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RESEARCH

Yield curve inversions, bank credit tightening, and the credit cycle

An econometric analysis

Quantitative Credit Strategy

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Will the credit cycle turn in 2007?

With volatility and credit spreads at or close to all-time lows, and previously unseen amounts of leverage going into the credit markets, the timing of any turn in the credit cycle is a key concern for investors.

The Federal Reserve Senior Loan Officer Survey for January 2007 suggests a benign credit environment for 2007. We demonstrate how loan standards can be used as a powerful leading indicator of a potential turn in the credit cycle. We also show that the latest results, at a 0% net tightening, counterbalance the bearish sentiment signalled by the current yield curve inversion.

Our quantitative framework uses Loan Officer data and information from the yield curve to determine turning points. Using a combination of econometric techniques, we conclude the following:

- The Loan Officer survey's net-tightening standards variable is a strong predictor of credit cycle turning points.
- When used jointly with yield curve shape information, the indicator is even stronger.
- On the back of the Loan Officer tightening data and the shape of the yield curve, we calculate the probability of entering an extended spread-widening regime during 2007 to be 4-18%.
- Although lending standards seemed to ease during 2006, we believe that the recent turn in this variable to neutral, accompanied by the modest inversion of the US yield curve, would suggest that we may see a tightening of standards during 2007.
- The lag effect of curve inversion often occurs up to four quarters before credit begins to underperform.

Our macro-econometric model has consistently forecast the timing of credit underperformance jumps during 1967-2006. In this report, we describe both the methodology and robustness testing of our frameworks, finding consistently strong results.

Micro-level liquidity: The Loan Officer survey

Loan Officer survey: micro-level information on the corporate liquidity situation

Recent academic research has shown how micro-level information, such as the Federal Reserve's survey of Loan Officers, can generate strong signals on the direction of real GDP (Lown and Morgan, 2006). The survey contains a number of questions regarding the extent to which Loan Officers have adjusted their lending standards and amounts, and how they have done it. Figure 1 shows an excerpt from the survey published in January 2007.

The survey can capture dimensions of corporate creditworthiness that are not usually monitored

The survey results may illustrate a bottoms-up perspective of the perceived risk in commercial lending. Smaller-sized companies are much more dependent on bank financing, compared with larger companies that use a wide spectrum of financing options – from bonds, to loans, to asset backed securities. We believe Loan Officers may have unique insights into corporate health on a granular level. Specifically, small companies are likely to be less financially bolstered and to experience effects of a profit downturn more quickly than larger corporates. The survey will also be able to capture more geographic diversity, as it is conducted on a district-by-district basis. Consequently, any districts leading the cycle will be captured in the survey.

Tightening lending standards have consistently been leading recessions

In Figure 2, we plot how tightening lending standards have been leading recessions each time since inception of the data series. "Tightening standards" is defined as the ratio of senior Loan Officers at a large cross-section of US banks indicating that they have tightened Commercial and Industrial (C&I) loan standards, versus those indicating that they have relaxed standards. Hence, increasing values in the figure imply that Loan Officers are restricting lending.

Figure 1: Excerpt from the Federal Reserve Senior Loan Officer survey

January, 2007

Questions 1-6 *ask about* ***commercial and industrial*** *(C&I) loans at your bank. Questions 1-3 deal with changes in your bank's lending policies over the past three months. Questions 4-5 deal with changes in demand for C&I loans over the past three months. Question 6 asks about changes in prospective demand for C&I loans at your bank, as indicated by the volume of recent inquiries about the availability of new credit lines or increases in existing lines. If your bank's lending policies have not changed over the past three months, please report them as unchanged even if the policies are either restrictive or accommodative relative to longer-term norms. If your bank's policies have tightened or eased over the past three months, please so report them regardless of how they stand relative to longer-term norms. Also, please report changes in enforcement of existing policies as changes in policies.*

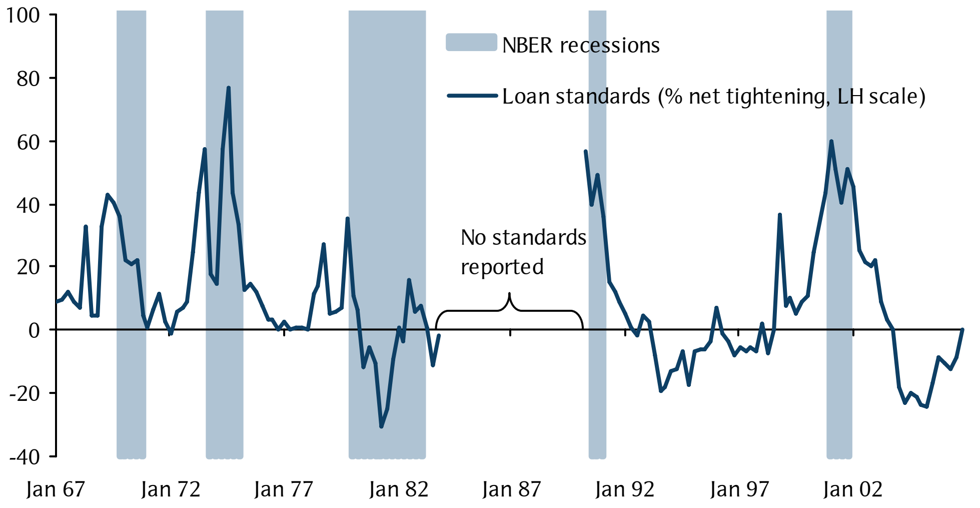
1. Over the past three months, how have your bank's credit standards for approving applications for C&I loans or credit lines--other than those to be used to finance mergers and acquisitions--to large and middle-market firms and to small firms changed? (If your bank defines firm size differently from the categories suggested below, please use your definitions and indicate what they are.)

a. Standards for large and middle-market firms (annual sales of $50 million or more):

	All Respondents		Large Banks		Other Banks	
	Banks	Percent	Banks	Percent	Banks	Percent
Tightened considerably	0	0.0	0	0.0	0	0.0
Tightened somewhat	3	5.3	1	2.7	2	10.0
Remained basically unchanged	51	89.5	34	91.9	17	85.0
Eased somewhat	3	5.3	2	5.4	1	5.0
Eased considerably	0	0.0	0	0.0	0	0.0
Total	57	100.0	37	100.0	20	100.0

Source: Federal Reserve.

Figure 2: Reported tightening in lending standards preceding recessions, 1967-2006



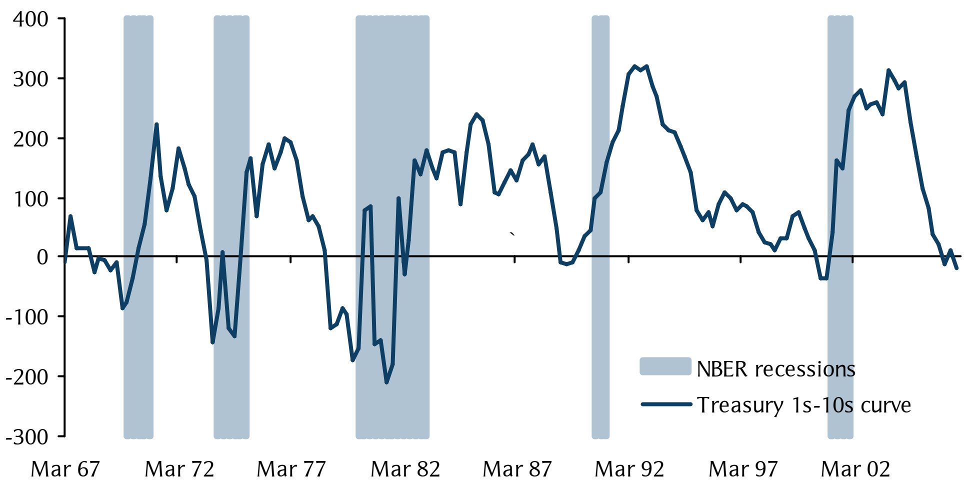
Source: Barclays Capital, National Bureau of Economic Research, Federal Reserve.

Macro liquidity: The shape of the Treasury curve

The yield curve inversion effect on credit appears to have decoupled during 2006

Looking at the liquidity question from the other end of the scale involves the dynamics of the US yield curve. At the end of December 2005, the 2-10s Treasury curve inverted for the first time since 2001. This sent shudders through the investor community, as an inverted curve historically has been viewed as the harbinger of a recession (Figure 3). More than a year later, we have seen the curve steepen back to small positive levels only to invert again several times, without the economy slipping into recession. In credit, defaults have remained at historical lows – and with good issuance in terms of nominal amounts, as well as record LBOs and M&As, the usual signs of the turning of the credit cycle are not present. Thus, one could argue that the traditional link between yield curve inversions and downturns in credit has decoupled. We believe that, supported by the below quantitative analysis, these macro liquidity dynamics should be complemented by what is happening at the micro level.

Figure 3: Treasury curve inversions and recessions, 1967-2006 (bp)



Note: We use the Treasury 1-10s curve, since the data goes back to 1967 for that time series, whereas there is only 2 yr data from 1977 onwards. Our analysis is not substantially altered when applying the 2 yr rate in a shorter sample setting. Source: Barclays Capital, National Bureau of Economic Research, Federal Reserve.

In *Yield curve regime behaviour in US Credit: Quantitative sector selection*, 26 January 2006, we developed a model of how credit performs as an asset class based on the shape of the 2-10s Treasury curve. Figure 4 presents excess returns under the different regimes, with the bottom row highlighting the (estimated) threshold between the regimes. We can see a clear pattern of credit performing better as the yield curve steepens, with marked underperformance in the inverted regime. That credit has not underperformed during the year, despite the inversion having breached our threshold, points at the need for further variables to explain the full liquidity dynamics.

Figure 4: Index excess returns, yield curve slope regimes

	Steep	P-value	Flat	P-value	Inverted	P-value
Credit index	15 bp	0%	11 bp	0%	-48 bp	0%
Treasury curve, 2-10s monthly average	>88 bp		Between -11 and 88 bp		<-11 bp	

Source: Barclays Capital, Yieldbook.

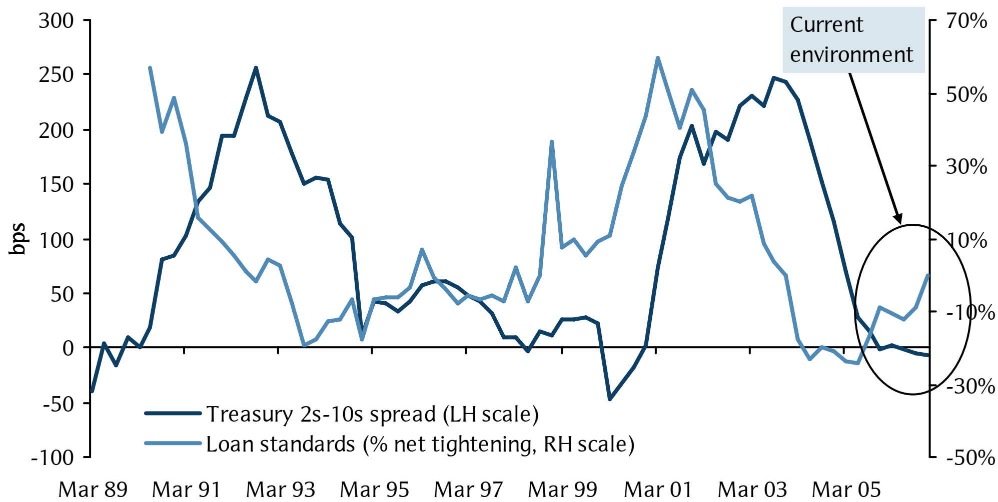
Standards and the Treasury curve inter-relationships

Treasury curve leads tightening of lending standards

These results suggest a similar pattern of substantial regime changes predating actual effects in the broader macro-economy. So, what is the relationship between the Treasury yield curve and the micro-data from the Loan Officer survey? We plot this relationship in Figure 5 for the past two credit cycles. It appears that the 2s-10s curve leads the tightening of loan standards, that is, we see the Treasury curve invert fairly close in time to the peak of the loan standards tightening.

On the surface, this is not too surprising. Bank lending usually stays in the short end of the curve, and when the relative cost of short-term loans increases, banks are less willing to lend and, thus, tighten their standards. However, that is not the whole story. Bank lending profiles have been broken down into two parts in the Fed survey: first, the standards (requirements) to get a loan, and second, the spread charged over, for example, the fed funds rate. Typically, the shape of the 2-10s curve would influence the spread charged, rather than the standards required for the loan. Hence, a main component of changes in standards would reflect fundamental views on repayment capacity, rather than the banks' financing costs.

Figure 5: Yield curve inversions appear to lead to lending standards tightening



Source: Federal Reserve.

Tightening loan standards ahead?

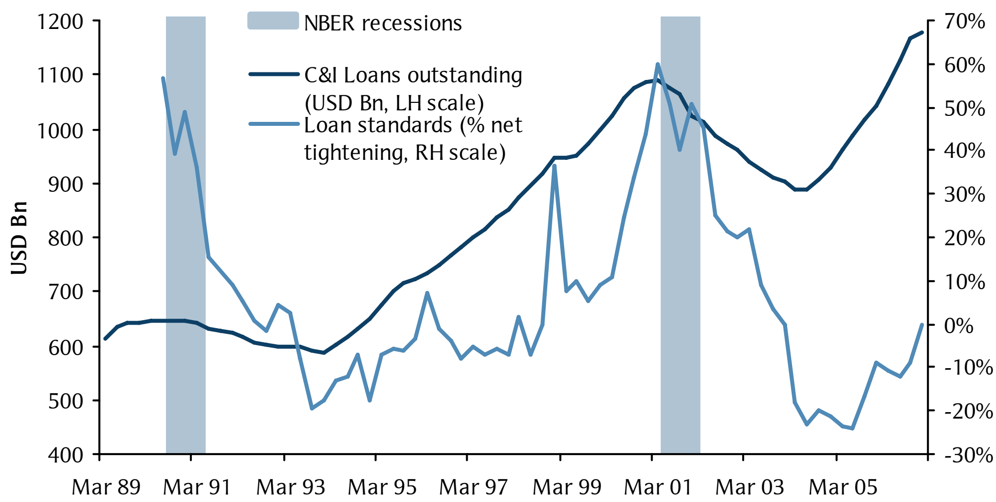
Loan standards were relaxed over 2006 but are trending toward tightening…

We note that standards have been easing during 2006. The number of officers reporting a looser loan standard has been 8% higher than those reporting a tightening standard, on average. Recently, however, there has been a shift toward tightening standards. The numbers reported at the end of January showed a 0% net tightening, meaning that we are not in a tightening environment just yet but are heading in this direction. Directionally, the change in the amount of tightening has been upward sloping from the mid 2005 trough up until now. The January number reiterated the result of the October survey and although this plateau may persist for a while due to the benign macroeconomic environment, we believe there is momentum for the standards to continue on its tightening trend.

… C&I loan growth is healthy but appears to be abating

As another component of the current market environment, we have looked at how the amount of Commercial and Industrial (C&I) lending has developed (Figure 6). In the previous credit cycles, the amount of C&I loans outstanding peaked at the same point as the tightening standards. Over the past quarter, the growth rate has subsided but still remains positive, suggesting that we may be nearing the peak in C&I lending for this cycle.

Figure 6: C&I lending enjoys a healthy growth rate, but at a slowing pace



Source: National Bureau of Economics Research, Federal Reserve.

... 2s-10s inversion has marginally breached our earlier predicted credit underperformance threshold

We also highlighted in Figure 5 how the data looks in the current environment in terms of the Treasury curve. Post the initial inversion around the turn of the year in 2005/06, the 2-10s reverted to an upward sloping shape in March. The current period of an inverted curve commenced in August with a trough in late November, where the inversion was down to -15 bp on a month-on-month average basis. This has eased somewhat, but we still see a monthly average inversion in excess of the -11 bp threshold we estimated in 2006 for credit to start underperforming. To contrast this inversion with the latest one, in March to December 2000, the degree of inversion has been smaller. It topped -40 bp in the summer of 2000. We have also seen the current inversion for a more protracted time than we did then.

Forecasting the turn of the credit cycle: A statistical framework

We now turn to integrating the data above into a quantitative framework. We employ two different types of analysis, to verify robustness of the results and to avoid model-dependency.

The first type, a regime switching model, enables us to generate quarter-on-quarter probabilities to enter a higher spread environment using yield curve and Loan Officer data. This model captures the asymmetry in different credit regimes, taking into account, for instance, the large differences in volatility between high and low spread conditions.

In our second approach, a vector auto-regression, we analyse the anticipated average effect of movements in the yield curve and the Loan Officer data in a continuous framework. This allows us to simulate the effect in yield differentials or spreads of a given movement in tightening standards or the yield curve.

Both these models corroborate the importance of the standards and yield curve data. We are able to build a robust system for leading indicators of credit cycle turn points on a historical basis.

The data

We measure credit deterioration by examining the spread between Baa and Aaa rated corporate bond yields

To obtain as many credit cycles as possible for our investigation, we use a merged sample of Moody's and Yieldbook data on yields of seasoned Aaa, AAA/AA and Baa, BBB corporate bonds. The Moody's data set extends back to 1967, giving us 13 more years of data than Yieldbook, which only starts in 1980. On inspection, the Yieldbook data seems more reliable than the Moody's data for the later time periods. For example, the Moody's time-series shows the utilities sector dropping out of the Aaa index in December 2001, which results in a jump that is hard to correct for, as the credit cycle was close to a turning point at that time. Consequently, we use the Moody's time-series for the run up to 1980, and Yieldbook data thereafter.

To derive a measure of credit performance, we look at the differential between the Baa/BBB and Aaa/AAA bond yields.[1] For simplicity, we will refer to this number as the BBB/AAA yield spread.

Loan standards tightening lead peaks in the BBB/AAA yield spread

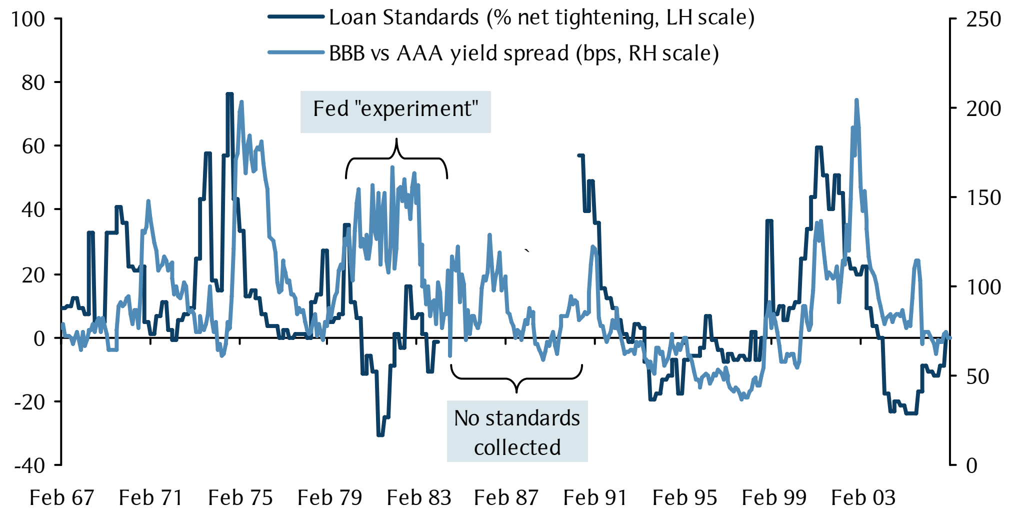
Figure 7 plots this spread between 1990 and 2006 alongside the loan standards series. We see that there is a strong leading effect of loan standards tightening prior to Baa yields increasing over AAAs in each of the significant credit downturns. Specifically, we see spikes in loan standards tightening in 1970, ahead of the 1971 spread hike, in 1974/5, ahead of the 1975-1977 increase in volatility, and in 1979, ahead of the extended high spread differential regime between 1980 and 1983. When the Fed data collection resumed in 1990, it came in at a massive 57% net tightening and was subsequently followed by a spike in spread differential in the first half of 1991.

We also see the same pattern in 2000, ahead of the 2001/02 credit downturn. Note also that the 1990 survey, the first after the 1980s break in the time-series, immediately shows a significant tightening around the time of the 1990/91 downturn. The only occasion where the relationship breaks down is in connection with the Russian crisis of 1998/9, where we see only a contemporaneous tightening of standards resulting from the credit shock. However, we would not expect a prediction of such a shock by endogenous factors such as Loan Officers' tightening standards. Another example of

[1] As duration data is unavailable on these time series, we make the assumption that durations are similar between the two aggregates.

tightening standards not predicting this type of idiosyncratic and short-lived shock is the US autos blow-up in early 2005. As we can see, however, these types of shocks have dissipated fairly quickly, and the yield differential has reverted in a matter of months after the shock.

Figure 7: Tightening in standards has led to increasing yield differentials between BBB and AAA corporate bonds



Source: Federal Reserve, Moody's Investor Services.

Turning points as switches between credit regimes

Deriving high spread/volatility regimes and turning points

In order to derive turning points in the credit cycle using this data, we first establish low yield differential/volatility and high differential/volatility regimes in the data by applying a regime-switching model in the spirit of Hamilton (1989). The key feature of this model is that it does not specify the characteristics of regimes subjectively but instead derives the regimes that best fit the data. The model was originally designed to capture swings in the business cycle, for which any recession classification is subjective. The dependent variable in our credit specification is the differential between Baa and Aaa bond yields:

$$y_t = \mu_1 \cdot \text{Prob}(\text{Low spread regime}) + \mu_2 \cdot \text{Prob}(\text{High spread regime}) + \varepsilon_{t,S_t} \quad (1)$$

where the coefficients μ_1, μ_2 are the average spreads in their respective regime. We also allow for different volatilities in each regime through the state dependence of the residual ε_{t,S_t} . In other words, the residual ε_{t,S_t} is assumed to be normally distributed with volatility σ_{S_t} .

The probabilities of switching between regimes is governed by a transition matrix with elements P_{ij} . For example, given that we are certain to be in the credit benign environment today, the element P_{12} is the probability that we switch from that environment to the high spread/volatility regime. For more detail on the model, please refer to the technical notes below.

Figure 8: Parameter estimates in the regime switching model

	Quarterly data		Monthly data	
Parameter	**Value**	S.E.	Value	S.E.
μ_1	0.74	0.02	0.69	0.01
σ_1	0.16	0.01	0.16	0.01
P_{11}	0.95	0.16	0.98	0.12
μ_2	1.29	0.05	1.25	0.02
σ_2	0.28	0.04	0.27	0.02
P_{22}	0.88	0.32	0.95	0.19
Log likelihood	11.09		93.55	

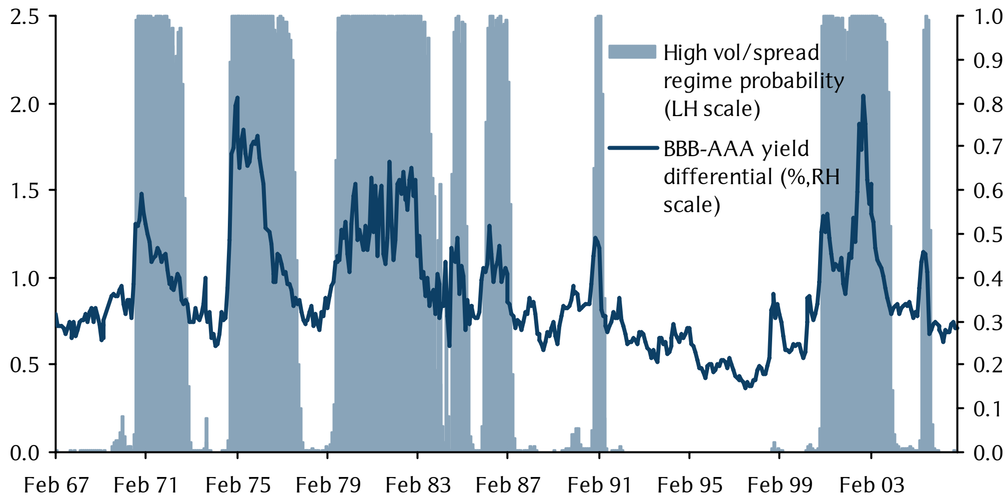
Source: Barclays Capital.

Our estimated high vol regimes conform with commonly recognised periods of increased credit volatility

The output from estimating (1) is produced in Figure 9. From 1967 to 2006 we find five distinct periods when BBB yields have been significantly higher than AAA in "normal" periods. We measure the average yield difference during those periods as 1.29 (Q/Q volatility of 28%), compared with the low differential/volatility environment average of 0.74 (Q/Q volatility of 16%).

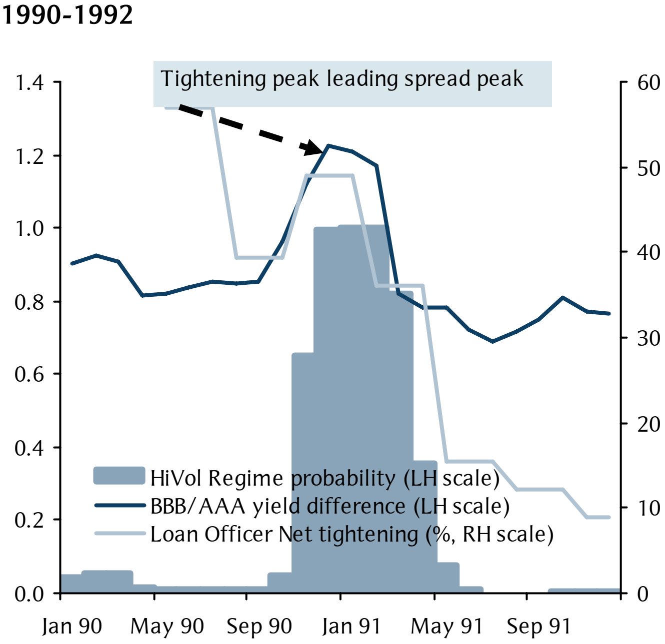
Figure 9 plots the probabilities of the high vol/spread regime versus the yield differential. We see how the model captures periods of significantly wider differentials. For example, in recent history, the model captures the 2001-2003 period, as well as the short-lived volatility uptick in May 2005. The November 1990 to March 1991 spike is picked up, as well as the period during the 1970s and 1980s when AAA versus BBB yields increased dramatically. The Fed experiment, during 1980-83, shows up as a high volatility regime, with high frequency oscillation around the general yield spread trend.

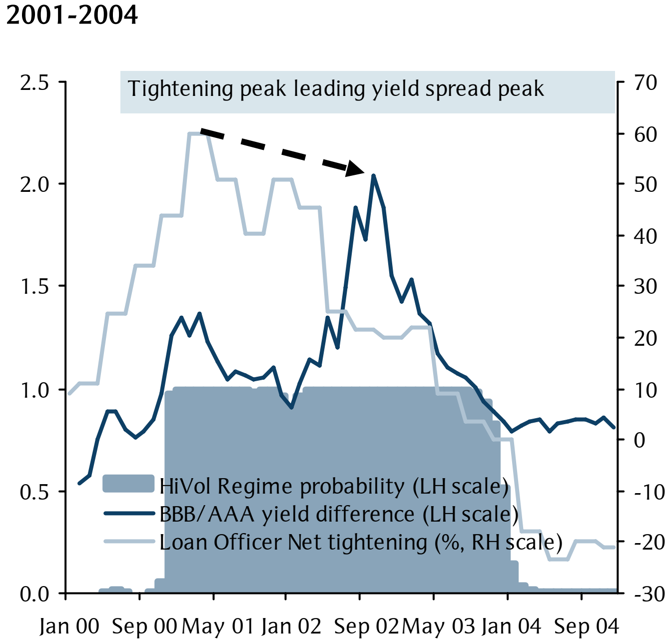
Figure 9: The model produces discrete states, with the BBB/AAA differential shifting in both levels and volatility



Source: Barclays Capital, Moody's Investor Services.

Figure 10: Spread differential and tightening standards during recent turns of the cycle





Source: Yieldbook, Federal Reserve, Barclays Capital.

We also take a look at the dynamics of the elevated volatility regime for each of the five instances in our sample. For this, we use data sampled monthly rather than quarterly. Figure 10 shows specific developments over the two last turns of the credit cycle, October 1990 and December 2000. In the former example, the spread differential started climbing a few months earlier but in a fairly orderly manner, leading us to wait until October to identify it as a higher spread and volatility regime. The Loan Officer tightening was strong at 60% as the spread differential was increasing, and the peak of the tightening standards pre-dated the yield differential peak in December that year.

The turn of 2000/01: a double-peak turn of the cycle

The turn of the cycle in 2000/01 involved some interesting dynamics. We saw a year-long continuous widening of the BBB-AAA differential from January 2000, followed by a tightening of the differential from 135 bp to 90 bp in January 2002. During this period, the model designated the regime as high-spread/volatile. The second peak is reached in October 2002. Interestingly, we see that the Loan Officers had started increasing the rate of tightening already in 2000 and continued to do so until the first half of 2001. The height of this tightening cycle was reached approximately 18 months prior to the peak of the yield differential. It is important to note that net tightening remained positive through the whole period, until late 2003: banks kept tightening their standards, quarter after quarter.

The model: predicting turning points using the yield curve slope and loan standard variables

Our qualitative evidence on the 2-10s and Loan Officer tightening standards leading real GDP as a whole suggest that these variables could be instrumental in designing a more flexible transition probability to enter the credit-worsening regime. We could estimate such a model directly using the framework in (1), but due to the hole in the survey data, this becomes computationally difficult. Instead, we use a probit model to estimate the following model:[2]

[2] *We have evaluated which lag length yields the most information when using a single variable in the probit model. Whereas the standards variable benefits from using the most recent data, the yield curve slope gives the strongest signal when using the four quarter lag. This corroborates the findings above on the yield curve having a leading effect on tightening standards.*

$$D_{t+1} = \Phi\left[\alpha + \beta_1 \cdot Slope_{t-3}^{Treasury\,1-10s} + \beta_2 \cdot Tightening_t\right] + u_t \qquad (2)$$

where D_{t+1} takes on the value 1 for the quarters in which we switch from benign to volatile regimes, as estimated in (1), and 0 otherwise. Equation (2) transforms the data contained in the Slope and Tightening variables into probabilities of D_{t+1} being equal to one. Hence, if the 1-10s curve and the Loan Officer net tightening data are important leaders in terms of predicting switches to a higher spread regime, the coefficients β_1, β_2 should turn out to be significant. This model directly produces a probability that we will have a shift in regime, ie, that we will experience a turning point, on the basis of the tightening and yield curve variables.

Figure 11: Turning point binary model estimates

	α_1	β_1	β_2
Value	-2.21	-1.15	3.12
Standard error	0.00	0.04	0.05
LR statistic; 2 d.f.	15.72	McFadden R^2	0.42

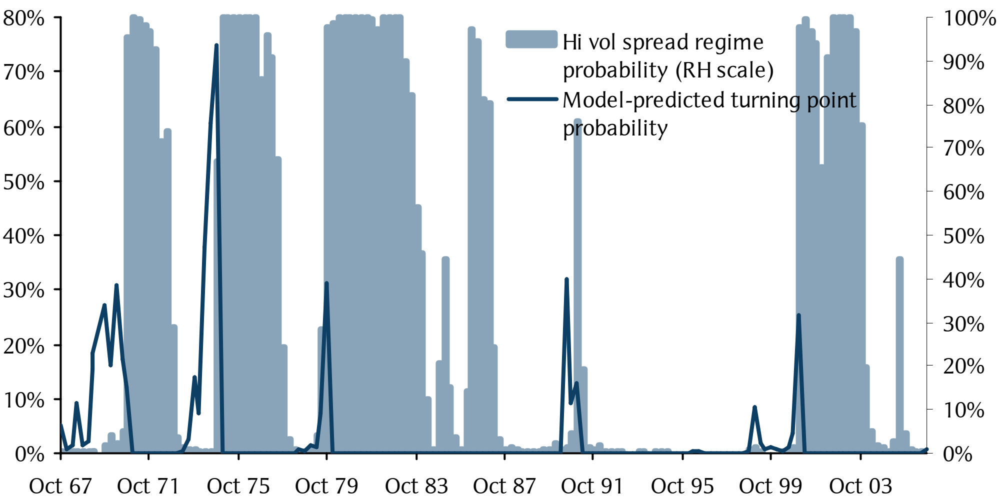
Source: Barclays Capital.

The result of estimating (2) on quarterly data is presented in Figure 11. The estimated parameters have the right sign: a decrease in the 1-10s spread increases the probability of a turning point through the negative value of β_1, and an increase in tightening translates into a rise in probability through β_2 being positive. The model is jointly significant (the LR statistic translates into a probability of <0.00), and the parameters are individually significant as well. With a McFadden R^2 of 42%, summing the diagnostics together, we find quite a good model fit.

Quarterly model produces strong contemporaneous switching probabilities

Estimating (2) yields ex ante probabilities of being at the credit cycle turning point for each point in time in the sample, as we depict with the solid line in Figure 13. In the graph, we see how the forecasted probabilities of turning points are high prior to, or right at, the inception of the high volatility regimes in 1970, 1974, 1990 and 2000.

Figure 12: Turning point probabilities, quarterly data



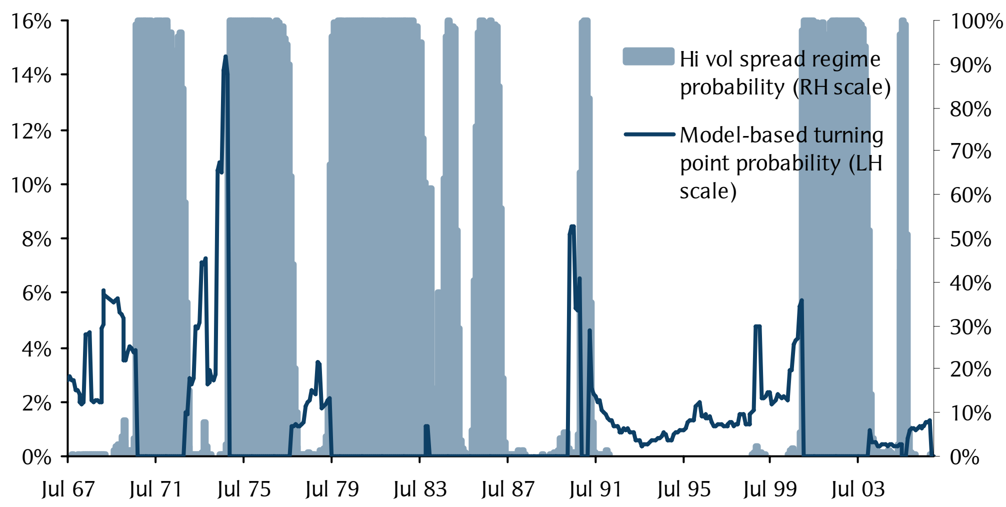
Source: Barclays Capital.

The main critique of the results of the quarterly model would be that some of the probabilities appear contemporaneous rather than leading. For example, we do not appear to get a solid pick-up of the switching probability in the run-up to the turn of the cycle in 2000/01. Instead, we see a hike in the probability in the same quarter as the cycle turns.

Monthly model shows strong leading effects of turning points

Quarterly data is fairly imprecise in the sense that it does not account for the timing of data-releases in the case of loan standards, or continuous data feeds, as in the case of the Treasury slope data. Hence, we investigate the same type of dynamics using monthly data instead. For the Loan Officer data, we make it piecewise constant, ie, to each month, we assign the value of the latest data release at that time, whereas we use the real-time 1-10s slope as well as the dependent variable. The trade-off is that the statistical framework for the binary model becomes more complicated, as the dependent variable becomes much more skewed. The ratio of 1 to 0s in the sample goes from 5/79 to 6/240 and this will have a detrimental effect on the measurement of standard errors in the model.

Figure 13: Turning point probabilities, monthly data



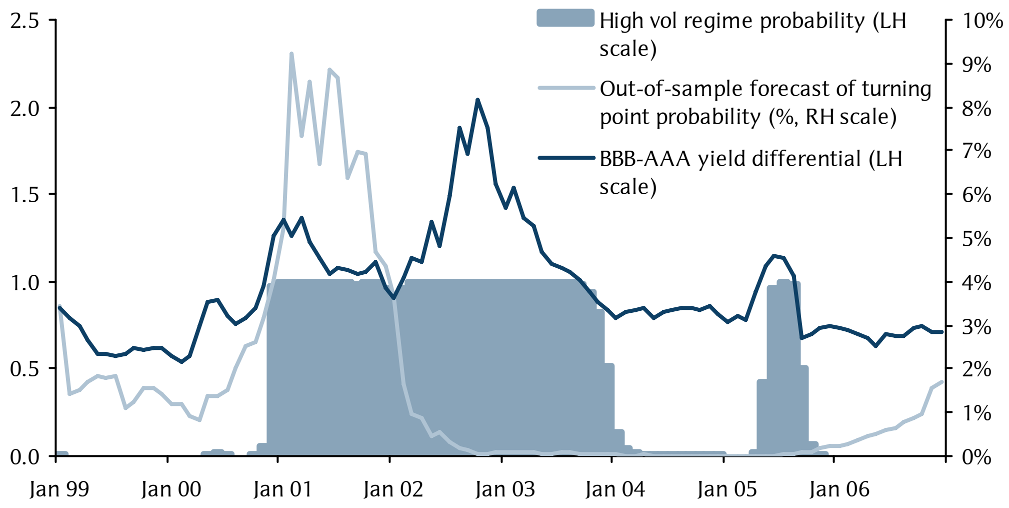
Source: Barclays Capital.

Figure 13 plots the probabilities of a transition to the high volatility regime based on the monthly data. We can see that the build-up of the probabilities now is leading the switch rather than being contemporaneous with it. We also see the current forecasted probability, which amounts to 1.8% month-on-month.

Structural stability? The model retains performance in out-of-sample testing

To test the structural stability of the model, we also conduct out-of-sample testing. We conduct the following experiment: "Given the model and the information set available at 1999, would we have been able to forecast the 2000/01 turn of the cycle?" If the relationship between the yield curve, tightening standards and the yield spread we have uncovered is a statistical artefact rather than a structural relationship, out-of-sample forecasting would be poor. The out-of-sample forecasts in Figure 14 confirm, however, that there is a structural link between variables: the strong forecasting properties remain even if we have estimated the model on a reduced data-set.

Figure 14: Out-of-sample forecasts of the 2000/01 turning point of the credit cycle



Source: Barclays Capital.

The bank tightening and credit link: A Vector Auto-Regression Approach

Vector Auto-Regressions study interrelations in multi-equation systems

The main drawback of the regime-switching approach is that it is limited in the number of sample points. As we only have five to six real switches into the high volatility regime, our sample size is fairly small. Another way to quantify the link between loan standards, the yield curve slope and credit relative performance is to build a system of equations where innovations in one variable can feed over into the other variables as well as into itself in a continuous fashion. A Vector Auto-Regression (VAR) is ideal for this type of analysis, which is what is employed by the original Lown and Morgan (2006) paper on the Loan Officer tightening standards. Please see the appendix for a brief technical introduction to this econometric model.

The VAR confirms the leading effects of standards and the yield curve slope on the BBB/AAA yield spread

First, we want to test the hypothesis if there is a leading effect of standards tightening or yield curve flattening on the yield differential. The tests are performed by means of a Granger causality test which is outlined in Appendix A. Results from this analysis are presented in Figure 15. To summarise, we find that standards appear not to be driven by the other variables in the system, as measured by the block exogeneity test. For the BBB/AAA yield spread, we find that there is a leading effect of both the standards and the Treasury slope variables, as signified by low/significant p-values.

Figure 15: Standards appear to be a leading indicator in the system, monthly data – the lower the p-value, the stronger the lead lag relationship

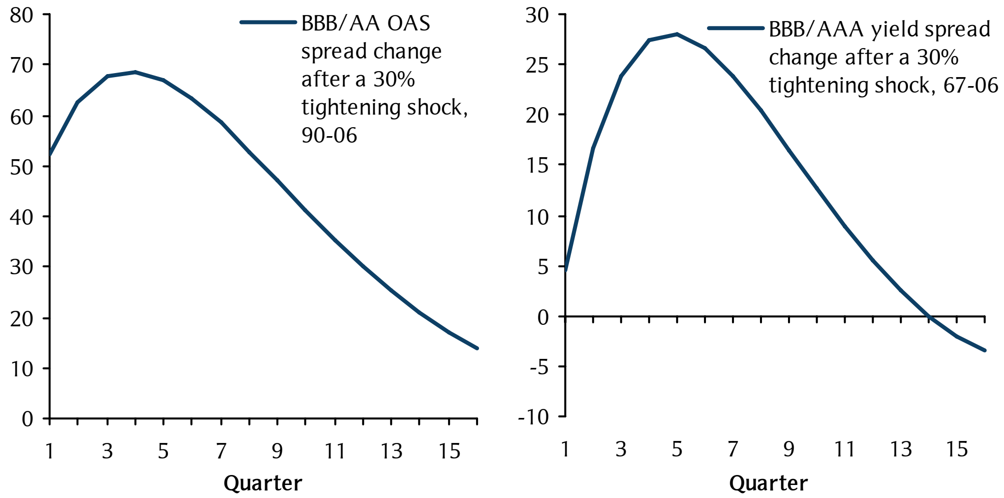
p-values	Does the below variable lead the dependent variable?			
Dependent variable	Standards	Treasury slope	BBB/AAA yield spread	Block exogeneity
Standards	n.a.	0.33	0.10	0.09
Treasury slope	0.04	n.a.	0.00	0.00
BBB/AAA yield spread	0.02	0.00	n.a.	0.00

Source: Barclays Capital.

The VAR also gives us a structural relationship by which we can conduct scenario analysis. We do this by “shocking” the system, ie, assuming that, for example, the tightening variable jumps up by 30 percentage points, and deriving how this shock is transmitted in the system.

We illustrate in Figure 16 how a 30% tightening of standards translates into spread widening. We do this by deriving the impulse-response functions the VAR in which we have the tightening standards variable and the difference between BBB and AAA option adjusted spread (OAS over Treasuries) for the period 1990-2006. Details are provided in the technical appendix.

Figure 16: Effects of tightening standards on the difference between BBB and AA OAS spreads (bp)



Source: Barclays Capital, The Yieldbook, Moody's Investor Services.

Scenario analysis: expected effect of tightening standards on BBB underperforming AAA/AA

We find that a 30% tightening shock would translate in BBBs widening over AAs by 26 bp in the same quarter in terms of OAS spreads. Over four quarters, the effect is 34 bp; ie, one year after the tightening numbers being released, we would expect the spread difference between BBBs and AAs to have widened to 34 bp. This leading effect is even stronger when considering the full sample, as we do in the right hand panel of Figure 16. We see an instantaneous effect of the yield spread widening around 2 bp, with a total effect of 14 bp one year lagging.

Appendix A: Vector Auto-Regressions

We apply vector auto-regressions to model lead/lags and causality. A vector auto-regressive model of a vector X_t of covariance stationary variables $x_{i,t}$ can be expressed as:

$$X_t = \mu + A(L)X_t + \varepsilon_t$$

For example, in a bi-variate first order VAR, we could the structure the model as follows:

$$\begin{bmatrix} y_t \\ z_t \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \begin{bmatrix} \phi_{11} & \phi_{12} \\ \phi_{21} & \phi_{22} \end{bmatrix} \begin{bmatrix} y_{t-1} \\ z_{t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}$$

For a bi-variate first p:th order VAR, we have:

$$\begin{bmatrix} y_t \\ z_t \end{bmatrix} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} + \sum_{i=1}^{p} \begin{bmatrix} \phi_{11}^i & \phi_{12}^i \\ \phi_{21}^i & \phi_{22}^i \end{bmatrix} \begin{bmatrix} y_{t-i} \\ z_{t-i} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \end{bmatrix}$$

From this, lead-lag effects between the variable can be inferred via the individual AR parameters ϕ_{kl}^i. For example, suppose that z has a 1 period lead effect on y: we would expect the parameter ϕ_{12}^1 to be statistically significant. A more intricate way to model these lead-lag effects is to derive impulse response functions of the VAR, in effect measuring $\partial y_t / \partial z_{t-1}$ using the full dynamics of the systems, albeit this may only be done with additional assumptions regarding the structure of the variance-covariance matrix of residuals.

Testing for the order of the VAR system boils down to evaluating the fit of the model at different lag lengths. Either one uses minimising information criteria (with the multivariate AIC and SBC being most frequently used) or testing down using likelihood ratio statistics (conditional on the distribution of the errors).

The impulse response functions derived in Figure 16 are based on a 2 variable VAR. We have tested for Granger causality, which in both cases have resulted in us not being able to reject the hypothesis that the Loan Standards variable does not Granger cause our credit performance variable. The opposite has not been true, leading to a statistical confirmation of the hypothesis that Loan Standards have a leading effect on credit performance. Our impulse response functions are calculated using the generalised impulse response function in which the ordering of the variables of the VAR does not matter for the results, see Pesaran and Shinn (1998).

Please note that the impulse response functions are based on shocks to the VAR (as in the residual of the regression) rather than the current level of the system. In our example above, these are equivalent since we are currently at a 0% net tightening level. In other circumstances, this is likely not to be true – the impulse outlined above should be read as "given a current net tightening of X%, how will spreads change if the next number comes in at X+30%".

Important concepts regarding causality are (i) block-exogeneity and (ii) Granger causality:

(i) We would like to ask the questing whether a variable is interesting for the system or not by looking at the effect of excluding it completely. If we accept block-exogeneity, the variable does not affect any other variable, nor is it affected by other variables in the system.

(ii) Granger causality refers not to causality in the ordinary sense but the possibility of forecasting one variable with the help of another. For example, a dragonfly flying low prior to rainfall obviously does not cause the actual rainfall. It does, however, Granger cause the rainfall since it is an effective predictor of future events.

Appendix B: Technical notes on regime switching

The underlying process driving the switches between regimes in equation (1) is, in this framework, assumed to be a hidden Markov process with two states with transition matrix **P**. Each i,j, element in **P** refers to the probability of switching into state j conditional on being in state j. The model is estimated via maximum likelihood.

We do not formally test for the significance of two or more separate regimes since this requires extensive Monte Carlo simulation, or similar computationally demanding procedures (see for example Cheung and Erlandsson, 2005). The likelihood ratio statistic between the single state and 2 state models is 159.97, which is a very large value in this context.

We have also tested the equivalent of the probit specification of turning points via a Markov regime switching model as in (1) but with a time varying transition matrix. This however requires a full data set, as the Markovian property of the underlying regimes does not allow for breaks in the data. An alternative way is to estimate this extended model separately for each sub-sample, which we have also done. Results are similar to those presented using the probit approach but with an overly large fluctuation in the estimated standard errors.

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