Banks' balance sheets, uncertainty and macroeconomy*

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Abstract: Motivated by data on weak credit growth despite highly accommodative monetary policy in many advanced economies and by ample evidence on important effects of uncertainty in the course of the financial crisis of 2007-2009, this paper studies relationships between economic uncertainty and asset portfolio allocation of the banking sector. Our theoretical model is guided by an empirical finding showing that an increase in uncertainty leads to reallocation of portfolio of assets by commercial banks: banks reduce issuance of loans, in particular, of commercial and industrial loans, while increasing the stock of safe assets - cash and Treasury and agency securities. To account for this evidence, we propose a DSGE model that incorporates a portfolio-optimizing banking sector facing non-diversifiable credit risk, where banks' attitude to risk and expected profitability help to explain the endogenous movements of the risk premium. Precautionary mechanism is in play: in addition to remunerating for risk of defaults, the premium charged by risk-averse banks provides self-insurance from profitability reduction brought about by heightened uncertainty about entrepreneurial productivity. Banks reduce their exposure to credit risk by cutting down the share of risky lending in their asset portfolios and increasing the share of risk-free assets. Financial accelerator mechanism amplifies the portfolio reallocation effect of uncertainty shock, as increased external finance premium reduces entrepreneurial demand for capital, putting downward pressure on real price of capital and on borrowers' net worth, what depresses demand for capital further.

Keywords: Uncertainty shocks, DSGE model, Stochastic volatility, Financial accelerator, Bank Portfolio.

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1 Introduction

Being an important factor of slow economic recovery, weak growth of credit in the aftermath of the financial crisis of 2007-2009 has been a serious concern of policymakers. Despite highly accomodative stance of monetary policy and various policies to enhance credit supply and to support credit demand, near-zero or negative growth of bank lending has been experienced by many advanced economies for a number of years[1] (see Figures A.1 and A.2 in Appendix A). Given that efficient credit allocation is one of the pillars of growth[2], its weakness hinders the full and sustained economic recovery.

A number of recent studies demonstrated that uncertainty have played a prominent role in shaping credit market developments during the financial crisis of 2007-2009[3]. In this paper we provide empirical evidence, showing that banks reallocate their portfolios of assets following uncertainty shocks by reducing issuance of loans and increasing holdings of safe assets - cash and Treasury and agency securities, what suggests that uncertainty operates (at least partly) via a precautionary motive of banks[4]. Based on this finding and responding to calls for more sophisticated modeling of financial intermediaries due to their nontrivial role in the recent financial crisis, we build a general equilibrium model, introducing two features into the banking sector modelling. First, we use a firm-theoretical model of bank behaviour and model banks as optimizing their balance sheet structure by solving the porfolio problem, where banks choose to allocate their funds between risky lending to entrepreneurs and risk-free government bonds. Second, we model banks as risk-averse agents. Banks have to comply with the value-at-risk constraint and should hold a sufficient level of capital to

[1]For details see IMF Global Financial Stability Report, October 2013).

[2]The importance of intermediation-growth nexus in data is studied by King and Levine (1993), Demirguc-Kunt and Maksimovic (1998), Jayaratne and Strahan (1996), Carbo-Valverde, Rodriguez-Ferdandez and Udell (2005) and Rousseau and Wachtel (1998, 2000), among others. Chretien and Lyonnet (2014) show that cutbacks in lending by commercial banks was the main reason for the contraction in the balance sheet of the overall financial system during the 2008-2009 financial crisis.

[3]See, for example, Stock and Watson (2012), Balke and Zeng (2013), Caldara et al. (2016), Baum et al. (2008) and Quagliariello (2008).

[4]An empirical study of impacts of uncertainty shocks on all the types of bank loan components is provided in Pirozhkova (2016).

protect themselves from the risk of insolvency, what underpins their negative attitude to uncertainty about future profitability. Assuming concave preferences allows uncertainty to play a non-trivial role as a factor that affects the portfolio allocation decision of banks.

Banking sector in our model faces non-diversifiable credit risk that emerges, because loans are subject to default, and because an interest rate on non-defaulted loans specified in the loan contract is not state-contingent on future aggregate outcomes. We modify the standard framework of Bernanke et al. (1999) with nominal rigidities and a financial accelerator mechanism to allow lending rates be non-contingent on realization of shocks, such that banks could obtain non-zero profits, if the realized level of defaults on loans is different from what was expected at the time of setting the lending rate. Heightened idiosyncratic uncertainty - a greater cross-sectional dispersion of productivity, - increases the rate of entrepreneurial defaults, and banks respond by increasing risk premium. Importantly, precautionary mechanism is in play: risk-averse banks charge lending rate, which in addition to remunerating for the increased expected defaults, provides self-insurance from profitability reduction. Thus, banks' expectations about their future profitability play a key role in driving the endogenous movements of credit spread. In this respect our model is in line with Aksoy and Basso (2014), where term spreads' variations are brought about by expectations of banks of their future profitability[5]. Due to increasing external finance premium, the demand for loans falls. The asset portfolios of banks are reallocated: the share of risky lending goes down, while the share of risk-free assets (government bonds), acting as a buffer stock, goes up.

Thus, a general equilibrium setup of our model allows to reproduce a pattern, specified by a key postulate of the modern portfolio theory - that choices of an agent with concave preferences are characterized by a positive premium to the amount that she is willing to pay to avoid a fair gamble. There are important differences in the ways how this result is obtained in the modern portfolio theory and in our model. First, in our case risk is not measured by the variance of distribution of returns, as it is done commonly in the modern

[5] Aksoy and Basso (2014) also provide empirical evidence that corroborates the link between expected bank profitability and term spreads movements.

portfolio approach[6]. Instead, in our model the risk is a downside measure, specifically, it is a probability that idiosyncratic productivity of a borrower is lower than the one that allows her to pay back the loan (a borrower who cannot pay back the loan declares default). The size of credit risk, that the bank is prone to, is determined endogenously and follows from the structure of the optimal debt contract between banks and entrepreneurs. Second, we don't employ a quadratic utility function, which is conventionally used in the modern portfolio theory to analyze the problem of portfolio allocation of the risk-averse investor and to demonstrate how concavity of investor's preferences affects the optimal choice of the fraction of portfolio invested in the risky asset. We assume a constant relative risk aversion type of utility function for banks. Third, risk-free rate in our model is not known in advance as the modern portfolio theory assumes, instead, it is determined endogenously, responding to movements in output gap and in inflation according to the Taylor rule.

Selected literature. Uncertainty has received a substantial attention as a factor that exerts an important impact on economic developments during the Great Recession. Stock and Watson (2013) argue that the decline of output and employment in the Great Recession was mainly due to financial and uncertainty shocks. Recent empirical macro- and microeconomic research documents strong negative relationship between uncertainty and growth. This is demonstrated, for example, in cross-country studies of Ramey and Ramey (1995) and Engle and Rangel (2008). A VAR approach is used by Bloom (2009) to show that there is a drop and rebound of industrial production following the impact of uncertainty shock. By estimating a fully fledged DSGE model Justiniano and Primiceri (2008) demonstrate that decline in the volatility of output in the mid-1980s happened due to change in volatility of various types of technology shocks[7]. Additionally, Aastveit et al. (2013) and Bloom et al. (2012) show that increased uncertainty weakens the effectiveness of monetary policy. As for microeconomic evidence, significant negative effect of uncertainty on investment in the firm-

[6]There is a growing amount of works, however, where risk is characterized by a downside measure. See, for example, Chaigneau and Eeckhoudt (2016).

[7]Among other papers, showing that uncertainty shocks produce economic contractions are Bachmann et al. (2013), Alexopoulos and Cohen (2009), Bachmann and Bayer (2011) and Knotek and Khan (2011).

level panel data is shown by Leahy and Whited (1996). Guiso and Parigi (1999) document the negative impact of uncertainty on firms' expectations of demand. Bloom, Bond and van Reenen (2007) demonstrate that uncertainty gives rise to the "caution effect", while Panousi and Papanikolaou (2012) show that negative effect of uncertainty appears to be management risk-aversion. To sum up, uncertainty is demonstrated to be an important factor that drives the dynamics of economy at both macro and micro levels.

In existing literature some papers analyze the effects of heightened uncertainty about total factor productivity[8], while other works investigate the impact of shocks to idiosyncratic productivity of firms[9]. We contribute to this literature by evaluating the impact that idiosyncratic uncertainty makes on the portfolio reallocation of the banking sector and the resulting general equilibrium effects for the economy. The uncertainty is modelled as a time-varying volatility of idiosyncratic productivity component of entrepreneurs, so that in times of heightened uncertainty the probability of the events on the tails of the distribution of entrepreneurial productivity is higher. This implies not only increased credit risk, what induces risk-neutral banks to charge a higher risk premium to compensate for the greater possible losses, but also greater uncertainty about the future bank profitability, what makes risk-averse banks increase risk premium further to self-insure against profitability reduction. We find that the proposed mechanism of precautionary motive of risk-averse banks produces significant portfolio reallocation effects, it helps to explain an additional portion of the risky lending reduction and business cycle movements.

Another stream of literature, related to our work, explores the role of credit frictions as a factor that contributes to business cycle fluctuations. Despite employing different workhorse models with various types of frictions, the key studies in this literature - Bernanke et al. (1999), Holmstrom and Tirole (1997), Kiyotaki and Moore (1997) and Carlstrom and Fuerst

[8]See, for example, Fernandez-Villaverde and Rubio-Ramirez (2007), Justiniano and Primiceri (2008), Fernandez-Villaverde et al. (2011), Basu and Bundick (2012), Bloom et al. (2012), among others.

[9]Bloom et al. (2012), Christiano et al. (2013) and Bachmann and Bayer (2011) study the effect of changing volatility of cross-sectional dispersion of firm-level productivity. The relative importance of aggregate and idiosyncratic uncertainty, which are sometimes referred to as macro and micro uncertainty, is studied in Balke et al. (2012) and Cesa-Bianchi and Fernandez-Corugedo (2014).

(1997), - agree that financial frictions have significant effects on movement of aggregates. They don't only make an impact as amplifying the effect of exogenous shocks[10], but also act as a source of disturbancies that play an important role for business cycles[11]. The recent and growing literature anlyses the role of credit market imperfections in amplifying the effect of uncertainty. Among those, Arellano et al. (2012) demonstrate that higher uncertainty might be a factor that reduces factor inputs of firms and their output, when firms are subject to costly default. Christiano et al. (2013) and Gilchrist et al. (2013) show that idiosyncratic uncertainty shocks increase the external financial premium in presence of asymmetric information in lending relationships. Benes and Kumhof (2015) also analyze the general equilibrium model with financial accelerator and endogenous risky lending; they focus on bank capital adequacy requirements and demonstrate that countercyclical capital buffers increase welfare. Bonciani and van Roye (2013) show that stickiness of banking retail interest rates amplifies the effect of TFP uncertainty uncertainty on economy. Balke and Zeng (2013) show that the financial crisis of 2008-2009 was mostly due to decline in financial intermediation that originated from output and uncertainty shocks.

We contribute to the literature on credit frictions by showing that in the financial accelerator framework a la Bernanke et al. (1999), where lenders are risk-averse and choose their balance sheets volumes before observing shock values, heightened idiosyncratic uncertainty leads, first, to widening of credit spread, and second, to lowering of the volume of bank credit. We demonstrate that allowing for concave preferences of banks gives rise to the precautionary savings motive, such that assets portfolios of banks are reallocated, what we observe in the data. We show that financial accelerator mechanism works to amplify these effects, as the reduced demand for capital from entrepreneurs induces price of capital to go down, such that entrepreneurial net worth decreases, implying even higher risk premium

[10] See, for example, Gertler and Karadi (2011) and Balke (2000) on this.

[11] For example, Christiano et al. (2010) distinguishes between a banking technology shock and a bank reserve demand shock, which have consequential effects on movements of total output. Hafstead and Smith (2012) examine the role of a shock to bank-specific loan productivity or a shock to the cost of bank intermediation).

charged by banks and further reduction of bank credit.

In section 2 we present a partial equilibrium model of bank portfolio choice. Econometric evidence in favour of portfolio reallocation effects of uncertainty shocks is presented in section 3. Section 4 describes the general equilibrium model and calibration strategy. Section 5 discusses the results of our model simulations and the effects of uncertainty shocks on model economy.

2 Uncertainty and banks' portfolio reallocation: Empirical evidence

In this section we study the effects of uncertainty shock on reallocation of banks' portfolios of assets in data. Following Bachmann et al. (2013), we use the forecasters' disagreement about future inflation as a benchmark measure of uncertainty. We also consider other measures of uncertainty for robustness check of results: the news-based uncertainty index, economic policy uncertainty index and the commonly used in the literature VIX/VXO index[12] (Bloom, 2009).

The forecasters' disagreement about future inflation measures the dispersion between individual forecasters' predictions about future levels of the Consumer Price Index and is used with data coming from the Federal Reserve Bank of Philadelphia's Survey of Professional Forecasters. News-based uncertainty index quantifies newspaper coverage of economic uncertainty, related to policy. In particular, it is the index of search results from 10 large newspapers, from which a normalized index of the volume of news articles discussing economic policy uncertainty is constructed[13]. The composite economic policy uncertainty index developed in Baker, Bloom and Davis (2016) captures the compound effect on policy uncertainty of several factors, including, first, the news-based uncertainty, second, uncertainty

[12] Instead of VIX, we use the VXO index - a CBOE S&P 100 Volatility Index that features a longer data series, starting from 1986Q1 instead of 1990Q1, as in the case of VIX.

[13] For details, see www.policyuncertainty.com

Table 1: Sample pairwise correlation coefficients for the uncertainty measures

	Disagreement	News	Policy Uncertainty	VXO
Disagreement	1	0.14	0.49	0.24
News		1	0.88	0.53
Policy uncertainty			1	0.41
VXO				1

about the future path of the federal tax code, and third, disagreement of professional forecasters about government spending and inflation. The VXO index is a market estimate of implied volatility, calculated using quotes on S&P 100 Index option, and is often used as a measure of short-term uncertainty. This stock market volatility has also been previously used as a proxy for uncertainty at the firm level (see, for example, Leahy and Whited (1996) and Bloom et al. (2007)).

With an exception of news-based uncertainty index and policy uncertainty index, these four measures are correlated weakly or moderately (see Table 1 for sample pairwise correlation coefficients). Despite the differences in the time series of our uncertainty measures, we find that the effects of uncertainty shocks on banks' assets portfolio reallocation in the estimated VAR model are remarkably similar across alternative uncertainty measures.

We estimate a structural orthogonalized VAR on the U.S. 1985-2015 quarterly data to analyze the impact of uncertainty shock on the components of bank assets: safe assets (which include cash and Treasury and agency securities, i.e. assets with low/minimal level of risk) and loans issued for non-financial corporations (commercial and industrial loans). The baseline VAR model includes, in the following order, eight variables: an uncertainty measure, the real GDP, the GDP deflator, the indebtedness of corporate sector measured by its leverage, simple capital ratio of banks, a component of banks' assets (safe assets or commercial and industrial loans), portfolio credit risk, measured by charge-off rate on loans, and the Federal Funds rate[14]. Thus, we include in a model a standard set of variables that

[14]The shock in the Federal Funds rate equation is considered the monetary policy shock; we go along McCallum (1983), Bernanke and Blinder (1992), Bernanke and Mihov (1998), Sims (1986) and Sims (1992) in that.

comprise a small-scale monetary policy VAR, an uncertainty measure and a set of financial and credit variables, which are potentially important as determinants of banks' balance sheet structure, and thus, should be controlled for. The sample covers the period from 1985Q1 to 2015Q3[15].

We place the uncertainty measure as the first variable in the VAR model. This Cholesky ordering implies that uncertainty shocks influence all other variables contemporaneously, such that uncertainty is an underlying characteristic of the state of economy being unaffected by other shocks within the same period (i.e. within a quarter)[16]. In subsequent periods uncertainty responds to all shocks through its relation to the lags of other variables as specified in the VAR model.

Federal funds rate is placed the last in the VAR. The assumption is that monetary authority observes and responds to contemporaneous information on all other variables. We consider this is a plausible assumption given that data on prices, industrial output, aggregate employment and other indicators of aggregate real economic activity are available to the FED on monthly basis. Leverage of non-financial corporates is placed after real activity and inflation measures based on the assumption that companies observe contemporaneous values of uncertainty, real activity and inflation, when making decision about how much debt to incur, whereas all credit variables are not observed by them. Capital ratio of banks is placed before loans. Capital adequacy requirements affect the amount of risky assets banks can have on their balance sheets, and that is the reason why we assume that banks see and take into account the level of their capital ratio when making decisions about risky loans issuance. Assets' components variable (safe assets or loans) is placed after the capital ratio. The assumption is that banks observe contemporaneous information on uncertainty, real activity, inflation, indebtedness of corporates and capital ratio, when deciding on loans

[15]The model with VXO index as uncertainty measure ranges from 1986Q1 to 2015Q3 - from the earliest date that VXO index series is available for.

[16]The recursively identified vector autoregressions with uncertainty measures to trace the dynamic responses of measures of economic activity to surprise increases in uncertainty are also used in Bloom (2009), Baker, Bloom and Davis (2016) and Bachmann et al. (2013), where in the latter one the uncertainty measure is ordered first in the VAR.

issuance and how much safe assets to hold. Charge-off rate on loans is placed after loan volumes. We assume that the value of loans removed from the books and charged against loss reserves is affected by the volume of loans issued by banks to firms contemporaneously.

Estimation results are shown in Appendix B as impulse responses to one standard deviation innovation in uncertainty with 90% bias-corrected bootstrap confidence bands calculated as in Kilian (1998). We report here the impulse responses for the benchmark uncertainty measure - the forecasters' disagreement about future inflation, the result of robustness checks, where alternative measures of uncertainty are used, are available from the author upon request.

Figure B.1 shows that a positive shock to uncertainty induces a significant reduction of output (by 0.09% on impact and by 0.25% after 3 quarters), inflation (by 0.03% on impact and by 0.05% after 5 quarters) and federal funds rate (by 0.09 annual % after 9 quarters from the shock impact), while capital ratio and charge off rate on business loans go up (the former - by 0.43% and the latter - by 4.31% after 3 quarters from the shock impact). Controlling for aggregate demand, inflation, corporate sector indebtedness and capital ratio of banks, commercial and industrial loans go down following an uncertainty shock, by 0.48%. Figure B.2 demonstrates that there is a significant increase of the safe assets holdings by banks after an exogenous spike in uncertainty - by 0.5% after 4 quarters and by 1.12% after 8 quarters from the impact of uncertainty shock. Figure B.3 shows that the result of the business loans reduction following an exogenous increase of uncertainty holds not only for the volume of loans inssued, but also for the share of commercial and industrial loans in portfolios of assets of banks. The share of business loans goes down by 0.05 pp and stays reduced for a period up to 11 quarters after a positive shock to uncertainty. Figure B.4 demonstrates that the result of the safe assets increase after an uncertainty shock holds for the share of safe assets in the portfolios of banks: this share goes up by 0.22 pp with this increase being significantly positive for after 15 quarters after the impact of the shock. Finally, we look at the response of the share of total loans in banks' portfolios to a positive uncertainty shock. The share of total loans in total banks' assets is essentially the share of risky loans that banks choose to issue. Apart from commercial and industrial loans, total loans include consumer loans and real estate loans. Figure B.5 shows that the share of risky lending in banks' assets goes down after an uncertainty shock; the decrease is 0.1 pp and it stays significantly negative for 15 quarters after the shock impact. The differences between the dynamics of the share of business loans and the total share of risky lending in the assets of banks are explained by the fact that these are substantially different factors, which determine the dynamics of consumer and real estate loans' issuance as compared with commercial and industrial loans (see Pirozhkova (2016) for details). As a robustness check, we use other measures of uncertainty - news-based uncertainty index, economic policy uncertainty index and the VXO index, - and the result of the reduction of business loans (and the share of risky loans in total assets of banks) and the increase of safe assets (and the share of safe assets in the portfolios of banks) after a positive shock to uncertainty continue to hold[17].

As additional robustness checks, we use an alternative estimation period, which excludes the time interval following the financial crisis: the estimation period is 1985-2007. We also use an alternative identification scheme, which assumes that uncertainty reacts to movements in all the other model variables within a quarter, and place an uncertainty measure the last in the VAR. These robustness checks confirm our findings.

Our empirical study of the impacts of uncertainty shocks in the vector autoregression framework reveals that there are significant portfolio reallocation effects in bank assets following surprise increase in uncertainty. Specifically, banks increase their holding of riskless asset, while the risky lending issuance is reduced.

3 Uncertainty and risk-averse banking sector

This section is intended to provide intuition for the dynamics of bank portfolio that we obtain later in the general equilibrium setup of our model. It introduces the idea of bank's

[17]The results of all the robustness checks are available from the author upon request.

precautionary motive when there is uncertainty about bank profitability.

Consider a case with a representative risk-averse bank in the economy. The bank funds its activity by issuing deposits for households D_t and allocates its funds to corporate loans L_t and riskless government bonds B_t. Issuing loans is risky and more profitable than buying government bonds: risk premium compensates for riskiness of borrowers. A stock of government bonds could be thought of as bank's savings. Bank's stylized balance sheet constraint is:

$$D_t = L_t + B_t, \tag{1}$$

and the profits of the bank are:

$$\mathbb{E}_t(\pi_{t+1}) = (r_t^l L_t)\nu_t + r_t^g B_t - r_t^d D_t, \tag{2}$$

where r_t^l is the bank's lending rate, r_t^g is risk-free rate on government bonds, r_t^d is rate on deposits and ν_t is the share of non-defaulted loans[18].

Under the assumption of bank being risk-neutral the no-arbitrage condition implies that deposit rate coincides with risk-free rate, and risk spread is accounted by default rate on loans (bank gets no profit):

$$r_t^d = r_t^g = r_t^l * \nu_t. \tag{3}$$

In this case bank would satisfy all the demand for loans and deposits adjusting the volume of govenment bonds held on its balance sheet.

Instead of risk-neutrality let's now assume that bank's preferences are represented with utility function $u(\cdot)$ featuring risk-prudence, following the definition of prudence from Kimball (1990): $u'(\cdot) > 0$, $u''(\cdot) < 0$ and $u'''(\cdot) > 0$[19]. Then the portfolio problem of the bank is:

$$\max_{L_t, B_t, D_t} E(u(\pi_{t+1})) \quad s.t.(1) \tag{4}$$

[18]Throughout the paper all the interest rates are gross rates. Lower case letters denote nominal interest rates and upper case letters denote real interest rates.

[19]The terms risk-averse and risk-prudent are used interchangingly here.

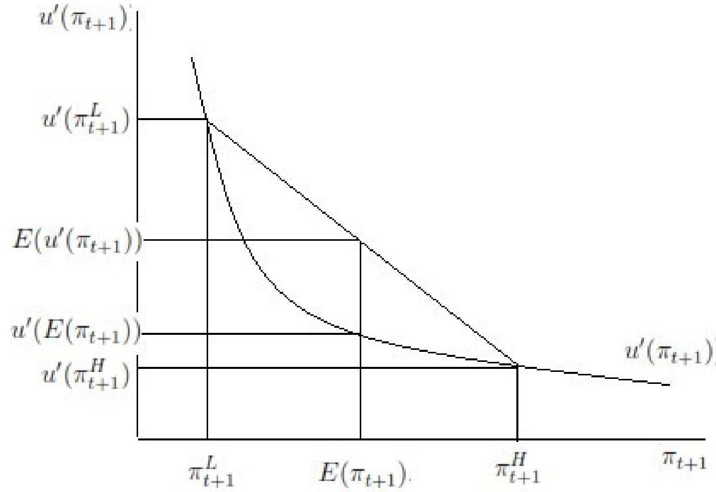


Figure 1: Impact of uncertainty on expected profit of a bank

The optimizing behaviour of a risk-averse bank is different from that of a risk-neutral one. In maximizing its expected utility, risk-averse bank takes into account the stochastic nature of the share of non-defaulted firms ν_t[20]. Ultimately, ν_t could depend on stochastic properties of idiosyncratic return to capital (including its time-varying volatility that we refer to as idiosyncratic uncertainty) or/and on stochastic properties of the aggregate productivity process.

To examine the impact of uncertainty on bank's choice of risky and safe assets share in its portfolio, consider that increased uncertainty induces banks to take into account a wider range of possible values of future profits around $E(\pi_{t+1})$: from the lowest possible π^L_{t+1} to the highest possible π^H_{t+1} (see Figure 1). Because the function of marginal profit $u'(\pi_{t+1})$ is convex ($u'''(\cdot) > 0$), Jensen inequality implies $E(u'(\pi_{t+1})) > u'(E(\pi_{t+1}))$. Thus, when there is uncertainty about future returns, expected marginal utility is higher than in the case of no uncertainty. Higher expected marginal utility of profit in period $t+1$ requires lower level of profit π_{t+1}, what is attained by changing the structure of its portfolio: issuing less risky

[20]In the general equilibrium setup of the model this share is endogenous: it is a function of the equilibrium threshold level of idiosyncratic productivity shock that separates bankrupt and non-bankrupt entrepreneurs. This cut-off value is a solution of the entrepreneurial maximization problem. See the Optimal Debt Contract section for details.

loans L_t, which pay higher return, and increasing the holdings of safe low-yield government bonds B_t. Hence, the effect of heightened uncertainty on the portfolio of risk-averse bank is a greater share of safe assets; risk-averse banks smooth out their profit across states of nature by increasing their riskless bonds holding motivated by precautionary considerations, specifically, to ensure the stability of the profit aiming at avoiding the possible realisation of critically high level of defaults rate.

4 The general equilibrium model

The baseline model in our paper is a general equilibrium model with costly state verification setup and financial accelerator mechanism as formulated by Bernanke et al. (1999), where credit risk is non-diversifiable and risk-averse portfolio optimizing banking sector is introduced. We endogenize bank credit spread and analyze the impact of idiosyncratic uncertainty shocks on portfolio reallocation of bank sector and macroeconomic outcomes. The model economy is populated by a continuum $i \in [0, 1]$ of households, entrepreneurs, banks, capital goods producers, final good producers, the government and a monetary policy authority. Households consume, supply labour and save via bank deposits. Entrepreneurs produce intermediate goods using capital, financed either internally from the net worth or externally by borrowing funds from the banks. The banking sector allocates deposits raised from households to risky loans and risk-free bonds. Capital goods producers sell capital, that they create, to entrepreneurs. Final good producers resell intermediate goods, produced by entrepreneurs, with a markup. The government issues riskless bonds and buys the final good. The central bank implements monetary policy.

4.1 Banking sector

There is a representative bank in economy owned by households, that provides loans to entrepreneurs and funds its investments by households' deposits. The bank also buys government bonds that pay risk-free rate. At time t the balance sheet of the bank is:

$$D_t = L_t + B_t, \tag{5}$$

where current period deposits D_t constitute liabilities, and loans L_t issued for entrepreneurs and risk-free government bonds B_t purchased today comprise asset side of the balance sheet. At the end of period t the bank chooses how to allocate its funds in portfolio of assets that will generate the return in period $t+1$: L_t and B_t are chosen, i.e. the timing of bank assets corresponds to the time, when the loans are issued and bonds are purchased and not when the payoff occurs. Drawing from Christiano et al. (2012), a specialized loan branch within the bank issues the loans for entrepreneurs and performs the loans monitoring function. It receives L_t from its parent branch at period t and commits to pay back at time $t+1$ a non-state contingent nominal interest rate r_t^e, chosen by the parent branch. The allocation of assets between lending and safe assets holding is also decided by the parent branch.

The expected profit Π_{t+1} of the banking sector is the difference between its expected income and expenses, where incomes comprise the principal and interest on non-defaulted loans, the assets of defaulted entrepreneurs less the costs of monitoring them and the principal and interest on government bonds, while expenses paid include the principal and interest on deposits issued to households in period t:

$$\mathbb{E}_t\Pi_{t+1} = \mathbb{E}_t[(1 - F(\bar{\omega}_{t+1}))r_t^L L_t + (1 - \mu)V_{t+1}^d + r_t^G B_t - r_t^D D_t] \tag{6}$$

where $(1 - F(\bar{\omega}_{t+1}))$ is an ex-post share of non-defaulted borrowers, r_t^L is lending rate for loans issued at time t, $(1 - \mu)V_{t+1}^d$ is the value of assets of defaulted firms took over by the bank after paying the monitoring costs μ, $r_t^D D_t$ is bank's payment for households' deposits issued at t and $r_t^G B_t$ is the return on govertment bonds purchased at t. All interest rates are gross nominal rates. Bank's profit Π_{t+1} is transferred lump-sum to households at the end of period $t+1$.

We assume concave preferences of the bank. This assumption is a common one in the literature on financial intermediation[21]. Ross (1973) demonstrates that in a principal-agent problem with unobservable management actions, which determine the probability distribution of the shareholders' payoff, an optimal fee schedule for bank management can be derived; this fee schedule, determined to provide incentives for the management to deliver the highest utility to the shareholders, makes management act as to maximize its own expected utility. Aksoy and Basso (2014) show that choices of the portfolio-optimizing risk-neutral bank, which faces maturity risk and is subject to VaR constraint[22], are the same to choices of risk-averse bank, such that risk-aversion assumption is isomorphic to modelling risk-neutrality of risk-constrained banks[23].

We assume constant relative risk aversion (CRRA) type of utility function. The flow of utility is separable across periods and takes the form:

$$u(\Pi_t) = \frac{(\Pi_t)^{1-\kappa}}{1-\kappa} \tag{7}$$

At time t the bank, in particular, the management of the parent branch of the bank, chooses the share of the portfolio, invested in risky loans $\alpha_t = \frac{L_t}{D_t}$ to maximize its expected utility, taking into account the balance sheet constraint and taking as given interest rates r_t^G, r_t^D and r_t^L:

$$\max_{\alpha_t} \mathbb{E}_t \sum_{s=0}^{\infty} S_{t,t+s+1} u(\Pi_{t+s+1}), \tag{8}$$

where $S_{t,t+1} = \beta \frac{C_{t+1}^{-\sigma}}{C_t^{-\sigma}\pi_{t+1}}$ is the households' stochastic discount factor. Using the simplifying assumption that $r_t^G = r_t^D$ in each period, we rearrange the expression for bank profit (6) (see

[21]See, for example, Parkin (1970), Pyle (1971), Hart and Jaffee (1974), Koehn and Santomero (1980) and textbooks on microeconomics of banking: Matthews and Thompson (2008) and Freixas and Rochet (2008).

[22]VaR constraint is a quantile measure of losses distribution, which limits the probability of portfolio losses. It states that losses of bank portfolio should not exceed the value of its net worth NW_t, thus, ensuring solvency of the bank with probability $(1-\alpha)$: $VaR_\alpha(Loss_t) \leq NW_t$. Importance of accounting for VaR constraint has been emphasized, for example, by Adrian and Shin (2013).

[23]See also Danielsson et al. (2011) on this.

Appendix D for details) and obtain

$$\mathbb{E}_t\Pi_{t+1} = \mathbb{E}_t[L_t((1-F(\bar{\omega}_{t+1}))r_t^L - r_t^G) + (1-\mu)V_{t+1}^d]. \tag{9}$$

for optimality condition derivation. The first order condition of the bank problem is (details are in Appendix D)

$$\mathbb{E}_t[\Pi_{t+1}^{-\kappa}(r_t^L(1-F(\bar{\omega}_{t+1})) - r_t^G)] = 0. \tag{10}$$

To emphasize, the decision about the share of risky loans in portfolio α_t made at time t (accordingly, interest rate on loans r_t^L is set at t), while the expected value of future profitability at $t+1$ is taken into account. In contrast, risk-neutral banks, who are profit maximizers, have linear preferences about their future profit, such that $u'(\Pi_{t+1}) = 1$. Hence, the optimality condition of risk-neutral banks is:

$$r_t^{L,RN}\mathbb{E}_t[(1-F(\bar{\omega}_{t+1}))] = r_t^G. \tag{11}$$

Both types of banks charge a lending rate, which is set to compensate for the risk of defaults on entrepreneurial loans $F(\bar{\omega}_{t+1})$. The difference is that banks with concave preferences also take into account the expected value of their future profitability, specifically, the marginal utility of future profit. By using the fact that r_t^L becomes known at t and applying the definition of covariance and the linearity property of expectations to (50), we expand this optimality condition to

$$r_t^{L,RA}[\frac{\mathrm{Cov}(\Pi_{\mathrm{t+1}}^{-\kappa}, (1-\mathrm{F}(\bar{\omega}_{\mathrm{t+1}})))}{\mathbb{E}_t[\Pi_{t+1}^{-\kappa}]} + \mathbb{E}_t[(1-F(\bar{\omega}_{t+1}))]] = r_t^G. \tag{12}$$

The difference between lending rates charged by two types of banks depends on the sign of covariance in the left hand side of (52): $\mathrm{Cov}(\Pi_{\mathrm{t+1}}^{-\kappa}, (1-\mathrm{F}(\bar{\omega}_{\mathrm{t+1}})))$. This term is negative: the share of non-defaulted entrepreneurs is correlated with the marginal utility of profit negatively, given that its correlation with profitability is positive. This decreases the multiplier of $r_t^{L,RA}$ in the left hand side of (52) comparing to the multiplier of $r_t^{L,RN}$ in the left hand side of (11). Therefore, under equal risk-free rates and under the same expected rate of entrepreurial defaults, the lending rate charged by risk-averse banks is greater than the one charged by risk-neutral banks $r_t^{L,RA} > r_t^{L,RN}$.

The difference in risk premia charged by risk-neutral and risk-averse banks is explained by the precautionary mechanism: in view of heightened uncertainty risk-averse banks insure themselves from future profitability reduction anticipating increasing defaults. They increase risk premium today to diminish profitability reduction tomorrow. Thus, banks' expectations about their future profitability play a key role in driving the endogenous movements of credit spread in our model. This link between bank spreads and their expected profitability was first used in Aksoy and Basso (2014) to deliver endogenous movements in term spreads' variations; they also provide empirical evidence to corroborate it.

To show the effect of default risk and expected profitability on risk premium, we manipulate the optimality condition for risk-averse banks to obtain (see Appendix D for details)

$$RP_t^{RA} = \frac{1 - \frac{\mathrm{Cov}(\Pi_{t+1}^{-\kappa}, (1-\mathrm{F}(\bar{\omega}_{t+1})))}{\mathbb{E}_t[\Pi_{t+1}^{-\kappa}]} - \mathbb{E}_t[(1 - F(\bar{\omega}_{t+1}))]}{\frac{\mathrm{Cov}(\Pi_{t+1}^{-\kappa}, (1-\mathrm{F}(\bar{\omega}_{t+1})))}{\mathbb{E}_t[\Pi_{t+1}^{-\kappa}]} + \mathbb{E}_t[(1 - F(\bar{\omega}_{t+1}))]} r_t^G, \tag{13}$$

what implies that risk premium of risk-averse banks is increasing in expected default risk and decreasing in expected profitability, with the latter reflecting the effect of precautionary mechanism. In contrast to it, risk premium charged by risk-neutral banks is affected only by expected risk of enrepreneurial default, while precautionary mechanism is muted:

$$RP_t^{RN} = \frac{1 - \mathbb{E}_t[(1 - F(\bar{\omega}_{t+1}))]}{\mathbb{E}_t[(1 - F(\bar{\omega}_{t+1}))]} r_t^G, \tag{14}$$

Importantly, our analytical result is in line with the conclusions of the modern portfolio theory that are derived under different assumptions.

4.2 Households

A representative household chooses consumption C_t, total labour supply H_t^h and bank deposits D_t to maximize its expected discounted lifetime utility

$$\max_{C_t, H_t, D_t} \mathbb{E}_t \sum_{k=0}^{\infty} \beta^k [\ln(C_{t+k}) + \xi \ln(1 - H_{t+k}^h)] \tag{15}$$

subject to budget constraint

$$P_t C_t + D_t \leq W_t H_t^h + \Pi_t + r_{t-1}^D D_{t-1}, \tag{16}$$

where P_t is aggregate price level, W_t is nominal wage, Π_t is the profit of banks paid out to households, who own the banks, as dividends, and $r_{t-1}^D D_{t-1}$ is the nominal return on savings deposits issued in $t-1$.

The first-order conditions for consumption, labour and depostis are:

$$C_t^{-1} = \beta \mathbb{E}_t [C_{t+1}^{-1} r_t^D \pi_{t+1}^{-1}], \tag{17}$$

$$\xi \frac{1}{1 - H_t^h} = C_t^{-1} W_t / P_t, \tag{18}$$

where the first one is Euler equation for real consumption, and the second one is intratemporal condition that determines tradeoff between real consumption and leisure. Stochastic discount factor of a representative household is defined as

$$SDF_{t,t+1} = \beta \mathbb{E}_t \frac{C_{t+1}^{-1}}{C_t^{-1} \pi_{t+1}}. \tag{19}$$

4.3 Entrepreneurs

Entrepreneurs are producers of the wholesale output Y_t. They live for a finite number of periods and are risk-neutral; in each period a probability of survival is constant (γ).

Entrepreneurs combine capital K_t, purchased in period $t-1$, with labour H_t hired in t to produce wholesale output in the period t. Production function is assumed to be constant returns to scale, what enables using it as an aggregate relationship, rather than focusing on production function of each entrepreneur:

$$Y_t = A_t K_t^{\alpha} H_t^{1-\alpha}, \tag{20}$$

where A_t is an exogenous parameter of aggregate productivity.

Following Bernanke et al. (1999) and Carlstrom and Fuerst (1997), it is assumed that entrepreneurs supply labour in the general labour market to supplement their income. This assumption is made for a technical reason, in order for new and bankrupt entrepreneurs to have some net worth that allows them to start operations. Total labour input, used in the wholesale good production, is a composite of labour, supplied by entrepreneurs H_t^e, and the household labour supply H_t^h:[24]

$$H_t = (H_t^e)^{1-\Omega}(H_t^h)^{\Omega}. \tag{21}$$

Net worth of entrepreneurs is composed of entrepreneural equity V_t (i.e. the wealth gained by operating the firm, defined in details below) and of entrepreneurial wage w_t^e. At the end of period t aggregate entrepreneural net worth NW_{t+1} is

$$NW_{t+1} = \gamma V_t + w_t^e, \tag{22}$$

where γV_t is time t equity value of entrepreneurs, who survive. Those entrepreneurs, who don't survive, consume their equity: $C_t^e = (1-\gamma)V_t$.

Entrepreneurs sell their output to final good producers at the wholesale price P_t^W, so the gross markup of retail goods over wholesale goods is $X_t = \frac{P_t}{P_t^W}$ and the marginal product

[24]It is assumed that entrepreneurs supply their labour inelastically (it does not enter their utility) with total entrepreneurial labour input being equal to one. The share of income that goes to entrepreneurial labour is set small enough in calibrations, as a result, there is no significant impact of this production function alteration on our results.

of capital is $\alpha(\frac{P_t^W}{P_t})\frac{Y_t}{K_t}$. Undepreciated capital is sold back to capital producers at the end of every period, so ex-post aggregate return to holding a unit of capital from t to $t+1$ is the sum of capital gains from reselling the capital and capital rents (Q_t is the real price of capital):

$$R_{t+1}^k = \frac{\alpha(\frac{P_t^W}{P_t})\frac{Y_{t+1}}{K_{t+1}} + Q_{t+1}(1-\delta)}{Q_t}. \tag{23}$$

Demand for household and entrepreneurial labour is obtained by setting the respective real wages w_t and w_t^e to marginal products of labour:

$$w_t = \Omega(1-\alpha)\frac{Y_t}{H_t^p}\frac{P_t^W}{P_t}, \tag{24}$$

$$w_t^e = (1-\Omega)(1-\alpha)\frac{Y_t}{H_t^e}\frac{P_t^W}{P_t}. \tag{25}$$

4.4 The optimal debt contract

We modify the conventional structure of the optimal debt contract as suggested by Bernanke et al. (1999) to allow the bank lending rate be non-contingent on future shocks. In the original formulation of the financial accelerator framework the risk of entrepreneurial default is idiosyncratic and diversifiable, such that lending rate is contingent on future realisation of productivity shocks. In our model credit risk is non-diversifiable and lending rate in debt contract is not made contingent on future productivity outcomes. Hence, in our formulation zero-profit condition of banks is replaced with incentive compatibility constraint that allows for non-zero profit outcomes for banks.

Entrepreneurs purchase capital, which is going to be used in production in $t+1$, in the end of t. This capital acquisition is financed either through enterpreneurial net worth NW_t or by borrowing from banks L_t:

$$Q_t K_{t+1} = L_t + NW_t. \tag{26}$$

There is an idiosyncratic disturbance ω^j to firm j's return on capital, so that ex-post gross return to capital of firm j is $\omega^j_{t+1} R^k_{t+1}$. ω^j is i.i.d. across entrepreneurs and time and $F(\omega)$ is a continuous cumulative distribution function over a non-negative support $\mathbb{E}(\omega^j) = 1$ with $\mathbb{P}[\omega \leqslant x] = F(x)$. Information about a realized return to capital of an enterpreneur is private and bank has to pay a monitoring cost to observe it. The monitoring cost[25] is a constant share μ of the realized gross return on capital of a firm: $\mu\omega^j R^k_{t+1} Q_t K^j_{t+1}$.

$\bar{\omega}$ is as a cutoff value of idiosyncratic shock such that entrepreneurs, who receive any value lower than this threshold, are unable to repay their loans:

$$\bar{\omega}_{t+1} R^k_{t+1} Q_t K_{t+1} = r^L_t \pi^{-1}_{t+1} L_t. \tag{27}$$

Entrepreneurs with $\omega^j \geqslant \bar{\omega}$ are able to pay back their loans and receive $\omega^j R^k_{t+1} Q_t K^j_{t+1} - r^L_t \pi^{-1}_{t+1} L_t$. Entrepreneurs with draws $\omega^j < \bar{\omega}$ default and receive nothing, leaving the bank with $(1-\mu)\omega^j R^k_{t+1} Q_t K^j_{t+1}$. Due to constant returns to scale assumption, $\bar{\omega}$ specifies, how the expected aggregate gross return of entrepreneur $R^k_{t+1} Q_t K_{t+1}$ is divided between the bank and the entrepreneur. $\Gamma(\bar{\omega})$ is the expected gross share of entrepreneurial return going to the bank

$$\Gamma(\bar{\omega}) \equiv \int_0^{\bar{\omega}} \omega f(\omega) d\omega + \bar{\omega} \int_{\bar{\omega}}^{\infty} f(\omega) d\omega, \tag{28}$$

while $\mu\Xi(\bar{\omega})$ is the expected monitoring costs:

$$\mu\Xi(\bar{\omega}) \equiv \mu \int_0^{\bar{\omega}} \omega f(\omega) d\omega, \tag{29}$$

where $\Gamma'(\bar{\omega}) = 1 - F(\bar{\omega})$ and $\mu\Xi'(\bar{\omega}) \equiv \mu\bar{\omega} f(\bar{\omega})$. Hence, the net fraction of entrepreneurial return going to the bank is $\Gamma(\bar{\omega}) - \mu\Xi(\bar{\omega})$, and the share of return that stays with entrepreneur is $1 - \Gamma(\bar{\omega})$.

The optimal loan contract maximizes the gross return on capital of entrepreneur subject

[25]The monitoring cost is also referred to in literature as auditing cost or the cost of bankruptcy.

to incentive compatibility constraint of the bank:

$$\max_{K_{t+1},\bar{\omega}_{t+1}} \mathbb{E}_t[(1-\Gamma(\bar{\omega}_{t+1}))R^k_{t+1}Q_tK_{t+1}] \tag{30}$$

subject to

$$\mathbb{E}_t[(\Gamma(\bar{\omega}_{t+1})-\mu\Xi(\bar{\omega}_{t+1}))R^k_{t+1}Q_tK_{t+1}] = r^e_tL_t/\mathbb{E}_t\pi_{t+1}, \tag{31}$$

where the incentive compatibility constraint formulates that the amount of real receipts of the bank loan branch from issuing loans at time t, which must be paid to the parent branch, is equal to the expected value of aggregate entrepreneurial return that goes to the bank, where r^e_t is defined as:

$$r^e_tL_t = \mathbb{E}_t[(1-F(\bar{\omega}_{t+1}))r^L_tL_t + (1-\mu)V^d_{t+1}]. \tag{32}$$

Hence, the lending rate r^L_t[26], the amount of loans L_t issued and the interest rate r^e_t that the loan branch must pay back to the parent branch, satisfy the incentive compatibility constraint of the bank and maximize the entrepreneurs' expected return at the moment, when loans mature.

Solving this optimization problem yields the following optimality condition:

$$\frac{R^k_{t+1}}{r^e_{t+1}\pi^{-1}_{t+1}} = \frac{\Gamma'(\overline{\omega}_{t+1})}{(1-\Gamma(\bar{\omega}_{t+1}))(\Gamma'(\overline{\omega}_{t+1})-\mu\Xi'(\overline{\omega}_{t+1}))+\Gamma'(\overline{\omega}_{t+1})(\Gamma(\overline{\omega}_{t+1})-\mu\Xi(\overline{\omega}_{t+1}))}, \tag{33}$$

which, together with the incentive compatibility constraint, pins down the optimal choice of capital K_{t+1} and of the threshold value of idiosyncratic shock to capital return $\bar{\omega}_{t+1}$. In its turn, $\bar{\omega}_{t+1}$ and the variance of idiosyncratic productivity shock, being time-varying in the case of idiosyncratic uncertainty, specify the rate of default on loans, which triggers changes in risk premium that the banking sector charges. Additionally, these optimality conditions introduce the financial accelerator mechanism to the model: external finance

[26] In notation of Berkanke et al. (1999), this is the gross interest rate Z_{t+1}.

premium increases in the leverage ratio of entrepreneurs.

4.5 Idiosyncratic uncertainty

To introduce idiosyncratic uncertainty, we follow Christiano et al. (2010) and Dorofeenko et al. (2008) and assume that the variance of entrepreneurial idiosyncratic productivity shocks ω is time-varying. Because ω is distributed log-normally (as noted earlier, $\omega \sim \log N(1, \sigma_\omega^2)$), the log of ω is normally distributed. We fix the mean of ω to one, and define the variance of the log-normal distribution as $(\sigma^{Id})^2 = \log(1 + \sigma_\omega^2)$. This variance σ^{Id} is assumed to be varying and is affected by shock, which we refer to as the source of idiosyncratic uncertainty[27]. The log-deviation of σ_t^{Id} from its steady state is modeled as:

$$\log(\frac{\sigma_t^{Id}}{\sigma^{Id}}) = \rho_\sigma \log(\frac{\sigma_{t-1}^{Id}}{\sigma^{Id}}) + \sigma^\sigma \epsilon_t^\sigma. \tag{34}$$

σ^σ is the standard deviation of innovations to σ_t^{Id} and ϵ^σ follows standard normal distribution. Positive innovations to idiosyncratic uncertainty shocks increase the dispersion of entrepreneurial return to capital σ_t^{Id}. The illustration of this increase is given at Figure 2: higher variance of idiosyncratic shock to entrepreneurs' productivity changes the shape of the distribution shifting the mass of distribution to the left tail even when the mean of the distribution is unaffected. The intuition behind idiosyncratic shock is the following: the higher dispersion of productivity implies a higher probability of defaults on loans, and given costly state verification, a higher risk premium and lending rates, what leads to lower entrepreneurial demand for capital.

4.6 Capital goods producers

A competetive sector of capital goods producers buys final goods from retailers as investment goods and existing undepreciated capital $(1-\delta)K_t$ from entrepreneurs and combines

[27]Empirical evidence that corroborates dispersion of idiosyncratic entrepreneurial productivity as a source of uncertainty has been provided, for example, in Bloom et. al (2012).

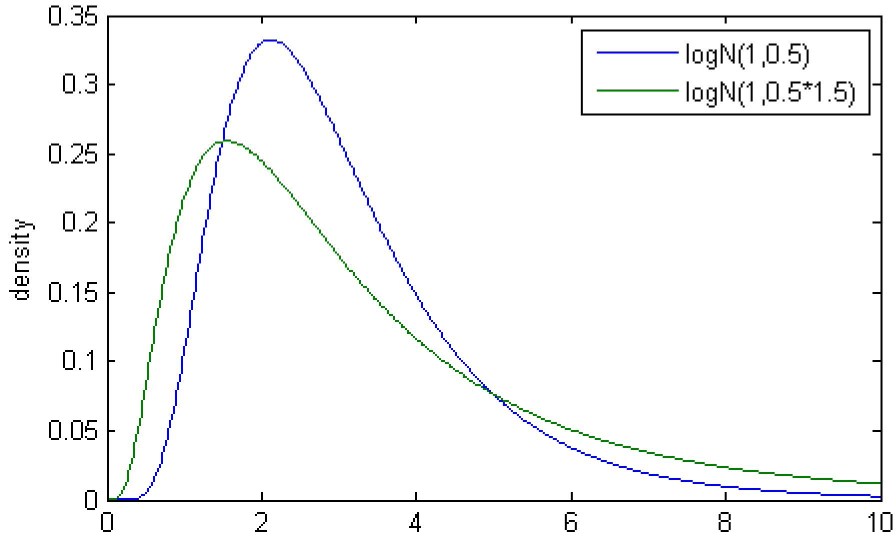


Figure 2: The effect of an idiosyncratic uncertainty shock.

them to create capital for the next period K_{t+1}, which is then sold to entrepreneurs[28]:

$$K_{t+1} = I_t + (1-\delta)K_t. \tag{35}$$

Capital adjustment costs are introduced to allow for the price of capital to vary, following Kiyotaki and Moore (1997). Drawing from Christensen and Dib (2008), we adopt a quadratic capital adjustment costs function, specified as $\frac{\chi}{2}(\frac{I_t}{K_t}-\delta)^2K_t$. The optimization problem of the capital goods producers is to choose the value of investment I_t that maximizes their profits:

$$\max_{I_t}[Q_tI_t - I_t - \frac{\chi}{2}(\frac{I_t}{K_t}-\delta)^2K_t]. \tag{36}$$

The first-order condition is

$$Q_t = 1 + \chi(\frac{I_t}{K_t}-\delta). \tag{37}$$

[28]We assume that capital producers rent the capital stock from entrepreneurs and use it to produce new capital; since this rent and subsequent return of capital happen within one period, the rental price is supposed to be zero.

This standard condition of Tobin's Q relates the real price of capital to the marginal adjustment costs. Due to capital adjustment costs, the response of investment to various shocks slows down, which it its turn has an impact on the real price of capital. Variations in the price of capital, absent if there are not capital adjustment costs, contribute to volatility of net worth of entrepreneurs, what has a direct impact on workings of the financial accelerator mechanism. Hence, (37) represents the supply of capital and the demand for capital from entrepreneurs is formulated by (33) together with (31).

4.7 Retailers

The sector of retailers is introduced into the model to incorporate price rigidity. Specifically, we adopt Calvo price setting framework. There is a unit mass of monopolistically competitive retailers. They purchase wholesale goods from entrepreneurs at the nominal wholesale price P_t^w and resell them at their own retail price. Let $Y_t(i)$ denote the quantity of output resold by retailer i and let $P_t(i)$ denote the nominal price the retailer receives. Total final goods are a composite of individual retail goods

$$Y_t = [\int_0^1 Y_t(i)^{(\eta-1)/\eta} di]^{\frac{\eta}{\eta-1}}, \tag{38}$$

and the corresponding aggregate price index is given by

$$P_t = [\int_0^1 Y_t(i)^{1-\eta} di]^{\frac{1}{1-\eta}}, \tag{39}$$

where $\eta > 1$ is elasticity of substitution in the retail market.

The standard monopolistic competition demand curve for individual retailers is

$$Y_t(i) = (\frac{P_t(i)}{P_t})^{-\eta} Y_t. \tag{40}$$

The retailer chooses its sale price $P_t(i)$ to maximize its profits taking as given the aggregate demand, price level and wholesale good price.

To incorporate price stickiness, we introduce Calvo pricing such that retailers are free to change their price each period with probability $1-\theta$. Let $P_t^*(i)$ denote the price chosen by retailers who are able to change their price. The aggregate price evolves according to (see Appendix D for details)

$$P_t = [\theta P_{t-1}^{1-\eta} + (1-\theta)(P_t^*)^{1-\eta}]^{\frac{1}{1-\eta}}. \tag{41}$$

4.8 Monetary authority

We assume that monetary policy instrument is the nominal risk-free interest rate r_t^G that the central bank is able to set following the standard Taylor rule with interest rate smoothing, responding to deviations of inflation and output:

$$\log(\frac{r_t^G}{r^G}) = \rho_r \log(\frac{r_{t-1}^G}{r^G}) + \psi_\pi \log(\frac{\pi_t}{\pi}) + \psi_y \log(\frac{y_t}{y}) - \epsilon_t^m, \tag{42}$$

where π and y are the steady state levels of inflation and output and ϵ_t^m in an i.i.d. white noise process with standard deviation σ^m denoting monetary policy shock. It is assumed that the supply of risk-free government bonds is perfectly elastic, such that any volume of demand for bonds from the banking sector is met.

4.9 Market clearing

The final good market clearing condition states that total output equals the sum of households' and entrepreneurial consumption, government spending, total resources used to create new capital goods and the monitoring costs of banks:

$$Y_t = C_t + C_t^e + G_t + I_t + \mu V_t^d. \tag{43}$$

4.10 Calibration

We calibrate the model at a quaterly frequency, setting fairly standard values for the DSGE model parameters. The discount rate β is set to 0.99 to target an annualized average risk-free interest rate of 3.8%, what is the average rate of three-month Treasury bills in 1983Q1-2016Q3. The capital share α is set to 1/3, the share of entrepreneurial labour income $(1-\Omega)$ is set to 0.01, such that the labour share of households $(1-\alpha)(1-\Omega)$ is 0.66. The parameter of leisure utility, ξ (1.87) is set to target the time that households spend working to 1/3. The elasticity of substitution between final goods η is set to 5, and θ, the Calvo parameter, is set to 0.75; these values imply that firms are able to adjust their prices on average once in four quarters and that a steady state value of markup of 25%.

We choose the quadratic adjustment costs functional form of the capital goods production function drawing from Christensen and Dib (2008), because quadratic adjustment costs, being a type of smooth "convex" adjustment costs that increase in the squared rate of investment, do not generate real options effects of uncertainty on economy. We want to analyze banks' precautionary mechanism of uncertainty as the main channel of influence of uncertainty on variables, that is why we aim at leaving aside other potential channels of impact. We set the marginal adjustment cost parameter χ equal to 0.5882 - the parameter estimate from Christensen and Dib (2008). Depreciation rate δ is set to its standard value of 0.025. The steady state share of government expenditures in total output is taken to be 0.2.

The values for monitoring costs μ, for the steady state of the variance of idiosyncratic productivity shock σ^{Id} and for the survival rate of entrepreneurs γ are set jointly to match the data on entrepreneurial defaults (the average number of non-performing loans in 1988Q1-2016Q1 equal to 2.23%), the leverage ratio of entrepreneurs of 1.84 (measured as the average value of total assets to net worth of nonfinancial corporate business in 1983Q1-2016Q2)) and the real rate of return on capital expenditures of 15.4% in the steady state (estimate of Poterba (1998)). In that way, the fraction of realized payoffs lost in bankruptcy, μ, is set to

0.21 (a number inbetween of that from Carlstrom and Fuerst (1997) - 0.25, and Bernanke et al. (1999) - 0.12), the survival rate of entrepreneurs γ is set to 0.95 (the value in Carlstrom and Fuerst (1997) is 0.947, and the one in Bernanke et al. (1999) is 0.97), while steady state standard deviation of idiosyncratic productivity shock is set to 0.364 (somewhat higher than in Carlstrom and Fuerst (1997) - 0.207, and in Bernanke et al. (1999) - 0.28). The steady state annualized value of lending rate r^L is set to 6.86% to match the average of prime loan rate on historical data from 1983Q1 to 2016Q3. We draw the parameters of the Taylor rule followed by monetary authority from the estimated values in Christiano et al. (2010): ψ_π is set to 2.39, ψ_y - to 0.36 and ρ_r - to 0.85. From Christiano et al. (2010) we also use the estimated parameter values for autoregressive process of the level TFP and government expenditure shocks and idiosyncratic uncertainty shock[29]: $\rho_a = 0.9$, $\rho_g = 0.938$, $\sigma^g = 0.021$, $\rho_\sigma = 0.79$ and $\sigma^\sigma = 0.05$.

4.11 Solution method

The traditional linear approximation of the model solution implies that uncertainty shocks do not play a role due to certainty equivalence. For the variability of the second moment to enter the decision rules of economic agents, a third-order approximation is used. As discussed in Fernandez-Villaverde et al. (2010), the third-order Taylor expansion allows to simulate and to evaluate the effect of an uncertainty shock. We use the perturbation method to solve the model.

Dynare 4.4 is used to compute the third-order approximation around the non-stochastic steady state. As Fernandez-Villaverde et al. (2010) note, the third-order approximation moves the simulated paths of states and controls away from their steady state values, because the expected value of the variables depends on the variance of shocks[30]. Hence, we compute impulse responses as deviations from the mean of ergodic distributions of the data generated

[29]Christiano et al. (2010) refer to idiosyncratic uncertainty shock as to 'risk shock'.

[30]As has been shown by Schmitt-Grohe and Uribe (2004), the expected value of any variable in high order approximations differs from its deterministic steady-state value.

by the model, rather than deviations from the steady states, as this allows to take into account the second-order effects in a more comprehensive way. This approach is proposed by Fernandez-Villaverde et al. (2010) and is used in other studies investigating the effects of uncertainty shocks (see, for example, Born and Pfeifer (2011) and Cesa-Bianchi and Fernandez-Corugedo (2014)). The details of the computation of impulse responses functions are given in Appendix D.

We employ the prunning procedure proposed by Kim et al. (2008) to deal with the problem of explosive behaviour of the simulated time series when high-order perturbations are used to approximate the solution of the model.

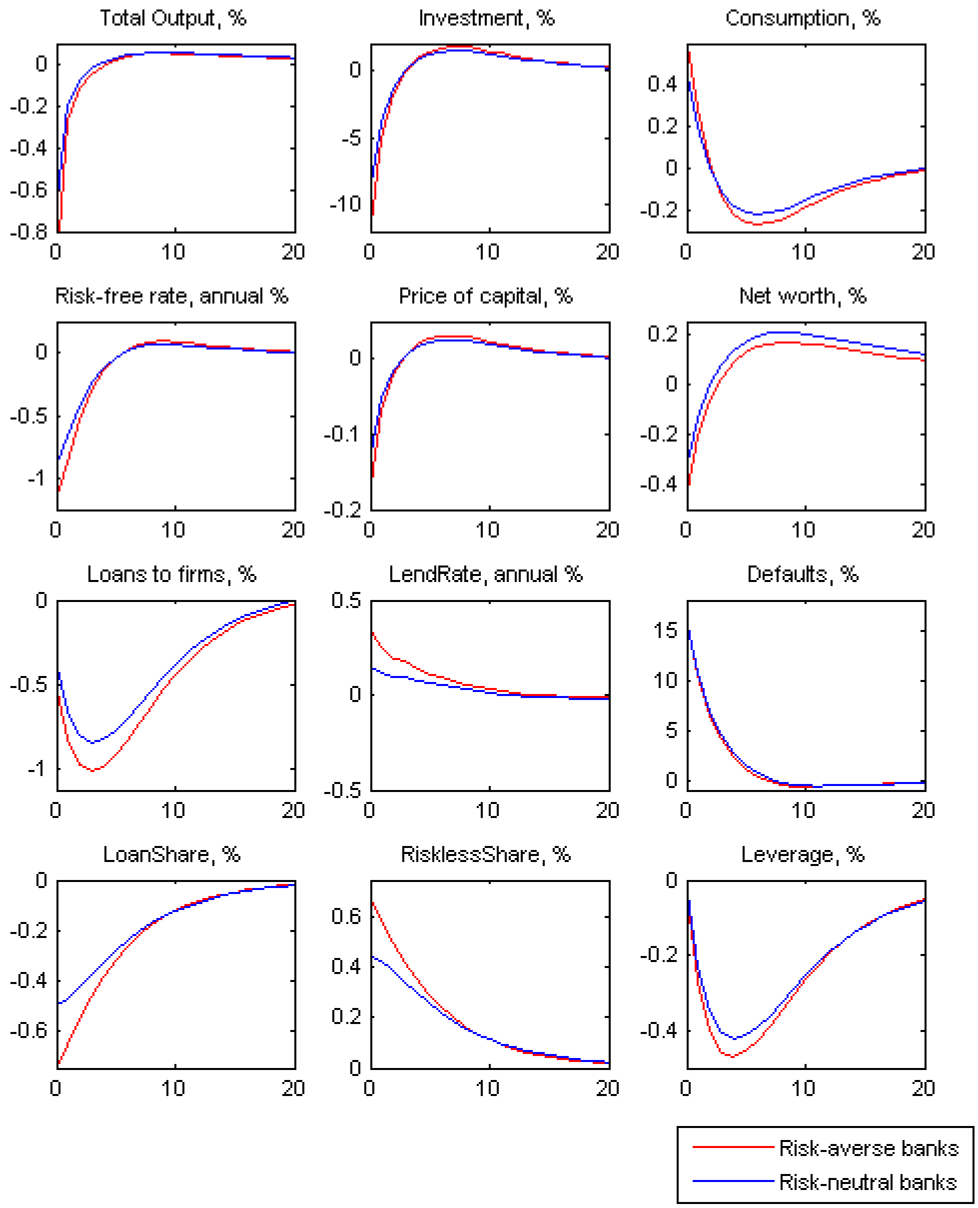
5 The effect of uncertainty shocks

In this section we analyse the effect of an exogenous increase in idiosyncratic uncertainty on the model economy, and specifically, on banks' portfolio allocation. We consider two versions of the model - with risk-averse banking sector and with risk-neutral banks - to compare the features of portfolio reallocation following uncertainty shock for two types of preferences of lenders. We find that idiosyncratic uncertainty shock is propagated via financial accelerator, and attitude to risk of the banking sector makes a difference for banks portfolio reallocation. We analyse impulse responses to a 2 standard deviation increase of idiosyncratic uncertainty innovation (ϵ_t^{σ})[31]. Figure 3 plots impulse responses of the model variables to an idiosyncratic uncertainty shock.

Heightened idiosyncratic uncertainty is an increase of dispersion of entrepreneurial productivity, implying that some entrepreneurs earn higher returns, while other entrepreneurs bear greater losses. Hence, a greater fraction of entrepreneurs is unable to pay back their loans, meaning that default rate on loans goes up. It increases for risk-neutral and risk-averse banks by 15% reflecting the spike of idiosyncratic uncertainty. Banks' expected costs associ-

[31] It is a convention in the literature on the effects of uncertainty shocks to look at exogenous increase of uncertainty equal to 2 standard deviations.

Figure 3: Impulse response functions to idiosyncratic uncertainty shock



ated with bankruptcies go up, so they increase their lending rate to compensate for it. As a result of heightened cost of external debt, entrepreneurs reduce their demand for capital, and investment falls. Importantly, there are two counteracting forces that have a potential to drive the entrepreneurial demand for capital. The partial equilibrium effect implies that an increased cost of borrowing induces entrepreneurs to reduce their optimal choice of leverage, such that capital demand also goes down. The general equilibrium effect takes into account that as a result of capital reduction, following a spike in uncertainty, the rental rate of capital goes up. Hence, entrepreneurs have an incentive to increase their leverage to benefit from this high value of capital return, which would give rise to an upward pressure on the demand for capital. Our model simulations show that the partial equilibrium effect dominates the general equilibrium one: the forces that bring entrepreneurs' demand for capital down due to the increase of the interest rate on loans overpower the general equilibrium incentives to build up leverage because the return on capital has gone up. The entrepreneurial leverage and investment fall.

The presence of financial accelerator amplifies the effect of uncertainty shock. In particular, due to reduced capital demand, the price of capital falls, making entrepreneurial net worth go down, what reduces the demand for capital further.Lower investment forces consumption to go up on uncertainty shock impact. A similar result is documented by Bloom et al. (2012) and by Christiano et al. (2014). In the latter, they draw an analogy of the effect of uncertainty shock to the increase of tax rate on capital return, which hinders saving and investment, while boosting consumption, in a way similar to a spike in the tax rate. Monetary authority responds to depressed output by easing monetary conditions: nominal interest rate is reduced, what together with heightened inflation implies decreasing real saving rate, such that households are encouraged to consume more and work less. After 2 quarters the negative wealth effect builds up, weaker capital demand acts to reduce output further, so the consumption also goes down.

Responding to an increased default rate, risk-averse banks charge higher interest rates on loans than risk-neutral banks do. The additional premium that the former require over and above the lending rate charged by the latter reflects the negative attitude of risk-averse banks to uncertainty about their future profitability. In addition to adverse effect of the higher expected default rate per se, risk-averse banks take into account the negative effect, which increased defaults have on their future profits. They foresee that marginal utility of profit will go up tomorrow, and they want to compensate for this detrimental impact today by charging a higher lending rate. As a result their lending rate is by 0.2 pp higher than the one charged by risk-neutral banks. Hence, the equilibrium volume of loans issued by risk-averse banks following uncertainty shock is less than the volume of loans issued by risk-neutral banks by 0.18 pp: risk-averse banking sector reduces loans issuance by 1.01% after 3 quarters from the shock impact, whereas the risk-neutral one - by 0.83%[32]. As for the portfolio structure, risk-averse banks choose to increase the share of risk-free assets in their portfolios in times of heightened uncertainty by 0.23 pp more than risk-neutral banks do, while the share of risky assets in their portfolios is reduced by 0.25 pp more than the reduction of risk-neutral banks. We consider this excess of risk-free bonds' share in portfolios of banks with concave preferences over the share of riskless assets in portfolios of risk-neutral banks following an uncertainty shock a form of precautionary savings.

Our model simulations show that these bank portfolio reallocation effects make a sizable impact on the economy aggregates. The most important implications are for aggregate investment, which falls by 3.2 pp more under the risk-averse banking sector specification than in a model with risk-neutral banks. Total output goes down by 0.23 pp more and consumption - by additional 0.05 pp (after 6 quarter from the shock impact) as a result of higher risk premium charged by the banking sector with negative attitude to risk and lower volume of loans issued.

6 Conclusion

In this paper I propose a DSGE model with a portfolio-optimizing banking sector to account for reallocation effects in banks' asset portfolios following uncertainty shocks. I model uncertainty as a time-varying cross-sectional dispersion of entrepreneurial productivity. I modify the standard Financial Accelerator framework of Bernanke, Gertler and Gilchrist

[32]This result is similar to the one obtained by Christiano et al. (2010), where risk-neutral banks cut down risky lending by 1% following an uncertainty shock.

(1999) to allow bank lending rates be non-contingent on aggregate shocks. Risk-averse banks face non-diversifiable credit risk and, by invoking a precautionary mechanism, increase risk premium following a spike in uncertainty by more than risk-neutral banks do. My result is in line with the conclusions of the modern portfolio theory, but the approach used here is advantageous comparing to that of the modern portfolio theory in several aspects. First, the risk of investment is not measured by variance of returns, but is a downside measure, what is a more adequate approach for the case of default risk. Second, the don't employ a quadratic utility function, but assume a more plausible representation of preferences characterized by constant relative risk aversion. Third, I adopt the general equilibrium approach, such that default risk is endogenous and also time-varying, as well as risk-free rate not being known in advance and being determined endogenously responding to movements in output gap and inflation. The suggested model allows to replicate the significant effect of uncertainty on the dynamics of banks balance sheet items, observed in the data, and to explain the case of weak credit growth despite highly accommodative monetary policy in many advance economies in the course of the financial crisis of 2007-2009.

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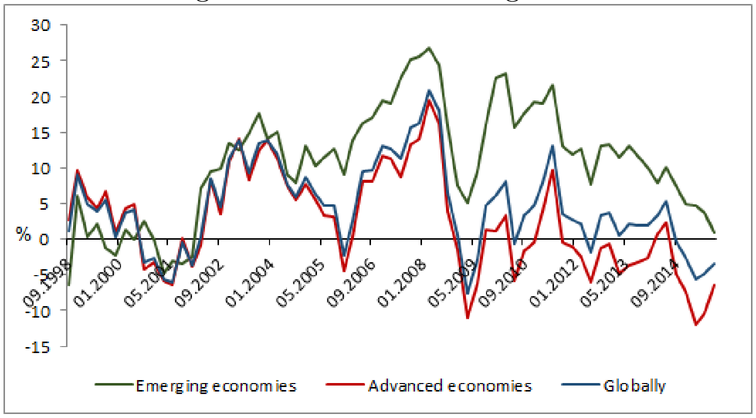
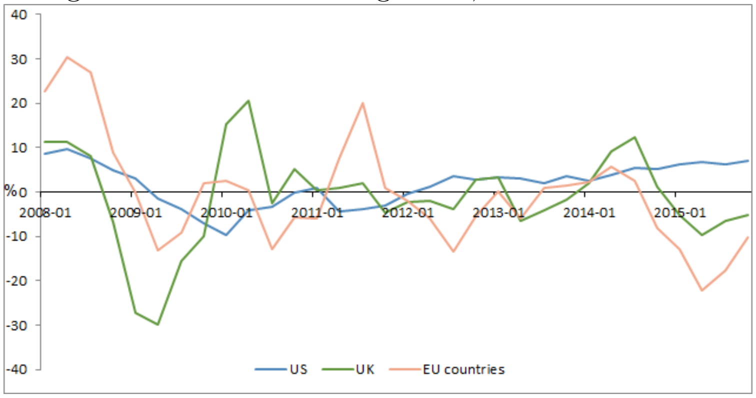
Appendix A Credit market conditions

Figure A.1: Bank credit growth



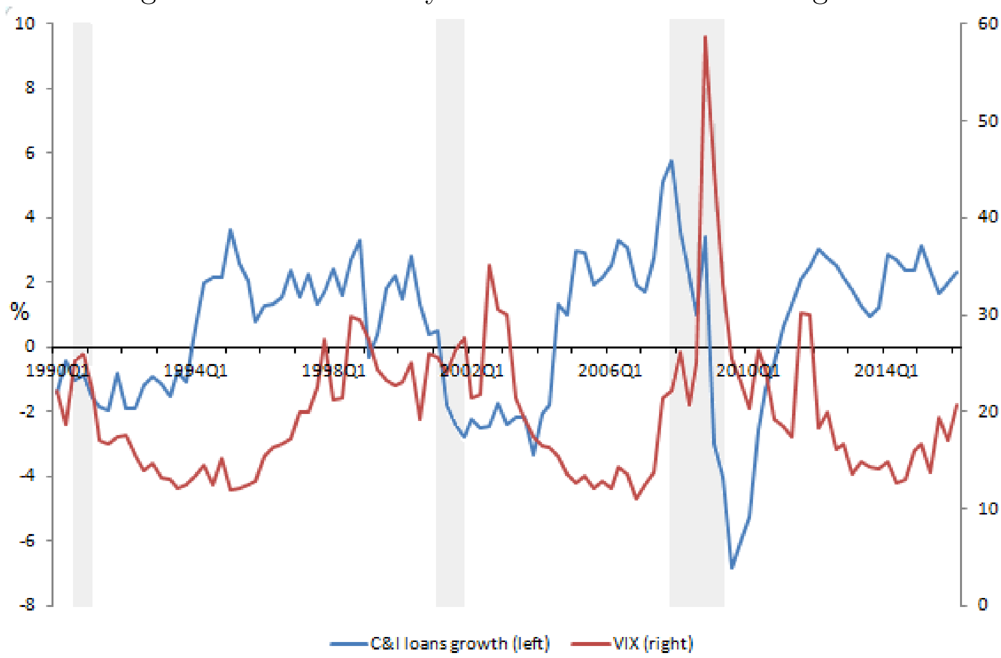
Note. The plotted numbers are year over year real quarterly credit growth figures. Source: BIS.

Figure A.2: Bank credit growth, selected countries



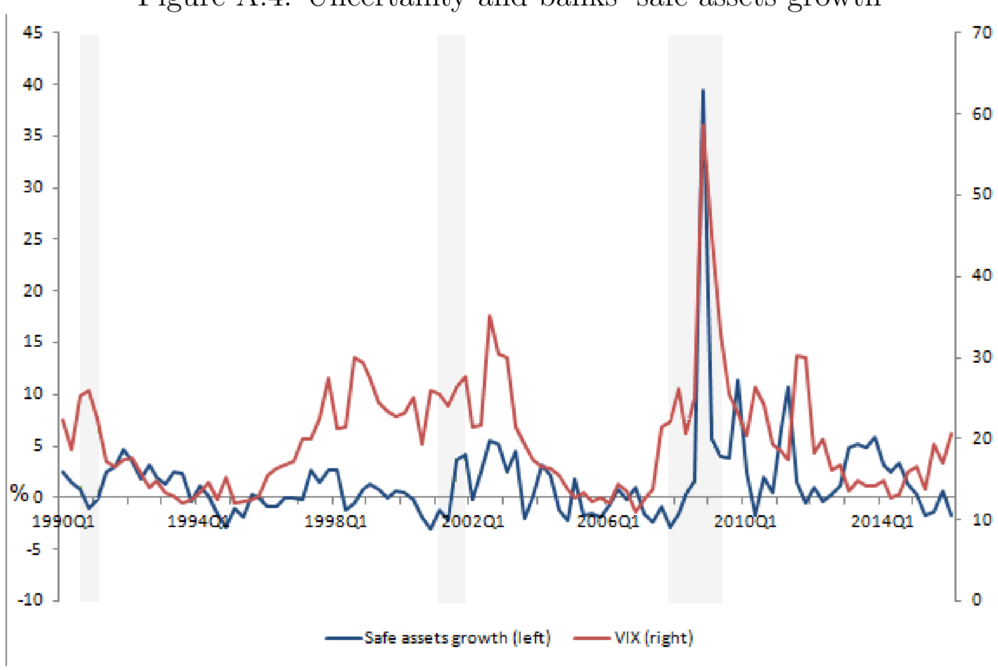
Note. The plotted numbers are year over year real quarterly credit growth figures. Source: BIS.

Figure A.3: Uncertainty and banks' business loans growth



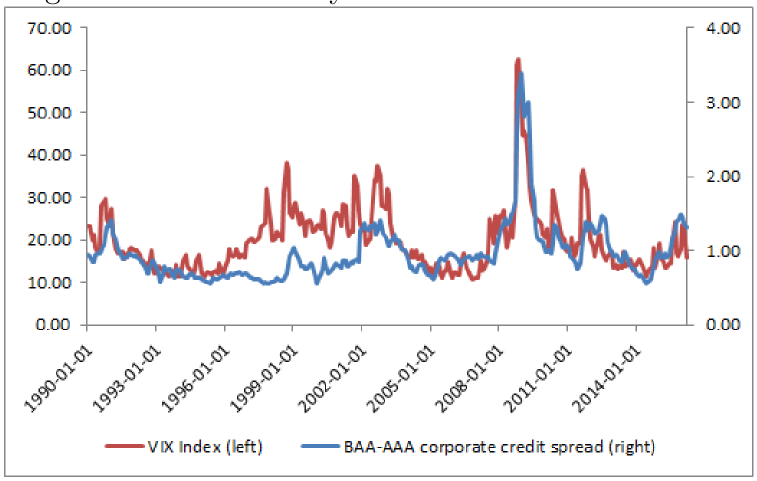
Note. Shaded areas are NBER recessions. Sources: Federal Reserve Board H.8 Release, NBER.

Figure A.4: Uncertainty and banks' safe assets growth



Note. Shaded areas are NBER recessions. Sources: Federal Reserve Board H.8 Release, NBER.

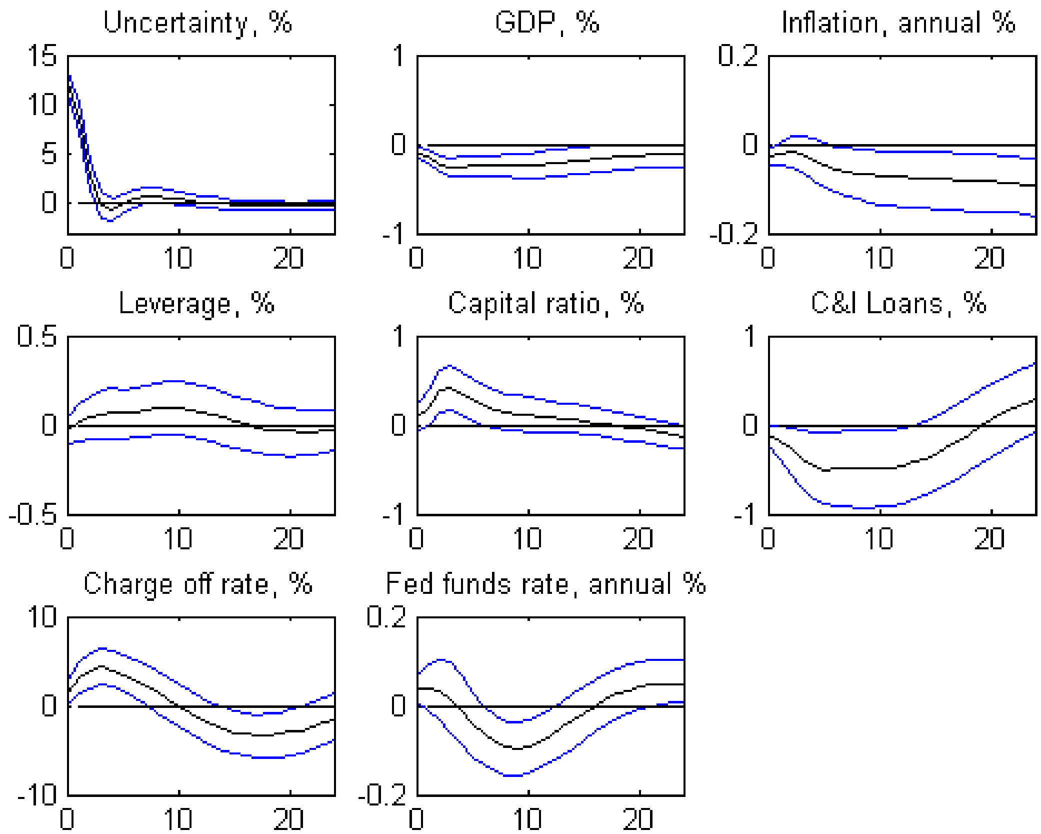
Figure A.5: Uncertainty and credit market conditions



Source: Chicago Board Options Exchange.

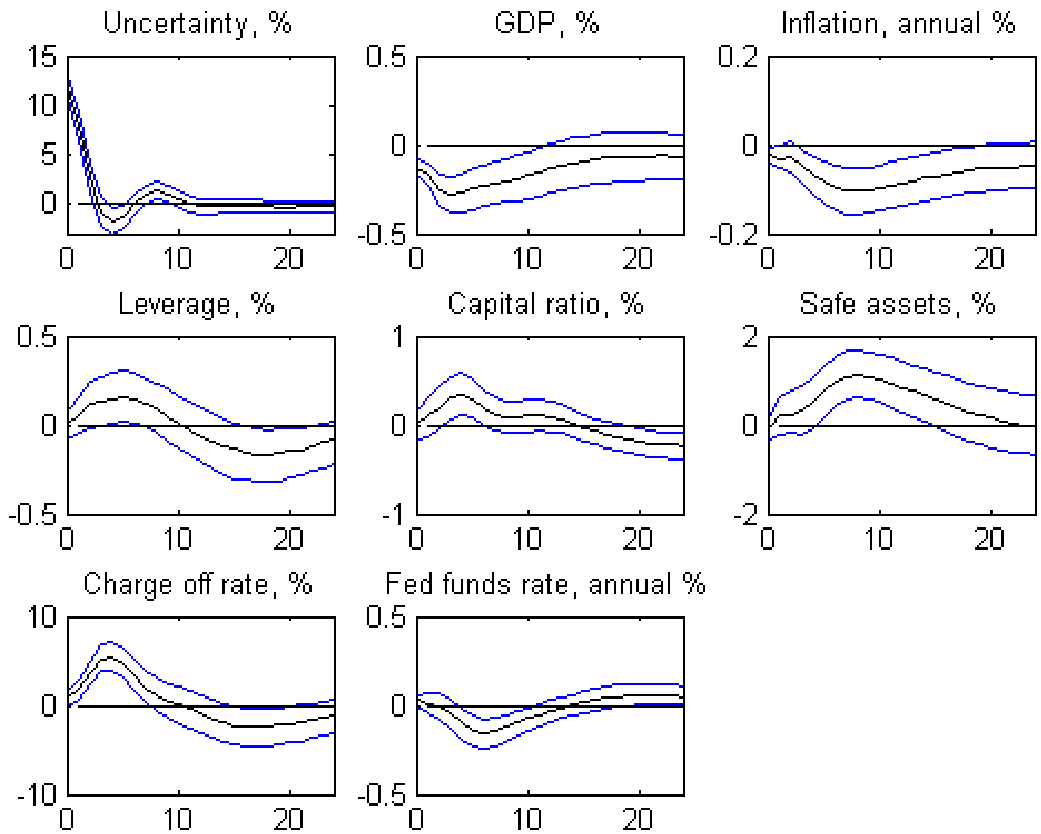
Appendix B VAR evidence on effects of uncertainty shocks

Figure B.1: Impulse responses to an uncertainty shock of a model with commercial and industrial loans: 1985-2015.



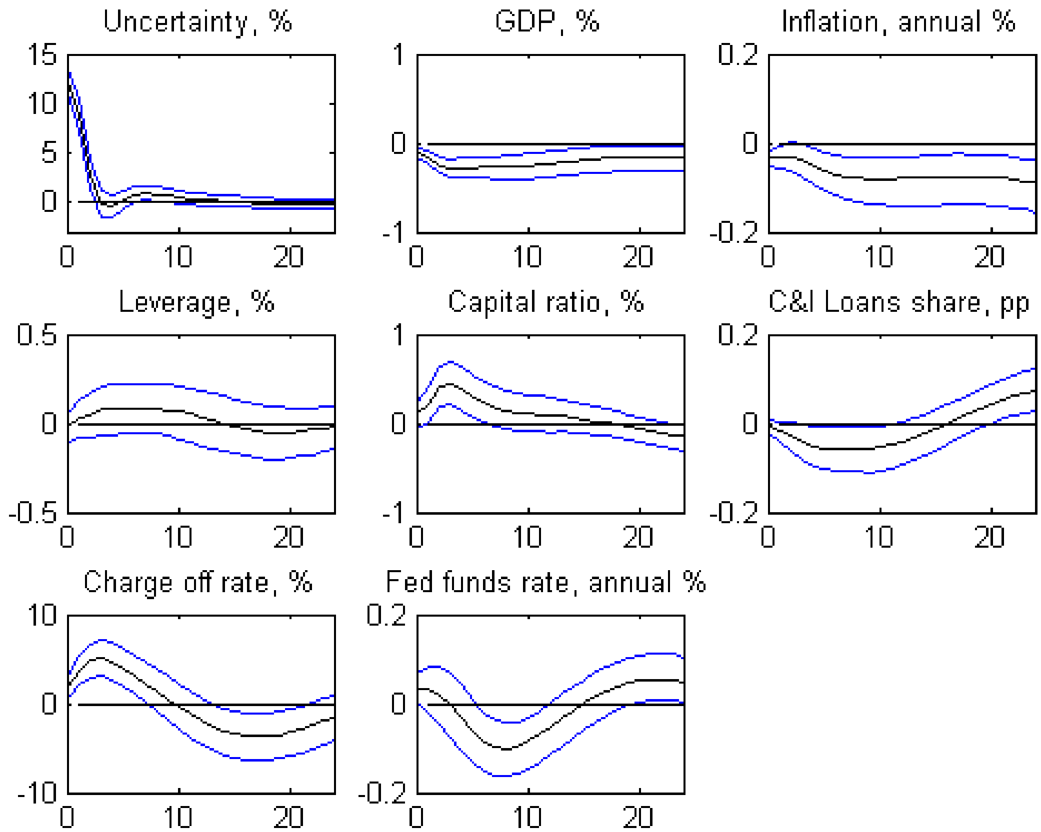
Note. The responses of the model's variables to one-standard deviation shock to uncertainty. The solid black lines represent median responses, the solid blue lines represent the 90% bias-corrected bootstrap confidence bands, which are calculated as in Kilian (1998). The units of the horizontal axes are quarters. The units of the vertical axis are percents. According to Akaike information criterion, the VAR order includes four lags.

Figure B.2: Impulse responses to an uncertainty shock of a model with safe assets: 1985-2015.



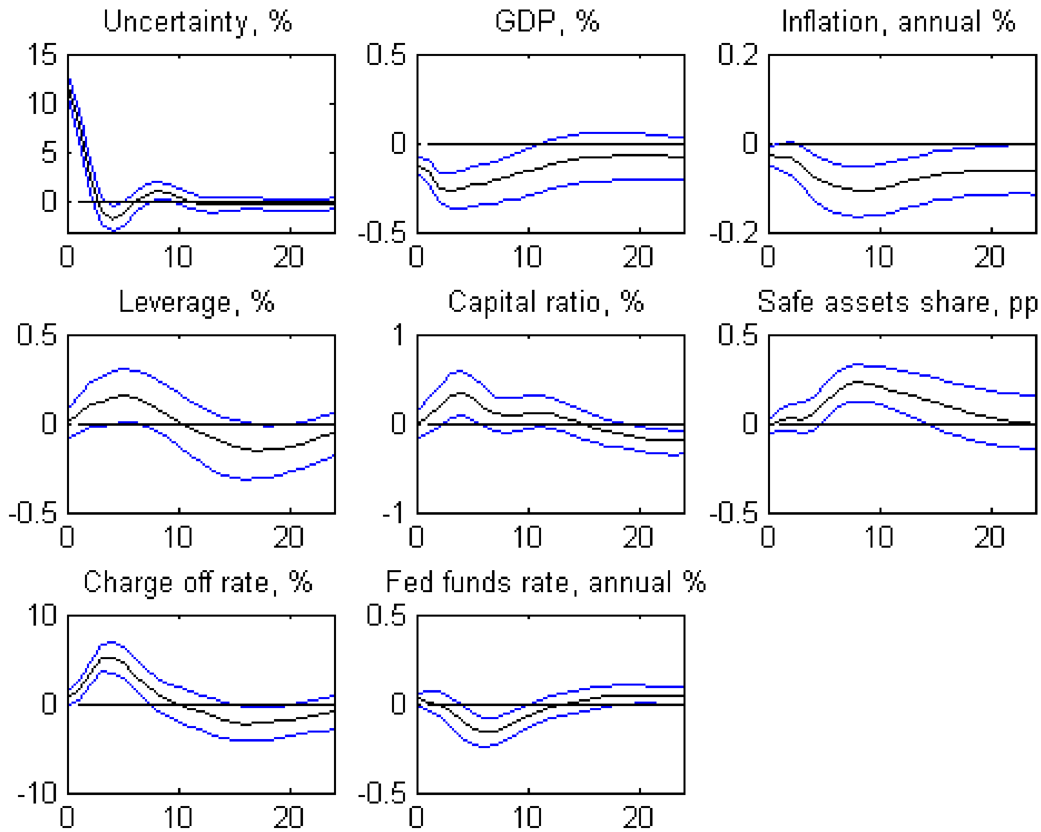
Note. The responses of the model's variables to one-standard deviation shock to uncertainty. Safe assets include cash and Treasury and agency securities. The solid black lines represent median responses, the solid blue lines represent the 90% bias-corrected bootstrap confidence bands, which are calculated as in Kilian (1998). The units of the horizontal axes are quarters. The units of the vertical axis are percents. According to Akaike information criterion, the VAR order includes four lags.

Figure B.3: Impulse responses to an uncertainty shock of a model with the share of commercial and industrial loans: 1985-2015.



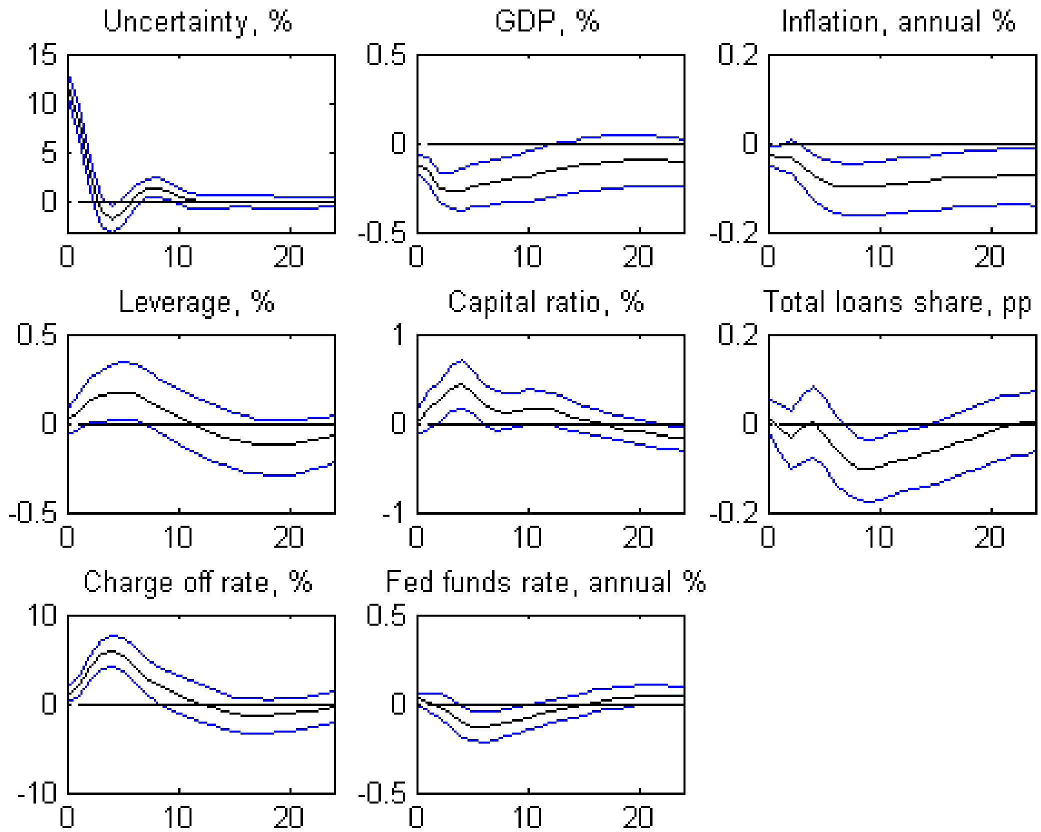
Note. The responses of the model's variables to one-standard deviation shock to uncertainty. The share of commercial and industrial loans in banks' portfolios is calculated as the percentage in the total banks' assets. The solid black lines represent median responses, the solid blue lines represent the 90% bias-corrected bootstrap confidence bands, which are calculated as in Kilian (1998). The units of the horizontal axes are quarters. The units of the vertical axis are percents. According to Akaike information criterion, the VAR order includes four lags.

Figure B.4: Impulse responses to an uncertainty shock of a model with the share of safe assets: 1985-2015.



Note. The responses of the model's variables to one-standard deviation shock to uncertainty. The share of commercial and industrial loans in banks' portfolios is calculated as the percentage in the total banks' assets. The solid black lines represent median responses, the solid blue lines represent the 90% bias-corrected bootstrap confidence bands, which are calculated as in Kilian (1998). The units of the horizontal axes are quarters. The units of the vertical axis are percents. According to Akaike information criterion, the VAR order includes four lags.

Figure B.5: Impulse responses to an uncertainty shock of a model with the share of total loans: 1985-2015.



Note. The responses of the model's variables to one-standard deviation shock to uncertainty. The share of total loans in banks' portfolios is calculated as the percentage of the sum of commercial and industrial loans, real estate loans and consumer loans in the total banks' assets. The solid black lines represent median responses, the solid blue lines represent the 90% bias-corrected bootstrap confidence bands, which are calculated as in Kilian (1998). The units of the horizontal axes are quarters. The units of the vertical axis are percents. According to Akaike information criterion, the VAR order includes four lags.

Appendix D Technical appendix

Appendix D.1 Banking sector

At time t the balance sheet of the bank is:

$$D_t = L_t + B_t. \tag{44}$$

The profit of the bank is the difference between its income and expenses:

$$\mathbb{E}_t \Pi_{t+1} = (1 - F(\bar{\omega}_{t+1})) r_t^L L_t + (1-\mu) V_{t+1}^d + r_t^G B_t - r_t^D D_t. \tag{45}$$

Using the simplifying assumption that $r_t^G = r_t^D$ in each period t, we rearrange the expression for bank profit ($\mathbb{E}_t \Pi_{t+1} = (1 - F(\bar{\omega}_{t+1})) r_t^L L_t + (1-\mu) V_{t+1}^d + r_t^G B_t - r_t^D D_t$), between the third and the forth lines below we use the balance sheet identity holding at time t:

$$\begin{aligned}
\Pi_{t+1} = (1 - F(\bar{\omega}_{t+1})) r_t^L L_t + (1-\mu) V_{t+1}^d + r_t^G B_t - r_t^D D_t = \\
= (1 - F(\bar{\omega}_{t+1})) r_t^L L_t + r_t^G B_t - r_t^G D_t + (1-\mu) V_{t+1}^d = \\
= (1 - F(\bar{\omega}_{t+1})) r_t^L L_t + r_t^G (B_t - D_t) + (1-\mu) V_{t+1}^d = \\
= (1 - F(\bar{\omega}_{t+1})) r_t^L L_t - r_t^G L_t + (1-\mu) V_{t+1}^d = \\
= L_t ((1 - F(\bar{\omega}_{t+1})) r_t^L - r_t^G) + (1-\mu) V_{t+1}^d.
\end{aligned}$$

The Lagrangian of the problem is given by

$$\mathcal{L}_t = \mathbb{E}_t \sum_{s=0}^{\infty} S_{t,t+s+1} u(\Pi_{t+s+1}). \tag{46}$$

The first order condition is:

$$\frac{\partial \mathcal{L}_t}{\partial \alpha_t} = \mathbb{E}_t [u'(\Pi_{t+1}) \frac{\partial \Pi_{t+1}}{\partial L_t} \frac{\partial L_t}{\partial \alpha_t}] = 0, \tag{47}$$

implying that

$$\mathbb{E}_t [\Pi_{t+1}^{-\kappa} (r_t^L (1 - F(\bar{\omega}_{t+1})) - r_t^G) D_t] = 0, \tag{48}$$

where we used the fact that $\alpha_t = \frac{L_t}{D_t}$. Because D_t is chosen, and therefore, known at time t and is a non-zero value, (48) means that the first order condition is actually

$$\mathbb{E}_t[\Pi_{t+1}^{-\kappa}(r_t^L(1 - F(\bar{\omega}_{t+1})) - r_t^G)] = 0, \tag{49}$$

or

$$r_t^L \mathbb{E}_t[\Pi_{t+1}^{-\kappa}(1 - F(\bar{\omega}_{t+1}))] = r_t^G \mathbb{E}_t[\Pi_{t+1}^{-\kappa}]. \tag{50}$$

By using the fact that r_t^L becomes known at t and applying the definition of covariance and the linearity property of expectations to (50), we expand this optimality condition to

$$r_t^{L,RA}[\mathrm{Cov}(\Pi_{\mathrm{t+1}}^{-\kappa}, (1 - \mathrm{F}(\bar{\omega}_{\mathrm{t+1}}))) + \mathbb{E}_t[\Pi_{t+1}^{-\kappa}]\mathbb{E}_t[(1 - F(\bar{\omega}_{t+1}))]] = r_t^G \mathbb{E}_t[\Pi_{t+1}^{-\kappa}] \tag{51}$$

hence,

$$r_t^{L,RA}[\frac{\mathrm{Cov}(\Pi_{\mathrm{t+1}}^{-\kappa}, (1 - \mathrm{F}(\bar{\omega}_{\mathrm{t+1}})))}{\mathbb{E}_t[\Pi_{t+1}^{-\kappa}]} + \mathbb{E}_t[(1 - F(\bar{\omega}_{t+1}))]] = r_t^G. \tag{52}$$

To derive expression for the risk premium, we perform manipulations with (50):

$$\frac{r_t^L}{r_t^G} = \frac{\mathbb{E}_t[\Pi_{t+1}^{-\kappa}]}{\mathbb{E}_t[\Pi_{t+1}^{-\kappa}(1 - F(\bar{\omega}_{t+1}))]}, \tag{53}$$

then

$$\begin{aligned} \frac{r_t^L - r_t^G}{r_t^G} &= \frac{\mathbb{E}_t[\Pi_{t+1}^{-\kappa}] - \mathbb{E}_t[\Pi_{t+1}^{-\kappa}(1 - F(\bar{\omega}_{t+1}))]}{\mathbb{E}_t[\Pi_{t+1}^{-\kappa}(1 - F(\bar{\omega}_{t+1}))]} = \\ = \frac{\mathbb{E}_t[\Pi_{t+1}^{-\kappa}] - \mathrm{Cov}(\Pi_{\mathrm{t+1}}^{-\kappa}, (1 - \mathrm{F}(\bar{\omega}_{\mathrm{t+1}}))) - \mathbb{E}_t[\Pi_{t+1}^{-\kappa}]\mathbb{E}_t[(1 - F(\bar{\omega}_{t+1}))]}{\mathrm{Cov}(\Pi_{\mathrm{t+1}}^{-\kappa}, (1 - \mathrm{F}(\bar{\omega}_{\mathrm{t+1}}))) + \mathbb{E}_t[\Pi_{t+1}^{-\kappa}]\mathbb{E}_t[(1 - F(\bar{\omega}_{t+1}))]} &= \\ = \frac{1 - \frac{\mathrm{Cov}(\Pi_{\mathrm{t+1}}^{-\kappa}, (1 - \mathrm{F}(\bar{\omega}_{\mathrm{t+1}})))}{\mathbb{E}_t[\Pi_{t+1}^{-\kappa}]} - \mathbb{E}_t[(1 - F(\bar{\omega}_{t+1}))]}{\frac{\mathrm{Cov}(\Pi_{\mathrm{t+1}}^{-\kappa}, (1 - \mathrm{F}(\bar{\omega}_{\mathrm{t+1}})))}{\mathbb{E}_t[\Pi_{t+1}^{-\kappa}]} + \mathbb{E}_t[(1 - F(\bar{\omega}_{t+1}))]} & \end{aligned}$$

Appendix D.2 Households

Households maximize their expected discounted lifetime utility

$$\max_{C_t, H_t, D_t} \mathbb{E}_t \sum_{k=0}^{\infty} \beta^k [\ln(C_{t+k}) + \xi \ln(1 - H_{t+k}^h)] \tag{54}$$

subject to budget constraint

$$P_t C_t + D_t \leq W_t H_t^h + \Pi_t + r_{t-1}^D D_{t-1}. \tag{55}$$

The first-order conditions for consumption, labour and depostis are:

$$\beta^k C_{t+k}^{-1} P_{t+k}^{-1} = \lambda_{t+k} \tag{56}$$

$$\beta^k \xi \frac{1}{1 - H_{t+k}^h} = \lambda_{t+k} W_{t+k} \tag{57}$$

$$\lambda_{t+k} = \mathbb{E}_{t+k}[\lambda_{t+k+1} r_{t+k}^D], \tag{58}$$

where λ_t is Lagrange multiplier. These first-order conditions could be written as

$$C_t^{-1} = \beta \mathbb{E}_t[C_{t+1}^{-1} r_t^D \pi_{t+1}^{-1}], \tag{59}$$

$$\xi \frac{1}{1 - H_t^h} = C_t^{-1} W_t / P_t. \tag{60}$$

Appendix D.3 Optimal debt contract

ω^j is assumed to be i.i.d. across entrepreneurs and time and follow log-normal distribution: $\omega \sim \log N(1, \sigma_\omega^2)$. Thus, $\log(\bar{\omega}_{t+1}) \sim N(-0.5(\sigma_t^{Id})^2, (\sigma_t^{Id})^2)$. Given this assumption, Bernanke et al. (1999) formulate the following distributions for the debt contract:

$$z_{t+1} = \frac{\ln(\overline{\omega}_{t+1}) + 0.5(\sigma_t^{Id})^2}{\sigma_t^{Id}} \tag{61}$$

$$\Xi(\overline{\omega}_{t+1}) = \Phi^N(z_{t+1} - \sigma_t^{Id}) \tag{62}$$

$$\Gamma(\overline{\omega}_{t+1}) = \Phi^N(z_{t+1} - \sigma_t^{Id}) + \overline{\omega}_{t+1}(1 - \Phi^N(z_{t+1})) \tag{63}$$

$$\Xi'(\overline{\omega}_{t+1}) = \frac{1}{\sigma_t^{Id}\sqrt{2\pi}} exp(-\frac{(\ln(\overline{\omega}_{t+1}) + 0.5(\sigma_t^{Id})^2)^2}{2(\sigma_t^{Id})^2}) \tag{64}$$

$$\Gamma'(\overline{\omega}_{t+1}) = 1 - \Phi^N(z_{t+1}) \tag{65}$$

where $\Phi^N(\cdot)$ is the standard normal c.d.f.

Appendix D.4 Retailers

Retailers choose $P_t^*(i)$ to maximize expected profits given by

$$\mathbb{E}_t[\sum_{k=0}^{\infty} \theta^k SDF_{t+k}(\frac{P_t^* - P_{t+k}^w}{P_{t+k}}) Y_{t+k}^*(i)], \tag{66}$$

where $Y^*_{t+k}(i)$ is the demand in period $t+k$ given price P^*_t. The first-order conditions from maximizing expected profits can be written as

$$P^*_t = \frac{\eta}{\eta - 1} \frac{\mathbb{E}_t \sum_{k=0}^{\infty} \theta^k SDF_{t+k} X^{-1}_{t+k} Y_{t+k} P^{\eta}_{t+k}}{\mathbb{E}_t \sum_{k=0}^{\infty} \theta^k SDF_{t+k} Y_{t+k} P^{\eta-1}_{t+k}}, \tag{67}$$

where X_t is the optimal price markup such that $P_t = X_t P^w_t$.

To implement Calvo pricing equations without log-linearization, we summerize the optimal pricing equation with two recursive equations linked by the optimal pricing equation (67). The numerator n_t and denominator d_t in equation (67) can be written recursively as

$$n_t = P^{\eta}_t Y_t X^{-1}_t + \theta \mathbb{E}_t [SDF_{t+1} n_{t+1}] \tag{68}$$

$$d_t = P^{\eta-1}_t Y_t + \theta \mathbb{E}_t [SDF_{t+1} d_{t+1}]. \tag{69}$$

Thus, the optimal pricing rule can be written as

$$P^*_t = \frac{\eta}{\eta - 1} \frac{n_t}{d_t}. \tag{70}$$

Let $\hat{P}_t = P^*_t / P_t$ and $F_{1,t} = P^{-\eta}_t n_t$. From equation (68) $F_{1,t}$ is written recursively as

$$F_{1,t} = Y_t X^{-1}_t + \theta \mathbb{E}_t [SDF_{t+1} \pi^{\eta}_{t+1} F_{1,t+1}]. \tag{71}$$

Substituting $F_{1,t}$ into the rewritten optimal pricing rule (70) yields

$$P^*_t P^{-\eta}_t = \frac{\eta}{\eta - 1} \frac{P^{-\eta}_t n_t}{d_t}. \tag{72}$$

Let $F_{2,t} = P^*_t P^{-\eta} d_t = \hat{P}_t P^{1-\eta}_t d_t$. From equation (69) $F_{2,t}$ is written recursively as

$$F_{2,t} = Y_t \hat{P}_t + \theta \mathbb{E}_t [SDF_{t+1} (\frac{\hat{P}_t}{\hat{P}_{t+1}}) \pi^{\eta-1}_{t+1} F_{2,t+1}]. \tag{73}$$

Using variables $F_{1,t}$ and $F_{2,t}$ the optimal pricing rule is

$$F_{2,t} = \frac{\eta}{\eta - 1} F_{1,t}. \tag{74}$$

P^*_t is the same for all the retailers in each period. Therefore, in each period $1 - \theta$ retailers reset their price to P_t^* and he aggregate price evolves according to

$$P_t = [\theta P_{t-1}^{1-\eta} + (1-\theta)(P_t^*)^{1-\eta}]^{\frac{1}{1-\eta}}. \tag{75}$$

Appendix E Impulse Response Functions Computation

In line with Fernandez-Villaverde et al. (2011) and the approach of Dynare to calculate impulse responses, the following procedure was used to compute impulse responses:

1. We draw a series of random shocks $\epsilon_t = (\epsilon_t^A, \epsilon_t^W, \epsilon_t^\sigma, \epsilon_t^g, \epsilon_t^m)$ for 2096 periods. Starting from the steady state, we simulate the model using ϵ_t.

2. We disregard the first 2000 periods as a burn-in. Based on the last 96 periods, we compute the mean of the ergodic distribution for each variable in the model.

3. Starting from the ergodic mean, we hit the model with a series of random shocks ϵ_t^W for 96 periods. Simulation Y_t^1 is obtained.

4. Obtain $\tilde{\epsilon}_t^W$ by adding one standard deviation to ϵ_t^W in period 1 and simulate the model starting from ergodic mean and hitting it with $\tilde{\epsilon}_t^W$ to get Y_t^2.

5. We obtain IRFs as $Y_t^2 - Y_t^1$.