

BANKS' LOAN LOSS EXPECTATIONS OVER THE BUSINESS CYCLE: FROM PESSIMISM TO OVER-OPTIMISM

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Abstract: This paper analyzes the dynamics of loan loss expectations over the business cycle. We study the process of probability-updating of lenders (i.e., banks) assuming on the side of the bank a Bayesian rational updating in a business cycle environment modeled as a Markov chain. We show that with a limited memory span lenders are liable to overestimate default risks early in the boom and to underestimate the probability of credit default as the boom lasts. The simulations presented in the paper are calibrated on US business cycle and default data. Our analysis helps to understand the historical recurrence of credit cycles.

1. Introduction

When addressing banks' contribution to the emergence of credit cycles analysts often focus on over-confidence as a factor leading to over-lending. In the words of the then chairman of the Federal Reserve Board Alan Greenspan (2002):

“Moreover, behavioral factors, even if there were no rules or regulations, would still be a formidable force in inducing cyclical changes in both the quantity and the quality of assets acquired and issued in the financial sector. The most basic is human response to risk. The often-repeated pattern in financial markets has been the periodic shift in risk attitudes, initiated by the state of the economy, among lenders and other asset holders. History instructs us that, during recoveries and booms, risk discounts erode as the level of optimism lowers the barriers to prudence. Even those lenders less inclined to reach for more risk-laden proposals are driven to maintain their share of the rising credit flow, if not to increase it.”

Recent years have seen the development of several empirical and theoretical analyses of changing lending standards as factors in the credit cycle (see, e.g. Rajan, 1994, Weinberg 1995, Kiyotaki and Moore, 1997, Asea and Blomberg, 1998, and Lorenzoni 2008). These approaches base their explanations on various frictions of the credit market. None of these studies focus on the mechanism of expectations formation as a determinant of lending cycles. It is this gap that the present study attempts to fill, thus making a contribution to a theory of the credit cycle induced by bounded rationality. The paper is organized as follows. The next section presents a simple Markov model of the business cycle and of loan losses. Section 3 calibrates the model to U.S. data. In section 4 we present the results of computational experiments that document the course of loan-loss expectations over a standard recession-boom cycle. Section 5 discusses how bankers' loan-loss expectations interact with borrowers' expectations to generate an aggregate credit cycle. Section 6 concludes the article.

2. The outline of the model

We are looking here at a stationary economy that can take on the two states “good times” with a high level of output and “bad times” with low output. A Markov chain governs the transition between these two states whereby p is the probability that good times follow good times and q is the probability that bad times follow bad times. Correspondingly, $1-p$ is the probability that good times are followed by bad times and likewise $1-q$ is the probability that bad times are followed by good times. In good times the charge-off due to defaulting loans is d_L and in bad times it is d_H . The subscripts L and H indicate a low and a high level of loan loss, respectively. In the simplest setup the bank assesses the expected loss on a one-period loan. Later we look at how lengthening the lending horizon influences expected losses. The banker in our model bases his expectations formation on the correct assumption that the state of the economy follows a Markov process. However, the lender does not know the objective transition probabilities of this stochastic process. Instead, he looks backwards in time and estimates these probabilities. The key point here is the time horizon over which the decision maker looks back. We model the decision maker as forming a Bayesian estimate of the probabilities p and q by using a limited historical data sample. It is this limitation of the memory span that makes for the bounded rationality of the decision maker. More concretely, the banker looks back over a limited historical time span of N periods. In these N periods we have n instances (i.e., quarters) of good times and m instances of bad times (where $N = n + m$). The Bayes estimate of the probability p then is

$$\hat{p} = \frac{1+k}{2+n}, \quad (1)$$

where k the number of observations where good times are followed by good times.¹

Correspondingly, the Bayes estimate of probability q is

$$\hat{q} = \frac{1+l}{2+m}, \quad (2)$$

where l the number of observations where bad times are followed by bad times. Typically, a bank employs individuals with different memory spans. Hence, in order to model a typical bank's behavior we have to take into account the distribution of N across individual employees. These are the general outlines of our model. The next section develops a computational version of this model by turning toward empirical information regarding the business cycle, loan charge-off data, and the distribution of N within a bank.

3. Model calibration

In order to empirically calibrate the transition probabilities and the length of the learning horizon we use business cycle reference data provided by the National Bureau of Economic Research. Quarters during which the economy expands are interpreted here as “good times” and quarters with recession are taken as “bad times”. According to the NBER data and looking back over 10 complete cycles (from 1945 until 2001) the average duration of a cycle is 22.33 quarters (67 months) where the average recession lasts 3.33 quarters (10 months) and the average expansion lasts 19 quarters (57 months). For the estimation of the objective transition probabilities of the Markov chain we take the Bayesian estimate of the two probabilities based on the data from 1945.Q2 till 2001.Q2. Based on the historical US data

¹ The Bayes estimator differs from the maximum likelihood estimator of this probability (k/n) in that the Bayes estimator chooses the average of the posterior density whereas the ML estimate chooses the maximum of the posterior density. For small data sample the Bayes estimator gives a more reasonable estimate than the ML-estimator (see Amemiya, 1994, p. 174).

these estimates are $\hat{p}=0.943$ and $\hat{q}=0.703$. In the simulations in section 4 we use these estimates as the objective values of p and q .

To guide our modeling regarding bankers' memory span N we take a bank manager description on this issue (cited in Keenan, 2007) "In all of its top credit and lending positions, New Alliance has made sure it has executives who have been through one or two downturns in the credit cycle. [CEO Patterson] "They are the ones in the key jobs because they have seen what a bad loan can do to profitability.'" This statement is informative because it hints at the heterogeneity of N across the decision makers within a bank and further provides evidence concerning the distribution of this variable. For our behavioral model we take the given statement to indicate that (i) the population of decision makers follows a normal distribution, (ii) the average decision maker has an experience span (i.e., memory base) of 1.5 times the length of the average business cycles (i.e., 33 quarters), (iii) twice the length of an average business cycle (i.e., 44 quarters) and one average business cycle (i.e., 22 quarters) mark the mean of the memory span plus/minus one standard deviation. Hence, we compute the probability updating process of agents with different memory spans and weight their probability estimates according to the above distributional information in order to reach a typical bank's probability assessment. Two aspects of Bayesian probability learning should be noted here: (i) the agent starts his professional education process (before his decision making life) with values of the probabilities p and q of 0.5, respectively, and (ii) with an infinite memory span the agent's subjective probabilities converge to the respective objective probabilities.

In order to quantify losses from defaulting loans we use charge-off data provided by the Federal Reserve Board (Federal Reserve Statistical Release, 2009). The Fed defines the charge-off rate as the flow of a bank's net charge-offs (gross charge-offs minus recoveries)

over a quarter divided by the average level of its loans outstanding. For the purpose of this study we use the charge-off data concerning residential and commercial real estate loans. This quarterly series goes as far back as 1985 and shows the highest absolute correlation (-0.41) of all sub-aggregates listed with the business cycle (as dated by the National Bureau of Economic Research). When assessing the average charge-off numbers across boom (recession) quarters we find a rate of 0.328 (0.821). Hence, the charge-offs are 2.5 times higher during a recession than during an upswing.²

4. The computational experiment

Our fictitious decision makers live in a Markov economy as described before. They experience business cycle states that are randomly drawn from the objective probabilities for p of 0.943 and for q of 0.703. We call these random draws of good times and bad times the prehistory of our experiment. The actual experiment in which we study the course of loan loss expectations is a sequence of events where the economy first undergoes a typical recession lasting for three periods (quarters). After that the economy experiences an extended period of good times. We continue the upswing without interruption and study how loss expectations vary over the life span of the boom. Figure 1 shows one such scenario with a stochastically generated business cycle history (the grey line) followed by the standardized recession-boom scenario (the dark line) that begins in period 1. Turning to the process of probability updating it is clear that the specific course of the prehistory influences the individual's probability assessment as he enters the standardized recession-boom phase. This is precisely why we run many simulations of prehistory (here we consider 70 quarters before the initial recession). To make sure that the derived time paths for subjective probabilities are not biased by any one possible specific prehistory we simulate 1000 prehistories followed by the recession-boom

² Bruche and González-Aguado (2008) give a much more detailed analysis of losses over the cycle by modeling default probabilities and recovery rates and their determinants.

scenario described above and then take the average of the resulting probability values. This procedure is tantamount to taking different possible starting values for the transitions probabilities at time 1 and weighting them with the probability of their occurrence.

Figure 1 about here

We document the outcome of these computations graphically. Figure 2 shows the subjective probability of a continuation of a boom. At the beginning of the experiment (with the economy entering bad times in period 1) this probability lies below the relevant objective probability. As bad time continue the difference between subjective and objective probability rises and then slowly decreases as the economy enters good times. As a result, for the first six and a half years of the boom the probability of its continuation is underestimated. As the boom outlives this length of the expansion (the longest post-war expansion lasted for 41 quarters), expectations turn toward over-optimism. The initial over-pessimism is moderated by the course of the subjective expectation of an end of a recession (Figure 3). The short sequence of three quarters of good times brings a decline of the subjective probability to its objective value. Afterwards – as the economy experiences good times – the subjective probability of the end of (future) bad times is overly optimistic and increases steadily. In fact, this probability approaches 0.5 as the boom continues because (considering the distribution of N) fewer and fewer bankers will have experienced a recession during their professional life.

Figures 2 and 3 about here

In order to make the step toward the loan loss expectations we have to consider the loan charge-offs in either state of the economy, the state of the economy when expectations are formed, and the probabilities p and q .³ We assume that our bank has a well diversified loan

³ Asarnow and Edwards (1995) document that loan losses besides charge-offs can encompass additional elements such as costs for recovery. In this sense the data used here must be understood as the lower limit of losses due to default.

portfolio so that the bank experiences a loss of 0.328 percent on its money lent in a good quarter and 0.821 percent in a bad quarter. Hence, for the simplest case of a one-quarter loan – looking at the period of repayment of the loan – where the economy can only either continue to good times or change to bad times the expected loan loss looking from a quarter with good times is

$$l_{1,good}^e = 0.328p + 0.821(1 - p) . \quad (3)$$

In a bad quarter the expected loss is

$$l_{1,bad}^e = 0.328(1 - q) + 0.821q . \quad (4)$$

Quantifying these expectations using the objective values of the probabilities p and q leads to the rationally expected loan loss of 0.356 percent in good times and 0.674 percent in bad times. While the rational loan loss expectations are based on objective probabilities the corresponding subjectively expected losses are based on the subjective probabilities calculated before and displayed in figures 2 and 3. Figure 4 shows the objective and the subjective loss expectation for a one-quarter loan over the course of our standard cycle. Here we see that during the short (standard length) recession the subjective loss expectation is mostly lower than the objective, that is, rational expectation. As the state of the economy turns to the better (starting in period 4) over-pessimism peaks. In the case of a short-term loan the phase of excessive pessimism lasts for almost seven years. As the boom lasts longer (around the 27th quarter of good times) expectations turn overly optimistic.

Figure 4 about here

This picture is somewhat altered when we consider a longer term loan. For evaluating the expected loss for loans with a longer duration it becomes important to consider the interplay

of the probabilities p and q . Consider, for example, the case of a two-quarter loan.⁴ Here, the expected loss seen from a quarter of good times is

$$l_{2,good}^e = \frac{1}{2}[0.328p + 0.821(1-p)] + \frac{1}{2}[0.328[p^2 + (1-p)(1-q)] + 0.821[p(1-p) + (1-p)q]]. \quad (5)$$

By taking into account the possible business cycle outcomes at any payment date in the future (and the different possible paths leading to any of these outcomes) together with the corresponding probabilities we can compute the expected loss for a loan of any duration. Figure 5 shows the results for the case of a 10-year loan. The rationally expected level of loan losses for this contract is 0.373 in good times and 0.585 in bad times. Comparing the paths of rational and subjective loss expectations show that for this longer-term loan the over-pessimism already starts during the initial recession. This over-pessimism continues in the early part of the expansion and around six years into the boom (i.e., roughly a year earlier than in the case of the one-quarter loan) subjective expectations turn over-optimistic. Not only does over-optimism set in earlier in the case of long-term lending but here we can also document that the magnitude of over-optimism becomes more important compared to the case of short-term lending. This implies that the expectations effects documented here tends to favor long-term lending over short-term lending as the expansion ages.

Figure 5 about here

The dynamics of bankers' expectations documented here would be enough to generate an inefficient cycle with excessively low lending and investment followed by excessively high lending and investment later in the boom. However, this pattern is strengthened if borrowers (i.e., investors) also form boundedly rational expectations. It is to this issue that we turn next.

⁴ For all computations underlying figures 4 and 5 we assume that the interest rate is zero. These calculations are not only adequate for the case where the actual (default risk-free) loan rate is zero. The calculation is also exact if we discount the losses with this interest rate.

5. Lenders' and borrowers' contributions to inefficient credit cycles

Consider the following setup. Banks discussed in the previous sections lend to investors (e.g., businesses). In the simplest setup these investors operate a one-period investment project and borrow all invested funds through a one-period loan. An investor considers the following scenarios. In good times he receives his output with a probability of α and with probability $1-\alpha$ he receives nothing. In bad times the investor earns his output with probability β and with probability $1-\beta$ he gets nothing. Clearly, $\alpha > \beta$. We call the situation where the investor realizes his output the good outcome and the situation where he receives nothing the bad outcome. Under the good outcome investors pay back the credit with interest and under the bad outcome they default on their obligation. Tying the parameters α and β to the previously used data of charge-offs these parameters could be calibrated as $\alpha = 0.99673$ and $\beta = 0.99179$. We model output as the natural log of invested (i.e., borrowed) funds K . The investor expects good times to happen with the subjective probability ϕ and expects bad times with probability $1-\phi$. We will not go into a detailed probabilistic analysis of the dynamics of ϕ here. However, it is straight-forward to generalize our findings from the previous section. Agents with a finite memory span will tend to under-estimate ϕ relative to its objective value early in the boom and over-estimate it late in the boom.

In order to draw out the conclusions with respect to lending we assume for simplicity that borrowers and lenders are risk-neutral and that there is perfect competition in the credit market. For the lender (i.e., the bank) this means that he lends at the (assumedly fixed) real interest rate (r) augmented by the loan-loss expectation (l^e). The representative investor maximizes his expected profit which is

$$\pi^e = \phi\alpha \ln K + (1-\phi)\beta \ln K - (r + l^e)K . \quad (6)$$

Solving the first-order condition for this optimization problem we find the solution for the level of borrowing (and investment)

$$K = \frac{\beta + \phi(\alpha - \beta)}{r + l^e}. \quad (7)$$

Let us look at the previously discussed situation where the economy comes out of an average-length recession. In this situation banks will lend at an l^e that exceeds its objective value and investors will borrow on an ϕ that falls short of its objective value. Both of these tendencies will contribute to a depressed level of aggregate lending and investment early in the boom. As expectations of lenders and borrowers turn toward over-optimism late in the boom inefficient over-lending occurs.

6. Conclusions

This study is a contribution to a theory of inefficient credit cycles induced by bounded rationality. We show that Bayesian rational learning with a limited memory span leads to the pattern described in the literature: over-pessimism regarding expected loan losses early in the upswing turns to over-optimism and over-confidence as the boom ages. This effect is shown to be stronger the longer term the lending contract is.

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Figure 1: One simulated business cycle history with a standardized recession-boom scenario beginning in period 1

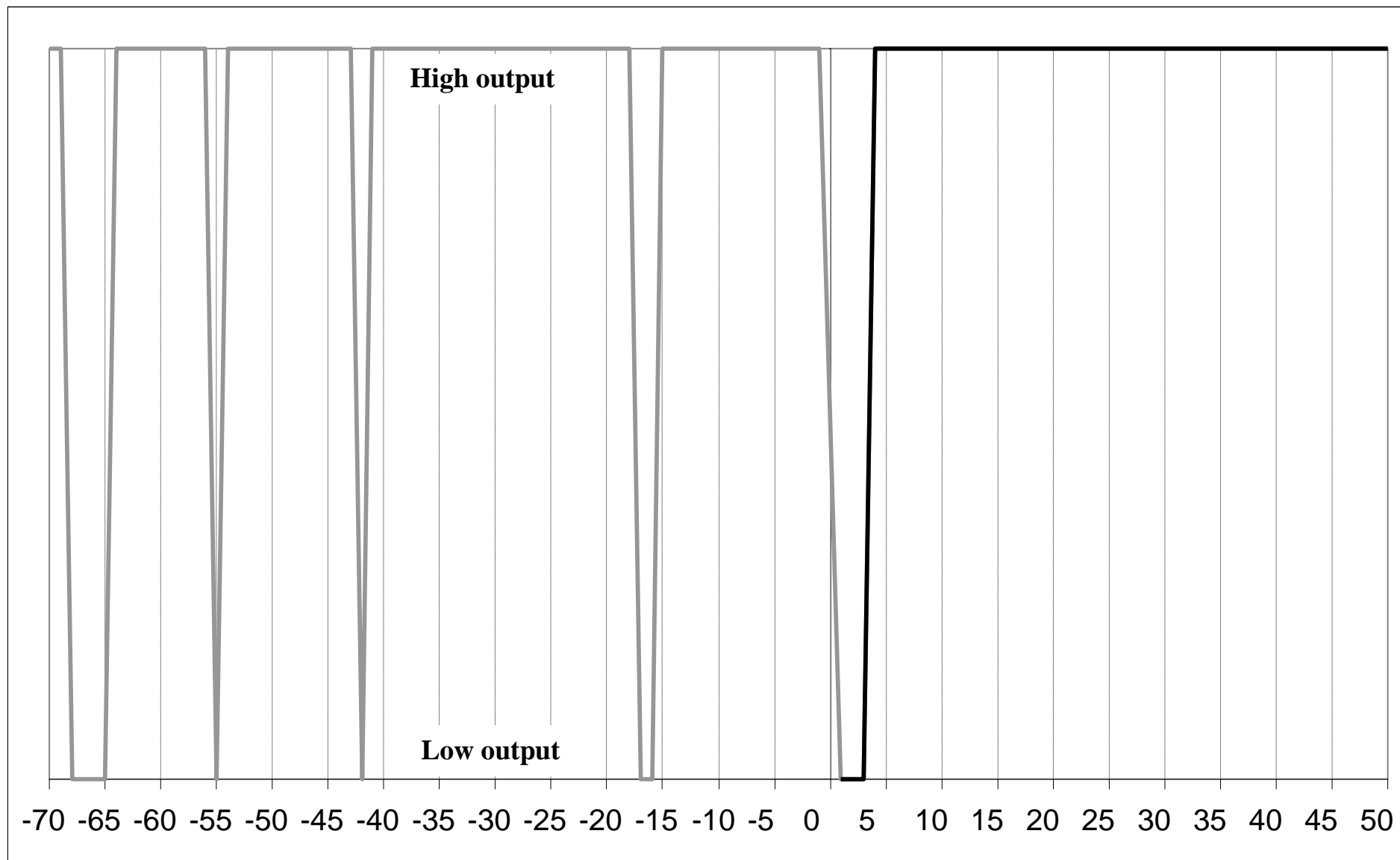


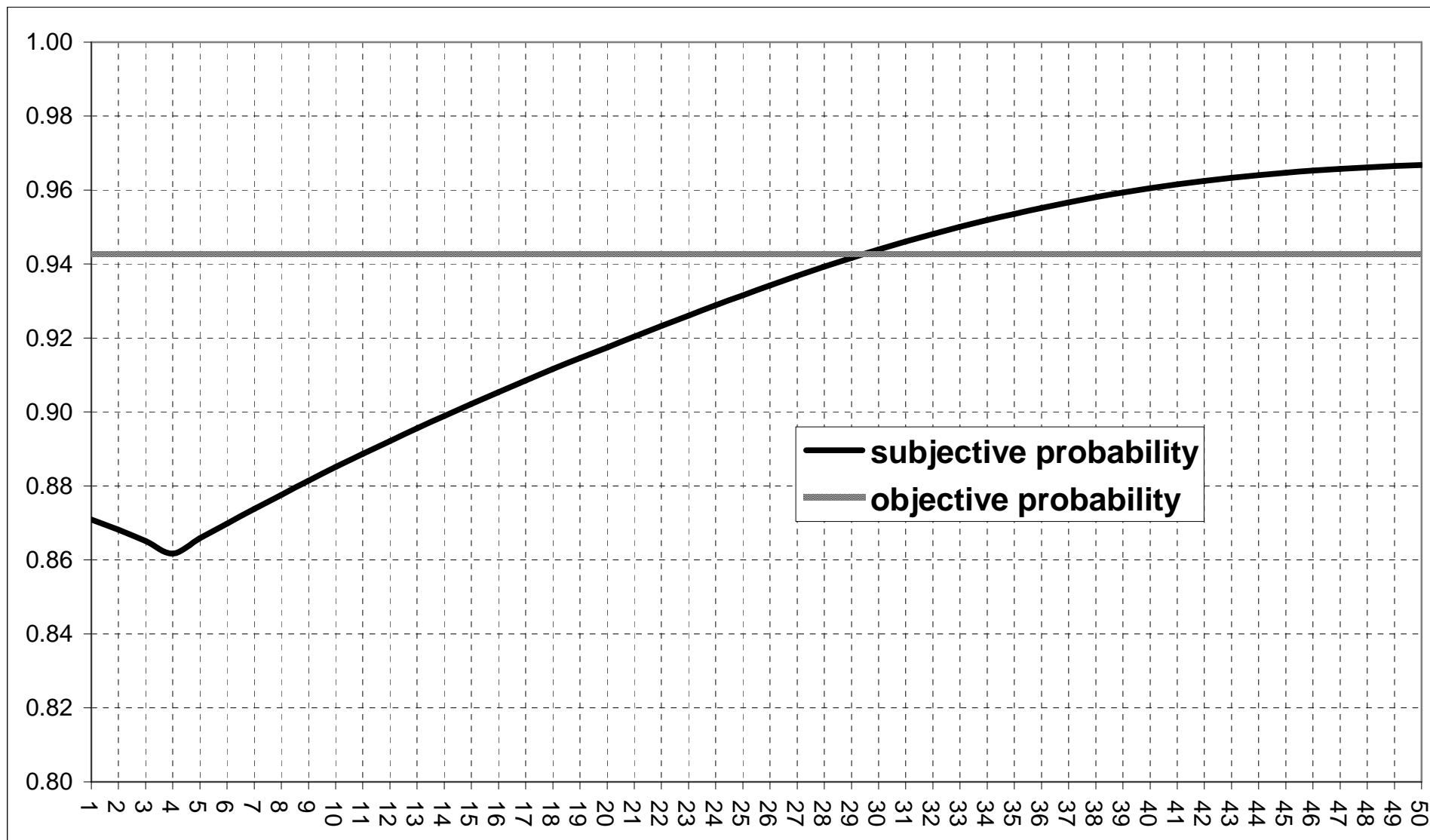
Figure 2: Subjective and objective probability of a continuation of a boom

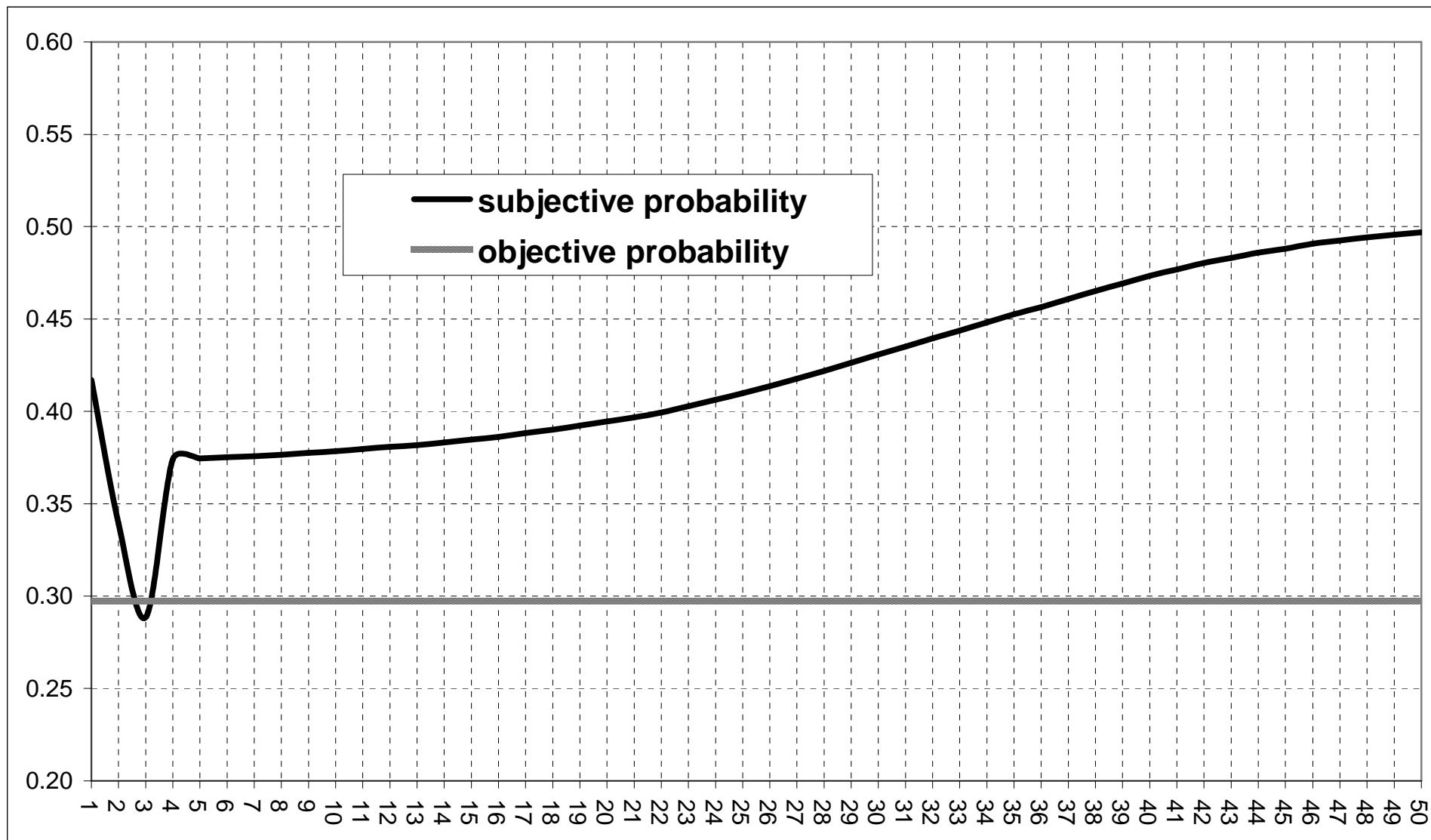
Figure 3: Subjective and objective probability of an end of a recession

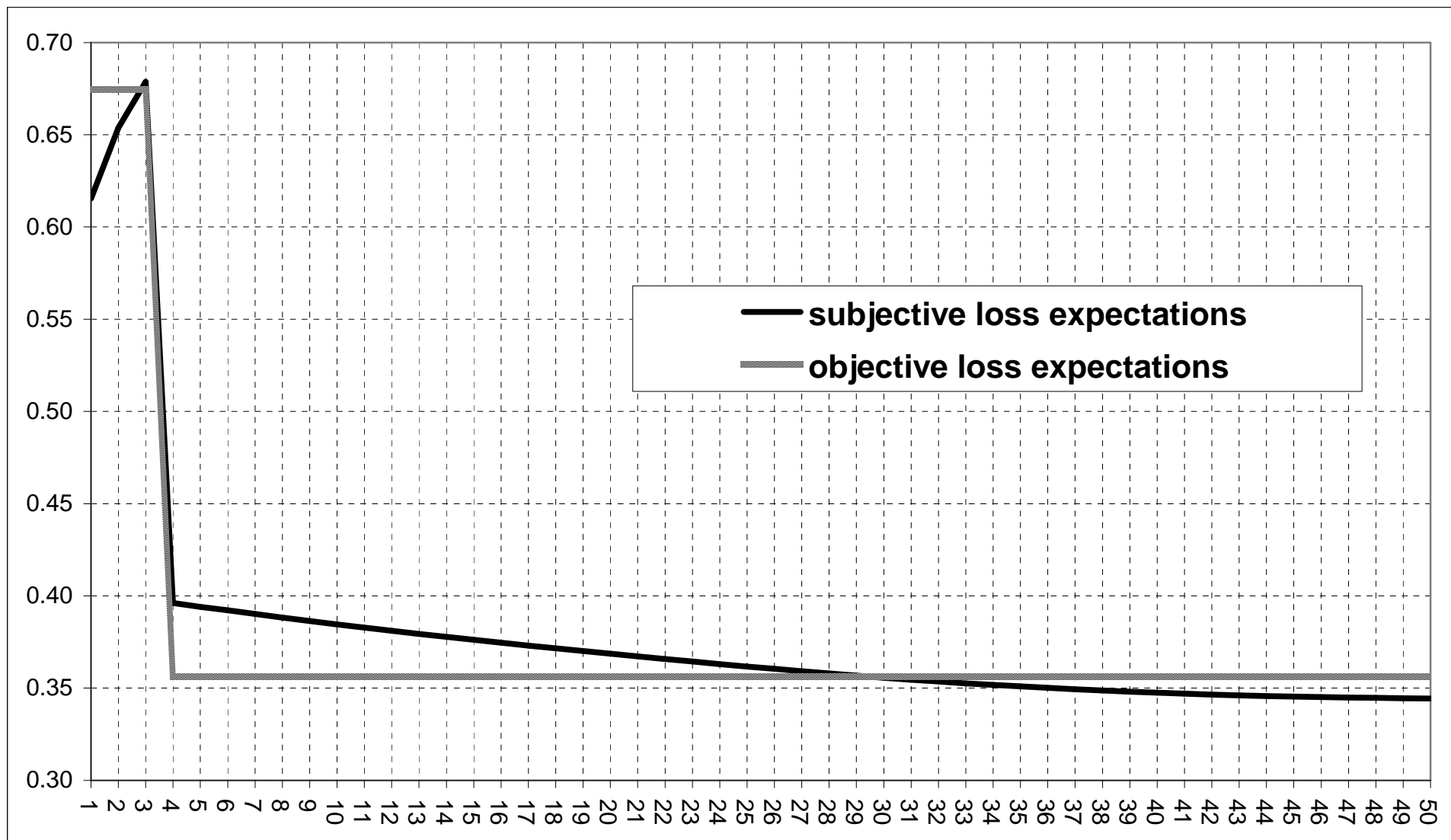
Figure 4: Subjectively and objectively expected loss on a one-quarter loan

Figure 5: Subjectively and objectively expected loss on a ten-year loan