Bank stock volatility, news and asymmetric information in Banking: an empirical investigation

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1. Introduction

The main objective of this paper is to provide a framework to empirically assess the issue of asymmetric information in banking. While the theory of financial intermediation has been substantially reshaped in the past 20 years with the advances in information economics the extent to which asymmetric information is relevant for the banking firm has rarely been questioned empirically. The seminal contributions of Leland and Pyle (1977) and Diamond (1984) on the existence of financial intermediaries, and those of Bryant (1980) and Diamond and Dybvig (1983) on bank runs have nourished the banking literature in a substantive way. Banks and financial intermediaries are considered as agents that play a major role in the financial system as information intermediaries. They collect and process information namely about loan customers (Diamond 1984, 1991) which implies that they possess private information. As such, market participants (outsiders) should have limited ability to monitor banks and market discipline in the banking industry should not play a prominent role.

Under market discipline (Flannery (2001)) market prices and returns reflect individual bank riskiness because uninsured debt holders will require a risk premium from banks as a compensation of the risk they have to bear. In return, banks have less incentive to increase their asset risk to avoid a higher cost of liabilities and regulators can directly infer information from the market to improve their assessment of bank risk. On the whole, the accuracy of market discipline and the existence of private information in the banking industry is purely an empirical concern. Specifically, this work examines the concept of private information held by banks, and the extent to which market discipline in the banking industry can be improved. This issue is of a major importance because the new regulatory framework proposed by the Basel Committee on Banking and Supervision (2001) explicitly includes market discipline as one of the three pillars.

This study considers a sample of European listed banks and focuses on the behaviour of bank stock returns and on the estimation of an empirical variable to capture asymmetric information. Specifically, we test for the presence of abnormal volatility in bank stock returns during periods of financial distress, which we try to link to a measure of asymmetric private information in banking. We start by comparing the reaction of bank stock indexes and several other stock indexes to major events (news) worldwide affecting financial markets. For that purpose we consider several announcements dates during the 1997 Asian crises and the 1998

Russian crises. Under the private information assumption bank stocks should exhibit higher volatility. Our findings show that bank stock indexes were on average more volatile than other indexes but that higher volatility cannot systematically be detected in individual bank stock returns. We then model asymmetric information as the residual of an earnings prediction model using public information (macro-variables and balance sheet and income statement data) following the method proposed by Park (1999). Several proxies of asymmetric information are then constructed which are used as regressors in a logit model to explain significant shifts in stock price volatility. Tests are also carried out to check for the robustness of financial ratios, which are commonly used to proxy asymmetric information and discriminate among banks. Since positive volatility shifts can also be explained by higher uncertainty several risk measures are also introduced in the estimations. Our results show that among the various risk and asymmetric information measures broadly used in the literature market based measures perform relatively well to explain volatility shifts. Also, the proxies that we construct to capture asymmetric information are able to detect higher bank stock volatility.

The paper is laid out as follows. Section 2 describes the data and the choice of events enabling us to carry out an event study. Section 3 discusses the approach that is used to study the pattern followed by bank stocks and the method implemented to measure asymmetric information. Section 4 presents the results of the empirical investigation and Section 5 concludes.

2. Data, method and choice of events

Our aim in this study is to explore the information contained in market prices and public financial statements (balance sheets and income statements). Our sample consists in 145 European banks established in 10 countries (6 for Austria, 6 for Belgium, 29 for France, 7 for Germany, 43 for Italy, 4 for Luxembourg, 8 for the Netherlands, 15 for Spain, 17 for Switzerland and 9 for the UK) all listed on official European stock markets. The financial institutions chosen to conduct our tests are commercial banks and mutual and cooperative banks. Daily stock indexes and individual bank stock prices, for the 1993-2000 period, are taken from Datastream International and annual income statements and balance sheets for individual banks from 1993 to 2000 come from Bankscope. Banks with discontinuously traded stocks were omitted in our sample. Out of the 155 banks reported in Datastream international we eliminated 10 banks. Because we are concerned with the link between the pattern followed by stock prices and private information held by bank insiders we follow an event study methodology initially proposed by Fama et al. (1969) and later developed to account for volatility forecasting by market participants in the presence of conditional heteroskedasticity. We therefore need to select major innovations affecting European stock markets. Because European banks were greatly involved in the Asian crisis and the Russian crisis (BIS (1997) BIS (1998 (b)) we consider key events regarding these financial crisis.

2.1. Events

During the 90s, international lending to East Asian countries and Russia sharply increased. According to the BIS, this greater involvement was mostly the fact of European banks, particularly German, French and UK banks (see BIS (1997), BIS 1998 (b)). In Asia, bank lending was mainly spread among South Korea, Thailand, Indonesia and Taiwan and to a lesser extent in Malaysia. As shown in table A1 in appendix, European banks were even more heavily committed in Russia (respectively 89% and 66% of foreign bank lending for 1995 and 1997). Specifically, German banks accounted for almost half of Russia's foreign for bank lending. Because European banks had accumulated large exposures in both East Asia and Russia bank stock prices are expected to be very sensitive to economic events in these two regions.

Table 1 presents important events of the Asian crisis and the Russian crisis, as well as extended backward event windows, selected for our study. For simplicity, we only considered the most significant dates and periods reported in most studies (BIS (1998 (a)), BIS (1999), Kho and Stulz (2000), King (2001)). The events we consider for the Asian financial crisis include the two widely documented stages of the crisis[1]. The first stage began with the devaluation of the Thai bath on July 2 1997 (ASIA2). This date corresponds to the beginning of the financial panic that spread to all East Asian "tigers" (Malaysia, Philippines and Singapore). The second stage began in late October 1997 centred on Hong Kong and South Korea and spread to Indonesia and Taiwan. Financial turmoil occurred on October 22 in South Korea and Hong Kong (ASIA3). On this same day Hong Kong raised official rates from 7 percent to 300 percent and Standard & Poor's downgraded Korea's foreign causing a massive outflow of capital. In the case of the Russian crisis speculative attacks against the Rouble began during the first semester of 1998. The deepening of the financial difficulties led

[1] King (2001) provides a detailed review of the Asian crisis.

the authorities to widen the band of fluctuation of the exchange rate and to suspend interest payments on public debt on August 17 (RUSSIA2). The government stopped supporting the rouble on September 1 (RUSSIA3).

Since the market might have anticipated the crises before the announcement dates, we also consider 2 extended backward event windows for each event date including respectively 15 days and 60 days (ASIA1a and ASIA1b for the Asian crisis and RUSSIA1a and RUSSIA1b for the Russian crisis).

Table 1. Selected events and event windows of the Asian and Russian crises

Event date or event window	Description
ASIA1a : 16/06/97 - 30/06/97 ASIA1b : 01/05/97 - 30/06/97	Anticipation of the crisis
ASIA2 : 02/07/97	Floating of the Thai bath
ASIA3 : 22/10/97	Financial turmoil in Hong Kong and South Korea
RUSSIA1a : 05/08/98 - 14/08/98 RUSSIA1b : 15/06/98 - 14/08/98	Anticipation of the crisis
RUSSIA2 17/08/98	Modification of the exchange rate regime in Russia, and suspension of interest payments on public debt
RUSSIA3 : 01/09/98	Authority stop supporting the rouble

2.3 Summary statistics

Table 2 provides summary statistics for financial statement and stock market variables for our pooled sample of 145 individual banks from 1993 to 2000. Balance sheet and income statement annual data and ratios provide information about bank size (log of total assets), bank profitability measured by the return on assets, and deposits and loans as a percentage of total assets. For each bank we computed the daily stock return over the same period (January 1, 1993 to December 29, 2000). The daily return is defined as $R_t = \log(P_t/P_{t-1})$, where P_t is the price on day t. We also computed a value-weighted bank stock index comprising the 145 banks in our sample. Table 2 also shows summary statistics on daily returns calculated with our bank index (R^{EUBANK}) and daily returns on the European Market overall index taken from Datastream International (R^{EUMK})[2].

[2] In Datastream International this index is named TOTMKEU and is the broadest index defined for Europe.

Table 2. The sample of banks: summary accounting and market statistics (pooled sample from 1993 to 2000)

	Mean	Median	Standard deviation	Minimum	Maximum
Balance sheet and Income statement ratios(%)					
LOANS	57.69	56.17	18.42	6.47	94.71
LIQUY	27.96	27.29	15.67	0.72	89.90
DEPOSITS	74.96	78.51	15.09	2.21	94.14
MARKET_FUND	9.86	5.96	11.93	0	69.70
ROA	0.83	0.56	1.84	-19.19	18.02
OVERHEAD	4.78	4.33	2.68	1.47	28.57
NIM	2.65	2.43	1.38	0.10	10.31
TA	58 554.08	7 915.26	122 000	19.06	838 000
Stock market variables (%)					
R_t	0.073	0.063	0.082	-0.045	0.598
R_t^{EUBANK}	0.076	0.076	1.139	-4.393	7.896
R_t^{EUMK} (index)	0.042	0.056	1.121	-4.391	5.571

LOANS = Ratio of loans to total assets; LIQUY = Ratio of liquid assets to total assets; DEPOSITS = Ratio of deposits to total assets; MARKET_FUND = Ratio of market funded liabilities (bonds, securities > 5 years, mortgage bonds, subordinated debt, hybrid capital) to total assets ; ROA = Ratio of net income to total assets; OVERHEAD = Ratio of expenses (personnel expenses + other interest expenses) to total assets; NIM = Net interest margin defined as (interest received – interest paid)/total assets; TA = Total assets in millions of US \$; R_t^{EUBANK} = Daily return on value-weighted bank stock index calculated with our sample of 145 banks; R_t^{EUMK} = Daily return on overall European market stock index as defined by Datastream International.

2.3 Method and links with related literature

The issue we address is related to the literature on efficient markets in the steps of Fama (see Fama (1991)). The efficient market hypothesis states that all prices fully reflect all relevant information. This hypothesis requires that stock prices adjust quickly and accurately in response to new public information. A strand of this literature investigated the effect of announcements and news on stock returns by following an event-study methodology. Event studies focusing on the presence of significant abnormal returns have been widely applied to study the behaviour of bank stocks. Among others Cornell and Shapiro (1986), Mathur and Sundaram (1997), Kilic, Tufte and Hassan (1999), Bessler and Nohel (2000) followed this methodology to look at the implications of the international debt crisis of the 80's or Latin America currency crises of the 90's. A usual assumption under the abnormal return event-study approach is that the mean of the distribution is only temporarily affected by the event and that the variance of returns is supposed to be constant.

The approach used in this paper differs from these frameworks in several respects. Because modern banking theory and namely the contributions of Diamond (1984) and Boyd and Prescott (1986) suggest that bank insiders are likely to be in possession of vast amount of private information we consider that, under certain conditions, outsiders should not be able to precisely estimate the impact of new public information. As a consequence, the market should not know the accurate price value reflected by the news and bank stock prices could therefore experience high and persistent volatility shifts. Hence, our purpose is to study the reaction of bank stock volatility to major events and to test the private information assumption using a proxy derived from an earnings prediction model. Our work is also linked to the "excess volatility" literature ((Shiller (1981), Campbell and Shiller (1987), Cuthbertson and Hyde (2002)). The main objective of this literature is to assess whether stock prices are too volatile compared to implied theoretical stock prices and thus whether the market is efficient. Eden and Jovanovic (1994) argue that some of the volatility of stock prices in excess of fundamentals may result from fluctuations in the amount of public information over time. Within a theoretical framework they show that the degree of information asymmetry can influence stock prices when agents are subject to adverse selection. Whereas these empirical or theoretical works focus on equilibrium returns and volatility or on the theoretical link between asymmetric information and volatility, our aim is solely to detect significant volatility shifts in response to public information disclosure. Volatility shift measures are then used to empirically study the relationship between stock price behaviour and asymmetric information. We therefore rely on an analytical framework which is widely used in the news-volatility literature discussed in the next section.

3. Measuring volatility and asymmetric information

3.1 Modeling unexpected volatility shifts

The finance literature provides several approaches to model and forecast volatility in financial markets[3]. The most popular are the GARCH models proposed by Bollerslev (1986)

[3] See Schwert (1990) for a review of alternative volatility models.

which are a generalized version of the auto regressive conditional heteroskedasticity models (ARCH models), introduced by Engle (1982). They present the advantage of incorporating the time-varying properties of volatility. In this framework different methodologies are used to examine the relationship between the release of new public information and the increase in stock price volatility. Some works (Kane and Unal (1988), Kane and Susmel (1998) adapt the regime switching model proposed by Hamilton ((1989), (1994)) to event studies to capture significant permanent (regime dependent) deviations in the conditional mean and variance. Other studies (Jones, Lamont and Lumsdaine (1998), Bomfim (2003)) build on the method proposed by Andersen and Bollerslev (1997) to model the dynamics of intraday volatility. Whereas these methods focus either on regime changes or on time dependence, our aim is solely to capture transitory deviations in volatility.

We therefore rely in our study on traditional GARCH models in which we introduce a dummy variable to take the event into account. Within this framework whereas volatility persistence in stock returns is well taken into account, asymmetric effects cannot be captured. Asymmetric or leverage effects were reported by Black (1976), Nelson (1990) and Schwert (1990). These effects occur when unexpected drops in stock prices (bad news) increase volatility more than unexpected increases in stock prices (good news) of the same magnitude. Asymmetric effects can be captured with the EGARCH model by Nelson (1990) and the GJR model proposed by Glosten, Jagannathan and Runkle (1993). Thus, we consider two steps in our investigation of changing volatility. Firstly, we start by estimating three different models: a simple GARCH(1,1) model, an EGARCH model and a GJR model. Secondly, asymmetric tests are conducted following Engle and Ng (1993) to detect the existence of leverage effects. When such effects are detected, we choose the best model that permits to capture them. In this sense our second step consists in checking the adequacy of the volatility model using the joint test proposed by Engle and Ng. To consider each event defined in table 1, we introduce a dummy variable in the specification of the conditional variance.

Formally, let R_t be the daily return on a stock at time t, R_t^{EUMK} the return on the market (Datastream European Market Index) at time t, I_{t-1} the set of information available at time t-1, h_t the variance of R_t, $?_t$ the innovation at time t and D_t a dummy variable to measure the impact of the event on conditional volatility. Dummy variables (D_t) were constructed for each event period defined in Table 1. Dummies defined for backward event windows D_{ASIA1a}, $D_{RUSSIA1a}$, D_{ASIA1b} and $D_{RUSSIA1b}$ take the value 1 throughout the event window (15 or 60 days preceding and including the event day) and 0 otherwise. Event day dummies D_{ASIA2}, D_{ASIA3},

$D_{RUSSIA2}$, $D_{RUSSIA3}$ which are related to one-day events take the value 1 for a period of 3 days (event-day, day before and day after) and 0 otherwise.

The conditional mean R_t and the conditional variance h_t of the three different models are given by:

Conditional mean		
	$R_t ? ? ? ? R_t^{EUMK} ? ?_t$	[1]
Conditional variance		
GARCH	$h_t ? ? ? ? ?^2_{t?1} ? ? h_{t?1} ? ? D_t$	[2]
EGARCH[4]	$\log ?h_t ? ? ? ? ? \log ?h_{t?1} ? ? ? \frac{?_{t?1}}{\sqrt{h_{t?1}}} ? ? \left\| \frac{?_{t?1}}{\sqrt{h_{t?1}}} \right\| ? ? D_t$	[3]
GJR	$h_t ? ? ? ? ?^2_{t?1} ? ?? \,^{?}_{t?1} ?^2_{t?1} ? ? h_{t?1} ? ? D_t$	[4]
where $?^{?}_{t?1}$ is a dummy variable equal to one if $?_{t?1}$ <0, and 0 otherwise		

The quasi-maximum likelihood (QML) estimation method is used to estimate these models[5] using daily data from January 1, 1993 to December 29, 2000. The coefficient ? associated to the dummy variables D_t measures the volatility effect of the event. A positive and significant coefficient means that there is a significant increase in volatility during this period.

3.1.1 Results using stock indexes

The three volatility models are first estimated for a broad set of industrial sector indexes[6]: Banks, Building and Construction, Chemicals, Electrical Equipment, Pharmaceuticals, and Oil Engaged Companies (see Table A2 in appendix for a detailed description). At this stage, our aim is solely to check for industry specific volatility shifts. We use the daily returns on European indexes provided by Datastream International[7], denoted R_t^{EUx}, where x stands for the sector name. Estimation results are summarised in Table 3 which

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[4] The specification for the log conditional variance used for the estimation assumes normally distributed errors.

[5] We use the method by Bollerslev and Wooldridge (1992) that provides QML standard errors that are consistent and robust when the assumed distribution for the normalized residuals is false.

[6] As a preliminary step, standard descriptive statistics and tests were carried out to detect ARCH effects and serial correlation. In each case the results supported the use of ARCH specifications.

[7] Except for the bank index which is presented in section 2.3 we used harmonized industrial sector indexes provided by Datastream International at the European level.

reports the sign of significant ? coefficients at the 5% level. The model which better fits the data for each industry index is presented in bold (Engle and Ng asymmetric test).

The results suggest that there is a significant increase in volatility for the banking index compared to the other sectors before the beginning of the Russian and the Asian crisis ($D_{RUSSIA1a}$, $D_{RUSSIA1b}$, D_{ASIA1a} and D_{ASIA1b}). These results are obtained with the Egarch which is the model that best fits banking industry data. This could be interpreted as an expectation of these events by the market. We also obtain a significant effect for bank stock volatility for one event of the Russian crisis (the suspension of interest payments on public debt in Russia on August 17, 1998 ($D_{RUSSIA2}$)). On the whole, almost no other industrial index experienced a significant increase in volatility. Only two sectors were sensitive to one of the events: the real estate holding and development sector and the oil industry.

3.1.2 Results for individual bank data

Table 4 sums up the estimation results for the 145 banks of our sample by showing the number of banks for which we find a significant positive volatility change running the 3 models and the model which best fits each bank's data[8]. This number is higher for the events related to the Russian crisis which is in line with the heavier exposure of European banks in Russia outlined in section 2.

[8] As for index data, preliminary tests were conducted to detect ARCH effects and serial correlation for each bank's daily return data. The null hypothesis of normality was rejected in each case and the presence of serial correlation was systematically detected.

Table 3. Volatility shift (sign of significant ? coefficients) for 9 industrial sector indexes during the Asian and Russian crises

		D_{ASIA1a}	D_{ASIA1b}	D_{ASIA2}	D_{ASIA3}	$D_{RUSSIA1a}$	$D_{RUSSIA1b}$	$D_{RUSSIA2}$	$D_{RUSSIA3}$
R^{EUBK}	Garch	NS	NS	+	NS	+	NS	+	+
	Egarch	**+**	**+**	**NS**	**NS**	**+**	**+**	**+**	**NS**
	GJR	+	+	+	NS	+	NS	+	NS
R^{EUBMAT}	**Garch**	**NS**	**NS**	**NS**	**NS**	**-**	**NS**	**NS**	**NS**
	Egarch	-	NS	NS	NS	NS	NS	NS	-
	GJR	NS	NS	NS	NS	NS	NS	NS	-
R^{EUOTHC}	Garch	NS	NS	NS	NS	NS	NS	NS	NS
	Egarch	**NS**	**NS**	**NS**	**NS**	**NS**	**NS**	**NS**	**NS**
	GJR	NS	NS	NS	NS	NS	NS	NS	-
R^{EUCHEM}	Garch	NS	NS	NS	NS	_	NS	NS	NS
	Egarch	**NS**	**NS**	**NS**	**NS**	**NS**	**NS**	**NS**	**NS**
	GJR	NS	NS	NS	NS	NS	NS	NS	NS
R^{EUELQ}	**Garch**	**NS**	**NS**	**NS**	**NS**	**NS**	**NS**	**NS**	**NS**
	Egarch	NS	+	NS	NS	NS	NS	NS	NS
	GJR	NS	NS	NS	NS	NS	NS	NS	NS
R^{EUELT}	**Garch**	**NS**	**NS**	**NS**	**NS**	**NS**	**NS**	**NS**	**NS**
	Egarch	+	+	NS	NS	NS	NS	NS	NS
	GJR	NS	NS	NS	NS	NS	NS	NS	NS
R^{EUOIL}	Garch	+	+	+	NS	NS	NS	-	NS
	Egarch	**NS**	+	**+**	**NS**	**NS**	**NS**	**-**	**NS**
	GJR	+	+	+	NS	NS	NS	NS	NS
R^{EUPHA}	Garch	NS	NS	-	-	NS	NS	-	NS
	Egarch	**NS**	**NS**	**NS**	**NS**	**NS**	**NS**	**NS**	**NS**
	GJR	NS	NS	NS	NS	NS	NS	NS	NS
R^{EURLD}	Garch	NS	NS	NS	NS	+	+	+	NS
	Egarch	**-**	**NS**	**+**	**NS**	**+**	**+**	**NS**	**NS**
	GJR	NS	NS	NS	NS	+	+	+	NS

NS: non significant at the 5% level; +/- stand for positive/negative significant ? coefficients which capture the volatility effect; R^{EU}: daily returns on sector index with x = BK (banks), BMAT (buildings and construction materials), OTHC (other constructions), CHEM (chemicals), ELQ (electrical equipment), ELT (electronic equipment), OIL (oil industries), PHA (pharmaceuticals) and RLD (real estate holding and development. Bold letters refer to the model that best fit the data following the test by Engle and Ng (1993).

Table 4. Number of banks with a positive volatility shift (significant positive ? coefficients) during the Asian and Russian crises

	D_{ASIA1a}	D_{ASIA1b}	D_{ASIA2}	D_{ASIA3}	$D_{RUSSIA1a}$	$D_{RUSSIA1b}$	$D_{RUSSIA2}$	$D_{RUSSIA3}$
Best model* 5% level	1	0	5	5	25	9	21	14
Best model* 10% level	3	2	8	9	34	11	29	28
* Engle and Ng asymmetric test								
Garch								
5% level	0	0	2	0	16	7	18	11
10%level	2	1	5	2	25	10	20	24
Egarch								
5% level	10	3	17	23	33	21	43	39
10% level	16	10	23	33	39	28	50	49
GJR								
5% level	1	1	1	0	14	7	16	10
10%level	3	1	2	1	25	12	24	22

Note: number of banks out of our sample of 145 banks.

3.2. Measure of private information

Because modern banking theory assumes that banks acquire private information on borrowers our aim now is to construct a measure reflecting the information possessed by bank insiders and ignored by outsiders. In the banking literature it is common to use proxies to capture this private information by looking at the information content of financial statements. Specifically, the opacity on the loans portfolio that comes from the intermediation function of banks is often proxied by the ratio of loans to total assets. Since deposit interest rates are not marked to market the ratio of deposits to total assets is also frequently used as a proxy of balance sheet's opacity. Conversely, a high proportion of market funding on the liability side of the balance sheet (bonds, subordinated debt, uninsured time deposits…) is a signal for outsiders. Our purpose in this paper is to consider alternative proxies of asymmetric information building on the measure proposed by Park (1999). Following his work we assume that asymmetric information may be represented by the residual of an earnings prediction model based on publicly available information. However, our approach differs from his in the sense that we provide three different measures to add for the robustness of our empirical tests performed in section 4.

3.2.1. Earnings prediction model

Assuming that prices in stock markets incorporate estimates of future earnings based on publicly available information, on average, the rational prediction of stock markets may be captured by the prediction of a well-specified regression models based on publicly available information. Under this assumption, a positive residual of the regression means that stock markets underestimated the bank's earnings and hence the bank's stock was undervalued, that is the actual earning turns out to be larger than the ones predicted by the stock market model. On the contrary, the residual of regression is negative when the earning predicted by the stock market is larger than the actual earning. In his work Park (1999) considers that the residual of an earnings prediction model can be used as a proxy to measure banks private information. The residual consists mainly of three parts: (i) the component that comes from the misspecification of the model; (ii) the component associated with the unexpected shocks (unexpected by insiders and outsiders); (iii) the part expected by insiders (managers) but not by outsiders which represents the private information component. Thus, the residual can be considered as a good measure of private information only if the first two components are low. To minimise the misspecification component we introduced a large set of exogenous variables and to lower the unexpected shocks component we considered ex-post earnings in our model specification.

Formally our earnings prediction model consists in the regression of the earnings of year t+1 on lagged earnings and other relevant variables. The dependent variable is the return on assets in year t+1 for bank i ($ROA_{i\ (t+1)}$) which is a common measure of bank profitability and which is regressed on lagged values and a set of bank specific variables and macroeconomic variables:

$$ROA_{i\ (t+1)} = ?_0 + ?_1\ ROA_{i\ (t)} + ?_2\ ROA_{i\ (t-1)} + ?_3\ OVERHEAD_{i\ (t-1)} + ?_4\ DEPOSITS_{i\ (t-1)} + ?_5\ LOANS_{i\ (t-1)} + ?_6\ LIQUY_{i\ (t-1)} + ?_7\ GDP_{i\ (t)} + ?_8\ EUBKROA_{i\ (t)} + ?_9\ SPREAD_{i\ (t)} + ?_{i\ (t+1)} \qquad [5]$$

where ? is the disturbance term.

A large set of variables allows to minimize the noise caused by the omission of variables and thus should improve our measure of bank private information. The ratio of expenses on assets ($OVERHEAD_{(t-1)}$) reflects operating efficiency. A bank with a large amount of deposits ($DEPOSITS_{(t-1)}$) may enjoy a low funding cost. The ratio of loans to total assets ($LOANS_{(t-1)}$) may have large impacts on revenue. The share of liquid assets ($LIQUY_{(t-}$

$_{1)}$) represents both the liquidity and the safety of asset portfolios. We added macroeconomic variables to control for differentials in general economic conditions. We considered the G.D.P. growth rate (GDP_t) for each country in our sample, the interest rate spread ($SPREAD_t$) defined as the difference between the rate on 10 year government bonds and the three months interbank rate, and the average return on assets for the European banking industry ($EUBKROA_t$)[9]. A higher growth rate and a high spread are both expected to improve bank profitability. The variable $EUBKROA_t$ is introduced to account for the soundness of the banking system.

The model is estimated by ordinary least squares (OLS). Equation [5] is estimated for the pooled sample of banks from 1993 to 2000 and in cross section for each of year t, 1993-2000.

Table 5. Earnings prediction model for each year t

Explanatory Variables	1994	1995	1996	1997	1998	1999
Constant	-4.6809	-3.6261	-0.0799	0.8136	-2.1163	1.2632
	(-3.199)	(-0.982)	(-0.154)	(1.106)	(-1.703)	(1.796)
$ROA_{(t)}$	0.7316	0.0849	0.0789	0.5728	0.5393	0.2550
	(1.972)	(0.325)	(1.525)	(6.553)	(3.436)	(1.213)
$ROA_{(t-1)}$	0.1139	0.3801	0.1702	0.1184	0.5477	0.5121
	(0.494)	(1.788)	(0.753)	(4.151)	(2.543)	(3.538)
$DEPOSITS_{(t-1)}$	0.0283	0.0186	-0.0266	-0.0127	0.0306	-0.0066
	(3.011)	(0.565)	(-5.371)	(-3.091)	(1.182)	(-1.118)
$LOANS_{(t-1)}$	0.0273	0.0043	0.0143	-0.0022	-0.0013	-0.0062
	(2.001)	(0.441)	(2.316)	(-0.343)	(-0.098)	(-0.766)
$LIQUY_{(t-1)}$	0.0272	-0.0188	0.0234	0.0020	0.0030	-0.0199
	(1.490)	(-0.559)	(2.696)	(0.261)	(0.254)	(-1.432)
$OVERHEAD_{(t-1)}$	0.0858	0.2627	0.2713	0.1487	0.0934	0.1659
	(1.022)	(1.875)	(3.617)	(4.151)	(1.560)	(2.078)
GDP_t	0.0285	-0.0338	-0.1329	0.0031	-0.0418	0.0324
	(0.155)	(-0.120)	(-0.887)	(0.076)	(-0.326)	(0.441)
$EUBKROA_t$	0.1804	1.0169	1.3953	0.3899	-0.9386	-0.1268
	(0.564)	(1.032)	(2.978)	(1.323)	(-1.742)	(-0.398)
$SPREAD_t$	-0.2050	0.9777	0.1802	0.0596	-0.0300	-0.05466
	(-0.584)	(0.910)	(2.2477)	(1.327)	(-0.227)	(-0.597)
Adjusted R^2	0.683	0.436	0.797	0.932	0.690	0.878
Observations	78	93	104	109	120	126

The dependent variable is the return on assets for year t+1. Lagged and forward variables imply that 1993 and 2000 are excluded. Numbers in brackets are t-statistics; t-statistics are corrected for heteroskedasticity following White's methodology.

[9] GDP and interest rate data come from Datastream International and average return on asset data for the European banking industry are provided by Bankscope.

Table 5 provides the results of the estimations. The adjusted R^2 are comprised between 0.4 and 0.9. Those values are higher than those obtained by Park which are comprised between 0.4 and 0.54. The introduction of macroeconomic variables allows to increase the overall fit of the model and overall our regressions appear to produce reasonable earnings forecasts. Our concern here is not the significance of a particular variable and we focus on the value of the estimated residual $?_i$. If the model misspecification component and the unexpected shocks component are reasonably low then the absolute value of $?_i$ for bank *i* will reflect the extent to which the assumption of private information holds for bank *i*.

3.2.2. Measures of private information

More precisely, we consider that for a bank i the asymmetric information between insiders and outsiders is important when the residual of the regression $?_i$ reaches a relatively high or low value that is when the absolute value of the residual reaches a critical value. Because the residuals contain noise that we need to rule out (model misspecification and unexpected shocks) our method consists in selecting observations (banks) for which $|?_i|$ is not only relatively high at a given point in time but also persistently high during the whole sample period. Thus, we use different proxy measures based on: (i) the absolute value of the residuals; (ii) the dispersion of the residuals to isolate banks with a high level of private information ; (iii) the time persistence to check if banks exhibiting a high value a given year systematically exhibit a high value for each year.

The absolute value measure (AbsV)

In Table 6 descriptive statistics are reported for the residuals obtained by running the regression on pooled data and cross section for the different years. The results show that on average $|?_i|$ is comprised between 0.4 and 0.51 but that for individual banks it can reach very high values.

Table 6. Descriptive statistics for the absolute value of the residual (AbsV) for the pooled sample and each year t*

	AbsV_Pool (Pooled sample 1994-1999)	AbsV_94	AbsV_95	AbsV_96	AbsV_97	AbsV_98	AbsV_99
Mean	0.405	0.434	0.510	0.439	0.495	0.447	0.400
Median	0.215	0.226	0.351	0.294	0.187	0.253	0.224
Q_{75}	0.456	0.494	0.665	0.591	0.391	0.529	0.419
Maximum	6.705	4.713	2.816	2.963	2.105	2.844	4.213
Minimum	0.0004	0.009	0.018	0.004	0.003	0.0004	0.001
Std. Dev.	0.663	0.684	0.530	0.471	0.341	0.515	0.592
Observations	630	76	93	104	109	120	126

** Lagged and forward variables imply that 1993 and 2000 are excluded; AbsV_year t = absolute value of the residual for the year t; Q_{75} = the third quartile.*

The measure of dispersion

We use two indicators of dispersion to distinguish banks with a "high level of private information": the quartile and the standard deviation of the absolute value of residuals $\left|?_i\right|$ for the whole sample provided in Table 6. Observations for which $\left|?_i\right|$ is greater than the third quartile are classified as HLPI that is as banks with a "relatively high level of private information". We then define a variable, denoted DISPERSION_1, that takes the value of 1 for such banks and 0 otherwise. This method classifies banks without considering the distribution of $\left|?_i\right|$ and thus without giving a more important weight to the high values of $\left|?_i\right|$. Therefore, we add a measure of dispersion based on the standard deviation to classify banks. As previously, observations for which the absolute value of the residuals $\left|?_i\right|$ is greater than the standard deviation plus the mean are classified as HLPI. The variable DISPERSION_2 takes the value of 1 for these banks and 0 otherwise.

The measure of persistence

When a bank is classified as HLPI a given year, we have to check that this result holds for every year. We count for each bank *i* the number of years for which it is classified as HLPI. We define a variable PERSISTENCE_x (x=1, 2) by dividing the previous number by the number of years for which the variable could be computed. Variable PERSISTENCE_1 is based on the variable DISPERSION_1 to classify banks whereas variable PERSISTENCE_2 is based on the standard deviation classification. The obtained persistence measures are comprised between 0 (the bank is never considered as exhibiting private information during the sample period) and 1 (the bank is always considered as exhibiting private information during the sample period). Banks that present "a high level of private information" at least 4 times out of 6 (PERSISTENCE$_x$? 0.67) are then considered as banks with "persistently high level of private information".

Table 7 gives the number of banks detected as HLPI (DISPERSION$_1$ and DISPERSION$_2$? 0) and the number of banks detected as persistently HLPI (PERSISTENCE$_x$? 0.67). The proxy DISPERSION$_1$ shows that on average 48 banks can be classified as HLPI whereas only 19 such banks are detected with the measure DISPERSION$_2$. Thus, the measure of dispersion based on the standard deviation is more restrictive. Moreover, the statistics show that a relatively high number of banks can be persistently considered as HLPI.

Table 7. Number of banks classified as HLPI and persistently HLPI

Asymmetric information variable	1994	1995	1996	1997	1998	1999
DISPERSION$_1$? 0	38	45	50	54	59	43
DISPERSION$_2$? 0	10	21	21	21	25	26
PERSISTENCE$_1$? 0.67				35		
PERSISTENCE$_2$? 0.67				8		

4. Results of empirical investigation

Building on the results obtained in section 3 we constructed several binary variables reporting significant positive volatility shifts for each event. The variables take the value 1 when a significant (5% level) positive change is obtained and 0 otherwise. The variables are named VOL$_1$, VOL$_2$, and VOL$_3$ respectively for the events D$_{RUSSIA1a}$ D$_{RUSSIA2}$,D$_{RUSSIA3}$. We also constructed a variable named VOL$_{TOT}$ which takes the value 1 when a positive significant shift is obtained at least one time over the 3 event windows. We deliberately ignored all the other events for which we obtain too few variables which take the value 1, that is D$_{ASIA1a}$, D$_{ASIA1b}$, D$_{ASIA2}$ and D$_{ASIA3}$. We consider that positive volatility shifts can be explained by asymmetric information between bank insiders and outsiders and/or higher uncertainty.

As a first step we regressed our binary volatility variables on bank risk measures to detect for the presence of higher risk and to look at the effect of risk on volatility. We use eight standard measures of risk commonly used in the literature: (i) the ratio of loan loss provisions to total assets (LLP); (ii) the ratio of loan loss reserves to total assets (LLR); (iii) the TIER1 capital ratio; (iv) the ratio of equity to total assets (EQUITY); (v) the ROA variance over the period 1993-2000 (Variance(ROA)) using yearly accounting data; (vi) the natural logarithm of total assets; (vii) a Z-score computed using market data (MDZ-score); (viii) a Z-score computed using accounting data[10] (ADZ-score). Z-scores[11] indicate the probability of failure of a given bank. Higher values of Z-scores imply lower probabilities of failure. For ADZ-score we consider, as in Goyeau and Tarazi (1992), two components[12] which we call ADZ_1 and ADZ_2. ADZ_1 is a measure of bank portfolio risk whereas ADZ_2 is a measure of leverage. Table 8 reports the results for this set of risk regressors. Because of frequent collinearity among the variables (see table A3 in appendix) each explanatory variable is separately included in the Logit estimation for each volatility shift binary variable[13]. We consider for each explanatory variable the values taken in 1997 and in 1998 (in line with the Russian crisis) and the arithmetic mean for the period 1993-2000 when computable.

On the whole, the coefficients for market estimates of Z-scores are negative and highly significant. An increase in MDZ-score implies a decrease in the probability of bank failure and thus lowers the probability of a positive volatility shift. Two risk measures based on balance sheet data, Variance(ROA) and TIER1, also have a significant effect. An increase in the Tier1 capital ratio has a negative effect on the probability of a positive volatility shift and the variance of the return on assets has a positive effect. We find also a positive and significant impact of bank size measured by the natural logarithm of total assets (LOG(TA)). According to the Too-Big-Too-Fail hypothesis the expected coefficient associated to LOG(TA) should be negative. However because large banks are expected to have higher exposures in international lending than smaller banks LOG(TA) can be interpreted as higher uncertainty.

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[10] MDZ-score = $\frac{\bar{R} ? 1}{?}$, where $\bar{R}$ and $?$ are respectively the mean and the standard deviation of the daily returns R for a given year.

[11] See Boyd and Graham (1986) for a definition of Z-scores.

[12] ADZ-score $= ADZ_1 + ADZ_2 = \frac{\overline{ROA}}{?_{ROA}} ? \frac{\overline{\left(\frac{EQUITY}{TA}\right)}}{?_{ROA}}$ computed using yearly accounting data over 1993-2000.

[13] It can be noted that similar results are obtained when all the regressors are introduced in a single estimation for each dependant variable after omitting variables to deal with collinearity.

Table 8. Logit estimations for volatility shift with a single risk measure

Explanatory Variable (Obs.)	*Dependent Variable* VOL$_1$ Coefficient (Z statistic)	VOL$_2$ coefficient (Z statistic)	VOL$_3$ coefficient (Z statistic)	VOL$_{TOT}$ Coefficient (Z statistic)
EQUITY$_{97}$	0.0111	0.0017	-0.0699	0.0071
(125)	(0.772)	(0.081)	(-0.699)	(0.502)
EQUITY$_{98}$	0.0165	0.0045	-0.0675	0.0115
(131)	(1.138)	(0.199)	(-0.997)	(0.791)
LLP$_{97}$	0.0161	-0.0160	0.6818	-0.2438
(116)	(0.021)	(-0.024)	(0.900)	(-0.355)
LLP$_{98}$	-0.5468	-0.2837	0.1796	-0.4545
(121)	(-0.930)	(-0.528)	(0.331)	(-0.821)
LLR$_{97}$	-0.3914	-0.2942	-0.6120	-0.5294
(68)	(-1.033)	(-0.743)	(-0.850)	(-1.197)
LLR$_{98}$	0.1058	0.1649	-0.4088	0.0249
(79)	(0.546)	(0.898)	(-0.853)	(0.116)
MDZ-score$_{97}$	**-0.0169***	**-0.0174****	**-0.0274****	**-0.0158****
(124)	**(-1.952)**	**(-2.004)**	**(-2.158)**	**(-2.277)**
MDZ-score$_{98}$	**-0.0186****	**-0.0246*****	**-0.0413****	**-0.0228*****
(124)	**(-2.218)**	**(-2.629)**	**(-2.334)**	**(-2.623)**
TIER1$_{97}$	**-0.2222***	**-0.2313***	-0.1055	-0.1247
(61)	**(-1.897)**	**(-1.953)**	(-0.812)	(-1.139)
TIER1$_{98}$	**-0.1719***	**-0.1898****	-0.0561	-0.0869
(71)	**(-1.833)**	**(-1.973)**	(-0.805)	(-1.178)
LOG(TA$_{97}$)	**0.3170****	**0.5100*****	**0.598*****	**0.3538****
(125)	**(2.016)**	**(3.271)**	**(3.873)**	**(2.428)**
LOG(TA$_{98}$)	**0.3220****	**0.5470*****	**0.5703*****	**0.3634****
(131)	**(2.025)**	**(3.387)**	**(3.794)**	**(2.489)**
ADZ-score	-0.0037	-0.0003	**-0.0143****	-0.0016
(141)	(-0.926)	(-0.121)	**(-2.184)**	(-0.676)
ADZ$_1$	-0.0214	0.0289	**-0.1035****	0.0116
(141)	(-0.679)	(1.068)	**(-2.436)**	(0.478)
ADZ$_2$	-0.0042	-0.0007	**-0.0160****	-0.0022
(141)	(-0.938)	(-0.274)	**(-2.113)**	(-0.781)
Variance(ROA)	**0.0139*****	**0.0148*****	-0.2261	**0.0122*****
(139)	**(3.503)**	**(3.768)**	(-1.172)	**(3.059)**
Mean(EQUITY)	0.0143	0.0043	-0.0772	0.0091
(145)	(0.953)	(0.187)	(-0.776)	(0.605)
Mean(LLP)	0.0173	**-1.7207***	-0.4008	-0.2162
(138)	(0.021)	**(-1.715)**	(-0.687)	(-0.258)
Mean(LLR)	0.1412	0.1186	**-2.7788*****	0.0610
(90)	(0.743)	(0.495)	**(-3.095)**	(0.283)
Mean(TIER1)	**-0.1776****	**-0.1954****	-0.1214	-0.1316
(88)	**(-2.044)**	**(-2.090)**	(-1.178)	(-1.631)
Mean(LOG(TA))	**0.3206****	**0.5540*****	**0.5871*****	**0.3695*****
(145)	**(2.094)**	**(3.505)**	**(4.028)**	**(2.604)**
N$_1$	117	121	128	110
N$_2$	25	21	14	32

*This table reports binary estimation results for 4 dependent variables (VOL_1,VOL_2,VOL_3,VOL_{TOT}). Each dependant variable is regressed on each explanatory variable. z-statistics are in brackets. ***, ** and * indicate significance respectively at the 1%, 5% and 10% levels. N_1 and N_2 are the number of observations respectively when the dependent variable is equal to 0 and 1. X_t is the value taken by X for year t. Mean(X) represents the arithmetic mean of X over the period 1993 to 2000.*

The results obtained here with simple logit estimations are confirmed by a standard stepwise procedure[14] (Table 9). We introduced in these estimations all the set of explanatory variables. To deal with collinearity we systematically considered variables which were not correlated. When two or more variables were highly correlated we only introduced the variable which was the most significant in our previous estimations. We find that uncertainty helps explaining a positive volatility shift. Market based measures of bank failure (MDZ-score) perform well compared to public accounting data to detect higher bank stock return volatility.

Table 9. Stepwise estimations for volatility shift with multiple risk measures

Explanatory variables	Dependent variable VOL_1 Coefficient (Z statistic)	VOL_2 Coefficient (Z statistic)	VOL_3 Coefficient (Z statistic)	VOL_{TOT} Coefficient (Z statistic)
MEASURES OF RISK				
MDZ-score	-0.028*	-0.025*	NS	-0.025**
	(-1.737)	(-1.755)		(-2.890)
Log(TA)	0.396**	1.201***	0.570***	0.409***
	(2.421)	(3.701)	(3.794)	(3.102)
LLR	NS	0.300*	NS	NS
		(1.771)		
	R^2 =0.163 N=109	R^2 = 0.449 N= 69	R^2 = 0.151 N= 128	R^2 = 0.167 N= 117

*This table reports binary estimation results for 4 dependent variables (VOL_1,VOL_2,VOL_3,VOL_{TOT}) obtained with stepwise procedure. z-statistics are in brackets. ***, ** and * indicate significance respectively at the 1%, 5% and 10% levels. N is the number of observations and R^2 is the McFadden R-squared.*

As a second step we look at the link between significant positive volatility shifts for individual bank returns and a set of proxies that measure the level of bank private information. We consider the three sets of measures computed in section 3 (AbsV, $DISPERSION_x$ and $PERSISTENCE_x$, x=1, 2) and a set of financial variables constructed using balance sheet and income statement data. Our aim is to detect the type of banks for which we find a significant positive change in volatility. Table 10 shows the results of Logit estimations when each explanatory variable is separately introduced.

[14] The Stepwise procedure stops as soon as it becomes impossible either to introduce any additional variable that would be significant at the 5 % level or to exclude any variable from the current estimation at the same 5 % level of probability for Type I error.

Table 10. Logit estimations for volatility shift with a single private information measure

Explanatory Variable (Obs.)	Dependent variable			
	VOL_1 coefficient (Z statistic)	VOL_2 coefficient (Z statistic)	VOL_3 coefficient (Z statistic)	VOL_{TOT} Coefficient (Z statistic)
$DEPOSITS_{97}$ (124)	-0.0033 (-0.249)	0.0077 (0.393)	0.0052 (0.486)	0.0010 (0.082)
$DEPOSITS_{98}$ (131)	-0.0058 (-0.494)	0.0096 (0.502)	0.0019 (0.197)	0.0001 (0.012)
$LOANS_{97}$ (125)	-0.0182 (-1.6030)	-0.0042 (-0.393)	-0.0179 (-1.597)	-0.0124 (-1.253)
$LOANS_{98}$ (131)	**-0.0256**** **(-2.048)**	-0.0114 (-0.983)	**-0.0227*** **(-1.898)**	**-0.0196*** **(-1.838)**
NIM_{97} (124)	-0.2316 (-0.719)	-0.1246 (-0.534)	**-0.4388*** **(-1.816)**	-0.0134 (-0.062)
NIM_{98} (131)	-0.3503 (-0.840)	-0.3188 (-1.145)	**-0.4438*** **(-1.735)**	-0.0976 (-0.365)
$MARKET\_FUND_{97}$ (120)	**-0.0568**** **(-2.150)**	**-0.0810***** **(-2.936)**	0.0013 (0.099)	**-0.057**** **(-2.485)**
$MARKET\_FUND_{98}$ (126)	**-0.0493**** **(-2.053)**	**-0.0894***** **(-3.437)**	0.0069 (0.510)	**-0.0484**** **(-2.321)**
Mean(DEPOSITS) (145)	-0.0106 (-0.979)	0.0029 (0.178)	-0.0018 (-0.207)	-0.006 (-0.586)
Mean(LOANS) (145)	**-0.0207*** **(-1.760)**	-0.0127 (-1.153)	**-0.0221*** **(-1.894)**	**-0.0171*** **(-1.687)**
Mean(NIM) (145)	-0.2353 (-0.794)	-0.1824 (-0.839)	-0.2916 (-1.408)	-0.0539 (-0.262)
Mean(MARKET_FUND) (144)	-0.0344 (-1.639)	**-0.0606**** **(-2.541)**	0.0058 (0.394)	**-0.0334*** **(-1.839)**
$ABSV_{97}$ (107)	0.4607 (0.803)	0.6895 (1.015)	0.1494 (0.198)	0.7334 (1.208)
$ABSV_{98}$ (118)	-0.0520 (-0.275)	-0.6858 (-1.170)	-0.0435 (-0.265)	-0.1165 (-0.552)
$DISPERSION1_{97}$ (106)	-0.0712 (-0.134)	-0.4054 (-0.713)	0.0631 (0.085)	-0.1576 (-0.326)
$DISPERSION1_{98}$ (118)	-0.0527 (-0.109)	-0.5806 (-1.121)	0.5877 (0.973)	-0.4201 (-0.942)
$DISPERSION2_{97}$ (107)	**1.1334**** **(2.005)**	0.1910 (0.301)	1.1631 (1.619)	0.8529 (1.631)
$DISPERSION2_{98}$ (119)	0.6072 (1.099)	-0.3259 (-0.481)	**1.0822*** **(1.727)**	0.4680 (0.902)
PERSISTENCE1 (121)	0.7682 (0.858)	-0.9076 (-0.996)	0.6022 (0.485)	-0.2037 (-0.236)
PERSISTENCE2 (121)	**1.821**** **(2.169)**	-0.6491 (-0.769)	**1.6859*** **(1.706)**	1.0422 (1.264)
N_1	117	121	128	110
N_2	25	21	14	32

*This table reports binary estimation results for 4 dependent variables (VOL_1,VOL_2,VOL_3,VOL_{TOT}). Explanatory variables are defined in Table 2. Each dependant variable is regressed on each explanatory variable. z-statistics are in brackets. ***, ** and * indicate significance respectively at the 1%, 5% and 10% levels. N_1 and N_2 are the number of observations respectively when the dependent variable is equal to 0 and 1. X_t is the value taken by X for year t. Mean(X) represents the arithmetic mean of X over the period 1993 to 2000.*

The results show that the measures of dispersion and persistence based on standard deviation have a positive effect on volatility. Thus, when banks are classified as "high level of private information", the probability of a positive volatility shift increases. Moreover, this probability increases when HLPI for banks persists over the period. Another variable which is highly significant is the ratio of non-insured market funded liabilities to total assets with a negative sign which could be interpreted as market discipline reducing the volatility of bank stock returns. The ratio of loans to total assets which is also frequently considered as a proxy of private information is rarely significant with the unexpected sign. On the whole except for size (log(TA)) and the extent to which liabilities in the balance sheet are market funded (MARKET_FUND) we are unable to detect other significant variables. Because a higher ratio of uninsured market funded liabilities to total assets (MARKET_FUND) is expected to increase market discipline our results suggest that market discipline may well reduce volatility and asymmetric information. The stepwise procedure (see Table 11) shows similar results.

Table 11. Stepwise estimations for volatility shift with multiple private information measures

Explanatory variables	Dependent variable VOL_1 Coefficient (Z statistic)	VOL_2 Coefficient (Z statistic)	VOL_3 Coefficient (Z statistic)	VOL_{TOT} Coefficient (Z statistic)
MEASURES OF PRIVATE INFORMATION				
MARKET_FUND	-0.051**	-0.1025***	NS	-0.048**
	(-2.25)	(-3.699)		(-2.321)
$PERSISTENCE_2$	2.036**	NS	1.774*	NS
	(1.985)		(1.761)	
NIM	NS	-0.467*	-0.472**	NS
		(-1.673)	(-1.952)	
	R^2 = 0.072 N=112	R^2 = 0.109 N=123	R^2 = 0.072 N= 116	R^2 = 0.03 N=123

*This table reports binary estimation results for 4 dependent variables (VOL_1,VOL_2,VOL_3,VOL_{TOT}) obtained with stepwise procedure. z-statistics are in brackets. ***, ** and * indicate significance respectively at the 1%, 5% and 10% levels. N is the number of observations and R^2 is the McFadden R-squared.*

As a final step, we included the two sets of variables used in the previous estimations (risk and private information measure)[15]. The optimal subset of explanatory variables was selected through a standard stepwise procedure. Table 12 shows the outcome of the stepwise procedure. These results reinforce the results shown in Tables 8, 9, 10 and 11. The probability of a positive volatility shift increases with bank size, the variance of returns on assets and higher market data estimated default risk (decrease in MDZ-score) and decreases with the proportion of market funding in the balance sheet.

Table 12. Stepwise estimations for volatility shift with multiple risk and private information measures

Explanatory variable	Dependent variable VOL_1 Coefficient (Z statistic)	VOL_2 Coefficient (Z statistic)	VOL_3 Coefficient (Z statistic)	VOL_{TOT} Coefficient (Z statistic)
MEASURES OF RISK AND PRIVATE INFORMATION				
MDZ-score	NS	-0.026** (-2.017)	NS	-0.029** (-2.349)
Log(TA)	0.538** (2.852)	0.691*** (4.137)	0.707*** (4.203)	0.419*** (3.085)
MARKET_FUND	-0.082** (-2.795)	-0.165*** (-3.860)	NS	-0.078** (-2.870)
$PERSISTENCE_2$	3.017* (1.883)	NS	5.128** (2.678)	NS
Variance(ROA)	0.013*** (2.930)	0.0161*** (3.688)	1.482** (2.084)	0.012** (2.724)
	R^2 = 0.235 N=112	R^2 = 0.354 N=113	R^2 =0.313 N = 117	R^2 = 0.221 N =113

*This table reports binary estimation results for 4 dependent variables (VOL_1,VOL_2,VOL_3,VOL_{TOT}) obtained with stepwise procedure. z-statistics are in brackets. ***, ** and * indicate significance respectively at the 1%, 5% and 10% levels. N is the number of observations and R^2 is the McFadden R-squared.*

5. Concluding remarks

The aim of this paper was to carry out an empirical investigation of the link between the volatility of bank stock returns and the private information hypothesis in banking. Considering major events of the Asian and Russian financial crisis we first showed that, compared to other stocks, bank stocks frequently exhibited high abnormal volatility. We then looked at the relationship between volatility, risk and private information by constructing

[15] To deal with collinearity we only introduced the variable which was the most significant in our previous estimations when two or more variables were highly correlated.

several asymmetric information proxies based on an earnings prediction model. Our results first show that higher volatility cannot be easily detected in public accounting financial data but that market based bank risk measures perform relatively well. Our measures of asymmetric information are often significant and have the expected sign. An interesting result is that among the commonly used proxies of private information in the banking literature only the ratio of non-insured market funded liabilities to total assets is significant with the expected sign. This result suggests that heavier reliance on non insured liabilities such as subordinated debt may well contribute to reduce asymmetric information in banking.

Appendix

Table A1. Distribution of international bank lending by nationality of reporting banks (in %)

Position vis-à-vis		of which European banks	North American banks	Japanese banks
Asia	1995	37	9.1	38.5
	1997	43.8	10.1	31.8
Latin America	1995	51.9	31.2	7.1
	1997	58.2	27.9	5.8
Middle East	1995	64.2	8.5	8.7
	1997	63.9	10.1	5.8
Africa	1995	78	4.6	6.1
	1997	69.3	13	6.4
Eastern Europe	1995	83	3.3	6.3
	1997	79.0	10.4	3.3
of which Russia	1995	88.92	1.76	1.80
	1997	65.83	10.92	1.15

(Source: BIS(1997); (1998(b)))

Table A2. Definition of the industrial sector indexes

	Datastream European indexes
BMAT	Buildings and construction materials: producers of materials used in the construction and refurbishment of building and structures (16 firms)
OTHC	Other construction: constructors of non-residential buildings. Civil engineering and infrastructure contractors (16 firms)
CHEM	Chemicals, commodity: producers of commodity and industrial chemicals, industrial gases, coating and paints, fibres and films (12 firms)
ELQ	Electrical equipment: producers of electrical components and equipment (16 firms)
ELT	Electronic equipment: producers of electronic components and equipment not classified elsewhere (Aerospace and defence, household appliances and technology) (34 firms)
OIL	Oil integrated: companies engaged in the exploitation for production, refining, distribution and supply of mineral oil and gas products (6 firms)
PHA	Pharmaceuticals: biotechnology and drug research and development and/or exploitation (26 firms)
RLD	Real estate holding and development: companies specialising in the ownership and/or development of property assets (43 firms)

Table A3. Correlation matrix

	DEPOSITS	EQUITY	LOANS	LLP	LLR	NIM	MARKET_FUND	LOG(TA)	TIER1	MD Z-score	AD Z-score
DEPOSITS	1.000000										
EQUITY	-0.038488	1.000000									
LOANS	-0.413963	0.176949	1.000000								
LLP	-0.151932	0.027709	0.281151	1.000000							
LLR	0.084458	-0.019666	0.283983	-0.250463	1.000000						
NIM	0.210607	0.491360	0.185978	0.341358	-0.332825	1.000000					
MARKET_FUND	-0.921470	-0.049372	0.581529	0.178462	-0.016795	-0.171758	1.000000				
LOG(TA)	0.019698	-0.515359	-0.452609	-0.078764	-0.079632	-0.521067	-0.241680	1.000000			
TIER1	0.026980	0.841892	-0.091108	-0.069367	0.027395	0.309220	-0.163786	-0.276821	1.000000		
MD Z-score	0.162969	0.074373	-0.098183	0.106300	0.044690	0.178332	-0.173873	0.070188	0.149408	1.000000	
AD Z-score	0.132246	0.133781	0.211054	0.062098	0.566967	0.059569	-0.082414	-0.179105	0.125022	0.439644	1.000000

LOANS = Ratio of loans to total assets; EQUITY = Ratio of equity to total assets; DEPOSITS = Ratio of deposits to total assets; MARKET_FUND = Ratio of market funded liabilities (bonds, securities > 5 years, mortgage bonds, subordinated debt, hybrid capital) to total assets; NIM = Net interest margin defined as (interest received – interest paid)/total assets; LLP = Ratio of loan loss provisions to total assets; LLR_TA = ratio of loan loss reserves to total assets; LOG(TA) = logarithm of total assets; TIER1 = the TIER1 capital ratio; MDZ-score = Z-score computed using market data; ADZ-score = Z-score computed using accounting data.

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