the same default threshold ($\omega_{i,j,t+1} = \omega_{i,t+1}$), lending rate ($R_{i,j,t+1}^L = R_{i,t+1}^L$) and leverage ratio

$$\kappa_{i,j,t} \equiv \frac{Q_{i,t} K_{i,j,t}}{N_{i,j,t}} = \kappa_{i,t}. \hspace{1cm} (1.17)$$

Thus, we can drop the entrepreneur’s $j$ notation as only the country’s aggregate variables matter, not the distribution inside the country.

It is convenient to follow BGG and define the function $\Gamma(\omega_{i,t+1})$ to denote the next period’s expected gross share of outcome going to the bank,

$$\Gamma(\omega_{i,t+1}) \equiv \int_0^{\omega_{i,t+1}} \omega dF(\omega) + \omega_{i,t+1} \int_{\omega_{i,t+1}}^{\infty} dF(\omega), \hspace{1cm} (1.18)$$

and the function $G(\omega_{i,t+1})$ to denote expected monitoring costs,

$$G(\omega_{i,t+1}) \equiv \int_0^{\omega_{i,t+1}} \omega dF(\omega). \hspace{1cm} (1.19)$$

Combining the previous definitions with household’s Euler equation (1.9) and with (1.14) we obtain lenders’ participation constraint,

$$\mathbb{E}_t \left[ M_{i,t+1} \kappa_{i,t} R_{i,t+1}^K \left[ \Gamma(\omega_{i,t+1}) - \mu G(\omega_{i,t+1}) \right] \right] = \kappa_{i,t} - 1, \hspace{1cm} (1.20)$$

which is the credit supply equation. Equation (1.20) includes households’ stochastic discount factor ($M_{i,t+1}$) as banks’ ability to raise funds depends on households’ willingness to provide them at the risky deposit rate. Thus, (1.20) captures lenders’ exposure to aggregate risk.

\subsection*{1.4.3 Capital Producers}

Capital is non-tradable across countries. In each country there is a representative capital producer owned by the domestic households. It buys goods ($I_{i,t}$) from the

\textsuperscript{15}The online appendix has the detailed derivation of all the results in this section.
firms, and the undepreciated capital \((1 - \delta)K_{i,t-1}\) from the entrepreneurs, to produce new net capital investment \(I_{i,t}^n\) according to

\[
I_{i,t}^n = \left[ 1 - \frac{\phi_I}{2} \left( \frac{I_{i,t}}{I_{i,t-1}} - g \right)^2 \right] I_{i,t},
\]

(1.21)

where \(I_{i,t}\) is gross investment. The parameter \(\phi_I\) controls the capital adjustment cost that ensures that the price of capital varies endogenously, affecting entrepreneurs’ equity. The parameter \(g\) is the growth rate along the balanced-growth path.

The law of motion of the capital stock is

\[
K_{i,t} = (1 - \delta)K_{i,t-1} + I_{i,t}^n.
\]

(1.22)

The capital producer sells the capital to the entrepreneurs at price \(Q_{i,t}\) making profits:

\[
\Pi_{i,t}^c = Q_{i,t}I_{i,t}^n - I_{i,t}.
\]

(1.23)

The capital producer chooses investment to maximize the present discounted value of its profits

\[
\max_{I_{i,t}} \mathbb{E}_0 \sum_{t=0}^{\infty} \beta^t U(C_{i,t}, H_{i,t}) \Pi_{i,t}^c,
\]

subject to (1.21).

1.4.4 Consumption Goods Producers

Firms producing consumption goods \((Y_{i,t})\) use labor \((H_{i,t})\) and capital \((K_{i,t-1})\) according to the production function

\[
Y_{i,t} = K_{i,t-1}^\alpha (Z_{i,t}H_{i,t})^{1-\alpha},
\]

(1.25)

where \(Z_{i,t}\) is a non-stationary TFP shock cointegrated across-countries that we define below.
Consumption goods producers hire labor and rent capital to maximize profits\textsuperscript{16}:

$$\Pi_{i,t} = Y_{i,t} - W_{i,t}H_{i,t} - r_{i,t}K_{i,t-1}. \quad (1.26)$$

1.4.5 Market Clearing

International bonds are in zero net supply across countries,

$$B_{1,t} + B_{2,t} = 0. \quad (1.27)$$

In each country, households’ supply of deposits equals entrepreneurs’ borrowings,

$$D_{i,t} = L_{i,t}. \quad (1.28)$$

From the balance sheet of the entrepreneurs (1.11), the value of the capital stock of country $i$ equals the sum of debt and equity of the entrepreneurs:

$$Q_{i,t}K_{i,t} = L_{i,t} + N_{i,t}. \quad (1.29)$$

The current account is the change in the net foreign asset position,

$$\text{Current Account}_{i,t} = B_{i,t} - B_{i,t-1}. \quad (1.30)$$

The trade balance is the current account adjusted by the net interest payments:

$$\text{Trade Balance}_{i,t} = B_{i,t} - R_{f,t-1}B_{i,t-1}. \quad (1.31)$$

1.4.6 Technology

As it is standard in the two-country RBC literature with non-stationary shocks, we assume that the TFP processes of each country have a common unit root and are cointegrated across countries (see for example Rabanal, Rubio-Ramirez and Tuesta\textsuperscript{16} because of the constant returns to scale production function, these profits are zero in equilibrium.

\textsuperscript{16}Because of the constant returns to scale production function, these profits are zero in equilibrium.
That is, we assume the following representation for the law of motion of the first differences of log TFP in each country:

\[
\Delta \log (Z_{1,t}) = (1 - \rho_z) \log (g) + \rho_z \Delta \log (Z_{1,t-1}) + \\
\varphi [\log (Z_{1,t-1}) - \log (Z_{2,t-1})] + \epsilon_{\sigma,1,t}^{z_{1,t}} + \epsilon_{\sigma,2,t}^{z_{2,t}},
\]

\[
\Delta \log (Z_{2,t}) = (1 - \rho_z) \log (g) + \rho_z \Delta \log (Z_{2,t-1}) + \\
- \varphi [\log (Z_{1,t-1}) - \log (Z_{2,t-1})] + \epsilon_{\sigma,1,t}^{z_{1,t}} + \epsilon_{\sigma,2,t}^{z_{2,t}}.
\]

where $\Delta$ is the first-difference operator. $\epsilon_{z,1,t}$ and $\epsilon_{z,2,t}$ are Gaussian innovations with mean zero, unit variance, and correlation $\vartheta_z$. The parameter $g$ is the long-run growth rate of productivity, which is the same for both countries. The parameter $\varphi$ governs the rate of convergence between the two countries. It takes a small negative value such that when the cross-country differential $Z_{1,t-1} - Z_{2,t-1}$ is larger than its long-run value, then $\varphi < 0$ guarantees that $\Delta \log (Z_{1,t})$ will fall and $\Delta \log (Z_{2,t})$ will rise, driving the differential back to its long-run value. That is, no country grows so much in relative terms that at some point it becomes the whole world. Then, $\Delta \log (Z_{i,t})$ and $\frac{Z_{1,t}}{Z_{2,t}}$ are stationary and the detrended model has a well-defined deterministic steady state.

The country-specific volatility shock $\sigma_{i,t}$ follows a stationary AR(1) process,

\[
\sigma_{i,t} = (1 - \rho_\sigma)\sigma + \rho_\sigma \sigma_{i,t-1} + \sigma_\sigma \varepsilon_{\sigma,i,t},
\]

where $\varepsilon_{\sigma,i,t}$ are Gaussian innovations with mean zero and unit variance. $\sigma$ is the long-run mean. Like for TFP shocks, we allow a non-zero cross-country correlation ($\vartheta_\sigma$) between the volatility shocks.\(^{17}\) The parameter $\sigma_\sigma$, which is the same across countries, controls the size of the volatility shocks. TFP and volatility shocks are uncorrelated within each country.

\(^{17}\)Bekaert, Hodrick, and Zhang (2012) document that volatility is highly correlated across countries.
1.5 Volatility and Credit Supply

In this section, to build intuition for the key mechanism of the model, we show how credit supply reacts to changes in uncertainty in a partial equilibrium setting.$^{18}$ The next section solves the full general equilibrium model and contains the quantitative results.

Figure 1.3 plots the credit supply equation (1.20) for two levels of aggregate uncertainty. That is, Figure 1.3 plots the rates that lenders require to lend at a given leverage level. To construct Figure 1.3, first we use (1.13) to rewrite (1.20) as

$$\mathbb{E}_t \left[ M_{t+1} \kappa_t R_{t+1}^K \left[ \Gamma \left( \frac{R_{t+1}^L}{R_{t+1}^K} \left( \frac{\kappa_t - 1}{\kappa_t} \right) \right) - \mu G \left( \frac{R_{t+1}^L}{R_{t+1}^K} \left( \frac{\kappa_t - 1}{\kappa_t} \right) \right) \right] \right] = \kappa_t - 1. \quad (1.35)$$

Using a third-order approximation to (1.35) we solve for the leverage ratio $\kappa_t$ in the stochastic steady-state for different lending rates $R_{t+1}^L$.\(^{19}\) We set the stochastic discount factor $M_{t+1}$ at its steady state value and assume, in partial equilibrium, that the return on capital $R_{t}^K$ follows an AR(1) process with time-varying volatility:

$$R_{t}^K = (1 - \rho_z) R_{t}^K + \rho_z R_{t-1}^K + \sigma_t \varepsilon_t, \quad (1.36)$$

where $\sigma_t$ follows (1.34). The steady state value of volatility, $\sigma$, governs the long-run level of aggregate risk. We compare two values of $\sigma$.

Figure 1.3 shows that higher aggregate volatility (higher $\sigma$) contracts credit supply. This effect is due to the structure of debt contracts. Higher volatility of a borrower’s income increases the area of default and, since in debt contracts lenders’ payoffs are concave in the value of borrower’s income, it decreases lenders’ expected revenue. Thus, for the same leverage ratio, when aggregate volatility is higher, lenders charge more expensive credit to compensate them for bearing higher default risk.

\(^{18}\)Throughout this section, we drop country subscripts since it is a partial equilibrium analysis.

\(^{19}\)We set the steady state and parameter values as in the full general equilibrium model discussed in the next section. The results are robust to changes in parameters.
The effect of uncertainty on credit supply is non-linear in entrepreneurs’ leverage ratio. Lending rates react more to increases in aggregate volatility when the entrepreneurs have higher leverage. The reason is that for a given negative shock, default is more likely when leverage is higher.

In the next section we will show that the previous results are stronger in general equilibrium because households are risk-averse and their deposits are exposed to credit risk. That is, when higher aggregate volatility makes bank deposits riskier, households require larger risk premiums to supply bank deposits. The higher cost of raising deposits is a general equilibrium factor pushing lenders to raise their lending rates.

1.6 The Model with and without Credit Channel

In this section, we compare the model with the credit channel presented in Section 3.3 and another without it. First, we discuss how we parametrize the model, then the impulse responses and simulation results. We solve the stationary version of the model (that is, all trending variables deflated by their trends along the balanced growth path) using a third-order approximation.\textsuperscript{20}

1.6.1 Parametrization

We set some parameters exogenously following standard values in the literature. Then we estimate the rest of the parameters with a simulated method of moments (SMM).\textsuperscript{21} Table 1.3 contains the exogenous parameters.

\textsuperscript{20}Fernandez-Villaverde et al. (2011) show that this is the minimum order of approximation for volatility shocks to appear independently in the policy functions, and that model dynamics are unaffected by adding higher order terms to the approximations.

\textsuperscript{21}Ruge-Murcia (2012) shows that SMM delivers very accurate estimates when applied to non-linear DSGE models.
We use GHH preferences to avoid wealth effects on labor supply,

\[ U(C_{i,t}, H_{i,t}) = \frac{1}{1 - \gamma} \left( C_{i,t} - \eta Z_{i,t} \left( \frac{H_{i,t}}{1 + \frac{1}{\xi}} \right)^{1 + \frac{1}{\xi}} \right)^{1 - \gamma}, \]

where \( \xi \) is the elasticity of labor supply and \( \gamma \) controls the curvature of the utility function. We include \( Z_{i,t} \) in the labor disutility term to ensure that labor supply remains bounded along the balanced growth path (Aguiar and Gopinath 2007).

We choose the value of \( \eta \) so that the long-run mean of hours worked equals \( \frac{1}{3} \). We set a period in the model to be one quarter and pick standard values in the literature for the subjective discount factor \( \beta \), elasticity of labor supply \( \xi \), depreciation rate \( \delta \) and capital share in production \( \alpha \). For the long-run TFP growth parameter we use the 2% annual rate \( (g = 1.005) \), which corresponds to the average long-run output growth rate in our sample. The bond adjustment cost parameter \( \phi_B \) must be a positive number for the model to have a unique steady-state growth path (Boileau 2008). Following Fernandez-Villaverde et al. (2011) we set it to a very small positive number so that it does not affect the model dynamics.\(^{22}\) Similarly, following Kollmann (2016, 2017), we assign a small negative value to the technology convergence parameter \( \varphi \) to ensure a well-defined balanced-growth path.\(^{23}\) For the survival rate of entrepreneurs \( (\chi) \) we set a value (0.97) in the range of the values used in the financial frictions literature. For example, BGG set this parameter at 0.973, Christiano, Motto and Rostagno (2014) at 0.982, and Carlstrom, Fuerst and Paustian (2016) use 0.94.

We estimate the following parameters: 1) \( \gamma \), the inverse of the elasticity of intertemporal substitution (IES); 2) \( \phi_I \), the investment adjustment cost parameter; 3) \( \mu \),

\(^{22}\)Figure A6 of the online appendix shows that model dynamics are not affected when we halve the value of this parameter.

\(^{23}\)This parameter affects the relative persistence of the TFP shocks: the higher the absolute value of the convergence parameter, the lower is the relative persistence of the domestic TFP shock. Figure A5 in the online appendix illustrates this point. We experimented with different values of \( \varphi \) and found that as long as the model is re-estimated to match our empirical targets (which include the persistence of output growth) the results are unaffected.
the monitoring cost; 4) $\sigma_\omega$, the cross-sectional standard deviation of entrepreneur’s idiosyncratic productivity; 5) $\rho_z$, the persistence of the first-difference of (log) TFP; 6) $\rho_\sigma$, the persistence of the volatility shock; 7) $\sigma$, the steady-state value of the volatility shock; 8) $\sigma_\sigma$, the standard deviation of the volatility shock; 9) $\vartheta_z$, the cross-country correlation of productivity shocks; and 10) $\vartheta_\sigma$, the cross-country correlation of volatility shocks.

We target the following 10 moments from the data analyzed in Section 1.3: 1-5) standard deviations of output growth, investment growth, consumption growth, trade balance-to-output ratio, and relative stock market returns volatility; 6-7) persistence of output growth and relative stock market returns volatility; 8) the cross-country correlation of output growth rates; 9) the cross-country correlation of stock market returns volatility; 24 and 10) long-run mean of entrepreneurs’ leverage ratio, which comes from Gourio (2013). 25

To estimate the endogenous parameters we minimize the squared percent deviation between the moments of the model simulations and the actual data. 26 To obtain a model counterpart of the volatility measure, we follow Basu and Bundick (2017) and define the model-implied stock returns volatility, $\Omega_{model}^{i,t}$, as the conditional standard

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24 We measure persistence with the AR(1) coefficient. Standard deviations, persistence coefficients, and international correlations are averages across the countries in our sample.

25 With high-order perturbations, deterministic steady states of stationary endogenous variables are in general different from their long-run means defined as stochastic steady-states (Juillard and Kamenik 2005).

26 The algorithm is as follows: let $m_j(X)$ be an empirical moment $j$ computed from the data $X$. Denote by $m_j(X^{sim}(\theta))$ the model-implied moment from simulating the model using the parameter vector $\theta$. Starting from the stochastic steady state we simulate the stationary model for 180 periods (length of our dataset) with all the shocks. We simulate the model 20 times saving the results of country 1 to generate a world economy of 20 countries. Then, we compute the moments of interest in exactly the same way as in the actual data. We repeat this procedure 50 times such that the model-implied moment $m_j(X^{sim}(\theta))$ is the average over 50 repetitions of the 20-country world economy. The estimated parameter vector $\hat{\theta}$ minimizes the squared percent deviation: $\hat{\theta} = \arg\min_{\theta} \sum_j \left[ \frac{m_j(X^{sim}(\theta)) - m_j(X)}{m_j(X)} \right]^2$. 21
deviation of the returns on entrepreneurs’ equity,

\[
\Omega_{i,t}^{\text{model}} = 100 \sqrt{E_t\left[\left(R_{i,t+1}^K\right)^2\right] - \left[E_t\left(R_{i,t+1}^K\right)\right]^2}.
\] (1.37)

As in Section 1.3, we define the relative volatility measure as domestic volatility minus foreign volatility. In the symmetric two-country world model this implies,

\[
\Omega_{1,t}^{R,\text{model}} = \Omega_{1,t}^{\text{model}} - \Omega_{2,t}^{\text{model}}.
\] (1.38)

Table 1.4 reports the results of the estimation. Table 1.5 shows the model-implied moments and empirical targets. The model is successful at matching the targets and accurately estimates the parameters. The estimated parameters are within the range of the values used in the RBC and financial frictions literature. For example, the estimated curvature parameter \(\gamma\) implies an IES of about 0.30 that is within the range used in the literature.\(^{27}\) The estimated values for \(\sigma_\omega\) and \(\mu\) are close to the values used in BGG and to those estimated by Christiano, Motto and Rostagno (2014). The persistence \(\rho_z\) and steady-state standard deviation \(e^\sigma\) of the productivity growth are in the range used in the RBC literature (see for example, Aguiar and Gopinath 2007, Ireland 2013, or Cicco, Pancrazi and Uribe 2010). Concerning the volatility shocks, the estimated persistence \(\rho_\sigma\) and standard deviation \(\sigma_\sigma\) are similar to the values used by Fernandez-Villaverde et al. (2011), Born and Pfeifer (2014), and Kollmann (2016).

1.6.2 Impulse Responses

Figures 1.4 and 1.5 compare impulse responses to an unanticipated one standard deviation aggregate volatility shock in country 1.\(^{28}\) The solid line is the

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\(^{27}\)Ogaki and Reinhart (1998) estimate the IES to be around 0.30. Fernandez-Villaverde et al. (2011) use GHH preferences with the IES of 0.20. Basu and Kimball (2002) find an IES of about 0.50.

\(^{28}\)The impulse responses display the trending variables as percent deviations from their balanced-growth path. Stationary variables are in percentage point differences from their balanced-growth path.
model with the credit channel presented in Section 3.3, and the dashed line is the same model but with no financial frictions and no entrepreneurs. That is, the dashed line is basically the IRBC model of Fogli and Perri (2015) but with the volatility shocks in the log first-differences of productivity to avoid Fogli and Perri’s transitory TFP shocks with nearly unit roots. Figure 1.4 focuses on the responses that are similar across the models while Figure 1.5 highlights the differences.

Figure 1.4 shows that both the model with and the model without the credit channel predict that consumption and the risk-free rate decrease in the country that becomes more volatile (country 1). These results are due to a precautionary savings motive and to a flight-to-quality mechanism. Higher volatility induces prudent households to consume less and save more. Higher demand for the international bonds implies a fall in the risk-free rate.

In both models higher volatility induces a surplus in the trade balance of the volatile country. However, the reaction of the trade balance is larger and more persistent in the model with the credit channel. This is because in both models the surge in domestic savings push towards a surplus. Moreover, with a credit channel, higher volatility induces lower investment, as Panel b in Figure 1.5 shows. Thus, in the model with a credit channel, both the investment collapse and a surge of savings push the trade balance towards surplus. Without the credit channel, investment increases, pushing the trade balance towards a deficit.

Figure 1.5 shows that for output and investment, the reaction to a volatility shock has opposite signs in the model with a credit channel relative to the model without it. When the labor input can be adjusted freely and investment is reversible, output and stochastic steady state values. To compute the stochastic steady-state we simulate the detrended model for many periods with zero innovations of exogenous shocks until the economy converges to a point where all the stationary variables are constant. Following Fernandez-Villaverde et al. (2011), we use this stochastic steady state as the initial point for computing the impulse response functions.
investment are convex functions of productivity and thus, by Jensen’s inequality, their expected values increase in the volatility of TFP. Thus, the standard IRBC without a credit channel predicts that higher uncertainty leads to higher investment and output, which contradicts the empirical evidence of Section 1.3.

Adding the credit channel fixes the comovement problem because it makes investment depend on credit (entrepreneurs need to borrow to finance their capital purchases). Panels c and d of Figure 1.5 plot the reaction of the domestic credit market. Higher uncertainty increases default risk and triggers the contraction of credit supply discussed in Section 1.5. Moreover, households are now more exposed to the risk of losing their deposits. Thus, they reduce their credit supply, asking for a higher risk premium, which leads to higher funding costs for banks. This general equilibrium effect reinforces the contraction in credit supply. Credit to entrepreneurs falls, investment, output and the price of capital collapse, triggering a financial accelerator à la BGG in which lower entrepreneurs’ equity makes their cost of external funds even higher. Employment drops as lower capital stock in the next period implies lower returns to the labor supply. Thus, the model with the credit channel is consistent with the comovements reported in Section 1.3.

1.6.3 Quantitative Assessment of the Credit Channel

To gauge the quantitative importance of the credit mechanism, we investigate how well the estimated model with the credit channel matches the empirical associations between the trade balance, investment, output growth and volatility documented in Section 1.3. Since the estimation in Section 1.6.1 does not use this information, the successful performance of the model will strongly support the plausibility of our mechanism.
We simulate the IRBC model with and without the credit channel, and using the simulated data, we redo Table 1.2 Panel A following the simulation procedure described in Section 1.6.1. Table 1.6 contains the results. The first row displays the regression coefficients reported in Table 1.2 Panel A for the actual data for OECD countries. The second row has the regression coefficients from the artificial data generated by simulating the model with the credit channel. The last row reports the results for the model without the credit channel.

Table 1.6 shows that both versions of the model predict a positive correlation between aggregate volatility and the trade balance-to-output ratio, as in the data. Importantly, the model with the credit mechanism is much closer to the data because in that model the trade balance is driven by both an increase in savings and a collapse of investment when volatility rises.

The second and third columns of Table 1.6 highlight the problem of the model without a credit channel. It predicts a positive correlation between aggregate volatility and investment and output. However, in the data these correlations are negative. Incorporating the credit channel allows us to generate the correlations found in the data. These results provide strong evidence supporting the credit channel.

Figure A4 in the online appendix shows that incorporating the credit channel does not prevent the model from being consistent with other stylized facts. For example, Hoffmann, Krause and Tillmann (2016) provide evidence that the trade balance-to-GDP ratio is less countercyclical when the volatility of output growth is high. We show that the same fact holds in the model with the credit channel. The mechanism is as follows: a positive TFP shock causes the trade balance to deteriorate, but less when uncertainty is high. Consumption reacts less because of precautionary savings. Investment is less responsive because credit reacts less to good TFP news when uncertainty is high.
1.7 Global versus Domestic Banks

The analysis so far has assumed that domestic entrepreneurs are financed by domestic lenders. In this section we analyze the implications of allowing foreign financing of the domestic entrepreneurs. To keep the analysis tractable, we consider two different small open economy versions of the model of Section 3.3. First, we study only domestic lenders as in the credit supply equation (1.20). Second, we assume that domestic entrepreneurs are financed by a global bank which collects funds from international investors and builds a diversified portfolio of loans across-countries that allow the global bank to diversify the individual country shocks. Thus, with a global bank, the credit supply equation (1.20) is replaced by

\[
\mathbb{E}_t \left[ M \kappa_t R_{t+1}^{K} \left( \Gamma (\varpi_{t+1}) - \mu G (\varpi_{t+1}) \right) \right] = \kappa_t - 1, \tag{1.39}
\]

where the global bank’s stochastic discount factor \( M \) is fixed at its steady state value.\(^{29}\)

Figure 1.6 compares the reaction of both versions of the model (domestic banks versus global bank) to the same uncertainty shock analyzed in Section 1.6.2. Qualitatively both models display the same dynamics, although the global bank significantly mitigates the effects of volatility shocks. Since the global bank has a diversified portfolio, higher volatility in one country does not alter the ability of the global bank to raise funds. That is, credit supply contracts only because of the mechanism of Section 1.5 without the amplification generated by households’ aversion to the higher risk of their deposits.

Thus, global banks mitigate the contraction of credit supply and the fall in investment and output, associated with higher volatility. This result is relevant for policymakers. Banking globalization has been in retreat since the 2008 financial crisis (Forbes, Reinhart and Wieladek 2017), while, in many countries, aggregate volatility

\(^{29}\)This is equivalent to a risk-neutrality assumption.
has increased since that crisis (Baker, Bloom and Davis 2016). Our model suggests that the more domestic the financial system becomes, the larger are the effects of volatility.

1.8 Interest Rate Volatility

In a seminal paper, Fernandez-Villaverde et al. (2011) show that volatility shocks to interest rates have an important effect in small open economies. In this section we compare the model with TFP volatility and the credit channel of Section 3.3 with interest rate volatility shocks à la Fernandez-Villaverde et al. (2011). To do so, we study a small open economy version of Section 3.3 but we now assume that the risk-free rate on international bonds is subject to volatility shocks. That is, we make the households net borrowers in the international bonds market and the international rate follows an AR(1) process with time-varying volatility as in Fernandez-Villaverde et al. (2011),

\[ R_t^f = (1 - \rho_R) R_{t-1}^f + \rho_R e^{\sigma_{R,t}} \varepsilon_{R,t}, \]  
\[ \sigma_{R,t} = (1 - \rho_{\sigma_R}) \sigma_R + \rho_{\sigma_R} \sigma_{R,t-1} + \sigma_{\sigma_R} \varepsilon_{\sigma_R,t}. \]

Households borrow from international lenders in order to finance their own consumption and to give loans to domestic entrepreneurs. When interest rate volatility increases, households translate this into their lending conditions to the entrepreneurs. Thus, the analysis in this section allows to compare volatility that comes from the borrower side as entrepreneurs’ income fluctuates with TFP volatility, and volatility emanating from the lenders’ side, with the fluctuations in the international rate.

\[ We use the quarterly equivalents of the parameters estimated by Fernandez-Villaverde et al. (2011), \rho_R = 0.91, \rho_{\sigma_R} = 0.83, \sigma_R = -5.71, \sigma_{\sigma_R} = 0.8. \]
Figure 1.7 compares the impulse responses to volatility shocks to the international rate and to TFP. In both models the size of the shock is one standard deviation. Figure 1.7 shows that the two shocks are observationally equivalent. That is, higher volatility in borrowers income generates the same dynamics as higher volatility in lenders’ cost of funds. Thus, the time-varying volatility of interest rates studied by Fernandez-Villaverde et al. (2011) can be due to volatility on the borrower’s income, or to volatility in lenders’ cost of funds.

Table 1.7 presents an additional exercise inspired by Fernandez-Villaverde et al. (2011). It measures the contribution to aggregate fluctuations of each of the shocks. Fernandez-Villaverde et al. (2011) discuss that in this class of models the precautionary savings motive is so strong that following TFP level shocks consumption is less volatile than output. The second column of Table 1.7 confirms this result. In the data, for most emerging economies, consumption is more volatile than output. Table 1.7 shows that the key to making consumption more volatile than output is to depart from TFP level shocks. For example, column 5 shows that when the economy borrows from abroad to finance their entrepreneurs, fluctuations in interest rates make consumption much more volatile than output.

1.9 Conclusions

This paper contributes to the growing literature studying the international dimensions of volatility changes. We show that open-economy models built around the precautionary savings channel can explain the positive correlation between volatility and current account dynamics, but generate counterfactual comovements concerning investment and output in OECD economies.
We show that when the precautionary savings channel is complemented with a credit supply channel, the model can simultaneously be consistent with all the comovements. Higher uncertainty increases default risk and credit supply contracts, while spreads rise and investment collapses leading to a current account surplus. For this credit channel to match the data, the financial contract cannot have a predetermined lenders' return, as is common in the BGG literature. Lenders need to be exposed to aggregate credit risk.

Our results suggest that the link between credit supply and uncertainty is important in understanding recent cross-country dynamics. Future research may further study how this matters for optimal policy. For example, some authors argue that recent regulations have encouraged banking deglobalization after the 2008 financial crisis. Our paper shows that this may make economies more vulnerable to increases in uncertainty.
### Table 1.1: Correlations with relative volatility

<table>
<thead>
<tr>
<th></th>
<th>$\frac{TB}{Y}$</th>
<th>$\Delta \log Y$</th>
<th>$\Delta \log I$</th>
<th>$\Delta \log(\text{Bank credit})$</th>
<th>Credit spread</th>
</tr>
</thead>
<tbody>
<tr>
<td>AUS</td>
<td>0.08</td>
<td>0.00</td>
<td>-0.01</td>
<td>-0.02</td>
<td>0.35</td>
</tr>
<tr>
<td>AUT</td>
<td>0.45</td>
<td>-0.10</td>
<td>-0.03</td>
<td>-0.15</td>
<td>0.09</td>
</tr>
<tr>
<td>BEL</td>
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<td>-0.03</td>
<td>0.00</td>
<td>-0.03</td>
<td>0.06</td>
</tr>
<tr>
<td>CAN</td>
<td>0.28</td>
<td>-0.01</td>
<td>-0.01</td>
<td>0.08</td>
<td>0.07</td>
</tr>
<tr>
<td>CHE</td>
<td>-0.15</td>
<td>-0.07</td>
<td>-0.05</td>
<td>-0.05</td>
<td>0.05</td>
</tr>
<tr>
<td>DEU</td>
<td>0.18</td>
<td>0.06</td>
<td>0.04</td>
<td>-0.01</td>
<td>0.17</td>
</tr>
<tr>
<td>ESP</td>
<td>0.30</td>
<td>-0.24</td>
<td>-0.12</td>
<td>-0.32</td>
<td>-0.04</td>
</tr>
<tr>
<td>FIN</td>
<td>0.67</td>
<td>0.08</td>
<td>0.00</td>
<td>0.16</td>
<td>0.01</td>
</tr>
<tr>
<td>FRA</td>
<td>-0.02</td>
<td>0.04</td>
<td>-0.03</td>
<td>-0.15</td>
<td>0.21</td>
</tr>
<tr>
<td>GBR</td>
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<td>-0.07</td>
<td>-0.01</td>
<td>-0.07</td>
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</tr>
<tr>
<td>GRC</td>
<td>0.40</td>
<td>-0.21</td>
<td>-0.17</td>
<td>-0.51</td>
<td>0.65</td>
</tr>
<tr>
<td>IRL</td>
<td>0.07</td>
<td>-0.29</td>
<td>-0.11</td>
<td>-0.38</td>
<td>0.21</td>
</tr>
<tr>
<td>ITA</td>
<td>0.03</td>
<td>-0.03</td>
<td>-0.18</td>
<td>-0.30</td>
<td>0.36</td>
</tr>
<tr>
<td>JPN</td>
<td>0.08</td>
<td>-0.06</td>
<td>0.05</td>
<td>0.05</td>
<td>0.08</td>
</tr>
<tr>
<td>KOR</td>
<td>0.21</td>
<td>-0.12</td>
<td>-0.24</td>
<td>-0.22</td>
<td>0.43</td>
</tr>
<tr>
<td>MEX</td>
<td>0.40</td>
<td>-0.14</td>
<td>-0.19</td>
<td>-0.09</td>
<td>0.62</td>
</tr>
<tr>
<td>NLD</td>
<td>-0.24</td>
<td>-0.03</td>
<td>-0.06</td>
<td>-0.04</td>
<td>0.03</td>
</tr>
<tr>
<td>NOR</td>
<td>-0.35</td>
<td>0.08</td>
<td>0.00</td>
<td>-0.08</td>
<td>-0.06</td>
</tr>
<tr>
<td>SWE</td>
<td>0.18</td>
<td>-0.03</td>
<td>-0.12</td>
<td>-0.06</td>
<td>-0.05</td>
</tr>
<tr>
<td>USA</td>
<td>0.23</td>
<td>-0.09</td>
<td>-0.17</td>
<td>0.03</td>
<td>0.19</td>
</tr>
<tr>
<td>Mean</td>
<td>0.16</td>
<td>-0.07</td>
<td>-0.08</td>
<td>-0.11</td>
<td>0.20</td>
</tr>
</tbody>
</table>

Note: This table reports correlations, at the individual country level, between relative volatility and each variable of interest. All variables, unless otherwise noted, are expressed in percentages. Volatility is defined as the quarterly standard deviation of daily stock market returns, computed using the MSCI index. Relative volatility is domestic volatility minus average volatility in the other countries of the sample. $\frac{TB}{Y}$ denotes trade balance-to-GDP ratio. $\Delta \log Y$, $\Delta \log I$ and $\Delta \log(\text{Bank credit})$ denote quarterly real growth rates of GDP, investment and bank credit. Credit spread is the difference between the domestic lending rate to corporations and the interest rate of long-term US government bonds (in annualized percentage points). The sample period is 1970:q1-2014:q4 (subject to data availability as reported in the appendix).
Table 1.2: Aggregate uncertainty and macroeconomic dynamics

<table>
<thead>
<tr>
<th>Panel A</th>
<th>$\frac{TB}{Y}$</th>
<th>$\Delta \log Y$</th>
<th>$\Delta \log I$</th>
<th>$\Delta \log (\text{Bank credit})$</th>
<th>Spread</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relative volatility</td>
<td>1.16**</td>
<td>-0.21**</td>
<td>-0.59**</td>
<td>-0.76***</td>
<td>1.77**</td>
</tr>
<tr>
<td>Controls</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Country &amp; time FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>3264</td>
<td>3264</td>
<td>3264</td>
<td>3239</td>
<td>2640</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.67</td>
<td>0.29</td>
<td>0.14</td>
<td>0.22</td>
<td>0.53</td>
</tr>
</tbody>
</table>

<p>| Panel B. Adding control variables |</p>
<table>
<thead>
<tr>
<th>$\frac{TB}{Y}$</th>
<th>$\Delta \log Y$</th>
<th>$\Delta \log I$</th>
<th>$\Delta \log (\text{Bank credit})$</th>
<th>Spread</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relative volatility</td>
<td>1.07**</td>
<td>-0.16*</td>
<td>-0.53**</td>
<td>-0.56**</td>
</tr>
<tr>
<td>Controls</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Country &amp; time FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>3098</td>
<td>3098</td>
<td>3098</td>
<td>3073</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.70</td>
<td>0.34</td>
<td>0.16</td>
<td>0.24</td>
</tr>
</tbody>
</table>

$p$-values are in parentheses (*$p$-value<0.10, **$p$-value<0.05, ***$p$-value<0.01). Robust standard errors are clustered at the country level. All variables, unless otherwise noted, are expressed in percentages. Volatility is defined as the quarterly standard deviation of daily stock market returns, computed using the MSCI index. Relative volatility is domestic volatility minus average volatility in the rest of the countries in our sample. $\frac{TB}{Y}$ denotes trade balance-to-GDP ratio. $\Delta \log Y$, $\Delta \log I$ and $\Delta \log (\text{Bank credit})$ denote quarterly real growth rates of GDP, investment and bank credit. Credit spread is the difference between the domestic lending rate to corporations and the interest rate of long-term US government bonds (in annualized percentage points). Panel A reports the results from fixed effects regressions. Panel B adds control variables: CPI inflation, change in exchange rate (national currency per USD), trade openness ($\frac{\text{Exports}+\text{Imports}}{GDP}$), Chinn-Ito index of financial openness, growth of real government spending, and stock market returns. The sample period is 1970:q1-2014:q4 (subject to data availability as reported in the appendix).
Table 1.3: Exogenous parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discount factor</td>
<td>0.99</td>
</tr>
<tr>
<td>Frisch elasticity of labor supply</td>
<td>0.5</td>
</tr>
<tr>
<td>Labor weight in utility function</td>
<td>14.26</td>
</tr>
<tr>
<td>Depreciation rate</td>
<td>0.025</td>
</tr>
<tr>
<td>Capital share in production</td>
<td>0.33</td>
</tr>
<tr>
<td>Bond adjustment cost</td>
<td>0.001</td>
</tr>
<tr>
<td>Trend growth rate</td>
<td>1.005</td>
</tr>
<tr>
<td>Convergence parameter</td>
<td>-0.001</td>
</tr>
<tr>
<td>Survival rate of entrepreneurs</td>
<td>0.97</td>
</tr>
<tr>
<td>Transfers to entrepreneurs</td>
<td>T^E</td>
</tr>
</tbody>
</table>

Table 1.4: Estimated parameters

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inverse of IES</td>
<td>3.35</td>
</tr>
<tr>
<td>Investment adjustment cost</td>
<td>1.94</td>
</tr>
<tr>
<td>Std. dev. of entrepreneurs productivity</td>
<td>0.29</td>
</tr>
<tr>
<td>Bankruptcy cost</td>
<td>0.26</td>
</tr>
<tr>
<td>Persistence of TFP growth</td>
<td>0.19</td>
</tr>
<tr>
<td>Persistence of volatility shock</td>
<td>0.79</td>
</tr>
<tr>
<td>Steady state value of volatility shock</td>
<td>-4.57</td>
</tr>
<tr>
<td>Std. dev. of volatility shock</td>
<td>0.62</td>
</tr>
<tr>
<td>Correlation of innovations to TFP growth</td>
<td>0.29</td>
</tr>
<tr>
<td>Correlation of volatility shocks</td>
<td>0.56</td>
</tr>
</tbody>
</table>

Standard errors are in parentheses and computed as in Lee and Wolpin (2010). Section 1.6.1 describes the estimation exercise.
Table 1.5: Model versus empirical targets

<table>
<thead>
<tr>
<th></th>
<th>Model</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\sigma (\Delta \log Y)$</td>
<td>1.19</td>
<td>1.14</td>
</tr>
<tr>
<td>$\sigma (\Delta \log I)$</td>
<td>3.32</td>
<td>3.33</td>
</tr>
<tr>
<td>$\sigma (\Delta \log C)$</td>
<td>1.06</td>
<td>1.05</td>
</tr>
<tr>
<td>$\sigma \left( \frac{TB}{Y} \right)$</td>
<td>2.81</td>
<td>2.81</td>
</tr>
<tr>
<td>Std. dev. of relative volatility</td>
<td>0.37</td>
<td>0.38</td>
</tr>
<tr>
<td>Persistence of output growth</td>
<td>0.23</td>
<td>0.22</td>
</tr>
<tr>
<td>Persistence of relative volatility</td>
<td>0.72</td>
<td>0.73</td>
</tr>
<tr>
<td>Cross-country corr. of output growth</td>
<td>0.19</td>
<td>0.19</td>
</tr>
<tr>
<td>Cross-country corr. of volatility</td>
<td>0.57</td>
<td>0.60</td>
</tr>
<tr>
<td>Mean leverage ratio</td>
<td>1.77</td>
<td>1.80</td>
</tr>
</tbody>
</table>

$\Delta \log Y$, $\Delta \log I$ and $\Delta \log C$ denote quarterly growth rates (in percentages) of output, investment and consumption. $\frac{TB}{Y}$ is the trade balance-to-output (in percent). $\sigma (x)$ denotes standard deviation of variable $x$. Section 1.6.1 discusses the details.

Table 1.6: Quantitative assessment of the credit channel

<table>
<thead>
<tr>
<th>$\frac{TB}{Y}$</th>
<th>$\Delta \log Y$</th>
<th>$\Delta \log I$</th>
<th>$\Delta \log$ (Bank credit)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Data (Table 2, Panel A)</td>
<td>1.16</td>
<td>-0.21</td>
<td>-0.59</td>
</tr>
<tr>
<td>With credit channel</td>
<td>0.88</td>
<td>-0.20</td>
<td>-0.67</td>
</tr>
<tr>
<td>Without credit channel</td>
<td>0.15</td>
<td>0.12</td>
<td>0.27</td>
</tr>
</tbody>
</table>

The first row copies the regression coefficients from Table 1.2, Panel A. The second row has the regression coefficients estimated with data generated from the model with the credit channel. The third row is like the second row but the data come from the model without credit channel. Both models are simulated with all the shocks. Section 1.6.3 discusses the details.
Table 1.7: Conditional standard deviations

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>All shocks</td>
<td>TFP level</td>
<td>Int. rate level</td>
<td>TFP volat.</td>
<td>Int. rate volat.</td>
</tr>
<tr>
<td>$\sigma (\Delta \log Y)$</td>
<td>1.40</td>
<td>0.73</td>
<td>0.22</td>
<td>0.02</td>
<td>0.01</td>
</tr>
<tr>
<td>$\sigma (\Delta \log I)$</td>
<td>12.88</td>
<td>2.90</td>
<td>4.17</td>
<td>0.43</td>
<td>0.29</td>
</tr>
<tr>
<td>$\sigma (\Delta \log C)$</td>
<td>2.32</td>
<td>0.72</td>
<td>0.61</td>
<td>0.08</td>
<td>0.09</td>
</tr>
</tbody>
</table>

This table reports conditional standard deviations of growth rates (in percentages) of output, investment and consumption, when we feed into the small open economy model of Section 1.8 different combinations of the shocks. That is, we compare: (1) all shocks; (2) only TFP level shocks; (3) only interest rate level shock; (4) only TFP volatility shock, and (5) only interest rate volatility shock.
Figure 1.1: Within-country correlations.

Note: Each bar-chart plots the country-specific correlation between the variable of interest against the relative volatility of stock market returns.
Figure 1.2: Scatter plots.

Note: Each panel plots a binned scatterplot of the variable of interest (trade balance-to-GDP, real quarterly growth rates of GDP, investment, bank credit, and credit spread) against the relative volatility of stock market returns. The variables are defined as in Figure 1. Each scatterplot has 20 equally sized bins, each with around 166 observations. The fitted line comes from the OLS regression.
Figure 1.3: Volatility and credit supply.

Note: This figure plots the leverage ratios and gross lending rates that satisfy the lenders’ participation constraint (1.20) for a high \((-2.5)\) and a low \((-4.57)\) value of the steady state volatility parameter \(\sigma\).
Figure 1.4: Common patterns in the models with and without credit channel.

Note: This figure compares the responses to a one standard deviation volatility shock in country 1 in the models with and without a credit channel.
Figure 1.5: Differences between models with and without credit channel.

Note: This figure compares the responses to a one standard deviation volatility shock in country 1 in the models with and without a credit channel.
Figure 1.6: Domestic bank versus global bank.

Note: This figure compares the responses to a one standard deviation volatility shock in the model with a domestic bank and in the model with a global bank. See Section 1.7 for details.
Figure 1.7: TFP growth volatility versus interest rate volatility.

Note: This figure compares the responses to shocks to TFP growth volatility and to shocks to interest rate volatility in a small open economy version of the model with the credit channel. Both shocks are one standard deviation shocks. The solid line is the same as in Figure 1.6. Section 1.8 discusses the details.
2.1 Introduction

Following the last financial crisis, there has been a renewed interest in designing last-resort lending arrangements among countries. For example, since 2008, China has entered into more than 50 bilateral agreements that can be used to obtain lending of last resort (LOLR). Argentina, Pakistan and Venezuela have already used China’s facilities.\footnote{Argentina has been actively negotiating a further extension of the swap line with China in an attempt to cope with recent economic turbulence (Wheatley 2018).} While there exists a literature started by Bagehot (1878) analyzing the usefulness of lending of last resort, the issue of sustainability of international LOLR arrangements has not been explored within a quantitative macro framework. This is the main contribution of our paper.

We study a small open economy whose banking system borrows from international financial markets. Banks can default and a costly-state-verification friction generates an endogenous spread between banks’ cost of funds and the exogenous risk free rate. The model has the “liability dollarization” channel surveyed in Mendoza (2016) as debt is denominated in units of tradables and collateral is posted in terms of nontradables (capital). Adverse financial shocks increase the probability of bank failures, lower banks’ access to credit and trigger a negative financial accelerator mechanism à la
Bernanke et al. (1999), which is specially intense when banks are highly leveraged.\textsuperscript{2} As in the data, systemic banking crises in the model are infrequent, but relatively persistent events, featuring a sharp rise in spreads, a reversal of the current account and a drop in aggregate consumption and banks’ equity.

In the model, the LOLR commits to partially finance the banks during the financial crises.\textsuperscript{3} The LOLR allows the distressed banking sector to borrow at an interest rate lower than what private lenders would have charged without the intervention. This policy is effective at helping the banking sector to cope with financial distress and mitigates the negative financial accelerator. However, the anticipation of such interventions encourages banks to take more leverage ex-ante. We solve the model with global methods to capture this moral hazard.

LOLR policies generate a tradeoff between financial fragility (due to more highly leveraged banks) and milder crises since the policies are effective once in a crisis. For our calibration the crisis mitigation effect dominates the moral hazard problem and the economy is better off having access to a lender of last resort.

The previous result takes us to the question of how to implement the LOLR. Bagehot proposed the central bank to be the LOLR. However, many central banks cannot act as successful last-resort lenders because their financial sector borrows in foreign currency (usually in dollars) and their reserves are not large enough.\textsuperscript{4} Thus, we

\textsuperscript{2}In the model, banks are exposed to idiosyncratic asset quality shocks. The aggregate shock that triggers the financial crisis is an increase in the cross-sectional dispersion of the bank idiosyncratic shock. Christiano et al. (2014), Elenev et al. (2016, 2018), Faria-e-Castro (2017), Alfaro et al. (2018), Bloom et al. (2018), among others, study financial crises driven by these shocks.

\textsuperscript{3}See Jeanne and Wyplosz (2001) for a similar approach to modeling LOLR support to domestic banking system.

\textsuperscript{4}Areas as Latin America are de facto mostly dollarized (Corbo 2001 and Salvatore 2001). Moreover, dollar-denominated debt keeps increasing rapidly. In 2014, non-U.S. debt issuers had $6.04 trillion in outstanding bonds, up nearly fourfold since 2008 (Talley and Trivedi 2014).
study whether international LOLR arrangements are sustainable when the alternative is tax-financed LOLR, which in practice is how Ireland, Portugal and Spain supported their domestic financial systems during most of the 2008 financial crisis (Santos 2014, Zeissler et al. 2015).

We characterize the conditions under which pools of small economies can be a sustainable multilateral arrangement. In addition, we assess the ability of China to be an international LOLR. At the end of 2015, China accounted for 85 percent of all global swap lines (Lagarde 2016). Aizenman et al. (2015) describe the strategy as a bundling of finance (lending, swap-lines and trade credit) in tandem with outward FDI to promote a new type of Chinese-outward mercantilism. Importantly, China seems to attach minimal conditions to its loans. The absence of conditionality may make China a popular LOLR because countries have been reluctant to use lending of last resort programs from the IMF to avoid the stigma and conditionality attached to them (Allen and Moessner 2015, Cecchetti 2014 or Landau 2014).

We obtain two main results: (i) Pools of small economies do not seem feasible arrangements for lending of last resort, because, for the levels of liquidity support documented by Laeven and Valencia (2013), they need unrealistically large number of uncorrelated countries, or large initial levels of reserves, to have small probabilities of failure. (ii) A country with ample reserves like China can be a sustainable international LOLR. We input into the model the ratio of China’s foreign reserves to the total GDP of the countries that have signed lending agreements with China over the last nine years. Model simulations show that, as long as China receives some compensation from the insured countries, it is able to provide the levels of liquidity support documented by Laeven and Valencia (2013) with low probabilities of failure. However, our results also suggest that China may have overreached its capacity to be LOLR. In 2009, China’s reserves were 50% of the total GDP of countries with lending agreements. By
2015, the rapid expansion in the number of agreements had brought the ratio to 15%. Moreover, the GDP correlations between the countries and China are high, hindering China’s ability to provide insurance.

The previous result is related to Obstfeld et al. (2009), who expressed concern that the scale of reserves needed to backstop financial crises in emerging markets surpassed the resources of the multilateral organizations and all but the largest reserve holders in the world. We confirm that the largest reserve holders can play the role of international LOLR. Thus, the recent Chinese initiatives seem to benefit many countries since self-insurance against domestic financial instability is one of the main drivers of reserve accumulation (Aizenman and Lee 2007, Obstfeld et al. 2010), but this accumulation comes at substantial costs (Reinhart et al. 2016 or Rodrik 2006). Aizenman et al. (2011, 2015) confirm that long-lasting LOLR agreements lead to lower reserve accumulation.

In terms of methodology, our paper contributes to the literature by developing a quantitative macro framework to think about the usefulness and sustainability of different types of LOLR arrangements. While most LOLR papers focus on setups with multiple equilibria and analyze qualitative properties (see, for example, Goodhart and Huang 2000, Corsetti et al. 2006, Morris and Shin 2006 or Bocola and Lorenzoni 2018), we study a financial frictions setup that allows a quantitative analysis of LOLR policy. Our paper thus connects with models of financial frictions between borrowers and lenders with endogenous accelerator mechanisms (like Bernanke et al. 1999, Christiano et al. 2014, Fernandez and Gulan 2015, Gertler and Karadi 2011 or Akinci and Queralto 2016 among many others). Like Bianchi (2016) or Bianchi and Mendoza (2018) we solve the model with global methods to capture the trade-off between the ex-post benefits of liquidity support and the ex-ante moral hazard in the banking sector triggered by the LOLR.
The paper proceeds as follows: Sections 3.3 and 2.3 describe the benchmark country and the LOLR policies that we study. Section 2.4 discusses the calibration. Section 3.5 analyzes banking crises and lending of last resort policies. Section 2.6 studies the sustainability of an international LOLR with an application to China. Section 3.7 concludes. The appendices contain the optimality conditions of the model, the numerical algorithm, and the data sources.

2.2 The Benchmark Country

The benchmark country is a small open economy with households, banks and firms. Banks borrow in international financial markets and invest in domestic assets. Banks can default and face an endogenous borrowing spread like the borrowers in Bernanke et al. (1999). The model is real with consumption serving as numeraire. Only consumption goods are tradable.

2.2.1 Banks

Every period there is a continuum of measure one of banks. At time $t$, bank $j$ purchases capital $K_{j,t+1}$ at unit price $p_t$, using her own net worth $N_{j,t}$ and new debt $B_{j,t+1}$ bought by international lenders at price $q_t$. In period $t + 1$ the banks rent the capital to perfectly competitive firms at rental rate $r_{t+1}$. Then banks resell the capital to households at price $p_{t+1}$.

The individual bank’s balance sheet is thus

$$p_t K_{j,t+1} = N_{j,t} + q_t B_{j,t+1}. \quad (2.1)$$

After purchasing capital, banks are hit by idiosyncratic i.i.d. shocks $\omega$, that capture the idea that some banks hold high quality assets while others hold low quality assets. This is consistent with the evidence discussed in Bindseil and Laeven (2017) that
interbank markets (banks’ lenders in the model) ex-ante do not observe how credit losses are distributed across individual banks because the quality of banks’ assets is opaque. Once an individual banker receives a shock $\omega$, its time $t+1$ gross return on assets is $\omega (r_{t+1} + p_{t+1}) K_{j,t+1}$.

The idiosyncratic shock $\omega$ has a unit-mean log normal distribution with cumulative distribution function $F(\omega, \sigma_t)$, and is subject to aggregate shocks to the volatility parameter $\sigma_t$ as in Christiano et al. (2014) that satisfy

$$E(\omega) = \mu_t + \frac{\sigma_t^2}{2} = 1, \forall t.$$ (2.2)

We use the notation $F_t(\omega)$ to indicate the time-varying nature of the distribution function. Assumption (3.1) guarantees that the $\omega$ shocks are redistribution shocks to make banks’ assets unevenly distributed across banks such that some banks cannot repay their borrowings.

After the idiosyncratic and aggregate shocks are realized, some banks will default. The default threshold $\omega_{t+1}$ is determined by the bank with idiosyncratic shock such that given the prices the bank is unable to pay its debt,

$$\omega_{t+1} (r_{t+1} + p_{t+1}) K_{j,t+1} = B_{j,t+1}.$$ (2.3)

Banks with idiosyncratic shock $\omega \geq \omega_{t+1}$ repay their debt, and those with $\omega < \omega_{t+1}$ default.\(^5\) We assume that, due to costly bankruptcies, lenders can only recover a fraction $(1 - \mu)$ of the defaulting banks’ assets.

An individual bank’s net worth at $t+1$ is

$$N_{j,t+1} = \int_{\omega_{t+1}}^{\infty} [\omega (r_{t+1} + p_{t+1}) K_{j,t+1} - B_{j,t+1}] dF_{t+1}(\omega).$$ (2.4)
Banks' debt is priced in the international interbank markets such that, net of default, it ensures that banks’ lenders, who we assume are risk-neutral, obtain an expected rate of return equal to the risk free rate 

\[ q_{t}B_{j,t+1} = \mathbb{E}_{t}\left\{ \int_{\omega_{t+1}}^{\infty} B_{j,t+1}dF_{t+1}(\omega) + (1 - \mu) \int_{0}^{\omega_{t+1}} \omega (r_{t+1} + p_{t+1}) K_{j,t+1}dF_{t+1}(\omega) \right\}. \]

(2.5)

That is, for an investor lending \( q_{t}B_{j,t+1} \) today to the banks, the expected inflows accounting for the probability of bank default must equal the return of those funds in a risk-free investment \( \left( \frac{q_{t}B_{j,t+1}}{q_{f}} \right) \).

Like in Bernanke et al. (1999), banks die with an exogenous probability \( (1 - \gamma) \) and transfer their resources to households in the form of dividends. Surviving banks reinvest all their net worth. At the end of period \( t \), before a death shock is realized, an individual banker chooses a sequence of debt issuance and asset purchases to maximize the present discounted value of terminal equity,

\[ V_{j,t} \equiv (1 - \gamma) \mathbb{E}_{t}\left\{ \sum_{s=0}^{\infty} \gamma^{s}m_{t,t+s}N_{j,t+s} \right\}, \]

(2.6)

subject to the balance sheet constraint (3.5), the definition of default threshold (3.3), the evolution of individual net worth (2.4), and to the debt pricing equation (2.5).

Since households are the recipients of bank dividends, the banks use the household’s stochastic discount factor to value future profit streams,

\[ m_{t,t+s} \equiv \beta^{s} \frac{u_{C}(C_{t+s},L_{t+s})}{u_{C}(C_{t},L_{t})}. \]

(2.7)

In the Appendix we show that, because of constant returns to scale technology, a bank’s value function is linear in net worth, allowing for simple aggregation. The linearity of the value function implies that all banks have the same default threshold, debt-to-net worth ratio, and face the same market price of debt. Therefore, we only
need to keep track of aggregate banking-sector variables to characterize the dynamics of our economy.

Banks that die are replaced by an equal number of new bankers, which start with small amount of equity $T_b$ obtained from households in a lump-sum manner. Thus, aggregate net worth of the banking sector evolves according to

$$N_t = \gamma \int_{\omega_t}^{\infty} \left[ \omega (r_t + p_t) K_t - B_t \right] F_t(\omega) + T_b,$$

and total dividends received by households from the banking sector are

$$\Omega_t = (1 - \gamma) \int_{\omega_t}^{\infty} \left[ \omega (r_t + p_t) K_t - B_t \right] F_t(\omega).$$

### 2.2.2 Firms

Firms hire labor from households and rent capital from banks to produce consumption goods according to a Cobb-Douglas technology

$$Y_t = K_t^\alpha L_t^{1-\alpha},$$

The firms maximize profits,

$$\Phi_t = K_t^\alpha L_t^{1-\alpha} - r_t K_t - W_t L_t,$$

which in equilibrium will be zero because of the constant returns to scale production function.

### 2.2.3 Households

There is a continuum of homogeneous households who maximize utility over consumption $C_t$ and labor hours, $L_t$. They receive labor income and dividends from banks and firms. Households are hand-to-mouth and solve a static optimization problem:

$$\max_{C_t, L_t} u(C_t, L_t)$$
subject to the budget constraint,

\[ C_t = W_t L_t + \Omega_t + \Phi_t - T_b, \]  

(2.13)

where \( W_t \) is the wage per unit of labor, \( \Omega_t \) are dividends from banks, \( \Phi_t \) are firm profits, and \( T_b \) denotes transfers to the new banks.

### 2.2.4 Definitions

The current account is the negative of the change in banks' foreign debt,

\[ CA_t = -(B_{t+1} - B_t). \]  

(2.14)

We define the leverage of the banking sector as bank assets-to-equity ratio,

\[ lev_t = \frac{p_t K_{t+1}}{N_t}. \]  

(2.15)

The credit spread is the difference between banks' cost of funds and the risk free rate,

\[ spread_t = \frac{1}{q_t} - \frac{1}{q_f}. \]  

(2.16)

We assume that capital is in fixed supply and normalize its value to one, i.e.

\[ K_t = 1, \quad \forall t. \]  

(2.17)

### 2.2.5 Aggregate Shocks

We assume that the standard deviation of banks' idiosyncratic asset quality \( (\sigma_t) \) follows a standard two-state, regime-switching Markov process with high and low states, \( \{\sigma_h > \sigma_l\} \).\(^6\) We refer to states with \( \sigma_l \) as normal times, when domestic

\(^6\)Christiano et al. (2010, 2014) refer to these shocks as "risk shocks" and attribute them most of the macro fluctuations in the U.S. and euro area. Akinci (2014) documents the importance of these shocks for emerging markets. This type of cross-sectional dispersion shocks have also been extensively used in the more recent macro-finance literature. See, for example, Elenev et al. (2016, 2018), Alfaro et al. (2018), Faria-e-Castro (2017).
banks have regular access to private credit markets. States with $\sigma_h$ are financial stress periods when banks’ access to external financing is impaired and bank defaults are high. The transition probability matrix is

$$\Pi = \begin{bmatrix} \pi_{hh} & 1 - \pi_{hh} \\ 1 - \pi_{ll} & \pi_{ll} \end{bmatrix},$$

where $\pi_{hh}$ and $\pi_{ll}$ denote the probability of remaining in the high and low-risk states, respectively.

### 2.3 Lending of Last Resort

We assume that in times of financial stress, that is, when $\sigma_t = \sigma_h$, there is a lender of last resort (LOLR). We discuss below two ways to finance this LOLR. In both cases, the LOLR operates in the same way that assumes full commitment: in case of financial stress the LOLR commits to financing a $\psi$ fraction of the banks debt $B_{j,t+1}$. Thus, with LOLR, the banks’ debt pricing equation becomes

$$\frac{q_t B_{j,t+1}}{q_f} = \psi \mathbb{I}_{\{\sigma_t = \sigma_h\}} B_{j,t+1} + \left(1 - \psi \mathbb{I}_{\{\sigma_t = \sigma_h\}}\right) \mathbb{E}_t \left\{ \sum_{\tau=1}^{\infty} B_{j,t+1} dF_{t+1}(\omega) + (1 - \mu) \int_0^{\pi_{tt}+1} \omega (r_{tt} + p_{tt+1}) K_{j,t+1} dF_{t+1}(\omega) \right\}.$$  

That is, the first term in the right-hand side of (2.19) is the debt that the LOLR assumes in case of financial stress in the country. The second term is the expected repayments from the banks absent the LOLR policy like in equation (2.5). In fact, comparing (2.19) and (2.5) we can anticipate that LOLR policy, by committing to provide funds in the bad state of nature, also lowers banks’ borrowing costs in the good state.
2.3.1 Financing the Lending of Last Resort

The LOLR policy is costly because it involves a credit subsidy. The LOLR commits to financing a $\psi$ fraction of the banks debt $B_{j,t+1}$ but for those banks that default the LOLR only recovers their assets, which by definition of default are lower than their debt. Thus, the expected costs of the LOLR policy are

$$\Xi_{t+1} = \psi \mathbb{I}_{(\sigma_t = \sigma_h)} \left[ \int_0^{\omega_{t+1}} [B_{j,t+1} - \omega (1 - \mu) (r_{t+1} + p_{t+1}) K_{j,t+1}] dF_{t+1}(\omega) \right].$$  \hspace{1cm} (2.20)

Next, we analyze two ways to finance $\Xi_{t+1}$. First, through taxes on the countries’ households. Second, through an international organization.

**Single-country Lending of Last Resort**

First, we assume that the lender of last resort in country $i$ is financed with taxes from the households of country $i$. This case gives us a benchmark to compare the international LOLR. We refer to this case as the "single-country LOLR". This case applied to Ireland, Portugal and Spain during the 2008 financial crisis. Households in those countries paid higher taxes to support their domestic financial systems until the EU allowed the European Stability Mechanism and the ECB to exert as LOLR (Santos 2014, Zeissler et al. 2015).

Formally, in the single-country LOLR, the households’ budget constraint (3.16) becomes

$$C_t = W_t L_t + \Omega_t + \Phi_t - \Xi_t - T_b$$  \hspace{1cm} (2.21)

to incorporate the cost of the lending of last resort ($\Xi_t > 0$).

**International Lending of Last Resort**

We refer to "international LOLR" when the lender of last resort is a pool of countries that starts with some endowment of reserves $M_0$ and every period charges a
participation premium ($\rho$) to each country in the pool. Assuming that past reserves return the risk-free rate $\frac{1}{q_f}$, and that there are $n$ countries paying the participation premium, then the reserves of the international LOLR evolve as

$$M_t = \frac{M_{t-1}}{q_f} + n\rho - \sum_{i=1}^{n} \Xi_{i,t},$$  \hspace{1cm} (2.22)

where $\Xi_{i,t} \geq 0$ are the losses incurred in country $i$. These losses are zero for country $i$ if in period $t$ the country’s domestic banking system is not in financial distress.

The international LOLR fails if $M_t < 0$. That is, when the LOLR lacks resources to fulfill its role as LOLR. If the LOLR does not fail, (3.37) specifies that its reserves are the sum of the return on the past reserves, plus the insurance premiums paid by the countries in the pool ($n\rho$), minus the sum of the losses incurred with the countries in the pool.

We use as participation premium the maximum amount that a country would be willing to pay for access to the international LOLR. This premium is the rate at which the households of the country obtain the same expected utility between the autarky single-country LOLR discussed in Section 2.3.1 and the international LOLR. That is, in the stationary distribution, $\rho$ solves

$$\mathbb{E}[u(C_{\rho,t}, L_{\rho,t})] = \mathbb{E}[u(C_{T,t}, L_{T,t})],$$  \hspace{1cm} (2.23)

where $C_{\rho,t}$ and $L_{\rho,t}$ are consumption and labor supply when the country pays $\rho$ to belong to the international LOLR. $C_{T,t}$ and $L_{T,t}$ are consumption and labor supply as in the single-country LOLR. An important remark is that the premium $\rho$ has to be paid every period while the taxes $\Xi_t$ in (2.21) only need to be paid when there is a financial turmoil.
2.4 Calibration

We calibrate the model to quarterly frequency. First, we set some parameters exogenously following standard values in the literature. Then we endogenously select the rest of the parameters to match some targets. Table 2.1 summarizes the parameter values and Table 2.2 contains the targets and moments of the model.

We use GHH preferences to avoid wealth effects on labor supply,

$$u(C_t, L_t) = \frac{1}{1-\eta} \left( C_t - \theta \frac{L_t^{\frac{1+\xi}{1+\xi}}}{1+\xi} \right)^{1-\eta},$$

where $\xi$ is the elasticity of labor supply and $\eta$ controls the curvature of the utility function. We choose the value of $\theta$ so that the long-run mean of hours worked equals $\frac{1}{3}$. We assign standard values to the subjective discount factor ($\beta = 0.98$), the elasticity of labor supply ($\xi = 1$), the risk-aversion parameter ($\eta = 2$), capital share in production ($\alpha = 0.33$), and the annualized risk-free interest rate of 4% (i.e., $\frac{1}{q_f} = 1.01$). We set transfers to banks to be a very small positive number ($T_b = 0.0001$). These transfers are a technical device to insure a non-zero equity of the banking sector and do not affect the quantitative results.

Next, we endogenously choose the values for the remaining parameters to target the following empirical targets:

An annualized spread between banks’ borrowing costs and the international risk free rate of 4.62 percentage points. In the data average EMBI spread for emerging market economies is around 5 percentage points (see, for example, Fernandez and Gulen 2015). Akinci and Queralto (2016) estimate average country spreads of about 3 percentage points for 6 advanced OECD economies.

An average leverage ratio of 3.33 and an average dividend payout-to-bank value ratio of 8.5%. These values are in the range of the values estimated by Fernandez and
Gulan (2015) for 12 emerging market economies, and by Faria-Castro (2017) for the U.S. commercial banks. In order to hit the above targets, we set $\mu$ to 0.20, $\sigma_h$ to 0.252, and $\gamma$ to a value of 0.915.

We choose the value of $\sigma_l$ so that during a crisis interest rate spread rises by about 4.5 percentage points relative to its mean. This is consistent with the empirical evidence in Akinci and Queralto (2016).

We calibrate the transition probabilities of the financial risk process so that the frequency and average duration of banking crises in the no-LOLR economy are like in the empirical literature. Following Bianchi and Mendoza (2018) we define a crisis as an event whose current account is above two standard deviations from its long-run mean. This captures the well-established fact that financial crises in small open economies have large current account reversals because of disruptions in the banking sector and large drops in foreign financing of the domestic economy. We are also consistent with Laeven and Valencia (2013) and Jorda et al. (2016) definitions of financial crises. As we will discuss later, crises in our model feature a sharp jump in banks’ bankruptcy rates and in the ex-post government losses associated with last-resort interventions. We set $\pi_{ll}$ to 0.97 and $\pi_{hh}$ to 0.80, which imply a frequency of banking crises of 6 percent, and an average duration of a crisis of about 2 years. These values are in the range estimated by Jorda et al. (2016), Laeven and Valencia (2013), and Reinhart and Rogoff (2009);

Finally, we set the LOLR parameter $\psi$ to 0.096 so that the LOLR economy directly matches the liquidity support (as % of banks’ total liabilities) of 9.6%, documented by Laeven and Valencia (2013).

We solve the model using global methods. We follow the policy function iteration algorithm developed by Colleman (1990). Thus, the decision rules take into account
the moral hazard induced by the LOLR policy. Appendix B describes the numerical algorithm in detail.

2.5 Quantitative Results I. Banking Crises with and without Lending of Last Resort

Figure 2.1 plots impulse responses to study how the economies with and without LOLR react to a financial shock. We focus on the single-country LOLR defined in Section 2.3.1. We follow the methodology of Bianchi (2016) in constructing the non-linear impulse response functions. In all the panels, the solid line corresponds to the no-LOLR economy, and the dashed line refers to the economy with LOLR.

An adverse shock increases the probability of bank defaults and banks’ lenders price it with higher spreads (lower $q_t$). This increase in spreads leads to higher borrowing costs for banks forcing them to reduce their borrowings ($q_tB_{t+1}$ falls). The demand for assets decrease, as do asset prices. Falling asset prices further reduce banks’ aggregate net worth, and dividends, through the standard financial accelerator of Bernanke et al. (1999). Households consumption falls. Lending of last resort significantly mitigates the negative effects of the financial shock as banks can borrow at cheaper rates than otherwise.

Since LOLR is an ex-post policy, it can induce a moral hazard problem. That is, banks anticipate that the LOLR will help them in a crisis and lower their precautionary savings motives to take higher risk through higher leverage. That is, even though

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7 Figures A1-A3 in the Online Appendix plot the policy functions for banks’ next period debt, price of debt, and price of capital.
8 We set the initial debt level in each economy at its corresponding unconditional mean values. We then simulate the shock process of length 20 periods for 100,000 times and feed them into the policy functions to produce 100,000 paths for the endogenous variables. For each economy we compute the average differences of the variables of interest between the paths that start with $\sigma_h$ and those that start with $\sigma_l$. 
banks are risk-neutral in our model, they use households stochastic discount factor to value future profit streams. Therefore, precautionary savings motive is present in banks’ financial decisions.

Figure 2.3 confirms the moral hazard. It compares the long-run distributions of bank leverage with and without the LOLR policy. The ergodic distribution of bank leverage puts larger mass at higher leverage ratios with LOLR policy, than without it. Figure A3 in the Online Appendix confirms, using the policy functions, that in low risk states banks do borrow more in the economy with the LOLR. The moral hazard problem is stronger when the current debt level is high. This occurs because large amounts of debt today makes future crisis more likely and in this scenario banks’ precautionary savings motive is much stronger when there is no LOLR than in the LOLR economy.

Due to the moral hazard problem, the economy with the LOLR may be more likely to move to states with large amount of debt, so that when an adverse financial shock hits the economy in these states, its negative effects are more amplified. Figure 2.1 does not fully capture the previous effect, since when deriving the impulse response functions, we fixed the initial debt levels to their corresponding unconditional mean values in the two economies. To fully account for the policy-induced moral hazard when evaluating the effectiveness of the LOLR, we study an average crisis episode in the two economies using the methodology of Mendoza (2010), Bianchi (2016) and Schmitt-Grohé and Uribe (2017). Figure 2.2 plots the resulting event-windows.

Several results stand out in Figure 2.2: 1) In the model, like in the data, credit spreads rise sharply once in a crisis. There is a current account reversal as banks

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9That is, we simulate economies with and without LOLR for 100,000 periods, discarding the first 5000 periods as burn-in. Then, we identify banking crises, center these crisis episodes at date 0, and take 20 periods before and after each crisis date. We compute averages for each variable across the entire set of the crises and associated time windows.
cannot borrow and asset prices fall sharply deteriorating banks’ equity. Households cut back on consumption spending in response to a collapse in bank dividends. The magnitudes are comparable to the data. For example, Akinci and Queralto (2016) find that in the average systemic banking crisis in advanced OECD economies, the credit spreads rise by about 5 percentage points, while bank equity falls by about 60%. The LOLR significantly stabilizes the economy in a crisis because it provides funds to the banks and this mitigates the fall in asset prices. As a consequence, dividends and household consumption drop by less.

Figure 2.2 indicates that the positive ex-post effects of LOLR in mitigating the severity of crises outweighs the ex-ante excessive risk taking by the banking sector. Importantly, the consumption gains from LOLR are larger than the losses incurred by the LOLR during the crisis. At the peak of the crisis the losses are around 2.5% of output, which is the same order of magnitude as in Laeven and Valencia (2013). Despite the increase in lump sum taxes the fall in household consumption is still about 3 percentage points lower with the last resort lending, than without it. This is because the disruptions in the banking sector and in bank dividends, are less severe under the LOLR.

2.6 Quantitative Results II. Sustainability of an International Lender of Last Resort

This section analyzes the sustainability of an international lender of last resort that starts with some endowment of reserves contributed by the participating countries, and charges a participation premium every period to each country in the pool. We compare different cross-country correlations of the banking crises, different number of
participating countries and different initial levels of reserves. Then we ask whether a country with ample reserves like China can be a sustainable international LOLR.

2.6.1 Probability of Failure of an International Lender of Last Resort

Figures 2.4 and 2.5 analyze the probability of failure of the international LOLR for different cases. In all of them the analysis is based on the benchmark calibration and a horizon of 50 years. The international LOLR fails when $M_t < 0$ in equation (3.37). In that case the disbursements due to the countries in crisis are larger than the sum of the inflows from new participation premiums and the existing stock of reserves.

Figure 2.4 focuses on the case when the initial level of resources is zero. That is, countries do not make any contribution of reserves to join the LOLR pool. However, they pay the participation premiums defined in (2.23). Figure 2.4 has two main results: 1) Without initial reserves, for the levels of liquidity support documented by Laeven and Valencia (2013), pools of small economies are unlikely to be sustainable LOLR. For example, even with 100 uncorrelated countries the probability of failure of the international LOLR is around 40%. 2) If the shocks are correlated then adding new countries does not help to reduce the probability of failure. The Law of Large Numbers fails to bring benefits from pooling risks for highly correlated shocks. In fact, Figure 2.4 shows that the higher the correlations, the more likely is the pool to fail.

Figure 2.5 plots the case when countries do make contributions of reserves to join the LOLR pool and in addition pay the participation premiums defined in (2.23). There are several results to highlight: 1) A country alone needs to have a large ratio of reserves-to-GDP (around 30%) to have a sustainable domestic LOLR to the financial sector in a crisis. Bussière et al. (2016) report that the average level of reserves-to-GDP in non-advanced countries was below 20% until 2007, since then
many countries boosted their reserves and the average level is closer to 25%. 2) If the cross-country shocks are uncorrelated (Panel a) then pooling with an international LOLR allows to dramatically reduce the need to contribute reserves. For example, an international LOLR formed by more than 10 uncorrelated countries, each contributing initial reserves of about 10% of GDP and paying the participation premiums, basically eliminates the risk of default. 3) For highly correlated cross-country shocks (Panel b) there are no gains from pooling and the levels of initial reserves need to be as high as when the country self-insures. These results suggest that LOLR through regional agreements among small correlated countries are unlikely to be feasible.

2.6.2 An Application to China

In this subsection we evaluate whether it is feasible that a country with a large stock of reserves becomes the international LOLR. This country would receive benefits from being the LOLR that could be explicit (that is, collect insurance premiums) or implicit (for example, political influence or trade benefits). The insured countries would not need to contribute reserves, just to pay the participating premium.

The natural candidate to become the international LOLR is China because it is the country with the largest stock of foreign reserves. Figure 2.6 plots the dynamics of these reserves.

Since December 2008, China has entered into more than 30 bilateral currency swap agreements. Moreover, China has created an even larger network of lending agreements through its development and export-import banks. Aizenman et al. (2015) describe the strategy as a bundling of finance dealing (lending, swap-lines and trade credit) to promote a new type of Chinese-outward mercantilism. Table 2.3 summarizes the evolution of these agreements.
China’s lending agreements have multiple goals: facilitate settlement in renminbi, promote trade and also serve as a source of liquidity as a lender of last resort. For example, in 2013 Pakistan reportedly borrowed an equivalent of US$ 600 million to avert a domestic crisis (later it received a US$6.6 billion loan from the IMF). In a similar move, in 2014 Argentina drew $2.7 billion upon its swap line with China to combat a shortage of dollar funding. China does not provide dollar liquidity but both Pakistan and Argentina were able to convert renminbi to dollars in the offshore market. Venezuela has also relied on China’s lending of last resort. Contrary to the IMF, China seems to attach minimal conditions to its loans.

Figure 2.7 (a) plots both the evolution of the number of countries with which China has a lending agreement, and the average correlation of output between China and the countries with which it has signed agreements. As pointed out by Aizenman et al. (2015), the correlation is relatively high because China has given preference to countries with natural resources or whose economies are strategic for the Chinese economy. The correlation has fallen as more countries have signed agreements. Figure 2.7 (b) plots the foreign reserves of China as % of the GDP in the pool of countries with an agreement with China. This ratio has decreased over time since China’s foreign reserves have been flat or decreasing since 2012 while the number of agreements keeps increasing. Even so, in 2016, if we exclude the euro area from the covered countries, China has foreign reserves that are around 15% of the GDP of the pool of countries with an agreement.

Figure 2.8 uses the model to simulate the likelihood that China fails to be a sustainable LOLR. We calibrate the initial level of reserves in equation (3.37) to match the foreign reserves of China as percentage of poolwide GDP excluding the euro area,

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11Morelli et al. (2015) show that during the recent financial crisis the U.S. lending was directed towards those countries more important for the stability of the U.S. financial system.
reported in Figure 2.7 (b). The simulation assumes that the cross-country correlation is 0.88, which is the average from Figure 2.7 (a). Countries pay the participation premium defined in (2.23). China’s reserves evolve as in equation (3.37). Reserves are invested at the international risk-free rate. Inflows are the participation premiums collected from the insured countries. Outflows are the lending of last resort subsidies provided to the countries in banking crises.

Figure 2.8 compares the likelihood of failure over different time periods. The longer the time period, the more likely that a bad shock in multiple countries arrives and China fails as LOLR. The probability that China fails as an international LOLR is below 1% for the reserve levels above 30% of total insured GDP. This probability rises to about 8% when China’s reserves cover 15% of total GDP of the insured pool. Thus, given its large stock of foreign reserves, it seems that China can be a sustainable LOLR.

However, Figure 2.8 also suggests that China might be tending to overreach its capacity to be a sustainable international LOLR. In 2016, the number of countries that were insured under China’s lending programs rose to 55 (excluding the euro area). China’s reserves covered about 15% of this insured pool’s GDP. As Figure 2.8 shows, under the previous conditions, the probability of China failing as LOLR over the next 50 periods rises to 8%. We interpret this result as suggesting that it may not be optimal for China to further expand the number of countries with which it has lending agreements as long as these countries have high positive correlations between themselves and with China.

\[12\] The calibration may be conservative in this regard because it is based on CRRA preferences with a risk aversion of two. This is a standard value in macro models but fails to generate the risk premiums implicit in asset prices.
2.7 Conclusions

This paper studied banking crises and lending of last resort (LOLR) policies in a quantitative model in which banks can default and there is costly-state-verification. LOLR policies are beneficial in crises because they mitigate negative financial accelerators. We solved the model non-linearly to capture the moral hazard induced by the policies. LOLR induces higher banks’ leverage and makes crises more likely. However, LOLR seems beneficial overall.

Then we studied mechanisms to implement LOLR. Pools of small countries do not seem to be feasible lenders of last resort for empirically reasonable levels of liquidity support. They require too many uncorrelated countries, or large contributions to the initial stock of reserves, to be sustainable. However, an economy with a large stock of reserves like China appears to be a sustainable international LOLR. Thus, through the lenses of the model, the recent Chinese initiatives to increase its clout as an international LOLR seem beneficial and long-lasting.

The model is real and has the “liability dollarization” channel surveyed in Mendoza (2016) as debt is denominated in units of tradables and collateral is posted in terms of the nontradable sector. However, the model abstracts from monetary policy and nominal exchanges rates. An interesting avenue for future research is to integrate these nominal factors. We expect the core results to remain but this new framework would allow to study related questions like exposing the LOLR to exchange rate risk.
### 2.8 Tables and Figures

Table 2.1: Parameters

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<th>Exogenously determined</th>
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<td>$\beta$ 0.98</td>
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</tr>
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<td>$\eta$ 2</td>
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<td>$\alpha$ 0.33</td>
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<td>$T_b$ 0.0001</td>
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<td>$\frac{1}{\psi}$ 1.01</td>
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<table>
<thead>
<tr>
<th>Endogenously determined</th>
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<tr>
<td>$\mu$ 0.20</td>
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<td>$\gamma$ 0.915</td>
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<td>$\sigma_l$ 0.18</td>
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<tr>
<td>$\sigma_h$ 0.252</td>
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<td>$\pi_{hh}$ 0.80</td>
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<td>$\psi$ 0.096</td>
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Note: See Section 2.4 for the calibration strategy.
Table 2.2: Model moments and targets

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<tr>
<th>Moment</th>
<th>Model</th>
<th>Target</th>
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<tr>
<td>Banks’ borrowing spread (annual)</td>
<td>4.62%</td>
<td>3% – 7%</td>
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<tr>
<td>Dividend payout rate</td>
<td>8.5%</td>
<td>5% – 10%</td>
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<tr>
<td>Leverage ratio</td>
<td>3.33</td>
<td>3 – 6</td>
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<td>Increase in credit spread during a crisis</td>
<td>4.4 p.p.</td>
<td>4.5 p.p.</td>
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<td>Frequency of a crisis</td>
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<td>4% – 10%</td>
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<td>Duration of a crisis (years)</td>
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<td>1 – 3</td>
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<td>Liquidity support (as % of bank liabilities)</td>
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<td>9.6%</td>
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</tbody>
</table>

Note: See Section 2.4 for details. Percentage points are abbreviated as p.p.
Table 2.3: China’s lending programs

<table>
<thead>
<tr>
<th>Lending programs</th>
<th>(Year of the agreement)</th>
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<tr>
<td></td>
<td>2007 and before</td>
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<td>Angola</td>
<td>Argentina</td>
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<td>Brazil</td>
<td>Equatorial Guinea</td>
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<td>Ghana</td>
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<td>Nigeria</td>
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<td>*Iceland</td>
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<td>*Singapore</td>
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<td>Bahamas</td>
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<td>*Mongolia</td>
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<td>*Kazakhstan</td>
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<td>*New Zealand</td>
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<td>Zimbabwe</td>
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<td>*Australia</td>
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<td>Guyana</td>
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<td>*United Arab Emirates</td>
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<td>2013</td>
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<td>*Albania</td>
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<td>*Euro Area</td>
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<td>*Hungary</td>
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<td>Mexico</td>
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<td>Trinidad and Tobago</td>
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<td>*United Kingdom</td>
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<td>*Tajikistan</td>
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<td>Since 2016</td>
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<td>*Morocco</td>
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<td>*Serbia</td>
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<td></td>
<td>*Egypt</td>
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</table>

Note: Countries with the symbol * only have currency swap agreements. See Appendix C for data sources.
Figure 2.1: No lending of last resort vs lending of last resort: Impulse responses.

Note: This figure reports the responses to an increase in risk. Section 3.5 contains the numerical details, which follow Bianchi (2016).
Figure 2.2: No lending of last resort vs lending of last resort: Average crisis episode.

Note: This figure reports the crises in the economies with and without LOLR. Time 0 denotes the crisis date. The variables are in percent deviations (or in differences) relative to their respective unconditional mean values. Section 3.5 contains the details.
Figure 2.3: No lending of last resort vs lending of last resort: Ergodic distributions of banks’ leverage.

Note: This figure plots the stationary distribution of banks’ leverage (i.e. assets-to-equity ratio) for the economies with and without LOLR.
Figure 2.4: Sustainability of the international lender of last resort. The role of shock correlation and the number of participating countries.

Note: This figure plots the probability that the international LOLR fails for different cross-country correlations of shocks and different number of participating countries. The figure assumes that participating countries pay the participation premium defined in Section 2.3.1. The LOLR starts with no initial reserves. The probability of failure is computed over a 50 years period.
Figure 2.5: Sustainability of the international lender of last resort. The role of the initial level of reserves and the number of participating countries.

Note: This figure plots the probability that the international LOLR fails for different initial levels of reserves and different number of participating countries. Both panels assume that participating countries pay the participation premium defined in Section 2.3.1. The cross-country correlation of the shocks is zero in the top panel and 0.8 in the bottom panel. The probabilities of failure are computed over a 50 years period.
Figure 2.6: China’s foreign exchange reserves.

Data source: People’s Bank of China.
Figure 2.7: Evolution of China’s lending programs

**a) China’s lending program**

- Number of countries (left axis)
- Average correlation with China’s GDP (right axis)

**b) China’s reserves as % of associated countries’ total GDP**

- Without euro area
- With euro area

Note: The top panel plots the number of countries with which China has signed lending agreements, and the average correlation over the 2000-2017 period between China’s GDP and the GDP of the countries with signed agreements at a given date. Section 2.6.2 has more details. The bottom panel plots China’s foreign exchange reserves as % of the total GDP of the countries that have signed lending agreements with China. One line excludes the euro area. For data sources see Appendix C.
Figure 2.8: Probability China would fail as international lender of last resort for different sizes of the insured pool.

Note: This figure plots the probability that the international LOLR fails when the reserves of the LOLR are calibrated to match China’s agreements reported in Figure 2.7, excluding the euro area. Each line plots the probability of failure over different time horizons. Insured countries pay the participation premium defined in Section 2.3.1.
Chapter 3

Banking Crises, Sovereign Risk, and Supranational Deposit Insurance

3.1 Introduction

The link between banking sector instability and domestic sovereign credit risk was at the core of the recent European debt crisis. Figure 3.1 illustrates the comovement between bank and sovereign credit risk (as measured by credit default swap spreads) in selected periphery countries (Ireland, Italy, Portugal and Spain) for the period 2009Q1-2017Q4. Figure 3.2 then shows that actual funding costs for banks and sovereigns also strongly co-move. The common narrative behind these comovements emphasizes the existence of a two-way feedback loop, or ‘doom loop’, in which financial sector distress deteriorates sovereign creditworthiness due to increased bailout costs. In turn, higher sovereign risk weakens the financial sector because banks are exposed to domestic sovereign debt. The economy tanks as a result of the credit crunch, further shrinking the tax base for the government.

A growing body of theoretical and empirical literature emphasizes that the link between banking sector stress and sovereign default risk amplifies financial crises (e.g., Acharya et al. 2014, Brunnermeier et al. 2016, Jorda et al. 2017, Farhi and Tirole 2017, Abad 2018, among others). In the wake of the European debt crisis, severing the doom loop has been at the center of policymakers’ broader agenda to improve financial stability and crisis management. The creation of a Banking Union is a major
component of this agenda. The Banking Union project consists of three pillars, two out of which are already fully operational. The third pillar - a common European deposit insurance fund, however, has not been established yet. Our paper focuses on the role of the supranational deposit insurance in mitigating the negative effects of doom-loops on the economy.

We analyze financial crises in a model in which a bank-sovereign doom loop has quantitatively meaningful effects on macroeconomic dynamics. The calibrated model generates a typical financial crisis that features increased bank funding costs, sovereign spreads, and depressed real economic activity, with the magnitudes comparable to the data from the four Eurozone periphery countries. The common deposit insurance fund brings about sizable economic benefits by weakening the link between banking sector stress and sovereign risk. At the peak of a typical financial crisis the fall in output is about 1 percentage points lower in the economy with the common deposit insurance fund than with the national deposit insurance.

The model has three key ingredients: (i) endogenously financially constrained banks that can default on their debt; (ii) a sovereign that issues long-term default-risky bonds; and (iii) partial deposit insurance. In the model, banks obtain deposits from households which they combine with their own wealth (net worth) to lend to firms and to buy long-term government bonds. Banks are forward-looking and entirely owned by risk-averse agents (i.e., households) so that their portfolio decisions are based on standard risk vs. return tradeoff. Banks are endogenously fragile: They are exposed to

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1 That is, a Single Supervisory Mechanism (SSM) and a Single Resolution Mechanism (SMR). Under the SSM, the European Central Bank (ECB) is the central prudential authority directly supervising the largest banks in the euro area. The purpose of the SRM is to insure an orderly and cost-efficient resolution of failing banks. The Banking Union, however, remains incomplete since it is missing the third pillar - a common European deposit insurance fund (see "What is the banking union", European Commission, available at https://ec.europa.eu/info/business-economy-euro/banking-and-finance/banking-union/what-banking-union_en).
aggregate and idiosyncratic financial shocks, as well as to their own sovereign’s default risk. When banks make large enough losses, they default on their deposits.

We assume that the deposit insurance scheme guarantees only a fraction of bank deposits. This assumption is motivated by the fact that in practice not all deposits are covered by national insurance schemes.\(^2\) Thus, deposits in the model are risky debt, and if banks default their depositors bear some losses. Households anticipate bank failures and factor this default risk into the price of bank deposits ex-ante. These assumptions together with the costly-state-verification friction à la Bernanke et al. (1999) give rise to an endogenous bank funding constraint that will be at the core of the model’s financial accelerator.

We consider two types of deposit insurance schemes: (i) a national deposit insurance (DI) scheme in which the domestic government serves as a fiscal backstop to the insurance fund, and (ii) a supranational deposit insurance fund which collects insurance premiums from participating countries and finances losses incurred by depositors due to bank defaults in the member countries. One of the main results of the paper is that supranational DI scheme makes financial recessions milder by weakening the negative link between banking sector instability and domestic sovereign’s creditworthiness.

To understand the mechanisms behind our results imagine that a banking sector is hit by an adverse financial shock which triggers bank failures.\(^3\) Under the national

\(^2\)Demirguc-Kunt et al. (2015) provide a comprehensive database describing the existing deposit insurance schemes around the world. They find that in most of the cases, deposit insurance schemes cover deposits only up to a limit. In 2010 only about 40% of total deposits were covered by national deposit insurance schemes in the periphery countries. In addition, the experience of Iceland shows that the government can also renege on some part of its deposit insurance liabilities.

\(^3\)In the model, banks are exposed to idiosyncratic asset quality shocks. The aggregate shock that triggers the financial crisis is an increase in the cross-sectional dispersion of the bank idiosyncratic shock. Christiano et al. (2014), Elenev et al. (2016, 2018), Faria-e-Castro (2017), Alfaro et al. (2018), Bloom et al. (2018), among others, study financial crises driven by these shocks.
deposit insurance scheme, the domestic government has to absorb some losses made by banks’ depositors during the financial crisis. We assume that the government finances these costs by issuing more debt.\textsuperscript{4} This additional stock of debt lowers the price of sovereign debt through two channels. First, increased supply of sovereign bonds lowers their equilibrium price \textit{ceteris paribus}. Second, the probability of sovereign default is increasing in the degree of sovereign’s indebtedness. New debt issuance thus increases sovereign risk premiums. Falling sovereign bond prices hurt banking sector net worth by diluting the value of existing sovereign debt on banks’ balance sheets. A resulting reduction in banks’ equity induces even more bank failures and increased bailout costs for the government. In addition, since the credit crunch lowers output in the economy, the tax base shrinks, which further deteriorates the sovereign’s creditworthiness.

Importantly, the debt dilution channel described above operates even if sovereign default does not materialize. This would not be the case, however, if sovereign debt were one-period only.\textsuperscript{5} During the Eurozone crisis, sovereigns in the periphery countries did not default on their debt, but the banking sector still made losses due to their exposures to risky sovereign bonds. Modeling long-term sovereign debt is thus key to capture the negative feedback from sovereign risk to banking sector instability in an empirically realistic way.

Now suppose that the economy has access to a supranational deposit insurance fund that finances the bailout costs. In this scenario, the domestic sovereign does not

\textsuperscript{4}This assumption is especially relevant for EU member countries, because their central banks can not monetize the bailout cost by printing money. The governments of Ireland, Spain, Portugal also raised taxes to finance increased bailout costs. In most of the cases higher taxes were distortionary making financing bailouts costly for the economy. We abstract from distortionary taxation, but the approach we take is consistent with the idea that financing bailouts were costly for the economy.

\textsuperscript{5}The reason is that, if sovereign does not actually default in the current period, then in the case of one-period debt, banks would just obtain the face value of government bonds, and their net worth would not be affected by sovereign default risk.
have to issue additional debt to raise resources for bailouts. As a result, sovereign’s
creditworthiness is intact, and the negative feedback loop from bank failure risk to
sovereign risk is eliminated. While weakening of the bank-sovereign loop has a positive
crisis-mitigation effect, access to a supranational DI fund increases banks’ ex-ante
risk taking incentives. In our model, banks have infinite horizons and use households
stochastic discount factor to value future profit streams. As a result, banks have a
precautionary savings motive. When the economy has access to the supranational DI,
this precautionary motive is weakened and banks take on more leverage.\textsuperscript{6} More highly
leveraged banks are more vulnerable to adverse financial shocks. In our calibrated
model, this effect is quantitatively dominated by weaker doom-loop effect, and the
overall result is that financial recessions become milder under the supranational DI
scheme.

EU policymakers have been actively discussing the design of a common European
DI scheme. That is, under what conditions is a supranational deposit insurance scheme
sustainable? Is the sustainable fund feasible? That is, in case of country asymmetries,
do countries with strong fundamentals participate in the fund?

We use a multi-country extension of the benchmark model to answer these questions.
We obtain two main results: (i) a supranational fund needs to have a certain number of
member countries with strong fundamentals to be sustainable; (ii) a sustainable fund
is feasible if insurance premiums are risk-based. That is, countries with riskier banking
sectors should contribute proportionally more to the fund than safer countries.

These results are related to recent policy proposals on the design of the European
Deposit Insurance Scheme (see, for example, Gros 2014, Gros and Schoenmaker 2015,
Bénassy-Quéré et al. 2018, Carmassi et al. 2018, Schoenmaker 2018), which argue that
\textsuperscript{6}Under the supranational DI scheme sovereign bonds effectively becomes less risky. Banks
increase holdings of both sovereign bonds as well as loans to the firms, leading to higher
leverage ratio.
the premiums must be risk-based to avoid core countries, like Germany, financing the weaker banking systems elsewhere. We confirm that insurance premiums tied to the riskiness of a member country’s financial sector avoids this cross-subsidization without jeopardizing the welfare of the member countries with riskier banks. The intuition for the latter result is that insurance premiums serve like a tax on bank leverage. Since banks in our model have incentives to take excessive risk higher premiums make them internalize, to some extent, the social costs of their borrowing decisions, rendering the economy more financially stable.

The rest of the paper is organized as follows: Section 3.2 discusses the related literature. Section 3.3 describes the model. Section 3.4 discusses the calibration and empirical fit of the model. Section 3.5 analyzes a typical banking crisis in the model vs. data, and quantifies the benefits of supranational DI. Section 3.6 studies the sustainability of a supranational insurance scheme with an application to the European Deposit Insurance Scheme. Section 3.7 concludes. The appendices contain the optimality conditions of the model and the numerical algorithm.

3.2 Related Literature

This paper connects to several strands of the literature. First, it relates to the theoretical literature on the two-way feedback loop between financial sector instability and sovereign credit risk (e.g., Gennaioli et al. 2014, Acharya et al. 2014, Brunnermeier et al 2016, Farhi and Tirole 2017, Leonello 2018). Our model shares several mechanisms with these papers, most notably the adverse link between financial sector distress and sovereign risk. We contribute to this literature by studying the quantitative effects of the bank-sovereign doom loop on macroeconomic dynamics and the supranational deposit insurance fund as a way to deal with its negative effects.
This paper is most closely related to the quantitative literature on sovereign risk and financial sector instability (e.g., Bocola 2016, Abad 2018, Sosa-Padilla 2018, Perez 2018). Bocola (2016) studies the pass-through of sovereign default risk on real economic activity in an estimated model in which banks, modeled in the style of Gertler and Karadi (2011), are exposed to exogenous sovereign default risk. The model abstracts from bank defaults and deposit insurance. Abad (2018) is the first paper that develops a quantitative model in which there is a two-way feedback loop between sovereign risk and bank failure risk. In this environment, he studies bank capital requirements and shows that regulating banks’ sovereign exposures weakens the feedback loop. Our paper instead focuses on supranational deposit insurance as a way to sever the link between financial sector stress and sovereign risk. We also characterize conditions for resilience and feasibility of such a fund. Sosa-Padilla (2018) extends a standard strategic sovereign default model with a banking sector. A sovereign default event triggers a banking crisis that, through credit crunch, contracts the economy. Perez (2018) quantifies the effects of sovereign default on the domestic economy and the government’s ability to provide liquidity to the banking sector. These papers do not have equilibrium bank defaults and government guarantees.

The results of this paper speak to the recent theoretical literature on banking unions. Segura and Vicente (2018) develop a theoretical model where banking union can arise as an optimal risk-sharing arrangement between countries. Abraham et al. (2018) build a calibrated model of European Stability Fund. Both of these papers find

---

While the mechanism behind the two-way feedback is similar, there are several important modelling differences between the two papers. First, in our model, forward-looking banks that have precautionary motives are endogenously financially constrained and their funding costs move non-linearly over the cycle. This is important to generate typical boom-bust crisis episodes that resemble the data. In Abad (2018) one-period lived banks face an exogenous regulatory limit, which is always binding. In addition, our model allows for long-term maturity of sovereign bonds, which we find is important in matching a typical financial crisis episode in the data.
that properly designed risk-sharing arrangements can be welfare-improving for the participating countries. Our results have similar implications: countries can gain from the common deposit insurance fund, as it breaks the vicious cycle of bank-sovereign risk. Risk-based premiums then can insure that no country systematically subsidizes riskier banking systems in other countries.

This paper also shares the endogenous financial accelerator mechanism of seminal papers like Bernanke et al. (1999), Christiano et al. (2014), Gertler and Karadi (2011), among others.

3.3 The Model

We consider an economy with households, banks, capital good producers, final good producers and a government. Households supply labor and save in bank deposits. Banks combine deposits with their own net worth and use the funds to lend to final good producing firms, and to the government. The government issues long-term default-risky debt and raises taxes to finance its spending. Banks can default on their debt and there is a costly state verification friction à la Bernanke et al. (1999). Government insures only a fraction of bank debt (i.e. deposit insurance). The banks thus face endogenous funding cost that depends on the health of their balance sheets. The model is real with consumption serving as numeraire.

3.3.1 Banks

There is a continuum of large number of banks. Banks are special to the economy as all loanable funds have to be intermediated through the banking system. Banks combine their own net worth (retained earnings) with households’ deposits,
which they then use to lend to firms and buy long-term government bonds.\textsuperscript{8} Banks are exposed to both aggregate and idiosyncratic shocks. If a bank is hit by a sufficiently bad idiosyncratic shock, it may be unable to repay its depositors in which case the bank declares bankruptcy.

An individual bank enters a period $t$ with outstanding deposits, $b_t$, claims on firms, $k_t$, and on government, $b^g_t$. Let $Q_t$ be a market price of a unit claim on a representative firm, and $q^g_t$ be the price of a unit of government bond. Similarly, we denote by $R^k_{t+1}$ and $R^g_{t+1}$ the realized time $t+1$ gross payoffs on firms’ loans and government debt, respectively.

After purchasing firms’ securities, banks are hit by idiosyncratic i.i.d. shocks $\omega$, that capture the idea that some banks hold high quality assets while others hold low quality assets. This is consistent with the evidence discussed in Bindseil and Laeven (2017) that banks’ lenders ex-ante do not observe how credit losses are distributed across individual banks because the quality of banks’ assets is opaque. Once an individual banker receives a shock $\omega$, its time $t$ gross return on loans is $\omega R^k_t Q_{t-1} k_t$.

The idiosyncratic shock $\omega$ has a unit-mean log normal distribution with cumulative distribution function $F(\omega, \sigma_t)$, and is subject to aggregate shocks to the volatility parameter $\sigma_t$ as in Christiano et al. (2014) that satisfy

$$\mathbb{E}(\omega) = \mu_t + \frac{\sigma^2_t}{2} = 1, \forall t. \quad (3.1)$$

We use the notation $F_t(\omega)$ to indicate the time-varying nature of the distribution function. Equation (3.1) guarantees that the $\omega$ shocks are redistribution shocks to make banks’ assets unevenly distributed across banks such that some banks cannot repay their borrowings.

\textsuperscript{8}Banks in this model also engage in maturity transformation which is a risky activity: deposits are short-term (one-period) debt, while government bonds and loans to firms are long-term securities.
After the idiosyncratic and aggregate shocks are realized, an individual bank’s gross earnings are given by

\[ n_t = \omega R^k_t Q_{t-1} k_t + R^g_t q^g_{t-1} b^g_t - b_t. \] (3.2)

Banks that are unable to fully repay their depositors default. The default threshold \( \varpi_t \) is given by

\[ \varpi_t R^k_t Q_{t-1} k_t + R^g_t q^g_{t-1} b^g_t = b_t. \] (3.3)

Banks with idiosyncratic shock \( \omega \geq \varpi_t \) repay their debt, and those with \( \omega < \varpi_t \) default. In case of default, the bank exits and lenders seize all its assets after paying bankruptcy cost which is a fraction \( (1 - \mu) \) of the value of the defaulting bank’s assets. The exiting banks are replaced by an equal mass of new banks, starting with some initial funds. If a bank does not default, it has to pay a constant fraction \( (1 - \gamma) \) of its earnings to households in the form of dividends.\(^9\) The remaining fraction of realized earnings is retained as equity capital,

\[ \bar{n}_t = \gamma \left( \omega R^k_t Q_{t-1} k_t + R^g_t q^g_{t-1} b^g_t - b_t \right). \] (3.4)

We assume that a fraction \( \psi \in (0, 1) \) of bank deposits is insured by the government. That is, the government promises depositors a guaranteed return on a fraction \( \psi \) of their savings. In each period banks have to pay a deposit insurance fee which is proportional to the amount of their deposits, \( \kappa b_{t+1} \). An individual bank’s flow-of-funds constraint requires that the sum of the value of loans given to firms and the value of government bonds purchased must be equal to the bank’s retained earnings and the value of deposits net of insurance fee:

\[ Q_t k_{t+1} + q^g_t b^g_{t+1} = \gamma n_t + \left( q_t - \kappa \mathbb{I}_{\{b_{t+1} > 0\}} \right) b_{t+1}. \] (3.5)

\(^9\)This assumption is a common technical device in the financial frictions literature to insure that banks never accumulate enough earnings so that they always stay financially constrained.
Because deposits are not fully insured, the equilibrium price of bank debt will reflect the probability of bank default and associated expected losses on deposits. Banks’ debt is priced by households through their Euler equation,

\begin{equation}
q_t = \mathbb{E}_t m_{t,t+1} \begin{cases}
\psi \frac{\omega}{\text{insured}} + \\
+(1 - \psi) \frac{\omega}{\text{uninsured}}
\end{cases} + \\
\int_{\omega_{t+1}}^{\infty} dF_{t+1}(\omega) + \left(1 - \mu\right) \int_0^{\omega_{t+1}} \left[\omega R_{t+1}^k Q_{t+1} k_{t+1} + R_{t+1}^q q^g b_{t+1}\right] dF_{t+1}(\omega)
\end{equation}

(3.6)

where \( m_{t,t+1} \) is the households’ stochastic discount factor,

\begin{equation}
m_{t,t+1} \equiv \beta u_C(C_{t+1}, L_{t+1}) u_C(C_t, L_t).
\end{equation}

(3.7)

In addition to default risk, the price of bank debt also reflects its hedging properties. That is, since banking crises in the model are the times when households income from other sources is also low, banks will be asked to pay positive risk premium on their debt. Equation (3.6) endogenously limits the amount of assets that banks can buy every period. Like in Bernanke et al. (1999), the endogenous banks’ funding costs linked to the strength of their balance sheets will be at the core of the model dynamics.

We assume that banks are fully owned by households. The bank’s problem, conditional on not defaulting in the current period, is thus to maximize the present discounted value of dividends

\begin{equation}
V_t(n_t) = \max_{b_{t+1}, q^g_{t+1}, k_{t+1}} \left\{ (1 - \gamma) n_t + \mathbb{E}_t \int_{\omega_{t+1}}^{\infty} m_{t,t+1} \max \{0, V_{t+1}(n_{t+1})\} dF_{t+1}(\omega) \right\},
\end{equation}

(3.8)

subject to the balance sheet constraint (3.5), the debt pricing equation (3.6), the evolution of individual net worth (3.2), and the definition of default threshold (3.3).
In the Appendix we show that the bank’s value function is linear in its individual net worth, \( V_t(n_t) = (1 - \gamma + \gamma \Lambda_t) n_t \), where \( \Lambda_t \) can be interpreted as the marginal value of bank net worth.\(^\text{10}\) The linearity of the value function implies that each bank makes decisions that are proportional to its individual net worth. Hence, there is no cross-sectional variation in ratios of each choice variable to net worth, implying that all banks have common default threshold, and face common price of deposits. Therefore, we only need to keep track of aggregate banking-sector variables to characterize the dynamics of our economy.

**Aggregation and credit market clearing.** Let \( f_t(n) \) denote the density of banks with earnings \( n \). The aggregate banking-sector net worth, at time \( t \) is defined as

\[
N_t = \gamma \int_0^\infty n_t df_t(n) \, dn. \tag{3.9}
\]

Banks that default are replaced by an equal mass of new bankers, each receiving small initial set-up transfer \( \frac{T_b}{F_t(\omega_t)} \) from households. Aggregate net worth of the banking sector then evolves according to

\[
N_t = \gamma \int_0^\infty \left( \frac{\omega R^b_t Q_{t-1} K_t + }{\text{return from loans}} + \left[ \pi + (1 - \pi) (\omega + q^b_\omega) \right] B^g_t (1 - d_t \vartheta) - \right. \left. \frac{B_t}{\text{return from sovereign bonds}} + \right. \left. \frac{\omega k_{t+1} d F_t(\omega) + T_b}{\text{repayments}} \right) \, df_t(\omega) \, d\omega. \tag{3.10}
\]

where I imposed the following market clearing conditions for

- **Deposits:** \( B_{t+1} = \int_0^\infty b_{t+1} df_t(n) \, dn \), \( \tag{3.11} \)

- **Government bonds:** \( B^g_{t+1} = \int_0^\infty b^g_{t+1} df_t(n) \, dn \), \( \tag{3.12} \)

- **Firm loans:** \( K_{t+1} = \int_0^\infty \int_0^\infty \omega k_{t+1} d F_t(\omega) \, df_t(n) \, dn \). \( \tag{3.13} \)

Aggregate dividends obtained by households from the banking sector are given by

\[
\Omega_t = \frac{1 - \gamma}{\gamma} \left( N_t - T_b \right). \tag{3.14}
\]

\(^{10}\)This is because the bank’s problem is homogeneous of degree 1 in the level of current earnings.
3.3.2 Households

There is a continuum of homogeneous households who maximize utility over consumption $C_t$ and labor hours, $L_t$. They receive labor income, payments on bank deposits, and dividends from banks and firms. They use these resources to buy consumption goods and bank deposits. Households solve the following optimization problem:

$$\max \{C_t, L_t\} \mathbb{E}_t \sum_{t=0}^{\infty} \beta^t U(C_t, L_t) \tag{3.15}$$

subject to the budget constraint,

$$C_t + q_t B_{t+1} = W_t L_t + q_t B_t + \Omega_t + \Pi_t - T_t - T_b, \tag{3.16}$$

where $W_t$ is the wage per unit of labor, $\Omega_t$ are dividends from banks, $\Pi_t$ are firm profits, and $T_b$ denotes transfers to the new banks. $q_t$ denotes the ex-post realized payoff on a unit of bank deposit,

$$q_t = \psi + (1 - \psi) \left[ \int_{\omega_t}^{\infty} dF_t(\omega) + (1 - \mu) \int_0^{\omega_t} \frac{\omega R_t^k Q_{t-1} K_t + R_t^0 q_{t-1} B_t^0}{B_t} dF_t(\omega) \right]. \tag{3.17}$$

which households take as given. Household’s Euler equation with respect to bank deposits is

$$q_t = \mathbb{E}_t (m_{t+1} q_{t+1}). \tag{3.18}$$

Equation (3.18) says that the price of bank deposits will reflect banks’ expected default risk as well as households attitudes towards risk (i.e. risk premium).

3.3.3 Producers

There are two types of producers in the model: capital good producers and final good producers. The capital good producers build new capital by combining the
depreciated capital and new investment. They solve:

$$\max_{K_{t+1}, I_t} [Q_t K_{t+1} - I_t - Q_t (1 - \delta) K_t],$$  \hspace{1cm} (3.19)$$

subject to

$$K_{t+1} = \Phi \left( \frac{I_t}{K_t} \right) K_t + (1 - \delta) K_t,$$  \hspace{1cm} (3.20)$$

where \( \delta \) is the depreciation rate of capital. \( \Phi \left( \frac{I_t}{K_t} \right) \) captures increasing marginal adjustment costs in the production of capital, where \( \Phi ( \cdot ) \) is increasing and concave, and \( \Phi (0) = 0 \). These adjustment costs insure that price of capital varies over time.

The optimality condition of capital good producers is given by

$$Q_t = \Phi' \left( \frac{I_t}{K_t} \right)^{-1}. \hspace{1cm} (3.21)$$

At the end of period \( t \), a representative final good firm purchases capital \( K_{t+1} \) at price \( Q_t \) from capital producers for use in production in the next period. After production takes place in period \( t + 1 \), the firm sells the depreciated capital back to capital producers. The firm hires labor from households and purchases capital to produce consumption goods according to a Cobb-Douglas technology

$$Y_t = K_t^\alpha L_t^{1-\alpha}, \hspace{1cm} (3.22)$$

Profit maximization implies the following optimality conditions:

$$W_t = (1 - \alpha) \frac{Y_t}{L_t}, \hspace{1cm} (3.23)$$

$$r_t = \alpha \frac{Y_t}{K_t}. \hspace{1cm} (3.24)$$

The final good firms need external finance to purchase capital to be used in production in the next period. As in Gertler and Karadi (2011), we assume that in order to acquire capital the firm has to obtain funds from banks. In particular, the firms issue claims \( S_t \) equal to the number of units of capital purchased \( K_{t+1} \). Each
claim is priced at the price of a unit of capital $Q_t$.\footnote{Here we impose that by arbitrage the price of claims to bankers must be the same as a price of new capital goods.} We assume that there are no financing frictions between firms and banks. The firms in exchange of loans today, promise the bankers the realized return on a unit of capital stock next period,

$$R_{t+1}^k = \frac{r_{t+1} + (1 - \delta) Q_{t+1}}{Q_t}.$$  \hspace{1cm} (3.25)

3.3.4 Government

The formulation of the government sector closely follows Bocola (2016). The government finances its expenditures by issuing long-term bonds to banks and by raising lump-sum taxes from households. In every period a fraction $\pi$ of bonds matures, and the government pays the principal to bondholders. On the non-maturing fraction $(1 - \pi)$ of debt, the government pays the exogenous coupon $\iota$, and the bondholders retain the principal in the future. In every period, the government can default on its debt by imposing a haircut of fraction $\vartheta \in [0, 1]$ on its outstanding liabilities. The realized gross return on a dollar invested in government bonds is

$$R_{t+1}^g = (1 - d_{t+1}) \vartheta \left[ \frac{\pi + (1 - \pi) (\iota + \frac{q_{t+1}^g}{q_t^g})}{q_t^g} \right],$$  \hspace{1cm} (3.26)

where $d_{t+1}$ is an indicator variable equal to 1 if the government defaults in the next period, and to 0 otherwise. The realized return on sovereign debt will vary over time because of sovereign defaults, but also because of the movements in the price of government debt. The latter is an important source of generating quantitatively meaningful effects of sovereign risk-bank balance sheet loop: declining sovereign bond prices will generate capital losses for the banks by lowering the value of existing debt on their balance sheets. The previous channel operates even if the government does not default in a given period.
The budget constraint of the government is given by

\[ q^g_t [B^g_{t+1} - (1 - \pi) B^g_t (1 - d_t \vartheta)] = [\pi + (1 - \pi) t] B^g_t (1 - d_t \vartheta) + \Xi_t + \Xi_t B^g_t (1 - d_t \vartheta) + G_t - T_t - \kappa (B^g_{t+1} > 0) B^g_{t+1}, \]  

where the bailout costs are given by

\[ \Xi_t = \psi \int_0^{\Xi_t} \left( B^g_{t+1} \right) \left( 1 - \mu \right) \left[ \omega R^t K_{t-1} + R^g_t q^g_{t-1} B^g_t \right] \right)^{dF_t (\omega)}. \]  

We assume that government spending is constant, \( G_t = \bar{G} \), and the taxes follow the fiscal rule,

\[ \frac{T_t}{Y_t} = \tau + \tau \frac{B^g_t}{Y_t}. \]  

**Sovereign default.** We need to specify how sovereign default risk evolves over time. We follow Bi (2012) and Abad (2018) in assuming that government default is driven by a stochastic fiscal limit. Denote by \( \kappa_{t+1} \) the sovereign debt-to-output ratio,

\[ \kappa_{t+1} \equiv \frac{B^g_{t+1}}{4Y_t}. \]  

In each period a realized effective fiscal limit \( \kappa^*_t \) is drawn from its distribution \( X^* \). The government defaults in the next period if its outstanding obligations exceed the fiscal limit,

\[ d_{t+1} = \begin{cases} 
1 & \text{if } \kappa_{t+1} \geq \kappa^*_t \\
0 & \text{otherwise} 
\end{cases} \]  

In addition, we assume that the CDF of the fiscal limit follows a standard logistic distribution with parameters \( \xi_1 \) and \( \xi_2 \). The conditional probability of sovereign defaulting in time \( t + 1 \) is then given by

\[ p^d_t = \operatorname{Pr} (d_{t+1} = 1 | \kappa_{t+1}) = \frac{e^{\xi_1 + \xi_2 \frac{\nu^g_{t+1}}{4Y_t}}}{1 + e^{\xi_1 + \xi_2 \frac{\nu^g_{t+1}}{4Y_t}}}. \]
This specification implies that when the government absorbs some losses in banking system in a crisis, the probability of sovereign default rises.\textsuperscript{12}

3.3.5 Some Useful Definitions

We define the leverage of the banking sector as bank assets-to-equity ratio,

\[
lev_t = \frac{Q_t K_{t+1} + q_t^g B_{t+1}^g}{N_t}.
\]  \hfill (3.32)

The bank funding cost is the interest rate on bank deposits,

\[
R_t^d \equiv \frac{1}{q_t}.
\]  \hfill (3.33)

We assume that bankruptcy costs associated with bank failures are deadweight loss to the society,

\[
\Theta_t \equiv \mu \int_0^{\omega t} \left[ \omega R_t^g Q_{t-1} K_t + R_t^g q_{t-1}^g B_t^g \right] dF_t (\omega).
\]  \hfill (3.34)

The consumption good’s market clearing then implies,

\[
Y_t = C_t + I_t + \bar{G} + \Theta_t.
\]  \hfill (3.35)

3.3.6 Aggregate Shocks

We assume that the standard deviation of banks’ idiosyncratic asset quality \((\sigma_t)\) follows a standard two-state, regime-switching Markov process with high and low states, \(\{\sigma_h > \sigma_l\}\).\textsuperscript{13} We refer to states with \(\sigma_l\) as normal times, when domestic

\textsuperscript{12}Even though the model does not feature a benevolent government who behaves strategically when making default decisions (as in Arellano 2008, Chatterjee and Eyigungor 2012), it still captures the key implication of strategic sovereign default models: the probability of sovereign default increases with the stock of outstanding debt.

\textsuperscript{13}Christiano et al. (2010, 2014) refer to these shocks as "risk shocks" and attribute them most of the macro fluctuations in the U.S. and euro area. This type of cross-sectional dispersion shocks have also been extensively used in the more recent macro-finance literature. See, for example, Elenev et al. (2016, 2018), Alfaro et al. (2018), Faria-e-Castro (2017).
banks have regular access to private credit markets. States with $\sigma_h$ are financial stress periods when banks’ access to external financing is impaired and bank defaults are high. The transition probability matrix is

$$P = \begin{bmatrix} p_{hh} & 1 - p_{hh} \\ 1 - p_{ll} & p_{ll} \end{bmatrix},$$  \hspace{1cm} (3.36)

where $p_{hh}$ and $p_{ll}$ denote the probability of remaining in the high and low-risk states, respectively.

### 3.3.7 Supranational Deposit Insurance Fund

We refer to supranational deposit insurance fund as a pool of countries that starts with some initial resources $M_0$ and every period charges participation premiums ($\kappa_i$) to each country in the pool. Assuming that the existing funds earn the risk-free rate of return $R_f$, and that there are $h$ countries paying the participation premium, then the funds of the supranational DI system evolve as

$$M_{t+1} = R_f M_t + \sum_{i=1}^h \kappa_i B_{i,t+1} - \sum_{i=1}^h \Xi_{i,t},$$  \hspace{1cm} (3.37)

where $\Xi_{i,t} \geq 0$ are the losses incurred in country $i$.

When a country has access to the supranational DI, then the terms capturing bailout cost ($\Xi_t$) and insurance premiums ($\kappa B_{t+1}$) drop from equation (3.27) and the domestic government’s budget constraint becomes,

$$q_t^g [B_{t+1}^q - (1 - \pi) B_t^q (1 - d_t \vartheta)] = \left[ \pi + (1 - \pi) \vartheta \right] B_t^q (1 - d_t \vartheta) + G_t - T_t,$$  \hspace{1cm} (3.38)

By looking at (3.38) we can anticipate that the key benefit that the country gets from supranational DI fund is to sever the link between domestic banking sector’s fragility and domestic public finances.
3.4 Calibration

We calibrate the model to quarterly frequency. First, we set some parameters exogenously following standard values in the literature. Then we endogenously select the rest of the parameters to match relevant targets. Tables 3.1 and 3.2 summarize the parameter values and Table 3.3 contains the targets and moments of the model.

We use GHH preferences to avoid wealth effects on labor supply,

\[ u(C_t, L_t) = \frac{1}{1 - \eta} \left( C_t - \theta \frac{L_t^{1 + \frac{1}{\chi}}}{1 + \frac{1}{\chi}} \right)^{1-\eta}, \]

where \( \chi \) is the elasticity of labor supply and \( \eta \) controls the curvature of the utility function. We choose the value of \( \theta \) so that the long-run mean of hours worked equals \( \frac{1}{3} \).

We assign standard values to the subjective discount factor \( (\beta = 0.99) \), the elasticity of labor supply \( (\chi = 1.5) \), the risk-aversion parameter \( (\eta = 2) \), capital share in production \( (\alpha = 0.33) \), depreciation rate of capital \( (\delta = 0.025) \), the annualized risk-free interest rate of 3.2\% \( (R^f = 1.008) \). We set transfers to banks to be a very small positive number \( (T_b = 10^{-4}) \). These transfers are a technical device to insure a non-zero equity of the banking sector and do not affect the quantitative results. The fraction of earnings retained by banks is set to a value standard in the financial frictions literature \( (\gamma = 0.92) \).

For the parameters pertaining to government long-term debt, we rely on estimates for duration and coupon payments of European sovereign bonds provided by Bocola (2016) and Bi and Traum (2012). We set the fraction of sovereign bonds maturing in a given period, \( \pi \), to 0.057, implying the average maturity of about 4.4 years. We set \( \iota = 0.02 \), corresponding to an annual coupon rate of 8 percent. The haircut parameter \( \vartheta \) is set to 0.35. This in the range of the values estimated by Bocola (2016) and by
Bi (2012). We set exogenous insurance premium $\kappa$ to 0.001, which corresponds to an average premium in the Eurozone periphery countries (Demirguc-Kunt et al. 2015).

Next, we endogenously choose the values for the remaining parameters to target the relevant empirical targets. We set $\mu$ to 0.30, $\sigma_l$ to 0.22, implying an annualized bank funding cost of about 2.35%, and average leverage ratio of 3.53. In the data, an average deposit interest rate in the periphery countries is 2.46%, and an average leverage ratio is about 5. We choose the value of $\sigma_h$ so that during a crisis bank funding costs in the model economy is about the same as in the data. We set capital adjustment cost parameter $\varphi = 6.72$ so that investment is about 3 times more volatile than output.

We calibrate the transition probabilities of the financial risk process so that the frequency and average duration of banking crises in the doom loop economy is like in the empirical literature. We define a crisis as an event when bank funding cost is above 2 standard deviations from its long-run mean. This definition is consistent with Laeven and Valencia (2013) and Jorda et al. (2016) definitions of financial crises. As we will discuss later, model dynamics of key macro aggregates in the average crisis episode closely replicates their empirical counterparts. We set $\pi_{ll}$ to 0.97 and $\pi_{hh}$ to 0.80, which imply a frequency of banking crises of 4 percent, and an average duration of a crisis of about 1.6 years. These values are in the range estimated by Jorda et al. (2016), Laeven and Valencia (2013), and Reinhart and Rogoff (2009).

Parameters governing fiscal policy are calibrated to match standard targets: government spending-to-GDP ratio of 0.25, tax revenues-to-GDP ratio of 0.25 and sovereign debt-to-GDP ratio of 0.50. The parameter values implied by these targets are $\overline{G} = 0.22$, $\tau = 0.23$, $\tau_{B_g} = 0.046$. We set $\xi_1 = -6.7$, and $\xi_2 = 7.2$, which imply that the annualized long-run sovereign default probability of 0.16%, and that in a crisis sovereign default probability rises by about 2.5 percentage points, consistent with the empirical evidence
in Bi and Traum (2012) and Bocola (2016). Finally, we set the deposit insurance parameter $\psi$ to 0.40 so that the economy directly matches the average share of covered deposits in total deposits in the periphery countries (Demirguc-Kunt et al. 2015).

We solve the model globally using the policy function iteration algorithm developed by Coleman (1990). Appendix B describes the numerical algorithm in detail.

3.5 Quantitative Results

**Impulse responses.** Figure 3.3 plots impulse responses to study how the economies with national and supranational DI schemes react to a financial shock. We follow the methodology of Bianchi (2016) in constructing the non-linear impulse response functions.\footnote{We set the initial levels of the endogenous state variables in each economy at their corresponding unconditional mean values. We then simulate the shock process of length 15 periods for 100,000 times and feed them into the policy functions to produce 100,000 paths for the endogenous variables. For each economy we compute the average differences of the variables of interest between the paths that start with $\sigma_h$ and those that start with $\sigma_l$. We assume that sovereign default does not materialize along these simulated paths.} In all the panels, the solid line corresponds to the benchmark model-economy with the national DI, and the dashed line refers to the economy with supranational DI, that is, when the domestic government’s budget constraint is given by (3.38).

An adverse financial shock increases the probability of bank defaults and since deposits are risky, households price it with higher interest rate (lower $q_t$). As a result of the higher funding costs, banks give out fewer loans to final good producing firms. The firms demand less capital and price of capital falls. Falling capital prices deteriorate banks’ balance sheets and reduce their net worth, pushing some banks into insolvency.

The increased bank failure rate pushes up bailout costs. Under the national DI scheme, the domestic government finances these costs by issuing additional bonds which lowers the price of sovereign debt through two channels. First, increased supply
of sovereign bonds lowers their equilibrium price *ceteris paribus*. Second, the probability of sovereign default is increasing in the degree of sovereign’s indebtedness. New debt issuance thus increases sovereign risk premium. Falling sovereign bond prices hurt banking sector net worth even further by diluting the value of existing sovereign debt on banks’ balance sheets. The weaker financial sector, in turn, induces higher bailout cost for the domestic government and the loop continues. In addition, since the credit crunch lowers output in the economy, the tax base shrinks, which further imperils public finances and deteriorates the sovereign’s creditworthiness.

Quantitatively, this mechanism generates a deep slowdown in real economic activity: Banking sector net worth falls by around 40 percent on impact in response to a financial shock. Banks’ impaired balance sheets translate into lower investment, because firms now obtain fewer and more expensive loans to purchase capital goods. On impact investment falls by about 30 percent. At the peak, output is 3 percent lower relative to its steady state value. The fall in output is driven by lower employment and capital stock in the subsequent period.¹⁵

Figure 3.3 illustrates the effect of supranational DI that weakens the link between banking sector stress and domestic public finances. The economy that has access to the supranational DI fund experiences a milder financial recession. The fall in bank equity, investment and output are much smaller compared to the benchmark scenario. This is because when bank insolvencies rise due to an adverse financial shock, the domestic government’s debt burden does not rise, since the country has access to common insurance pool. In fact, government debt falls on impact, because banks reduce their holdings of both firm loans as well as sovereign debt. As a result, sovereign spreads fall.

¹⁵Notice that on impact output does not respond because of GHH preferences that eliminate wealth effect on labor supply. Employment falls in the next period because lower capital implies lower marginal product of labor and wages.
**Crisis analysis.** To study how a typical banking crisis looks like in the model economy we analyze an average crisis episode using the methodology of Bianchi (2016) and Akinci and Queralto (2017).\(^{16}\) We define a systemic banking crisis as an event when bank funding cost rises by more than 2 standard deviations above its mean. In the data, crisis date is defined as a quarter in which bank funding costs peaked within the systemic banking crises episodes identified in Laeven and Valencia (2012). The event windows are then centered around these crisis dates, denoted by time 0 on the graphs.

Figure 3.4 plots the resulting event-windows centered around crisis episodes. Several results stand out: The benchmark model is successful at replicating an average crisis scenario in the selected periphery countries. Like in the data, during the crisis episode bank funding costs and sovereign spreads rise while output falls. The magnitudes are comparable to the data.

Figure 3.3 showed that supranational DI is effective at mitigating the negative effects of a financial shock. However, since the initial values of the endogenous state variables are fixed in the impulse response exercise, Figure 3.3 does fully capture the effects supranational DI on the crisis dynamics. For example, Figure 3.5 shows that under the supranational DI, banks take on more leverage which may make them more vulnerable to negative financial shocks. In order to take this effect into account, Figure 3.6 compares average crisis episodes in the economies with supranational and national DI (i.e. the benchmark model). Figure 3.6 illustrates that despite higher leverage, a typical financial crisis in the economy with access to supranational DI is milder. This

\(^{16}\)That is, we simulate the model-economies for 100,000 periods, discarding the first 5000 periods as burn-in. Then, we identify banking crises, but we drop the periods for which sovereign default actually occurs. We center the remaining crisis episodes at date 0, and take 5 periods before and 10 periods after each crisis date. We compute averages for each variable across the entire set of the crises and associated time windows.
is because the crisis-mitigation effect that results from weakening the negative link between banking sector instability and sovereign risk is stronger.

Interestingly, in the run-up to the crisis, the deviation of output from its long-run mean is higher in the economy with supranational DI scheme. This is because, under this latter scheme banks lever up by more when the economy experiences favorable sequence of financial shocks.

3.6 SUSTAINABILITY AND FEASIBILITY OF A SUPRANATIONAL DEPOSIT INSURANCE SCHEME

This section analyzes the sustainability of a supranational deposit insurance fund that starts with some initial resources, and charges an insurance premium every period to each country in the pool. We compare different cross-country correlations of the banking crises, different number of participating countries, and different initial levels of funds. Then we study how country asymmetries affect the design of sustainability and feasibility of the supranational scheme.

3.6.1 PROBABILITY OF FAILURE OF A SUPRANATIONAL DEPOSIT INSURANCE SCHEME

Figures 3.7 and 3.8 analyze the probability of failure of the supranational DIS for different cases. In all of them the analysis is based on the benchmark calibration and a horizon of 50 years. The supranational DI fund fails when $M_t < 0$ in equation (3.37). In that case the disbursements due to the countries in crisis are larger than the sum of the inflows from new insurance premiums and the existing resources.

Figure 3.7 focuses on the case when the initial level of resources is zero, and each country pays common insurance fee $\kappa = 0.001$. Figure 3.7 has two main results: 1)
Without initial funds, for the benchmark insurance fee, the supranational insurance fund is unlikely to be sustainable. For example, even with 30 uncorrelated countries the probability of failure of the fund is around 35%. 2) If the shocks are correlated then adding new countries does not help to reduce the probability of failure.

Figure 3.8 plots the case when the fund starts with some initial resources and in addition countries pay common insurance premiums. For comparison, the targeted fund size for the EDIS is 0.8% of total covered deposits in the EU. There are several results to highlight: 1) For realistic calibrations of an initial fund size, the supranational scheme is very likely to fail if cross-country correlation of financial shocks is not zero (bottom panel). This is because for correlated cross-country shocks there are no gains from risk-sharing. 2) If the shocks are uncorrelated across countries (top panel), then common insurance fund is likely to be sustainable if the number of participating countries and the initial fund size are large enough. For example, the probability that a fund with 30 uncorrelated countries and initial size of 1.5% of total insured deposits fails within the next 50 years is around 5%. However, this is an empirically unrealistic scenario, because financial shocks are usually very contagious across countries, especially so in the EU. For example, the Eurozone countries have cross-country average correlation of detrended output of about 0.5.

So far we have only considered forming the supranational insurance fund with economies that are very vulnerable to financial crises (i.e. benchmark calibration). In practice, some countries in the Eurozone have much stronger fundamentals and do not experience severe crises. I next consider how different compositions of the member countries affect the sustainability of the fund.

We refer to the benchmark country as ‘weak’ country. We define a country with strong fundamentals or a ‘strong’ country for short, whose high value of risk shock is 50% lower than that of a weak country. That is, $\sigma_h^s = 0.233$. We keep $\sigma_f^s$ the same
as for the weak country, $\sigma^*_t = \sigma_t = 0.22$. Figure 3.9 contains the results for different compositions of the fund. It shows that as the number of strong member countries increases, the sustainability prospects for the fund improve. For example, with 15 strong countries in the fund, the probability of fund failing falls to 5% when the initial fund size is 0.8% of total insured deposits.

3.6.2 Feasibility of a Supranational Deposit Insurance Scheme

The next question is whether a sustainable fund is feasible. That is, under what conditions do all countries participate in the fund? Figure 3.9 assumed that all countries in the fund pay the common insurance fee $\kappa = 0.001$. Section 3.5 shows that 'weak' countries benefit from this arrangement. However, under common insurance premiums a country with strong fundamentals (i.e., that experiences much milder financial crises) on average, provides net transfers equal to 0.6 percent of its GDP to the fund in every period. This type of arrangement is thus welfare reducing for strong countries.\(^1\)

We illustrate, by example, that properly designed risk-based insurance premiums can achieve a sustainable and feasible common insurance arrangement without even jeopardizing the welfare of weak countries. First, we lower the premium for the strong countries, so that they are indifferent between participating and not participating in the supranational DIS.\(^2\) In addition, we increase the premium for the ‘weaker’ countries

\(^{17}\)Our metric of welfare is unconditional mean of household’s value function:

$$W = \mathbb{E} \sum_{t=0}^{\infty} \beta^t \left[ \frac{1}{1-\eta} \left( C_t - \theta \frac{(L_t)^{1+x}}{1 + \frac{1}{x}} \right)^{1-\eta} \right].$$

\(^{18}\)The premium of $\kappa^s = 0.0004$ achieves this goal.
to $\kappa^w = 0.002$. Figure 3.10 shows that the sustainability of a fund remains unchanged, even slightly improving, because ‘weaker’ countries are now paying proportionally higher premiums.

Table 3.4 shows that an increase in the premium does not lower a ‘weak’ country’s welfare. The intuition for this result is as follows. Insurance premiums serve like a tax on bank leverage. Banks in this model have incentives to take excessive risk because of government guarantees. Higher premiums then make banks internalize, to some extent, the social costs of their borrowing decisions, rendering the economy more financially stable. As Table 3.4 shows, the average capital stock and output fall as a result of higher insurance fee, because banks lower their leverage. For this latter reason bank default rates and therefore, deadweight losses associated with bank defaults also fall, leaving household’s consumption almost unaffected.

3.7 Conclusions

This chapter studied a quantitative model of financial crises in which a bank-sovereign doom loop plays quantitatively important role in driving macroeconomic dynamics. Then we analyzed a mechanism to weaken the doom loop: countries can form a common deposit insurance fund to decouple their national public finances from the health of domestic banking systems. We used the model and numerical simulations to characterize the conditions for resilience and feasibility of such a supranational fund. Risk-based contributions to the fund help achieve feasibility when country asymmetries are large.
### 3.8 Tables and Figures

Table 3.1: Exogenously set parameters

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<tr>
<th>Description</th>
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<th>Value</th>
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</tr>
<tr>
<td>Coupon payments</td>
<td>$\iota$</td>
<td>0.02</td>
</tr>
<tr>
<td>Risk free rate</td>
<td>$R_f$</td>
<td>1.008</td>
</tr>
</tbody>
</table>

Note: See Section 3.4 for the calibration strategy.
Table 3.2: Endogenously calibrated parameters

<table>
<thead>
<tr>
<th>Description</th>
<th>Symbol</th>
<th>Value</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labor disutility</td>
<td>( \theta )</td>
<td>3.14</td>
<td>Labor hours</td>
</tr>
<tr>
<td>Bankruptcy cost</td>
<td>( \mu )</td>
<td>0.30</td>
<td>Bank lev.&amp;funding cost</td>
</tr>
<tr>
<td>Low risk</td>
<td>( \sigma_l )</td>
<td>0.22</td>
<td>Bank lev.&amp;funding cost</td>
</tr>
<tr>
<td>High risk</td>
<td>( \sigma_h )</td>
<td>0.35</td>
<td>Funding cost in a crisis</td>
</tr>
<tr>
<td>Prob. of staying in ( \sigma_l )</td>
<td>( p_{ll} )</td>
<td>0.97</td>
<td>Freq.&amp;duration of a crisis</td>
</tr>
<tr>
<td>Prob. of staying in ( \sigma_h )</td>
<td>( p_{hh} )</td>
<td>0.80</td>
<td>Freq.&amp;duration of a crisis</td>
</tr>
<tr>
<td>Capital adj. cost</td>
<td>( \varphi )</td>
<td>6.72</td>
<td>( sd(I)/sd(Y) )</td>
</tr>
<tr>
<td>Tax rule param.</td>
<td>( \tau )</td>
<td>0.23</td>
<td>Tax revenues-to-GDP</td>
</tr>
<tr>
<td>Tax rule param. ( \tau_{Bg} )</td>
<td></td>
<td>0.046</td>
<td>Sov. debt-to-GDP</td>
</tr>
<tr>
<td>Gov. spending</td>
<td>( \bar{G} )</td>
<td>0.22</td>
<td>Gov. spending-to-GDP</td>
</tr>
<tr>
<td>Share of insured deposits</td>
<td>( \psi )</td>
<td>0.40</td>
<td>Share of covered deposits</td>
</tr>
<tr>
<td>Gov. default risk param.</td>
<td>( \xi_1 )</td>
<td>-6.7</td>
<td>Prob. of sovereign default</td>
</tr>
<tr>
<td>Gov. default param.</td>
<td>( \xi_2 )</td>
<td>7.2</td>
<td>Sov. default prob. in a crisis</td>
</tr>
</tbody>
</table>

Note: See Section 3.4 for the calibration strategy.
Table 3.3: Model moments and targets

<table>
<thead>
<tr>
<th>Moment</th>
<th>Model</th>
<th>Target</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labor hours</td>
<td>0.33</td>
<td>0.33</td>
</tr>
<tr>
<td>Bank leverage</td>
<td>3.53</td>
<td>3 – 8</td>
</tr>
<tr>
<td>Deposit interest rate (annual)</td>
<td>2.35%</td>
<td>2.46%</td>
</tr>
<tr>
<td>Prob. of a crisis</td>
<td>4%</td>
<td>2 – 8%</td>
</tr>
<tr>
<td>Duration of a crisis (years)</td>
<td>1.6</td>
<td>1 – 3</td>
</tr>
<tr>
<td>sd.(I)/sd.(Y)</td>
<td>3.2</td>
<td>3.4</td>
</tr>
<tr>
<td>Tax revenues-to-GDP</td>
<td>0.26</td>
<td>0.25</td>
</tr>
<tr>
<td>Sov. debt-to-GDP</td>
<td>0.48</td>
<td>0.5</td>
</tr>
<tr>
<td>Gov. spending-to-GDP</td>
<td>0.25</td>
<td>0.25</td>
</tr>
<tr>
<td>Share of guaranteed deposits</td>
<td>0.40</td>
<td>0.40</td>
</tr>
<tr>
<td>Long-run prob. of sov. default</td>
<td>0.16%</td>
<td>0.19%</td>
</tr>
</tbody>
</table>

Note: See Section 3.4 for details. Percentage points are abbreviated as p.p.
Table 3.4: The effects of risk-based premiums

<table>
<thead>
<tr>
<th></th>
<th>$\kappa^w = 0.001$</th>
<th>$\kappa^w = 0.002$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(% change)</td>
<td></td>
</tr>
<tr>
<td>Capital</td>
<td>6.264</td>
<td>-2.4%</td>
</tr>
<tr>
<td>Output</td>
<td>0.856</td>
<td>-0.78%</td>
</tr>
<tr>
<td>DWL</td>
<td>0.017</td>
<td>-26%</td>
</tr>
<tr>
<td>Consumption</td>
<td>0.452</td>
<td>-0.001%</td>
</tr>
<tr>
<td>Welfare (% CE)</td>
<td>0.000%</td>
<td></td>
</tr>
</tbody>
</table>

Note: This table shows the effect of higher insurance fee charged to a ‘weak’ country. The second column reports percent changes relative to the benchmark scenario, $\kappa^w = 0.001$. See Section 3.6.2 for the details.
Figure 3.1: Bank and sovereign credit default swap spreads.

Note: This figure plots bank (left axis) and sovereign (right axis) 5-year credit default swap spreads in the selected EU periphery countries. Quarterly CDS spreads are obtained by averaging daily CDS. Source: Datastream.
Figure 3.2: Funding costs for banks and sovereigns.

Note: This figure plots the interest rate on bank deposits (new businesses) (left axis) and sovereign bond spreads (right axis) in the selected EU periphery countries. Sovereign spreads are the difference between the yields of 10-year sovereign bonds in a given country and Germany. Source: ECB Statistical Data Warehouse and Datastream.
Figure 3.3: Impulse responses.

Note: This figure reports the responses to a financial shock (risk shock) in the benchmark model with national DI, and in the model with supranational DI. Each panel plots the deviations between the simulated path that starts with $\sigma_h$ relative to the simulated path that starts with $\sigma_l$. 3.4 contains the numerical details, which follow Bianchi (2016).
Figure 3.4: Crisis episodes: Model vs data.

Note: This figure reports the average crisis episode in the benchmark model-economy and in the data. Deviations in the model variables are from their respective unconditional mean values. In the data, output series is HP-detrended, and the deviation is from the HP-trend. The data is average of four periphery countries (Ireland, Italy, Portugal, Spain). Time 0 denotes the crisis date. Section 3.5 contains the details.
Figure 3.5: Ergodic distributions of bank leverage.

Note: This figure plots the stationary distribution of banks’ leverage (i.e. assets-to-equity ratio) for the economies with national and supranational DI.
Figure 3.6: The effects of supranational deposit insurance.

Note: This figure plots output dynamics around an average crisis episode in the model-economies with national and supranational DI, and in the data. Deviations in the model variables are from their respective unconditional mean values. In the data, output series is HP-detrended, and the deviation is from the HP-trend. The data is average of four periphery countries (Ireland, Italy, Portugal, Spain). Time 0 denotes the crisis date. Section 3.5 contains the details.
Figure 3.7: Sustainability of the supranational deposit insurance fund. The role of shock correlation and the number of participating countries.

Note: This figure plots the probability that the supranational DIS fails for different cross-country correlations of shocks and different number of participating countries. The figure assumes that all participating countries pay the common fee defined in 3.4. The DIS starts with no initial funds. The probability of failure is computed over a 50 years period.
Figure 3.8: Sustainability of the supranational deposit insurance fund. The role of the initial fund size and the number of participating countries.

Note: This figure plots the probability that the supranational DIS fails for different initial fund size and different number of participating countries. Both panels assume that participating countries pay common insurance premium. The cross-country correlation of the shocks is zero in the top panel and 0.5 in the bottom panel. The probabilities of failure are computed over a 50 years period.
Figure 3.9: Sustainability of the supranational deposit insurance fund. The role of composition of member countries.

Note: This figure plots the probability that the supranational DIS fails for different country compositions (i.e. number of ‘weak’ vs ‘strong’ countries). All countries pay common insurance premium. The cross-country correlation of the shocks is 0.5. The probabilities of failure are computed over a 50 years period.
Figure 3.10: Sustainability of the supranational deposit insurance fund. The role of risk-based premiums.

Note: This figure plots the probability that the supranational DIS fails in the case of risk-based premiums. The number of participating countries is 30, with 15 ‘strong’ and 15 ‘weak’ countries. The cross-country correlation of the shocks is 0.5. The probabilities of failure are computed over a 50 years period.
Figure 3.11: Policy functions.

Note: This figure plots selected policy functions against current period capital, $K$, and bank debt, $B$. Sovereign debt is set at its stochastic steady-state value. The functions are plotted for low risk state, $\sigma = \sigma_l$, and no current sovereign default state, $d = 0$. The figure illustrates non-linearities in the policy functions.
Figure 3.12: Crises windows in the data

Note: This figure reports time series of selected variables around a crisis episode. Time 0 denotes the crisis date. Output series is HP-detrended, and the deviation is from the HP-trend. Data sources: OECD Quarterly National Accounts; ECB Statistical Data Warehouse.
Appendix A

Banking Crises, Sovereign Risk, and Supranational Deposit Insurance

A.1 Derivation of Optimality Conditions

A.1.1 Banks

Denote by $b_{k,t}$ and $b_{k,t}^g$ bank deposits-to-capital and sovereign bond holdings-to-capital ratios,

$$b_{k,t} \equiv \frac{b_t}{k_t}, \quad b_{k,t}^g \equiv \frac{b_t^g}{k_t}.$$  \hfill (A.1)

Using the above definitions I rewrite the expression for realized earnings,

$$n_{t+1} = (\omega R_{t+1}^k Q_t + R_{t+1}^g q_{t+1}^g b_{k,t+1}^g - b_{k,t+1}) k_{t+1},$$  \hfill (A.2)

bank funding constraint,

$$k_{t+1} \left[ Q_t + q_{t+1}^g b_{k,t+1}^g - (q_t - \kappa) b_{k,t+1} \right] = \gamma n_t,$$  \hfill (A.3)

default threshold,

$$\overline{\omega}_{t+1} = \frac{b_{k,t+1} - R_{t+1}^g q_{t+1}^g b_{k,t+1}^g}{R_{t+1}^k Q_t},$$  \hfill (A.4)

and bank debt pricing equation,

$$q_t = \mathbb{E}_t m_{t,t+1} \left\{ \psi + (1 - \psi) \left( \int_{\overline{\omega}_{t+1}}^{\infty} dF_{t+1} (\omega) + (1 - \mu) \int_{0}^{\overline{\omega}_{t+1}} \frac{\omega R_{t+1}^k Q_t + R_{t+1}^g q_{t+1}^g b_{k,t+1}^g}{b_{k,t+1}} dF_{t+1} (\omega) \right) \right\}$$  \hfill (A.5)
Conjecture that the value function is linear in bank’s earnings,

\[ V_t(n_t) = v_t n_t. \] (A.6)

Using conjecture (A.6) and definition (A.1), we can rewrite the bank’s problem as

\[
\max_{b_{k,t+1},i_{k,t+1},r_{k,t+1}} \left\{ \begin{array}{l}
(1 - \gamma) n_t + \\
+ E_t \left[ m_{t,t+1} v_{t+1} + \int_{\omega_{t+1}}^{\infty} \left( \omega R_{t+1}^k Q_t + R_{t+1}^q q_t^q b_{k,t+1}^q - b_{k,t+1} \right) k_{t+1} dF_{t+1}(\omega) \right] \end{array} \right.
\]

subject to (A.3), (A.4), and (A.5). The Lagrangian for this problem is:

\[
L_t = (1 - \gamma) n_t + \\
+ E_t \left\{ m_{t,t+1} \int_{\omega_{t+1}}^{\infty} v_{t+1} \left( \omega R_{t+1}^k Q_t + R_{t+1}^q q_t^q b_{k,t+1}^q - b_{k,t+1} \right) k_{t+1} dF_{t+1}(\omega) \right\} + \\
+ \Lambda_t \left\{ \gamma n_t - k_{t+1} \left[ Q_t + q_t^q b_{k,t+1}^q - (q_t - \kappa) b_{k,t+1} \right] \right\},
\]

with \( q_t \) and \( \omega_{t+1} \) given by (A.4) and (A.5).

FOC with respect to \( k_{t+1} \):

\[
\Lambda_t \left[ Q_t + q_t^q b_{k,t+1}^q - (q_t - \kappa) b_{k,t+1} \right] = \mathbb{E} \left\{ m_{t,t+1} \int_{\omega_{t+1}}^{\infty} v_{t+1} \left( \omega R_{t+1}^k Q_t + R_{t+1}^q q_t^q b_{k,t+1}^q - b_{k,t+1} \right) dF_{t+1}(\omega) \right\}. 
\] (A.7)

FOC with respect to \( b_{k,t+1} \):

\[
\Lambda_t \left( q_t - \kappa + \frac{\partial q_t}{\partial b_{k,t+1}} b_{k,t+1} \right) = \mathbb{E} \left\{ m_{t,t+1} v_{t+1} \left[ 1 - F(\omega_{t+1}) \right] \right\}. \] (A.8)

FOC with respect to \( b_{k,t+1}^q \):

\[
\Lambda_t q_t^q = \mathbb{E} \left\{ m_{t,t+1} v_{t+1} \left[ 1 - F(\omega_{t+1}) \right] R_{t+1}^q q_t^q \right\} + \Lambda_t \frac{\partial q_t}{\partial b_{k,t+1}^q} b_{k,t+1}. \] (A.9)

Using (A.7) and (A.3) we can rewrite the value function as

\[
V_t(n_t) = (1 - \gamma) n_t + \Lambda_t \left[ Q_t + q_t^q b_{k,t+1}^q - (q_t - \kappa) b_{k,t+1} \right] k_{t+1}
\]

\[
= (1 - \gamma) n_t + \Lambda_t n_t = [(1 - \gamma) + \gamma \Lambda_t] n_t. \] (A.10)
This verifies our initial conjecture that value function is linear in net worth,

$$v_t = (1 - \gamma) + \gamma \Lambda_t.$$  \hfill (A.11)

It is convenient to denote the partial expectation of $\omega$ by

$$G_t(\omega_t) \equiv \int_0^\omega_t \omega dF_t(\omega).$$  \hfill (A.12)

At this stage we need to compute partial derivatives of debt pricing equation that appear in FOCs (A.8) and (A.9). We have,

$$\frac{\partial q_t}{\partial b_{k,t+1}} = -\mathbb{E}_t m_{t,t+1} (1 - \psi) \left\{ \mu F'(\omega_{t+1}) \frac{1}{b_{k,t+1}} + F(\omega_{t+1}) \frac{R_{k,t+1} q_{t+1}^g}{b_{k,t+1}^g} + (1 - \mu) G(\omega_{t+1}) \frac{R_{k,t+1} Q_t}{b_{k,t+1}^g} \right\},$$  \hfill (A.13)

and

$$\frac{\partial q_t}{\partial b_{k,t+1}^g} = \mathbb{E}_t \left\{ m_{t,t+1} (1 - \psi) \frac{R_{k,t+1} q_{t+1}^g}{b_{k,t+1}^g} \left[ F(\omega_{t+1}) + \mu G'(\omega_{t+1}) \right] \right\}.$$  \hfill (A.14)

The FOCs then become:

$$\Lambda_t \left[ Q_t + q_t^g b_{k,t+1}^g - (q_t - \kappa) b_{k,t+1} \right] =$$

$$= \mathbb{E}_t \left\{ m_{t,t+1} [(1 - \gamma) + \gamma \Lambda_{t+1}] [1 - G_{t+1}(\omega_{t+1})] - [1 - F_{t+1}(\omega_{t+1})] \omega_{t+1} \right\} R_{k,t+1} Q_t \right\},$$  \hfill (A.15)

$$\Lambda_t = \frac{\mathbb{E}_t \left\{ m_{t,t+1} [(1 - \gamma) + \gamma \Lambda_{t+1}] [1 - F(\omega_{t+1})] \right\}}{\mathbb{E}_t \left\{ m_{t,t+1} (\psi + (1 - \psi) [1 - F(\omega_{t+1})] - \mu G'(\omega_{t+1}) - \kappa) \right\}},$$  \hfill (A.16)

$$\Lambda_t q_t^g = \mathbb{E}_t \left\{ m_{t,t+1} [(1 - \gamma) + \gamma \Lambda_{t+1}] [1 - F(\omega_{t+1})] (1 - d_{t+1} \vartheta) \right\} +$$

$$+ \Lambda_t \mathbb{E}_t \left\{ m_{t,t+1} (1 - \psi) q_t^g R_{k,t+1}^g \left[ F(\omega_{t+1}) + \mu G'(\omega_{t+1}) \right] \right\}.$$  \hfill (A.17)

### A.1.2 Capital producers

Capital producers solve:

$$\max_{K_{t+1}, I_t} [Q_t K_{t+1} - I_t - (1 - \delta) Q_t I_t],$$  \hfill (A.18)
subject to

\[ K_{t+1} = (1 - \delta)K_t + I_t - \frac{\varphi}{2} \left( \frac{K_{t+1} - (1 - \delta)K_t}{K_t} - \delta \right)^2 K_t. \]  

(A.19)

The FOC implies:

\[ Q_t = \varphi \left( \frac{K_{t+1} - (1 - \delta)K_t}{K_t} - \delta \right) + 1. \]  

(A.20)

### A.1.3 Firms producing final goods

The firm’s optimality conditions with respect to capital and labor are standard:

\[ r_t = \alpha K_t^{1 - \alpha} L_t^{\alpha - 1}, \]  

(A.21)

\[ W_t = (1 - \alpha) K_t^{\alpha - \alpha}. \]  

(A.22)

### A.1.4 Households

The household’s optimality conditions are standard. Euler equation with respect to bank deposits is

\[ q_t = \mathbb{E}_t \left( m_{t,t+1} \varrho_{t+1} \right). \]  

(A.23)

where

\[ \varrho_t = \psi + (1 - \psi) \left[ \int_{\bar{\omega}}^{\infty} dF_t(\omega) + (1 - \mu) \int_0^{\bar{\omega}} \frac{\omega R_t K_{t-1} + R_t q_{t-1} B_t}{B_t} dF_t(\omega) \right]. \]  

(A.24)

Labor choice decision is characterized by the following FOC,

\[ W_t = -\frac{U_L(C_t, L_t)}{U_C(C_t, L_t)}. \]  

(A.25)

With GHH preferences, equation (A.25) becomes

\[ W_t = \theta L_t^{\frac{1}{2}}. \]  

(A.26)
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