LENDING BEHAVIORS OF BANKS UNDER UNCERTAINTY

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Contents

Chapter 1

Introduction

1.1 Motivation

In this thesis, we focus on the lending behaviors of banks under uncertainty by presenting models based on two different theories, the rational expectation theory and the behavioral finance theory, and by providing empirical evidence.

Banking sector has been absent from the economic literature primarily because the standard references for micro and macroeconomics have been, for some time, unable to explain the role of banks in the economy. In the ideal economy, which is the basis of the traditional economic theory, markets are frictionless. In the frictionless market, financial institutions are a veil that only provides an allocation mechanism without affecting it. Such an ideal market, however, is rarely achieved in practice. Although, the short-run influence of financial factors on the real economy is a significant concept in macroeconomics, the controversial question is whether the financial factor has large and persistent effects on the real economy. In addition, a recent crisis has revealed that it is necessary to rethink issues relating to the effects. Wickens (2012, Chapter 15) discussed this matter, and Woodford (2010) discussed the significance of financial intermediation and credit friction in macroeconomics. Financial crisis was created partly due to failure of banks (and other financial institutions) to correctly assess their asset risks. The impact on the economy was enormous. Then, it is necessary to clarify how risk (macroeconomic uncertainty in particular) affects banks' abilities to forecast returns from loans.

In addition, banks are the largest financial intermediaries in our economy, which channel funds from saver–lenders, who have an excess of funds, to borrower–spenders, who have shortage of funds and productive investment opportunities. To reallocate funds to high value investment opportunities, banks obtain costly information, reduce transaction costs, and facilitate risk management. A healthy and vibrant economy requires a well-functioning banking system. By efficient allocation of funds, banks contribute to higher production and efficiency for the overall economy. The link between financial intermediaries and economic growth is supported in the literature (Odedokun, 1996; Rajan and Zingales, 1996; Levine and Zervos, 1998; Levine, Loayza, and Beck, 2000; Beck and Levine, 2004; Deidda and Fattouh, 2008; Luintel, et al., 2008. Gertler (1988) and Levine (1997, 2005) reviewed this field.[1] Moreover, banks directly improve the well-being of people by allowing them to better time their consumption. As Merton states, "A well-functioning financial system facilitates the efficient inter-temporal allocation of household consumption and the efficient allocation of economic resources to the most productive use in the business sector" (Merton, 1993, p. 21).

While banks provide the beneficial economic function of channeling funds, they

[1] Opinions of economists about the link between the function of financial intermediation and economic growth are still polarized. In addition, existing research on financial intermediation and growth do not distinguish banks from financial intermediaries. However, almost all papers use the same indicators, which refer to financial intermediation by banks.

also cause a crushing blow to the economy. When banks go bankrupt, depositors lose their deposits, borrowers (mainly client firms) lose the relationship with their banks, and other stakeholders, (*e. g.*, stock and debt holders of the bank) lose their assets. Simply because a bank's balance sheet begins to deteriorate, the bank will begin to fail. Fear can spread from one bank to another, causing even healthy banks to go under.[2] Moreover, Bernanke (1983), Peek and Rosengren (2005), and Ashcraft (2005) showed that bank failures have a negative impact on the real economy, identified as the "credit crunch"[3] in the economic recession.[4]

Moreover, governments often provide support to domestic banks facing bankruptcy in order to avoid panic and large-scale bank runs. Support is provided in three ways: "lender of last resort," the central bank and government capital injections, and nationalization.[5] For example, during the financial crisis of 1997, the Japanese government conducted capital injections of 1.8 trillion yen in March 1998 and 7.5 trillion yen in March 1999 into city banks, trusted and long-term credit banks, and other regional banks. Governments regulate banks primarily in order to promote banks to provide information to depositors and to ensure the soundness of the financial system. Additional problems for banks result from high levels of government borrowing and the consequent threat of

[2]The seminal work of Diamond and Dybvig (1983) is a major reference in the literature on bank runs. In a real world, for example, in September 2007, the British bank Northern Rock arranged an emergency loan facility from the Bank of England, which it claimed was the result of short-term liquidity problems The resulting bank run leads to a financial crisis; in December 2003, a run on the Bank of Saga in Japan was an unusual case, cased by a chain e-mail.

[3]Here, the term "credit crunch" means that firms with profitable investment opportunities are unable to get loans due to the external shock.

[4]Minamihashi (2011) showed that the credit crunch was caused by bank failures in Japan. Although Hayashi and Prescott (2002) stated that the " credit crunch " hypothesis is applicable only for the brief period of late 1997 through early 1998, however it generally disagreed with the view that investments were constrained by bank lending in the 1990s.

[5]We use the term "lender of last resort" here as the strategic support of lending from the central bank to troubled banks, and the term "nationalization" as the takeover by governments of troubled banks.

sovereign default.[6] In most countries, the implementation of these rescue or regulation systems has been justified by the dramatic consequences of risks to which banks are subject. These facts show the importance of the banking system in our economy and reveal the need to rethink some aspects of economic theory and policy. It is time for us to have alternative monetary policies but setting the official interest rate.

Reflecting on the relationship between the current theory of banks, events in the real world, and the importance of banks in our economy, we examine the lending behaviors of banks acting with imperfect information under an uncertain environment. Why do we focus on bank' lending behaviors, imperfect information and uncertainty? Because the economic viability of banks teeters in the balance under these conditions.

1.2 Related literature

Lucas (1972) published a seminal paper on the imperfect information model. This paper provided the theoretical foundations for models of economic fluctuations in which money is the fundamental driving factor behind movements in real output. Lucas's model clarified the distinction between expected and unexpected changes in money. Economic agents face a signal extraction problem because they have imperfect information about the current money supply. If changes in the nominal supply of money were perfectly predictable, money would have no real effect. Although fluctuations in money are a short-run problem, it causes movements in the real economy (such as output and employment). Lucas (1972) also provided a monetary macroeconomic system based on a microeconomic foundation, and first applied the concept of rational expectations in macroeconomics. In the rational expectation model, errors are attributed to

[6]The ratio of Japanese general government gross debt to nominal GDP was 231.9% at FY2014.

information gaps such as unanticipated shocks to the economy. In addition, this seminal paper indicated that the short-run relationship between output and inflation will depend on the relative variance of real variables and nominal price (money supply) disturbances. In other words, it showed that variations in the predictability of monetary policy, which determines the volume of the money supply, are negatively associated with the cross-sectional variance of the distribution of output. Lucas (1973) detected this negative association and investigated it on the basis of annual time series from 18 countries over the period 1951–1967.

These two papers form the model of bank lending behaviors used in this thesis. In Chapters 2, 3, and 4, the cross-sectional distribution of output is replaced by the cross-sectional distribution of banks' optimal shares of lending, and the variation in predictability of monetary policy is replaced by the variation in the default risk predictability of loans due to macroeconomic uncertainty.

Here banks are associated with portfolio managers. Parkin (1970), Pyle (1971), Hart and Jaffee (1974), Koehn and Santomero (1980), and so on. examined banks' optimal behaviors when selecting a mean–variance efficient portfolio. Although they failed to successfully describe bank behaviors, their studies garnered considerable attention because of the obvious applications of portfolio choice modeling of financial institutions.

Banks that modeled on microeconomics (Freixas and Roche, 1997; Santomero, 1984) surveyed the modeling of banking firms. However, the direct impact of unexpected macroeconomic uncertainty on bank lending behaviors is not modeled in the literature. In addition, the seminal contributions of Bernanke and Gertler (1989), Kiyotaki and Moore (1997), and Bernanke, Gertler and Gilchrist (1999) reveal several important credit channels where financial frictions affect the macroeconomy.[7] These all are based

[7] Bernanke and Gertler (1995) summarized the view of the credit channel and its role inside a monetary

on the rational expectation theory. Chapter 2 provides the model of a bank' s portfolio selection model based on the rational expectation model. The development of asset pricing theory is indirectly related to our current thesis. Asset pricing by rational expectation models can not sufficiently explain the excess volatility of stock prices, which has prompted academic researchers to explore the possibility of alternative paradigms. Behavioral finance is one such alternative model. Shiller (2003) clarified the details. Hence, we applied the behavioral finance theory to describe bank lending behaviors. We examine an irrational bank's lending behavior, in Chapter 4.

According to the developments in these fields, we specifically explore these behaviors under uncertainty.

policy transmission mechanism at that time.

Chapter 2

Theory of Bank Lending Behaviors under Uncertainty

2.1 Introduction

In an ever-changing world, banks not only find new opportunities for loans to make profits, but also have imperfect knowledge of future events. Uncertainty and imperfect information are a resource for profits but are also operational risks for the banks. Given that banks are profit-maximizing enterprises, which must acquire costly information on borrowers, the decisions to extend loans to new or existing customers are affected by the current and expected states of the macroeconomy. Since risk premia are largely driven by the effects of macroeconomic shocks on asset prices, banks' lending behavior are affected by macroeconomic uncertainty. That is, greater uncertainty about economic conditions (and the likelihood of loan default) significantly affects on bank lending strategies or its investment decisions beyond the constraints posed by monetary policymakers' actions.

In this chapter, we use a simple signal extraction framework to demonstrate that variations in macroeconomic uncertainty affect banks' asset allocations, i.e., lending behaviors. This model offers an unambiguous prediction for bank lending behaviors. An intuitive explanation of this linkage is as follows: greater economic uncertainty hinders banks' ability to accurately forecast returns from loans; therefore, banks rebalance their portfolios toward assets containing more predictable returns. In other words, macroeconomic uncertainty makes it difficult for banks to predict future returns from lending, that affects their investment decisions, and results in having a effect on the bank lending behaviors.

Although assets are effectively allocated in an economy where Say's Law holds,[1] there are a number of models describing an economy in which the law does not.[2] For example, a model for an economy with imperfect information that shows imperfect information on the price system results in less efficient allocation of resources. Lucas (1973) explained this problem using a representative model called the "island model." We use Lucas's island model to describe a bank lending behavior under uncertain macroeconomic conditions. In his model, the situation perceived by individual suppliers is quite different from the aggregate situation as seen by an outsider. This situation may hold true in a loan market, where we can see that banks face the situation of imperfect information.

Beaudry, et al. (2001) proposed an analytical framework whereby firms' investment decisions have the same structure as that of Lucas' island model. Baum, et al. (2005) proposed a model for banks' portfolio selections in line with the model of Beaudry, et al.

[1]Say's law is an idea founded on classical economics, which states that "supply creates demand." In such an economy, money is only a "veil" and has no real effect.

[2]There are many examples supporting that the fact that the transaction between goods and money is not smooth. Lucas (1972, 1973) proposed such mechanisms by assuming imperfect information.

In their analysis, macroeconomic uncertainty is negatively associated with bank lending behaviors. Following their model, we explain these behaviors under macroeconomic uncertainty.

2.2 Proposed model

Here, we provide a model to illustrate how macroeconomic uncertainties can affect bank lending behaviors through its effect on the informational content on returns from lending. We focus on variations in the predictability of macroeconomic conditions as a source of changes in the informational content of the returns-from-loans market signals. In particular, the model shows how macroeconomic uncertainty is related to banks' expectations of a return from lending, and how this consequently affects bank lending behaviors. The environment we consider modifies the island model used by Lucas (1973) such that it emphasizes the implications for lending as opposed to employment.

As in Lucas (1973), we assume that there are a large number of banks indexed by i. Banks are located in physically separate and competitive markets.[3] Each bank has its own market and is isolated from the other banks so that a bank's information cannot be transmitted to others. Demand for loans in each period is distributed unevenly over markets. Moreover, banks can only observe imperfect (or partial) information about future returns from lending. Consequently, the situation faced by individual banks will be quite different from the aggregate situation as seen by outside banks.

Bank assets are comprise reserves and cash items, securities, and loans.[4] Securities

[3] Each market has a bank.

[4] Table 2.1 shows assets in banking accounts of Japanese banks. Loans account for the largest share about 50% of total assets and Securities have about 30% in recent years.

are made up entirely of debt instruments, because regulations do not necessarily allow banks to hold stock.[5] Although securities can be classified into three categories (i.e., government and agency bonds, local government bonds, and other securities), because these bonds are liquid and marketable, for the sake of simplicity, we assume that there are only two classes of assets: loans (risky assets) and others (risk- free assets). Loans involve uncertain outcomes, are not necessarily marketable, and have a high default risk. On the other hand, bonds yield stable returns, are marketable, and have less default risk.[6]

In this economy, bank i manages its assets and liabilities to make profits. Banks are assumed to be risk-averse,[7] and each period rebalance their asset portfolios to maintain an appropriate level of risk and expected returns. To describe a bank's portfolio selection, we extend the standard portfolio optimization model by allowing the bank to acquire imperfect information about the rate of return from loans through a noisy signal. To maintain tractability, we consider a one-period decision problem. Let x be the ratio of loans to total assets. A bank allocates $100x$ percent of total assets to firms as loans and $100(1 - x)$ per cent to other risk-free assets (bonds).

The risk free asset yields a rate of return of r_f that is nonstochastic and identical for all banks. The risky asset yields a rate of return of r_i that exceeds r_f by risk premium. A risk premium consists of a certain part ρ_i and the random element ϵ_i, $\rho_i + \epsilon_i$. Hence, the rate of return from loans is compounded from a risk free rate r_f, a certain part of a

[5]Table 2.1 gives details about securites. Government bonds are the majority of securities, which account for share larger than 50%, whereas stocks account for only a few percent of the share of securities.

[6]We obtain a consistent result with this model even though the other assets (bonds and securities) are treated with distinction.

[7]We justify this assumption on the fact that banks are equity-constrained. Banks need to accrue debt that increases the probability of bankruptcy, and the costs associated with bankruptcy lead to risk averse behavior. For further explanations, see Stiglitz and Greenwald (2003)

premium ρ_i, and the random element ϵ_i:

$$r_i = r_f + \rho_i + \epsilon_i, \tag{2.1}$$

where ϵ_i is assumed to be normally distributed with zero mean and variance σ_ϵ^2.[8] Variations in σ_ϵ^2 may be regarded as reflections of uncertainty in the economy. This random element ϵ_i describes an unexpected stochastic part of the premium and refers to a default risk. While the exact value of ϵ_i is unknown ex ante, its distribution is known among all banks. Although bank lending is secured by various methods,[9] default risk is inevitable because banks cannot accurately forecast the future economic situation. To make our analysis lucid, we assume that the source of risk for lending comes only from ϵ_i and banks must always manage the default risk.

Prior to allocating bank assets between risky and risk-free alternatives, if it is possible for banks to estimate such stochastic parts using some information, the estimation will improve the naive prediction of a zero value for $\mathrm{E}[\epsilon_i]$. Now, we introduce a signal S_i. Bank i acquires noisy signal S_i that is related to ϵ_i:

$$S_i = \epsilon_i + \nu, \tag{2.2}$$

where ν is noise distributed as $N(0, \sigma_\nu^2)$, and its distribution is known by banks ex ante. Noise ν is assumed to be independent of ϵ_i and identical for all banks.[10] Here, the noise variance refers to macroeconomic uncertainty in this economy.

[8]Note that we refer to r_i as the rate of return from loans (*i.e.*, the risky assets) of bank i's portfolio. In this thesis, we do not distinguish among individual loans.

[9]They have informed about their borrowers through relationships, "monitoring," "screening," and so on.

[10]We will later consider the case where each bank has its own noise variance.

Obviously, S_i has a normal distribution with mean 0 and variance $\sigma_\epsilon^2 + \sigma_\nu^2$, and Equation (2.2) shows that S_i differs from ϵ_i by the noise fluctuation ν. By assumption, banks cannot distinguish between the exact default risk ϵ_i and the noisy signal ν from the signal S_i, which obscures the bank i's estimation of ϵ_i. The variance of S_i shows how the signal is obscured.

Using this signal, banks extract the default risk ϵ_i to ensure their return from lending. We assume that banks estimate ϵ_i by the linear least squares estimate of ϵ_i. This method is known as the "signal extraction model" in Lucas (1973). In this system, a bank' s optimal estimate of ϵ_i from noisy random variable S_i is equal to the conditional mathematical expectation of ϵ_i on S_i,[11] which can form an optimal forecast of ϵ_i as

$$\mathrm{E}[\epsilon_i | S_i] = \lambda S_i, \tag{2.3}$$

where

$$\lambda = \frac{\sigma_\epsilon^2}{\sigma_\epsilon^2 + \sigma_\nu^2}. \tag{2.4}$$

The coefficient λ varies with σ_ν^2 as σ_ϵ^2 is constant. λ can be interpreted as the weight that a bank has to assign its own signal. The larger the noise variance σ_ν^2, the less weight the bank assign to this signal.

In this rational expectation model, bank i rationally chooses the estimation coefficient λ, and the estimation is executed purely to reflect economic fundamentals. Therefore, we postulate that Equation (2.3) is the bank i's optimal estimate of ϵ_i based on fundamentals.

[11] In general, the mathematical expectation is not a linear function. However, since we suppose that $\epsilon_i S_i$ follows a multivariate normal distribution, the conditional mathematical expectation $\mathrm{E}[\epsilon_i | S_i]$ is linear in S_i.

Next, we show the conditional variance of ϵ_i on S_i:

$$\mathrm{Var}[\epsilon_i|S_i] = \lambda\sigma_\nu^2. \tag{2.5}$$

Variance indicates how the estimation disperses. Greater variance indicates greater uncertainty of future economic situations, which decreases the precision of bank i's estimation of the default risk of loans. This variance increases when either σ_ϵ^2 or σ_ν^2 increases. As mentioned earlier, the magnitude of the noise variance σ_ν^2 indicates the macroeconomic uncertainty. Hence, Equations (2.3) and (2.5) indicate that macroeconomic uncertainty is related to bank i's prediction of the default risk of loans and its precision, respectively.

The following lemma expresses the link between bank i's estimation of default risk and macroeconomic uncertainty σ_ν^2.

Lemma 1. Given σ_ϵ^2, the macroeconomic uncertainty σ_ν^2 is related to bank i's estimation of the default risk of loans $\mathrm{E}[\epsilon_i|S_i]$, the weight to its own signal λ, and the precision of its estimation $\mathrm{Var}[\epsilon_i|S_i]$.

Lemma 1 means that the larger the macroeconomic uncertainty, the less precision in bank i's estimation of its default risk. Moreover, a greater macroeconomic uncertainty causes the bank to give less importance to the signal. In other words, the macroeconomic uncertainty increases the signal ambiguity. Equivalently, if the signal is uncertain, estimation from the signal is imprecise.

In what follows, we develop bank i's asset allocation and portfolio selection. We normalize the total assets of bank i to unity. Then, bank i's total expected returns conditional on the signal will take the form of

$$\begin{aligned} \mathrm{E}[Y_i|S_i] &= x_i \mathrm{E}[r_i|S_i] + (1 - x_i) r_f \\ &= x_i (r_f + \rho_i + \lambda S_i) + (1 - x_i) r_f, \end{aligned} \tag{2.6}$$

where Y_i denotes total returns, and the conditional variance of Y_i will be

$$\mathrm{Var}[Y_i|S_i] = \lambda \, \sigma_\nu^2 \, x_i^2. \tag{2.7}$$

Suppose that bank i's objective function can be modeled in a simple expected utility framework and expressed in the form of the following exponential utility function with parameter α. Then, the expected utility function of a normal random variable Y_i conditioned on S_i takes the form of

$$\begin{aligned} \mathrm{E}[U_i|S_i] &= \mathrm{E}[e^{-aY_i}|S_i] \\ &= \exp\left\{-\alpha\left(r_f + x_i \rho_i - \frac{1}{2}\lambda(\sigma_\nu^2 \, \alpha \, x_i^2 + 2x_i \, S_i)\right)\right\}, \end{aligned} \tag{2.8}$$

where α is the coefficient of risk aversion.[12] After solving the utility maximization problem with respect to x_i, the optimal share of lending is given by

$$x_i^* = \frac{\rho_i - \lambda S_i}{\alpha \lambda \sigma_\nu^2}. \tag{2.9}$$

Here, we describe bank lending behaviors in terms of a distribution of x_i^*, especially

[12]Random gains, x, are ordered by means of an expected utility function $u(x)$. Usually the function $u(x)$ has the following basic properties; $u(x)$ is twice differentiable: $u'(x) > 0$ and $u''(x) < 0$.

by the mean and variance of distribution:

$$\mathrm{E}[x_i^*] = \frac{\rho_i}{\alpha\lambda\sigma_\nu^2}, \tag{2.10}$$

$$\mathrm{Var}[x_i^*] = \frac{\sigma_\epsilon^2 + \sigma_\nu^2}{\alpha^2(\sigma_\nu^2)^2}. \tag{2.11}$$

From equations (2.10) and (2.11), we examine the effect of macroeconomic uncertainty σ_ν^2 on the optimal lending behavior. Now, we differentiate the mean and variance of the optimal lending share with respect to σ_ν^2, respectively, as

$$\frac{\partial \mathrm{E}[x_i^*]}{\partial \sigma_\nu^2} = -\frac{\rho_i}{\alpha(\sigma_\nu^2)^2} < 0, \tag{2.12}$$

and

$$\frac{\partial \mathrm{Var}[x_i^*]}{\partial \sigma_\nu^2} = -\frac{1}{\alpha^2(\sigma_\nu^2)^2}\left[\frac{2\sigma_{\epsilon_t}^2}{\sigma_\nu^2} + 1\right] < 0. \tag{2.13}$$

The next lemma describes the association between bank i's optimal lending behavior and macroeconomic uncertainty.

Lemma 2. The mean and variance of distribution of x_i^* decrease with increasing σ_ν^2.

Lemma 2 shows that, given that σ_ϵ^2 is constant, the larger the macroeconomic uncertainty becomes, the less the mean and variance of the lending share become. If each bank' s lending behavior is negatively related to macroeconomic uncertainty, the aggregate behavior moves in the same direction. That is, bank lending share homogeneously decreases. Conversely, when the uncertainty of the information decreases, the share heterogeneously increases. We call the former behavior "bearish" (diffident) and the latter "bullish" (confident). Moreover, since we may interpret the noise variance as the precision of a bank' s information, given σ_ϵ^2 as constant, we say that Lemma 2 indicates the effect of signal precision on bank lending behaviors. Equations (2.12) and (2.13) also show how these behaviors are affected by the precision of the signal, or equivalently, by the precision of bank i's estimation of the terminal default risk with a noisy signal.

2.3 Results

From Lemma 1, we obtained the following results: (1) Banks forecast the default risk ϵ_i using imperfect information S_i using the signal extraction model, (2) The estimated coefficient is related to macroeconomic uncertainty σ_ν^2, (3) The conditional variance of ϵ_i on S_i suggests the extent of uncertainty of the estimated default risk, and (4) Both λ and $\text{Var}[\epsilon_i|S_i]$ vary with σ_ν^2: λ is an increasing function of σ_ν^2, and $\text{Var}[\epsilon_i|S_i]$ is a decreasing function of σ_ν^2.

From Lemma 2, we obtained the following results: (1) Macroeconomic uncertainty affects the optimal lending behavior of bank i through variations in bank i's estimation of the rate of return from loans, (2) The larger the macroeconomic uncertainty, the less the mean and variance of the optimal lending share of bank i, and (3) When macroeconomic uncertainty increases, the aggregate banks' lending share homogeneously decreases.

These results show that greater macroeconomic uncertainty negatively associates with bank lending behaviors. When financial markets break down during financial crises, it results in severe economic hardship. Historically, many financial crises have been associated with banking panics, and many recessions coincided with these panics. It is often said that financial crisis have stemmed, in part, from the inability of financial institutions, especially banks, to effectively judge the riskiness of their investments. Faced with imperfect information about the likelihood of default on loans, banks not only ration credit but also change their asset portfolios. This negative association suggests that monetary policy does not only consists in setting the official interest rate and that there is an alternative credit channel.

Table 2.1: Assets of Domestically Licensed Banks - Banking Accounts (% distribution)

	Cash and due from banks (%)	Investment securities (%)					Loans and bills discounted (%)	Others (%)	Total assets (%)
			Government bonds (%)	Corporate bonds (%)	Stocks (%)	The other investment securities (%)			
1975	7.9	12.7	2.3	4.9	2.3	3.2	61.5	18.0	100
1980	7.7	17.4	6.6	4.3	2.9	3.6	59.1	15.8	100
1985	6.9	15.4	4.3	3.9	3.1	4.0	63.0	14.7	100
1990	10.2	16.4	4.0	3.3	4.5	4.6	58.5	14.9	100
1995	6.0	16.6	3.8	3.1	5.9	3.8	64.8	12.6	100
2000	3.8	21.6	9.0	2.4	5.7	4.4	61.1	13.5	100
2005	4.8	26.4	12.9	4.0	2.8	6.7	54.6	14.1	100
2010	2.8	29.2	17.1	4.0	2.4	5.6	54.5	13.5	100
2011	3.9	31.7	19.2	4.0	2.2	6.2	52.2	12.3	100
2012	3.2	33.1	20.5	3.8	2.1	6.7	51.1	12.6	100
2013	4.1	32.3	19.4	3.7	1.9	7.3	50.9	12.7	100
2014	9.5	28.1	15.3	3.6	1.7	7.5	51.1	11.4	100

Source: Author's calculation using the data of "*Bank of Japan Statistics Financial Institutions accounts*."

Appendix

When we normalize bank i's total asset to 1, the total returns from assets' allocation will be

$$Y_i = x_i(r_f + \rho_i + \epsilon_i) + (1 - x_i)r_f. \tag{A-1}$$

$$\begin{aligned} \mathrm{E}[Y_i|S_i] &= r_f + x_i\rho_i + x_i\mathrm{E}[\epsilon_i|S_i] \\ \mathrm{Var}[Y_i|S_i] &= x_i^2\mathrm{Var}[\epsilon_i|S_i] \end{aligned} \tag{A-2}$$

$$\begin{aligned} r_i(Y_i|S_i) &= -\frac{u''(Y_i|S_i)}{u'(Y_i|S_i)} \\ &= -\frac{\rho_i + \lambda S_i - \alpha x_i\lambda\sigma_\nu^2}{-\lambda\sigma_\nu^2} \end{aligned} \tag{A-3}$$

In terms of the certainty equivalent, a choice between a random return and a fixed gain to its expectation is made under the following condition:

$$U(Y_i) = \mathrm{E}[U(Y_i)].$$

We will examine the case that the random component ϵ_i is conditionally distributed on a signal $S_i = \epsilon_i + \nu$. In this case ϵ_i follows a conditional distribution on S_i. Before showing the conditional distribution of ϵ_i on S_i, we are equipped with the following functions;

$$
\begin{aligned}
f(\epsilon, S) &= \left(\frac{1}{\sqrt{2\pi}}\right)^2 \begin{vmatrix} a & a \\ a & a+b \end{vmatrix}^{-\frac{1}{2}} exp\left\{-\frac{1}{2}\left((\epsilon\, S),\ \begin{bmatrix} a & a \\ a & a+b \end{bmatrix}^{-1} (\epsilon\, S)\right)\right\} \\
&= \left(\frac{1}{\sqrt{2\pi}}\right)^2 \frac{1}{\sqrt{ab}}\ \exp\left\{-\frac{1}{2ab}((a+b)\epsilon^2 - 2a\epsilon S + a S^2)\right\} \\
&= \left(\frac{1}{\sqrt{2\pi}}\right)^2 \frac{1}{\sqrt{ab}}\ \exp\left\{-\frac{a+b}{2ab}\left(\epsilon^2 - \frac{2a\epsilon S}{a+b}\right) - \frac{aS^2}{2ab}\right\} \\
&= \left(\frac{1}{\sqrt{2\pi}}\right)^2 \frac{1}{\sqrt{ab}}\ \exp\left\{-\frac{a+b}{2ab}\left(\epsilon^2 - \frac{2a\epsilon S}{a+b} + \left(\frac{aS}{a+b}\right)^2 - \left(\frac{aS}{a+b}\right)^2\right) - \frac{aS^2}{2ab}\right\} \\
&= \left(\frac{1}{\sqrt{2\pi}}\right)^2 \frac{1}{\sqrt{ab}}\ \exp\left\{-\frac{a+b}{2ab}\left(\epsilon - \frac{aS}{a+b}\right)^2 + \frac{(aS)^2}{2ab(a+b)} - \frac{aS^2}{2ab}\right\} \\
&= \left(\frac{1}{\sqrt{2\pi}}\right)^2 \frac{1}{\sqrt{ab}}\ \exp\left\{-\frac{a+b}{2ab}\left(\epsilon - \frac{aS}{a+b}\right)^2 - \frac{S^2}{2(a+b)}\right\} \\
&= \left(\frac{1}{\sqrt{2\pi}}\right)^2 \frac{1}{\sqrt{ab}}\ \exp\left\{-\frac{a+b}{2ab}\left(\epsilon - \frac{aS}{a+b}\right)^2\right\}\ \exp\left\{-\frac{S^2}{2(a+b)}\right\}
\end{aligned}
$$

is a p.d.f. of $N\left(0, \begin{bmatrix} a & a \\ a & a+b \end{bmatrix}\right)$ and the probability of $S \in ds$ is

$$
\begin{aligned}
\mathbf{P}[S \in ds] &= \int_{-\infty}^{\infty} d\epsilon\, f(\epsilon, S)\, ds \\
&= \int_{-\infty}^{\infty} d\epsilon \left(\frac{1}{\sqrt{2\pi}}\right)^2 \frac{1}{\sqrt{ab}}\ \exp\left\{-\frac{a+b}{2ab}\left(\epsilon - aS\right)^2\right\}\ \exp\left\{-\frac{S^2}{2(a+b)}\right\} ds,
\end{aligned}
$$

here, we set $\sqrt{\frac{a+b}{2ab}}\left(\epsilon - aS\right) = K$, then, $d\epsilon = \sqrt{\frac{2ab}{a+b}}\, dK$,

$$
\begin{aligned}
&= \int_{-\infty}^{\infty} dK\, \sqrt{\frac{2ab}{a+b}} \frac{1}{\sqrt{2\pi}} \frac{1}{\sqrt{ab}}\, e^{-K^2}\, \frac{1}{\sqrt{2\pi}}\, \exp\left\{-\frac{S^2}{2(a+b)}\right\}\, ds \\
&= \frac{1}{\sqrt{a+b}} \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} \frac{1}{\sqrt{\pi}}\, e^{-K^2}\, dK\, \exp\left\{-\frac{S^2}{2(a+b)}\right\}\, ds \\
&= \frac{1}{\sqrt{a+b}} \frac{1}{\sqrt{2\pi}} \exp\left\{-\frac{S^2}{2(a+b)}\right\}\, ds
\end{aligned}
$$

By the definition of a conditional distribution:

$$
\mathbf{P}[\boldsymbol{Z} \in d\epsilon \,|\, \epsilon + \nu = ds] = \frac{\mathbf{P}[Z_1 \in d\epsilon, Z_2 \in ds]}{\mathbf{P}[Z_2 \in ds]} = \frac{f(\epsilon, S) d\epsilon\, ds}{\mathbf{P}[Z_2 \in ds]}.
$$

Then, the conditional distribution of ϵ_i on S_i is

$$
\begin{aligned}
g(\epsilon, S)\, d\epsilon\, ds &\equiv \mathbf{P}[\boldsymbol{Z} \in d\epsilon \,|\, \epsilon + \nu = ds] \\
&= \frac{\left(\frac{1}{\sqrt{2\pi}}\right)^2 \frac{1}{\sqrt{ab}}\, \exp\left\{-\frac{a+b}{2ab}\left(\epsilon - \frac{aS}{a+b}\right)^2\right\}\, \exp\left\{-\frac{S^2}{2(a+b)}\right\}\, d\epsilon\, ds}{\frac{1}{\sqrt{a+b}} \frac{1}{\sqrt{2\pi}} \exp\left\{-\frac{1}{2(a+b)} S^2\right\}\, ds} \\
&= \frac{\frac{1}{\sqrt{2\pi}} \sqrt{a+b}\, \exp\left\{-\frac{a+b}{2ab}\left(\epsilon - \frac{aS}{a+b}\right)^2\right\}\, \exp\left\{-\frac{S^2}{2(a+b)}\right\} d\epsilon\, ds}{\sqrt{ab}\, \exp\left\{-\frac{1}{2(a+b)} S^2\right\}\, ds} \\
&= \frac{\sqrt{a+b}}{\sqrt{ab}} \frac{1}{\sqrt{2\pi}} \exp\left\{-\frac{a+b}{2ab}(\epsilon - \frac{aS}{a+b})^2\right\}\, d\epsilon \\
&= \sqrt{\frac{1}{a} + \frac{1}{b}} \frac{1}{\sqrt{2\pi}} \exp\left\{-\frac{1}{2ab(a+b)}((a+b)\epsilon - aS))^2\right\} d\epsilon\, ds. \qquad \text{(A-4)}
\end{aligned}
$$

Now we apply (A-4) to the previous maximization problem.

$$
\begin{aligned}
\mathrm{E}[U(Y)|S] &= \int -\exp\{-\alpha(r_f + x\rho + x\epsilon)\}g(\epsilon, S)d\,\epsilon \\
&= -e^{-\alpha(r_f+x\rho)}\int e^{-\alpha x\epsilon}\sqrt{\frac{1}{a}+\frac{1}{b}}\frac{1}{\sqrt{2\pi}}\exp\left\{-\frac{1}{2}\frac{1}{ab(a+b)}((a+b)\epsilon - aS)^2\right\}d\epsilon \\
&= -e^{-\alpha(//)}\int \sqrt{\frac{1}{a}+\frac{1}{b}}\frac{1}{\sqrt{2\pi}}\exp\left\{-\alpha x\epsilon - \frac{1}{2}\frac{1}{ab(a+b)}((a+b)\epsilon - aS)^2\right\}d\epsilon \\
&= -e^{-\alpha(//)}\int \sqrt{\frac{1}{a}+\frac{1}{b}}\frac{1}{\sqrt{2\pi}}\exp\left\{-\frac{(2ab(a+b)\alpha x\epsilon + (a+b)^2\epsilon^2 - 2a(a+b)\epsilon S + a^2S^2)}{2ab(a+b)}\right\}d\epsilon \\
&= -e^{-\alpha(//)}\int \sqrt{\frac{1}{a}+\frac{1}{b}}\frac{1}{\sqrt{2\pi}}\exp\left\{-\frac{(a+b)^2\epsilon^2 + 2a(a+b)(b\,\alpha\,x - S)\epsilon + a^2S^2}{2ab(a+b)}\right\}d\epsilon \\
&= -e^{-\alpha(//)}\int \sqrt{\frac{1}{a}+\frac{1}{b}}\frac{1}{\sqrt{2\pi}}\exp\left\{-\frac{\left((a+b)\epsilon - a(S-b\alpha x)\right)^2 - a^2(S-b\alpha x)^2 + a^2S^2}{2ab(a+b)}\right\}d\epsilon \\
&= -e^{-\alpha(//)}\int \sqrt{\frac{1}{a}+\frac{1}{b}}\frac{1}{\sqrt{2\pi}}\exp\left\{-\frac{\left((a+b)\epsilon - a(S-b\alpha x)\right)^2 - a^2(-2b\alpha xS + b^2\alpha^2x^2)}{2ab(a+b)}\right\}d\epsilon \\
&= -\exp\left\{-\alpha\left(r_f + x\rho - \frac{ab\alpha x^2}{2(a+b)}\right)\right\} \\
&\qquad \int \sqrt{\frac{1}{a}+\frac{1}{b}}\frac{1}{\sqrt{2\pi}}\exp\left\{-\frac{\left((a+b)\epsilon - a(S-b\alpha x)\right)^2 + a^2 2b\alpha xS}{2ab(a+b)}\right\}d\epsilon \\
&= -e^{-\alpha(//)}\int dL\frac{\sqrt{2ab(a+b)}}{a+b}\sqrt{\frac{a+b}{ab}}\frac{1}{\sqrt{2\pi}}\exp\left\{-L^2 - \frac{a\alpha xS}{a+b}\right\} \\
&= -e^{-\alpha(//)}\int dL\frac{1}{\sqrt{\pi}}\exp\{-L^2\}\exp\left\{-\frac{a}{a+b}\alpha xS\right\} \\
&= -\exp\left\{-\alpha\left(r_f + x\rho - \frac{1}{2}\frac{a}{a+b}(b\alpha x^2 + 2xS)\right)\right\} \qquad \text{(A-5)}
\end{aligned}
$$

$$\frac{\partial \mathrm{E}[U(Y)|S]}{\partial x} = \exp\left\{-\alpha\left(r_f + x\rho - \frac{1}{2}\frac{a}{a+b}(b\alpha x^2 + 2xS)\right)\right\}\left(\rho - \frac{a}{a+b}(b\alpha x + S)\right) = 0$$

$$x^* = \frac{\rho(a+b) - aS}{ab\alpha} \tag{A-6}$$

For my context, (2.9) is

$$x_i^* = \frac{\rho(\sigma_\epsilon^2 + \sigma_\nu^2) - \sigma_\epsilon^2 S_i}{\sigma_\epsilon^2 \sigma_\nu^2 \alpha}, \tag{A-7}$$

equations (2.10) and (2.11) are

$$\begin{aligned} \mathrm{E}[x_i^*] &= \frac{\rho(\sigma_\epsilon^2 + \sigma_\nu^2)}{\sigma_\epsilon^2 \sigma_\nu^2 \alpha} \\ \mathrm{Var}[x_i^*] &= \frac{\sigma_\epsilon^2 + \sigma_\nu^2}{(\sigma_\nu^2)^2 \alpha^2}, \end{aligned} \tag{A-8}$$

and equations (2.12) and (2.13) are

$$\begin{aligned} \frac{\partial \mathrm{E}[x_i^*]}{\partial \sigma_\nu^2} &= -\frac{\rho}{\alpha(\sigma_\nu^2)^2} \\ \frac{\partial \mathrm{Var}[x_i^*]}{\partial \sigma_\nu^2} &= -\frac{2\sigma_\epsilon^2 + \sigma_\nu^2}{\alpha^2(\sigma_\nu^2)^3}. \end{aligned} \tag{A-9}$$

Chapter 3

Empirical Study of Bank Lending Behaviors under Uncertainty

3.1 Introduction

On the basis of the results in Chapter 2, we empirically examine how Japanese banks choose loans and other assets under uncertain macroeconomic environments. Specifically, we investigate whether macroeconomic uncertainty is negatively associated with bank lending behaviors.[1]

Our empirical results are as follows. We find a significant negative association between macroeconomic uncertainty and *regional* bank lending behaviors, whereas we find no significant evidence in *city* bank lending behaviors.

The Japanese financial system has often been referred to as "bank-centered finance." This nomenclature still reflects our distinctive financial system following the financial

[1] Our study is supported by the result of Baum, et al. (2009) for the case of the U.S., and Quagliariello (2009) for the case of Italy.

transformation resulting from deregulation. Table 3.1 shows how Japanese businesses financed their activities during the period 1980-2012. On average, loans accounted for about 40% of fund-raising by the domestic nonfinancial sector during the sample period. In particular, for small- and medium-size firms, banks are the dominant fund providers. For example, Bolton and Freixas (2000) provided a model of financial markets and corporate finance, where equity issues, bank loans, and bond financing coexist in equilibrium. They showed that firm financing is segmented in equilibrium, which is proportionate to its risk; that is, the riskier firms prefer bank loans, the safer ones prefer securities issued by themselves, and ones in between are able to use bank loans and securities like equities and bonds. This segmentation is consistent with a stylized fact. Petersen and Rajan (1994, 1995) found that bank loans are main source of funding for small and immature firms. Table 3.2 shows the ratio of outstanding amounts of loans and bills for manufacturing firms discounted by scale of businesses, to total loans of Japanese licensed banks in the period 1990-2014. The ratio of loans for small- and medium size firms to total loans of Japanese banks has been more than 50% during this period, and the ratio of loans for large size firms increases in recent years.

Bank lending behaviors have changed over time because of turbulent economic conditions and shifting regulations. Given such changes in the macroeconomic environment, foresight into future economic conditions becomes more uncertain. This affects the degree of accuracy of bank managers' predictions of future expected returns from loans.

The primary role of banks is to channel assets toward good quality projects, *i.e.*, accumulating small deposits and investing them into large loans. Banks overcome friction in the credit market by acquiring costly information on borrowers and extending credit on the basis of this information along with market conditions. Thereby, banks contribute to effective asset allocation. In these two aspects, it is worthwhile to examine how macroeconomic conditions are associated with bank lending behaviors.

Beaudry, et al. (2001) presented an analytical framework with a variant of the "island model" by Lucas (1973) and empirically examined the relationship between firms' investment rates and macroeconomic uncertainty. Baum et. al. (2005) applied this model to describe a relation between banks lending behavior and macroeconomic uncertainty. By reducing the informational content of expected returns, macroeconomic uncertainty reduces the capacity of banks' loanable funds. In turn, the cross-sectional variance of bank loan-to-asset (LTA) ratios becomes small. This argument implies that under higher macroeconomic uncertainty, banks behave more homogeneously. Using the framework of Baum, et al.(2005, 2009), we investigate the lending behaviors of Japanese banks.

Our empirical analysis exploits a panel data set covering Japanese banks over the period 1975-2007. We show that there are substantial changes in the cross-sectional variances of the LTA ratio. Figure 3.1 shows variances of the LTA ratios of Japanese banks from 1975 to 2007. The distribution of the LTA ratio narrowed in the 1970s and 1990s and widened in the 1980s and 2000s. The recent history of Japanese economy is often characterized by the following episodes: the breakdown of the Bretton Woods system and the oil crises of the 1970s, blowing and popping investment bubbles in the 1980s, followed by banking and economic crises in the 1990s, and a long and stable economic recovery from 2000. These situations offer a preferable setting for our study.

Our empirical analysis aims to supplement the argument (Beaudry, et al., 2001; Baum et al., 2009) with econometric evidence. Econometric analysis reveals the following observation: there is a significant negative association between variances of macroeconomic uncertainty and the cross-sectional variances of banks' LTA ratios; *i.*

e., bank lending behaviors become more homogeneous as macroeconomic uncertainty increases. While the negative association is significant in regional banks, is not detected in the city banks. This is a distinctive result of our study.

The remainder of this chapter is organized as follows. In Section 3.2, we revisit the theoretical results in Section 3.2, i.e., Lemma 2, as well as construct an empirical model. In Section 3.3 we propose a proxy for macroeconomic uncertainty and provide the empirical findings. Section 3.4 evaluates these findings and explains the implications from the empirical results obtained. Finally, Section 3.5 concludes this chapter.

3.2 Revisit of theoretical hypothesis

In the previous chapter, we derived theoretical model of bank lending behaviors under macroeconomic uncertainty. Equations (2.12) and (2.13) related to Lemma 2 state that macroeconomic uncertainty is negatively associated with banks' LTA ratios. In other words, an increase in microeconomic uncertainty leads to a decrease in the share of loans to banks' total assets.

Now, we examine the association between macroeconomic uncertainty (σ_v^2) and bank lending behaviors, represented by the distribution of the optimal lending share x_i^*.To test this hypothesis, we use the Equations (2.11) and (2.13) in Chapter 2. To provide support for our result, equation (2.13), we consider the following empirical model;

$$Disp_t(L_{i,t}/TA_{i,t}) = \beta_0 + \beta_1 \sigma_{v,t}^2 + e_t, \tag{3.1}$$

where $Disp_t(L_{i,t}/TA_{i,t})$ is a measure of the cross-sectional dispersion of banks' LTA ratios at time t, $\sigma_{v,t}^2$ represents the macroeconomic uncertainty at time t, and e_t is an error term.[2]

From Equation (3.1), we expect that β_1 should be negative because greater turmoil in the macroeconomy is associated with a smaller dispersion of banks lending behaviors.

3.3 Empirical findings

3.3.1 Data

The data-set to describe bank lending behaviors was taken from *Financial Statements of All Banks (Zenkoku Ginko Zaimusyohyobunseki)* via *Nikkei NEEDS Financial Quest*, which has covered all banks in Japan on an annual basis from 1975 to 2007. This data-set is drawn up depending on banks' asset and liability reports.

The 1990s witnessed a long period of economic stagnation, which began with a sharp fall in stock and land prices. Some banks went into bankruptcy because of the accumulation of non-performing loans, depreciation of land prices, and losses in the value of their own security holdings. City banks (Toshi-ginko) were consolidated at the beginning of the 2000s. Figure 3.2 show standard deviations of the ratio of loans to deposits over the period 1975-2009. The ratios sharply disperse in 1997 and 2002 for city banks and in 1996 and 1999 for regional II banks (Dai-ni chiho ginko). For regional I banks (Dai-ichi chiho ginko), the standard deviation of the ratios keep the same level.

The number of banks in our sample period changed, and, especially, the number of city banks decreased because of bank consolidations. Tables 3-5 summarize the characteristics and distributions of the LTA ratios annually. The last columns of Tables 3.3-3.5 present the number of banks per year.

---

[2]The subscript t denotes a specific time period.

We built up banks' LTA ratios using their reported financial accounts. From the means of the LTA ratios, we find that loans constitute approximately 50% of total assets for city banks and approximately 70% for regional banks(Chiho-ginko) over the sample period. Japanese corporate financing patterns changed dramatically between 1970 and 1990. The shift away from bank financing peaked in the late 1990s[3]. Tables 3.3-3.5 show that the lowest point of LTA-ratios was in 1990. These findings are two sides of the same coin. After 1990, LTA ratios increased until 2000 and have decreased since then.

Our concern is the dispersion of banks' LTA ratios around their mean values. We use the variance of the LTA ratios as a measure of the cross-sectional dispersion of bank loans. Figure 1 displays the time series of the variances of LTA ratios for city banks, regional banks, and all types (aggregate) of banks. The city bank cross sectional dispersion has more up and down swings than those of regional banks'.

The macroeconomic variables are taken from the OECD main economic indicators dataset. The time span of the series is from January 1975 to September 2007. There are several macroeconomic proxies for , such as GDP and money supply. We employ consumer price index (CPI) for two reasons in particular. The first is empirical: we need higher frequency data in a time series analysis for unit root test which is used to ensure a time series is not an unstationary process. The second is a theoretical: CPI is a proxy for price. As we focus on the uncertainty of future returns from lending, the inflation rate provides a direct proxy for uncertainty. In addition, CPI is frequently used as a short-term indicator of the business cycle. Therefore, we use the monthly series of the CPI.

[3] See Hoshi and Kashyap (2001, p. 245).

3.3.2 Identifying macroeconomic uncertainty

As Engle (1982) mentioned in his seminal paper, the variance of inflation is a determinant of the response to various shocks, although there are several ways to measure macroeconomic uncertainty. Here, we employ the conditional variance of a variable, which depends on its past values estimated by the generalized autoregressive conditional heteroscedasticity ((G)ARCH) model, as the proxy of macroeconomic uncertainty. In general. the conditional variance of a variable can be estimated by the following (G)ARCH(p,q)[4] specifications:
ARCH(p) model:

$$\begin{cases} y_t = \gamma y_{t-1} + u_t \\ h_t^2 = \omega + \alpha_1 u_{t-1}^2 + \alpha_2 u_{t-2}^2 + \cdots + \alpha_p u_{t-p}^2, \end{cases} \tag{3.2}$$

and GARCH(p,q) model:

$$\begin{cases} y_t = \gamma y_{t-1} + u_t \\ h_t^2 = \omega + \alpha_1 u_{t-1}^2 + \cdots + \alpha_p u_{t-p}^2 + \beta_1 h_{t-1}^2 + \cdots + \beta_q h_{t-q}^2, \end{cases} \tag{3.3}$$

where y_t is a macroeconomic variable, u_t is the error term, and h_t^2 is the variance of u_t, which is proxy for economic uncertainty as perceived by a bank manager. Provided that the coefficients on the (G)ARCH effects are statistically significant[5], we use the fitted value as proxies for uncertainty.

Some macroeconomic indicators are used to describe the state of the economy. In this paper, we use the CPI because CPI data are available at a higher (monthly) fre-

[4] p is the order of the autoregressive GARCH terms and q is the order of the moving average ARCH terms.

[5] See Tables 3.8 and 3.9

quency than other alternatives and is seasonally adjusted.

Conditional variance as a measure of uncertainty assumes that the series is stationary and GARCH effects are present in the series. We transform the CPI series into the log difference of CPI (called as *INF*) to obtain a stationary series.

Conditional variance as a measure of uncertainty assumes that the series is stationary and GARCH effects are present in the series. We transform the CPI series into the log difference of CPI (called as *INF*) to obtain a stationary series.

We tested the constructed proxy *INF* for stationarity via the augmented Dicky–Fuller (ADF) test by Dickey and Fuller (1979) and Dicky–Fuller GLS test by Elliot, Rothenberg, and Stock (1996). The results of the unit roots tests are reported in Tables 6 and 7. The null hypothesis of unit roots is rejected at a significance level of 1% in ADF test and a significance level of 5% in Dicky–Fuller GLS test, respectively. The results are reported in Tables 3.6 and 3.7.

A Lagrange multiplier test of ARCH against the null hypothesis of no ARCH effects is conducted by computing $\chi^2 = TR^2$ in the regression of e_t^2 on constant and q-lagged values. The result provides evidence supporting ARCH effects in *INF* (Table 3.8). The Autoregressive (AR) model was applied to the *INF* series to remove serial correlation. To determine the appropriate lags for these regressions, Schwert's suggestion (Schwart, 1989) is used and the AR(11) model is selected. The (G)ARCH model is applied to this AR residual series.

To test the (G)ARCH effects, Bollerslev (1986) suggested that a test for GARCH effects should be performed first. Hence, we fit a GARCH(1,1) model to the residual series. The result is reported in Table 3.9. The table 3.9 shows that the coefficient of ARCH and GARCH terms are significantly different from zero for the *INF* series. Hence, we employ the result of the GARCH (1,1) model for the *INF* series.

To convert a series from monthly to annual frequency, the February observation is selected as a representative of the corresponding year.[6] We use the February observation for a theoretical reason. Under standard assumptions, the one-period before the forecast, which is based on past information, is equal to the conditional expectation on past information, i.e., $E[x_t|x_{t-1}] = x_{t-1}$.[7] Hence, we select the February observation as the forecast of the account term' s (March) value.[8]

3.4 Estimation results

We examine the relation between the dispersion of banks' LTA ratios and macroeconomic uncertainty, using the OLS estimation[9]. Table 10 presents the univariate OLS estimation result. Each series of cross-sectional variance of LTA ratios is plotted in Figure 3.1.

LTA dispersion of regional banks is negatively related with macroeconomic uncertainty at % significant level. All bank lending behaviors are also negatively associated with macroeconomic uncertainty, but insignificantly. Although we could not obtain a significant result for city banks, the coefficient is positive.

From Figure 1, we can see that the lending behaviors of city banks are quite different from those of regional banks, and sometimes runs adverse to them. This variation may

[6]There are several frequency conversion methods: average observations, sum observations, first observation, last observation, maximum observation, minimum observation, and no down conversions.

[7]This is the simplest one.

[8]Although we perform an OLS estimation using the average of 12-month GARCH variances, we obtain the same result.

[9]The univariate OLS seems simple to test this relationship because $\hat{h}_t$ is a generated regressor. Baum, et al. (2009) and Quagliariello (2009) used the instrumental variable generalized moment method (IV-GMM) method to mitigate the problems of measurement error in the construction of these proxies. However we use the OLS because our sample size is too small (32 observations) to test with a method such as the IV, which is valid for a large sample test.

affect our estimation results. Why then, the lending behaviors of city bank different from those if regional banks? Why does macroeconomic uncertainty differently affect the lending behaviors of the two banks?

One explanation that city banks are rely heavily on loans to customers, who can then gain access to capital markets. Hence, such banks should have under-performed after deregulation. We conjecture that the effect of deregulation is so large that we cannot detect the impact of uncertainty on city bank lending behaviors using this simple model. These results imply that it is possible to explain the relationship between bank lending behaviors and macroeconomic uncertainty. The estimation results are summarized in Table 3.9.

For reference, we consider an alternative proxy for macroeconomic uncertainty. For instance, the index of industrial production (IP) is a suitable proxy for our analysis. In the Appendix, Table 3.10 provides the result of a regression of bank lending on two kinds of proxies for macroeconomic uncertainty. For the *INF* conditional variance series, we obtain the similar result to that of the univariate regression. Whereas for the *IP* conditional variance-series, city bank lending behaviors show significant positive association with the *IP* proxy. For all banks and regional banks, however, we could not obtain significant results. Table 3.11 is a summary of the results.

Since we perform simple OLS regression with only 32 observations, one may question whether these findings are driven by other factors as well, which might affect bank lending behavior. To test this, we need data-set at a higher frequency. Instead, we can confirm the negative association between macroeconomic uncertainty and bank lending behaviors in regional and all banks datasets.

Because the main customers of regional banks are small- and medium-size firms, the default risk of such loans is more directly affected by macroeconomic environments than that of loans for large-size firms. Hence, macroeconomic uncertainty may have a larger impact on the lending behaviors of regional bank than on city banks. Consequently, we could detect the significant impact of macroeconomic uncertainty on variances of regional bank lending behaviors. This result provides supportive evidence for the argument that bank lending is a more important financial resource for small-and medium-size firms than for larger companies. This analysis could be helpful to examine the banks lending behaviors of Japanese banks.

3.5 Conclusion

In this paper, we investigate whether macroeconomic uncertainty is negatively associated with the lending behaviors of Japanese banks. In Japan, the financial system is bank-centered; therefore, bank lending behaviors more clearly affect firms' finances compared with those of other countries, which may have many alternatives or substitutes for bank lending.

The estimation results confirm that macroeconomic uncertainty play a role in Japanese banks' investment decisions. In periods of increasing uncertainty, banks behave more homogeneously. These results correspond with other analyses of bank lending behavior, such as "herd behavior" of Japanese banks and "credit rationing" of the 1990s. Although our empirical findings are very restrictive, we can confirm the negative association between macroeconomic uncertainty and bank lending behaviors.

Macroeconomic uncertainty is an important factor in banks lending behaviors and a cause of distortion in asset allocation. For non-rated small firms, bank lending is a more important resource of finance. From the perspective of monetary policy making, this association is remarkable. Since bank loans are a relevant source of financing for firms, policy makers should strive to reduce the degree of uncertainty in order to achieve effective asset allocation and long-term, stable economic growth.

Table 3.1: Fundraising by nonfinancial sector (% distribution)

	By channels of fundraising								
	1980FY(%)	1985FY(%)	1990FY(%)	1995FY(%)	2000FY(%)	2005FY(%)	2010FY(%)	2011FY(%)	2012FY(%)
(1-1) of (1): Fundraising by domestic nonfinancial sector	95	93	86	88	86	81	80	79	77
I. of (1-1): Via domestic market	98	98	96	96	97	96	95	95	94
i. of I: Via financial institutions	62	67	65	67	69	66	64	64	65
a. Loans	47	50	50	49	45	39	35	35	34
b. Securities other than shares	14	16	13	16	22	25	27	28	29
of which: public securities	13	15	12	14	20	23	25	26	28
c. Shares and other equities	1	1	2	2	2	1	1	1	1
ii. of I: Fundraising from domestic nonfinancial sector	8	8	8	8	9	12	14	13	13
iii. of I: Trade credits etc.	28	23	23	21	19	18	17	17	17
II. of (1-1): Via overseas market	2	2	4	4	3	4	5	5	6
(1-2) of (1): Fundraising by overseas sector	5	7	14	12	14	19	20	21	23
III. of (1-2): Via domestic financial institutions	55	63	67	65	60	58	61	59	61
IV. of (1-2): Other fundraising from domestic nonfinancial sector	45	37	33	35	40	42	39	41	39
(1) Fundraising by nonfinancial sector	100	100	100	100	100	100	100	100	100

Source: Bank of Japan, *Economic Statistics Quarterly*.

Table 3.2: Outstanding amounts of loans and bills discounted by scale of businesses of Japanese licensed banks. (% distribution)

Manufacturing firms	Small enterprises		Medium-sized enterprises		Large enterprises	
	Total (%)	of Loans for fixed investment (%)	Total (%)	of Loans for fixed investment (%)	Total (%)	of Loans for fixed investment (%)
Mar-1990	65.7	21.6	8.9	19.3	25.4	25.8
Mar-1991	66.1	24.1	8.5	22.5	25.4	27.3
Mar-1992	64.7	27.2	8.3	26.2	26.9	29.9
Mar-1993	64.6	28.4	8.2	27.9	27.2	32.2
Mar-1994	58.9	24.8	7.9	22.5	33.1	21.1
Mar-1995	60.5	23.7	7.8	20.5	31.8	20.8
Mar-1996	62.8	22.5	7.4	19.2	29.8	21.0
Mar-1997	63.5	22.1	7.3	18.4	29.2	20.7
Mar-1998	63.4	22.1	7.4	18.0	29.2	19.2
Mar-1999	60.4	21.5	7.5	17.9	32.1	18.5
Mar-2000	57.5	19.7	6.9	17.1	35.6	16.5
Mar-2001	61.0	18.4	4.0	15.7	35.0	15.4
Mar-2002	59.6	17.9	4.0	15.3	36.4	14.1
Mar-2003	58.2	17.0	3.9	14.5	37.8	12.9
Mar-2004	59.1	15.6	3.5	15.7	37.4	11.2
Mar-2005	60.5	15.2	3.5	15.3	36.0	11.0
Mar-2006	60.5	14.8	3.3	16.4	36.3	10.2
Mar-2007	59.7	14.6	3.3	16.8	37.0	9.8
Mar-2008	57.6	14.6	3.2	16.7	39.1	9.7
Mar-2009	49.6	13.9	2.9	17.6	47.5	8.8
Mar-2010	49.3	13.4	2.8	17.7	47.9	10.1
Mar-2011	50.5	12.8	2.7	15.3	46.8	11.2
Mar-2012	49.8	12.4	2.6	15.9	47.6	10.3
Mar-2013	48.9	11.9	2.4	16.1	48.7	10.2
Mar-2014	48.9	12.4	2.4	16.5	48.7	9.3

Note: Small enterprises are capitalized at 100 million yen or less; Large enterprises are capitalized at 10 billion yen or more; Medium enterprises are other than small and large enterprises by 2000. After 2001FY, small enterprises are capitalized at 300 million yen or less.
Source: Bank of Japan, *Economic Statistics Quarterly*.

Table 3.3: Descriptive statistics: all banks' LTA ratios

All banks' LTA ratios					
Year	Mean	Std. Dev.	Maximum	Minimum	No. obs.
1975	0.660	0.062	0.778	0.333	91
1976	0.653	0.060	0.766	0.330	91
1977	0.649	0.058	0.768	0.330	91
1978	0.651	0.053	0.749	0.363	91
1979	0.642	0.054	0.731	0.360	91
1980	0.628	0.063	0.740	0.332	91
1981	0.625	0.063	0.739	0.369	91
1982	0.626	0.067	0.732	0.354	91
1983	0.627	0.068	0.747	0.395	91
1984	0.632	0.065	0.761	0.413	91
1985	0.635	0.065	0.763	0.424	91
1986	0.628	0.058	0.754	0.424	93
1987	0.624	0.058	0.750	0.443	93
1988	0.625	0.055	0.722	0.444	93
1989	0.622	0.064	0.738	0.416	93
1990	0.622	0.075	0.760	0.393	93
1991	0.634	0.066	0.766	0.407	92
1992	0.643	0.063	0.780	0.442	92
1993	0.661	0.051	0.764	0.468	92
1994	0.657	0.050	0.765	0.467	92
1995	0.658	0.052	0.775	0.461	92
1996	0.665	0.054	0.779	0.465	92
1997	0.669	0.053	0.763	0.513	91
1998	0.675	0.056	0.786	0.518	90
1999	0.676	0.054	0.789	0.521	90
2000	0.684	0.057	0.795	0.502	90
2001	0.664	0.073	0.823	0.440	90
2002	0.669	0.068	0.795	0.484	89
2003	0.679	0.075	0.827	0.490	87
2004	0.675	0.083	0.831	0.455	87
2005	0.670	0.088	0.854	0.433	87
2006	0.670	0.083	0.807	0.473	86
2007	0.673	0.075	0.798	0.485	86
33 terms			Total 2,991 observations		

Table 3.4: Descriptive statistics: regional banks' LTA ratios

Regional banks' LTA ratios					
Year	Mean	Std. Dev.	Maximum	Minimum	No. obs.
1975	0.674	0.042	0.778	0.570	78
1976	0.669	0.038	0.766	0.585	78
1977	0.667	0.039	0.768	0.573	78
1978	0.665	0.038	0.743	0.575	78
1979	0.659	0.043	0.761	0.559	78
1980	0.640	0.045	0.754	0.537	78
1981	0.638	0.040	0.722	0.553	78
1982	0.641	0.041	0.738	0.544	78
1983	0.652	0.047	0.760	0.557	78
1984	0.655	0.045	0.766	0.566	78
1985	0.664	0.043	0.780	0.583	78
1986	0.652	0.046	0.764	0.532	80
1987	0.644	0.044	0.765	0.514	80
1988	0.642	0.048	0.775	0.520	80
1989	0.638	0.054	0.767	0.449	80
1990	0.637	0.059	0.752	0.471	80
1991	0.645	0.060	0.786	0.450	80
1992	0.648	0.061	0.775	0.460	81
1993	0.681	0.056	0.795	0.489	81
1994	0.680	0.058	0.823	0.477	81
1995	0.683	0.058	0.795	0.500	81
1996	0.700	0.060	0.827	0.512	81
1997	0.701	0.063	0.831	0.513	81
1998	0.709	0.060	0.854	0.522	81
1999	0.704	0.054	0.807	0.521	81
2000	0.694	0.057	0.798	0.502	81
2001	0.681	0.064	0.794	0.483	81
2002	0.677	0.067	0.836	0.486	82
2003	0.672	0.065	0.803	0.473	82
2004	0.667	0.068	0.792	0.501	82
2005	0.658	0.067	0.783	0.499	82
2006	0.659	0.068	0.811	0.522	82
2007	0.667	0.067	0.799	0.519	82
33 terms			Total 2,640 observations		

Table 3.5: Descriptive statistics: city banks' LTA ratios

City banks' LTA ratios					
Year	Mean	Std. Dev.	Maximum	Minimum	No. obs.
1975	0.563	0.072	0.620	0.333	13
1976	0.560	0.072	0.606	0.330	13
1977	0.558	0.072	0.607	0.330	13
1978	0.569	0.065	0.622	0.363	13
1979	0.564	0.064	0.626	0.360	13
1980	0.529	0.066	0.619	0.332	13
1981	0.525	0.060	0.637	0.369	13
1982	0.509	0.064	0.631	0.354	13
1983	0.511	0.055	0.628	0.395	13
1984	0.517	0.048	0.613	0.413	13
1985	0.514	0.040	0.588	0.424	13
1986	0.531	0.041	0.601	0.424	13
1987	0.527	0.035	0.602	0.443	13
1988	0.536	0.045	0.635	0.444	13
1989	0.524	0.054	0.626	0.416	13
1990	0.560	0.058	0.603	0.393	13
1991	0.548	0.060	0.624	0.407	12
1992	0.560	0.062	0.671	0.442	11
1993	0.628	0.066	0.728	0.468	11
1994	0.631	0.066	0.728	0.467	11
1995	0.632	0.069	0.725	0.461	11
1996	0.647	0.067	0.715	0.465	11
1997	0.667	0.049	0.732	0.562	10
1998	0.633	0.054	0.716	0.518	9
1999	0.644	0.048	0.728	0.557	9
2000	0.648	0.055	0.731	0.531	9
2001	0.572	0.073	0.672	0.440	9
2002	0.589	0.062	0.685	0.484	7
2003	0.567	0.056	0.674	0.490	5
2004	0.541	0.060	0.650	0.455	5
2005	0.523	0.060	0.620	0.433	5
2006	0.530	0.058	0.635	0.473	4
2007	0.554	0.062	0.650	0.485	4
33 terms				Total 351 observations	

Table 3.6: ADF test for unit roots

ADF test for unit roots		
Variable	Z(t) statistics	P value
LDCPI	−2.719 ***	0.007
Interpolated Dickey–Fuller		
1% critical value	5% critical value	10 % critical value
−2.571	−1.942	−1.616
MacKinnon (1996) one-sided p-values.		

Notes: *** indicates that the coefficient is different from zero at a significance level of 1%. Augmented Dickey–Fuller test for unit roots. Selection of the auxiliary regression using Schwert's suggestion. 11 lags included in the regression.

Table 3.7: DF-GLS test for unit roots

DF-GLS tests for unit roots		
Variable	DF-GLS t stat.	SC
LDCPI	−2.555 **	−8.116
Interpolated $DF - GLS^{\tau}$		
1% critical value	5% critical value	10% critical value
−2.571	−1.942	−1.616

Notes: ** indicates that the coefficient is different from zero at a significance level of 5% . Modified version of the Dickey–Fuller t-test by Elliot, Rothenberg, and Stock. Selection of the auxiliary regression using Schwert's suggestion. DF-GLS t stat.: Dicky–Fuller generalized least squares t statistics. SC: Schwarz criterion. 11 lags and a constant included in the regression.

Table 3.8: LM test for ARCH effects

LM TEST for ARCH effects			
Variable	χ^2	DF	P value
LDCPI	4.925 *	0	0.027

Notes: Lagrange multiplier test for ARCH effects. 11 lags included in the auxiliary autoregression for LDCPI.

Table 3.9: GARCH models proxy macroeconomic uncertainty

	INF
ω	2.09E-10 ***
	(1.95E-11)
α	0.150 ***
	(0.020)
β	0.600 ***
	(0.020)

Notes: *** indicates that the coefficient is different from zero at a significance level of 1% (standard errors of estimates in parentheses). LDCPI is called as INF. ω, α, β are a constant, the ARCH coefficient, and the GARCH coefficient in Equations (3.2) and (3.3), respectively.

Table 3.10: Econometric results

Variables	Coeff.	Std. error	P value
AllBK			
C	0.004 ***	0.000	0.000
CV-INF	−48811.4	75403.0	0.523
Test for heteroscedasticity: White = 2.754 [0.252], Breush-Pagan-Godfrey = 1.450 [0.229].			
Test for serial correlation (lag = 2) : Breusch-Godfrey ($T * R_0^2$) = 19.575.[0.000]			
CityBK			
C	0.003503 ***	0.000	0.000
CV-INF	102699.0	69372.32	0.149
Test for heteroscedasticity: White = 1.672 [0.433], Breush-Pagan-Godfrey = 1.396 [0.237.			
Test for serial correlation (lag = 2) : Breusch-Godfrey ($T * R_0^2$) = 14.452 [0.000].			
RegionalBK			
C	0.003 ***	0.000	0.000
CV-INF	−159756.1 ***	553543.0	0.007
Test for heteroscedasticity: White = 0.206 [0.724], Breush-Pagan-Godfrey = 0.124 [0.902].			
Test for serial correlation (lag = 2) : Breusch-Godfrey ($T * R_0^2$) = 22.793 [0.000].			
No. of obs.: 32			

Notes: *** indicates that the coefficient is different from zero at significance level of 1%. Conditional variance series generated by GARCH model with *INF* is called CV-INF. Figures in square brackets are P-values. The 95 percent critical values of chi-sqiared with 2 and 1 degree of freedom are 5.99 and 3.84, respectively.

Table 3.11: Regression results on the relationship between macroeconomic uncertainty and bank lending behaviors

	AllBK		CityBK		RegBK	
	(1)	(2)	(1)	(2)	(1)	(2)
CV-INF	−	−	+	+	− ***	− ***
CV-IP		+		+		+

Appendix: Multiple Regression Result

Table 3.12: Econometric results

Variables	Coeff.		Std. error	P value
AllBK				
C	0.000667		0.002869	0.1242
CV-INF	−60827.70		15.95704	0.4270
CV-IP	23.71526		19.59158	0.2362
CityBK				
C	−0.003703		0.002336	0.0000
CV-INF	77653.02		61461.90	0.2169
CV-IP	49.43042	***	15.95704	0.0044
RegionalBK				
C	−0.000922		0.002011	0.6502
CV-INF	−174202.3	***	52902.62	0.0027
CV-IP	28.51068		13.73484	0.0472
No. of obs.: 32				

Notes: *** indicates that the coefficient is different from zero at a significance level of 1%. CV-IP: conditional variance series generated by GARCH model with detrended log(IP).

Figure 3.1: Variances of the LTA ratios for each type of banks

Figure 3.2: Standard deviation of the ratio of loans to deposits

Source: Financial Statements of All Banks.

Chapter 4

Bank Overconfidence and Irrational Lending Behavior

4.1 Introduction

The theory of rational expectations and the efficient market hypothesis had been successfully applied to macroeconomic theories based on microeconomic foundations until the crash in October 1987 (called “Black Monday”)[1] and the crash in March 2000 (called the “Tech Crash”).[2] These two crashes caused many economists to question the validity of the rational expectation theory and efficient market hypothesis. Because they do not believe that in efficient markets, rational economic agents could have created such a massive swing in stock prices. Since then, economists have discussed the consistency of the efficient markets’ model for the aggregate stock market with econometric evidence

[1] The Dow Jones industrial average declined more than 20% on October 19, 1987, which was the largest one-day decline in the U.S. history.

[2] The collapse of high-tech company share prices caused the heavily tech-laden NASDAQ to fall from around 5,000 in March 2000 to around 1,500 in 2001 2002, a decline of over 60%.

about the time series properties of prices and economic fundamentals[3] such as dividends and earnings. Their concern was whether stock prices show excess volatility relative to their fundamental values.

The study of behavioral finance emerged in response to these questions regarding efficient markets and the rational expectations framework. Although many studies have investigated excess volatility of stock prices,[4] only a few of them are applied to bank behaviors. For example, Japanese banks promoted loans backed up by properties and lent excessive loans to real estate developers in the latter half of the 1980s. Another example is the "credit crunch" in the early 1990s. These lending behaviors can be regarded as the over and under-reactions of banks. If so, then it is at least true that these experiments present a challenge in explaining the lending behaviors of banks within the rational expectations equilibrium (REE) framework. Instead, we examine bank lending behaviors by applying the behavioral finance theory. Simply put, by applying the behavioral finance theory, our model becomes "an irrational expectations model with a noisy signal."[5]

The basic structure of our model is as follows; in an uncertain economic situation, a bank forecasts future returns from lending using two kinds information, i.e., private and public. By the assumption of imperfect information, each bank receives its own private information along with common public information and forecasts the rate of return from loans. In subsequent sections, we will see a source of irrational lending behavior in this simple situation.

Since behavioral finance theory has developed an alternative REE theory, it is bene-

[3]The word economic "fundamental(s)" here is used as actual subsequent dividends accruing to the share of a company; roughly speaking, the firm's book value or liquidation price of a company.

[4]For example, Siegel (2002) presented a good discussion in this field.

[5]Diamond and Verrecchia (1981) examined "a noisy rational expectations economy."

ficial to ensure the conditions imposed on the REE model.[6] In the rational expectations theory, two conditions are assumed: individual rationality and mutual consistency of perceptions about the environment. The consistency of beliefs (perceptions) that involves individuals' having consistent (homogeneous) beliefs and adopting a common system to update information is called " Bayesian updating." More precisely, "consistent beliefs" mean that agents' beliefs are correct: the subjective distribution that agents use to forecast future realizations of unknown variables is indeed the distribution from which these realizations are drawn. This requires agents to not only process new information accurately, but also to have enough information about the structure of the economy in order to determine correct distributions for their variables interest.

There are several cases where people do not have consistent beliefs, and "overconfidence" is a major example of this inconsistency. Psychological research shows that people are overconfident in their judgments.[7] Evidence of overconfidence has been found in several contexts. Griffin and Tversky (1992) and suggested that experts tend to be more overconfident than inexperienced individuals. Furthermore, overconfidence can be found in the fundamental valuation of securities (forecasting long-term returns). Odean (1998) argued why overconfidence should dominate in financial markets. Tasks in banks are applied to these cases, they are experts, and valuate future returns from loans, which are long-term loans. These things justifies us in relaxing the consistency of belief.

In our model, a bank's belief is not simply updated in the manner following Bayes's law. Alternatively, the bank fails to update their beliefs correctly. This failure has two causes. First, because banks have only have partial information to know the actual distri-

[6]Surveys in this field can be found in Sheflin (2000), Sheleifer (2000), Shiller (2002), and so on.

[7]Fischhoff et al. (1977), Alpert and Raiffa (1982), and Lichtenstein, et al. (1982) present evidence of overconfidence in people' s judgments

bution of returns from loans. Second, because we assume that banks are overconfident. Although overconfidence is just one example of individual irrationality, it is consistent with the experimental studies of cognition and behavioral finance. For example, Barberis and Thaler (2003) briefly showed an example of people's overconfidence in their judgments. Daniel, et al. (1998) examined considerable evidence of overconfidence in judgment in several contexts. In addition, the imperfect information postulation is a more plausible setting to describe the real world. In fact, banks can forecast the future returns from lending as best as they can from the available information. As a result, each bank has its own information and forms its own estimation. This causes heterogeneous beliefs and lending behaviors among banks.[8]

Being overconfident, banks believe that their private information is excessively precise. Why do banks become overconfident? Possibly, because when banks face uncertainty and imperfect information, their experience, pride, and a great desire to seek higher returns make an individual's judgment biased.

The main implications of this paper are as follows:

1. Bank overconfidence leads to an irrational increase of the mean and the variance of the optimal lending share.

2. The distribution of the overconfident bank' s lending share is more severely affected by a change in uncertainty relative to that of the rational bank.

3. Overconfidence causes more fragile lending behavior than rational confidence.

Our study follows the basic insight of Daniel, et al. (1998) and Scheinkman and Xiong (2003); we learned about Scheinkman and Xiong (2003) after completing the

[8] Scheinkman and Xiong (2003) examined overconfidence as a source of disagreements among investors under short-sale conditions. Although we are not concerned about short-sale constraints, we also regard " overconfidence" as the source of heterogeneous beliefs.

early draft of this paper. Our model differs from Daniel, et al. (1998) in that we focus on lending behavior, whereas they examined the pricing behaviors of risky assets. Our model is different from Scheinkman and Xiong (2003) that they focus on links between asset price, trading volume, and price volatility. We simply focus on lending behavior and the effect of biased updating on lending behavior. While Scheinkman and Xiong (2003) investigates speculative bubbles, we examine the so-called "pure" bubble. Applying overconfidence to the standard rational expectation model of banks, we find that bank lending behavior increases irrationally and heterogeneously.

Although previous literature theoretically and empirically argued this irrational lending behavior, we think that this field requires further research for a better understanding. Our contribution is that we provide an alternative means to express the implications of overconfidence and the system for banks to confirm the precision of their private information. In short, we provide a behavioral finance model to describe a bank' s lending behavior.

The remainder of this chapter is structured as follows. In Section 4.2, we describe the economic setting, define some notions used and provide an overconfident single information model. Section 4.3 extends the single information model to two kinds of information cases. In Section 4.3, results based on these models are reported, and we summarize our findings.

4.2 Overconfidence model

In this section, we develop a standard portfolio selection model that takes overconfidence into consideration. The basic idea of our model originates from bank overconfidence. We investigate bank lending behaviors in an uncertain economy with imperfect information. This model falls into the category of a "bounded rationality" or a "structural uncertainty" model.[9] As discussed in Chapter 1 in Thaler (2005) by Barberis and Thaler, in a bounded rationality model, "*investors do not know the growth rate of an asset's cash flow but learn it as best as they can from available data*". Their concept is straightforwardly applied to explain bank lending behaviors in our setting.

This analysis is different from the REE framework. As mentioned in the previous section, the REE framework requires two rationality conditions. One is that the solution of an individual optimization problem should be equal to the solution of an average one. Another is the consistency of expectations (perceptions postulate). In this section, we do not assume the consistency of expectations. In fact, it is plausible to assume that banks can observe partial information and they each have a different method of forecasting.[10]

In this model, as well as in the standard portfolio selection model with perfect information, a bank maximizes its objective function subject to some conditions. However, the consistency of solutions of our maximizing problem is not satisfied owing to assumption of imperfect information and bank overconfidence.[11]

To analyze a bank' s behavior in such a situation, the basic portfolio model is extended by allowing banks to acquire imperfect (partial) information on a true rate of return from risky loans. Basically, this model has a structure identical to that of the "island-model"[12] of Lucas (1972, 1973), where investors extract information from noisy signals. Hence, our model can also be viewed as an extension of his model, which we

[9]See Sargent (1993) and Barberis and Thaler, Chapter 1 in Thaler (2005).

[10]Sargent(1993) claimed that the bounded rationality model requires *people to form beliefs about others' decisions, about their decision process, and even about their beliefs*".

[11]Our concerning is partly along the line of Scheinkman and Xiong (2003). Whereas they assume that disagreement among investors is caused by institutional friction and short selling constraints, we assume that heterogeneous beliefs are caused by overconfidence, imperfect information and uncertainty.

[12]In his model, individuals can obtain imperfect information, since they are isolated in the sense that their information cannot be transmitted to other individuals. Then, the expected price formed in each market is different from an aggregate price throughout all markets.

call a noisy "irrational" expectations model.

4.2.1 Effect of irrational forecast

First, we review results from a basic model in Section 3 without irrationality (overconfidence), where banks are rational and their lending behavior exactly reflect economic fundamentals.

Equations (2.10) and (2.11) in Chapter 2 express the link between the precision of bank i's estimation and the noise variance σ_ν^2. Equations (2.12) and (2.13) show the effect of noise variance on the optimal lending share. The results are

$$\frac{\partial \mathrm{E}[x_i^*]}{\partial \sigma_\nu^2} = -\frac{\rho_i}{\alpha(\sigma_\nu^2)^2} < 0, \tag{4.1}$$

and

$$\frac{\partial \mathrm{Var}[x_i^*]}{\partial \sigma_\nu^2} = -\frac{1}{\alpha^2(\sigma_\nu^2)^2}\left[\frac{2\sigma_\epsilon^2}{\sigma_\nu^2} + 1\right] < 0, \tag{4.2}$$

respectively.

We take these results as a benchmark of bank lending behaviors based on fundamentals. Our analysis is sequentially developed on the basis of variations in the model.

An irrational bank uses its own assessment of the noise variance $\sigma_{\nu i}^{2\,OC}$ instead of σ_ν^2. Here, superscript "OC" indicates "overconfidence." This kind of irrationality is explained in Barberis and Thaler (2005). If a bank is overconfident, it does not update its beliefs correctly in the manner described by Bayes's law. However, our agents still have normatively sensible preferences. The rationale for the assumption of this overconfidence is that banks have a personal attachment to their own signals.[13] More generally, there is much psychological evidence that shows people tend to overestimate the precision of their knowledge. Now, we investigate the case of irrational banks. As discussed in Section 4.1, bank i rationally forecasts a default risk of lending, except for their perception of their own information precision. To forecast the default risk, bank i receives signal S_i, which is normally distributed with the mean 0 and variance $\sigma_\epsilon^2 + \sigma_{vi}^{2\,OC}$. Here, we note that the noise variance is indexed by i. This is because each bank not only receives its own signal but also faces uncertainty. We call this "private information." As mentioned above, banks have a special attachment to acquire information and have confidence in their own information. By assumption of overconfidence, bank i underestimates the uncertainty of its private information signal. Therefore, we define the bank's irrational belief or overconfidence by the next inequality,

$$\sigma_{vi}^{2\,OC} \leq \sigma_v^2. \tag{4.3}$$

In short, an overconfident bank receives its own private signals and uses its own assessment of its noise variance $\sigma_{vi}^{2\,OC}$. As a result, the coefficient of the linear projection of ϵ_i given S_i, is estimated as

$$\lambda_i^{OC} = \frac{\sigma_\epsilon^2}{\sigma_\epsilon^2 + \sigma_{vi}^{2\,OC}}, \tag{4.4}$$

where λ is also indexed by i.

By the definition of overconfidence (Equation (4.3)), the coefficient λ_i^{OC} is larger than λ in the rational projection. An overconfident bank sets more weight on its own private information than a rational bank. Then, an overconfident bank estimates the

[13]There is much evidence of banks' irrational belief. See Daniel, et al. (1998) and Staël von Holstein (1972) for calibration.

expected return from lending to be higher than a rational bank' s expected return and the variance to be smaller than that of a rational bank. It is well-known that investors value their assets with more highly precise information and at a higher price. The results from bank overconfidence coincides with this thesis.

4.2.2 Distribution of optimal lending share of overconfident banks

Next, we investigate the result of overconfidence of banks. The optimal lending share is determined by

$$x_i^{*OC} = \frac{\rho_i + \lambda_i^{OC} S_i}{\alpha \lambda_i^{OC} \sigma_{\nu i}^{2OC}}. \tag{4.5}$$

Here, the bank' s lending behavior is described by the expectation and variance of the distribution of lending share.

$$\mathrm{E}[x_i^{*OC}] = \frac{\rho_i}{\alpha \lambda_i^{OC} \sigma_{\nu i}^{2OC}}, \tag{4.6}$$

$$\mathrm{Var}[x_i^{*OC}] = \frac{\sigma_\epsilon^2 + \sigma_{\nu i}^{2OC}}{\alpha^2 (\sigma_{\nu i}^{2OC})^2}. \tag{4.7}$$

Equations (4.6) and (4.7) explicitly show the association between bank i's lending behavior x_i^{*OC} and "overconfidence" $\sigma_{\nu i}^{2OC}$.

The effect of a change in the precision of the private information on the optimal lending behavior is obtained by the derivative of $\mathrm{E}[x_i^{*OC}]$ and $\mathrm{Var}[x_i^{*OC}]$ with respect to $\sigma_{\nu i}^{2OC}$. The result is consistent with Lemma 2 in Chapter 2. The optimal lending behavior of an irrational bank is negatively associated with overconfidence $\sigma_{\nu i}^{2OC}$.

Now, we compare irrational lending behavior, expressed in the above Equations (4.6) and (4.7), with rational lending behavior, expressed in Equations (2.10) and (2.11) in Chapter 2. We find the next relationship as a corollary of the definition of overconfidence.

$$\mathrm{E}[x_i^*] < \mathrm{E}[x_i^{*OC}] \tag{4.8}$$

$$\mathrm{Var}[x_i^*] < \mathrm{Var}[x_i^{*OC}]. \tag{4.9}$$

We summarize these relationship as the next corollary.

Corollary 1a. The expectation and variance of the probability distribution of x_i^{*OC} are larger than those of the probability distribution of x_i^*.

Corollary 1a suggests that overconfidence causes the "bubble." This possibility is depicted in Figure 4.1, which provides a graphical representation of Corollary 1a.[14] The probability distribution of x_i^{*OC} is located to the right side of that of x_i^* and the variance of x_i^{*OC} is larger than x_i^*'s. That is, the ratio and variation of an irrational bank's optimal lending share are larger compared with those of a rational bank. This implies that overconfidence causes irrational lending behaviors.

We compare the magnitude of the effects of a change in the noise variance on this distribution and the magnitude of the effects in the rational lending behavior. Since $\sigma_{\nu i}^{2OC} < \sigma_\nu^2$, we have the following two relationships:

$$\left|\frac{\partial \mathrm{E}[x_i^{*OC}]}{\partial \sigma_{\nu i}^{2OC}}\right| > \left|\frac{\partial \mathrm{E}[x_i^*]}{\partial \sigma_\nu^2}\right|, \tag{4.10}$$

$$\left|\frac{\partial \mathrm{Var}[x_i^{OC*}]}{\partial \sigma_{\nu i}^{2OC}}\right| > \left|\frac{\partial \mathrm{Var}[x_i^*]}{\partial \sigma_\nu^2}\right|. \tag{4.11}$$

[14] Figure 4.1 displays a graphical representation of the distribution of an irrational bank's lending share compared with that of a rational bank.

Equations (4.10) and (4.11) indicate the next corollary:

Corollary 1b:

A change in the noise variance (a change in the precision of the information) results in a more severe change in the distribution of x_i^{*OC} than in the distribution of x_i^*.

Corollary 1b suggests that a shift in a bank's overconfidence leads to more severe changes of lending behavior. That is, changes in the overconfident bank's beliefs about the precision of its own signals lead to highly volatile lending behaviors relative to fundamental-based beliefs. Figure 4.2 displays a graphical representaion of the gap between a change in lending behavior of a rational bank and that of an irational bank.

We conclude this section with the following findings. The more overconfident a bank becomes, the more bullish its lending behavior. Corollary 1a suggests that overconfidence causes irrational bubble in bank' s lending. Corollary 1b suggests that over confidence leads to more volatile lending behaviors. In other words, overconfidence creates irrationally overheated and more fragile lending behavior than fundamental-based lending behavior.

4.2.3 Model with two kinds of information signals

So far, we have examined banks' lending behaviors with single information. We obtained implications that banks' overconfidence causes bubbles or volatile lending behaviors. In this section, we will examine the case where two kinds of informations are available. Actually, banks use their own information as well as publicly available information. For those investigation, we extent the model in Section 4.2.1 to that with two kinds of information signals, *i.e.*, private and public.

Private information is defined as that which banks obtain by themselves. Private information cannot be transmitted to others. We denote private information as $S_{1,i}$, which is normally distributed as mean 0 and variance $\sigma^2_{S_{1i}}$. Since bank i is overconfident, it overestimates the precision of its private information, *i.e.*, $\sigma^{2\ OC}_{\nu_{1i}} < \sigma^2_{\nu_1}$. The variance of noise in private information signal $\sigma^2_{\nu_1}$ is the true variance of noise in its private information signal; therefore, it is the exact precision of its information.

Public information as what is defined as that which is observed by all banks; hence, public information is not indexed by i. We denote it by S_2 which is normally distributed with mean 0 and variance $\sigma^2_{S_2}$ and is independent of $\epsilon_{i,t}$ and ν_1. Unlike the precision of private information, the noise variance of a public information signal $\sigma^2_{\nu_2}$ is correctly received by all banks.

According to Daniel, et al. (1998), we define an overconfident bank as one that overestimates the precision of its private information signal, which is different from an information signal publicly received by all banks. These kinds of information have the following structures:

$$S_{1,i} = \epsilon_{i,t} + \nu_{1i}, \tag{4.12}$$

$$S_2 = \epsilon_{i,t} + \nu_2. \tag{4.13}$$

4.2.4 Forecast of a default risk with two kinds of information signals

We consider the situation where a bank can use both its private and public information signals to forecast the default risk $\epsilon_{i,t}$. Therefore, the problem to be solved is the stochastic estimation with two kinds of information.

As before, the optimal estimate of $\epsilon_{i,t}$ is the conditional expectation, given $S_{1,i}$ and S_2.[15] Hence, the mean and variance of this error distribution, respectively, are

$$\begin{aligned}
\mathrm{E}_{oc}[\epsilon_{i,t}|\mathbf{S}] &= \boldsymbol{\lambda}_i{}'\mathbf{S} \\
&= \lambda_{1,i}S_{1,i} + \lambda_2 S_2 \\
&= \frac{\sigma_\epsilon^2\sigma_{\nu_2}^2}{A}S_{1,i} + \frac{\sigma_\epsilon^2\sigma_{\nu_1 i}^2{}^{OC}}{A}S_2
\end{aligned} \tag{4.14}$$

$$\begin{aligned}
\mathrm{Var}_{oc}[\epsilon_{i,t}|\mathbf{S}] &= \sigma_\epsilon^2 - \boldsymbol{\lambda}_i{}'\boldsymbol{\Sigma}_{S\epsilon} \\
&= \frac{\sigma_\epsilon^2\sigma_{\nu_1 i}^2{}^{OC}\sigma_{\nu_2}^2}{A},
\end{aligned} \tag{4.15}$$

where $A = \sigma_\epsilon^2(\sigma_{\nu_1 i}^2{}^{OC} + \sigma_{\nu_2}^2) + \sigma_{\nu_1 i}^2{}^{OC}\sigma_{\nu_2}^2$.[16]

[15]In this model, we adopt the linear least squares estimation to estimate the return from loans. Therefore, coefficients of $S_{1,i}$ and S_2 and $\lambda_{1,i}$ and λ_2 are chosen such that the random variable $\epsilon_{i,t}$ is as close to the true value of $\epsilon_{i,t}$ as possible, meaning that $\mathrm{E}[(\epsilon_{i,t} - \mathrm{E}[\epsilon_{i,t}])^2]$ is minimum.

[16]$\boldsymbol{S} = \begin{bmatrix} S_{1,i} \\ S_2 \end{bmatrix} = \begin{bmatrix} \epsilon + \nu_{1,i} \\ \epsilon + \nu_2 \end{bmatrix}$, $\boldsymbol{\lambda}_i = \boldsymbol{\Sigma}_{SS}{}^{-1}\boldsymbol{\Sigma}_{S\epsilon}$, and

$$\begin{aligned}
\boldsymbol{\Sigma} &= \mathrm{E}\left[\begin{bmatrix} \epsilon \\ \nu_{1,i} \\ \nu_2 \end{bmatrix}\begin{bmatrix} \epsilon & \nu_{1,i} & \nu_2 \end{bmatrix}\right] \\
&= \left[\begin{array}{c|cc} \sigma_\epsilon^2 & \sigma_\epsilon^2 & \sigma_\epsilon^2 \\ \hline \sigma_\epsilon^2 & \sigma_\epsilon^2 + \sigma_{\nu_1 i}^2{}^{OC} & \sigma_\epsilon^2 \\ \sigma_\epsilon^2 & \sigma_\epsilon^2 & \sigma_\epsilon^2 + \sigma_{\nu_2}^2 \end{array}\right] \\
&= \begin{bmatrix} \Sigma_{\epsilon\epsilon} & \boldsymbol{\Sigma}_{\epsilon \mathbf{S}} \\ \boldsymbol{\Sigma}_{\mathbf{S}\epsilon} & \boldsymbol{\Sigma}_{SS} \end{bmatrix}.
\end{aligned}$$

4.2.5 Distribution of optimal lending share with two kinds of information signals

Using Equations (4.14) and (4.15), the expectation and variance of lending return are, respectively, calculated as

$$\mathrm{E}_{oc}[r_{i,t}|\boldsymbol{S}_i] = r_f + \rho_i + \boldsymbol{\lambda}_i \boldsymbol{S}_i, \tag{4.16}$$

$$\mathrm{Var}_{oc}[r_{i,t}|\boldsymbol{S}_i] = \sigma_\epsilon^2 - \boldsymbol{\lambda}_i{}' \Sigma_{\boldsymbol{S}\boldsymbol{\epsilon}}. \tag{4.17}$$

Then, bank i' s optimal lending share $x^*_{i,12}$ is

$$x^*_{i,12} = \frac{\rho_i + \boldsymbol{\lambda}_i' \mathbf{S}}{\alpha \mathrm{Var}[\epsilon_{i,t}|\mathbf{S}]}. \tag{4.18}$$

Therefore, the distribution of this share is written as

$$\mathrm{E}[x^*_{i,12}] = \frac{\rho_i}{\alpha \mathrm{Var}[\epsilon_{i,t}|\mathbf{S}]}, \tag{4.19}$$

$$\mathrm{Var}[x^*_{i,12}] = \frac{\boldsymbol{\lambda}_i' \Sigma_{SS} \boldsymbol{\lambda}_i}{\alpha^2 \mathrm{Var}[\epsilon_{i,t}|\mathbf{S}]^2}. \tag{4.20}$$

Ceteris paribus, the effect of a change in bank i's overconfidence on this distribution is calculated as

$$\frac{\partial \mathrm{E}[x^*_{i,12}]}{\partial \sigma^{2\ \ OC}_{v_1 i}} = -\frac{\rho_i}{\alpha} \frac{\boldsymbol{\lambda}_i' \boldsymbol{\iota} \boldsymbol{\lambda}_i}{(\mathrm{Var}[\epsilon_{i,1}|\boldsymbol{S}])^2} < 0, \tag{4.21}$$

where $\boldsymbol{\iota} = \begin{bmatrix} 1 & 0 \\ 0 & 0 \end{bmatrix}$. This inequality arises because $\boldsymbol{\Sigma}_{SS}{}^{-1}$ is a positive definite matrix.

In addition, the effect on the variance is given by

$$\frac{\partial \mathrm{Var}[x^*_{i,12}]}{\partial \sigma^2_{\nu_1 i}{}^{OC}} = -\frac{\boldsymbol{\lambda}_i' \boldsymbol{\iota} \boldsymbol{\lambda}_i}{\alpha^2 \mathrm{Var}[\epsilon_{i,1}|\boldsymbol{S}]^2}\left[1 + \frac{2\Sigma_{\epsilon \boldsymbol{S}} \Sigma^{-1}_{\boldsymbol{SS}} \Sigma_{\boldsymbol{S}\epsilon}}{\mathrm{Var}[\epsilon_{i,1}|\boldsymbol{S}]}\right] < 0. \tag{4.22}$$

Equations (4.21) and (4.22) suggest that a change in overconfidence is negatively associated with both the expectation and variance of the optimal lending share. In other words, the more that bank i underestimates the precision of its own private information, the more heterogeneously its lending share increases. Now, to investigate the effect of the public information signal on the lending behavior, we compare these results with those of one kind of information.

First, we examine the gap between expectations.

$$\mathrm{E}[x^*_{i,1}] - \mathrm{E}[x^*_{i,12}] = \frac{\rho_i}{\alpha \mathrm{Var}[\epsilon_i|S_{i,1}]} - \frac{\rho_i}{\alpha \mathrm{Var}[\epsilon_i|\boldsymbol{S}]} < 0,$$

because $\mathrm{Var}[\epsilon_i|S_{1,i}] > \mathrm{Var}[\epsilon_i|\boldsymbol{S}]$. As a result, we obtain

$$\mathrm{E}[x^*_{i,1}] < \mathrm{E}[x^*_{i,12}]. \tag{4.23}$$

This result is summarized in the next proposition.

Proposition 1a:

Given that public information is normally distributed as $N(0, \sigma^2_{\nu_2})$, $S_{1,i}$ is independent of S_2, and the other conditions are same, the expected optimal lending share with two kinds of information signals is larger than that with the one kind of information signal.

Proposition 1a indicates that public information increases the expected share of lending. One reason being that the uncertainty of the default risk is reduced by a bank's taking advantage of the public information.

Next, we obtain the gap between the variances:

$$\mathrm{Var}[x_{i,1}^*] - \mathrm{Var}[x_{i,12}^*] = \frac{\sigma_\epsilon^2 + \sigma_{\nu_1}^{2\ OC}}{\alpha^2 \sigma_{\nu_1}^{4\ OC}} - \frac{\boldsymbol{\lambda}' \boldsymbol{\Sigma}_{SS}^{-1} \boldsymbol{\lambda}}{\alpha^2 \mathrm{Var}[\epsilon|\boldsymbol{S}]^2} < 0.$$

$$\mathrm{Var}[x_{i,1}^*] < \mathrm{Var}[x_{i,12}^*]. \tag{4.24}$$

Proposition 1b:

The variance of the optimal lending share with two kinds of information is larger than that with one kind of information.

Propositions 1a and 1b indicated that when two kinds of information are available, the optimal lending share shifts more heterogeneously, possibly because gaining more information releases banks from the constraint of uncertainty. Banks believe that they can more accurately forecast a default risk and thereby have various lending strategies to adopt more aggressive lending behaviors. Therefore, when additional public information is available, bank lending behaviors become more confident.

Next, we compare the effects of a change in overconfidence on the optimal lending behaviors between two cases. The results are

$$\left| \frac{\partial \mathrm{E}[x_1^*]}{\partial \sigma_{\nu_1}^2} \right| > \left| \frac{\partial \mathrm{E}[x_{12}^*]}{\partial \sigma_{\nu_1}^2} \right|$$

and

$$\left|\frac{\partial V[x_1^*]}{\partial \sigma_{\nu_1}^2}\right| > \left|\frac{\partial V[x_{12}^*]}{\partial \sigma_{\nu_1}^2}\right|. \tag{4.25}$$

Proposition 1c:

A massive effect of a change in overconfidence on lending behavior is reduced by using two kinds of information.

Proposition 1c indicates that additional public information reduces the volatility of a bank's lending behavior. Therefore, public information can diminish the irrational fragility of this behavior.

4.3 Conclusion

We summarize Section 4.2 as follows. If two kinds of information are available, the public information enhances bank's bullish lending behavior, but diminishes the fragility of its lending behavior. Our results show that overconfidence causes irrational and more fragile lending behavior. Once banks become overconfident the irrational bubble lasts, and it is hard to make it disappear. This implication is consistent with other studies.[17]

In this chapter, we theoretically investigate bank's irrational lending behavior. Our main results are as follows: (1) A bank's overconfidence leads to irrational lending behaviors, (2) The distribution of an overconfident bank's lending share is more severely affected by a change in uncertainty compared with that of the rational bank's, and (3) Overconfidence causes more fragile lending behaviors than rational confidence.

[17] For example, see Daniel, et al. (1998) and Scheinkman and Xiong (2003).

These implications are consistent with our evaluation regarding bank lending behaviors. Indeed, there is some evidence that banks tend to be overconfident. When asset price bubbles occurs, it can spill over into a credit boom. Bubbles is also driven by optimistic expectations.[18] Banks know very well about their borrowers and their environments through various means including having close relationships with borrowers and by monitoring, screening, and so on. Therefore, we may consider banks as experts.

In this chapter, we theoretically examined bank lending behaviors. We intend to develop this theoretical analysis to an empirical one and apply to a more sophisticated model.

[18]Former chairman of the Fed. in the U.S., Alan Greenspan, referred the latter bubble to as "irrational exuberance."

Figure 4.1: Graphical representation of the distribution of an irrational bank's lending share

Notes: This figure shows the distribution of an irrational bank's lending share compared with that of a rational bank. The possible values and probabilities of the lending share are shown. The area covered with horizontal stripes describes a possibility of irrational lending.

Figure 4.2: A shift in lending behavior.

Notes: This figure shows the gap between a change in lending behavior of a rational bank and that of an irrational bank. Area B is always bigger than Area A. This shows that the change in uncertainty leads to a more severe shift in an irrational bank's lending behavior compared with that of a rational bank.

Chapter 5

Conclusion

Macroeconomic uncertainty affects bank lending behaviors. Using rational expectation theory and behavioral finance theory, we develop models of bank lending behaviors in uncertain environments. Empirical data are presented to identify the distributions of lending share and macroeconomic uncertainty. We empirically examine the association between Japanese banks' lending behaviors and macroeconomic uncertainty. The role of overconfidence and irrational lending behaviors by banks are also discussed.

The main results are as follows: In Chapter 2, we obtained Lemma 1and 2. Lemma 1 states that macroeconomic uncertainty relates to a bank's estimation of the default risk of loans, its assignment of the weight to its own signal, and the precision of its estimation. Lemma 2 states that macroeconomic uncertainty is negatively associated with lending behaviors of banks. These results reinforce the argument that financial crisis is caused, in part, from the inability of banks to accurately judge the riskiness of their investments. This association empirically examined in Chapter 3. The estimation results confirm that macroeconomic uncertainty affects Japanese banks' lending behaviors, especially, Japanese regional banks' lending behaviors. We cannot detect this negative link between macroeconomic uncertainty and Japanese city banks' lending behaviors. The number of city banks has been reduced by one thirds (from 13 to 4) during the sample period. Patterns of fundraising by Japanese nonfinancial sector have shifted from bank-centered system to self-financing system. In particular, large size firms has become to have various options of financing. We conjecture that these shifts have critical effects on city bank's lending behaviors. Chapter 4 investigated the bank lending behavior from another point of view. We examined the role of overconfidence in rational/irrational forecasting and lending on the basis of private and public information signals, and their influence on bank lending behaviors. Overconfidence has an additional effect on rational bank lending behaviors. Overconfidence causes more fragile lending behaviors than rational confidence.

In this thesis, we find that uncertainty and imperfect information do play a significant role in bank lending behavior or investment decisions. Moreover, we find that these behaviors become more homogeneous among banks as uncertainty increases. This study also empirically examines this negative link and investigates the role of overconfidence in rational/irrational forecasting and lending. Although the data for this study have been assembled from the time series of financial reports by Japanese banks, there are large similarities in terms of risk management, portfolio management, and other lending behaviors among banks all over the world.

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