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**The Use of Financial Spreads as Indicator Variables:
Evidence for the U.K. and Germany**

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Abstract

There has been growing interest in the use of financial spreads as advance indicators of real activity and inflation. Empirical evidence is marshalled on a range of spreads when these are used in vector autoregressive models of the UK and German economies. It is found that they do have significant information, even after allowing for the effects of other influences upon macro-economic activity.

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Summary

There has been considerable attention paid to the possibility that financial spreads might be useful for predicting cyclical movements in aggregate output. Spreads are thought to contain timely information for a number of reasons, including the sensitivity of spreads to changes in expectations of cyclical changes. Spreads may widen due to anticipated increases in default risk as an economy slows down, or as monetary policy is tightened. It is natural to ask what additional explanatory power financial spreads have for predicting changes in aggregate output when other information, including lagged changes in output and other macro economic variables, are taken into account?

In this paper, empirical models are used to investigate this question with reference to the United Kingdom and Germany. The same methodology is followed for each case. Four financial spreads are used. The first is the long-term credit quality spread, which is the difference between yields on corporate and government bonds of the same maturity. The second is the yield curve, the differential between long and short rates. The final two are both reverse yield gaps. One is defined as the spread between the long-term bond yield and the dividend yield, the other is between bond yields and the earnings yield. The empirical tests consist of first estimating a robust and well-fitting Vector-Auto Regression (VAR) model of the economy, including output, the output deflator, and other macrovariables (six are used in total). Each model is then augmented by the four spreads, and a ten-equation VAR is estimated for each country. A variety of tests of the information contained in the spreads shows that they clearly contribute significantly to explaining changes in activity. In addition, ex-post tests of the predictive properties of the models indicate that the models that include spreads are more accurate in anticipating the recent cyclical downturn that occurred in the United Kingdom and Germany than the VAR models that do not include spreads.

The paper concludes that, on the basis of these tests, financial spreads may have an important empirical role in accounting for cyclical movements in aggregate activity.

1. Introduction

There has been increasing attention paid recently to indicator models for the prediction of real activity and inflation. This branch of forecasting has very long antecedents of course, beginning with the pioneering work on business cycle prediction at the National Bureau by Burns and Mitchell(1946) using a quantitative methodology which has been applied more or less continuously since, most recently by Moore, Zarnowitz and others (see Zarnowitz and Moore (1991)). In many countries, government agencies and others derive and monitor leading and concurrent indicators for predicting output. These exercises frequently select variables which are judged to correlate with current or lagged output, and are combined in some form to provide indices which - on the basis of past behavior - can have predictive power. (For an example, see the CSO's index of leading indicators for the UK. (CSO 1983)). Other, related, work derives indicators which are useful for predicting inflation, including joint models of output and inflation. Examples of the latter are given in Artis et.al. (1993), Davis and Henry(1992), and in Davis, Henry, and Pesaran (1993).

A major reason for this renewed interest in indicator methods is the perceived failure of structural macro - economic models in many countries to forecast the recent falls in, and indeed the subsequent increases in, output. Structural models are widely thought to be conspicuously bad at predicting turning points. These considerations are at the centre of the influential work by Stock and Watson (1989), whose indicator model is expressly designed to predict turning points. This is also one of the concerns of the present work, and towards the end of the paper the results of an ex-ante forecasting exercise is reported, which shows that our indicator model may be particularly useful in capturing turning points. More generally, indicator models are "non-structural" approaches to prediction. So where monetary indicators, for example are used, they are not based on an explicit model of the transmission mechanism of monetary policy. Rather, they are--as their description implies--indicative of monetary conditions--a looser idea taken to mean a "generally correlated with" rather than being based on e.g. specific transmission mechanisms of changes in interest rates or monetary aggregates upon particular categories of spending. This avoidance of specific structural hypotheses may indeed be an advantage of indicator models since it avoids the strictures of Sims (1980), who argued that structural models applied "incredible" identification restrictions.

Much new work on indicator models has focussed on the possibility of there being advance information in financial markets, so that financial asset prices may give early warnings of changes in activity and inflation. Stock market prices, and the yield curve - the spread between the rates on long and short government debt - are fairly well known examples. But recent work on indicator properties of spreads has employed a range of different financial spreads, and there have been many encouraging results reported and it is from these that the present study starts. Stock and Watson (1989) is a seminal work in this area, and Friedman and Kuttner (1991) is a recent example in a similar mould.

The aim of the present paper is not to give new theoretical results but to provide an extensive empirical evaluation of spreads as indicators, the

aim being to comprehensively test them to predict output and inflation. The tests are done using non-structural Vector-Auto Regressive (VAR) models, which are initially quite large (six equation models are used), so that a significant amount of information is used to predict output before including the financial spreads. The tests are thus directed at whether the financial spreads add to the explanatory power of what is already a fairly extensive model. According to the empirical results reported here, for both Germany and the UK, the answer is that the financial spreads do have significant explanatory power. Thus, financial spreads appear to have information about the future behavior of output and inflation, over and above that contained in other macro economic variables.

Before describing these empirical results, the paper first discusses a-priori reasons for using financial spreads as indicators of changes in both real and nominal aggregates. Then Section III presents the empirical results for the UK and Germany, and Section IV concludes.

II. Financial Spreads

A spread is the difference between secondary market yields on financial assets. Generally speaking, spreads exist between the returns on financial assets because the assets are imperfect substitutes for each other. These spreads depend, in turn, on differences in liquidity, maturity, and risk of the different assets, modified by taxes and any portfolio regulations. For the present purpose, a key consideration is whether there are cyclical influences on these patterns of substitutability. Tax effects will generally not be cyclical for example, but, on the other hand, default risk clearly can be, as will effects on spreads originating from changes in monetary policy. It is precisely because spreads may have such cyclical determinants that they may be useful as leading indicators.

In the research reported in this paper, a wide set of spreads is used. The reason for using such a wide set is to have an extensive coverage as well as extending applications made for other countries - most particularly the USA (see especially Stock and Watson (op.cit)) - to the countries we study. The set comprises the long term credit quality spread, the yield spread, and two reverse yield spreads. Before describing empirical results, we describe these financial variables more fully and advance reasons for thinking why they might be useful for predicting inflation and output.

The first spread is the long term credit quality spread. This is the difference between yields on private and government bonds of the same maturity, and is used primarily because it may signal default risk. Default risk occurs when there is the possibility of not collecting coupon and principal as promised in a debt contract, so the lender demands a higher expected return in compensation. An indicator of the market's assessment of default risk is the differential between the yield on a private bond and a public bond of the same maturity, callability and tax features. Changes in this spread signify increases in market expectation of defaults, which may

itself be correlated with downturns in economic activity. Also this spread may widen when monetary policy is tightened, if firms shift their credit demands to the bond market. A question remains whether other indicators might capture this effect better, and one possibility is that a monetary aggregate might serve this purpose. But these have generally proved too unstable to be useful in many countries and this again proved the case for our tests on the UK although we do find some support for a broad aggregate in the German case.

The second indicator is the yield curve, the differential between long and short rates. The interpretation advanced here is that a declining yield curve signals a future slowdown in economic activity, because when short rates are relatively high this indicates restrictive monetary policy. Also the yield curve will tend to invert if expected inflation and activity fall. ^{1/} Finally, a shift in the yield curve might influence the attractiveness to banks of purchasing securities and making loans, which could--on a monetarist view--boost money and hence activity and inflation (Laurent (1988)). ^{2/}

The final set of spreads employed are reverse yield gaps, reflecting the difference in yield between bonds and equities. We use two here; that between the long term bond yield and the dividend yield, and the spread between bond yields and the earnings yield. The mechanisms implicit in these operate via agency costs of lending, which Bernanke and Gertler (1989) suggest are related to firms' net worth. Thus, if declining equity prices following a monetary tightening reduce net worth, then this in turn may make it more difficult for firms to obtain credit, because of increased moral hazard and adverse selection in lending to firms with low net worth. (There could also be effects from the anticipation of lower earnings or dividend growth in a recession, which need not be a direct manifestation of the monetary transmission mechanism).

The aforesaid are some reasons for expecting that spreads may be useful predictors, but the question of how useful they actually are is, of course, an empirical one. So the rest of this paper is given to evaluating their

^{1/} They are less consistent with a real business cycle model where the marginal product of capital equals the interest rates and where persistent productivity shocks drive the business cycle. In that case, a positive productivity shock would lead to a high marginal product of capital, which would decline over time as investment and output increase.

^{2/} It is important to add that yield curves may also have an important role in forecasting inflation (Mishkin (1989)), Browne and Manasse (1989)). The differential equals the expected change in inflation, if the expectations hypothesis applies (i.e. if the long term rate is the weighted average of present expected short term rates), there is no imperfect substitutability between issues of different maturities and the real rate is expected to be constant.

empirical value, using Vector Autoregressive (VAR) models. Before giving the results we give first a brief account of the methods we use.

III. Empirical results

This section reports tests on the information contained in financial spreads in accounting for the behavior of output and inflation. The examples used are the UK and Germany. For each country exercise the same methodology is used, the principal idea being to test whether spreads have significant explanatory power in equations which include other macro variables useful for predicting output and inflation. These other variables include the real exchange rate, monetary policy, measures of the fiscal stance and the external account. The question posed is whether spreads add to the explanation of inflation and output once the contribution of these other influences have been allowed. The procedure followed starts by testing the orders of integration of all the variables used. We find that some of the results here are ambiguous. So we first estimate models by first differencing non stationary variables. Tests on spreads then use a set of ten dynamic difference equations (a VAR) which is estimated using all variables in $I(0)$ form. A second exercise provides examples which include co-integration relationships between the $I(1)$ variables, and the tests here use a Vector Error Correction Model (VECM). Apart from the regression based tests of the information in financial spreads, further tests of ex-post prediction properties of the models are reported as well as their estimated variance decompositions. Details of some of the econometric issues involved are given in the Appendix, and the full regression results are relegated to the Appendix.

In all the exercises reported here, the data are quarterly and seasonally adjusted. The full sample for the UK is 1968 Q1 to 1991 Q1. The variables are real GDP, the GDP deflator (PGDP), the real exchange rate (RXR), the current balance (BAL) (normalized on nominal GDP), the PSBR (also normalized in the same way), and the three month interbank rate (R). In addition four financial spreads are used, as described above; (i) the long-term credit quality spread--yield on corporate bonds in the secondary market less 20 year government bond yield (CQS), (ii) the term structure or yield curve--the government bond yield in the secondary market less a short rate (this is taken to be the 3 month interbank rate) (YC), (iii) the reverse yield gap (earnings)--the yield on government bonds less the earnings yield on equities as measured by the FT-500 index (RYGE) and (iv) the reverse yield gap (dividends)--the yield on government bonds less the dividend yield on equities (RYGD).

For the empirical work on Germany the full sample is 1974 Q2, to 1992 Q2. (Data were obtained from the BIS macroeconomic database). The variables refer to West Germany and are real GDP, the GDP deflator (PGDP), the real exchange rate (RER), the current balance (BAL) (normalized on nominal GDP), the public sector deficit PSD (also normalized in the same way), and the one month euro-DM rate (R). In this case we used three financial spreads (i)

the long-term bank bond spread--the yield on bank bonds in the secondary market less government bonds (BBS); (ii) the term structure or yield curve differential--the government bond yield in the secondary market less a short rate (the 1 month euro-DM) (YC); (iii) the reverse yield gap (dividends)--the yield on government bonds less the dividend yield on equities (RYG). Given its key role as an indicator of German monetary policy, we also assess the usefulness of M3 itself. Note that the data period covers a single exchange rate regime--floating--and monetary policy strategy, of targeting growth in monetary aggregates. Problems of regime shifting should hence be avoided.

The empirical results are described next, starting with the UK.

1. United Kingdom

a. Time Series Tests of the Variables

Tests of the levels of integration of all the model variables are shown in Table 1.

Whilst many of these tests give straightforward results, some are ambiguous. Thus real interest rates are apparently I(1) which might appear somewhat surprising. (King et al (1991) report a similar result for the USA). The financial spreads appear I(1) also. YC in particular deserves further mention. This finding for YC is not very obvious from the results in the table, but it appeared from a number of ADF tests that this variable could be non-stationary. Its spectrum also clearly showed non-stationarity. The decision taken was that each of these variables could be treated as I(1), though clearly YC is borderline. There is a final ambiguity, however, with the price deflator. The Dickey-Fuller tests for this variable are again not clearcut. Treating it as I(1), as we do here, a VAR can be estimated in first differences. Later we consider the effects of treating the variable as I(2) which is a result also consistent with the Dickey-Fuller tests.

Table 1. U.K. Data: Tests for stationarity

	level 1/		first difference 2/	
	DF	ADF (4)	DF	ADF (4)
log GDP	-2.0	-1.4	-10.4	-6.6
log PGDP	-1.2	-1.8	-4.5	-2.6
BAL	-2.8	-2.1	-13.6	-9.2
PSBR	-3.8	-2.6	-12.9	-8.2
RXR	-2.5	-3.0	-8.0	-6.6
R	-2.6	-3.2	-7.8	-6.0
CQS	-2.21	-2.6	-8.7	-4.1
YC	-2.8	-3.6	-8.0	-4.2
RYGD	-3.0	-3.0	-9.0	-7.7
RYGE	-2.5	-3.3	-7.5	-6.4

1/ With trend; critical value -3.5.

2/ Without trend; critical value -2.9.

b. Estimation Results

In estimating the VAR model, the Akaike Information Criteria (AIC) is used to decide on the maximum lag length to employ. This suggests that a lag of four quarters is sufficient, the LR test gives $\chi^2(100) = 75.21$ which would not lead to the rejection of the null. A VAR with lags of four quarters on all variables, including lagged dependant variables, was chosen as the basic model.

The resulting OLS version of the model is given in Table A in the Appendix, which summarizes results for the parsimonious version of the model. An LR test for the whole model where zero restrictions have been applied gave $\chi^2(286) = 300.1$. This provides strong support for the exclusion restrictions imposed in this parsimonious version of the model. (A Seemingly Unrelated Regression (SUR) version of this model gave very similar results and is not repeated here) Finally, a block exogeneity test--which is essentially a multivariate generalization of the Granger-Sims test for causality--was done on a subsystem of the model obtained by dropping the equations for spreads. This tests for the exclusion of the spreads from the remainder of the macroeconomic model. The LR test for this gave $\chi^2(32) = 66.3$, which clearly rejects the null of exclusion. Further statistical tests for autocorrelation, normality and heteroscedasticity are all highly satisfactory; in addition the CUSUM and CUSUM squared tests showed that recursive residuals always remain in the 5 percent confidence interval, and the recursive coefficients are stable.

Finally a set of predictive tests were done on the preferred model. These first included orthodox parameter stability tests, which are ex-post tests of model stability. The table reporting the regression results gives tests of parameter stability, where we separate the sample to leave 11 1/2 years (46 quarters) on which to do this test. This is an extremely long period given that the sample is only 87 quarters. The tests here are generally acceptable, though as the explanatory power of the equations is not high, this is perhaps not as positive a result as it might appear. However, in this model, the root mean square errors of forecast for real growth and inflation are each only about 1% over an 8 quarter forecast horizon which small.

Having established that there are strong econometric grounds for including financial variables in a model of output and prices, the final step evaluates the quantitative effects of these variables. This orthogonalizes the estimated VAR model to identify the effect of shocks to the innovations in the X_t variables by adopting a "standard" approach, using a Choleski decomposition. Identification then uses the Sims's triangular ordering.(see the Appendix for details)

A well known problem with the Sims triangular ordering is that it is arbitrary, and most users normally provide impulse and variance decomposition for a set of alternative orderings. We do that here, and have computed results when the four financial spreads come last in the set of ten

variables and, as an alternative, when they are first. In our case the results did not vary much, so only the first set of results are commented upon further. Even so, with a model of this sort there is a large amount of output generated by this exercise: ten equations, subject to ten different shocks gives 100 different solutions. So to save space only the response of $\Delta LGDP$ to shocks in the innovations to the spreads is commented on. In summary these show that shocks to ΔYC account for about one percent of the variance in $\Delta LGDP$. A shock to ΔCQS on the other hand accounts for about 2.5 percent of the variance of $\Delta LGDP$. The other two spreads have relatively larger effects on output variance, averaging 8 percent and 4 percent respectively. Hence, it appears that the spread contribute in a small but significant way to the explanation of the movements in output.

c. Co-integration and identification

This section provides empirical results of a rather different nature compared to the model just reported, this time using co-integrating relations between the variables where these exist. A subset of the variables is used: the level of output (GDP), the price level (PGDP), and the real exchange rate (RXR). Only two financial spreads are included; the credit quality spread (corporate less safe rate, CQS) and the yield spread, (long minus short yields on Government bonds, YC).

First, we return to the evaluation of the orders of integration for variables shown in Table 1. As we have already noted, while some of these results are straightforward, others are not. CQS, YC and PGDP come in the latter category. The yield curve variable (YC) is even more border line. The ADF(4) results suggests it is stationary, whereas the DF implies that it is not. Finally the PGDP variable also appears I(1), according to the DF statistic although the ADF(4) (and augmented DFs at other lags) does not support this conclusion. There are ground therefore for treating this price variable as I(2).

These decisions are not unambiguous. It is clear that others could be made, leading to alternative specifications for the VECM. So in what follows we report on one version; where PGDP is taken to be I(2), CQS treated as I(1) and YC I(0).

(1) Co-integration Analysis

The co-integration tests then proceed with a set of three I(1) variables: output, inflation (DLPGDP) and the real exchange rate, plus the real interest rate and the two spreads which are treated as I(0) (by differencing CQS). The LR test of the number of cointegrating vectors suggests that there are probably two distinct vectors (LR -20.19 as compared with a 95% significance level of 15.4). These vectors estimated by the Johansen maximum likelihood method are shown next.

Table 2. Co-integrating Vectors

DLPGDP	LGDP	RXR
-1.00	3.94	-9.47
-0.78	-1.00	3.39

While we do not think it is possible to given a "structural" interpretation to these relationships, nonetheless the first vector is consistent with a relationship between inflation and the level of output (positively) and the real exchange rate (negatively). The second vector on the other hand, can be interpreted as a long run demand relationship, with higher inflation raising demand, and higher demand being associated with an increase in the real exchange rate.

(2) VECM

Estimating dynamic equations for the three I(1) variables in the system then gave the results reported in Table 3. These estimates are two-step error correction equations, using the results for the cv's from (i) above, where RES1 are the residuals for the first vector, RES2 those for the second.

Table 3. Vector Error Correction Model
(Sample 1968 Q3 - 199 Q1)

Equation	$\Delta LGDP$		$\Delta \Delta LPGDP$		ΔRXR	
ALGDP(-1)	-0.21	(2.35)	-7.66	(0.72)	0.28	(0.84)
$\Delta \Delta LPGDP(-1)$	-0.002	(1.95)	-0.49	(4.33)	0.001	(0.32)
$\Delta RXR(-1)$	-0.05	(1.60)	-0.48	(0.14)	0.09	(0.87)
DCQS	0.002	(0.32)	0.14	(0.25)	0.02	(1.06)
YC	0.001	(2.98)	-0.07	(1.31)	-0.004	(2.07)
RES1(-2)	0.01	(4.34)	-0.28	(3.31)	0.001	(0.51)
RES2(-2)	-0.006	(1.67)	0.07	(1.99)	0.004	(3.41)
R ²	0.53		0.34		0.20	
DW	1.86		1.95		2.03	
LM(4)	7.76		5.29		2.30	

These results are quite encouraging. At least one vector is highly significant in each of the dynamic equations, and there are significant effects from the yield spread in two of these. Again from this additional test of the informational content of spreads, the conclusion is that they have explanatory power when co-integration relationships between the variables are taken into account.

2. Germany

Since the methods used in this section closely follow that used above, discussion can be quite brief. Again, both stationary and non-stationary versions of the model are reported.

a. Time Series Tests

We start with tests of the levels of integration of all the model variables, which are shown in Table 4.

The results are broadly consistent with the bulk of the variables being $I(1)$, with the exception of the public sector deficit, the yield curve differential and the bank bond spread, all of which are stationary ($I(0)$). We accordingly proceed to estimate a VAR, first by differencing the $I(1)$ variables and treating the entire set as stationary.

b. Estimation Results for the Stationary Case

The approach adopted to estimation is identical to that used in the earlier case of the UK, so is described more briefly. As before in order to test for the effects of spreads and money as indicators, we first need a base model to which such variables may be added. We accordingly first estimated a restricted 6-equation VAR by OLS, with the variables being GDP, prices, the real exchange rate, the short term market interest rate, the balance of payments and the public sector deficit.

The test for lag length again supported restricting the model to four lags (LR = 44 for $\chi^2(60)$).

In general, this model estimated without money or financial spreads fared well. The individual equations are well determined and statistically satisfactory--tests of the absence of serial correlation, normality of errors, evidence against heteroscedasticity and against predictive failure were all acceptable, with the exception of the normality of the residuals in the interest rate equation, and autocorrelation and heteroskedasticity in the price equation. Hence the model provides a fairly stringent test bed to establish whether or not financial spreads add information in a dynamic VAR. Again using a LR test for the whole model restrictions gave $\chi^2(285) = 174.2$. This provides support for the exclusion restrictions imposed in this parsimonious version of the model used here.

Including financial spreads and the money supply to this model, effectively asks whether financial spreads and money add to the explanatory power of the model. The results of such a comparison are given in the Appendix; the first six equations are shown in Table B and the equations for spreads and the money supply are shown separately in Table C. Given that money was added to the equations on the basis of 't' values of at least 1.5, it is notable that the further addition of the spreads often makes money insignificant (notably in the GDP equation, and the interest rate function).

The spreads themselves are significant in virtually all the equations (effects in the PSD equation being the weakest). Again, the statistical performance of the model is broadly satisfactory. A notable feature of the M3 equation is that it is only determined by lags of itself and two of the spreads. (The VAR estimates do not, of course take account of cointegrating long run relationships where traditional determinants of money demand such as income and interest rates might be expected to appear).

Table 4. Germany; Stationarity tests (Sample 74:1 - 90:4)

	levels 1/	ADF	differences 2/	ADF
	DF		DF	
log GDP	-1.6 (-2.2)	-1.2 (-2.1)	-9.5 (-12.6)	-5.9 (-8.2)
log PGDP	-1.9 (-0.0)	-2.1 (0.5)	-8.0 (-13.4)	-3.8 (-6.4)
RER	-1.1 (-1.5)	-1.5 (-1.9)	-6.2 (-6.9)	-4.3 (-4.9)
R	-2.4 (-3.7)	-2.6 (-2.9)	-9.7 (14.0)	-7.2 (-6.5)
BAL	-2.2 (-2.9)	-1.7 (2.3)	-10.8 (13.4)	-6.3 (-8.3)
PSD	-8.3 (-8.3)	-5.4 (-5.3)	-14.9 (-15.6)	-8.0 (-8.3)
log M3	-1.5 (1.2)	-1.5 (1.4)	-7.6 (-8.6)	-5.1 (-5.5)
YC	-4.0 (-4.9)	-3.3 (-3.7)	-13.1 (-15.4)	-10.2 (-7.9)
BBS	-5.1 (-4.2)	-3.8 (-3.7)	-12.3 (-13.7)	-8.7 (-9.7)
RYG	-2.1 (-2.2)	-2.3 (-2.5)	-7.3 (-8.6)	-6.0 (-6.8)

1/ Critical value = -3.2

2/ Critical value = -2.9

Numbers in brackets are for full sample extending beyond 1974-90.

Further tests of restrictions included a test for block exogeneity, which powerfully rejects the exogeneity of the financial spreads and money jointly (the LR test for this gave $\chi^2(55) = 460$). A test for exogeneity of spreads gave $\chi^2(42) = 221$ and money $\chi^2(13) = 358$. Next a system exclusion test was done on the subsystem of the model obtained by dropping the equations for spreads and money. The LR test for exclusion of spreads and money gave $\chi^2(23) = 46.2$ which clearly rejects the null of exclusion, while exclusion of spreads alone was also rejected ($\chi^2(17) = 36.9$). It was less clear that money alone added information to the basic VAR ($\chi^2(6) = 9.3$).

The tests for improvement in explanatory power are thus fairly conclusive and positive, so implying that financial spreads have additional explanatory value for predicting the other variables in X_t . The equations once spreads are included are also successful overall; as before tests for autocorrelation, normality and heteroscedasticity are generally highly satisfactory.

Again in-sample predictive tests on the preferred model include orthodox parameter stability tests, which are reported in the table and show that most of the equations appear highly stable when estimated over subsamples--the exception is the real exchange rate (which could be related to the partial regime switch entailed in the "hardening" of the ERM in the late 1980s).

Having established that there are econometric grounds for including financial variables in a model of German output and prices, and that they seem useful in forecasting, in parallel with the UK study, the next step evaluates the quantitative effects of these variables using a Sim's triangular ordering.

The variance decompositions show a strong effect on the variance of both output and inflation of an innovation to the bank bond spread (11% and 9% of the variance respectively, is accounted for by this spread). The other spreads have smaller effects, but nonetheless are comparable to money in their effect on prices, and exceed it for output. An interesting feature of the results--in line with the "neutrality" of money--is that shocks to M3 appear to impact proportionately more heavily on prices than real output. This is also the case for interest rates.

c. Estimation Results for the Non-Stationary Case

This section reports estimates of a Vector Error Correction Model (VECM) featuring cointegrating effects. In effect, structural relationships (in levels) are incorporated that would otherwise be in the error term. For tractability, we again use a subset of the variables used in the previous section. They are the level of output (GDP), the price level (PGDP), the real exchange rate (RER) and short term interest rates (R). Only two financial spreads are included; the bank bond spread (BBS) and the yield spread (YC).

Again, we return to the orders of integration shown in Table 6. These show BBS and YC to be stationary according to the Dickey-Fuller tests. GDP, the real exchange rate, and the interest rate are shown to be I(1). Finally the PGDP variable also appears I(1), according to the DF and ADF statistics quoted although the ADF(3) does not support this. As in the UK case, there are grounds for treating this price variable as I(2).

In what follows we report on a version of the model; where PGDP is taken to be I(2), but the spreads are treated as I(0). To reiterate what was said in the case of the UK - and which applies equally here - other versions of the VECM based on rival interpretation of the orders of integration could also be estimated. They are not discussed in detail here in the interests of space.

The co-integration tests then proceed with a set of four I(1) variables: output, inflation (DLPDGP), the short rate and the real exchange rate, plus the two spreads which are taken to be I(0). The Johansen procedure indicates the presence of a single co-integrating vector (the LR test gives 63.2 compared to a 95% critical value of 27.1 for a single vector, and rejects the hypothesis of more than one vector). The Johansen co-integrating vector is shown next.

Table 5. Co-integrating Vector.
(normalized on LGDP)

The cointegrating vector			
LGDP	DLPDGP	RER	R
-1.0	-137.6	0.01	0.35

The vector suggests a relationship between inflation and output (negatively), the real exchange rate (positively) and the interest rate (positively). This is broadly consistent with a counter inflation policy by the Bundesbank that associates rising inflation (due to cost pressures) with monetary tightening, and hence low output.

Estimating equations for the four I(1) variables in the system then gave the results for a Vector Error Correction model (VECM) reported in Table 6. These estimates are two-step error correction equations, using the residuals from the cointegrating vector from (i) above (denoted RES(-1)).

Table 6. Vector Error Correction Model
Sample 1974 Q1 - 1990 Q4

Equation	$\Delta LGDP$	$\Delta \Delta LGDP$	ΔRER	ΔR
Constant	0.009(1.2)	0.019(4.3)	-6.4(2.1)	0.73(0.9)
$\Delta LGDP(-1)$	-0.3(2.4)	0.074(1.4)	60.4(1.7)	13.0(1.2)
$\Delta \Delta LGDP(-1)$	-	-0.27(2.4)	-160.4(2.2)	24.6(1.2)
$\Delta RER(-1)$	0.0006(1.4)	-	0.16(1.3)	-
$\Delta R(-1)$	0.004(2.9)	-	-	0.32(2.7)
$RES(-1)$	-0.002(0.8)	-0.006(4.7)	1.9(2.1)	-0.2(1.2)
BBS(-1)	-	0.0068(2.1)	-	-
YC(-1)	0.0033(2.7)	0.002(3.3)	-0.72(1.7)	0.22(1.8)
R ²	0.21	0.64	0.14	0.21
DW	2.25	2.0	1.99	2.1
LM(4)	8.6	2.0	2.18	4.3
PRED(20)	17.0	13.0	30.8	7.4

These results, albeit highly tentative, are again encouraging. There is the evidence here that spreads have explanatory power even when cointegrating relationships between other variables are taken into account.

IV. Forecasting the Recession

The final exercise we report returns to the issue raised in the Introduction; the usefulness of these indicator models in predicting turning points. Both economies have recently moved into recession, the UK in 1990Q2 and Germany in 199[]. So this last test considers how well the models cope with this downturn. It is recognized, of course, that the exercise is a limited one; only the 1990's recession is used. So no general propositions can be established about the performance of these indicator models using only one illustration. But the exercise is nonetheless of interest. As already noted, macro forecasting models generally did not capture this episode.

The same approach is used for each country. Full ex-ante predictions are made over the early part of the recessionary phase using a version of the model estimated on data up to the start of the recession. We then compare the predictions made by the version of the model which does not use financial spreads with that which includes them. For each country we use estimated VARs - i.e. models without co integrating relations - to do the forecasts.

In the U.K. case, predictions are made from the VAR model which is estimated on data up to 1989Q4. The estimation results show that the properties of the model would not differ much if an earlier vintage of the model were used. Predictions from the model from 1990:Q1 to 1991 Q3 are shown in Chart 1. This shows that output growth is predicted to be very sluggish in the first half of 1990, but that it is then predicted to be negative, and there is very slight positive growth in 1991Q2 only before growth falls again. If in 1989 this model had been used to make forecasts, there would have been a clear message from it about an impending recession.

A similar exercise is then done using the German model for the period 1991Q2 to 1992Q2. The results are shown in Chart 2. Three forecasts are shown, that for the basic six equation VAR, the model including the money supply only as a financial indicator, and the full ten-equation model with money and spreads. The main results in Chart 2 show that the spreads model outperforms the more restricted models. It captures the rise in GDP growth year on year followed by a sharp fall, whereas the others assume that growth remains rapid in mid-1992.

The conclusions drawn from such a short exercise must, of course, be tentative. But in this case there does seem to evidence that the use of financial spreads in the VAR models does improve their ability to track downturns.

IV. Conclusions

This paper has considered the empirical evidence that financial spreads have information in accounting, in part, for changes in output and inflation. The assessment has been conducted using non-structural models for both the UK and Germany. But we have taken several approaches to this assessment for each country; one using an $I(0)$ "stationary" model--which extends much similar work on this topic in the US--and an alternative which embodies co-integrating relations. There is, we believe, considerable evidence from both of the approaches illustrated here that financial spreads do contribute information in joint models of output and other macrovariables including inflation. We have also given some tentative evidence that using financial spreads in indicator models improves their performance around cyclical turning points.

Chart 1
United Kingdom
Quarterly Forecast for Real GDP Growth
(using estimates up to 89 Q4)

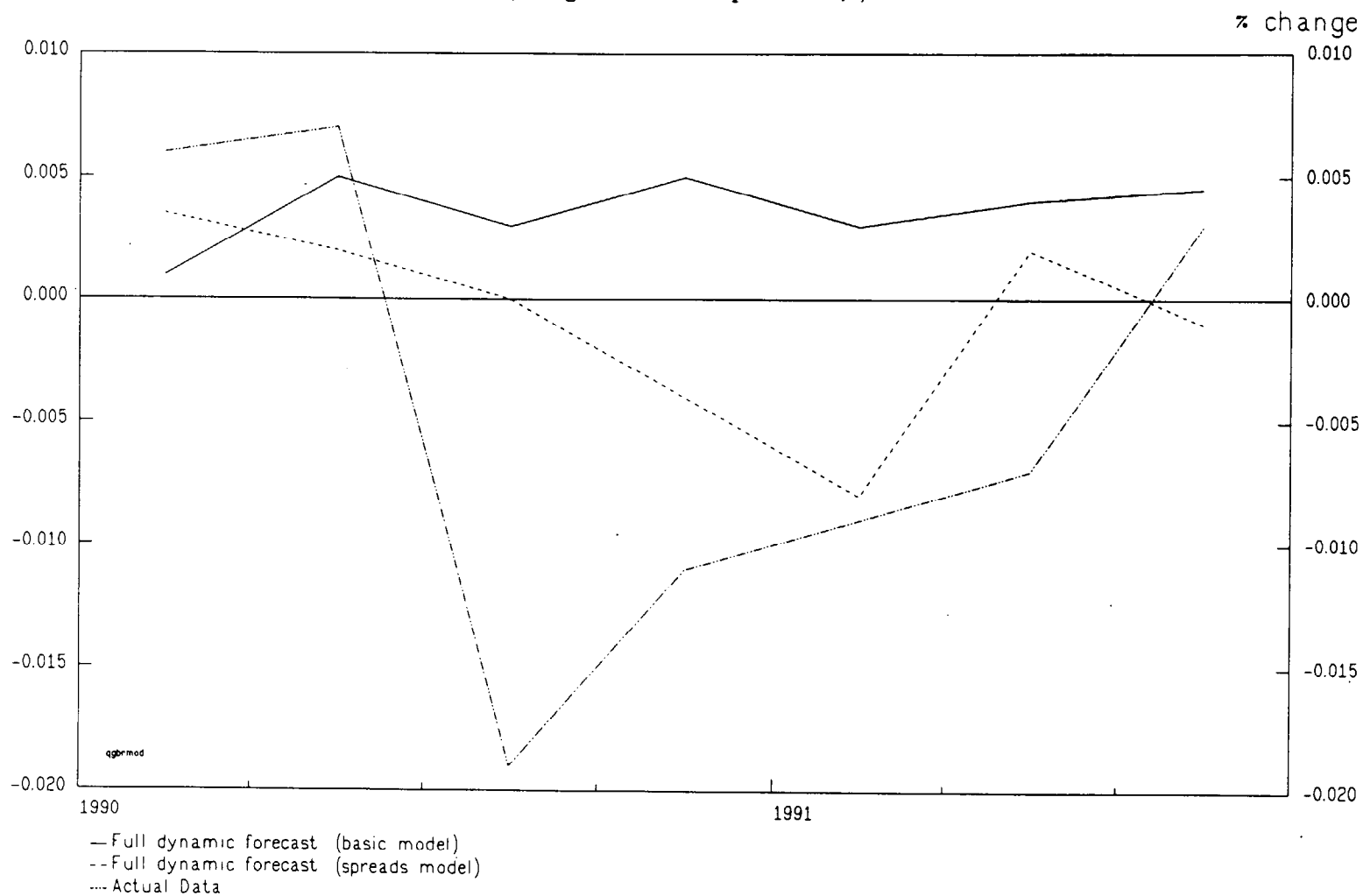
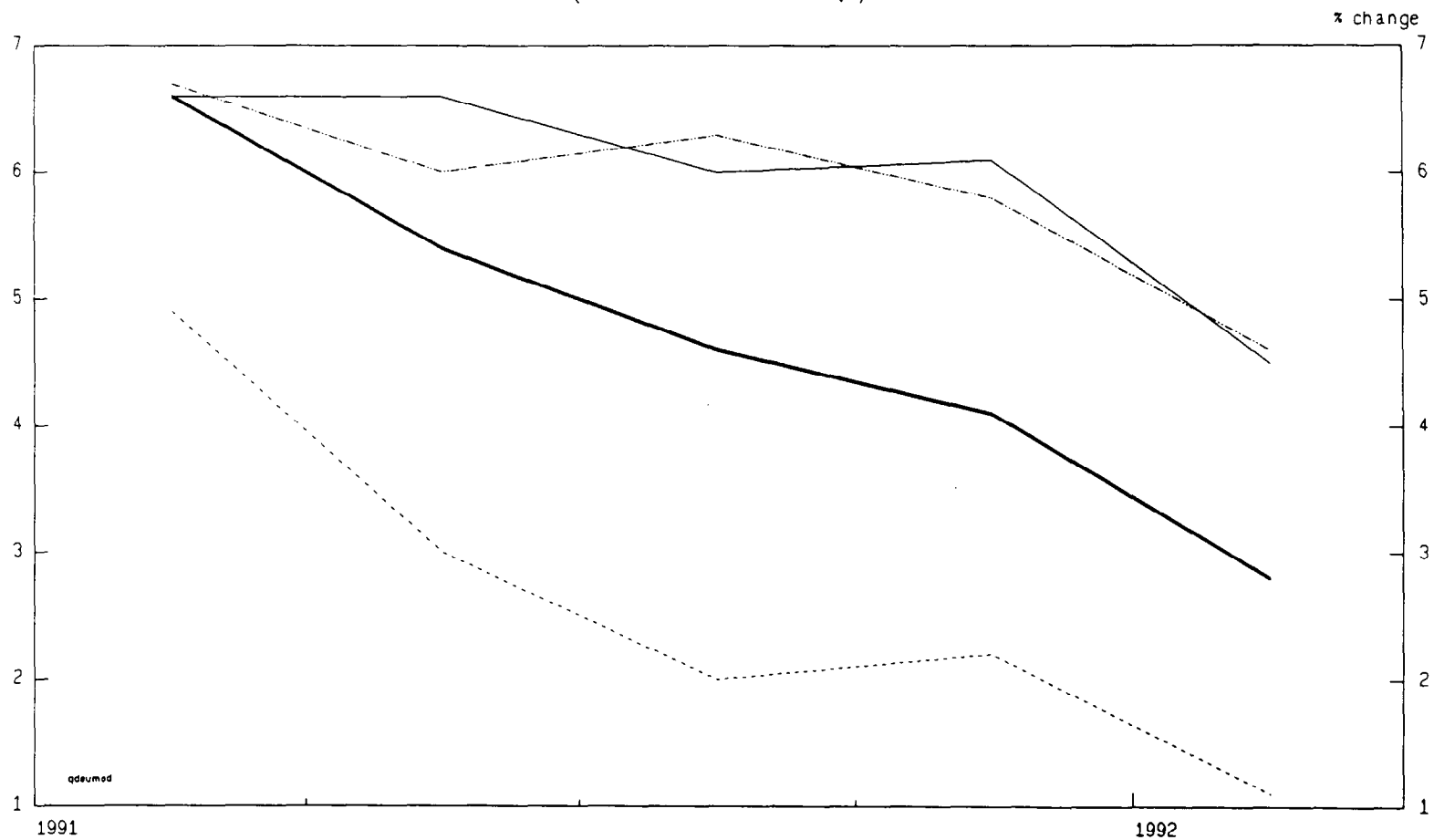


Chart 2
Germany
Quarterly Forecast for Real GDP Growth
(forecast from 1991 Q2)



- Full model dynamic forecast (basic model ex. money and spreads)
- Actual GDP growth
- Full model dynamic forecast (spreads and money model)
- Full model dynamic forecast (money model)

VAR Models: Econometric Issues

The empirical tests reported on here are conducted within the framework of a multi - equation VAR model. In all cases we report the VAR is autonomous, with no distinction between endogenous and predetermined or exogenous variables. However we distinguish two cases, VARs estimated using stationary variables, and Vars using non-stationary variables.

I. VAR Modelling with Stationary Variables

A VAR which treats all variables without regard to endogeneity, as part of a joint process, provided the variables are stationary, may be estimated by single equation procedures in the absence of any restrictions. Otherwise, if the VAR is restricted, an appropriate GLS procedure is necessary (Davis and Henry (1992a)).

An important problem in the multiple equation model arises with its evaluation. To conduct variance decomposition with a VAR leads to the problem of identification. (Sims (1980), Blanchard (1989) Robertson and Wickens (1991).) To describe these issues, consider a vector of a stochastic variables X_t (in our case, these include macroeconomic variables and spreads). A structural (but unknown) model for these may be defined as

$$B(L)X_t = Fd_t + Se_t \quad (1)$$

where B, F and S are matrices, L is the lag operator, and d_t is a set of deterministic variables (such as dummies). The error term e_t , is assumed serially independent, and its covariance matrix $E(e_t e_t') = I$. The reduced form of (1) is

$$\Gamma(L)X_t = Gd_t + \epsilon_t \quad (2)$$

where $\Gamma(L) = B(0)^{-1}B(L)$, and $E(\epsilon_t \epsilon_t') = \Omega_t$. In this form the impulse responses, of X_t following shocks to e_t , cannot be recovered - they are not identified. Equation (2) is obtained by assuming B(.) has roots all outside the unit circle, so that B can be inverted which is equivalent to assuming the variables are stationary. (See Wickens (1992)). In (2) $B(0) \epsilon_t = Se_t$. By inverting $\Gamma(L)$ (2) can be written in a MA form as

$$X_t = H(L)d_t + C(L)\epsilon_t \quad (3)$$

where $H(L) = \Gamma(L)^{-1}G$, and $C(L)^{-1}$.

To analyze the implications of the model, we suppose we have estimated the unrestricted version of (2) as a VAR. The general problem of identification is then to use minimal restrictions sufficient to calculate structural responses of the dependent variables to shocks in e_t using the estimated VAR.

As $\delta(X_{t+s})/\delta e_t = C_s B(0)^{-1} s = C_s R$, and R is of dimension $n \times n$ for an n^{th} order vector X_t , identification--necessary to evaluate these partials-- requires n^2 restrictions. The constraint

$$\begin{aligned} E\epsilon_t \epsilon_t' &= \Omega \\ &= E(R e_t e_t' R') = R R' \end{aligned}$$

given $n(n+1)/2$ of these. The remainder can be obtained using the Sims triangular ordering of the B matrix (i.e. assuming it is lower triangular), or the Blanchard Structural Vector Autoregression (SVA). Using either of these it is possible to recover the structural responses. Examples of the Sims method are provided in Section 4.

II. Non Stationary Variables

If variables are non-stationary but are differenced to induce stationarity and the previous methods used, important information is lost. Moreover, if co-integration exists between sets of the variables, then the estimated VAR in $I(0)$ variables will be inefficient. An appropriate method is to estimate a Vector Error Correction Model, or VECM. (See King et al (1991)). Thus from the reduced form of equation (2) above, by reparameterizing we get

$$A(L)\Delta X_t = A X_{t-1} + G d_t + \epsilon_t \quad (4)$$

where $\Gamma(L) = A(L)(1-L) - AL$.

If there are r co-ordinating vectors, this implies the rank of A is r , and $A = \alpha\beta'$ in the Johansen terminology, where β is the $r \times n$ set of co-integrating vectors, and α the $r \times n$ matrix of factor loadings. The VECM is then

$$A(L)\Delta X_t = \alpha V_{t-1} + G d_t + \epsilon_t \quad (5)$$

where $V_t = \beta' X_t$, is the set of r co-integrating residuals. Equation (5) is then expressed entirely in terms of $I(0)$ variables, and incorporates the information concerning the presence of co-integrating vectors. Identification and the interpretation of the policy properties of the model are more tricky in this case. Given r co-ordinating vectors there will be $(n-r)$ Common Stochastic Trends (CSTs), and the problem then is one of identifying the effects of shocks to the CSTs. King et al (op cit) use a mixture of co-integration and a triangularization of the combinations of CSTs to achieve this, and we provide illustrations of this method in section 4.

Table 1. Summary of VAR Equations Including Spreads, Estimated by OLS
(Sample 1969 Q2 - 1990 Q4)

Equation	$\Delta \log \text{GDP}$	$\Delta \log \text{PGDP}$	ΔBAL	ΔPSBR	ΔRXR	ΔR	ΔYC	ΔCQS
Lagged Regressions								
$\Delta \log \text{PGDP}$	** 1/	**	* 2/	**	**	**	*	**
$\Delta \log \text{GDP}$	**	**	**	**	0 3/	**		
ΔRXR	**	*	**			**	**	
ΔR	**		*	*	0		**	**
ΔBAL	**							
ΔPSBR			**		*	**		
ΔCQS	**	**		*	**	*	**	
ΔYC	**	*	*		*	**		**
ΔRYGD		*			*	**	*	
ΔRYGE	**	**		**	*	**	*	**
R^2	0.65	0.68	0.37	0.35	0.39	0.44	0.32	0.36
PRED(46)	39.0	33.0	30.0	86.0	58.0	27.0	28.0	58.0
	ΔRYGE	ΔRYGD						
$\Delta \log \text{PGDP}$								
$\Delta \log \text{GDP}$	**	**						
ΔRXR								
ΔR	**	**						
ΔPSBR								
ΔCQS	**	**						
ΔYC								
ΔRYGD	**							
ΔRYGE	**	*						
R^2	0.58	0.3						
PRED(46)	32.0	41.0						

1/ ** signifies at least one lagged value significant at 5 percent.

2/ * signifies that at least one lagged value is significant at 10 percent.

3/ 0 signifies variables are insignificant.

Table 2. VAR Equations with Financial Spreads, 1974 Q1 - 1990 Q4

$\Delta \ln GDP$		$\Delta \ln PGDP$		ΔRER		ΔR		ΔBAL		PSD	
const	0.012 (3.2)	const	0.004 (2.1)	const	-0.5 (0.36)	const	0.037 (0.1)	const	0.00008 (2.0)	const	0.15 (2.2)
$\Delta \ln GDP(-1)$	-0.42 (3.8)	$\Delta \ln GDP(-3)$	-0.07 (1.5)	$\Delta \ln GDP(-1)$	62.9 (2.0)	$\Delta \ln GDP(-1)$	10.4 (1.1)	$\Delta \ln GDP(-1)$	-0.0012 (1.1)	$\Delta \ln GDP(-1)$	-4.2 (2.7)
$\Delta \ln GDP(-4)$	0.16 (1.6)	$\Delta \ln PGDP(-1)$	-0.32 (2.9)	$\Delta RER(-1)$	0.34 (2.5)	$\Delta \ln GDP(-2)$	12.9 (1.5)	$\Delta \ln GDP(-2)$	-0.0037 (3.1)	$\Delta \ln GDP(-2)$	-3.2 (1.8)
$\Delta \ln PGDP(-2)$	-0.56 (2.4)	$\Delta \ln PGDP(-2)$	0.14 (1.3)	$\Delta RER(-3)$	0.14 (1.2)	$\Delta BAL(-2)$	-2060 (1.9)	$\Delta \ln GDP(-3)$	-0.0036 (3.1)	$\Delta \ln GDP(-3)$	-5.0 (3.4)
$\Delta \ln PGDP(-3)$	-0.66 (2.9)	$\Delta \ln PGDP(-3)$	0.08 (0.7)	$\Delta RER(-4)$	-0.26 (2.0)	$PSD(-1)$	-1.02 (2.1)	$\Delta \ln PGDP(-3)$	-0.0065 (3.1)	$\Delta \ln PGDP(-1)$	5.1 (1.6)
$\Delta RER(-1)$	0.0002 (0.6)	$\Delta \ln PGDP(-4)$	0.096 (0.9)	$\Delta R(-4)$	-0.46 (1.1)	$\Delta \ln M3(-4)$	13.3 (1.1)	$\Delta \ln PGDP(-4)$	-0.0067 (3.5)	$\Delta \ln PGDP(-2)$	3.6 (1.2)
$\Delta R(-4)$	-0.000009 (0.7)	$\Delta RER(-2)$	0.0005 (2.6)	$\Delta BAL(-1)$	-7427 (1.8)	$\Delta RYG(-1)$	0.26 (1.8)	$\Delta RER(-4)$	-0.0000068 (2.1)	$\Delta \ln PGDP(-3)$	2.0 (0.6)
$\Delta BAL(-1)$	-42.9 (3.2)	$\Delta RER(-4)$	-0.0005 (2.4)	$\Delta BAL(-2)$	7336 (1.8)			$\Delta R(-1)$	0.000028 (2.2)	$\Delta \ln PGDP(-4)$	4.3 (1.4)
$\Delta BAL(-2)$	-42.6 (3.1)	$\Delta R(-2)$	0.0023 (3.2)	$PSD(-1)$	-4.6 (2.4)			$\Delta R(-4)$	-0.000014 (1.1)	$\Delta RER(-1)$	-0.011 (2.0)
$\Delta \ln M3(-3)$	0.1 (0.7)	$PSD(-3)$	0.049 (1.6)	$PSD(-2)$	-2.2 (1.2)			$\Delta BAL(-1)$	-0.43 (3.4)	$\Delta RER(-4)$	0.005 (1.2)
$YC(-1)$	0.0015 (1.7)	$PSD(-4)$	0.0027 (1.0)	$PSD(-3)$	-5.3 (2.6)			$PSBR(-4)$	0.00012 (2.2)	$\Delta R(-1)$	-0.026 (1.3)
$BBS(-2)$	0.021 (2.5)	$\Delta \ln M3(-1)$	0.089 (1.4)	$PSD(-4)$	5.5 (2.9)			$\Delta \ln M3(-1)1$	0.0026 (2.1)	$\Delta BAL(-2)$	-422 (2.4)
$BBS(-3)$	0.013 (1.2)	$YC(-1)$	-0.00078 (1.9)	$\Delta \ln M3(-1)$	76.2 (1.6)			$YC(-2)$	-0.000019 (1.5)	$\Delta BAL(-3)$	-466 (2.4)
$BBS(-4)$	-0.024 (2.6)	$BBS(-1)$	0.0062 (1.8)	$\Delta \ln M3(-4)$	64.5 (1.5)			$YC(-4)$	0.000019 (1.7)	$\Delta BAL(-4)$	-287 (1.7)
		$\Delta RYG(-4)$	-0.0011 (1.3)	$BBS(-2)$	4.5 (1.9)			$\Delta RYG(-1)$	-0.000029 (1.4)	$PSD(-2)$	-0.13 (1.5)
				$BBS(-4)$	-3.8 (1.4)			$\Delta RYG(-3)$	0.00002 (1.1)	$PSD(-3)$	-0.14 (1.9)
				$\Delta RYG(-1)$	-0.73 (1.3)					$PSD(-4)$	0.55 (7.7)
				$\Delta RYG(-2)$	0.96 (1.8)					$BBS(-4)$	0.11 (1.1)
R^2	0.4		0.35		0.39		0.22		0.33		0.74
SE	0.008		0.004		2.5		0.74		0.000075		0.099
DW	2.4		2.2		2.0		1.6		2.1		1.5
LM(4)	8.4		15.6		6.1		3.6		4.7		4.7
RESET(1)	1.7		0.02		1.5		0.2		0.1		0.1
NORM(2)	0.2		1.4		1.1		63.1		0.1		2.7
HETERO(1)	1.1		5.4		2.3		0.0013		0.2		2.3
PRED(20)	12.2		11.5		33.4		7.2		18.5		11.2

Table 3. VAR Equations for M3 and Spreads, 1974Q1 - 1990Q4

$\Delta \ln M3$		YC		BBS		ΔRYG	
const	0.011 (5.7)	const	0.81 (3.6)	const	-0.1 (1.6)	const	0.32 (2.0)
$\Delta \ln M3(-3)$	0.18 (1.6)	$\Delta \ln GDP(-1)$	-17.7 (2.3)	$\Delta \ln GDP(-1)$	2.1 (1.4)	$\Delta \ln GDP(-2)$	-9.4 (1.2)
BBS(-1)	0.0087 (1.3)	$\Delta \ln GDP(-2)$	-17.3 (2.0)	$\Delta \ln PGDP(-1)$	6.7 (1.8)	$\Delta RER(-3)$	-0.06 (2.3)
BBS(-2)	0.0095 (1.2)	$\Delta \ln GDP(-3)$	-15.0 (1.9)	$\Delta \ln PGDP(-3)$	4.9 (1.5)	$\Delta R(-1)$	0.32 (3.4)
BBS(-3)	0.011 (1.4)	$\Delta RER(-1)$	0.097 (3.4)	$\Delta \ln PGDP(-4)$	5.7 (1.9)	$\Delta R(-3)$	-0.19 (1.9)
BBS(-4)	-0.017 (2.4)	$\Delta RER(-4)$	-0.056 (2.0)	$\Delta \ln M3(-3)$	3.6 (1.9)	PSD(-4)	-0.8 (1.9)
$\Delta RYG(-1)$	-0.0035 (2.7)	PSD(-4)	-0.6 (1.4)	$\Delta \ln M3(-4)$	-2.2 (1.1)	$\Delta RYG(-2)$	-0.13 (1.0)
$\Delta RYG(-2)$	-0.0041 (3.1)	$\Delta \ln M3(-2)$	-17.2 (1.6)	BBS(-1)	0.58 (5.8)		
		YC(-1)	0.68 (6.3)	$\Delta RYG(-1)$	-0.03 (1.4)		
		YC(-2)	0.35 (2.8)				
		YC(-4)	-0.12 (1.3)				
		$\Delta RYG(-4)$	-0.4 (2.6)				
R^2	0.35		0.83		0.59		0.15
SE	0.0068		0.63		0.12		0.6
DW	2.3		2.2		2.1		2.1
LM(4)	7.3		2.8		5.5		1.4
RESET(1)	6.4		0.8		1.0		0.1
NORM(2)	3.1		4.6		1.9		1.0
HETERO(1)	0.2		3.4		4.5		0.004
PRED(20)	18.4		11.8		24.7		24.8

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