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LENDING CYCLES

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ABSTRACT

We investigate the lending behavior of banks by exploiting a rich panel dataset on the contract terms of approximately two million commercial and industrial loans granted by 580 banks between 1977-1993. Using a Markov switching panel model we demonstrate that banks change their lending standards—from tightness to laxity—systematically over the cycle. We then use an efficient minimum chi-square estimator to examine the relationship between the cyclical component of aggregate unemployment and bank lending standards when both variables are jointly endogenously determined in a system of simultaneous equations with mixed, continuous/discrete dependent variables. The patterns we uncover suggest that lax lending standards that tend to occur during *expansions* exert considerable influence on the dynamics of aggregate fluctuations.

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1 INTRODUCTION

DO BANKS CHANGE THEIR LENDING STANDARDS systematically over the business cycle? If so, do these changes have a statistically discernable and economically important effect on aggregate fluctuations. It is surprising that economists do not have answers to these questions because several well known empirical regularities suggest that changes in bank lending standards—from tightness to laxity—may be an important factor in explaining the dynamics of aggregate fluctuations. First, during recessions, layoffs and other involuntary separations rise dramatically. This is an important empirical regularity because the utilization of labor is a key indicator of the state of the business cycle.[1] Second, there is a stable pro–cyclical relationship between broad credit aggregates (such as the total debt of U.S. non–financial sectors) and aggregate economic activity.[2] Third, there is a large body of evidence that suggests that cyclical changes in firm financing are dominated by changes in bank–lending, especially at the peak and during the downward phase of the cycle, Zarnowitz (1985).[3]

Several authors have attempted to explain the relationship between bank lending and aggregate fluctuations. For example, Farmer (1985, 1988) argues that financial contracting in the presence of asymmetric information and limited collateral (operating through nominal and real interest rates) can explain both cyclical and long–run movements in unemployment rates. Smith (1996) demonstrates that the presence of private information in a model of self–selection in labor markets generates cyclical fluctuations in unemployment. Gorton & Kahn (1993) argue that the ability to specify the terms of loan contracts enables banks not only to liquidate projects but also to influence borrowers' risk–taking activity.[4] Greenwald & Stiglitz (1993) argue that changes in firms' risk–taking behavior—as a result of financial

[1]The value of labor input in GNP or GDP is typically twice the value of all other factors combined.

[2]Friedman (1986) shows that the relationship between broad credit aggregates and GNP is more closely related to GNP than money stock and monetary base series.

[3]In the Federal Reserve November 1995 Survey of loan officers, 21 % of respondents said they had eased credit terms on large loans; 6.8 % on middle market loans; and 5.3 % on small business loans. A further 2 % said small business credit terms were being "eased considerably".

[4]This argument is based on the fact that bank loan contracts are typically secured senior debt with embedded options which enables banks to "call" the loan and consequently control firms' risk–taking behavior.

market imperfections—can have important implications for unemployment,

In this paper we explore the empirical relationship between changes in bank lending standards and cyclical fluctuations in aggregate unemployment. Unlike much of the literature which has focused on extreme and isolated periods of financial disintermediation such as the Great Depression, bank panics or credit crunches, we are interested in changes in bank lending standards (both tight and lax) as the outcome of "regular" bank lending activity. To the best of our knowledge, direct empirical evidence on the relationship between changes in lending standards and unemployment is nonexistent.[5] To shed light on this relationship we construct a panel dataset based on the contract terms of approximately two million commercial and industrial loans (C & I) granted by 483 banks between 1977–1993.[6]

The paper is divided into two parts. In the first part we investigate the contract terms on bank loans over the business cycle for evidence of systematic changes in lending standards. We use the Markov switching panel (MSP) model proposed by Asea (1996). The MSP model blends the classical Goldfeld & Quandt (1973) switching regression with the celebrated Hamilton (1988) Markov switching model. Heuristically, the MSP model relates a dependent variable to a set of independent variables (for each cross–sectional unit) through several regression planes with distinct regression parameter values. The regression planes describe the relationship between the dependent and independent variables under the various states of an unobserved Markov chain.

The MSP model is an appropriate method to address the questions we are interested in because it allows for the endogenous determination of temporal changes in the bank lending standards. Furthermore, it allows for statistical inference regarding the magnitude and signs of such changes to be made. For instance, we are able to differentiate two ways in which banks

[5]Farmer (1990) demonstrates that unemployment rates are positively correlated with nominal interest rates in annual time–series data for the United States over the period 1931–1986.

[6]Constructing this new dataset was necessary because publicly available bank–level data on the terms of individual loan contracts are nonexistent. In the United States, banks are not legally bound to disclose the terms of individual loan contracts. Even the information obtained by federal regulatory agencies remains confidential and is not subject to the Freedom of Information Act [5 U.S.C. 552 subsection (b)(8)].

might enforce tighter lending standards—price and non–price rationing—while allowing both to exist simultaneously in a non–linear two–state Markov switching panel model. We are also able to examine whether banks increase interest rates on new loans to compensate for higher agency costs of lending or maintain a sticky loan rate and ration candidate borrowers through loan denial.

The view that lending standards vary with aggregate conditions has been voiced in several professional banking journals and in speeches by the Chairman of the Federal Reserve Board and the Comptroller of the Currency, Weinberg (1995). Furthermore, several authors have examined changes in bank lending standards (though without taking into account the state of the economy).[7] For example, Berger & Udell (1990) find evidence for a key element of credit rationing in the form of a sticky response of bank loan rates to market interest rates, but find that other characteristics of rationing are absent. Failure to account for changes in bank lending standards over the cycle may explain the inconclusive results on the macroeconomic effects of credit rationing.

In the second part of the paper we investigate the joint relationship between bank lending standards and aggregate unemployment. We postulate that bank lending standards and unemployment are jointly endogenously determined in a system of simultaneous equations. The idea that bank lending and aggregate real activity may be jointly endogenous is not new, Christ (1971).[8] However, we are unaware of any empirical work that takes explicit account of the potential joint endogeneity.

The system of equations has both continuous and discrete dependent variables. To estimate the parameters of the model in the presence of mixed dependent variables we use a

[7]See the literature on credit rationing—which focuses on "excessively" stringent lending standards. The literature dates back to the availability doctrine which viewed credit rationing as a permanent disequilibrium phenomenon caused by specific institutional constraints such as interest rate ceilings. Jaffee & Russell (1976) provide an early demonstration of how credit rationing by loan size may occur as an equilibrium response to adverse selection in the presence of *ex ante* asymmetric information. Other influential papers are Stiglitz & Weiss (1981) and Williamson (1986).

[8]At a time when banks were considered a "veil", Christ (1971) argued that the process of intermediation in credit markets should be taken seriously and imbedded in econometric models of the aggregate economy.

minimum chi–square method—Amemiya's generalized least squares (GLS) estimator. The minimum–chi square method is attractive because it is efficient relative to many two–stage estimators and comes equipped with a convenient statistic for testing over–identification restrictions.

The empirical evidence suggests a systematic tendency for bank lending standards to vary over the business cycle. We find that in contractionary phases of the cycle, as unemployment rises, the risk premia banks charge on loans increases, loan size is unaffected and the probability of collateralization rises. In expansionary phases of the cycle, as unemployment falls, premia decline, loan size increases and the probability of collateralization declines.

How should these findings affect one's views on the relationship between credit markets and fluctuations in unemployment? What novel economic insights does the empirical evidence provide? First, the empirical evidence suggests that changes in bank lending standards may have a more profound effect on the economy during expansions—when the seeds of a future recession are sown — than during contractions. The contrast between this finding and the traditional view is striking. According to the standard view, credit market imperfections are "worse" in recessions in the sense that asymmetric information gives rise to an adverse selection problem that causes projects which are poor from the banks' point of view to drive out good projects (which would have otherwise been funded).

Our findings are consistent with the view that during booms asymmetric information in credit markets may cause good projects to draw in bad ones. This view is precisely the opposite of Akerlof's celebrated "Lemon's principle."[9] Since lax standards mean banks' grant loans to borrowers with higher risk of default, changes in lending standards can amplify swings in the economy. While it is well known that financial factors can propagate cycles one of the contributions of this analysis is to demonstrate that this is not limited to periods of

[9]After this paper was completed our attention was drawn to a paper by De Meza & Webb (1987) which shows that the inability of lenders to discover all the relevant characteristics of borrowers may result in lending (investment) in excess of the socially efficient level. However they do not consider the state of the economy over the business cycle as we do here neither do they provide any empirical evidence in support of the theory.

widespread intermediary break down (credit crunches etc.) but appears to be systematically present across the cycle.

The rest of the paper is organized as follows. In Section 2 we describe the construction of the bank–level panel dataset. In section 3 we identify contractionary and expansionary phases in unemployment. In Section 4 we describe the specification and estimation of the Markov switching panel regression. Empirical evidence on bank lending practices over the cycle is discussed. In Section 5 we describe the specification, identification and estimation of the mixed continuous/discrete simultaneous equations model and discuss the empirical evidence on the relationship between bank lending standards and unemployment. Concluding remarks are presented in Section 6. The Appendix contains a detailed description of the data.[10]

2 The Data

The empirical analysis is primarily based on a bank–level panel dataset that we constructed from approximately 2 million observations on the terms of individual loan contracts obtained from the *Federal Reserve Survey of Terms of Bank Lending.*[11] The survey is conducted during the first full business week of the middle month of each quarter. Over the period of the survey, a total of 580 different banks have been surveyed. To provide the widest possible distribution of banks, this survey comprises the largest 48 banks—with approximately 50 percent of all commercial and industrialized (C & I) loans—in addition to a random selection of 292 smaller banks. The information available in the dataset is based on every new loan made by these banks over 68 quarters from 1977 to 1993.

[10]In Appendix B of a longer version of this paper we propose a computationally tractable algorithm for evaluating the likelihood function and its derivatives by means of a recurrence relation. This Appendix is available on request from the corresponding author.

[11]While this survey has been used before (Berger & Udell 1992), to our knowledge this is the first study to exploit the panel characteristics of the data. It is well known that panel data offers a far richer opportunity for analyzing individual effects and controlling for individual "nuisance" variables than either cross-sectional or time series data, Hsiao (1993).

Respondent banks report the dollar amount and contract terms of all *new* commercial and industrial (C&I) loans made during the survey week. The contract terms include the following information: (i) the effective interest rate, (ii) months to maturity , (iii) whether the loan is backed by collateral, (iv) whether the loan is made under commitment and (iv) the total assets of the bank. Table A1 reports the mnemonics of the variables extracted from the Survey.

We use the following four criteria to construct the dataset. First, we delete any loan that had missing data for the entire sample period. Second, we delete loans with maturities greater than or equal to 360 months (30 years). The reason we exclude such observations is we want to match each loan with a comparable risk free rate, however 30 years is the highest available maturity for treasury bills. Third, we delete all loans with an average effective interest rate greater than 27%. Such loans amount to less than 1 % of the sample. These extreme outliers could arise from incorrect data entry during the survey or other forms of data contamination. We simply delete these outliers because they can affect the efficiency of the estimates.[12] Fourth, we delete all banks that appear in 10 or less surveys. After deletion the final sample had 1.65 million observations.

The next task is to construct several bank–level measures of lending standards. By the term "bank lending standards" we refer to the contractual terms imposed by banks on individual loans.[13] This suggests that we require a representative risk—free interest rate, the representative size, duration and interest rate of each loan, some proxy for the asset size of bank and the proportion of safe loans granted. We also require a measure of whether or not the loan was made with collateral. We describe the construction of each of these variables.

To construct a representative risk–free interest rate for each bank, we match the loan information in the bank–level dataset with the corresponding maturity of government security

[12]In general deleting extreme outliers in such an ad hoc fashion is perilous because it is difficult to separate genuinely contaminated data from observations that are unusual but valid. In principle, high breakdown point (robust) methods should be used to improve the efficiency of estimators in the presence of messy data. However, the small number of extreme outliers in this case did not warrant the use of such methods.

[13]We shall use the phrases "bank lending standards" and "bank lending behavior" interchangeably.

yields. The matching was performed according to the rule presented in Table A2.

To construct a representative risk premium (PREM) we subtract the bank specific risk–free rate from the representative interest rate on loans. We found no significant difference between our constructed measure of the risk premia (PREM) and an alternative measure calculated by subtracting the federal funds rate from the representative interest rate. To construct a measure of whether or not the loan was made with collateral (PR(COLL)) we weight the loans by the duration and size of the loan. Following Lang & Nakamura (1995) we also calculate a measure of the proportion of safe new loans each quarter denoted SAFE. Loans granted at interest rates below prime rate plus 1 % are categorized as safe loans. Loans at or above prime plus 1 % are categorized as risky.

The final bank–level dataset includes a representative risk–free interest rate (RATE), the asset size of the bank (SIZE), the representative loan size and representative interest rate charged on loans. The total number of observations in the panel is 18,371. Descriptive statistics are reported in Table 1. See the data appendix for further details on construction of variables in this dataset.

3 Identifying Cycles in Aggregate Unemployment

In this section we identify periods of contractions and expansions in unemployment. We also provide preliminary evidence on the relationship between various measures of bank lending behavior and aggregate unemployment. To avoid any confusion, we use the terms contraction and expansion to refer to the dynamics of unemployment and reserve the terms recession and boom to refer to the dynamics of the general business cycle. [14]

[14] The confusion may arise because in professional parlance the term "business cycle" is used to describe related fluctuations in a wide range of economic activities.

We use two methods to identify regimes because it is important to ensure that the periods we identify as contractions and expansions are close approximations to the true data generating process of the unemployment rate. The first method is Hamilton's Markov switching model with constant transition probabilities. Several authors have established that Hamilton's nonlinear Markovian model provides a good characterization of the intertemporal law of motion of quarterly GNP. There is less evidence on the time–series characteristics of other components of aggregate real activity such as unemployment. However, two features of unemployment data — nonlinearity and asymmetry—have been noted by several authors. For instance, Neftci (1984) estimates Markov models for unemployment rates and shows that the transition probabilities between rising and declining states of unemployment are not symmetric. Stock (1987) confirms the existence of asymmetry in unemployment rates with a time deformation model. Brock & Sayers (1988) discover nonlinearities in both employment and unemployment rate time series. Hamilton's Markov switching model is a natural choice because it provides a parsimonious characterization of the nonlinearity and asymmetry in aggregate unemployment.

The second method we use to identify regimes in unemployment is the Bry & Boschan algorithm. This method isolates local minima and maxima subject to constraints on both the length and amplitude of expansions and contractions. Watson (1994) has advocated using the Bry–Boschan algorithm on the grounds that it is based on a more objective definition of contractions and expansions.[15] We compare these two dating procedures (for the dynamics of aggregate unemployment) to the NBER Business Cycle Dating Committee chronology.[16]

The data are seasonally adjusted monthly unemployment rates from 1960–1994.The monthly unemployment rate series was obtained from the USECON database at the Federal Reserve Bank of New York. Following Boldin (1994) we use the following specification for

[15]See King & Plosser (1994) for a thorough description of the Bry–Boschan algorithm.

[16]The NBER has provided a business cycle chronology based on the collective subjective judgment of a panel of experts for several years. The NBER defines a recession as "...a recurring period of decline in total output, income, employment and trade usually lasting from six months to a year, and marked by widespread contractions in many sectors of the economy."

aggregate unemployment

$$\mathrm{UN}_t = \beta_{0s(t)} + \beta_{1,s(t)}\ \mathrm{UN}_{t-1} + \beta_{2,s(t)}\mathrm{UN}_{t-2} + \varepsilon_t \qquad s(t) = 1,2 \tag{1}$$

where UN_t denotes the level of the unemployment rate in period t and $\varepsilon \sim \mathcal{N}(0, \sigma_{s(t)})$. To select the appropriate number of lags to include in the unemployment equation, we use the Schwartz criteria and search over 1–12 lags of unemployment. We also consider, but reject a time trend.

The specification assumes that the state of aggregate unemployment at time t can be represented by a finite–state discrete–time homogeneous first–order Markov process. Consequently the state $S(t)$ at time t is one of a finite number of N states $s(t) \in (1, 2, \ldots, N)$. We restrict the number of states such that $s(t) = 1$ denotes a period of low unemployment and $s(t) = 2$ denotes a period of high unemployment. The transition probability matrix is $\mathcal{M} = (p_{ij})$ where

$$p_{ij} = \mathrm{prob}(s(t+1) = j | s(t) = i)$$

and of course $p_{ij} \geq 0$ and $\sum_{j=1}^{N} p_{ij} = 1$.

To write down the likelihood function, let y denote the left hand side of (1) and X the right hand side. Then the likelihood function for 2 sets of independent variables with standard errors in each regime is

$$\mathcal{L}(y, X, \beta, \sigma, \mathcal{M}) = \sum_{s(T)=1}^{2} \cdots \sum_{s(1)=1}^{2} \sum_{s(0)=1}^{2} \left[\prod_{t=1}^{T} f_{s,t} p_{(s(t-1),s(t))} \right] p_{0,s}$$

where $f_{s,t} = f(y_t - X_t\beta_s, \sigma_s)$ is the probability density function for each regime at each time period and $p_{0,s}$ is the initial probability.

We evaluate the likelihood function with an efficient numerical algorithm proposed by Boldin (1992). The estimated probabilities satisfy

$$p_{ij} = \frac{\sum p^{\star}_{ij,t}}{\sum p^{\star}_{i,t}}$$

where

$$p^{\star}_{i,t} = L\left(s(t) = i, y, X; \beta_s, \sigma_s, \sum p_{ij}\right) / L\left(y, X; \beta_s, \sigma_s, \sum p_{ij}\right)$$

$$p^{\star}_{ij,t} = \text{prob}(s(t-1) = i, s(t) = j|y)$$

denotes the full–sample probabilities computed using Bayes rule.

Table 2A reports maximum likelihood estimates of (i) the parameters of unemployment (β_1, β_2) in each state, (ii) the value of the maximized log likelihood function and (iii) the transition probability of switching from an expansion to a contraction

$$p_{12} = \text{prob}(s(t) = 2|s(t-1) = 1),$$

and from a contraction to an expansion

$$p_{21} = \text{prob}(s(t) = 1|s(t-1) = 2).$$

The specification of the transition probabilities postulates that if the unemployment rate increased ($s_t = 2$) last period, the probability of going into a contraction this period ($s_t = 1$) is a fixed constant p_{21} that does not depend on the duration of that particular state of unemployment rate or other measures of the duration of the state. We relax this assumption below.

From Table 2A, the probability of a contraction is estimated to be approximately 8 percent. The probability of switching from an expansion to a contraction (for every month of an expansion) is 3 percent. As mentioned above, the model we use to identify the contractions and expansions assumes constant transition probabilities. To account for the possibility of time variation in the probability of leaving a given state, we model the transition probabilities as a function of real industrial production growth. We find the dating of expansions and contractions to be similar.[17]

[17]To conserve space we do not report these results here. The results are available on request from the corresponding author.

Next, we conduct various dynamic specification tests of the model to evaluate whether the time series of aggregate unemployment is consistent with a Markov switching specification.[18] First, we test for several forms of autocorrelation. Then we test for remaining ARCH effects in the residuals from the estimated two-state model. Finally, we test for higher-order Markovian dynamics and violation of the presumed independence of the Markov process.

We report two sets of dynamic specifications tests. The first set of tests are due to White (1987), Newey (1985), and Tauchen (1985) and exploit the fact that the score statistics (the derivative of the conditional log likelihood of the t'th observation with respect to the parameter vector) of a correctly specified model should be serially uncorrelated.

The first row of Table 2B reports a test for first-order autocorrelation of the residual from regime 1 weighted by the current probability that observation t came from regime 1; plus, the innovation in the assessment of the categorization of regime 1 residuals. If the model is correctly specified, these innovations should be impossible to forecast. The 5 percent critical value for a $\chi^2(4)$ variate is 9.49 and the asymptotic p value of the test statistic is 0.078, implying overwhelming rejection of the null hypothesis.

The second row of Table 2B reports tests for violation of the assumption that the unobserved regime s_t follows a first-order Markov chain. The 5 percent critical value for a $\chi^2(1)$ variate is 3.84 and the asymptotic p value is 0.076, implying overwhelming rejection of the null hypothesis.[19]

The scores can also be used to evaluate Lagrange Multiplier (LM) tests. The last three rows of Table 2B report LM tests against the alternative hypotheses that there is omitted autocorrelation only in regime 1, autocorrelation only in regime 2 and autocorrelation across both regimes respectively. We find no evidence of autocorrelation in either regime or across

[18] We are grateful to James Hamilton for providing the GAUSS code for implementing the following specification tests. See Hamilton (1996) for a detailed treatment of these tests.

[19] Hamilton (1996) recommends using the F distribution rather than a $\chi^2(\cdot)$ distribution for statistical inference in small samples.

regimes with these LM tests.

Contractionary and expansionary phases in unemployment over the period 1977 to 1993 are displayed in Figure 1. The full-sample probabilities of contractionary phases identified by the Markov switching model are indicated by the shaded areas. Turning points identified by the Bry–Boschan algorithm are indicated with arrows. To facilitate comparisons we have indicated the NBER business cycle dates at the bottom of Figure 1. A clear asymmetric pattern is evident. The unemployment rates starts rising before the beginning of a recession (i.e. before a peak); it reaches a peak at the end of each recession then declines throughout each boom.[20]

One notable exception to this pattern is the mid–1980s when unemployment remained at 7 percent and maybe even rose slightly. Several authors have suggested that this was a mini–recession. The Markov switching model does show a brief spike during this period, however neither the transition–probability nor the duration is large enough to warrant classifying this as an actual change in regime. The results are not meaningfully different when we use prime–age male unemployment rather than aggregate unemployment rates to identify the cycle.

We thus conclude that the intertemporal law of motion of the aggregate unemployment rate is well represented by a Markov switching model. Furthermore, the periods of contractions and expansions in unemployment that we have identified are consistent with the Bry–Boschan algorithm and with turning points in the general business cycle as identified by the NBER reference chronology.

Figure 1 also displays the dynamics of the bank–level risk–free interest rate. This variable also appears to indicate switches in regime. The risk–free rate rises as the economy heads into

[20]Similar results were obtained by Boldin (1994) who notes that the fact that the cycles in unemployment closely matches NBER dates would surprise most economists who believe that unemployment rates lag the general business cycle.

each MSM–dated recession and then falls during each recession. The one notable exception is during the mid–1980s when the risk–free rate declined during an expansionary phase. This is disconcerting, however, as we explained above the markov switching model does identify a "mini"–recession during this period. The dynamics of the risk–free rate depicted in Figure 1 is not surprising given that the aggregate risk–free rate is highly correlated with the federal funds rate, which is known to be highly counter–cyclical, Bernanke & Blinder (1992).

In Figure 2 we display several measures of credit 4 quarters before and 6 quarters after each trough of the cycle.[21] Risk–premia tends to jump right before each trough and the percent of loans collateralized tends to decline after each trough. The average loan size appears to correspond closely to movements in the aggregate risk free rate.

Figure 3 depicts the relationship between RATE and the risk–premium PREM. Both variables appear to be negatively related throughout the sample period. This negative relationship is consistent with the findings of Berger & Udell (1992). Figure 4 displays the relationship between the aggregate risk free rate (RATE) and the average size of a loan (SIZE). Both variables are positively correlated when interest rates where high in the late 1970's and early 1980's and again in the late 1980's and early 1990's. However, the positive relationship appears to diminish in the mid–1980's.

4 A Markov—Switching Panel–Data Model

In this section we describe the Markov switching panel (MSP) model proposed by Asea

[21]We ignore the mini 1981–82 recession because it was so close to the 1980 recession.

(1996).[22] Suppose the market for bank loans can be in one of several unobservable states that can take on a total of $J = \{1, \ldots, J\}$ possible states such that $s_i = j$ denotes being in state j. In the two regime case s_1 may represent a loan market characterized by tight lending standards while s_2 represents a state of lax lending standards. The unobserved sequence of states is assumed to follow a homogeneous irreducible Markov chain with stationary transition probability matrix $\mathcal{M} = (p_{ij})$, where $\text{prob}(s_t = j | s_{t-1} = i) = p_{ij}$ and $\rho_j = p(s_o = j)$ is the probability that the initial state was $s_o = j$.

Suppose we have sample observations on $K(k = 1, \ldots, K)$ features of $I(i = 1, \ldots, I)$ individuals over $T(t = 1, \ldots, T)$ time periods. Suppose the value of the dependent variable for the i'th unit at time t y_{it} depends on (i) K exogenous variables $(x_{1it}, \ldots, x_{Kit})$ that differ across individuals at any given point in time and also exhibit variation through time and state (ii) as well as on a variable that is specific to the i'th unit and that stays constant over time and state. Both the dependent and independent variables are assumed to be dependent on the underlying state.

The Markov switching panel model (MSP) proposed by Asea (1996) satisfies the above suppositions and is given by

$$y_{it} = \beta_{1,i}(j) + \sum_{k=2}^{K} \beta_k(j) x_{kit} + e_{it}(j) \qquad \text{for} \quad s_t = j, \tag{2}$$

where $\beta_k(j)$ is the coefficient associated with explanatory variable k if regime $s_t = j$, the individual specific fixed effect in state $s_t = j$ is denoted by $\beta^{\star}_{1,i}(j)$ and the error term for the i'th equation in state $s_t = j$ after decomposing the fixed effect is denoted by $e_{i,t}(j)$.

Rewriting (2) in vector form yields

$$y_t = X_t \beta(j) + e_t(j)$$

where y_t is a I $\times$ 1 column vector, X_t is a 1 $\times$ (I + K $-$ 1) matrix of covariate values, β_j is a column vector of dimension (I + K $-$ 1) $\times$ 1, and $e_t(j) \sim \mathcal{N}(0, \sigma^2(j)) \cdot I_{I \times 1}$

[22] See Asea (1996) for formal proofs of the statistical properties of the MSP model including consistency and asymptotic normality of the maximum likelihood estimators.

For notational purposes let (i) $\lambda = ([p_{i,j}]_{J\times J}, [\beta(j)]_{j=1,\dots J}, [\sigma^2(j)]_{j=1,\dots,J}, [\rho_j]_{j=1,\dots,J})$; (ii) $\theta = ([\beta(j)]_{j=1,\dots J}, [\sigma^2(j)]_{j=1,\dots,J})$ (the parameters of the conditional likelihood) and (iii) $z_t = (s_t, X_t)$ (the explanatory variables that condition the likelihood function.)

The joint distribution of unobserved states and observables Y is,

$$\sum_{s_o=1}^{J} p(y_T, \dots, y_1, s_T, \dots s_1 | s_0; \lambda)\rho_{s_o} = p(Y, S; \lambda)$$

where Y is an IT $\times$ 1 column vector and X has dimension IT $\times$ (I + K $-$ 1).

The unconditional likelihood is

$$p(y_T, \dots, y_1, s_T, \lambda) = p(Y, S; \lambda) = \int_S p(Y, S; \lambda)$$

where $\int_S$ is the summation over all possible elements of $S = \{s_T, \dots, s_1\}$ $s_t \in \{1, \dots, J\}$ and s_o is the initial state of the world.

The conditional expectation of the log likelihood is,

$$Q(\lambda_{l+1}; \lambda_l, Y) = \int_S \log p(Y, S; \lambda_{l+1}) \bullet \frac{p(Y, S, \lambda_l)}{p(Y; \lambda_l)}.$$

Since $p(Y; \lambda_l)$ is a constant we can loosely define the expected likelihood as

$$Q(\lambda_{l+1}; \lambda_l, Y) = \int_S \log p(Y, S; \lambda_{l+1}) \bullet p(Y, S, \lambda_l).$$

Following Dempster, Laird, and Rubin (1977) and Hamilton (1990) it is possible to show that numerical evaluation of the likelihood function with a version of the EM algorithm provides a sequence of analytic solutions $\{\hat{\lambda}_l\}$. [23] The sequence converges almost surely to the estimator which achieves the local maximum of the likelihood. By starting at different initial conditions one can then attain the global maximum likelihood estimator

$$\lim_{l\to\infty} = \hat{\lambda}_{MLE}$$

For analytic optimization of the expected likelihood construct $Q(\lambda_{l+1}; \lambda_l, Y)$ we assume independence of $\{s_t\}_{t=o}^{T}$, $\{e_t\}_{t=0}^{T}$ and rewrite the joint distribution as,

$$p(Y, S; \lambda) \quad = \quad p(y_T|z_T; \theta) \bullet p(s_T|s_{T-1}; [p_{ij}]) \bullet p(y_{T-1}|z_{T-1}; \theta) p(s_{T-1}|s_{T-2}; [p_{ij}])$$

[23]Appendix B of a longer version of the paper describes the algorithm in detail.

$$, \ldots, p(y_1|z_1) \bullet p(s_1|s_0; [p_{ij}]), \rho_{s_o}$$

where

$$p(y_t|s_t, X_t; \theta) = \frac{I}{\sqrt{2\pi}\sigma(s_t)} \exp\left\{-\frac{1}{2\sigma^2(s_t)}\left[y_t - X_t\beta(s_t)\right]'\left[y_t - X_t\beta(s_t)\right]\right\} \tag{3}$$

The MSP model is closely related to several statistical models for variables that exhibit discontinuous changes at undetermined points in time. These include the Markov model for switching regressions proposed by Goldfeld & Quandt (1973) and the class of autoregressive AR(p) models with Markov changes in regime proposed by Hamilton (1988). The Hamilton class of model allows for changes in the mean and scale of the process, and in lagged variables according to an unobserved Markov chain with a given number of possible states. The MSP model is a blend of Goldfeld & Quandt's (1973) switching regression (GQSR) model and Hamilton's constant Markovian transition probability model.

Aside from the panel specification the main difference between the MSP model and the Hamilton and GQRS models is that in the MSP model both dependent and independent variables are random variables with distributions that are assumed to be dependent on the underlying state.[24] The MSP model is attractive because it facilitates the testing of more complicated behavioral models than is possible with either Hamilton's class of pure *time series* Markov switching models or with the GQRS model.[25] However, the MSP specification implies that the change in regime is solely a temporal factor. This is clearly a restrictive assumption. We attempt to mitigate this restriction by allowing the changes in regime to have a different impact on cross–sectional units through the individual specific parameter $\beta^{\star}_{1i}(j)$.[26]

[24]A more distant class of models is the dynamic linear model with switching proposed in Shumway & Stoffer (1991). These models are generalizations of state space models in which the observation equation measurement matrices are not known *a priori* but are allowed to switch among N related configurations.

[25]Coslett & Lee (1985) demonstrate that the dynamic dependence of the regimes in the GQSR model is irrelevant for estimation because the Markovian transition probabilities do not enter the likelihood function. In other words the log likelihood function of the GQRS model fails to take in to account the dependence of the current state on the realization of the previous state imposed by the Markovian structure.

[26]Having several observations with a common temporal component that faces a switch enables us to identify

4.1 *Are There Systematic Patterns in Bank Lending Behavior?*

In this subsection we use the Markov panel model described above to investigate whether there is statistically discernable evidence of systematic patterns in bank lending behavior. To focus the discussion, consider an environment in which a loan officers problem is to price loans to borrowers. The premia the officer charges depends (among other things) on the state of the loan market. However, as mentioned above, the market for loans is assumed to switch between two states. Loan officers do not observe the states directly but they form probabilities of each possible state conditional on all relevant current and past information. States are characterized by the variance of the densities of the two normal distributions used to generate the loan premia. We refer to the states as the "high–risk" and "low–risk" state to capture the notion that the variance of the distribution of loan premia is higher the greater the disparity between borrowers which in turn implies a greater risk of lending.

The model for loan rate premia assumes a 2–state random covariate unobserved Markov specification. The dependent variable is the representative loan rate premium charged by bank i at time t denoted PREM. The explanatory variables are proxies for the state of the loan market—the real cost of funds to bank i at time t denoted COST, the percentage of loans made at or above the prime rate plus 1 % denoted RISKY; controls for the macroeconomic environment and dummy variables for individual banks.

Before discussing the parameter estimates, a few remarks on the expected values of the estimated coefficient on COST will be helpful. If the estimated coefficient on COST is not statistically different from zero we interpret this as evidence that the "price" (interest rate) banks charge for new loans reflects a roughly constant mark–up over the cost of funds. An increase of 1 % in the cost of funds is reflected in an increase of similar magnitude in the price at which banks are willing to make loans. However, two other cases are of particular interest.

the switches more precisely by increasing the observations available which contain information about the shift. We therefore avoid the problem of a singularity of the likelihood function that is often a problem for mixing distributions.

When the sign of the estimated coefficient on COST is less than zero a 1% increase in the cost of funds is not matched by a concomitant increase in the loan rate—the mark–up falls. This is due to stickiness in the loan rate. We interpret this as Stiglitz–Weiss type credit rationing.[27] An increase of 1 % in the loan rate reduces the returns to the banks due to adverse selection. Instead the banks choose to fix the loan rate and ration the excess demand for credit. We shall refer to this as quantity rationing.

When the estimated coefficient on COST is greater than zero a 1 % increase in the cost of funds is met by an increase of greater than 1 % in the loan rate. The reason being that if banks increased the interest rate on loans by exactly 1 % they would attract a more risky class of borrower. As a result, the average level and the cost of default should increase with risk and banks will realize and increase the premium they charge between loan and deposit rates. We shall refer to this as price rationing.

Maximum likelihood estimates of the random covariate panel model are obtained by invoking the algorithm described in Asea (1996). The maximum likelihood estimates and corresponding standard errors are displayed in Table 3.[28] In Model (I) the estimated coefficient on COST in the high–risk state is consistent with price rationing. However, the estimated coefficient on COST in the low–risk state is not statistically different from zero. As mentioned above this finding suggests that the "price" (interest rate) banks charge for new loans reflects a roughly constant mark–up over the cost of funds. An increase of 1 % in the cost of funds is reflected in an increase of similar magnitude in the price at which banks are willing to make loans. The failure of banks to adjust loan rates for the risk of borrowers

[27]An alternative interpretation could be that banks offer implicit insurance to borrowers against changes in the interest rate. That is, banks do not raise rates so high when market rates are high and do not lower them when market rates are low. However, this argument is flawed because such behavior cannot persist in equilibrium for *new loans*. To see why note that borrowers will go to the "insuring" banks when interest rates are high and to the "non–insuring" banks when interest rates are low. On average banks that insure will lose money. It is also unclear what incentive banks have to offer insurance on *new* loans (although it may certainly be true for existing floating rate loans) which is the category of loans that we focus on in this paper.

[28]To conserve on space coefficient estimates of the control and dummy variables are not shown here but are available on request from the corresponding author.

during expansions is what we refer to as "lax standards."

If banks change their lending standards systematically over the cycle we should expect that during recessions (high–risk state) banks should tighten credit standards in the loan market leading to a reduction in the relative amount of lending to riskier borrowers. Likewise, during booms (low–risk state) banks should relax credit standards and lend to riskier borrowers. In Model (II) the estimated coefficient on *risky* in both states is consistent with precisely such a pattern. The premium declines as the level of risk increases, that is the estimated coefficient on RISKY in the high–risk state is less than the estimated coefficient in the low–risk state. These results suggest an increase in lending to riskier borrowers when times are "good"— the reverse of a "flight to quality", Gilchrist et al. (1994). In the next section we explore the consequences of this reversal for aggregate fluctuations.

Competitive pressures to lend and market imperfections have been suggested as possible explanations for the bias towards excessive risk–taking by banks during expansions. For instance, Rajan (1994) develops a model where the market imperfection is a herding mentality which leads bankers to lend because of a concern for their reputations. Rajan's model generates low frequency business cycles driven by bank credit policies. de Meza & Black (1994) demonstrate that hidden knowledge gives rise to over–lending if the returns distributions preferred by borrowers are also favored by lenders. The authors show that even the Stiglitz–Weiss model yields over–lending when entrepreneurs are sufficiently risk averse. Fixed rate deposit insurance is the other commonly advanced explanation for excessive risk tolerance.

A central hypothesis underlying our empirical exercise is that the density of loan premia is a multivariate mixture of two normals with different means and variances. An obvious way to test this hypothesis is to compare the likelihood ratio statistic of an unrestricted model with that of a model restricted to a single state, Turner et al (1989). However, under the null of a single state the transition probabilities are unidentified (nuisance) parameters. In this case, the likelihood ratio statistic is not asymptotically χ^2 distributed. To get around this problem we use a modified likelihood ratio statistic proposed by Wolfe (1971) that tests the hypothesis of a mixed multivariate normal distribution against the null of simple multivariate normality.[29] The test statistic is approximately distributed χ^2 with five degrees of freedom and has a value of 64.12 which is significant at the 1 % level.[30]

In addition to using the MSP model to estimate the degree of stickiness in loan rates in different states of the loan market we also use the model for state restoration — that is, to predict next periods (unobserved) state and next periods loan rate premia based on all available information. Restoration of the state sequence adds to our understanding of the process since it enables us to relate historical events (e.g. turning points in unemployment) to the state process. Even though the states are never observed, probabilistic statements can be made about the relative likelihood of their occurrence. We use the maximal a posteriori probability (MAP) state estimation method. The MAP estimates the unobserved state by that state s_i that maximizes the a posteriori state probability.[31]

We focus on smoothed state estimates based on the entire observed data.[32] To calculate smoothed change–point estimates we maximize over the posterior joint probabilities. Table 4 summarizes the results of the state restoration exercise.[33] This table describes the general behavior of the loan market by way of the posterior distribution of the state conditional on

[29] Hansen (1992) has proposed a likelihood ratio bound test to deal with the problem of statistical testing under nonstandard conditions that arise in Markov switching models. However, we were unable to apply this method to our model because it required multi-dimensional grid search which exceeded our computational capabilities.

[30] See Turner et al. (1989) on the power of this test.

[31] An alternative sequence estimator is the Viterbi state estimator. We found no need to use this method because Fredkin & Rice (1992) conclude that there is little difference in the performance of the marginal (MAP) and global Viterbi estimates. Furthermore, the MAP estimate is slightly less "sticky" and thus more responsive to rapid transitions.

[32] The prediction of the next periods state is called *smoothing* if $t = T$, *filtering* if $t = s$, and prediction if $t < s$.

[33] Figure 5 in a longer version of this paper displays plots of these smoothed posterior probabilities. The top panel in that figure shows the observed loan rate premia, the second panel shows the smoothed high–risk probabilities, the third panel shows the predicted high-risk probabilities and the bottom panel shows the smoothed (low–risk to high–risk) change–point joint probabilities.

all the data in the full sample. The first column lists the dates of the periods in which the probability of the high–risk state exceeded one half. The second column lists the length of these periods. The last column lists the length of intervening periods in which the low–risk state exceeds one half.

There are three episodes of high—risk over the sample period starting in 79:Q3, 81:Q2 and 90:Q3 respectively. These episodes occur several periods before NBER business cycles trough points (80:Q3, 82:Q4 and 91:Q1) and before periods of high unemployment as identified by our Markov switching model for unemployment. Point estimates of the self–transition probabilities ($P[s_t = 1|s_{t-1} = 1] = p$) suggest strong time–dependence in the Markov process generating the low–risk state. From the posterior probabilities it is evident that the quarters for which we would have concluded that the loan market is in a state characterized by high–risk leads periods in which aggregate unemployment is highest. Likewise the quarters for which we would have concluded that the loan market is in a state characterized by low–risk leads periods in which aggregate unemployment is lowest. We conclude that the evidence supports the view that bank lending behavior changes systematically over the cycle. Furthermore, at this point in our analysis, the evidence is suggestive that changes in lending standards may have an important influence on aggregate fluctuations in unemployment. In the next section we explore the relationship between bank lending standards and aggregate fluctuations in more detail.

5 Bank Lending Standards and Unemployment

In this section we discuss the specification, identification and estimation of the simultaneous equations model of bank lending and unemployment when there are both continuous and discrete endogenous explanatory variables.[34] The exposition focuses on estimation with a discrete endogenous variable because the classical continuous variables case is well known.[35]

Let UNEM_t denote the change in the aggregate civilian unemployment rate between time $t-1$ and t; $\text{RATE}_{i,t}$ denote the risk–free interest rate for bank i at time t. Whether bank i collateralizes a loan during period t, $\text{PR(COLL)}_{i,t}$, is modeled as an indicator of the latent variable $\text{PR(COLL)}^{\star}_{i,t}$. The latent variable interpretation is consistent with standard views on adverse selection in credit markets. The latent variable has the interpretation of the outcome of idiosyncratic supply considerations (including any agency problems due to asymmetric information) and idiosyncratic demand considerations such as the banks customer base.

The specification of the simultaneous equations model is

$$\begin{aligned} \text{PR(COLL)}^{\star}_{i,t} &= \beta_0 \mathbf{Z}_{i,t} + \beta_1 \text{PR(COLL)}_{i,t-1} + \beta_2 \text{PR(COLL)}_{i,t-2} + \beta_3 \text{UNEM}_t + \beta_4 \text{RATE}_{it} + \varepsilon^2_{i,t} \\ \text{UNEM}_t &= \alpha_0 \mathbf{Z}_{i,t} + \alpha_1 \text{UNEM}_{t-1} + \alpha_2 \text{PR(COLL)}_{i,t} + \alpha_3 \text{RATE}_{i,t} + \varepsilon^1_{i,t} \end{aligned} \tag{4}$$

The specification of the bank lending standards equation is taken from Berger & Udell (1992). It is a demand equation derived from the money market that states that the price (PR(COLL), PREM) or quantity (SIZE) of credit is linearly related to the cost of borrowing (RATE) and the state of the economy proxied by UNEM. The variables in **Z** control for the log change in real GDP, the log of bank assets, demographic shifts in the labor market and time–trends. The system accounts for the simultaneity of the discrete variable (the probability of collateral) and the continuous variable (the change in the unemployment rate) and focuses on a specific channel through which changes in bank lending standards can influence aggregate unemployment.

The unemployment equation is a modified supply equation that takes into account the role of credit in the economy. It can be interpreted as a dynamic version of Okun's Law

[34] The econometric methodology was developed by Heckman (1978), extended by Newey (1987) and used by Londregan & Poole (1990) and Blomberg (1996).

[35] See Christ (1995) for an excellent exposition of simultaneous equations estimation with continuous variables.

augmented to include credit variables.[36] The story that relates credit variables to the real economy is conceptually straightforward. As output rises in a boom, unemployed workers are hired to produce it. As output falls in recessions, some workers are no longer needed and lose their jobs. The credit variables enter the unemployment equation under the assumption that "money" broadly defined is an important input in firm–level production. Models of asymmetric information with limited collateral provide the necessary micro–foundations to generate a contract–based explanation for cyclical variations in unemployment.

To identify the model we seek linear estimable functions that link reduced–form and a priori information to the structural parameters. Identification is achieved according to the Cowles Commission approach and is based on the following reasoning. In equilibrium all information about a variable should be incorporated in the current value of that variable. Therefore, previous information about the value of credit should have little influence on the economy (or vice–versa) once the new information is known. As a consequence, in equilibrium, lagged values of credit should not affect unemployment. Neither should lagged values of unemployment influence credit. However, because it is likely that the data generating processes are autoregressive, we would expect lagged dependent variables to affect credit or unemployment, even in equilibrium. Hence, we use lagged dependent variables to identify the system.

It is important to point out that we do not claim that this is necessarily the only possible structural interpretation of the data.[37] What we do claim is that the empirical model of bank lending and unemployment is interpretable in terms of standard models of equilibrium credit rationing. In the next subsection we will show that the model is consistent with the

[36]It is straightforward to derive such a relationship from a production function which models output as a function of the unemployment rate and credit variables.

[37]For instance, one possible theoretical model underlying the empirical specification is likely to yield multiple equilibria. This raises several difficult technical issues. The Cowles Commission approach to identification assumes that once the exogenous data are specified the endogenous variables can be uniquely determined. However, Jovanovic (1989) writes," it is precisely this assumption that fails when a model has multiple equilibria". The issue of whether a given model with multiple equilibria is identified and how much predictive content such a model retains is beyond the scope of this paper.

data and is well designed according to a wide range of specification tests.

There are at least two reasons the Cowles Commission approach may be preferred over the more popular vector autoregression (VAR) approach. First, the assumptions used to identify the structural parameters in VARs; namely that the covariance matrix of structural errors is diagonal and the system is recursive are *a priori* no more or less credible than the exclusion restrictions used to identify parameters in the Cowles methodology. Pagan & Robertson (1995) emphasize this point. Furthermore, the atheoretical restrictions used in VARs typically impose a Wold causal ordering which results in an exactly–identified system. In contrast, the Cowles exclusion restrictions generally lead to over–identified systems. Consequently, the choice between the two methods reduces to a choice between a just–identified and an over–identified system. While models with over–identifying restrictions can be tested, the same is obviously not true for just–identified models.

To construct the likelihood function let $\mathbf{y}$ denote $(\text{UNEM}_t, \text{PR(COLL)}^{\star}_{it})$ and $\delta_{it} \equiv I_{\{\text{PR(COLL)}^{\star}_{it}>0\}}$ be a function that assumes a value of 1 if $\text{PR(COLL)}^{\star}_{it}$ is positive and zero otherwise. Denote the vector of variables that enter either equation as $\mathbf{X}_{it}$; the vector of errors by $\boldsymbol{\varepsilon}_{it}$; and the vector of coefficients, as $\boldsymbol{\beta}_{it}$ where $\mathbb{E}(\varepsilon\varepsilon') = \Omega$

The system of equations can be rewritten as

$$\mathbf{y}\Gamma(\boldsymbol{\beta}_{it}) = \mathbf{x}_{it}\Lambda(\boldsymbol{\beta}_{it}) + \boldsymbol{\varepsilon}_{it} \tag{5}$$

where the vector functions $\Gamma(\boldsymbol{\beta}_{it})$ and $\Lambda(\boldsymbol{\beta}_{it})$ are

$$\Gamma(\boldsymbol{\beta}) = \begin{bmatrix} I & -\alpha_2 \\ -\beta_3 & I \end{bmatrix} \tag{6}$$

$$\Lambda(\boldsymbol{\beta})' = \begin{bmatrix} \alpha_1, \alpha_0, \alpha_3, 0, 0 \\ 0, \beta 0, \beta_4, \beta_1, \beta_2 \end{bmatrix}, \tag{7}$$

The reduced form of the system (5) is

$$\mathbf{y} = \mathbf{x}_{it}\Pi(\boldsymbol{\beta}_{it}) + \boldsymbol{\epsilon}_{it} \tag{8}$$

where $\Pi(\boldsymbol{\beta}_{it}) = \Lambda(\boldsymbol{\beta}_{it})[\Gamma(\boldsymbol{\beta}_{it})]^{-1}$ is the matrix of reduced form parameters and $\boldsymbol{\epsilon}_{it}$ is the vector of disturbances which satisfies $\boldsymbol{\epsilon}_{it} = \boldsymbol{\varepsilon}_{it}[\Gamma(\boldsymbol{\beta}_{it})]^{-1}$.

The variance–covariance matrix of the reduced form parameters is given by

$$\Sigma = [\Lambda(\boldsymbol{\beta}_{it})^{-1}]'\Omega[\Lambda(\boldsymbol{\beta}_{it})^{-1}] \tag{9}$$

The variance of the discrete dependent variable is indeterminate when the probability law is normal. The indeterminancy is due to the invariance of the argument in the normal function to an equal rescaling of both the mean and the standard deviation of the disturbance. We follow standard practice and normalize the variance to unity which yields the following expression,

$$\omega_{22} = I - 2\beta_3\alpha_2 + \beta_3^2\alpha_2^2 - 2\alpha_2\omega_{I2} - \alpha_2^2\omega_{II}$$

where ω_{ij} and σ_{ij} denote the $(i,j)^{th}$ elements of Ω and Σ and

$$\Sigma = \begin{bmatrix} \sigma^2 & \rho\sigma \\ \rho\sigma & I \end{bmatrix} \tag{10}$$

where ρ is the correlation between the disturbances and σ^2 is the variance of the error in the first equation of the system.[38]

Under the assumption that each $(\bar{\epsilon}_{it})$ is normally distributed the disturbances will be distributed as a bivariate normal with joint density[39]

$$f(\bar{\epsilon}) = \frac{I}{2\pi\sigma\sqrt{(1-\rho^2)}}\exp^{\left\{-\frac{1}{2}(\bar{\epsilon})'\Sigma^{-1}(\bar{\epsilon})\right\}}. \tag{11}$$

Simplifying and completing the square yields,

$$f(\bar{\epsilon}) = \frac{I}{2\pi\sigma\sqrt{(I-\rho^2)}}\exp^{\left\{-\frac{I}{2(1-\rho^2)\sigma^2}(\bar{\epsilon}_I^2(I-\rho^2)+(\sigma\bar{\epsilon}_2-\rho\bar{\epsilon}_I)^2)\right\}}. \tag{12}$$

[38]Necessary and sufficient conditions for the existence of the reduced form of a simultaneous continuous/discrete models are provided in Theorem 3 of Gourieroux, Laffont & Monfort (1980). The Gourieroux, Laffont & Monfort conditions are global and do not depend on local differentiability or nonsingularity of the Jacobian. It is straightforward to demonstrate that the conditions that ensure the existence and uniqueness of the reduced form are satisfied in this case.

[39]For simplicity, we suppress the time subscripts from the immediate discussion.

The above equation can factored into two multiplicative arguments, each conditional on the parameters of the other. Hence, $f(\bar{\epsilon})$ is

$$f(\bar{\epsilon}) = \hat{f}(\bar{\epsilon}_I|\sigma)\hat{f}(\bar{\epsilon}_2 - \frac{\rho\bar{\epsilon}_I}{\sigma}|(I-\rho^2)^{\frac{I}{2}}). \tag{13}$$

Given that the product of densities across states makes up the likelihood function, the corresponding log–likelihood function is

$$\log \mathcal{L} = \Pi^\star \log\left(\int_{-\infty}^{X\Pi_2(\boldsymbol{\beta})} \hat{f}(\epsilon_2 - \frac{\rho}{\sigma}(\epsilon_I|(I-\rho^2)^{\frac{I}{2}}\right) d\epsilon$$
$$+(1-\Pi^\star)\log\left(\int_{X\Pi_2(\boldsymbol{\beta})}^{\infty} \hat{f}(\epsilon_2 - \frac{\rho}{\sigma}(\epsilon_I|(I-\rho^2)^{\frac{I}{2}}\right) d\epsilon + \log \hat{f}(\epsilon_I|\sigma)$$

where $\Pi^\star$ is a function that assumes a value of "I" if Π is positive, and equals zero otherwise.

Finally, substitute the reduced form equation for ϵ_I and change the appropriate variables to yield

$$\log \mathcal{L} = \Pi^\star \log \Phi\left(\frac{X\Pi_2(\boldsymbol{\beta}) - \frac{\rho}{\sigma}\epsilon_I}{(I-\rho^2)^{\frac{I}{2}}}\right) + (1-\Pi^\star)\log\left[I - \Phi\left(\frac{X\Pi_2(\boldsymbol{\beta}) - \frac{\rho}{\sigma}\epsilon_I}{(I-\rho^2)^{\frac{I}{2}}}\right)\right] + \log \hat{f}(\epsilon_I|\sigma)$$

where Φ is the cumulative density function corresponding to the marginal density functions.

Having derived the likelihood function we next turn to issues of estimation. The model is estimated with a minimum–chi square method — Amemiya's GLS, Lee (1992). This method is asymptotically equivalent to full information maximum likelihood, Newey (1987). In principle, simultaneous equations models with limited dependent variables can be estimated by full information maximum likelihood methods. However, computational constraints precluded the FIML estimator because our data set is comprised of repeated cross–sections on a large number of microunits.[40]

The estimation procedure is as follows. The reduced form equation for unemployment is estimated using OLS with the Berndt, Hall, Hall, and Hausman algorithm.[41] The reduced

[40]If there are $T^\star$ time series and $G^\star$ simultaneous equations limited dependent variable then maximum likelihood requires $TG^\star$ dimensional integration, if the correct joint likelihood is to be specified. For multivariate normal systems, these integrals have no closed form solutions and thus some type of numerical quadrature must be used.

[41]The algorithm converged in approximately 30 seconds using RATS 4.01 on a Sun Spark workstation.

form equation for the probability of collateralization is estimated using probit with the residuals from the unemployment equation included as regressors.[42] After correcting for correlation across equations, this procedure yields maximum likelihood estimates for the reduced form parameters. The structural parameters are then extracted from the reduced form using GLS. Effron's bootstrap estimate (with 1,024 iterations) of the variance–covariance matrix of the reduced form parameters is used to create the weighting matrix. As an alternative to the bootstrap we calculate the variance covariance matrix of the parameter estimates using the delta method.[43] The delta method, which takes a first order approximation to the inverse of the Hessian of the likelihood function, performs reasonably well and requires considerably less computational time than the bootstrap.[44]

5.1 *How is Bank Lending and Unemployment Related?*

In this subsection we present estimates of the joint relationship between bank lending standards and unemployment. We use the following aggregate variables drawn from the USECON database: UNEM is the aggregate unemployment rate, GDP is the log change of the real GDP growth rate, and CORE is the log change of the CPI less food and energy. All of the data are seasonally adjusted and cover the period 1977:Q1 to 1993:Q4. To match the frequency of the bank–level panel data we average the monthly unemployment data to obtain quarterly observations. The three measures of bank lending standards are: (i) the probability of collateralization, PR(COLL) (ii) the natural logarithm of the size of the loan, SIZE (iii) risk–premia, PREM. We consider the relationship between each of these measures of lending standards and unemployment in turn.

We begin with the case when the measure of bank lending standards is the probability of collateralization. Estimates of this specification are reported in Table 5. The second and

[42]Analogously, the reduced form equations for the premium and loan size equations are estimated using OLS with the residuals from the unemployment equation included as regressors.

[43]We thank an anonymous referee for this suggestion.

[44]The bootstrap requires approximately 12 hours whereas the delta method requires less than a minute.

third columns report estimates of the PR(COLL) equation while the fourth and fifth columns report estimates of the UNEM equation.

First, consider the estimated coefficient of UNEM in the PR(COLL) equation. This coefficient reflects the influence of aggregate unemployment UNEM on the probability that bank i seeks collateralization of a loan. The estimates indicate that in Regime 2 as aggregate unemployment increases the probability of collateralization increases. In Regime 1 as aggregate unemployment declines the probability of collateralization also declines.

To determine whether changes in interest rates influence the probability of collateralization consider the estimate of RATE in the PR(COLL) equation. We would expect RATE to be positive in the probability of collateral equation if the probability of collateralization increases as banks increase interest rates on loans. Interestingly, there is no statistically discernable evidence that changes in interest rates affect the probability of collateralization as unemployment falls. However, in Regime 2 as unemployment increases, reductions in interest rates lead to reductions in the probability of collateralization.

The simultaneous equations specification allows us to determine whether changes in the probability of collateralization influence aggregate unemployment. The estimated coefficients reported in columns four and five indicate that there is no statistically discernable relation between collateralization and aggregate unemployment. However, the signs of the coefficients are positive in Regime 2 (the bad state) and negative in Regime 1 (the good state) as expected.

We next consider the case when the measure of bank lending standards is risk–premia. Parameter estimates of this specification are reported in Table 6. The estimate of RATE in the risk premia equation indicates how risk–premia and the bank specific risk free rate are related in each regime. In good states there is no statistically discernable evidence that banks use risk premia to adjust for the risk of borrowers. However, in bad states the estimated coefficient of RATE has the expected negative sign suggesting that banks use the interest rate to reflect the agency costs of lending.

The estimate of UNEM in the risk premia equation reflects the importance of aggregate unemployment UNEM in influencing the risk–premia that bank i seeks at time t. In bad times, the negative sign of the estimated coefficient implies that as unemployment increases the premia charged by banks increases. In good times as unemployment falls the risk premia also falls. The estimate of PREM in the unemployment equation is positive. This means that if premia fall when credit markets are tight, then the fall in unemployment should reduce unemployment.

Finally, we consider the case when the measure of bank lending standards is loan size. Estimates of this specification are reported in Table 7. The estimate of SIZE in the unemployment equation indicates the importance of the average size of the loan awarded by bank i at time t in influencing aggregate unemployment. The estimated coefficient of SIZE in the unemployment equation is precisely measured and negative in the bad state. This indicates that as unemployment increases, loan size falls. However, in good states as unemployment falls loan size rises.

The estimate of RATE in the loan size equation is positive and precisely measured in the good state. This suggests that higher interest rates do not result in smaller loan size. However, higher interest rates result smaller loan size in the bad state. Furthermore, since UNEM in the size equation is precisely measured in the good state this suggests that average loan size does depend on the state of unemployment.

5.2 *Diagnostics and Robustness*

One of the strengths of the minimum—chi square method is that it comes equipped with test statistics for overidentification restrictions. The predicted value of $\text{vec}(\hat{\Pi})$ given by $\mathbb{E}[\text{vec}(\hat{\Pi})]$ provides a test of the model specification. If there are m over identifying restrictions,

$$(\mathbb{E}[\text{vec}(\hat{\Pi})] - \text{vec}(\hat{\Pi}))'\Delta_{\Pi}^{-1}(\mathbb{E}[\text{vec}(\hat{\Pi})] - \text{vec}(\hat{\Pi}))$$

is asymptotically χ^2 distributed with m degrees of freedom. We fail to reject the χ_1^2 test of one over–identifying restriction for specifications that include the probability of collateralization (PR(COLL)), and the average size of loan ((SIZE) at all conventional levels. However, certain specifications of PREM are rejected, particularly the one reported in Table 6, in terms of over–identifying restrictions. For robustness, we calculated the standard errors using the delta method to determine whether inference is sensitive to the method of calculating standard errors.

Finally, to evaluate the appropriateness of the identifying restrictions, we conduct a test of the direction of causality in the system. We re–estimate the system of equations assuming the model is just–identified and impose exclusion restrictions which facilitate Granger–causality tests. We jointly test whether lagged credit affects unemployment and whether lagged unemployment affects credit. The test is asymptotically equivalent to calculating the optimal minimum distance (OMD) of the constrained model from the unconstrained model. Under the null hypothesis, the minimized valued of the objective function is asymptotically distributed as χ^2 with k degrees of freedom which in this case is equal to two – the linear restrictions imposed on the model.

In each case, we fail to reject the hypothesis that lagged credit does not affect unemployment and lagged unemployment does not affect credit at all conventional levels. A typical χ^2 value is 0.0231 which is associated with a p-value of 0.998.[45] We conclude that there is statistical support for the identifying assumptions.

[45]In this example credit is defined as risk–premia in recessions.

Next we carry out single equation tests of the auxiliary assumptions of the model. These are assumptions that are not strictly required by economic theory nor necessary for statistical analysis. The goal of such tests is not the truth or falsity of the assumption but to reassure the researcher that there is no gross conflict between the auxiliary assumptions and the data.

The first important auxiliary assumption is normality of the errors in each equation. We use the Jarque–Bera (JB) test of the null hypothesis of normality against a class of alternatives known as the Pearson family of distributions.[46] The JB test is based on a weighted average of the skewness and kurtosis measure and rejects the null hypothesis for large values of the statistic. The single equation test statistics do not indicate any difficulty with the normality assumption. The χ^2 statistic for the unemployment equation is 0.034 with a p—value of 0.97. The χ^2 statistic for the bank lending standards equation when the dependent variable is PREM is 0.034 with a p-value of 0.97 and 0.046 with a p–value of 0.98 when the dependent variable is SIZE.

The second auxiliary assumption is equality of variances of the regression errors. We use the Eicker–White test to detect violations of this assumption. The Eicker–White test is a powerful diagnostic with which to evaluate this model because it is also a test for random parameter variation. If the regression coefficients fluctuate randomly instead of being constant, the errors in a model which assumes them to be constant will display precisely the type of heteroskedasticty which the Eicker–White test detects. Tests for both equations were significant at the 1 percent level suggesting parameter variation consistent with the analysis carried out with the Markov–switching panel regression in the previous section.

The third auxiliary assumption is lack of independence of the errors. We use the Hendry ADL test to detect violations of this assumption. The ADL test amounts to a test of mis–specified dynamics. To implement the test we rearrange each of the equations in the form $y_t = \beta' x_t + \alpha y_{t-i} + \beta_1' x_{t-i} + \epsilon$. Failure to reject the null hypothesis that $\alpha = 0$ and

[46]An alternative is the Kolomgorov test—based on a comparison of the empirical distribution function—is asymptotically effective against all alternative distributions however it is cumbersome to compute and it may be possible to improve the power of the test by focusing on a smaller class of suitable alternatives.

$\beta_1 = 0$ for lag i indicates that the residuals do not display noticeable correlation. As with all autocorrelation tests the goal of the ADL test is to discover if there are unmodelled effects from the previous period which influence variables in the current period. The ADL test can detect more general forms of mis–specification than standard tests such as the Durbin–Watson. The F statistic for the unemployment equation with two lags of UNEM on the right hand side is 23.65.[47] We cannot reject the null hypothesis and conclude that one lag of unemployment is sufficient to capture all significant dynamic effects. For three lags the F statistic for the bank lending standards equation when the dependent variable is PREM is 67.45 and 32.04 when the dependent variable is SIZE. We cannot reject the null hypothesis and conclude that two lags of CRED is sufficient.

How robust are the major conclusions to the treatment of time–trend and stationarity? The specification of the simultaneous equations model assumes that the unemployment rate is stationary in levels around a secular time-trend. To control for the secular increase in unemployment over the sample we included a linear time-trend in the Z vector. We tackle each of these issues in turn.

The first issue is whether the basic assumption of stationarity around a trend is consistent with the data. Standard Dickey–Fuller tests cannot reject the hypothesis that unemployment is stationary around a trend, Nelson & Plosser (1982). However, it is also well known that the data cannot reject the hypothesis that unemployment is nonstationary. These results have been attributed to size distortion and the low power of unit root test procedures against plausible alternatives, Blough (1992). The results from the exercise in the previous subsection are therefore dependent on accepting our a priori assumptions on the time series properties of the data.

The second issue is whether allowing for a linear time trend is an appropriate method of characterizing the cyclical variability in unemployment. Ideally, we would like a measure

[47] Note that the F statistic does not have an exact F distribution in finite samples in models with lagged regressors. However, it is still valid asymptotically. For the sample size we are working with here, there should be no difficulty in applying the asymptotic results.

of the unemployment rate that represents purely stationary cyclical movements in the utilization of the labor force. However, such a measure does not exist because unemployment rates are not measured against a trend (equilibrium or normal) benchmark. Unemployment rates are measured in absolute terms (number of persons looking for work or receiving unemployment benefits divided by the labor force.)

Fortunately, several statistical procedures are available to disentangle cyclical from trend components in time series data. The most common procedures are the Hodrick–Prescott (HP) filter, the Beveridge–Nelson (BN) filter and unobserved components (state space) models. There is no clear ranking among the various methods and considerable judgement must be used in choosing the appropriate method for the question at hand. Each of these models assumes the unemployment rate can be decomposed into a non–stationary trend component un_t^T and a stationary cyclical component un_t^c. We use the unobserved components model because it provides an extremely flexible and parsimonious method for removing trends in the data. In particular the unobserved components model allows for (i) constant drift in the trend (ii) variable trend growth rate with no discrete shifts in the underlying trend (iii) deterministic trend.

The model is specified in standard Kalman Filter form with a measurement and state (or transition) equation. Maximum likelihood estimation proceeds with an initial guess for the state vector and its covariance matrix and then recursive application of the Kalman prediction and updating equations to generate estimates of the innovations in UNEM_t finding the likelihood of these innovations and then repeating the process with a different set of parameters until the likelihood of the innovations is maximized.[48]

Estimates of the trend and cyclical components are obtained by Kalman smoothing. Having extracted the cyclical component of unemployment we compare the estimates from UN_t^c (in a modified specification that does not include time–trends) with the original specification. The coefficient estimates when we include UN_t^c are much more precisely estimated

[48]We use a Nelder–Mead simplex routine to search the parameter space.

than those with the base case. The signs and size of the coefficients are qualitatively similar to the base case estimates.[49]

6 Conclusions

In this paper we have demonstrated that the market for bank loans experiences systematic cycles of over and under–lending. In addition, we have shown that the cycles in bank lending exert considerable influence on aggregate fluctuations. The lending patterns suggests that loans extended on "easier" terms during expansions return to haunt banks as problem loans during contractions. As a consequence, credit market imperfections may have a more profound effect on aggregate activity during expansions—when the seeds of a future recession are sown — than during contractions. Interestingly, Azariadis & Smith (1995) develop a general equilibrium model with adverse selection in credit markets in which precisely these two results emerge: credit market problems are more severe in expansions than in contractions and all equilibria display endogenous (reflective) regime switches.

The empirical evidence on over–lending is novel and contrasts sharply with the usual view that if credit markets fail, the direction of bias is a reduction in lending below the socially efficient level. Recommendations for an interest rate tax to reduce the over–lending bias have been made by de Meza & Webb (1987). However, such recommendations should be reevaluated in the light of the evidence that banks change their lending standards systematically over the cycle. Imposing an interest–rate tax may confound the problem if over–lending arises endogenously from the very intrinsic nature of banking. Further empirical analysis along the lines of this study is required to isolate these effects more sharply.

[49]Because of the similarity in the qualitative features of the results and to conserve space we do not present these results here.These results are available on request from the corresponding author.

Data Appendix

This Appendix provides sources and definitions of the bank–level and aggregate data used in this paper. Bank–level data unless otherwise mentioned were obtained from the Federal Reserve's Survey of Terms of Lending (QTBL) database. Aggregate data unless otherwise mentioned were obtained from the Federal Reserve Bank of New York (FRBNY) database and USECON.

Bank–Level Variables — AVGASST is the sum of assets divided by the number of loans for a bank i in quarter t multiplied by core CPI. AVGLOAN is the sum of loans divided by the number of loans for bank i in a quarter t multiplied by core CPI. DUR is the ratio of the sum of durations of the loans divided by number of loans for bank i in quarter t.

Weighted Variables—Weights were calculated as the months to maturity multiplied by the amount of loan (where the weights sum to unity). The weights were then multiplied by bank–level variables and summed for each bank in each quarter to generate the following variables. (i) (RATE) = weight × effective interest rate. (ii) PREM= weight × effective interest rate minus the yield. (iii) RKFREE = weight × yield. (iv) WTLOAN = weight × AVGLOAN. (v) COLLATERAL = weight × loan secured? (vi) COMMITTMENT = weight × loan made under commitment?

Log Variables — The following variables were transformed by taking the natural logarithm: (i) SIZE = LOG(WTLOAN) . (ii) LOG(ASSER) = LOG(AVGASST) (iii) LOG(DUR) = LOG(WTDUR).

Dummy Variables

$$\text{BIG} = \begin{cases} 1 & \text{for top 48 banks with largest AVGASSET in a quarter} \\ 0 & \text{otherwise.} \end{cases}$$

$$\text{DCOMMIT} = \begin{cases} 1 & \text{if WTCOMMIT} \leq 1.5, \text{(QTBL1926 = 1 for committed, 2 not committed)} \\ 0 & \text{otherwise.} \end{cases}$$

$$\text{DCOLLATERAL} = \begin{cases} 1 & \text{if WTSECD} \leq 1.5 \text{ , (QTBL1929 = 1 for secured, 2 not secured)} \\ 0 & \text{otherwise.} \end{cases}$$

$$\text{DDUR} = \begin{cases} 1 & \text{if AVGDUR} < 12, \\ 0 & \text{otherwise.} \end{cases}$$

Aggregate Variables — The following variables were obtained from the USECON database. NBR: the log difference of nonborrowed reserves. MB: the log difference of monetary base. G: the log difference of government purchases. GROWTH: the log difference of real GDP. UNEM: the unemployment rate. The following variables were obtained from the Federal Reserve Bank of New York (FRBNY) database. SURP: government surplus as a percent of GDP. HISURP: hi-employment government surplus as a percent of GDP.

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Figure 1: Unemployment and Phases of the Business Cycle

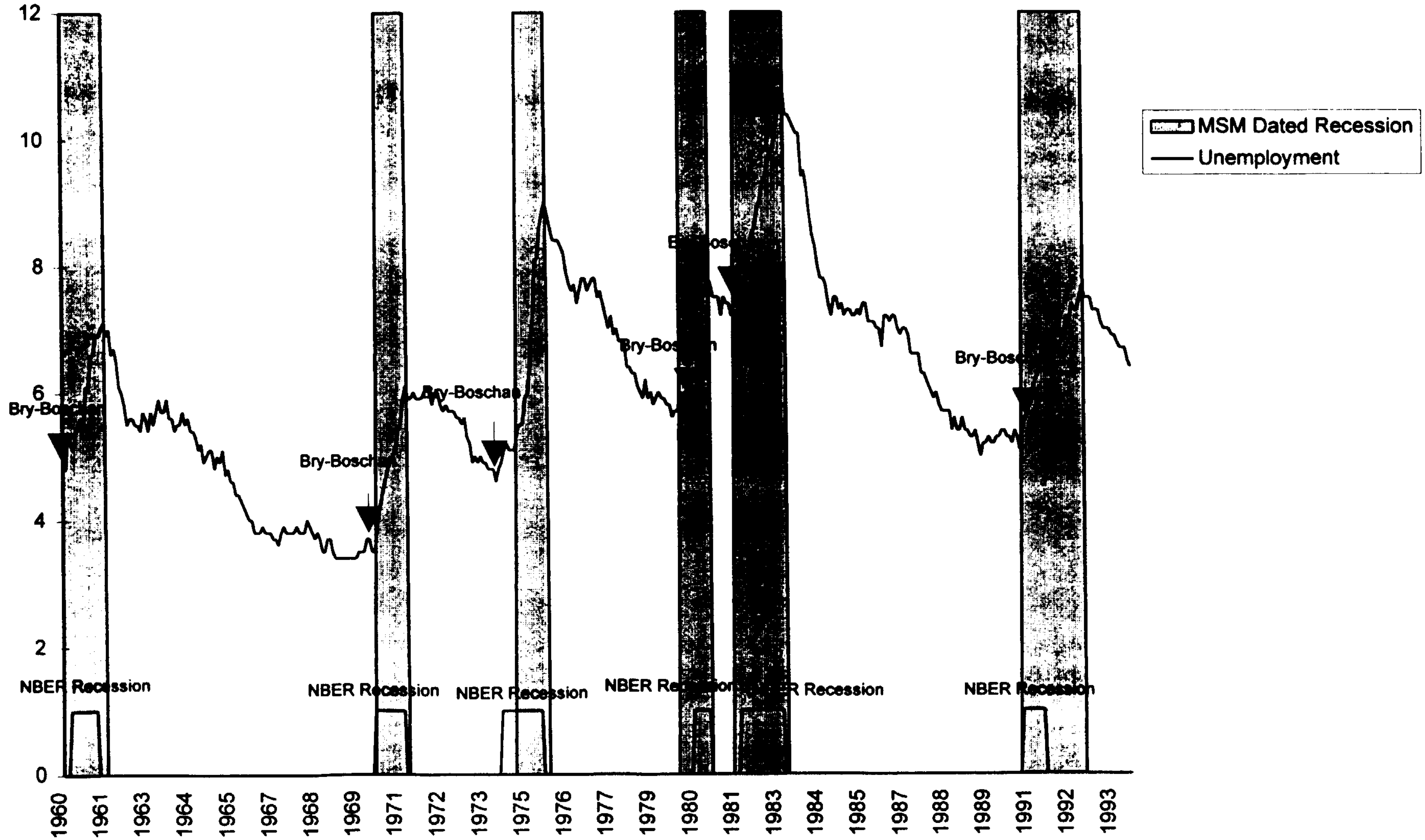
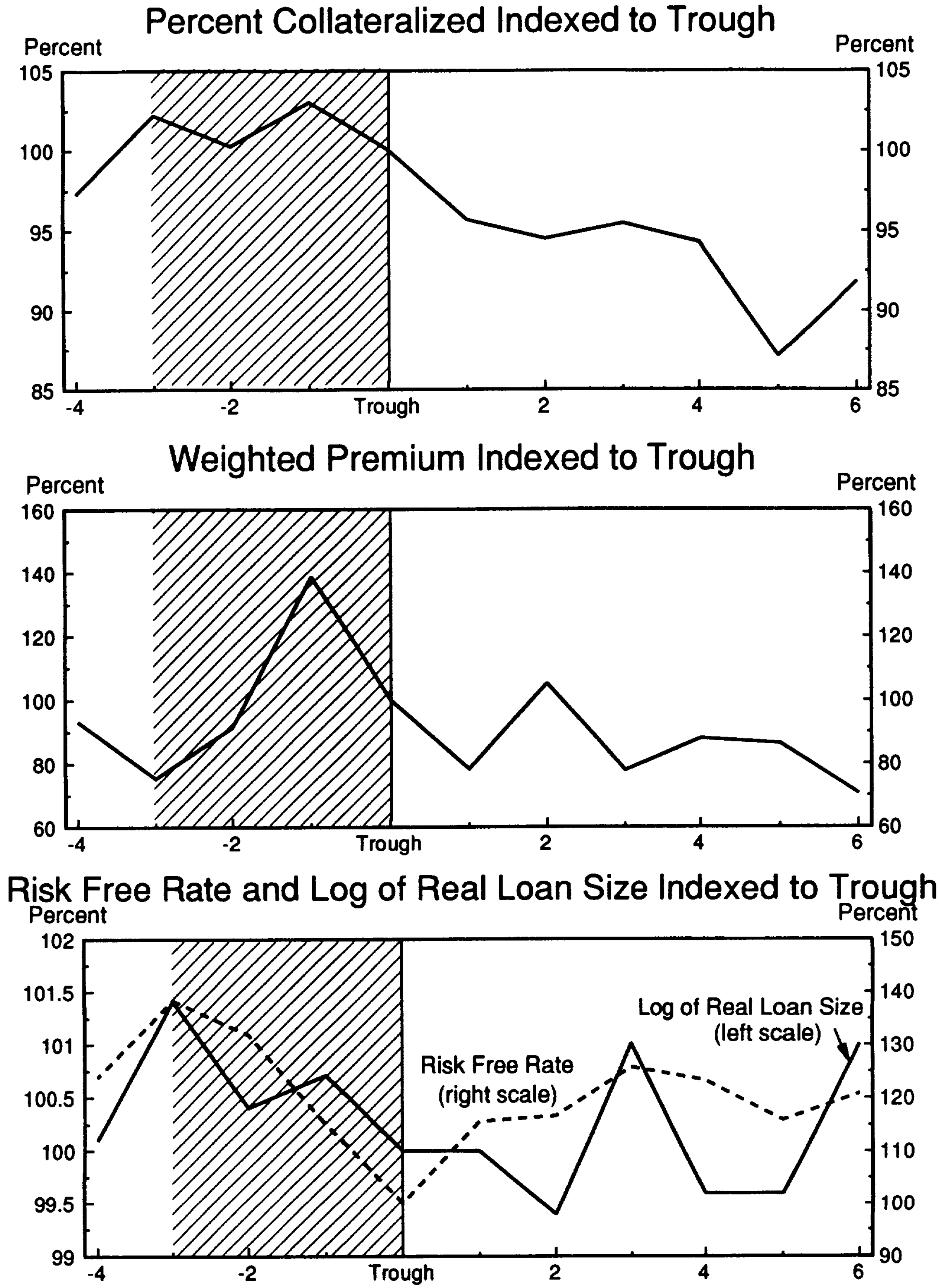


Figure 2: Credit Variables Indexed to NBER Troughs



Note: Shaded area represents the average recession cycle.

Figure 3: Risk Free Rates and Weighted Premiums

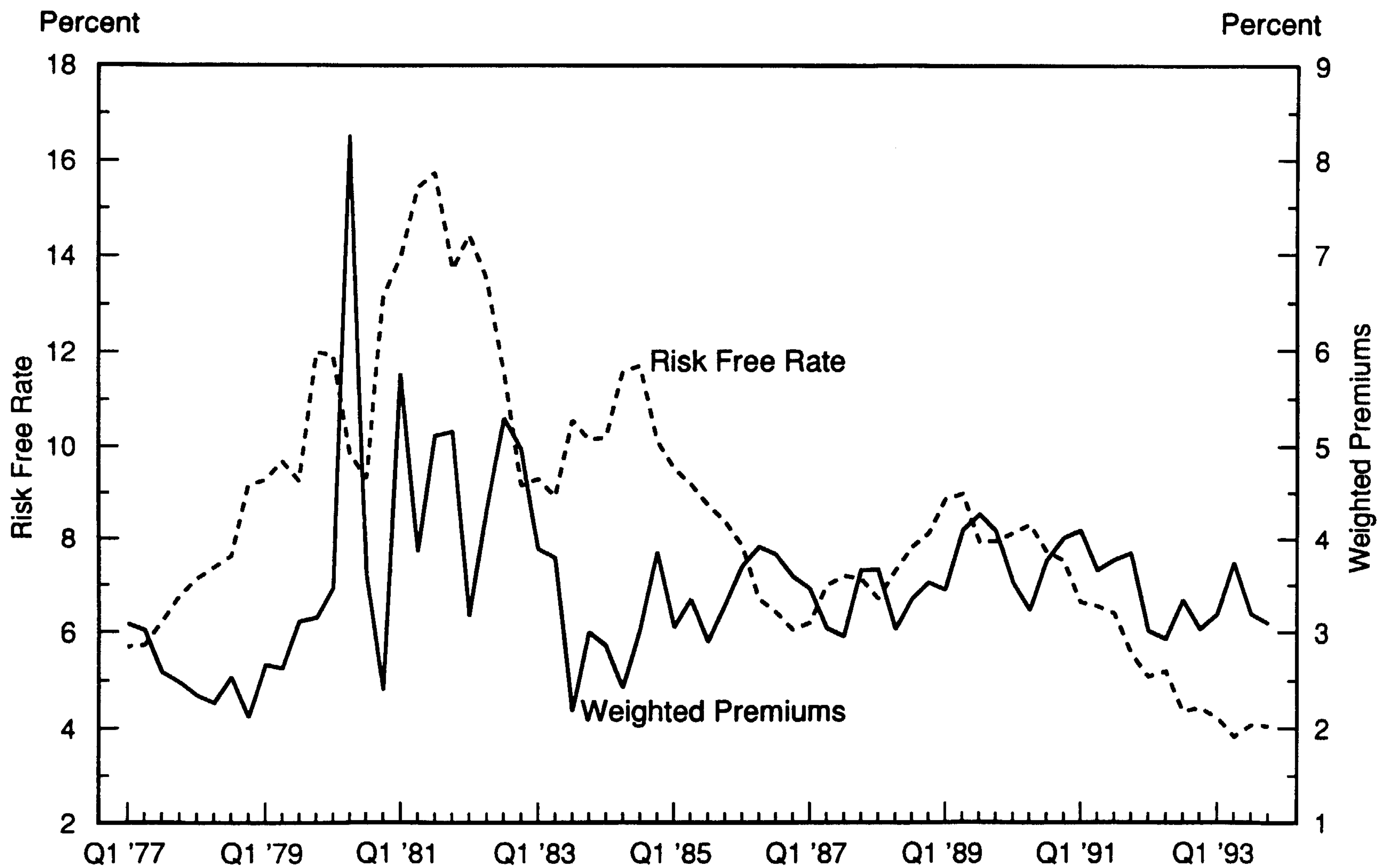


Figure 4: Average Loan Sizes and Interest Rates

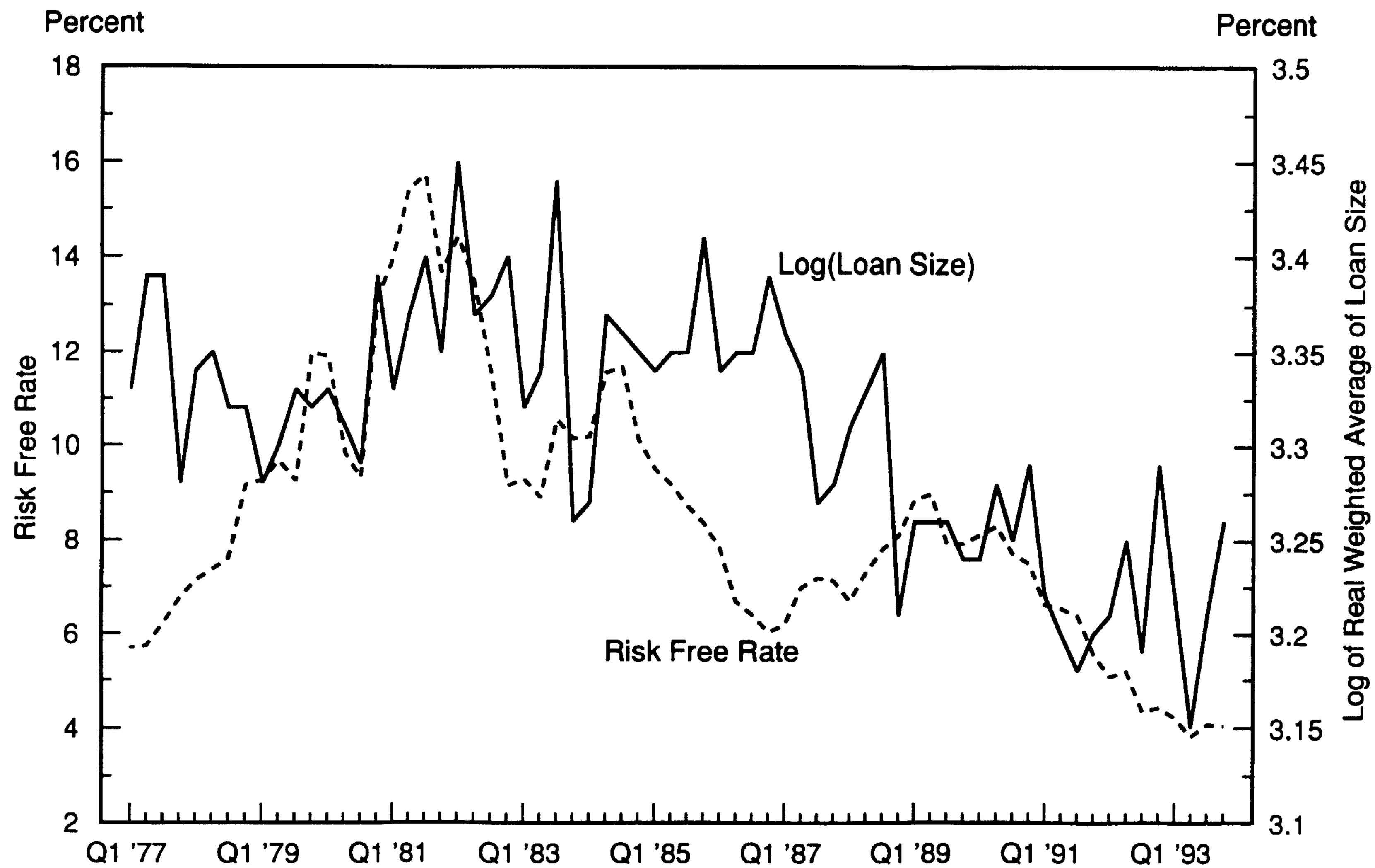


TABLE 1

DESCRIPTIVE STATISTICS FOR BANK–LEVEL PANEL DATA[a]

VARIABLE	MEAN	STD. DEV.	MIN	MAX
RKFREE	8.64	2.87	0.03	16.58
PREM	3.51	2.02	-5.49	17.11
WTRATE	12.15	3.55	2.02	26.82
AVGASSET[b]	2,979,415	7,521,502	1,430	117,186,743
AVGLOAN	318,263	919,775	662	29,065,683
AVGDUR[c]	8.71	9.42	0.00	300.00
DCOLLATERAL	0.71	0.45	0.00	1.00
UNEM	6.95	1.26	5.20	10.70
GROWTH	0.003	0.004	-0.011	0.014
MB	0.008	0.002	0.003	0.139

[a]See the data Appendix for details on the definition and construction of these variables.

[b]Units are thousands of 1987 United States dollars.

[c]Units are months.

TABLE 2A

Maximum Likelihood Estimates of a Markov–Switching Model for Unemployment[a]

	Regimes (s)	
Parameter	Regime 1	Regime 2
$\rho_{0,s}$	0.1175	0.1155
	(0.1047)	(0.0330)
$\rho_{1,s}$	1.0023	0.7060
	(0.1103)	(0.0592)
$\rho_{2,s}$	0.0034	0.2643
	(0.1121)	(0.0577)
$p_{1,s}$[b]	0.9223	0.0777
	(0.0453)	—
$p_{2,s}$	0.0283	0.9717
	(0.0128)	—
Log likelihood	142.7	
No. of Observations	408	

[a]Data is monthly aggregate unemployment. The sample period is 1960:1 to 1993:4. Transition probabilities are fixed. The subscript s refers to the unobserved regime. Regime 1 refers to periods of high unemployment. Regime 2 refers to periods of low unemployment. Asymptotic standard errors are in parentheses.

[b]$p_{i,j} = \text{prob}(s(t) = j | s(t-1) = i)$

TABLE 2B

DYNAMIC SPECIFICATION TESTS[a]

TEST	Distribution of Test Statistic	
White's test for autocorrelation	$\chi^2(4)$	1.76 [0.078]
White's test for Markov specification	$\chi^2(4)$	6.90 [0.14]
LM test for autocorrelation in regime 1	$\chi^2(1)$	0.01 [0.92]
LM test for autocorrelation in regime 2	$\chi^2(1)$	0.05 [0.82]
LM test for autocorrelation across regimes	$\chi^2(1)$	0.04 [0.84]

[a] p values are reported in square brackest.

TABLE 3

MAXIMUM LIKELIHOOD ESTIMATES OF A MARKOV–SWITCHING PANEL MODEL OF LOAN RATE PREMIA[a]

	Estimated Parameters [b]								
	High–Risk COST	Low–Risk COST	High–Risk RISKY	Low–Risk RISKY	High–Risk variance	Low–Risk variance	High–Risk transition probability	Low–Risk transition probability	Log – likelihood
(I)	0.0161	0.0005			22.2470	12.9902	0.6896	0.9917	-1743.41
	(0.0035)	(0.0003)			(6.0255)	(1.2011)	(0.0177)	(0.0030)	
(II)			-1.3891	-1.9371	43.0971	8.5031	0.7718	0.8233	-1843.25
			(0.0513)	(0.0600)	(11.0761)	(1.0209)	(0.0994)	(0.0011)	

[a]The sample period is 1977:Q1 to 1993:Q3. The dependent variable is the representative loan rate premium PREM, COST is the real cost of funds, RISKY is the percentage of loans made at or above the prime rate plus 1 %. States are denoted as high–risk or low–risk depending on the variance of the densities of the two normal distributions used to generate the loan premia in each state. The density is chosen each period by an unobserved dichotomous state variable. Each specification includes control variables for the macroeconomic environment and dummy variables for individual banks. Estimates of controls are not reported here.

[b]Asymptotic standard errors are in parentheses.

TABLE 4

POSTERIOR DISTRIBUTION OF HIGH–RISK STATE[a]

High–Risk Episodes	Length of High–Risk Espisodes	Length of Low–Risk Episodes
79:Q3 to 80:Q2	4	3
81:Q2 to 82:Q3	6	31
90:Q3 to 91:Q1	3	—

[a]This table describes the posterior distribution of the state conditional on all the data in the full sample. The first column list the dates in which the probability of a high–risk state exceeded 0.5. The second column lists the lengths of intervening periods in which the probability of the low–risk state exceeded 0.5 Periods are measured in quarters.

TABLE 5

MINIMUM CHI–SQUARE ESTIMATES OF UNEMPLOYMENT AND THE PROBABILITY OF COLLATERALIZATION[a]

$$\begin{aligned} \text{PR(COLL)}^*_{it} &= \beta_0\mathbf{Z}_{it} + \beta_1\text{COLL}_{it-1} + \beta_2\text{COLL}_{it-2} + \beta_3\text{UNEM}_t + \beta_4\text{RATE}_{it} + \varepsilon^2_{it} \\ \text{UNEM}_t &= \alpha_0\mathbf{Z}_{it} + \alpha_1\text{UNEM}_{t-1} + \alpha_2\text{PR(COLL)}_{it} + \alpha_3\text{RATE}_{it} + \varepsilon^1_{it} \end{aligned}$$

	DEPENDENT VARIABLE [b] PR(COLL)		DEPENDENT VARIABLE UNEM	
	REGIME 1 [c]	REGIME 2	REGIME 1	REGIME 2
PR(COLL)_{it}	—	—	0.2310	−0.0019
	—	—	(0.0021)	(0.0050)
	—	—	[0.0026]	[0.0020]
PR(COLL)_{it-1}	0.7347***	0.7523***	—	—
	(0.0274)	(0.0508)	—	—
	[0.0130]	[0.0336]	—	—
PR(COLL)_{it-2}	0.6967***	0.6265***	—	—
	(0.0298)	(0.0712)	—	—
	[0.0148]	[0.0510]	—	—
UNEM_t	−0.3353*	0.9058**	—	—
	(0.2080)	(0.4819)	—	—
	[0.1141)]	[0.5155]	—	—
UNEM_{t-1}	—	—	0.2192***	−0.1531***
	—	—	(0.0071)	(0.0131)
	—	—	[0.0063]	[0.0096]
RATE_{it}	−0.009	0.9556**	−0.0311***	−0.0089***
	(0.0077)	(0.0044)	(0.0012)	(0.0018)
	[0.0046]	[0.0034]	[0.0009]	[0.0011]
Over-Identifying Restriction	$\chi^2_{(df)} = 0.5199$			
	p value = 0.4709			

[a]The sample period is 1977:Q1 to 1993:Q4. Individual bank specific variables are indexed by i. Standard errors in parentheses were calculated using Effron's bootstrap method with 1,024 draws. Standard errors in brackets were calculated using the delta method.* significant at the 10 percent level in a two-sided test, ** significant at the 5 level in a two-sided test, *** significant at the 1 percent level in a two-sided test. Significance levels are calculated using the bootstrap standard errors.

[b]All specifications include a constant, a time trend, log change in real GDP, log change of real money base, log of bank asset and the log change in core CPI. Estimates of these coefficent are not reported. UNEM is the change in the unemployment rate. RATE is an individual bank specific riskfree interest rate. PR(COLL) is the probability of collateralization (a bank specific measure of the terms of lending). See the data appendix for further details on the construction and source of these variables.

[c]Regimes refer to phases of the unemployment cycle identified by a Markov switching model with constant transition probabilities. Regime 1 is the "good state" i.e. quarters of declining unemployment. Regime 2 is the "bad state" i.e. quarters of increasing unemployment.

TABLE 6

MINIMUM CHI–SQUARE ESTIMATES OF UNEMPLOYMENT AND LOAN RISK PREMIA[a]

$$\text{PREM}_{it} = \beta_0\mathbf{Z}_{it} + \beta_1\text{PREM}_{it-1} + \beta_2\text{PREM}_{it-2} + \beta_3\text{UNEM}_t + \beta_4\text{RATE}_{it} + \varepsilon^2_{it}$$

$$\text{UNEM}_t = \alpha_0\mathbf{Z}_{it} + \alpha_1\text{UNEM}_{t-1} + \alpha_2\text{PREM}_{it} + \alpha_3\text{INT}_{it} + \varepsilon^1_{it}$$

	DEPENDENT VARIABLE [b] PREM		DEPENDENT VARIABLE UNEM	
	REGIME 1[c]	REGIME 2	EXPANSION	CONTRACTION
PREM_{it}	—	—	0.0627***	−0.0113***
	—	—	(0.0009)	(0.0007)
	—	—	[0.0008]	[0.0005]
PREM_{it-1}	0.1660***	0.3347***	—	—
	(0.0130)	(0.0179)	—	—
	[0.0108]	[0.0193]	—	—
PREM_{it-2}	0.0774*	0.2719**	—	—
	(0.0458)	(0.1388)	—	—
	[0.0356]	[0.1476]	—	—
UNEM_t	−3.289***	−7.6240***	—	—
	(0.0960)	(0.0585)	—	—
	[0.2885]	[1.0927]	—	—
UNEM_{t-1}	—	—	0.1711***	−0.1472***
	—	—	(0.0071)	(0.0133)
	—	—	[0.0060]	[0.0092]
RATE_{it}	0.01588	−0.0899***	−0.0174***	−0.0111***
	(0.0175)	(0.0102)	(0.0011)	(0.0018)
	(0.0114)	(0.0229)	[0.0009]	[0.0011]
Over-Identifying Restriction	$\chi^2_{(df)} = 908.18$ p-value = 0.0000			

[a]The sample period is 1977:1 to 1993:4.

Individual bank specific variables are indexed by i. Standard errors in parentheses were calculated using Effron's bootstrap resampling procedure with 1,024 draws. Standard errors in brackets were calculated using the delta method. * significant at the 10 percent level in a two-sided test, ** significant at the 5 level in a two-sided test, *** significant at the 1 percent level in a two-sided test. Significance levels are calculated using the bootstrap standard errors.

[b]All specifications include a constant, a time trend, log change in real GDP, log change of real money base, log of bank asset and the log change in core CPI. These coefficent estimates are not reported. UNEM is the change in the unemployment rate. RATE is an individual bank specific riskfree interest rate. PREM is the difference between a bank specific market interest rate on loans and the risk–free rate (a bank specific measure of the terms of lending); See the data appendix for further details on the construction and source of these variables.

[c]Regimes refers to phases of the unemployment cycle identified by a Markov switching model with constant transition probabilities. Regime 1 is the "good state" i.e. quarters of declining unemployment. Regime 2 is the "bad state" i.e. quarters of increasing unemployment.

TABLE 7

MINIMUM CHI–SQUARE ESTIMATES OF UNEMPLOYMENT AND LOAN SIZE[a]

$$\begin{aligned} \mathrm{PR(COLL)}_{it} &= \beta_0 \mathbf{Z}_{it} + \beta_1 \mathrm{COLL}_{it-1} + \beta_2 \mathrm{COLL}_{it-2} + \beta_3 \mathrm{UNEM}_t + \beta_4 \mathrm{INT}_{it} + \varepsilon^2_{it} \\ \mathrm{UNEM}_t &= \alpha_0 \mathbf{Z}_{it} + \alpha_1 \mathrm{UNEM}_{t-1} + \alpha_2 \mathrm{PR(COLL)}_{it} + \alpha_3 \mathrm{INT}_{it} + \varepsilon^1_{it} \end{aligned}$$

	DEPENDENT VARIABLE [b] SIZE		DEPENDENT VARIABLE UNEM	
	REGIME 1 [c]	REGIME 2	REGIME 1	REGIME 2
SIZE_{it}	—	—	0.0061	−0.0873
	—	—	(0.0205)	(0.0357)
	—	—	[0.0178]	[0.0216]
SIZE_{it-1}	0.1460***	0.1296***	—	—
	(0.0094)	(0.0158)	—	—
	[0.0122]	[0.0166]	—	—
SIZE_{it-2}	0.1079***	0.1200***	—	—
	(0.0093)	(0.0160)	—	—
	[0.0121]	[0.0168]	—	—
UNEM_t	−0.0234***	−0.0015	—	—
	(0.0069)	(0.1555)	—	—
	[0.0008]	[0.2658]	—	—
UNEM_{t-1}	—	—	0.2182***	−0.1507***
	—	—	(0.0072)	(0.0132)
	—	—	[0.0063]	[0.0093]
RATE_{it}	0.0104***	−0.0286***	−0.0294***	−0.0093***
	(0.0024)	(0.0051)	(0.0013)	(0.0019)
	(0.0040)	(0.0058)	(0.0010)	(0.0010)
Over-Identifying Restriction	$\chi^2_{(df)} = 2.0330$	p-value = 0.1539		

[a]The sample period is 1977:1 to 1993:4. Individual bank specific variables are indexed by i. Standard errors in parentheses were calculated using Effron's bootstrap resampling procedure with 1,024 draws. Standard errors in brackets were calculated using the delta method. * significant at the 10 percent level in a two-sided test, ** significant at the 5 level in a two-sided test, *** significant at the 1 percent level in a two-sided test. Significance levels are calculated using the bootstrap standard errors.

[b]All specifications include a constant, a time trend, log change in real GDP, log change of real money base, log of bank asset and the log change in core CPI. These coefficent estimates are not reported. UNEM is the change in the unemployment rate. RATE is an individual bank specific riskfree interest rate. SIZE is the log of average loan size (a bank specific measure of the terms of lending). See the data appendix for further details on the construction and source of these variables.

[c]Regimes refer to phases of the unemployment cycle identified by a Markov switching model with constant transition probabilities. Regime 1 is the "good state" i.e. quarters of declining unemployment. Regime 2 is the "bad state" i.e. quarters of increasing unemployment.

TABLE A1

MNEMONICS FOR THE FEDERAL RESERVE SURVEY OF TERMS OF LENDING SERIES

QUARTERLY SERIES	DATES	MNEMONICS
Entity ID (580 banks)	770211 – 931101	BANKID
Reporting Date (Yr,Mo,Da)	770211 – 931101	DATE
Amount of Business Loans	770211 – 931101	QTBL1921
Loan Made Under Commitment?	770211 – 930531	QTBL1926
Loan Secured	770211 – 931101	QTBL1929
Total Assets	770211 – 931101	QTBL2170
Effective Interest Rate	770211 – 931101	QTBL7961
Months to Maturity	770211 – 931101	QTBL7969

TABLE A2

MATCHING RULE FOR CREATING RISK–FREE RATE FOR EACH LOAN [a]

$0 \leq x \leq 4$	3–month yield
$4 < x \leq 9$	6–month yield
$9 < x \leq 18$	1–year yield
$18 < x \leq 30$	2-year yield
$30 < x \leq 48$	3-year yield
$48 < x \leq 72$	5-year yield
$72 < x \leq 102$	7-year yield
$102 < x \leq 180$	10-year yield (and date < 870202)
$102 < x \leq 240$	10-year yield (and date ≥ 870202)
$180 < x \leq 300$	20-year yield (and date < 870202)
$300 < x < 360$	30-year yield (and date < 870202)

[a] x is the number of months to maturity of the loan. Corresponding yields were obtained from DFDATA