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Financial market volatility: informative in predicting recessions

Suomen Pankin keskustelualoitteita
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Financial market volatility: informative in predicting recessions

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Jan Annaert – Marc J.K. De Ceuster – Nico Valckx
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Abstract

It is commonly agreed that the term spread and stock returns are useful in predicting recessions. We extend these empirical findings by examining interest rate and stock market volatility as additional recession indicators. Both risk-return analysis and the theory of investment under uncertainty provide a rationale for this extension. The results for the United States, Germany and Japan show that interest rate and stock return volatility contribute significantly to the forecasting of future recessions. This holds in particular for short term predictions.

Key words: business cycles, stock market volatility, interest rate volatility, probit model

JEL classification numbers: E32, E44, C25

Rahoitusmarkkinoiden volatiilius: hyödyksi taantuman ennakoinnissa

Suomen Pankin keskustelualoitteita 14/2001

Jan Annaert – Marc J.K. De Ceuster – Nico Valckx
Tutkimusosasto

Tiivistelmä

On yleisesti tunnettua, että tietoja osaketuotoista ja lyhyiden ja pitkien korkojen erotuksesta voidaan käyttää hyväksi taloustaantumien ennakoinnissa. Tässä tutkimuksessa laajennamme tätä koskevia empiirisiä tuloksia tarkastelemalla korkojen ja osakemarkkinoiden volatiiliutta taantuman indikaattorina. Sekä riski-tuottotarkastelu että teoriat epävarmuuden vaikutuksesta investointeihin tukevat tätä laajennusta. Yhdysvaltojen, Saksan ja Japanin taloutta koskevat tulokset osoittavat, että korkojen ja osakekurssien volatiilius auttaa merkitsevästi ennustamaan tulevia taantumia. Tämä pätee erityisesti lyhyen aikavälin ennustamisessa.

Asiasanat: suhdannevaihtelut, osakemarkkinoiden volatiilius, korkojen volatiilius, probit-malli

JEL luokittelu: E32, E44, C25

Contents

Abstract ... 3

1 Introduction ... 7

2 Data and descriptive statistics ... 8

3 Empirical evidence ... 10
3.1 Probit results ... 10
3.2 Regression results ... 15

4 Conclusion ... 18

References ... 19

1 Introduction

Accurate forecasts of business cycles are extremely important for many economic decisionmakers. Policymakers need forecasts for proposing national budgets or when implementing monetary policy. Entrepreneurs often rely on such forecasts in order to schedule optimal production plans. In this respect, financial market information has proven its usefulness to enrich the information set of macroeconomic forecasters. Estrella and Mishkin (1997, 1998) point out that 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 industrialised countries.[1]

Although financial markets have gained the interest of macroeconomists searching for good leading indicators, remarkably little attention is given to volatility measures.[2] Still, it is well know that volatility increases after stock prices fall. It increases during recessions and also around major financial crises (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.

In macroeconomic applications, there may be important relationships between financial market volatility and real aggregates. Firstly, many studies document a wealth effect on consumption (see, e.g., Poterba and Samwick, 1995, Starr-McCluer, 1998, Otto, 1999). Hence, more uncertain financial wealth is likely to depress current consumption, which in turn will lead to a decline of economic growth. Secondly, several channels may transmit financial market volatility into corporate investment and hence (directly or indirectly) into real activity. The theory of irreversible investments argues that increased volatility gives rise to postponing investment decisions (see, e.g. Bernanke, 1983, and Dixit, 1992). Also the traditional investment theory relates the cost of capital to financial market volatility. If markets are turbulent and prices deviate from their fundamentals, a higher risk premium will be required and this, in turn, will depress investment (Hu, 1995). Finally, 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.

This paper aims to provide empirical evidence on the extra information value of financial volatility for business cycle forecasting in the US, Germany and Japan. We are aware of only a few studies that address this issue. Pindyck and Solimano (1993) find that volatility (of the marginal productivity of capital) reduces the rate of investment for a panel of LDC countries but not for a panel of OECD countries (decade average observations of 1960s, 1970, 1980s). Anderson and Breedon (1996) for the UK do not find any evidence that measures of asset price volatility (stocks, T-bills, bonds, exchange rate) have any consequences for

[1] See Harvey (1988), Hardouvelis (1988), Boulier and Stekler (2000), Campbell et al. (2001) 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.

[2] In finance theory, the behavior of market volatility crucially influences intertemporal decisionmaking under uncertainty. Furthermore, when modeling the term structure of interest rates, three factors are needed: the short rate, the long rate (or the spread) and the volatility of the short rate, see, e.g., Litterman and Scheinkman (1991), Gong and Remolona (1997).

investment or consumption; their data are quarterly, 1977–1995. Campbell et al. (2001) find that lagged volatility measures (disaggregate – firm, industry and market volatility) help to predict quarterly US GDP growth over 1962–1997. Our results confirm that both interest rate and stock market volatility add significant explanatory power, both in probit and OLS estimations, to predict future recessions or real growth. However, there appear to be regime shifts, differences between the information content of stock market and interest rate volatility and country differences (Japan versus the US and Germany). The paper proceeds as follows. In the next section the data are described and descriptive statistics are discussed. In a further section the empirical evidence is presented. The final section concludes.

2 Data and descriptive statistics

In this study, monthly data are used since most information from financial prices comes at high frequency and tends to become less useful vis-à-vis macroeconomic aggregates when measured over lower frequencies. It complements Boulier and Stekler (2000) who evaluate the findings of Estrella and Mishkin (1998) over a monthly interval. Long term interest rates refer to 10-year government bond yields, short term interest rates are 3-month euro interest rates (money market call rate for Japan). The yield spread measures the difference between these rates. Real stock returns were constructed from logarithmic changes of the (nominal) stock indices (S&P500 for the US, DAX for Germany and Nikkei-225 for Japan), corrected for inflation.[3] Financial series were taken from BIS. Inflation was measured by the logarithmic change of the CPI-index taken from IFS (series 64). Dates separating contractions and expansions are those reported by NBER for the US, Economic Planning Agency for Japan, and Centre for International Business Cycle Research for Germany.[4]

In order to measure volatility, several candidates come to mind. The most forward looking volatility estimate is the implied volatility from options. Unfortunately, options on stock indices and interest rates only became listed in the 1980s (US) or the 1990s (Germany, Japan). Consequently, we would be left with a too short time period in order to do forecasting. Another natural candidate is a GARCH-type model. GARCH, however, implies that volatilities behave in a deterministic way and can only have upward shocks. Moreover, Lamoureux and Lastrapes (1993) and Jorion (1995) both have shown that implied volatilities or even simple historical forecasts outperform GARCH-based volatility forecasts. Taking these facts into account, volatility estimates of stocks and bonds were constructed as mean absolute deviations, over a one month interval, of daily changes in 3-month euro interest rates[5] and daily logarithmic stock price changes. The mean absolute deviation is taken as a risk measure since for small sample

[3] The rationale is that economic activity is better measured by real rather than nominal magnitudes. Therefore, also stock prices are adjusted for the level of inflation.
[4] The average duration of a recession was 11 months in the US, 30 months in Germany and 22 months in Japan for the given sample periods.
[5] The US VOLR is also calculated for the 10-year constant maturity interest rate series, since this series is also available on a daily basis (source: Fed St. Louis). The results do not differ much, though.

sizes (as is the case here: one month of data, about 20 observations), it is superior to the otherwhise optimal standard deviation.[6] Compare with Campbell et al. (2001) who also use daily data to construct sample variances for that month.

Table 1. **Descriptive data statistics**

	SP	SR	VOLR	VOLS	SP	SR	VOLR	VOLS	SP	SR	VOLR	VOLS
United States												
	1963:7–2000:12				1963:7–1981:12				1982:1–2000:12			
Mean	0.13	0.27	0.08	0.60	–0.88	–0.25	0.10	0.53	1.12	0.77	0.05	0.67
Maximum	3.49	10.82	0.66	3.76	2.37	9.12	0.66	1.68	3.49	10.82	0.34	3.76
Minimum	–6.69	–13.49	0.00	0.17	–6.69	–12.48	0.00	0.17	–1.30	–13.49	$8\cdot10^{-6}$	0.25
Std. Dev.	1.86	3.47	0.08	0.30	1.89	3.53	0.09	0.25	1.17	3.35	0.05	0.33
Unit root ADF	–3.26	–8.20	–2.98	–5.03	–3.08	–5.60	–2.09	–2.98	–1.63	–6.48	–3.93	–4.21
Unit root PP	–3.57	–15.86	–6.18	–10.45	–3.38	–11.71	–4.96	–5.77	–1.88	–10.89	–4.89	–8.56
		SR	VOLR	VOLS		SR	VOLR	VOLS		SR	VOLR	VOLS
Correlations	SP	24.1[a]	–53.2[a]	–14.2[a]		34.7[a]	–57.4[a]	–38.1[a]		–5.0	–5.4	–29.1[a]
	SR		–17.7[a]	–33.5[a]			–13.7[b]	–43.8[a]			–14.3[b]	–34.6[a]
	VOLR			18.[a]				43.2[a]				15.8[b]
Germany												
	1965:1–2000:12				1965:1–1979:12				1980:1–2000:12			
Mean	1.56	0.34	0.12	0.73	2.47	–0.31	0.22	0.62	0.91	0.81	0.04	0.81
Maximum	8.80	13.16	1.62	3.00	8.80	13.16	1.62	1.40	2.99	10.59	0.42	3.00
Minimum	–2.79	–26.79	0.00	0.22	–2.79	–12.52	0.03	0.26	–2.36	–26.79	0.00	0.22
Std. Dev.	1.66	4.31	0.17	0.35	1.71	3.77	0.22	0.21	1.28	4.60	0.04	0.40
Unit root ADF	–3.23	–8.42	–3.09	–5.51	–2.54	–4.79	–2.49	–3.42	–2.35	–7.04	–3.66	–4.64
Unit root PP	–3.35	–15.16	–6.64	–10.61	–2.68	–10.15	–5.09	–8.36	–2.26	–11.52	–8.39	–8.14
		SR	VOLR	VOLS		SR	VOLR	VOLS		SR	VOLR	VOLS
Correlations	SP	0.042	28.2[a]	–6.8		16.7[b]	16.3[b]	–8.1		8.1	–43.3[a]	14.7[b]
	SR		–15.6[a]	–23.7[a]			–16.3[b]	–12.8[c]			–8.1	–33.8[a]
	VOL			–3.2				42.0[a]				–19.3[a]
Japan												
	1966:6–2000:12				1966:6–1976:12				1977:1–2000:12			
Mean	0,65	0,21	0,74	0,65	–0,37	0,18	0,96	0,47	1,10	0,22	0,64	0,73
Maximum	3,58	13,83	4,55	2,60	2,40	9,33	3,93	1,55	3,58	13,83	4,55	2,60
Minimum	–5,24	–18,27	$8\cdot10^{-18}$	0,08	–5,24	–16,26	$8\cdot10^{-18}$	0,08	–4,45	–18,27	$2\cdot10^{-5}$	0,09
Std. Dev.	1,66	4,27	0,80	0,41	1,96	4,36	0,91	0,26	1,26	4,25	0,73	0,44
Unit root ADF	–3,52	–8,09	–4,79	–4,13	–2,33	–4,60	–3,06	–4,19	–3,54	–6,59	–3,76	–3,63
Unit root PP	–3,23	–14,73	–4,50	–9,13	–1,48	–7,71	–2,51	–10,24	–3,47	–12,54	–3,73	–6,69
		SR	VOLR	VOLS		SR	VOLR	VOLS		SR	VOLR	VOLS
Correlations	SP	8.2[c]	–42.6[a]	9.7[c]		22.0[b]	–28.5[a]	–12.2		–0.1	–48.5[a]	1.4
	SR		–3.7	–34.7[a]			–10.7	–29.1[a]			0.2	–39.3[a]
	VOL			–12.2[b]				4.0				–11.6[b]

Notes

This table presents summary descriptive statistics of our dataset. Subsamples were delineated according to regression tests for structural stability (see below). Mean, maximum, minimum, standard deviation and correlations are percentage notations. Augmented Dickey-Fuller and Phillips-Perron unit root tests reject unit roots (MacKinnon critical values at 1%: –3.44, 5%: –2.87, 10%: –2.57).

Correlations are significant at [a]: 1%, [b]: 5%, [c]: 10%.

Variables are SP: yield spread (10-year government bond yield minus 3-month USD/DEM interest rate/call rate for Japan), SR: real stock return (monthly stock market index return minus CPI inflation – index is S&P500 for US, DAX for Germany and Nikkei-225 for Japan), VOLR interest rate volatility (mean absolute deviation of within-month changes in the short rate), VOLS: stock market volatility (mean absolute deviation of within-month stock market index returns).

For the US, the sample starts in 1963:7, for Germany in 1965:1 and for Japan in 1966:6. Table 1 presents descriptive statistics (mean, maximum and minimum, standard deviation, unit root tests and correlations) of the suggested explanatory variables. For each country, the sample was split based on regression tests for structural stability (see regression results below). In the US, the split coincides with the change in monetary policy procedures in the early 1980s. For Germany, the start of the European Monetary System in 1979 is a likely explanation. For

[6] The reason being that values far from the mean are less influential for the mean absolute deviaton than for the standard deviation (Sachs, 1984, p. 252).

Japan, financial market deregulation starting in the latter half of the 1970s may explain the break, see, e.g., Kim and Limpaphayon (1997).

Table 1 reveals that for the US and Japan, the yield spread was negative on average over the early subperiod but positive over the second subperiod. In Germany, the spread was positive in both, but about twice as high in the first subperiod. In the second subsample, the spread is about the same in each of the three countries, revealing some convergence in international bond rates. Real stock returns in the US and Germany were about the same magnitude during both periods; negative over sample I but positive during sample II. In Japan, real stock returns were slightly higher in the second period, after the financial market liberalisation. In each of the countries, interest rate volatility has declined over the second subsample while stock market volatility has increased, both in absolute levels as in variability. As can be seen, stock returns fluctuate most, while interest rate spreads and financial volatilities do less so. In all cases, unit root tests suggest that the data are stationary. Correlations between the explanatory variables are moderate and generally smaller than 0.50 in absolute values. Only between the yield spread and interest rate volatility, and real stock returns and stock return volatility, correlations are higher and mostly negative. This seems to confirm the leverage effect: the fact that volatility tends to rise when returns are diminishing or negative (Christie 1981). Remarkably, across the G-3, there is no clear correlation pattern between stock market and interest rate volatility: in the US, these series appear positively correlated (high in the first sample), in Germany there is no correlation overall (though very negative over sample I and positive over sample II), while in Japan, the series are slightly negatively correlated (due to sample II).[7] As such, the three countries' data provide a diverse enough information set to test the hypothesis that financial volatility adds to explaining and forecasting recessions. Besides, these countries constitute the G-3, accounting for 60% of OECD countries' GDP in 1999 (source: OECD Economic Outlook 1999) and therefore warrant special attention.

3 Empirical evidence

We provide measures of fit and significance for financial variables predicting recessions k months ahead, first, using a probit model. In the next subsection, we also investigate the issue using industrial production as a dependent variable using regression analysis.

3.1 Probit results

As stated above (see footnote 1), Estrella and Mishkin (1997, 1998) and many others have documented that yield spreads and changes in share prices have a noticable forecasting ability for recessions. In a probit context, negative signs are expected for the yield curve and changes in the real share price index, since increases in these variables reduce the probability of future recessions. For

[7] Note that there is never a problem of multicollinearity. When we perform the Belsley test (not reported), the condition numbers are always below 10, still far below the critical value of 20.

financial volatility, positive signs are expected, because higher financial volatility is assumed to increase the probability of future recessions, as argued in section 1.

Table 2. **Probit forecast of recession k months ahead in the G-3 countries $\mathrm{Prob}[R_{t+k} = 1] = \Phi(c_0 + c_1 SP_t + c_2 SR_t + c_3 VOLR_t + c_4 VOLS_t)$**

k	c_0	c_1	c_2	c_3	c_4	R^2
United States (1963:7–2000:12)						
3	–2.02	–31.92	–4.31	256.10	64.46	0.270
	(–7.87)[a]	(–5.48)[a]	(–1.67)[c]	(1.48)	(1.96)[b]	[0.000]
6	–1.57	–41.32	–5.98	64.31	11.43	0.288
	(–7.98)[a]	(–6.04)[a]	(–2.03)[b]	(0.37)	(0.51)	[0.000]
9	–1.45	–42.79	–1.92	304.21	–48.11	0.310
	(–6.97)[a]	(–6.17)[a]	(–0.70)	(2.05)[b]	(–1.53)	[0.000]
12	–1.38	–38.07	–0.35	287.85	–45.92	0.253
	(–6.22)[a]	(–6.42)[a]	(–0.14)	(2.17)[b]	(–1.39)	[0.000]
Germany (1965:1–2000:12)						
3	0.51	–43.98	–4.41	182.81	–32.11	0.263
	(2.74)[a]	(–7.56)[a]	(–2.60)[a]	(3.46)[a]	(–1.54)	[0.000]
6	0.78	–59.32	–6.73	312.18	–50.92	0.387
	(3.74)[a]	(–10.03)[a]	(–3.70)[a]	(4.79)[a]	(–2.24)[b]	[0.000]
9	0.68	–61.07	–6.27	349.05	–40.32	0.402
	(3.69)[a]	(–10.76)[a]	(–3.37)[a]	(5.23)[a]	(–1.94)[c]	[0.000]
12	0.65	–56.11	–6.91	335.89	–48.13	0.377
	(3.54)[a]	(–10.07)[a]	(–3.61)[a]	(5.25)[a]	(–2.24)[b]	[0.000]
Japan (1966:6–2000:12)						
3	–0.77	–23.16	–1.49	26.56	59.13	0.158
	(–4.73)[a]	(–5.09)[a]	(–0.86)	(2.94)[a]	(3.24)[a]	[0.000]
6	–0.74	–20.51	–2.50	28.55	50.88	0.150
	(–4.54)[a]	(–4.29)[a]	(–1.44)	(3.12)[a]	(2.86)[a]	[0.000]
9	–0.68	–14.53	–3.23	27.89	38.99	0.115
	(–4.36)[a]	(–3.07)[a]	(–1.91)[c]	(3.12)[a]	(2.30)[b]	[0.000]
12	–0.76	–4.59	–4.56	34.38	36.43	0.099
	(–4.83)[a]	(–1.01)	(–2.73)[a]	(3.88)[a]	(2.15)[b]	[0.000]

Notes

This table reports probit equations for recessions k months ahead, k = 3, 6, 9, 12. Coefficients and t-stats between brackets for constant (c_0), SP: yield spread (c_1), SR: real stock return (c_2), VOLR: interest rate volatility (c_3) and VOLS: stock return volatility (c_4).

t-stats are based on numerically calculated standard errors that are adjusted for heteroskedasticity and autocorrelation, $\Omega = H^{-1}gg'H^{-1}$ where g and H are gradient and Hessian of the probit function evaluated at the maximum likelihood estimates, Ω is the variance-covariance matrix of the coefficients.

R^2 is the Estrella (1998) measure of fit for probit, $R^2 = 1-(LL_u/LL_c)^{-2LLc/T}$ where LL_c and LL_u denote the loglikelihood of a model with only a constant, and with all variables, respectively. T is the number of observations. Between square brackets, the probability of the corresponding F-stat is reported, obtained analagously as to the linear regression relation, $F[K-1, T-K] = (T-K)R^2/[(K-1)(1-R^2)]$ where K is the number of coefficients to be estimated.

Significance level [a]: 1%, [b]: 5%, [c]: 10%.

The monthly probit results are reported in Table 2. Signs for the yield spread and real stock return are as expected for all three countries. In line with previous evidence for the US, stock returns are useful to predict recessions in the near future, while the spread remains significant beyond one year of data. In Japan, on the other hand, the real stock return is a significant recession indicator 9 and 12 months ahead while the yield spread gradually loses its information content. In Germany, both the spread and real stock return work well as recession indicators up to one year. These results are in line with previous studies (see footnote 1).

The extension of adding financial volatility is well supported by the data, for all three countries, based on the t-statistics.[8] Nevertheless, there appear to be some differences between the countries regarding horizon, sign and which of the volatility variables are significant. For Germany and Japan, higher interest rate volatility significantly increases the probability of entering a recession, consistently, 3 to 12 months ahead. In the US, it adds significant explanatory power 9 and 12 months ahead. This could indicate that interest rate volatility takes more time to negatively impact the US economy than it does in Germany and Japan. This may be explained by the difference of financial systems in Germany and Japan vis-à-vis the US: companies in the former rely more heavily on bank finance whereas stock market finance is more common among US firms. Hence, it may take more time before interest rate changes affect the stock market and corporate investments in the US than it does in Germany and Japan. Accordingly, higher stock return volatility, in the US, significantly increases the probability of recession for the 3-month ahead horizon, suggesting a high short-term exposure of the economy to stock market volatility. This finding is also consistent with Choe et al. (1993) and Campbell et al. (2001).[9] Note that there is a sign reversal on stock volatility, after 6 months; statistics remain insignificant though. In Japan, higher stock market volatility increases the probability of recession over all horizons up to 1 year. For Germany, it works in an opposite way, suggesting that higher stock volatility reduces the probability of recession. See section 3.2 for a tentative explanation.

Overall, the explanatory power of our financial variables probit equation is satisfactory, as captured by the R^2 and the F-test significance (see Estrella, 1998). It reaches a maximum of 0.31 for the US and 0.40 for Germany at a 9-month horizon, but only 0.16 for Japan at a 3-month horizon. Compare with Boulier and Stekler (2000) who find an R^2 of 0.26 (US, monthly 1953:4–1998:1, probit with yield spread) and Estrella-Mishkin (1997) who obtain an R^2 of 0.35 (US, monthly 1973–1994, probit with yield spread) and 0.57 (Germany, monthly 1973–1994, probit with yield spread).

To assess how well the probit forecasts predict actual recessions, one can use the quadratic probability score (QPS) as in Diebold and Lopez (1989) and Boulier and Stekler (2000): QPS = $\frac{1}{T}\Sigma_t 2(P_t - R_t)$, where R_t is the recession variable (0–1), and P_t is the model-probability of recession. The QPS ranges between 0 and

[8] t-statistics are based on numerically calculated standard errors that take into account heteroskedasticity and serial correlation. The are calculated from var(b) = $H^{-1}gg'H^{-1}$ where g and H are the gradient and Hessian of the log likelihood evaluated at the maximum likelihood estimates, var(.) denotes the variance-covariance matrix of the coefficients.

[9] Campbell et al. (2001), however, do not perform probit estimation; instead they present correlations between their volatility measures and the NBER dates. We obtain similar patterns of correlation (not reported).

Table 3. **Quadratic Probability Scores (QPS) of various recession forecasting models**

k	Model	QPS	1960s	1970s	1980s	1990s
United States						
3	FMVOL	0.1531	0.0563	0.1956	0.2182	0.1101
	FMBASE	0.1590	0.0918	0.1971	0.2156	0.1112
	ZEROPROB	0.2550	0.0000	0.4500	0.3667	0.1212
	NAIVE	0.2225	0.0000	0.4500	0.3667	0.1212
6	FMVOL	0.1435	0.0579	0.1556	0.2183	0.1112
	FMBASE	0.1438	0.0644	0.1517	0.2198	0.1107
	ZEROPROB	0.2568	0.0000	0.4500	0.3667	0.1212
	NAIVE	0.2238	0.0000	0.4500	0.3667	0.1212
9	FMVOL	0.1412	0.0342	0.1955	0.1819	0.1108
	FMBASE	0.1449	0.0387	0.1930	0.1967	0.1097
	ZEROPROB	0.2585	0.0000	0.4500	0.3667	0.1212
	NAIVE	0.2251	0.0000	0.4500	0.3667	0.1212
12	FMVOL	0.1662	0.0319	0.2610	0.2119	0.1055
	FMBASE	0.1705	0.0359	0.2638	0.2248	0.1036
	ZEROPROB	0.2603	0.0000	0.4500	0.3667	0.1212
	NAIVE	0.2264	0.0000	0.4500	0.3667	0.1212
Germany						
3	FMVOL	0.3590	0.4975	0.2776	0.3966	0.3389
	FMBASE	0.3891	0.4844	0.3459	0.3761	0.3991
	ZEROPROB	0.8531	0.9474	0.6667	1.0333	0.8182
	NAIVE	0.4892	0.8133	0.5760	0.8861	0.7041
6	FMVOL	0.3135	0.5016	0.2421	0.3304	0.2859
	FMBASE	0.3508	0.4778	0.3027	0.3226	0.3681
	ZEROPROB	0.8545	0.9630	0.6667	1.0333	0.8182
	NAIVE	0.4894	0.8242	0.5745	0.8839	0.7022
9	FMVOL	0.3040	0.5188	0.2470	0.3102	0.2672
	FMBASE	0.3410	0.4663	0.3176	0.3250	0.3285
	ZEROPROB	0.8463	0.9020	0.6667	1.0333	0.8182
	NAIVE	0.4884	0.7490	0.5517	0.8414	0.6727
12	FMVOL	0.3109	0.5438	0.2737	0.3210	0.2508
	FMBASE	0.3495	0.4757	0.3429	0.3390	0.3191
	ZEROPROB	0.8381	0.8333	0.6667	1.0333	0.8182
	NAIVE	0.4874	0.6799	0.5203	0.8028	0.6408
Japan						
3	FMVOL	0.3983	0.2570	0.3839	0.4127	0.4410
	FMBASE	0.4167	0.3950	0.3601	0.4245	0.4675
	ZEROPROB	0.7476	0.0000	0.7000	0.8833	0.8939
	NAIVE	0.4681	0.1561	0.4649	0.5463	0.5505
6	FMVOL	0.4013	0.2471	0.4204	0.4074	0.4217
	FMBASE	0.4180	0.3713	0.3940	0.4150	0.4557
	ZEROPROB	0.7531	0.0000	0.7000	0.8833	0.8939
	NAIVE	0.46.95	0.1465	0.4678	0.5528	0.5578
9	FMVOL	0.4178	0.2412	0.4494	0.4197	0.4330
	FMBASE	0.4310	0.3581	0.4303	0.4297	0.4516
	ZEROPROB	0.7586	0.0000	0.7000	0.8833	0.8939
	NAIVE	0.4709	0.1386	0.4696	0.5589	0.5621
12	FMVOL	0.4257	0.2142	0.4545	0.4421	0.4344
	FMBASE	0.4455	0.3376	0.4418	0.4706	0.4513
	ZEROPROB	0.7643	0.0000	0.7000	0.8833	0.8939
	NAIVE	0.4722	0.1327	0.4741	0.5622	0.5696

Notes

The QPS appreciates the performance of the recursive forecasts from this probit model (FMVOL) vis-à-vis other models. FMBASE refers to the Estrella-Mishkin (1998) recursive forecasts from a probit model with yield spread and stock returns only, ZEROPROB is a model that assumes no recessions, NAIVE takes as recession probability the recursively updated sample average of recessions.

QPS = $\frac{1}{T}\Sigma_t 2(P_t - R_t)$ where R_t is the recession variable (0–1), and P_t is the model-probability of recession. Lower QPS means better accuracy, QPS ranges between 0 and 2, see Diebold and Lopez (1989).

2 and a lower QPS implies a better accuracy. Table 3 compares the QPS for our financial market volatility-augmented recursive probit forecasts, FMVOL, with three other benchmark models. The first benchmark, FMBASE, is the Estrella-Mishkin (1998) recursive probit model with yield spread and stock returns. The second benchmark, ZEROPROB, assumes that the probability of a recession is zero in any period. The third benchmark, NAIVE, gives a recession probability equal to the average proportion of months that were recessionary from the starting date up to k months in advance of the forecast date. From Table 3, it is clear that overall, for each horizon, and for most decades, our extended FMVOL model is relatively more accurate than the other three benchmarks (except for 1960s in US and Japan, ZEROPROB is perfectly accurate because no recessions were actually registered).

In addition, there is a trade-off between making false recession forecasts and failing to forecast recessions. Generally, if the probit model yields a probability of recession exceeding a certain treshold, then the model is assumed to signal recession (and vice versa for expansion). If this matches reality, a correct signal is given, otherwhise a false signal has been given. Table 4 reports classification statistics for the probit model estimated in Table 1, both for a low 0.25 and a high 0.50 treshold.[10] When the low treshold is used, an impressive 88–90% of the months are correctly classified 3 to 12 months ahead for the US, including between 32 and 39 out of 57 recession months (56–68%) and between 353 and 359 out of 381–390 non-recession months (91–93%). This compares favourably to Boulier and Stekler (2000) who find 79% correct classifications (61% for recession months and 82% for non-recession months). The number of false signals is relatively large yet smaller than Boulier and Stekler's: 26–31 out of 60–69 versus 70 out of 111. Furthermore, with a treshold of 0.50, the correct classification percentage does not change, but this hides a decrease in the false recession rate and an increase in the missed recession rate (i.e., the false expansion rate). Still, the number of correct recession signals remains larger than the number of false alarms, contrary to Boulier and Stekler's analysis with just the yield spread included (18–26 vs. 8–12).

For Germany and Japan, the classification statistics are a bit weaker. The total correct classification percentage is about 66% and 55%, respectively, for a 0.25 treshold, and about 75% and 68%, for a 0.50 treshold. The number of false alarms versus correct recession signals is more balanced for the 0.25 treshold, but looks much more favourably in case of the 0.50 treshold.

[10] If estimated probabilities sharply distinguish between recession and non-recession months, then a high treshold would correctly classify the two types of periods. If predicted probabilities are positively correlated with the occurrence of recession but do not sharply distinguish between the two types, then months will be misclassified. If a low treshold is selected, probit will tend to correctly identify recesion months but will classify non-recession month as recessions (Boulier and Stekler, 2000, p. 82).

Table 4. **Recession Classification of the Probit Model $Prob[R_{t+k} = 19 = \Phi(c_0 + c_1SP_t + c_2SR_t + c_3VOLR_t + c_4VOLS_t)$**

k	Good R R=1 R*=1	Good E R=0 R*=0	False R R=0 R*=1	False E R=1 R*=0	Good R R=1 R*=1	Good E R=0 R*=0	False R R=0 R*=1	False E R=1 R*=0
	25% probability treshold				50% probability treshold			
United States								
3	38	359	31	19	20	381	9	37
	(8.5%)	(80.3%)	(6.9%)	(4.3%)	(4.5%)	(85.2%)	(2.0%)	(8.3%)
6	38	359	28	19	23	379	8	34
	(8.6%)	(80.9%)	(6.3%)	(4.3%)	(5.2%)	(85.4%)	(1.8%)	(7.7%)
9	39	358	26	18	26	376	8	31
	(8.8%)	(81.2%)	(5.9%)	(4.1%)	(5.9%)	(85.3%)	(1.8%)	(7.0%)
12	32	353	28	25	18	369	12	39
	(7.3%)	(80.6%)	(6.4%)	(5.7%)	(4.1%)	(84.2%)	(2.7%)	(8.9%)
Germany								
3	162	105	141	21	106	212	34	77
	(37.8%)	(24.5%)	(32.9%)	(4.9%)	(24.7%)	(49.4%)	(7.9%)	(17.9%)
6	158	131	113	24	118	211	33	64
	(37.1%)	(30.8%)	(26.5%)	(5.6%)	(27.7%)	(49.5%)	(7.7%)	(15.0%)
9	153	141	103	26	119	210	34	60
	(36.2%)	(33.3%)	(24.3%)	(6.1%)	(28.1%)	(49.6%)	(8.0%)	(14.2%)
12	150	130	114	26	115	213	31	61
	(35.7%)	(31.0%)	(27.1%)	(6.2%)	(27.4%)	(50.7%)	(7.4%)	(14.5%)
Japan								
3	131	115	143	23	57	230	28	97
	(31.8%)	(27.9%)	(34.7%)	(5.6%)	(13.8%)	(55.8%)	(6.8%)	(23.5%)
6	132	110	145	22	54	227	28	100
	(32.3%)	(26.9%)	(35.5%)	(5.4%)	(13.2%)	(55.5%)	(6.8%)	(24.4%)
9	138	79	173	16	48	222	30	106
	(34.0%)	(19.5%)	(42.6%)	(3.9%)	(11.8%)	(54.7%)	(7.4%)	(26.1%)
12	140	47	202	14	51	220	29	103
	(34.7%)	(11.7%)	(50.1%)	(3.5%)	(12.7%)	(54.6%)	(7.2%)	(25.6%)

Notes

Recessions and expansions can be signaled correctly or incorrectly. If the probit model yields a probability of recession (not) exceeding a –25% or 50%–treshold, then the model is assumed to signal a recession, R*=1 (expansion, R*=0). If this matches reality, a correct recession (expansion) signal is given, and if not, a false recession (expansion) signal has been given, R*=1 and R=0 (R*=0 and R=1).

This table reports classification statistics for the probit model estimated in table 1. Both the number of months and the sample percentages (between brackets) are reported.

3.2 Regression results

In this section, we investigate whether financial volatility adds significantly to the yield spread and real stock return to explain changes in industrial production (source: IFS line 66c), using monthly data. Table 5 reports regression results of 12-month changes in industrial production with ordinary least squares (t-stats are Newey-West corrected t-statistics). As indicated in section 2, there appeared to be structural instability in this regression. Checking for this using a CUSUM test resulted in a sample split at 1981:12 for the US, 1979:12 for Germany and 1976:12 for Japan (see also section 2). Clearly, coefficient estimates are very different over the two sample periods.

Table 5. **Regression Forecasts of 12-month ahead Industrial Growth $IP_{t+12,t} = c_0 + c_1 SP_t + c_2 SR_t + c_3 VOLR_t + c_4 VOLS_t$**

Period	c_0	c_1	c_2	c_3	c_4	R^2
United States						
1963:7–2000:12	0.043	0.012	0.187	–0.035	–1.492	0.335
	(4.45)[a]	(4.50)[a]	(2.91)[a]	(–0.54)	(–1.24)	[0.000]
1963:7–1981:12	0.072	0.022	0.00004	0.131	–6.009	0.617
	(7.44)[a]	(7.98)[a]	(0.00)	(2.33)[b]	(–3.80)[a]	[0.000]
1982:1–2000:12	0.009	0.009	0.287	–0.112	2.794	0.359
	(0.77)	(3.50)[a]	(2.91)[a]	(–1.44)[d]	(2.71)[a]	[0.000]
Germany						
1965:1–2000:12	–0.003	0.012	0.184	–0.041	1.001	0.208
	(–0.28)	(4.46)[a]	(2.94)[a]	(–1.58)[d]	(1.27)	[0.000]
1965:1–1979:12	0.022	0.008	0.359	–0.046	–0.265	0.168
	(1.12)	(2.07)[b]	(2.93)[a]	(–1.97)[b]	(–0.12)	[0.000]
1980:1–2000:12	–0.013	0.013	0.138	0.010	1.480	0.244
	(–1.03)	(3.27)[a]	(2.47)[b]	(0.13)	(1.96)[b]	[0.000]
Japan						
1966:6–2000:12	0.084	0.007	0.156	–0.020	–5.325	0.222
	(5.64)[a]	(1.63)[d]	(1.57)[d]	(–2.00)[b]	(–4.12)[a]	[0.000]
1966:6–1976:12	0.153	0.020	0.260	–0.053	–3.844	0.602
	(8.27)[a]	(3.56)[a]	(1.82)[c]	(–3.19)[a]	(–2.00)[b]	[0.000]
1977:1–2000:12	0.034	0.012	0.112	0.002	–3.271	0.210
	(3.09)[a]	(3.18)[a]	(1.28)	(0.30)	(–2.85)[a]	[0.000]

Notes
The table reports OLS results of 12-month industrial production growth using the same explanatory variables as in the probit model. t-stats are Newey-West corrected for heteroskedasticity and autocorrelation. Significance level [a]: 1%, [b]: 5%, [c]: 10%, [d]: 15%.
The samples were split since there was structural instability, as suggested by CUSUM tests.

For the US, the full sample results do not show any significant influence of volatilities in explaining industrial production growth, in addition to the yield spread and real stock returns (both of which are statistically significant with a correct sign). The two subsamples however do show a significant effect of market volatility, though the signs are ambiguous: in sample I, higher interest rate volatility seems to boost future growth while it tends to (marginally) reduce growth in sample II; higher stock market volatility is first significantly reducing, then significantly stimulating future growth. As for the sign reversal on interest rates, it might be tempting to relate this to Federal Reserve monetary policy, and interest rate policy in particular. Uncertainty about the monetary transmission mechanism may have been higher in the 1960s and 1970s (e.g., due to the Vietnam war, oil shocks, etc.), entailing a low signal-to-noise ratio, thereby raising induced interest rate volatility. In the 1980s and 1990s, the Federal Reserve may have become more succesful in steering market interest rate expectations (after the lifting of Regulation Q) and making the policy transmission channel much more straightforward, thereby reducing interest volatility and improving the signal-to-noise ratio.[11] The sign on stock volatility during sample I is in line with our hypothesis and consistent with the 3-month probit results.[12] In order to explain the positive sign on stock return volatility over the late sample, one needs to inspect the German results first.

In Germany, there is evidence of a marginally significant and negative effect of interest rate volatility on future growth, overall, and in the first subsample, consistent with our hypothesis and in line with the probit results.[13] Stock market volatility plays a significant role in the 1980s-90s, but again, as in the US, the sign is positive. Since this is also the case in the US for the 1980s–1990s, one may be willing to accept that there is a common source for these results. Given the time frame, one can think of the liberalisation of financial markets, and stock markets in particular, as a common explanation: capital flows and foreign direct investments have increased dramatically in and between the US and Europe since late 1970s, and this has lead to an increase in economic growth. It may also have lead to increased stock volatility (see Table 1). Theoretically, in the 1960s and 1970s, the US and German economy were subject to binding constraints with respect to capital flows, and the lifting of these constraints may have increased real growth and foreign direct investments, while at the same time also raising stock volatility.[14] Related, this may point to the fact that higher stock volatility during the 1980s and 1990s may be an indication of greater informational efficiency (or a higher signal-to-noise ratio), see Froot and Perold (1995). Note also that these regression results are consistent with the probit results of stock volatility in Table 2, for Germany (all horizons) and the US (12-month horizon; negative though not significant).

The Japanese results are consistent with the probit results of Table 1. Similarly, an increase in interest rate or stock market volatility significantly reduces growth of industrial production over the next year, both over the full sample as for the two subperiods (except for interest rate volatility, which is not significant over sample II). In addition to the pure financial volatility hypothesis, this may also be related to the special character of the boom-bust cycle of Japanese asset markets and the resulting negative wealth effects transmitted to the banking and business sector (see also Suzuki, 1997).

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[11] In addition, in the 1960s and 1970s, interest rates were bound by Regulation Q, and monetary policy was conducted using monetary targets (formally starting in 1972). In the 1980s and 1990s, interest rates have become more responsive to market conditions, and monetary policy has been based on interest rate targeting. Accordingly, investors have received much clearer signals as to properly evaluate the costs of borrowed funds and to discount risk premia and interest rate uncertainty into future cashflows than they had before, when interest rates had an upper bound. Therefore, interest rate volatility may have become part of US investors' information set in the way outlined in the introduction, and hence the sign reversal is consistent with the probit results.

[12] Our results are also in line with Campbell et al. (2001), over a 3-month forecasting horizon, 1963–1997. However, there also appeared to be structural instability in this forecasting equation.

[13] For Germany, there is no need to account for sign reversals on interest rate volatility. Contrary to the US, there has not been a major shift in monetary policy or interest rate policy. Germany has retained a largely independent central bank, also under the EMS, where it played a role as safe heaven and anchor currency. In fact, other European countries participating in the EMS have been forced to follow Bundesbank policy. The current ECB is also seen by many observers as a replica of the Bundesbank.

[14] Japan remains more of a closed economy with respect to foreign direct investment. Therefore, the story may not apply to Japan.

4 Conclusion

We confirmed and extended the findings of Estrella and Mishkin (1997, 1998) and Boulier and Stekler (2000) that financial variables are useful to predict recessions. In addition to the yield spread and stock returns, measures of financial market volatility were argued to signal recessions. The hypothesis was examined empirically using monthly data for the US, Germany, and Japan, with a prediction horizon of 3 to 12 months. Overall, we find that the estimation of recession probabilities is improved when financial volatility is taken into account, in addition to the yield spread and stock returns. More specifically, higher interest rate volatility proves to significantly increase the probability of a future recession, for all three countries, and, for Japan, stock market volatility has the same effect. For Japan, wealth effects associated with drastic domestic stock price movements support this finding. For Germany and the US, we argue that stock volatility has had another effect, because of financial market liberalisation and, correspondingly, increased capital flows that serve to increase growth, improve the informational market efficiency and raise financial volatility at the same time.

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