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Do Bank Loan Rates Exhibit a Countercyclical Mark-up?

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Abstract

Based on a switching-cost model, we examine empirically the hypotheses that bank loan mark-ups are countercyclical and asymmetric in their responsiveness to recessionary and expansionary impulses. The first econometric model treats changes in the mark-up as a continuous variable. The second treats them as an ordered categorical variable due to the discrete nature of prime rate changes. By allowing the variance to switch over time as a Markov process, we present the first conditionally heteroscedastic discrete choice (ordered probit) model for time-series applications. This feature yields a remarkable improvement in the likelihood function. Specifications that do not account for conditional heteroscedasticity find evidence of both countercyclical and asymmetric mark-up behavior. In contrast, the heteroscedastic ordered probit finds the mark-up to be countercyclical but not significantly asymmetric. We explain why controlling for conditional heteroscedasticity may be important when testing for downward stickiness in loan rates.

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Introduction

The observation that significant costs to customers of switching sellers can alter the nature of competition among sellers has found applications in industrial organization, macroeconomics and international trade [Klemperer (1995)]. A key implication is that switching costs make sellers imperfect competitors. An important example where switching costs are thought to pertain is the relationship between banks and their loan customers. In this article, we outline a model in which switching costs, combined with risk-averse bank management, lead to countercyclical mark-ups in the pricing of bank loans. Chevalier and Scharfstein (1995) find this motivation for countercyclical mark-ups to have more empirical basis than the idea that the degree of oligopolistic collusion is cyclical. This article presents two empirical tests for countercyclical mark-ups in the bank prime lending rate.

Banks specialize in acquiring costly information about their business loan customers. Consequently borrowers find it costly to switch from a lender who knows them to one who does not. Once a relationship is established, one might conclude that a bank could extract monopoly rents from its customers in the form of above-normal interest rates. Rajan (1992), however, argues that such opportunistic behavior may not fit into a bank's optimal long-run strategy, because rival banks could capture its customers by sharing the switching costs. Gilbert and Klemperer (1995) discuss ways in which competition among sellers leads to cooperation among buyers and sellers to mitigate the effects of switching costs.

Contracts in which sellers precommit to prices that compensate (at least partially) for start-up or switching costs serve this purpose. For example, business loans and lines of credit are often contractually tied to the prime lending rate, the London Inter-Bank Offering Rate (LIBOR) or other cost-of-funds indices. By tying loan rates to such indices, banks effectively pre-commit to prices that are state dependent, where the state is the prevailing index rate. In practice, a given loan's terms will adjust at regular intervals, based on a contractual agreement. An example would be to use the most recent monthly average of the LIBOR rate as the benchmark to update a loan's terms on a quarterly basis.

To test for countercyclical loan mark-ups, we need data on a loan index that includes a mark-up above banks' cost of funds.[1] Consequently, we focus on the prime rate, even though business borrowers might index to LIBOR plus a spread. In using the prime rate as a benchmark for bank lending rates, it is important to recognize that banks sometimes lend at rates below prime. Figure 1 shows the percentage of short-term and long-term loans made at or above the prime rate. While the percentage of short-term lending made at rates below prime has increased, the percentage of long-term loans made at or above prime has remained relatively steady. Moreover, because loans made at rates below prime may still use the prime rate as an index (either by explicit or implicit agreement) for making rate adjustments, a change in the prime tends to reflect a general shift in lending rates.

Although it serves as a precommitment device, the prevailing prime rate is not completely exogenous to a bank and certainly not to money-center banks as a group. Thus banks jockey to be among the first to adjust their prime rates while trying to avoid expensive

[1]LIBOR rates closely follow rates on certificates of deposit, which measure the cost of funds to banks. In fact, LIBOR rates denominated in other currencies also behave as if they were priced from bank deposit rates in the United States covered by forward foreign exchange contracts.

false starts. Imperfect competition rendered by switching costs leads a bank to consider the trade-off between enhancing its market share and monopoly pricing of its existing customer base. Several authors, including Chevalier and Scharstein (1994) and Klemperer (1995), have observed that the business cycle can affect this trade-off if firms prefer smooth profit streams. In cyclical downturns, firms with market power may smooth profits by charging relatively high prices, rather than seeking to expand market share. In this vein, Hughes, Lang, Mester and Moon (1995) present empirical evidence that bank managers behave as if they have convex, non-risk-neutral preferences over their profit stream. Banks must also consider that if they were to seek greater market share in a cyclical downturn, they would face adverse selection: the prospect of lending to businesses with the highest cyclical probabilities of failure. For either of these reasons, profit smoothing or adverse selection, cyclical downturns represent periods when bank managers would opt for a relatively high price-cost margin instead of greater market share. If bank managers generally behave this way, the prime rate should display a countercyclical mark-up.

In the next section we present a model in which a profit-smoothing manager of a monopolistically competitive bank would choose a countercyclical mark-up in loan pricing. The third section tests for a countercyclical mark-up empirically using weekly data. Because the prime rate changes by discrete amounts on an irregular basis, we present results from two estimation methods to scrutinize the robustness of the findings. The fourth section concludes.

2. A model of countercyclical loan mark-ups

Following Klemperer (1995), we argue that the existence of switching costs gives banks some degree of market power over their customer base. Consequently, bank managers can increase current-period profits, π, by increasing the mark-up, p, of their lending rates over the marginal cost of loanable funds, but only at the cost of reducing their market share heading into the future. Market share, σ, is assumed to be a decreasing function of last period's mark-up:

$$\sigma_t = \sigma(p_{t-1}), \qquad \text{where} \qquad \sigma' < 0.$$

Current-period profits are assumed to be a function of the mark-up, current market share, and an index for the phase of the business cycle, b, where larger values of b indicate economic booms:

$$\pi_t = \pi(p_t, \sigma_t(p_{t-1}), b_t).$$

The profit function shifts up in booms, because a given market share generates higher profits when credit demand is high. The choice variable is p.

As suggested by the empirical findings of Hughes, Lang, Mester and Moon (1995), bank managers are assumed to prefer smooth profit streams. Thus, the preference function, U, is concave in profit. The manager's infinite-horizon objective function is then

$$\max_{\{p_t\}} E_0 \sum_{t=0}^{\infty} \delta^t U\left(\pi_t(p_t, \sigma_t(p_{t-1}), b_t)\right) \tag{1}$$

where E is the expectations operator and δ is the subjective rate of time preference. Equation (1) can take the recursive form of the Bellman equation:

$$V_t(\sigma_t, b_t) = \max_{p_t} \left\{ U(\pi_t(p_t, \sigma_t(p_{t-1}), b_t)) + \delta E_t V_{t+1}(\sigma_{t+1}(p_t), b_{t+1} \mid b_t) \right\}. \tag{2}$$

The first-order condition is

$$\frac{\partial U_t}{\partial \pi_t} \frac{\partial \pi_t}{\partial p_t} + \delta E_t \frac{\partial V_{t+1}}{\partial \sigma_{t+1}} \frac{\partial \sigma_{t+1}}{\partial p_t} = 0. \tag{3}$$

The first-order condition equates the marginal benefit to current-period profits from raising today's price to the marginal cost of lost future profits from a diminished market share. The total differential of the first-order condition with respect to p and b is

$$\frac{dp_t}{db_t} = \frac{-\left(U''\pi_p\pi_b + U'\pi_{pb} + \delta E_t V_{\sigma b}(t+1)\sigma'_{t+1}\right)}{U'\pi_{pp} + U''\pi_p^2 + \delta E_t \left\{V_\sigma(t+1)\sigma''_{t+1} + V_{\sigma\sigma}(t+1)(\sigma'_{t+1})^2\right\}}. \tag{4}$$

Sufficient conditions for an unambiguously negative sign in equation (4) are that

$$\frac{\partial^2 \pi_t}{\partial p_t \partial b_t} = 0 \qquad \text{and} \qquad \frac{\partial^2 V_{t+1}}{\partial \sigma_{t+1} \partial b_{t+1}} = 0.$$

These conditions hold if the boom-bust state of the macroeconomy simply shifts a bank's profit function up and down without tilting its slope. Whether loan mark-ups are countercyclical remains an empirical issue, however. The rest of the paper consists of two tests of the validity of this proposition.

3. Empirical tests for a countercyclical mark-up in the prime rate

The spread between the prevailing end-of-week prime rate and the weekly average rate on 180-day certificates of deposit (CD) is a measure of the loan mark-up in the banking industry.[2] In the empirical analysis of loan mark-ups, it is assumed that banks obtain additional loanable funds by bidding for deposits at prevailing market deposit rates. The secondary-market CD rate is our measure of banks' cost of funds. Other types of deposits that affect banks' cost of funds, such as money market and negotiable order withdrawal accounts, were not available in the first part of our sample, which runs from January 1973 to February 1993. Our use of secondary-market quotes owes to the availability of such data, which are representative of prevailing rates in retail markets.

The prime rate generally changes at less than a weekly frequency (a change occurred in 20% of the weeks in our sample) and by discrete amounts in increments of 25 basis points or more. Thus changes in the prime rate - CD rate spread fall into several size categories based on the discrete change in the prime rate. Because changes in this interest rate spread are lumpy and heteroscedastic, ordinary least squares estimation is inappropriate. Recognizing this feature of the prime rate, other researchers have used discrete-choice models [Mester and Saunders (1995)] or friction models [Forbes and Mayne (1989)]. The former model consists of a simple logit model over short sample periods when the prime rate was either consistently increasing or consistently decreasing. The friction model of Forbes and Maynes (1989) imposes rigidity on the dependent variable, so it may remain unchanged in most

[2] All variables used in this study are weekly averages, except for the prime rate, which is the end-of-week value. Data are from Haver Analytics, except for the prime rate, which was taken from the Federal Reserve's data base.

periods, but adjusts by any amount to its optimal level whenever it changes. To apply the friction model, Forbes and Maynes (1989) used changes in the monthly average of the prime rate to convert the discrete variable into a more continuous one. In our case, however, the dependent variable is the change in the prime rate-CD rate spread. To ensure that the changes in the components of the spread are essentially simultaneous, we use weekly data. Monthly or quarterly averaging could mask or distort the timing of changes in the spread.

A test for countercyclical mark-ups in our sample requires a weekly indicator of the cyclical state of the economy. Friedman and Kuttner (1993) identify and document the remarkable ability of the spread between the commercial paper rate and the Treasury bill rate to predict economic activity, especially recessions. Friedman and Kuttner offer several explanations for the predictive power of the paper-bill spread including differential tax treatments, default risk and monetary policy effects. The paper-bill spread does not give equally clear signals of economic recoveries and booms, however.[3] Figure 2 illustrates that the paper-bill spread tends to increase prior to and throughout NBER recession dates, with the exception of the 1990 recession.[4] Despite its limitations, the paper-bill spread is a useful indicator of the business cycle phase that is available at a weekly frequency.

An increase in the paper-bill spread corresponds with a cyclical downturn, which is hypothesized to induce an increase in the loan mark-up according to equation (4). Therefore, the coefficients on lagged changes in the paper-bill spread should be positive. We also include lagged changes in deposit rates to account for the serial correlation observed

[3]We use weekly averages of the six-month Treasury bill and commercial paper rates.

[4]Many other indices of leading indicators also failed to anticipate the 1990 recession.

in interest rate changes. Furthermore, we partition the explanatory variables so as to estimate separate coefficients for positive and negative changes, because Mester and Saunders (1993) and others have observed that the prime rate is more responsive to impulses leading to increases than decreases. Neumark and Sharpe (1992) observe similar asymmetries in deposit rates.

Because we are primarily interested in the overall, multi-period response of the mark-up to a change in the paper-bill spread, we present results for sums of lag coefficients, using the identity

$$\begin{aligned}\beta_1 X_{t-1} + \beta_2 X_{t-2} + ... + \beta_k X_{t-k} &= (\beta_1 + ... + \beta_k) X_{t-1} \\ &\quad -(\beta_2 + ... + \beta_k)\Delta X_{t-1} - ... - \beta_k \Delta X_{t-k+1}. \end{aligned} \tag{5}$$

That is, the reported coefficients and standard errors are for $\Gamma_1 = (\beta_1 + ... + \beta_k)$, $\Gamma_2 = (\beta_2 + ... + \beta_k), ..., \Gamma_k = \beta_k$. The lag lengths were chosen informally, based on whether coefficients became insignificant at either four or six weeks; the same lag length was used for explanatory variables partitioned into increases and decreases. The explanatory variables are all lagged at least one period, so they are pre-determined relative to this week's change in the dependent variable. This avoids the problem of simultaneous determination of the dependent variable and an endogenous explanatory variable.

A second proxy for economic conditions that is available at the weekly frequency is the slope of the yield curve. Estrella and Mishkin (1995) describe the tendency of the yield curve to become inverted prior to recessions, essentially because future short-term interest rates are expected to decline for a lengthy period of time if a recession ensues. Thus, as a second test for countercyclical loan mark-ups, we use the slope of the yield curve, $ln(TBond/TB)$, as a recession indicator, where $TBond$ is the ten-year Treasury bond rate and TB is the three-month Treasury bill rate.

To check for robustness, results from two different estimation methods are presented. The first is an iteratively re-weighted least squares regression model of changes in the mark-up with category-dependent intercepts and variances. The second is a heteroscedastic ordered probit model of changes in the mark-up. To our knowledge, we are the first to estimate a heteroscedastic ordered probit model, allowing for conditional heteroscedasticity in a time-series application of a discrete-choice model. This feature seems particularly important for a time-series model of interest rate changes, given that interest rates were unusually volatile between 1979 and 1982. Moreover, the results strongly favor the conditionally heteroscedastic specification over the usual homoscedastic version.

3.1 An asymmetric regression model of changes in the mark-up

In this model, the observations are divided into seven different categories based on the size of the discrete change in the prime rate. Denoting the prime rate change as ΔPR, the seven categories are shown in Table 1. In practice, however, the prime rate has always changed by increments of 25 basis points.

Table 1: Observation categories based on size of prime rate change		
category	*criterion*	*frequency*
1	$\Delta PR < -.500$	9
2	$-.500 \leq \Delta PR < -.250$	52
3	$-.250 \leq \Delta PR < -.125$	38
4	$-.125 \leq \Delta PR \leq +.125$	840
5	$+.125 < \Delta PR \leq +.250$	62
6	$+.250 < \Delta PR \leq +.500$	33
7	$\Delta PR > +.500$	14

The dependent variable is the weekly change in the prime rate - CD spread. The intercept and residual variance are allowed to differ across categories.[5]

Estimation is carried out by iterative weighted least squares. Re-weighting takes place because estimates of the category-specific residual variances and means are updated between regressions.[6] Iterative weighted least squares converges to the maximum-likelihood estimates in this case [Kmenta (1986)]. The log-likelihood function is

$$\sum_{t=1}^{T}\sum_{i=1}^{7} Z_{it}\left(-.5ln(2\pi\sigma_i^2) - .5(y_t - X_t'\beta - \mu_i)^2/\sigma_i^2\right) \tag{6}$$

where Z_{it} is a dummy variable that equals one if the observation is in category i at time t, and μ_i and σ_i^2 are the category-specific intercept and variance.

The commercial paper rate is denoted CP. Changes in the commercial paper-Treasury

[5]The category-based heteroscedasticity permitted here is distinct from conditional heteroscedasticity. Conditional heteroscedasticity entails time dependence in the variance, as opposed to heterogeneities based on the size category. We do not attempt to address these two forms of heteroscedasticity simultaneously in the regression model. Instead, we deal with conditional heteroscedasticity in section 3.2.

[6]Estimation is carried out as follows: 1) Start with ordinary least squares estimates of the slope coefficients. 2) Calculate intercepts and residual variances by category. Use the residual variances to weight the observations. 3) Estimate the weighted least squares regression. 4) Repeat steps 2 and 3 until convergence.

bill rate spread and changes in the CD rate are partitioned into increases and decreases denoted as INC and DEC, respectively. The slope of the yield curve, $ln(TBond/TB)$, is partitioned into positive and negative values to indicate whether the yield curve is upward-sloping or inverted. The coefficient estimates for iterative weighted least squares estimation are in Table 2, where the Γ lag coefficients are defined below equation (5).

Table 2: Iterative Weighted Least Squares Estimation of Changes in Loan Mark-Up Asymmetric Regression Model st. errors are in parentheses			
variable	*parameter*	**Paper-Bill Spread**	**Yield Curve Slope**
$\Delta(CP-TB)(INC)$	Γ_1	.679 (.165)	
$\Delta(CP-TB)(DEC)$	Γ_1	.182 (.159)	
$\Delta(CP-TB)(INC)$	Γ_2	.326 (.152)	
$\Delta(CP-TB)(DEC)$	Γ_2	-.040 (.144)	
$\Delta(CP-TB)(INC)$	Γ_3	.263 (.125)	
$\Delta(CP-TB)(DEC)$	Γ_3	-.042 (.120)	
$\Delta(CP-TB)(INC)$	Γ_4	.105 (.096)	
$\Delta(CP-TB)(DEC)$	Γ_4	-.088 (.092)	
$ln(TBond/TB)(POS)$	β_1		.831 (.519)
$ln(TBond/TB)(NEG)$	β_1		-5.94 (2.42)
$\Delta(CD)(INC)$	Γ_1	.127 (.090)	.221 (.085)
$\Delta(CD)(DEC)$	Γ_1	.347 (.083)	.233 (.075)
$\Delta(CD)(INC)$	Γ_2	.314 (.087)	.369 (.085)
$\Delta(CD)(DEC)$	Γ_2	.320 (.075)	.396 (.069)
$\Delta(CD)(INC)$	Γ_3	.169 (.082)	.190 (.081)
$\Delta(CD)(DEC)$	Γ_3	.307 (.069)	.354 (.065)
$\Delta(CD)(INC)$	Γ_4	.060 (.061)	.063 (.075)
$\Delta(CD)(DEC)$	Γ_4	.149 (.065)	.306 (.062)
$\Delta(CD)(INC)$	Γ_5	.133 (.046)	.124 (.064)
$\Delta(CD)(DEC)$	Γ_5	.129 (.056)	.154 (.056)
$\Delta(CD)(INC)$	Γ_6	.170 (.092)	.024 (.047)
$\Delta(CD)(DEC)$	Γ_6	.127 (.043)	.112 (.043)
Probability values for Wald tests			
symmetry in both variables (p-value)		.040	.015
symmetry in $\Delta(CP-TB)$ (p-value)		.036	
symmetry in $TBond/TB$ (p-value)			.011
symmetry in ΔCD (p-value)		.737	.918

Two sets of results appear in Table 2, one based on using the paper-bill spread and the other based on the yield-curve slope. The model-implied sign for the coefficient on the paper-bill spread is positive, because an increase in the paper-bill spread ought to signal a risk of recession and an increase in the loan mark-up. Conversely, a negative sign is implied for the slope of the yield curve, because lower values for the slope signal recessions. Lagged changes in the paper-bill spread are included to reflect that upward movements signal recessions. The yield-curve slope is left in levels, because it is an inverted yield curve, rather than a downward shift in slope, that signals a recession. The yield-curve slope evolves slowly, so additional lags would contain roughly the same information as the first lag. Hence only the first lag is included.

The sum of lag coefficients, Γ_1, on the paper-bill spread is significantly positive, implying that the loan mark-up increases with the paper-bill spread, i.e., before cyclical downturns, as hypothesized. A Wald test of the hypothesis that the sum of lag coefficients is equal for increases and decreases is rejected at the 5% level. These estimates suggest that the paper-bill spread is more helpful for identifying increases than decreases in the loan mark-up. The lack of response to decreases in the paper-bill spread may reflect Friedman and Kuttner's (1993) conclusion that the paper-bill spread is a better indicator of recession than booms. On the other hand, no asymmetry is apparent in the response of the mark-up to changes in CD rates.

Qualitatively similar results are obtained with the yield curve slope. An inverted yield curve significantly predicts increases in the loan mark-up, but a positively sloped yield curve has no significant predictive power. A Wald test for the inequality of the β_1 coefficients across positive and negative slopes confirms this asymmmetry. Either the paper-bill spread or the yield-curve slope is a predictor of the timing of increases but not decreases in the loan mark-up.

3.2 A heteroscedastic ordered probit model of changes in the mark-up

The regression model from section 3.1 treated changes in the prime rate - deposit rate mark-up as a continuous variable, even though the prime rate has always changed by discrete amounts. To check for sensitivity, we also treat the dependent variable as an ordered categorical variable. Table 3 shows the seven categories of changes in the mark-up. These categories are similar to those in Table 1, but here they are used to define a categorical dependent variable, whereas in the weighted regression they gave groupings for category-specific means and variances for a continuous dependent variable.

Table 3: Observation categories based on size of change in loan mark-up

category	*criterion*	*frequency*
1	$\Delta\text{mark-up} < -.500$	29
2	$-.500 \leq \Delta\text{mark-up} < -.250$	81
3	$-.250 \leq \Delta\text{mark-up} < -.125$	131
4	$-.125 \leq \Delta\text{mark-up} \leq +.125$	558
5	$+.125 < \Delta\text{mark-up} \leq +.250$	137
6	$+.250 < \Delta\text{mark-up} \leq +.500$	75
7	$\Delta\text{mark-up} > +.500$	32

We define seven dummy variables, $Z_j, j = 1,..,7$, where $Z_{jt} = 1$ if the change in the mark-up is in category j at time t. An ordered probit model includes constants $c_5 > c_4 > ... > c_1$ and the following probabilities of being in each of the seven categories:

$$\begin{aligned}
\text{Prob}(Z_7 = 1) &= \Phi(X\beta) \\
\text{Prob}(Z_6 = 1) &= \Phi(X\beta + c_1) - \Phi(X\beta) \\
\text{Prob}(Z_5 = 1) &= \Phi(X\beta + c_2) - \Phi(X\beta + c_1) \\
\text{Prob}(Z_4 = 1) &= \Phi(X\beta + c_3) - \Phi(X\beta + c_2)
\end{aligned}$$

$$\begin{aligned}
\text{Prob}(Z_3 = 1) &= \Phi(X\beta + c_4) - \Phi(X\beta + c_3) \\
\text{Prob}(Z_2 = 1) &= \Phi(X\beta + c_5) - \Phi(X\beta + c_4) \\
\text{Prob}(Z_1 = 1) &= 1 - \Phi(X\beta + c_5) \qquad (7)
\end{aligned}$$

where $\Phi(.)$ is the cumulative standard normal density function, X is a vector of explanatory variables including an intercept and β is a vector of unknown coefficients to be estimated. These probabilities stem from the maintained hypothesis of a probit model, which is that the value of $X\beta$ and an unobservable mean-zero, normally distributed shock determine the category to which an observation belongs.[7] If the shock has variance σ^2, then we should formally write the $\text{Prob}(Z_7 = 1)$, for example, as $\Phi(\frac{X\beta}{\sigma})$. In the usual ordered probit model where the variance is constant, only $\frac{\beta}{\sigma}$ is identified, so it is customary to normalize $\sigma = 1$ in order to identify β and the constants, $c_1, .., c_5$.

The constant-variance assumption is not desirable for a weekly time series of interest rate changes in light of the interest-rate volatility witnessed from 1979 to 1982. For this reason, we introduce a conditionally heteroscedastic probit model suitable for time-series applications. One reason time-series applications of discrete-choice models have heretofore not allowed for conditional heteroscedasticity is that popular techniques, such as the Autoregressive Conditional Heteroscedastic (ARCH) model of Engle (1982), are not applicable to discrete choice models, because the the residuals are latent variables. This difficulty does not appear, however, if the variance changes over time as a discrete random variable. We operationalize this form of heteroscedasticity by allowing σ to vary over time as a binary

[7]Note that the conditionally heteroscedastic random disturbance is a continuous, non-categorical random variable.

random variable governed by a Markov process:

$$\begin{aligned}
\sigma_t &\in \{\sigma_0, \sigma_1\} \\
\sigma_0 &= 1 \\
\sigma_1 &> 1 \\
\text{Prob}(\sigma_t = 1 \mid \sigma_{t-1} = 1) &= p \\
\text{Prob}(\sigma_t = \sigma_1 \mid \sigma_{t-1} = \sigma_1) &= q
\end{aligned}$$

Normalizing the variance to one in the low-variance state permits identification of β. The transition probabilities, p and q, indicate the persistence of the volatility states and determine the unconditional probability of the low-variance state to be $(1-q)/(2-p-q)$. In this case, the $\text{Prob}(Z_{7t} = 1 \mid \sigma_t = 1) = \Phi(X\beta)$ and $\text{Prob}(Z_{7t} = 1 \mid \sigma_t = \sigma_1) = \Phi(\frac{X\beta}{\sigma_1})$. Bayes' Rule is used to obtain filtered probabilities of the states in order to integrate out the unobserved volatility states and evaluate the likelihood function, as in Hamilton (1990):

$$\text{Prob}(\sigma_t = \sigma_1 \mid Z_{jt} = 1) = \frac{\text{Prob}(\sigma_t = \sigma_1 \mid Z_{t-1})\text{Prob}(Z_{jt} = 1 \mid \sigma_t = \sigma_1)}{\sum_{s=0}^{1} \text{Prob}(\sigma_t = \sigma_s \mid Z_{t-1})\text{Prob}(Z_{jt} = 1 \mid \sigma_t = \sigma_s)} \quad (8)$$

$$\begin{aligned}
\text{Prob}(\sigma_t = \sigma_1 \mid Z_{t-1}) &= q\text{Prob}(\sigma_{t-1} = \sigma_1 \mid Z_{t-1}) \\
&\quad +(1-p)\text{Prob}(\sigma_{t-1} = 1 \mid Z_{t-1}) \quad (9)
\end{aligned}$$

The function maximized is then

$$\sum_{t=1}^{T}\sum_{j=1}^{7} Z_{jt} ln \left(\sum_{s=0}^{1} \text{Prob}(\sigma_t = \sigma_s \mid Z_{t-1})\text{Prob}(Z_{jt} = 1 \mid \sigma_t = \sigma_s)\right) \tag{10}$$

In maximizing equation (10), the explanatory variables are lagged changes in the paper-bill spread and lagged changes in the 180-day CD rate, with the variables partitioned into increases and decreases as before.[8] Positive coefficients on the changes in the paper-bill spread are consistent with a countercyclical mark-up, because signs of recession ought to make the probabilities of increases in the loan mark-up more likely (categories 7; 6; 5).

The allowance for conditional heteroscedasticity via Markov-switching variance in the ordered probit improved the log-likelihood tremendously from -1458 to -1389. Counting the two transition probabilities, the addition of three parameters produces a large difference in the likelihood function. In testing the significance of the conditional heteroscedasticity, the likelihood-ratio test statistic does not have a standard chi-square distribution, because the transition probabilities are not identified under the null. Nevertheless, the difference is so large that it appears likely that the extra parameters are significant, because even the true non-standard distribution is not so different from a chi-square to raise the critical value from 7.81 to 140.

The standard deviation of the disturbances, σ, is about 2.5 times as large in the high-variance state with an almost 95% chance of remaining in that state another period. Figure

[8]We do not present ordered-probit results for the specification that uses the yield-curve slope as the indicator of macroeconomic conditions, because the coefficients were not significantly different from zero.

3 provides a plot of the smoothed probabilities of the high-variance state over the sample period. Not surprisingly, the most notable high-volatility episode corresponds with the 1979-82 period. The second most important high-volatility period was 1974-75. The fact that high-volatility periods coincided with three of the four recessions contained in our sample highlights the importance of controlling for conditional heteroscedasticity and weighting the observations appropriately when testing hypotheses related to the cyclicality of variables, such as the mark-up in bank lending rates.

Table 4: Heteroscedastic Ordered Probit Estimation of Changes in Loan Mark-Up Asymmetric Model st. errors are in parentheses			
variable	**parameter**	**heteroscedastic**	**constant variance**
	log-lik.	-1388.7	-1457.8
$\Delta(CP-TB)(INC)$	Γ_1	5.61 (1.33)	4.03 (.840)
$\Delta(CP-TB)(DEC)$	Γ_1	2.67 (1.19)	1.34 (.802)
$\Delta(CP-TB)(INC)$	Γ_2	1.82 (1.11)	1.59 (.753)
$\Delta(CP-TB)(DEC)$	Γ_2	.253 (1.04)	.067 (.715)
$\Delta(CP-TB)(INC)$	Γ_3	1.73 (.951)	1.33 (.625)
$\Delta(CP-TB)(DEC)$	Γ_3	-.247 (.875)	-.11 (.599)
$\Delta(CP-TB)(INC)$	Γ_4	1.27 (.667)	1.04 (.449)
$\Delta(CP-TB)(DEC)$	Γ_4	-.234 (.656)	-.18 (.441)
$\Delta(CD)(INC)$	Γ_1	1.06 (.598)	.293 (.390)
$\Delta(CD)(DEC)$	Γ_1	1.29 (.516)	.947 (.328)
$\Delta(CD)(INC)$	Γ_2	2.52 (.593)	.948 (.394)
$\Delta(CD)(DEC)$	Γ_2	1.39 (.517)	1.01 (.321)
$\Delta(CD)(INC)$	Γ_3	2.26 (.573)	.622 (.373)
$\Delta(CD)(DEC)$	Γ_3	1.43 (.471)	1.13 (.304)
$\Delta(CD)(INC)$	Γ_4	.952 (.526)	.158 (.339)
$\Delta(CD)(DEC)$	Γ_4	1.75 (.485)	1.22 (.283)
$\Delta(CD)(INC)$	Γ_5	1.02 (.439)	.532 (.288)
$\Delta(CD)(DEC)$	Γ_5	.878 (.403)	.559 (.238)
$\Delta(CD)(INC)$	Γ_6	.341 (.366)	.079 (.221)
$\Delta(CD)(DEC)$	Γ_6	.646 (.314)	.557 (.188)
high variance	σ_1	2.48 (.203)	1
transition prob.	p	.977 (.008)	n.a.
transition prob.	q	.946 (.017)	n.a.
	c_1	1.67 (.269)	.703 (.076)
	c_2	2.61 (.294)	1.24 (.083)
	c_3	4.59 (.317)	2.77 (.093)
	c_4	5.40 (.334)	3.37 (.100)
	c_5	6.95 (.462)	4.05 (.119)
Wald tests for symmetry			
$\Delta(CP-TB)$ **(p-value)**		.112	.026
ΔCD **(p-value)**		.798	.240

The results for the heteroscedastic ordered probit in Table 4 show that the sums of coefficients, Γ_1, are positive and significant. The null hypothesis of symmetry is not rejected for the paper-bill spread, despite the fact that the estimated total response, Γ_1, for increases is more than double that for decreases. Hence, while the heteroscedastic ordered probit model and the weighted least squares regression concur that the loan mark-up is countercyclical, they reach opposite conlusions regarding the significance of asymmetry in the mark-up's response to increases and decreases in the paper-bill spread. The failure to reject the symmetry hypothesis in the heteroscedastic ordered probit model also runs counter to the asymmetry found in logit models by Mester and Saunders (1995) regarding the response of the prime rate to positive and negative impulses. The treatment of heteroscedasticity is a likely explanation of the difference in results, because a constant-variance ordered probit also finds significant evidence of asymmetry in the mark-up's response to changes in the paper-bill spread.

A further argument supporting this explanation begins by noting that the estimated standard errors of the coefficients will not be consistent if conditional heteroscedasticity is not addressed. Furthermore, the estimated standard errors ought to be biased downward. The second derivative of the ordered probit log-likelihood with respect to the slope coefficients is proportional to $X_t X_t' / \sigma_t^2$, where X is the vector of explanatory variables. In the constant-variance ordered probit, σ is normalized to one, whereas in the heteroscedastic ordered probit, the unconditional value of σ is greater than one. When applying the two models to the same data (same $X_t X_t'$), we would expect the heteroscedastic model to have larger standard errors. The apparent degree of precision in the estimates from the constant-variance ordered probit gives it considerable power to reject symmetry, even when symmetry holds, i.e., the test has the wrong size when it is presumed that σ is constant. The difference in the standard errors for Γ_1 in Table 4 between the heteroscedastic and constant-variance models conforms with this argument. Hence the failure to address heteroscedasticity can lead to misplaced confidence in the significance of parameter estimates pointing toward downward stickiness of the loan mark-up. In general, our results highlight the importance of controlling for conditional heteroscedasticity and weighting the observations correctly when testing hypotheses related to the cyclicality and symmetry of interest rates, such as the mark-up in bank lending rates.

Conclusions

A switching cost model along the lines of Klemperer (1995), together with the assumption that bank managers are risk-averse with respect to volatile profit streams, yields the prediction that the mark-up on bank loans is countercyclical. The maintained assumption that managers are not risk-neutral seems reasonable for firms whose equity value depends greatly on the value of a legal charter and goodwill, as opposed to tangible capital.

Using Friedman and Kuttner's (1993) observation that the commerical paper - Treasury bill rate spread is a predictor of the economy's cyclical behavior and its availability at the weekly frequency, we obtain evidence from two econometric models. The first, iteratively weighted least squares, finds evidence of both a countercyclical mark-up and asymmetry in the mark-up's response to recessionary versus expansionary impulses. The second, a conditionally heteroscedastic ordered probit model (the first discrete-choice model to allow for conditional heteroscedasticity in a time-series application), finds evidence of a countercyclical mark-up but not asymmetry. Because the constant-variance ordered probit model also finds asymmetric responses, it appears that the finding of asymmetry may result from not addressing the heteroscedastic nature of the interest-rate data.

In other contexts, countercyclical mark-ups have been attributed to capital market "imperfections," as in Chevalier and Scharfstein (1994), perhaps suggesting room for policy intervention. In the banking market, however, a firm could avoid switching costs only by making publicly available (most notably to its rivals) details of its strategic plans. Thus, while loan mark-ups appear to be significantly countercyclical, any attempt to attentuate business cycles by mitigating switching costs would likely entail a cure more expensive than the problem.

References

Chevalier, J. and D. Scharfstein, "Liquidity Constraints and the Cyclical Behavior of Markups." *American Economic Review Papers and Proceedings* 85 (May 1995), 390-96.

Chevalier, J. and D. Scharfstein, "Capital Market Imperfections and Countercyclical Mark-Ups: Theory and Evidence." NBER Working Paper No. 4614 1994.

Engle, Robert F., "Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation," *Econometrica* 50, 987-1007 1982.

Estrella, Arturo and Frederic S. Mishkin, "Predicting U.S. Recessions: Financial Variables as Leading Indicators," NBER Working Paper 5379 (1995).

Forbes, Shawn and Lucille Mayne, "A Friction Model of the Prime," Journal of Banking and Finance 13 (March 1989), 127-35.

Friedman, Benjamin and Kenneth Kuttner, "Why Does the Paper-Bill Spread Predict Real Economic Activity?" in James H. Stock and Mark W. Watson (eds.) **Business Cycles, Indicators, and Forecasting.** University of Chicago Press, 1993.

Gilbert, R. and P.D. Klemperer, "An Equilibrium Theory of Rationing." Oxford University Working Paper 1995.

Hamilton, James D., "Analysis of Time Series Subject to Changes in Regime," *Journal of Econometrics* 45, No. 1/2, 39-70 1990.

Hughes, J.P., W. Lang, L.J. Mester, C-G. Moon, "U.S. Banks' Efficient Risk-Return Trade-off under Interstate Branching." Federal Reserve Bank of Philadelphia Working Paper 1995.

Klemperer, Paul, "Competition when Consumers have Switching Costs: An Overview with Applications to Industrial Organization, Macroeconomics, and International Trade." *Review of Economic Studies* 62, 515-539 1995.

Kmenta, Jan,**Elements of Econometrics.** New York: Macmillan 1986.

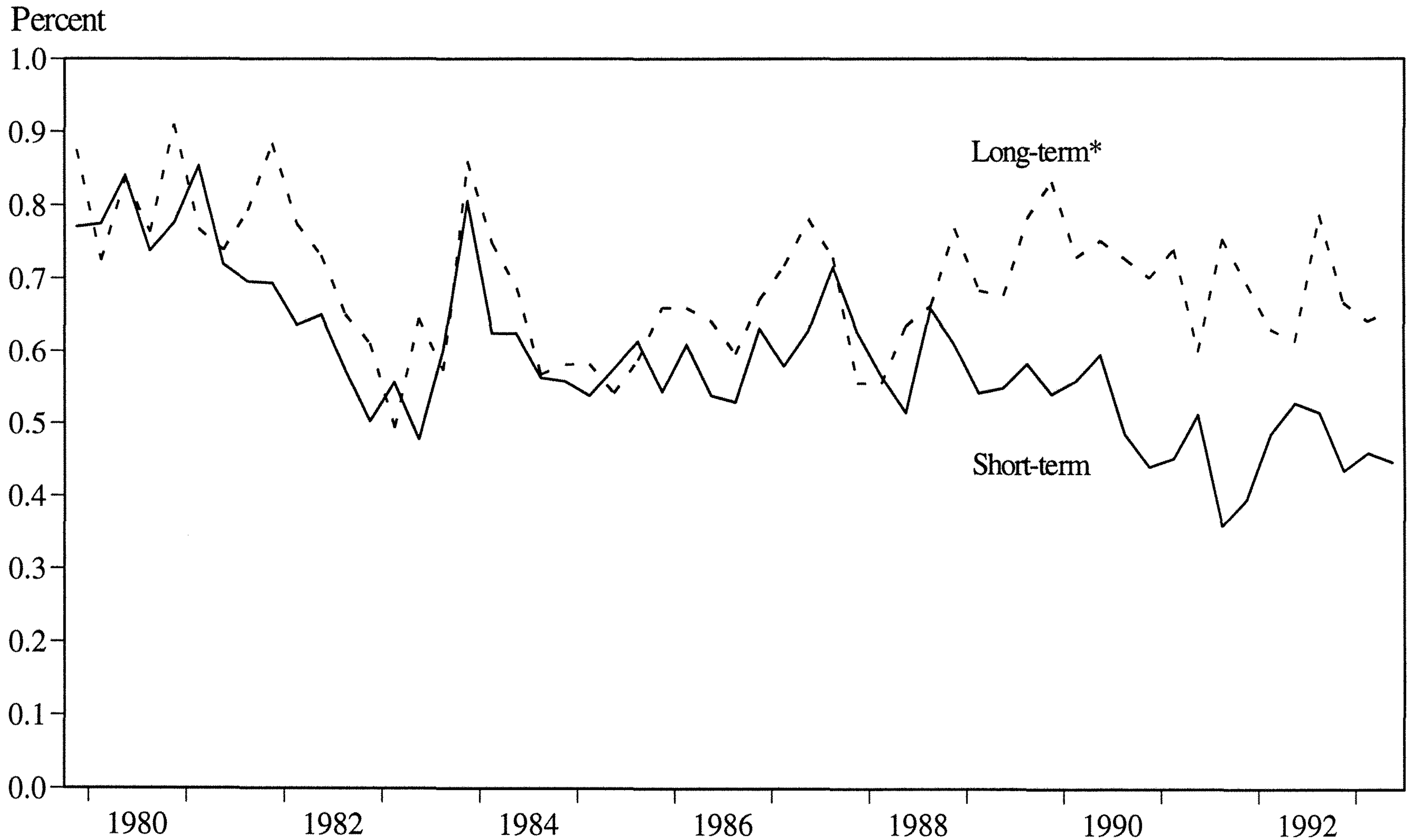
Maddala, G.S.**Limited-Dependent and Qualitative Variables in Econometrics.** New York: Cambridge Press 1983.

Mester, Loretta and Anthony Saunders, "When Does the Prime Rate Change?" *Journal of Banking and Finance* 19, 743-64.

Neumark, David and Steven A. Sharpe, "Market Structure and the Nature of Price Rigidity: Evidence from the Market for Consumer Deposits," *Quarterly Journal of Economics* 107 (May 1992), 657-80.

Rajan, Raghuram, "Insiders and Outsiders: The Choice between Informed and Arm's-Length Debt." *Journal of Finance* 47 (September 1992), 1367-1400.

Figure 1. Percentage of Business Loans Made at or Above the Prime Lending Rate



*Loans greater than one year.

Figure 2. Paper Bill Spread

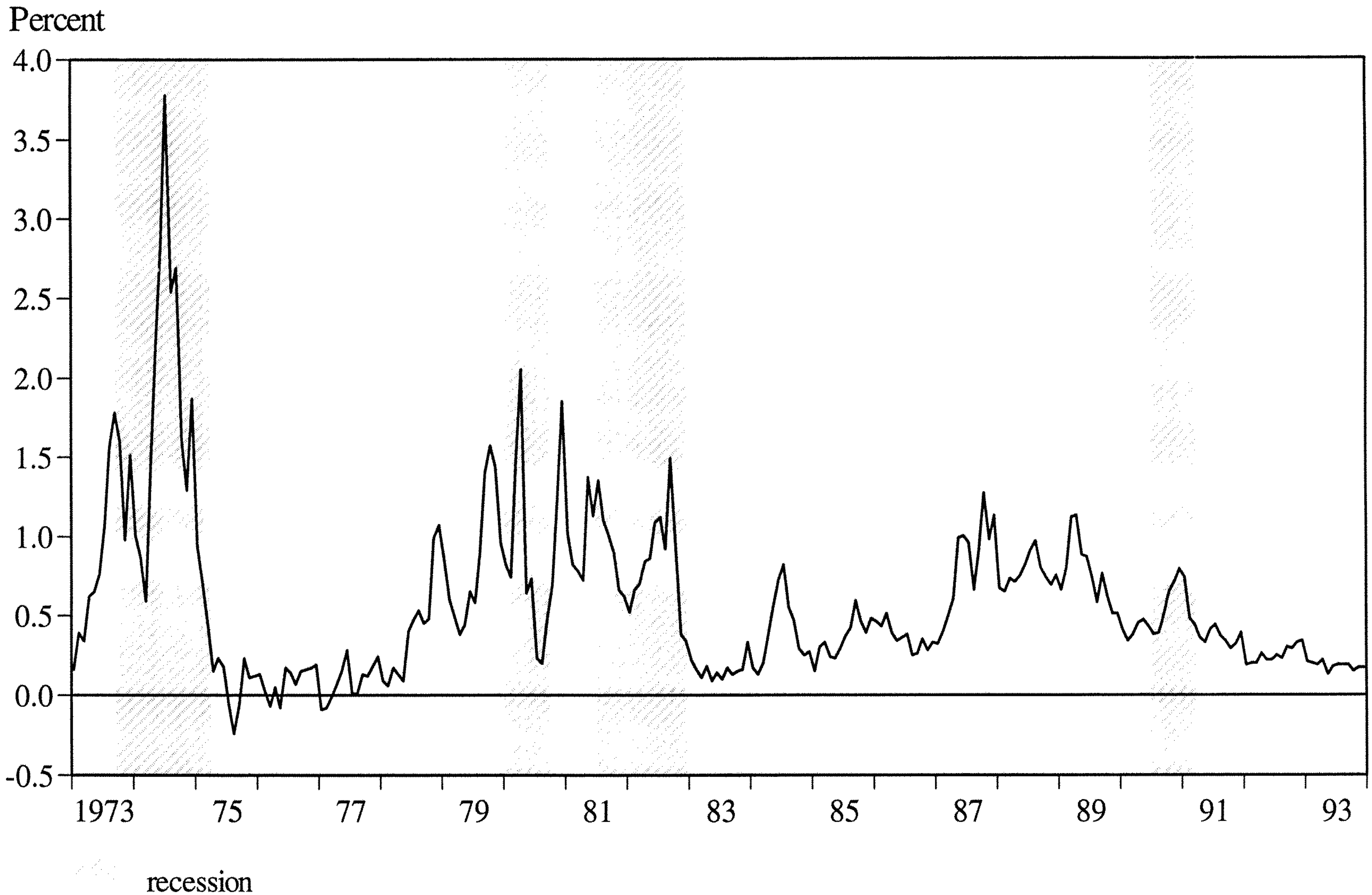
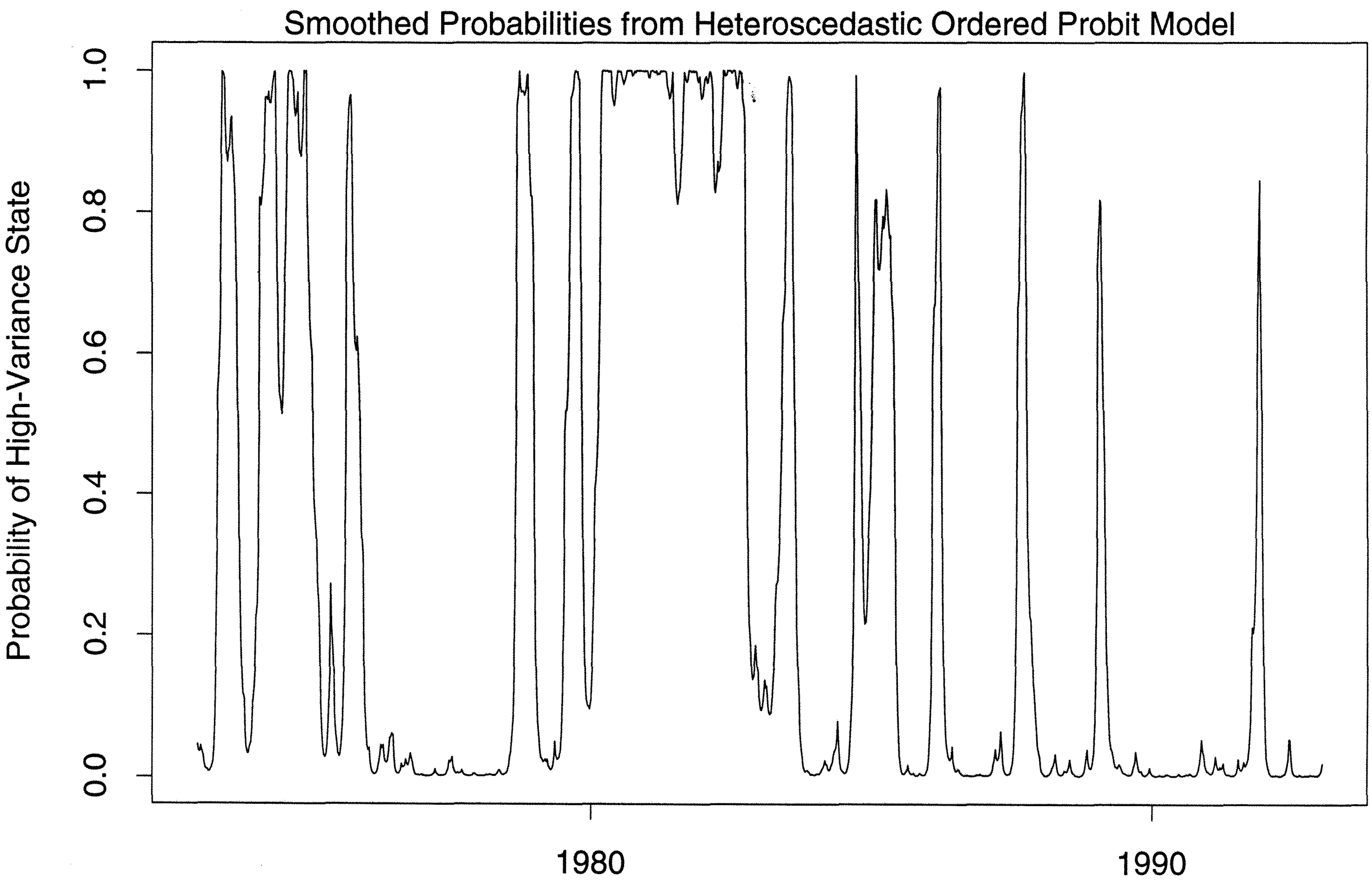


Figure 3



Smoothed Probabilities from Heteroscedastic Ordered Probit Model
Probability of High-Variance State
0.0
0.2
0.4
0.6
0.8
1.0
1980
1990