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# The Information Content of Interest Rate and Stock Market Volatility for Predicting Business Cycles in Probit Models †

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## Abstract

We extend the finding of Estrella and Mishkin (1997, 1998) that financial variables, esp. share returns and the yield curve, are useful to predict recessions toward including interest rate and stock volatility. This hypothesis was examined empirically for the US, Germany and Japan, both in-sample and out-of-sample. Instead of using nominal stock returns as in Estrella and Mishkin, we used real returns, because economic activity is better measured by real magnitudes. In-sample, the inclusion of interest rate volatility proved useful for all three countries, esp. for nearby prediction horizons. Stock volatility was informative in the short run for the US only. We interpreted this differing importance of stock and interest rate volatility as reflecting the firms' differential financial structure in these countries. The out-of-sample evidence for the US and Germany showed that financial volatility information added to better predicting the future state of the economy. The emergence of option markets, and hence of implied volatility, may give still better signals to predicting recessions in the future. For now, lack of data prohibit to evaluate quantitatively financial option volatilities as recession indicators.

**JEL-classification:** E32 ; E44 ; C25

**Keywords:** Business cycles, stock market volatility, interest rate volatility, probit model

# 1. Introduction

Accurate forecasts of business cycles are extremely important for many economic decision-makers. Policymakers need forecasts for proposing national budgets or when implementing a monetary policy. Businessmen often rely on such forecasts in order to schedule optimal production plans. Recent experiences, however, show that large forecasting errors occurred when forecasts were based solely on structural real (macro-economic) relationships (Andersen, 1997). In this respect, information signals from financial markets have proven their usefulness to enrich the information set of economic outlook forecasters.

Asset prices are commonly believed to absorb all relevant public information. Furthermore, due to this efficient information processing ability, not only facts about current micro- and macro-economic variables are already discounted into the prices. Also expectations about economic variables are implicitly captured in asset prices. Fairly recently, business cycle analysts have gained interest in financial market variables as (additional) predictors of recessions. Indeed, as Chen (1991) argues, since financial assets are claims against the output of the economy, changes in the macro-economy are reflected in the financial opportunity set.

There is mounting evidence that business cycles are affecting expected bond and stock returns. Chen, Roll and Ross (1986), Keim and Stambaugh (1986), Fama and French (1989), Fama (1990a), Schwert (1990) and Chen (1991) all have shown that fluctuations in the level of economic activity are an important determinant of stock market performance. Fama and French (1989) demonstrated that expected excess continuous returns (i.e. returns net of the one month Treasury bill rate) on both common stock and long-term bonds contain term premiums (difference between the AAA yield and the one-month bill rate) that have a similar short term business cycle pattern. On the other hand, the dividend yield and the default spread (difference between the yield on the market portfolio of corporate bonds and the yield on AAA bonds with an average maturity of over 10 years) are related to long run business episodes that may span several business cycles. Combining these results, expected returns were found to be lower in times of expansion and higher when business conditions are weak[1].

[1] Consumption smoothing is a common feature of the intertemporal asset-pricing models of Merton (1973), Lucas (1978) and Breeden (1979) and may account for the negative correlation between expected return and business conditions. These models predict that consumption depends on wealth rather than current income. When income is relatively high, investors will smooth consumption into the near future by saving more. Ceteris paribus, higher desired savings lead to lower expected security returns. Conversely, investors want to save less when income is

In times of recessions, the term spread was found to be low whereas the dividend yield and the default spread were high. In addition, Fama (1990b) shows that the term spread (5y-1y spot rates) forecasts that the real return on one-year bonds will rise in the years after business peaks and fall after troughs.

Not only expected returns are affected by business cycles. Also financial market volatility is. Hamilton and Lin (1996) argue that economic recessions are the primary factor that drives fluctuations in the volatility of stock returns. In the same line, Black and Fraser (1995) document that the conditional risk component of expected returns, modeled by a GARCH-in-the-mean model, can be captured by financial variables which proxy business conditions. Finally, for bond markets, Sill (1996) finds significant business cycle variability in short-term interest rates.

Whereas the influence of business cycles on financial markets is well documented by financial economists, macroeconomists typically have studied the reverse relationship. When studying the causal relations among stock returns, interest rates, real activity and inflation, Lee (1992) found evidence that stock market returns are leading real growth. Typically, stock prices start declining severely several quarters before the onset of a recession. They continue their decline in the early stage of the recession and begin a strong upswing before the end of the recession (Peek and Rosengren, 1988). Although not each decline has been followed by a recession, Fisher and Merton (1984) claim the stock market to be the best single predictor of US business cycles. They refer to Moore's (1983) tabulation of the stock markets forecasting record for 1873-1975 and measure the percentage of turning points predicted.

Also bond markets exhibit some stylized facts with respect to business cycles. Kessel (1965) and Fama (1976) have shown that interest rates are pro-cyclical. In every business cycle of the 1952-1988 period, the one-year spot rate is lower at the business trough than the preceding or following peak (Fama, 1990a). Spreads, on the other hand, are counter-cyclical: long rates rise less than short rates during business expansions and fall less during contractions (Fama and French, 1989). In every business cycle of the 1952-1988 period, the five-year yield spread (5y-1y spot rate) is higher at the business trough than at the preceding or following peak (Fama,

temporarily low and the lower desired savings tend to push expected returns up. Thus, Fama and French (1989) and Chen (1989) conclude that a variation in expected returns opposite to business conditions is consistent with

1990a). In the same line, Harvey (1988) showed that the real term structure contains useful information for forecasting consumption growth. Chen (1991) concluded that the term spread in bond markets has forecasting power for future growth rates of GNP up to 5 quarters ahead.

Theoretical arguments as to why the yield curve shows these stylized facts are at least threefold. Estrella and Mishkin (1997) argue that monetary policy is a driving factor. Cook and Hahn (1989) have shown monetary policy to have a more profound effect on short rates and less on long rates. Policy tightening therefore raises the short rate relative to the long rate and thus, tends to flatten (or even to invert) the yield curve. Over time, higher interest rates reduce consumption spending. Consequently, a smaller or negative yield spread will be associated with lower real future growth. The yield curve may reflect more than just monetary policy effects. It may reflect market expectations of future economic growth. As argued by Bonser-Neal and Morley (1997), businesses increase their borrowing and issue more (long-term) bonds while anticipating an increase in expected future real growth. Bond prices go down and long yields rise relative to short rates, and the yield curve will steepen. Finally, Fama and French (1989) argue that the term premium compensates for a discount-rate risk in the spirit of Hicks (1947) and Kessel (1965). This compensation is low around business cycle peaks and high around troughs.

In putting the predictive power of stock and bond markets into perspective, Watson (1991) concludes that the interest rate spreads predict recessions so well that they get much of the weight in the statistical fit. Other variables such as stock returns typically receive little weight. Estrella and Mishkin (1997, 1998) and Bernard and Gerlach (1996) point at the importance of the prediction horizon. Stock prices are useful predictors, particularly one to three quarters ahead. Beyond one quarter, the term spread becomes the best single predictor of recessions. This result not only holds for the US but also for most other industrialized countries [2, 3].

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modern asset pricing models.

[2] See Harvey (1988) and Hardouvelis (1988) for more US evidence; Harvey (1991) and Funke (1997) for Germany; Davis and Henry (1994) for Germany and UK ; Hu (1993) for the G-7 ; Bernard and Gerlach (1996) and Bonser-Neal and Morley (1997) for many industrial countries; Estrella and Mishkin (1997) for the big-4 of the EU ; Davis and Fagan (1997) for the EU countries; Fagan & Fell (1994) for Ireland.

[3] Only the Japanese results are poor. Kim and Limpaphayom (1997) and Bernard and Gerlach (1996) suggest that the restrictive financial market regulation and therefore, the limited role of market expectations in the determination of interest rates, causes the non-significance of the domestic spread in Japan before the 1980s.

Although financial markets have gained the interest of macroeconomists, remarkably little attention is given to volatility. Still, it is well know that volatility increases after stock prices fall. It increases during recessions and also around major financial crises (Schwert, 1989). The standard deviation of both stock returns and industrial production are higher during recessions than during expansions (Schwert, 1989). Also Hamilton and Lin (1996) suggest that volatility in the stock market may prove useful in forecasting the future trend in real economic activity.

This paper provides some preliminary evidence on this issue. The in-sample results confirm that volatility of interest rate and stock markets add significant explanatory power to the base case with yield spread and stock returns. Out-of-sample, the evidence is less favourable. We think that the nature of our volatility measure, viz. being based on historical data instead of really forward-looking, is responsable for this poor performance. The structure of the paper is as follows. Section 2 documents why stock and bond market volatility should be included in recession prediction models. Section 3 describes our estimation and testing methodology. The data used and the recession dating is described in section 4. Empirical evidence for the US, Germany and Japan is provided both in- and out-of-sample (Section 5). Finally, we conclude.

## 2. Why should stock and bond market volatility tell something about oncoming recessions?

Finance theory basically aims to study the intertemporal allocation process in an uncertain environment. Hence, the behavior of market volatility crucially influences financial decision-making. When modeling the term structure of interest rates, one typically models the short rate based on a mean reverting drift on which (possibly time-varying) random shocks are superimposed. This conforms to the intuition that the term structure can be captured by a three factor model based on the short and the long rate (the spread) and the volatility (Knez, Litterman and Scheinkeman, 1994). Models that try to predict business cycles, however, only consider the spread and leave bond market volatility out of the model. Similarly, stock market volatility, an obvious variable to relate to expected returns, is hardly ever mentioned in relation to the prediction of business cycles[4].

[4] One notable exception is Hamilton & Lin (1996).

Despite this apparent lack of interest, several channels may transmit market volatility into corporate investment and hence (directly or indirectly) into real activity. The theory of irreversible investments (e.g. Bernanke,1983 and Dixit, 1992) argues that increased volatility gives rise to postponing investment decisions. The 'option of waiting to invest' has more value in uncertain environments. Since investment projects normally do not disappear immediately, decision-makers have strong incentives to wait till new information arrives and uncertainty (partially) resolves. Choe, Masulis and Nanda (1993) provide empirical evidence showing that the corporate need for external financing depends on market volatility. In periods of high market volatility, common stock issues are scarcer than in tranquil periods. Also in traditional investment theory the cost of capital is related to market volatility. If markets are turbulent and prices deviate from their fundamentals, a higher risk premium will be required by investors which in turn will depress investment. Hu (1995, 1993) documents, on the one hand, a strong negative association between stock market volatility and real investment and on the other hand a significantly positive association between real growth and the yield curve, in a continuous-time model.

## 3. Estimation and testing procedures

Since the economy can be represented by either being in recession or not, we apply a dichotomous dependent variable (DDV) model. The dependent variable $R_t$ equals one if the economy is in recession in quarter $t$, and zero otherwise. This is in line with Hamilton's (1989) Markov switching models where business cycles are governed by an unobservable discrete variable. The exact dating of the recessions used, is discussed in section 4.

The model we estimate is defined as

$$R^*_{t+k} = \beta' X_t + \varepsilon_t \qquad \text{for } t = 1,2,...,T\text{-}k \qquad (1)$$

where $R^*_{t+k}$ is an unobservable variable that determines at time $t$ how probable a recession will be $k$ periods ahead. $X_t$ is a $(M+1)$ data vector (containing ones for the constant and $M$ independent variables) and $\beta$ is the parameter vector to be estimated. $\varepsilon_t$ is a symmetrically, mean-zero distributed error term with a cumulative distribution function (CDF) $F$. In practice, we do observe the DDV $R_{t+k}$. Formally $R_{t+k}$ is defined by

$R_{t+k} = 1$ if $R^*_{t+k} > 0$ and

$R_{t+k} = 0$ otherwise.

Thus Prob$[R_{t+k} = 1]$ = Prob$[\varepsilon_t > - \beta' X_t] = 1 - F(- \beta' X_t) = F(\beta' X_t)$.

Since the observed values of $R_{t+k}$ are realizations of a binomial distribution, the likelihood function L can be written as

$$L = \prod_{R_{t+k}=1} F(\beta' X_t) \prod_{R_{t+k}=0} \left(1 - F(\beta' X_t)\right).$$

Common choices for $F$ are the logistic and the normal distribution. We will use the probit specification, in line with Estrella and Mishkin (1998) among others. Since these cumulative distributions are very close to each other (Maddala, 1983 p. 23), except at the tails, our results do not differ qualitatively when choosing the logistic CDF instead.

This model is estimated by standard maximum likelihood procedures using the Marquardt algorithm. All calculations were performed with E-views (version 2.0) and Gauss (version 3.2.8).

As for significance, we will present coefficients and probability values of the corresponding t-statistics. These t-statistics must be corrected for heteroskedasticity and autocorrelation as there is an overlapping data problem whenever the forecasting horizon is longer than the observation interval. We follow Estrella & Rodriguez (1998) who investigated several remedies to get autocorrelation-consistent standard errors and apply both the Hansen and Newey-West correction (cf. the appendix for more information).

In addition, we test whether adding financial volatility to a base model improves the fit via a (pseudo) likelihood ratio (LR) test. Normally, this test is $\chi^2$ distributed with $i$ degrees of freedom, $i$ = 1 or 2, being the number of financial volatility variables added:

$$LR = -2(LL_b - LL_u) \sim \chi^2_{(i)}$$

where $LL_b$ : Log Likelihood of the constrained (base) model

$LL_u$ : Log likelihood of the unconstrained model

However, in our case, there are overlapping sample problems, causing autocorrelation in the residuals[5]. As such, the $\chi^2$-distribution does not necessarily yield the correct critical values. We therefore simulated the empirical critical values by setting up a Monte Carlo experiment

[5] In addition, there also exists a problem of heteroskedasticity, because of the time-series behaviour of the independent variables.

consisting of 1000 iterations. The appendix contains more information about the set-up of this experiment.

In order to measure the goodness of fit of a probit model, several measures based on maximum likelihood statistics have been proposed (cf. Estrella, 1998, for an overview). Let $N$ denote the number of contributions in the likelihood function (or observations), $LL_c$ the log likelihood of a model with constant term only and $LL_u$ the log likelihood of the full model. Estrella shows that the statistic

$$\phi_0 = 1-(LL_u/LL_c)^{-2/N\,LLc},$$

(commonly referred to as a pseudo-$R^2$), has desirable properties that the earlier proposals lack. More specifically, $\phi_0$ is properly scaled on the unit interval and has suitable interpretations at the endpoints of the interval: $\phi_0 = 0$ corresponds to no fit and $\phi_0 = 1$ corresponds to a perfect fit. Estrella's measure also has intuitive interpretations for interior values. For instance, 0.25 may be interpreted as "modest", 0.5 as "strong" and 0.75 as "very strong". Finally, analogous to the traditional F-test on an $R^2$ in a linear model, $\phi_0$ can also be transformed into an F-statistic (with $M$ and $N$–$M$–$1$ degrees of freedom):

$$F[M, N-M-1] = \phi_0/(1-\phi_0)\cdot(N-M-1)/M$$

This F-statistics gives strikingly similar significance levels as the Chi-squared-statistic of the log likelihood ratio (Estrella, 1998, Table 3) and tests the null hypothesis that all coefficients but the constant term are zero.

For appreciating the out of sample performance of our models, we will consider the quadratic probability score (QPS) as an *accuracy* measure, QPS = $\frac{1}{T}\Sigma_t\, 2(P_{t+k,t} - R_{t+k})^2$, with $P_{t+k,t}$ the forecast probability, $R_{t+k,t}$ the true value. Smaller values indicate a more accurate forecast (see Diebold & Lopez, 1989). Relatedly, we report the calibration and the resolution. *Calibration* refers to the closeness of forecast probabilities and observed relative frequencies and is measured by the global squared bias, GSB = $2(\overline{P}-\overline{R})^2$ and local squared bias, LSB = $\frac{1}{T}\sum_{j=1}^{J}2T^j\left(\overline{P}^j-\overline{R}^j\right)^2$, which is a partitioning of the probability forecasts in $j$=1 ,..., $J$ sets with $Tj$ forecasts in each cell ($\Sigma Tj = T$). *Resolution* measures the extent to which different forecasts are followed by different realizations. RES = $\frac{1}{T}\sum_{j=1}^{J} 2T^{j}\left(\bar{R}^{j}-\bar{R}\right)^{2}$. High resolution indicates that discriminating predictive information is available. There exists a decomposition of QPS:

$$\text{QPS} = \text{QPS}_{\text{constant}} + \text{LSB} - \text{RES},$$

where $\text{QPS}_{\text{constant}}$ is the QPS of the constant probability forecast $\bar{R}$. All the forementioned measures lie between 0 and 2.

In addition, the percentage of incorrect classifications will be reported, which is based on assigning the value zero or one to the forecasted recession probability. It is assigned the value one if a critical recession probability is exceeded and zero otherwise. This critical probability is found by minimizing the QPS w.r.t. *P*, yielding $P^{*} = \frac{1}{T}\Sigma_{t} R_{t+k}$, viz. the relative frequency of recessions up to that point of time. Herefrom, we can derive the false recession rate ('false alarm') and false non-recession rate ('missed call'). A false recession signal (*False R*) occurs when it is predicted but does not materialize and analogously for false non-recessions (*False E*). The false recession rate (in percent) is obtained as the number of false recessions over the total number that recessions were forecast, and vice versa for the false non-recession rate. It could be argued that false non-recession signals are more costly than false recession rates. We will also mention the percentage of incorrect classifications (relative to the number of predictions).

## 4. Data selection and descriptive statistics

### 4.1. Data

Contrary to popular statements, recessions are not "two or more quarters of consecutive decline in real GNP". The official NBER definition draws back on Burns and Mitchel (1946, p.5) who define a recession as one phase of a business cycle. A business cycle is defined as "a type of fluctuation found in the aggregate economic activity of nations that organize their work mainly in business enterprises: a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic; in duration business cycles vary from more than one year to ten or twelve years; they are not divisible in shorter cycles of similar character with amplitude approximating their own."

In our study, we will use monthly data as most information from financial prices is highly frequent, tending to become less useful vis-à-vis macroeconomic aggregates when measured over lower frequencies.

**Table 1 : Dating of recessions in the US, Germany and Japan**

| USA | | Germany | | Japan | |
|---|---|---|---|---|---|
| *NBER –BC* | *DUR* | *CICBR* | *DUR* | *EPA* | *DUR* |
| 60/5 - 61/2 | 10 | 61/3 - 63/2 | 24 | 62/1 - 62/10 | 10 |
| – | | 65/6 - 67/8 | 27 | 64/11 - 65/10 | 12 |
| 70/1 - 70/11 | 11 | 70/6 - 71/12 | 19 | 70/8 - 71/12 | 17 |
| 73/12 - 75/3 | 16 | 73/9 - 75/5 | 21 | 73/12 - 75/3 | 16 |
| 80/2 - 80/7 | 6 | – | | 77/2 - 77/10 | 9 |
| 81/8 - 82/11 | 16 | 80/3 - 83/7 | 41 | 80/3 - 83/2 | 36 |
| – | | 86/8 - 88/4 | 21 | 85/7 - 86/11 | 17 |
| 90/8 - 91/3 | 8 | 91/5 - 95/9 | 53 | 91/3 - 93/10 | 32 |
| *average DUR* | *11* | | *29* | | *18* |

*DUR* : duration (in months)
Sources : NBER and CIBCR: Balke & Wynne (1995)
EPA: direct information provided by Mr. Hirose (EPA)

Dates separating contraction and expansion phases are those reported by the country's official economic institutes: National Bureau of Economic Research (NBER) for the US, Economic Planning Agency (EPA) for Japan, and Centre for International Business Cycle Research (CIBCR) data for Germany. One can observe from the data in table 1 that, on average, recessions in the US are shorter than in Japan or Germany, with an average duration of 11 months versus 29 and 18, resp.

Our financial data consist of monthly interest rates and stock price indices. Long term interest rates were taken from the International Financial Statistics (IFS) CD-ROM, version 1997/8 (government bond yields on 10 year maturities, series 61). Short term rates are 3-month euro interest rates (on USD, DEM and JPY) from the BIS, available on a daily basis back to 1963:7 (1977:8 for Japan). The yield spread (YC) measures the difference between these rates.

Real stock returns (DRS) were constructed from three-month logarithmic changes of the available (nominal) stock indices (DJIA for the US, DAX for Germany and Nikkei-225 for Japan, source: Datastream), corrected for inflation[6,7]. Inflation was measured by the logarithmic change of the CPI-index (also over three months), taken from IFS (series 64).

[6] Peek and Rosengren (1988) argue that economic activity over time is measured by real rather than nominal magnitudes. Therefore, also stock prices should be adjusted for the level of inflation.

Volatility estimates of stocks and bonds were constructed as natural logarithms of mean absolute deviations[8] of daily changes in 3-month (nominal) interest rates[9] (VOLR) and of daily real logarithmic stock price changes (VOLSH), over a one month interval. Following French, Schwert and Stambaugh (1987), natural logarithms were taken in order to reduce the positive skewness of volatility estimates.

**Table 2 : Sample correlations (instantaneous)**

| | DRS | VOLR | VOLSH |
|---|---|---|---|
| **USA 1963:9 - 97:12** | | | |
| YC | 0.320 [a] | -0.445 [a] | -0.139 [b] |
| DRS | 1 | -0.269 [a] | -0.266 [a] |
| VOLR | | 1 | 0.347 [a] |
| VOLSH | | | 1 |
| **Germany 1965:3 - 97:12** | | | |
| YC | 0.061 | 0.125 [b] | -0.016 |
| DRS | 1 | -0.229 [a] | -0.156 [a] |
| VOLR | | 1 | 0.003 |
| VOLSH | | | 1 |
| **Japan 1980:3 - 97:12** | | | |
| YC | -0.039 | -0.367 [a] | 0.237 [a] |
| DRS | 1 | 0.035 | -0.448 [a] |
| VOLR | | 1 | -0.235 [a] |
| VOLSH | | | 1 |

Notes : Variables are YC : yield spread (government bond yield – 3 month euro rate); DRS : real stock return (over 3 months); VOLR: interest rate volatility (log of monthly mean absolute deviation of daily changes in 3 month euro rate); VOLSH: real stock return volatility (log of monthly mean absolute deviation of daily real stock returns)

Significance levels [a] : 1%, [b] : 5%, [c] : 10% (two-sided)
The significance of the correlation being statistically different from zero is assessed by computing

$t_{\alpha;T-2} = \frac{r\sqrt{T-2}}{\sqrt{1-r^2}}$ or equivalently $r^* = \frac{t_{\alpha;T-2}}{\sqrt{t^2_{\alpha;T-2}+T-2}}$

with $t$ : t-statistic for a significance level $\alpha$ and $T$–2 degrees of freedom; $r$ ($r^*$) the (critical) sample correlation; $T$ number of observations (Sachs, 1984, p. 424).

[7] Initially, we worked with monthly returns, but these were very noisy. In order to get a better approximation of the true expected real return, we therefore took a 3-month average.

[8] For small sample sizes (as here, one month of data), the mean absolute deviation is superior to the otherwhise optimal standard deviation, because values far from the mean are less influential than in the usual estimate (cf. Sachs, 1984, p. 252).

[9] For the US, there is one period during which interest rates remained unchanged (October 1964). This would create a missing value when taking logs. Our remedy was to set this month's value equal to the minimum over the whole sample, after excluding the zero-value observation.

The sample period is restricted due to the limited availability of daily stock price data for constructing stock volatilities. For the US, our sample starts in 1963:7, for Germany in 1965:1 and Japan in 1980:1. As the Japanese financial markets became liberalised and informative since the late 1970s only, this is not a real disadvantage (cf. Bernard and Gerlach 1996).

### 4.2. Descriptive statistics

The sample correlation matrices are shown in table 2. As can be seen, correlations between the explanatory variables are moderate and generally smaller than .30 in absolute values. Only between the yield spread and interest rate volatility, and real stock returns and real stock volatility, correlations are higher in the US and Japan. However, there is no problem of multicollinearity. When we perform the Belsley test[10], the condition numbers are around 10, still far below the critical value of 20.

Table 3 presents further statistics about the mean and median, maximum and minimum, standard deviation, skewness, kurtosis and Jarque-Bera normality test of the monthly observations, as well as about unit roots (ADF and Phillips-Perron t-tests) and autocorrelations (autocorrelation coefficient and p-value for significance are given). The volatility series appear to be extremely fat-tailed and have a high skewness and kurtosis, and hence normality of these series is strongly rejected . Relying on the unit root tests, all our variables seem to be stationary.

As can be seen from the autocorrelation statistics, the yield curve and volatility series are highly autocorrelated whereas real stock returns are not. As we shall see in our empirical evidence, once such an autocorrelated variable is informative over one specific horizon, it will tend to be significant over a related horizon too.

[10] The Belsley test for multicollinearity calculates the condition number of a matrix $X$ as the square root of the ratio of the largest to the smallest characteristic root. Belsley suggests computing this ratio for the moment matrix, $X'X$, after normalizing the data by dividing each column in $X$ by $\sqrt{x_k' x_k}$ (Greene, 1993, p. 269). Values in excess of 20 suggest potential problems. Our numbers are 8.807 for the US, 8.858 for Germany and 11.574 for Japan.

## Table 3 : Descriptive statistics

| | USA | | | | Germany | | | | Japan | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **YC** | **DRS** | **VOLR** | **VOLSH** | **YC** | **DRS** | **VOLR** | **VOLSH** | **YC** | **DRS** | **VOLR** | **VOLSH** |
| Mean | 0.14 | 0.53 | -2.903 | -0.580 | 1.57 | 0.77 | -2.875 | -0.444 | 0.47 | 0.79 | -3.343 | -0.437 |
| Median | 0.47 | 1.29 | -2.831 | -0.589 | 1.83 | 1.01 | -2.840 | -0.466 | 0.63 | 1.99 | -3.317 | -0.484 |
| Maximum | 3.87 | 20.50 | -0.521 | 1.395 | 8.12 | 27.32 | -0.260 | 1.098 | 2.15 | 20.82 | -0.981 | 0.957 |
| Minimum | -6.88 | -38.22 | -5.949 | -1.665 | -4.60 | -40.89 | -5.993 | -1.498 | -4.88 | -43.01 | -5.300 | -1.688 |
| Std. Dev. | 1.945 | 7.724 | 0.921 | 0.394 | 1.746 | 9.184 | 0.924 | 0.386 | 1.065 | 9.952 | 0.760 | 0.532 |
| Skewness | -0.79 | -0.77 | -0.441 | 0.382 | 0.07 | -0.68 | -0.079 | 0.410 | -1.39 | -0.81 | -0.093 | 0.264 |
| Kurtosis | 3.47 | 5.29 | 3.372 | 4.443 | 3.75 | 5.33 | 3.364 | 3.636 | 6.72 | 4.56 | 3.542 | 2.575 |
| Jarque-Bera | 46.1 | 130.4 | 15.8 | 45.9 | 9.50 | 119.5 | 2.60 | 17.8 | 194.5 | 45.4 | 2.96 | 4.13 |
| Probability | 0.000 | 0.000 | 0.000 | 0.000 | 0.009 | 0.000 | 0.273 | 0.000 | 0.000 | 0.000 | 0.228 | 0.127 |
| ADF - 4 lags | -3.11 [b] | -7.11 [a] | -3.32 [b] | -4.17 [a] | -3.20 [b] | -7.18 [a] | -4.19 [a] | -5.02[a] | -3.30 [b] | -4.88 [a] | -3.88 [a] | -3.00 [b] |
| PP - 5 lags | -3.48 [a] | -8.37 [a] | -6.89 [a] | -9.10 [a] | -3.61 [a] | -8.20 [a] | -8.96 [a] | -11.4 [a] | -3.14 [b] | -6.28 [a] | -6.99 [a] | -5.66 [a] |
| acf 1 | 0.94[a] | 0.698[a] | 0.787[a] | 0.661[a] | 0.93[a] | 0.70[a] | 0.833[a] | 0.524[a] | 0.88[a] | 0.68[a] | 0.681[a] | 0.735[a] |
| acf 3 | 0.83[a] | 0.077 | 0.741[a] | 0.511[a] | 0.84[a] | 0.07 | 0.772[a] | 0.338[a] | 0.77[a] | 0.04 | 0.495[a] | 0.524[a] |
| acf 6 | 0.70[a] | 0.004 | 0.717[a] | 0.443[a] | 0.70[a] | 0.02 | 0.729[a] | 0.275[a] | 0.54[a] | 0.01 | 0.398[a] | 0.427[a] |
| acf 9 | 0.63[a] | 0.039 | 0.654[a] | 0.360[a] | 0.53[a] | 0.06 | 0.741[a] | 0.198[a] | 0.38[a] | 0.12[c] | 0.395[a] | 0.276[a] |
| acf 12 | 0.53[a] | 0.017 | 0.657[a] | 0.273[a] | 0.40[a] | 0.02 | 0.713[a] | 0.210[a] | 0.30[a] | -0.03 | 0.361[a] | 0.208[a] |
| acf 15 | 0.45[a] | -0.028 | 0.635[a] | 0.272[a] | 0.27[a] | -0.12[b] | 0.684[a] | 0.076 | 0.26[a] | 0.07 | 0.227[a] | 0.245[a] |
| acf 18 | 0.32[a] | -0.029 | 0.573[a] | 0.228[a] | 0.14[a] | -0.03 | 0.687[a] | 0.091[c] | 0.24[a] | 0.15[b] | 0.177[a] | 0.221[a] |

Note :
Variables are YC : yield spread (government bond yield – 3 month euro rate); DRS : real stock return (over 3 months); VOLR: interest rate volatility (monthly mean absolute deviation of daily changes in 3 month euro rate); VOLSH: real stock return volatility (monthly mean absolute deviation of daily real stock returns). All variables are denoted as percentages per year (YC and VOLR) or per quarter (DRS and VOLSH).
The table presents mean, median, maximum and minimum, skewness and kurtosis statistics; normality test (Jarque-Bera plus probability value); ADF (Augmented Dickey-Fuller) en PP (Phillips-Perron) unit root tests of the series in levels (significance levels [a] : 1%, [b] : 5%, [c] : 10%) - 4/5 lags were optimal in the ADF/PP test regression ; autocorrelation coefficients and probability values (Ljung-Box statistics (not reported) were always significant at the .001 level).

# 5. Empirical evidence

## 5.1. In-sample

As mentioned in section 3, we provide measures of fit and significance for financial variables predicting recessions $k$ periods ahead. Since it is widely documented by Estrella & Mishkin (1997, 1998) and others that yield curve and changes in share price have a noticable forecasting ability for recessions, we start from a basic probit equation with these two variables (YC and DRS) and add, consecutively, short rate volatility (VOLR), real stock volatility (VOLSH) and both volatilities. The significance of these added variables is tested by performing a pseudo-LR test as described in section 3.

We expect negative signs for the yield curve and changes in the real share price index, as positive developments in these variables decrease the probability of future recessions. For volatilities, positive signs are expected, because higher volatilities are assumed to increase the probability of future recessions. The in-sample probit results are discussed below. A summary of our evidence is shown in the tables below. We also investigated sub-periods for the US and Germany (1973-97 and 1980-97) and found they were qualitatively in line with those reported here[11].

The basic finding of Estrella & Mishkin (1998) was that stocks were useful for short-term predictions of recession (1-2 quarters), in addition to the yield curve (up to 8 quarters). Our results confirm this finding. Regarding the significance of the coefficients, yield curve and real stock return do a good job. The yield curve is significant over a whole range of forecasting horizons, except in Japan (table 6), where it starts only from 9 months on. Real stock returns work well as additional recession indicators in Germany, up to one year (table 4) and in the US, 3 and 6 months ahead (table 5). In Japan, this variable starts playing a significant role for predicting recessions, only 9 months ahead. In the US, there appears a sign reversal on this variable, from 15 months ahead onwards. This may reveal some evidence in favour of consumption smoothing, in line with Balvers and Cosimano (1990), cf. footnote 1.

Our extension of introducing financial volatility is supported by the data, for all three countries, at least in the short run, based on the LR-statistic. For Germany and Japan, higher interest rate volatility significantly adds to a higher probability of ending in recessions, 3 to 9 months ahead. In the US, it only adds explanatory power for the nearby future. Real stock volatility works primarily for short horizons and only in the US . The Hansen and Newey-West (NW) corrected t-statistics of the volatility variables yield the same information as the LR test most of the time[13]. In addition, 18 to 24 months in the future, in the US, there seem to be significant non-zero effects of interest rate volatility upon the probability of arriving at recessions. In Japan, the interest volatility coefficient is very significant 3 months ahead and

[11] These results are available from the authors upon request.

[13] The appearant contradiction between the significance of the LR and t-statistics for VOLR in table 4 (3 and 6 periods ahead), tables 5 and 6 (3 periods ahead) may be explained by the construction of the test statistics. For the LR test, a probit equation with only VOLR added is estimated, whereas for the t-test, a probit equation with both VOLR and VOLSH is estimated, seemingly reducing the significance of VOLR downwards under the latter test.

makes up for the lack of significant estimates of YC and DRS. The Hansen and NW t-values are mostly of the same order of magnitude.

**Table 4 : Probit summary results for Germany**

| Periods ahead | $\phi$ prob-F | LR VOLR | LR VOLSH | LR VOL | Coefficient estimates and t-stats (Hansen, NW) C | YC | DRS | VOLR | VOLSH |
|---|---|---|---|---|---|---|---|---|---|
| | 0.283 | 7.57 | 0.46 | 8.28 | 1.295 | -0.406 | -0.028 | 0.229 | 0.1546 |
| 3 | 0.001 | 0.047 | 0.595 | 0.094 | 2.22 [a] | -4.36 [a] | -1.76 [c] | 1.38 | 0.52 |
| | | | | | 2.73 [a] | -5.40 [a] | -2.04 [b] | 1.70 [c] | 0.61 |
| | 0.374 | 15.17 | 0.509 | 16.07 | 1.778 | -0.497 | -0.032 | 0.3435 | 0.1813 |
| 6 | 0.001 | 0.03 | 0.645 | 0.059 | 2.46 [a] | -3.80 [a] | -1.66 [c] | 1.51 | 0.48 |
| | | | | | 3.05 [a] | -4.45 [a] | -1.88 [c] | 1.86 [c] | 0.56 |
| | 0.381 | 12.61 | 1.62 | 14.41 | 1.741 | -0.496 | -0.0348 | 0.3217 | 0.2570 |
| 9 | 0.001 | 0.090 | 0.446 | 0.119 | 2. 55 [a] | -2.73 [a] | -1.96 [b] | 1.35 | 0.56 |
| | | | | | 3.05 [a] | -3.13 [a] | -2.09 [b] | 1.60 | 0.64 |
| | 0.346 | 10.28 | 0.28 | 10.59 | 1.492 | -0.455 | -0.0367 | 0.289 | 0.1058 |
| 12 | 0.001 | 0.142 | 0.750 | 0.250 | 2.00 [b] | -2.38 [b] | -2.29 [b] | 1.09 | 0.21 |
| | | | | | 2.35 [b] | -2.73 [a] | -2.16 [b] | 1.28 | 0.25 |
| | 0.237 | 13.26 | 0.17 | 13.40 | 1.379 | -0.367 | -0.0170 | 0.315 | 0.0682 |
| 15 | 0.002 | 0.164 | 0.830 | 0.267 | 1.91 [c] | -1.97 [b] | -1.12 | 1.23 | 0.15 |
| | | | | | 2.05 [b] | -2.33 [b] | -1.22 | 1.34 | 0.17 |
| | 0.153 | 8.21 | 0.79 | 8.88 | 1.046 | -0.288 | -0.0039 | 0.238 | 0.1474 |
| 18 | 0.006 | 0.293 | 0.668 | 0.467 | 1.65 [c] | -1.50 | -0.31 | 1.11 | 0.41 |
| | | | | | 1.55 | -1.83 [c] | -0.31 | 1.05 | 0.42 |
| | 0.094 | 3.75 | 0.53 | 4.36 | 0.587 | -0.225 | 0.0031 | 0.1624 | -0.139 |
| 21 | 0.017 | 0.560 | 0.739 | 0.739 | 1.18 | -1.16 | 0.33 | 0.86 | -0.41 |
| | | | | | 0.90 | -1.43 | 0.27 | 0.73 | -0.39 |
| | 0.072 | 1.53 | 4.14 | 5.84 | 0.235 | -0.172 | 0.0123 | 0.110 | -0.373 |
| 24 | 0.030 | 0.720 | 0.364 | 0.686 | 0.77 | -0.97 | 1.07 | 0.68 | -1.03 |
| | | | | | 0.39 | -1.16 | 0.98 | 0.51 | -1.01 |

Notes : – Periods ahead refers to the prediction horizon (in months); $\phi$: pseudo-$R^2$ of Estrella (1998) for the full model; Prob-F: probability value of the F-test that all coefficients except the constant term are zero; LR : likelihood ratio test statistic and probability value of adding financial volatility variables VOLR, VOLSH or both (VOL) to a basic probit equation with C, YC and DRS only (p-values are based on Monte Carlo simulation, cf. appendix).
– Coefficient estimates [first line] and t-statistics (Hansen [second line] and Newey-West [third line] corrected for heteroskedasticity and autocorrelation, cf. Estrella & Rodriguez, 1998) for C: constant term; YC: yield spread (government bond yield – 3 month euro rate); DRS: real stock return (over 3 months); VOLR: monthly mean absolute deviation of daily changes in 3 month euro rate; VOLSH: monthly mean absolute deviation of daily real stock returns.
– Coefficients are significantly different from zero at the [a] : 1 % level; [b] : 5 % level, [c] : 10 % level.

Overall, the explanatory power of our financial variables probit equation is satisfactory, reaching a maximum of .40 for Germany and .30 for the US at a 9 month horizon and of .30 at a 24 month horizon for Japan. The F-test probability values reveal that there are always some significant variables besides the constant term.

**Table 5 : Probit summary results for the US**

| Periods ahead | $\phi$ prob-F | LR VOLR | LR VOLSH | LR VOL | Coefficient estimates and t-stats (Hansen, NW) C | YC | DRS | VOLR | VOLSH |
|---|---|---|---|---|---|---|---|---|---|
| 3 | 0.295 | 15.08 | 13.64 | 22.60 | 0.169 | -0.234 | -0.0274 | 0.417 | 0.758 |
| | 0.001 | 0.002 | 0.006 | 0.003 | 0.20 | -2.39 [b] | -1.46 | 1.15 | 1.98 [b] |
| | | | | | 0.24 | -2.81 [a] | -1.62 | 1.38 | 2.31 [b] |
| 6 | 0.302 | 1.65 | 3.04 | 3.72 | -0.867 | -0.366 | -0.0278 | 0.110 | 0.407 |
| | 0.001 | 0.432 | 0.547 | 0.471 | -0.89 | -3.16 [a] | -2.40 [b] | 0.27 | 0.93 |
| | | | | | -1.06 | -3.45 [a] | -2.08 [b] | 0.32 | 1.09 |
| 9 | 0.296 | 1.18 | 0.36 | 1.26 | -1.015 | -0.417 | -0.0084 | 0.124 | 0.080 |
| | 0.001 | 0.579 | 0.718 | 0.815 | -1.02 | -3.64 [a] | -0.68 | 0.29 | 0.17 |
| | | | | | -1.16 | -3.47 [a] | -0.62 | 0.33 | 0.19 |
| 12 | 0.256 | 1.87 | 0.42 | 1.90 | -0.878 | -0.386 | 0.0022 | 0.166 | 0.0475 |
| | 0.002 | 0.494 | 0.696 | 0.774 | -1.22 | -4.37 [a] | 0.27 | 0.55 | 0.12 |
| | | | | | -1.38 | -3.47 [a] | 0.17 | 0.59 | 0.12 |
| 15 | 0.236 | 4.67 | 0.01 | 5.75 | -0.581 | -0.384 | 0.0333 | 0.348 | -0.285 |
| | 0.002 | 0.343 | 0.962 | 0.526 | -0.79 | -3.75 [a] | 2.49 [a] | 1.35 | -1.10 |
| | | | | | -0.94 | -3.25 [a] | 2.27 [b] | 1.52 | -0.81 |
| 18 | 0.192 | 5.65 | 0.49 | 9.07 | -0.468 | -0.321 | 0.038 | 0.412 | -0.496 |
| | 0.004 | 0.343 | 0.761 | 0.442 | -0.69 | -4.35 [a] | 1.80 [c] | 2.13 [b] | -1.47 |
| | | | | | -0.74 | -3.85 [a] | 1.88 [c] | 1.97 [b] | -1.29 |
| 21 | 0.122 | 4.95 | 0.92 | 9.18 | -0.461 | -0.221 | 0.032 | 0.384 | -0.53 |
| | 0.011 | 0.418 | 0.663 | 0.505 | -0.77 | -2.34 [b] | 1.84 [c] | 2.29 [b] | -1.85 [c] |
| | | | | | -0.76 | -2.59 [a] | 1.94 [b] | 1.87 [c] | -1.48 |
| 24 | 0.075 | 2.40 | 3.39 | 10.06 | -0.641 | -0.141 | 0.0202 | 0.331 | -0.707 |
| | 0.030 | 0.611 | 0.444 | 0.513 | -1.13 | -1.54 | 3.23 [a] | 1.58 | -1.57 |
| | | | | | -1.09 | -1.65 [c] | 1.92 [c] | 1.49 | -1.74 [c] |

Explanatory notes: see table 4.

A remarkable observation is that in the US, stock volatility seems to matter in the short run, but not in Germany and Japan. We conjecture that this discloses a well known institutional difference between the (external) capital market-based versus the bank-based financial structure (and shareholdership) of US firms versus German and Japanese firms. As a logical result, one finds that stock market uncertainty matters more in an environment where stock market financing (and public shareholdership) is important, as is the case in the US, compared to Germany and Japan, where bank financing (and banks as shareholders) is more common.

### 5.2. Some out-of-sample results

For out-of-sample analysis (US and Germany), we rely on the QPS statistic as a measure of accuracy, and the decomposition into $QPS_{constant}$, LSB and RES. In addition, the percentage of incorrect classifications and false alarms (*False R*) and missed calls (*False E*) is reported. To do so, the probit equations are estimated recursively, starting with 1963:9(65:3)-79:12–*k* (*k*: the forecast horizon) performing one out-of-sample forecast (with perfectly known independent variables), add one observation and so on, iterating up to 1997:12 (the end of our sample period). The various results with financial asset volatilities are compared with the base model comprising the yield curve and real stock returns. If financial volatilities add to better forecasting recessions, prediction and classification errors should be lower.

**Table 6 : Probit summary results for JAPAN**

| Periods ahead | $\phi$ prob-F | LR VOLR | LR VOLSH | LR VOL | Coefficient estimates and t-stats (Hansen, NW) C | YC | DRS | VOLR | VOLSH |
|---|---|---|---|---|---|---|---|---|---|
| 3 | 0.167 | 23.06 | 0.59 | 23.06 | 1.970 | -0.227 | -0.007 | 0.635 | -0.004 |
| | 0.016 | 0.002 | 0.577 | 0.004 | 1.66 $^{c}$ | -1.19 | -0.37 | 1.74 $^{c}$ | -0.01 |
| | | | | | 2.01 $^{b}$ | -1.51 | -0.44 | 2.11 $^{b}$ | -0.01 |
| 6 | 0.193 | 18.13 | 0.41 | 18.13 | 1.826 | -0.347 | -0.020 | 0.582 | -0.002 |
| | 0.012 | 0.011 | 0.691 | 0.036 | 1.23 | -1.25 | -1.17 | 1.28 | 0.00 |
| | | | | | 1.45 | -1.62 | -1.21 | 1.52 | 0.00 |
| 9 | 0.230 | 11.54 | 1.08 | 11.96 | 1.408 | -0.484 | -0.038 | 0.465 | -0.138 |
| | 0.008 | 0.076 | 0.606 | 0.205 | 0.82 | -1.42 | -2.40 $^{b}$ | 0.91 | -0.25 |
| | | | | | 1.01 | -1.79 $^{c}$ | -2.49 $^{a}$ | 1.11 | -0.31 |
| 12 | 0.223 | 1.16 | 0.02 | 1.16 | 0.410 | -0.521 | -0.046 | 0.147 | 0.0001 |
| | 0.009 | 0.605 | 0.910 | 0.851 | 0.21 | -1.51 | -4.39 $^{a}$ | 0.26 | 0.00 |
| | | | | | 0.28 | -1.78 $^{c}$ | -3.94 $^{a}$ | 0.33 | 0.00 |
| 15 | 0.237 | 0.00 | 0.44 | 0.44 | -0.011 | -0.573 | -0.045 | 0.005 | 0.143 |
| | 0.008 | 0.938 | 0.917 | 0.954 | -0.01 | -1.94 $^{b}$ | -3.78 $^{a}$ | 0.01 | 0.28 |
| | | | | | -0.01 | -2.06 $^{b}$ | -3.93 $^{a}$ | 0.01 | 0.31 |
| 18 | 0.265 | 0.09 | 0.74 | 0.92 | -0.402 | -0.694 | -0.045 | -0.062 | -0.205 |
| | 0.006 | 0.897 | 0.686 | 0.900 | -0.29 | -2.14 $^{b}$ | -4.54 $^{a}$ | -0.15 | -0.51 |
| | | | | | -0.33 | -2.35 $^{b}$ | -3.33 $^{a}$ | -0.17 | -0.51 |
| 21 | 0.320 | 0.19 | 1.97 | 2.03 | -0.128 | -0.893 | -0.041 | 0.038 | -0.317 |
| | 0.004 | 0.855 | 0.502 | 0.496 | -0.12 | -2.07 $^{b}$ | -4.58 $^{a}$ | 0.13 | -1.53 |
| | | | | | -0.12 | -2.54 $^{a}$ | -3.23 $^{a}$ | 0.13 | -0.86 |
| 24 | 0.328 | 0.12 | 2.83 | 3.18 | -0.664 | -0.954 | -0.037 | -0.094 | -0.418 |
| | 0.004 | 0.860 | 0.429 | 0.706 | -0.99 | -1.87 $^{c}$ | -2.91 $^{a}$ | -0.61 | -3.87 $^{a}$ |
| | | | | | -0.91 | -2.32 $^{b}$ | -2.58 $^{a}$ | -0.48 | -1.05 |

Explanatory notes: see table 4.

With the QPS and a classification scheme that maps probability forecasts onto cycle phases (cf. section 3), we can assess whether financial volatility information contributes to better predictions of the business cycle. Though it is rarely found in applied research in this area, it is a more powerful test to examine the information value of asset prices and volatilities than in-sample estimations.

Different probit models are estimated, one base model (with YC and DRS), others extended with financial volatilities. There was a reasonably large sample for the US and Germany so that we could split it up, still resulting in enough data to start with. Bold-typed figures indicate a smaller error for the volatility-extended model. Being parsimonious, we only report the base model and the model with interest rate volatility, since including stock volatility did not produce consistently better results.

**Table 5 : Out-of-sample results Germany and USA**

| | Germany | | | | | | USA | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Base model | | | Extended model | | | Base model | | | Extended model | | |
| **Horizon** *k* | **Incorr** **FalseR** **FalseE** | **QPS** **$QPS_{const}$** | **GSB** **LSB** **RES** | **Incorr** **FalseR** **FalseE** | **QPS** **$QPS_{const}$** | **GSB** **LSB** **RES** | **Incorr** **FalseR** **FalseE** | **QPS** **$QPS_{const}$** | **GSB** **LSB** **RES** | **Incorr** **FalseR** **FalseE** | **QPS** **$QPS_{const}$** | **GSB** **LSB** **RES** |
| | 27.3% | 0.19007 | 0.00420 | 28.2% | **0.17918** | **0.00303** | 11.6% | 0.19110 | 0.00466 | 12.5% | **0.17929** | **0.00301** |
| 3 | 26.8% | 0.22631 | 0.02273 | **23.3%** | **0.22505** | 0.02701 | 40.7% | 0.22733 | 0.02273 | 45.2% | **0.22663** | 0.02462 |
| | 28.0% | | 0.05897 | 32.7% | | **0.07287** | 7.4% | | 0.05897 | **7.0%** | | **0.07197** |
| | 25.5% | 0.19425 | 0.00396 | 25.9% | **0.19082** | **0.00353** | 13.0% | 0.19500 | 0.00421 | **12.5%** | **0.19102** | **0.00357** |
| 6 | 25.6% | 0.23419 | 0.01383 | **22.2%** | 0.23446 | 0.01418 | 46.2% | 0.23494 | 0.01383 | **44.8%** | **0.23244** | 0.01499 |
| | 25.3% | | 0.05377 | 29.6% | | **0.05782** | 8.4% | | 0.05377 | **7.5%** | | **0.05641** |
| | 22.7% | 0.18598 | 0.00381 | **21.8%** | 0.18621 | **0.00346** | 11.6% | 0.18657 | 0.00408 | 12.0% | **0.18635** | **0.00350** |
| 9 | 24.4% | 0.22888 | 0.01362 | **18.9%** | 0.23133 | 0.01805 | 40.7% | 0.22947 | 0.01362 | 42.9% | 0.23000 | 0.01755 |
| | 20.0% | | 0.05653 | 24.8% | | **0.06317** | 7.4% | | 0.05653 | 7.4% | | 0.06119 |
| | 20.8% | 0.18783 | 0.00326 | 23.1% | **0.18711** | **0.00202** | 11.1% | 0.18856 | 0.00354 | 12.0% | **0.18732** | **0.00208** |
| 12 | 21.6% | 0.22703 | 0.02765 | **17.6%** | **0.22334** | **0.01751** | 40.6% | 0.22183 | 0.02051 | 44.4% | 0.22207 | **0.01852** |
| | 19.8% | | 0.06685 | 28.1% | | 0.05374 | 6.0% | | 0.05378 | **5.6%** | | 0.05327 |
| | 24.5% | 0.17601 | 0.00167 | 28.2% | **0.16890** | **0.00083** | 10.2% | 0.17650 | 0.00182 | 14.4% | **0.16881** | **0.00085** |
| 15 | 23.1% | 0.23373 | 0.02575 | **20.4%** | **0.22662** | 0.00367 | 40.0% | 0.23496 | 0.02858 | 51.0% | **0.22578** | **0.00353** |
| | 26.3% | | 0.08347 | 34.1% | | 0.06138 | 3.4% | | 0.08704 | 3.6% | | 0.06051 |
| | 30.6% | 0.17233 | 0.00081 | 31.5% | **0.16491** | **0.00014** | 13.4% | 0.17233 | 0.00081 | 15.7% | **0.16491** | **0.00014** |
| 18 | 26.9% | 0.23227 | 0.02221 | **19.2%** | 0.23373 | **0.01246** | 49.1% | 0.23227 | 0.02221 | 53.2% | 0.23373 | **0.01246** |
| | 34.3% | | 0.08215 | 38.4% | | 0.08128 | 1.8% | | 0.08215 | **0.6%** | | 0.08128 |
| | 33.8% | 0.20016 | 0.00005 | 33.8% | **0.19702** | 0.00016 | 22.7% | 0.20016 | 0.00005 | 24.1% | **0.19702** | 0.00016 |
| 21 | 22.8% | 0.23417 | 0.00891 | **14.8%** | **0.23177** | **0.00237** | 63.4% | 0.23417 | 0.00891 | 64.9% | **0.23177** | **0.00237** |
| | 40.1% | | 0.04292 | 41.3% | | 0.03712 | 2.8% | | 0.04292 | 2.8% | | 0.03712 |
| | 38.4% | 0.22836 | 0.00027 | **36.6%** | 0.23261 | 0.00134 | 35.2% | 0.22836 | 0.00027 | **33.3%** | 0.23261 | 0.00134 |
| 24 | 26.1% | 0.23941 | 0.00032 | **18.6%** | **0.22737** | 0.01164 | 78.0% | 0.23941 | 0.00032 | **75.6%** | **0.22737** | 0.01164 |
| | 44.2% | | 0.01137 | **43.3%** | | **0.00639** | 9.0% | | 0.01137 | **7.5%** | | 0.00639 |

Notes: Results are based on recursive probit estimations, initial period 63:9 (65:3)-79:12–*k*, *k*: horizon, with next period observation data used for one out-of-sample prediction, and iterations henceforth.

- Base model: probit equation with constant, yield curve and real stock return; Extended model: probit equation with constant, yield curve, real stock return and volatility of changes in 3-month interest rate.
- Incorr: percentage of misclassified forecasts (% of total number of observations=216); False R (False E): percentage of recessions (expansions) that were forecast but did not materialize relative to total number of recession (expansion) forecasts; 0–1 classifications were based on the comparison of probability forecast with a time-varying cut-off value (= relative frequency of recessions of the last probit estimation period): 1 if the probability forecast exceeded the cut-off value, 0 otherwise, cf. section 3.
- QPS: quadratic probability score; GSB: global squared bias; LSB: local squared bias (with quintiles); RES: resolution; $QPS_{const}$ : QPS of a constant recession probability, calculated as QPS–LSB+RES. All values lie between 0 and 2 (the lower (higher), the better for QPS, $QPS_{const}$ , GSB and LSB (RES)); definitions, cf. section 3.
- Numbers in the extended model columns are bold-typed if they yielded better outcomes than the base model (lower for Incorr, False R, False E, QPS, $QPS_{const}$, GSB, LSB and higher for RES).

The out-of-sample results suggested that stock volatility did not add much to better predicting the phase of the business cycle. Adding interest rate volatility leads to slightly better predictions, consistently, in terms of QPS, up to 21 months, for Germany and the US, and at varying degrees, also in terms of the other classification statistics. E.g., in Germany, the false recession rate is consistently lower and GSB is lower over horizons up to 21 months ahead, under the extended model; in the US, most classification statistics are better at a 3 and 6 month horizon, and GSB and LSB are lower in the medium run forecast horizon (12-18 months).

Overall, the improvements of the addition are quantitatively not very large, though. Perhaps, this is due to the nature of our data. We used the monthly volatility number, the log of mean absolute deviation, and assumed it had a forward-looking character. Out-of-sample, it may be too static and not fully capture forward-looking information, and therefore, not be useful. Option implied volatility that can explicitly be matched with the forecast horizon may give better and unbiased forward-looking volatility information. However, lack of data prevent us to further investigate this issue.

## 6. Concluding remarks

We extended the finding of Estrella and Mishkin (1997, 1998) that financial variables, esp. share returns and the yield curve, were useful to predict recessions toward including volatility of stocks and bonds. This hypothesis was examined empirically for Germany, the US and Japan, both in-sample and out-of-sample. Instead of taking nominal share returns, as Estrella and Mishkin did, we used real returns, because real activity is better measured in real terms. In line with the existing literature, a positive yield curve was found to reduce the probability of recession for all three countries, at all horizons. Positive real stock returns were found to significantly reduce a chance of recessions. The inclusion of interest rate volatility proved useful for Germany (3-9 months ahead), Japan (3-9 months ahead) and the US (3 months ahead). The significance of the coefficients, when properly assessed, yielded a smaller range of significant results than the usual maximum likelihood estimates. Real stock volatility was only informative 3 months ahead for the US, in addition to the base variables. We interpreted this differing findings as reflecting the firms' different financial structure in these countries. For the US, stock returns and stock volatility matter more, as many US firms depend on the stock market for their financing. Japanese and German firms are more dependent upon bank financing and consequently suffer more from interest rate uncertainty.

The out-of-sample evidence for the US and Germany also yielded some favourable results in terms of value added by financial volatility measures. The rise of option markets may enable the use of other, and perhaps better, implied volatility measures that are truly forward-looking. For the moment, lack of data prevent an in-depth quantitative investigation of this issue.

## References.


ANDERSEN P.S. (1997), Forecast Errors and Financial Developments, BIS Working Paper 50, November, 52 pp.

BALKE N.S. and WYNNE M.A. (1995), Are Deep Recessions Followed by Strong Recoveries? Results for the G-7 Countries, FRB Dallas, Working Paper 95-09, September, 26 pp.

BERNANKE, B.S. (1983), Irreversibility, Uncertainty, and Cyclical Investment, Quarterly Journal of Economics, 98 (1), February, 85-106

BERNARD H. and S. GERLACH (1996), Does the Term Structure Predict Recessions. The International Evidence, BIS Working Paper 37, September, 25 pp.

BLACK, A and P. FRASER (1995), UK Stock Returns : Predictability and Business Conditions, The Manchester School of Economics and Social Studies, Supplement, 63 (0), 85-102.

BONSER-NEAL C. and T.R. MORLEY (1997), Does the Yield Spread Predict Economic Activity? A Multicountry Analysis, Economic Review, FRB Kansas City, 82 (3), 3rd quarter, 37-54.

BURNS, A. and W.C. MITCHELL (1946), Measuring Business Cycles, NBER Studies in Business Cycles, No. 2, Columbia University Press, New York

CHEN, N.F. (1991), Financial Investment Opportunities and the Macroeconomy, Journal of Finance, 46(2), June, 529-554.

CHEN, N.F., R. ROLL and S.A. ROSS (1986), Economic Forces and the Stock Market, Journal of Business, 59 (3), July, 383-403.

CHOE, H., R.W. MASULIS and V. NANDA (1993), Common Stock Offerings across the Business Cycle: Theory and Evidence, Journal of Empirical Finance, June, 3-31.

COOK T. and T. HAHN (1989), The Effect of Changes in the Federal Funds Rate Target on Market Interest Rates in the 1970s, Journal of Monetary Economics, 24 (3), November, 331-351.

DAVIS E.P. and G. FAGAN (1997), Are Financial Spreads Useful Indicators of Future Inflation and Output Growth in EU Countries?, Journal of Applied Econometrics, 12 (6), November-December, 701-714

DAVIS E.P. and S.G.B. HENRY (1994), The Use of Financial Spreads as Indicator Variables : Evidence for the UK and Germany, IMF Staff Papers, 41 (3), September, 517-525

DIEBOLD, F.X. and J.A. LOPEZ (1989), Scoring the Leading Indicator, Journal of Business, 62 (3), Autumn, 369-391.

DIXIT, A. (1992), Investment and Hysteresis, Journal of Economic Perspectives, 6 (1), Winter, 107-32

ESTRELLA A. (1998), A New Measure of Fit for Equations with Dichotomous Dependent Variables, Journal of Business and Economic Statistics, 16 (2), April, 198-205

ESTRELLA A. and F.S. MISHKIN (1997), The Predictive Power of the Term Structure of Interest Rates in Europe and the United States: Implications for the European Central Bank, European Economic Review, 41 (7), July, 1375-1401

ESTRELLA A. and F.S. MISHKIN (1998), Predicting US Recessions: Financial Variables as Leading Indicators, Review of Economics and Statistics, 80 (1), February, 45-61

ESTRELLA A. and A.P. RODRIGUEZ (1998), Consistent Covariance Matix Estimation in Probit Models with Autocorrelated Errors, FRB New York Working Paper, April, 22 pp.

FAGAN G. and J. FELL (1994), Techniques for Forecasting the Irish Business Cycle, Central Bank of Ireland, Technical Paper 94/2, 73 pp.

FAMA, E.F. (1976), Forward Rates as Predictors of Future Spot Rates, Journal of Financial Economics, 3 (4), October, 361-377

FAMA, E.F. (1990a), Stock Retuns, Expected Returns, and Real Activity, Journal of Finance, 45 (4), September, 1089-1108.

FAMA, E.F. (1990b), Term-Structure Forecasts of Interest Rates, Inflation and Real Returns, Journal of Monetary Economics, 25 (1), January, 59-76.

FAMA, E.F. and K.R. FRENCH (1989), Business Conditions and Expected Returns on Stocks and Bonds, Journal of Financial Economics, 25 (1), November, 23-49.

FISHER S. and R. MERTON (1984), Macroeconomics and Finance: The Role of the Stock Market, Carnegie-Rochester Conference Series on Public Policy, 21 (0), Autumn, 57-108

FRENCH K.R., G.W. SCHWERT AND R.F. STAMBAUGH (1987), Expected Stock Returns and Volatility, Journal of Financial Economics, 19, 3-29

FUNKE, N. (1997), Predicting Recessions: Some Evidence for Germany, Weltwirtschafliches Archiv, 133 (1), 90-102

GREENE, W.H. (1993), Econometric Analysis, MacMillan Publishing Company, New York, 2nd edition, xxiii-791 pp.

HAMILTON J.D. (1989), A New Approach to the Economic Analysis of Nonstationary Time Series and the Business Cycle, Econometrica, 57 (2), March, 357-384

HAMILTON J.D. and LIN G. (1996), Stock Market Volatility and the Business Cycle, Journal of Applied Econometrics, 11 (5), September-October, 573-593.

HARDOUVELIS G.A. (1988), The Predictive Power of the Term Structure during Recent Monetary Regimes, Journal of Finance, 43 (2), June, 339-356

HARVEY C.R. (1988), The Real Term Structure and Consumption Growth, Journal of Financial Economics, 22 (2), December, 305-333

HARVEY C.R. (1991), Interest Rate Based Forecasts of German Economic Growth, Weltwirtschafliches Archiv, 127 (4), 701-718

HICKS J.R. (1946), *Value and Capital*, Oxford University Press, London, 2nd ed. , cited in Fama and French (1989)

HU Z. (1993), The Yield Curve and Real Activity, IMF Staff Papers, 40 (4), December, 781-806.

HU Z. (1995), Stock Market Volatility and Corrporate Investment, IMF Working Paper 95/102, October, 15 pp.

KEIM, DB. and R.F. STAMBAUGH (1986), Predicting Returns in the Stock and Bond Markets, Journal of Financial Economics, 17 (2), December, 357-390.

KESSEL R.A. (1965), The Cyclical Behavior of the Term Structure of Interest Rates, NBER Occasional Working Paper no. 91, cited in Fama and French (1989)

KIM K.A. and P. LIMPAPHAYOM (1997), The Effects of Economic Regimes on the Relation between Term Structure and Real Activity in Japan, Journal of Economics and Business, 49 (4), July-August, 379-92

KNEZ, P.J., R. LITTERMAN and J.A. SCHEINKMAN (1994), Explorations into Factors Explaining Money Market Returns, Journal of Finance, 49 (5), December, 1861-82

LEE, B.S. (1992), Causal Relations Among Stock Returns, Interest Rates, Real Activity, and Inflation, Journal of Finance, 48 (4), September, 1591-1603.

MADDALA, G.S. (1983), *Limited-dependent and Qualitative Variables in Econometrics*, Cambridge University Press, pages ix, 401

MOORE G.H. (1983), *Business Cycles, Inflation and Forecasting*, Cambridge, Ballinger

PEEK, J. and E.S. ROSENGREN (1988), The Stock Market and Economic Activity, New England Economic Review, May-June, 39-50.

SACHS, L. (1984), Applied Statistics, A Handbook of Techniques, Springer Series in Statistics, Springer-Verlag, New York, 2nd edition, xxii-707 pp.

SCHWERT, G.W. (1989), Business cycles, financial crises, and stock volatility, Carnegie-Rochester Conference Series on Public Policy, 31 (0), Autumn, 83-125

SCHWERT, G.W. (1990), Stock Returns and Real Activity: A Century of Evidence, Journal of Finance, 45 (4), September, 1237-57.

SILL, K. (1996), The Cyclical Volatility of Interest Rates, Business Review, FRB Philadelphia, January-February, 15-29

WATSON, M., (1991), Using Econometric Models to Predict Recessions, Economic Perspectives, Federal Reserve Bank of Chicago, November-December, 14-25.

# Appendix

**1. Hansen and Newey-West correction of t-statistics for overlapping samples.**

Briefly stated, the technique uses the first-order conditions $h$=0 to calculate sample autocovariances of $h$, viz. $\Omega_j$.

The first-order condition for the probit model imply

$$h_t = \frac{y_t - F_t}{F_t(1-F_t)} f_t X_t = 0$$

where $F_t = F(\beta' X_t)$

and $f_t = F'$, the first derivative of $F$ w.r.t. $\beta' X_t$.

The sample autocovariances of $h$ are $\Omega_j = \frac{1}{T} \sum_{t=j+1}^{T-k} h_t h'_{t-j}$ , for $j = 1, ..., m$.

These autocovariances can be used to construct a family of estimators of the covariance of $h$, viz.

$$S = \Omega_0 + \sum_{j=1}^{m} \lambda_j(\Omega_j + \Omega_j'),$$

where $\lambda_j = 1-j/(m+1)$ in case of a Newey-West correction, or $\lambda_j = 1$ in case of the Hansen adjustment.

The variance-covariance matrix of the coefficient estimates is given by $V$:

$$V = \frac{1}{T}(H'H)^{-1}H'SH(H'H)^{-1}$$

$$\text{where } H = \frac{1}{T}\,\partial h/\partial\beta = \frac{1}{T}\sum_t \frac{-f_t^2 x_t x_t'}{F_t(1-F_t)} + \frac{1}{T}\sum_t (y_t - F_t)\frac{\partial}{\partial\beta}\frac{f_t x_t}{F_t(1-F_t)}$$

and $S$ as defined above.

A further simplification results in $V = \frac{1}{T} H_0^{-1} S H_0^{-1}$ as $H$ converges to $H_0$ for large samples.

$$H_0 = \lim \frac{1}{T}\sum_t \frac{-f_t^2 x_t x_t'}{F_t(1-F_t)} \quad .$$

Estrella & Rodriguez (1998) find evidence that in their simulation with one explanatory variable, the Hansen estimator yielded superior standard error estimates when there was both positive autocorrelation in the disturbance and in the explanatory variables. In case they used a small sample (100 observations) or with little autocorrelation in the disturbances, the Hansen adjustment does not work well and other adjustments may be better. Therefore, we presented both the Hansen and Newey-West correction.

**2. Monte Carlo simulation of the likelihood ratio test statistic.**

In this experiment, we want to approximate the unobservable distribution of the LR statistic under heteroskedasticity and autocorrelation induced by overlapping sample errors, in order to derive the critical values and the probability distribution. The method is as follows.

First, pseudo sample data of our independent $X_t$ variables and of $R_t^*$, the latent variable, are generated. Specifically, the pseudo sample data are constructed by first analysing the time-series behaviour of the series itself and the covariances of their residuals. In the experiment, a matrix of *T*x4 random normals $\varepsilon$ is drawn, representing the residuals of the pseudo $X$ variables, after a scale adjustment:

$$\text{If } \varepsilon_t \sim N[\,\mathbf{0}\,,\mathbf{I}\,],\text{ then } \mathbf{A}\varepsilon_t \sim N[\mathbf{0}\,,\mathbf{AA'}\,]\,.$$

In our setup, **AA'** is the covariance of the true residuals, $\Omega$. We can obtain **A** from the Cholesky factorization of $\Omega$ to adjust $\varepsilon$ appropriately [Any symmetric positive definite matrix may be written as the product of a lower triangular matrix **L** and its transpose (which is an upper triangular matrix), **L'** = **U**. Thus $\Omega$ = **LU**, cf. Greene, 1993, p. 36, 77]. Given a vector of starting values of $X$, and using the ARMA coefficients and scaled random residuals, a pseudo sample of $X$ variables can be constructed.

Then, using the estimated $\beta$-coefficients from the original probit equation, the latent variable $R^*$ is constructed and the recession variable $R$ is derived by mapping $R_t^*$ onto $R_t$. $R_t$ is one if $R_t^*$ is positive and zero otherwise:

$$R_t^* = \beta^{probit}\ X_{t-k}^{sim} + u_t,$$

$$\text{where } u_t = \sum_{t=0}^{k-1}\left(e_t/\sqrt{k}\right) \text{ and } e_t \sim N\,[0,1]$$

$$R_t^{sim} = 1 \text{ if } R_t^* > 0,\ \ R_t^{sim} = 0 \text{ otherwise.}$$

As can be seen, a disturbance term $u$ that introduces the overlapping sample problem is added to $\beta X$.

Finally, a probit equation is estimated using these simulated data and the obtained likelihood ratio is noted. Repeating this exercise 1000 times then gives an approximate distribution of the true LR test statistic. Off course, one might iterate many more times, but the 95% critical value was fairly stable after 1000 iterations already.

In table A1, the ARMA behaviour of the $X$ variables is shown. Additional lags (AR-terms) or MA-terms of the variable were considered but not taken up if they did not improve the Akaike and Schwartz information criterion for a better time-series representation. As can be seen, the yield spread is best modelled as a simple first order autoregressive process. Real stock returns were measured over three months and thus, it comes as no surprise that an MA2 model is best. Financial volatilities have both AR and MA terms.

**Table A1. Time series behaviour of the independent variables**

| Variable | Constant | AR1 | MA1 | MA2 | AIC | SC | $R^2$adj |
|---|---|---|---|---|---|---|---|
| | | | GERMANY | | | | |
| **YC** | 0.113<br>(2.55) | 0.926<br>(49.0) | – | – | -0.8388 | -0.8187 | 0.858 |
| **DRS** | – | – | 0.981<br>(79.4) | 0.961<br>(68.0) | 3.333 | 3.354 | 0.669 |
| **VOLR** | -0.036<br>(-1.27) | 0.988<br>(101.5) | -0.550<br>(-11.0) | -0.155<br>(-3.08) | -1.507 | -1.468 | 0.734 |
| **VOLSH** | -0.034<br>(-1.97) | 0.920<br>(25.2) | -0.536<br>(-8.45) | -0.126<br>(-2.21) | -2.271 | -2.231 | 0.315 |
| | | | USA | | | | |
| **YC** | 0.0085<br>(0.26) | 0.942<br>(56.8) | – | – | -0.845 | -0.826 | 0.887 |
| **DRS** | 0.864<br>(1.48) | – | 0.986<br>(71.4) | 0.968<br>(78.8) | 2.975 | 3.004 | 0.674 |
| **VOLR** | -0.043<br>(-1.38) | 0.986<br>(94.4) | -0.632<br>(-12.5) | -0.080<br>(-1.58) | -1.351 | -1.312 | 0.697 |
| **VOLSH** | -0.054<br>(-3.0) | 0.904<br>(31.8) | -0.484<br>(-8.37) | – | -2.527 | -2.498 | 0.490 |
| | | | JAPAN | | | | |
| **YC** | – | 0.930<br>(36.5) | – | – | -1.663 | -1.647 | 0.833 |
| **DRS** | 2.353<br>(2.0) | – | 0.957<br>(109.7) | 0.980<br>(2380) | 3.563 | 3.610 | 0.649 |
| **VOLR** | -0.171<br>(-2.07) | 0.952<br>(38.7) | -0.536<br>(-7.28) | -0.175<br>(-2.43) | -1.292 | -1.229 | 0.533 |
| **VOLSH** | -0.058<br>(-2.10) | 0.846<br>(17.5) | -0.261<br>(-2.98) | – | -2.055 | -2.008 | 0.544 |

Variables are YC: yield spread (government bond yield – 3 month euro rate); DRS: real stock return (over 3 months); VOLR: log of monthly mean absolute deviation of daily changes in 3 month euro rate; VOLSH: log of monthly mean absolute deviation of daily real stock returns.

Notes : Constant, AR1, MA1 and MA2 refer to the time series behaviour coefficients, t-stats are in parentheses; – indicates that the AIC or SC did not decrease when it was considered.
AIC : Akaike information criterion, SC : Schwartz criterion (lower values mean better fit), $R^2$adj : degrees of freedom adjusted $R^2$.