Bank Characteristics and Cyclical Variations in Bank Stock Returns

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July 2003

Abstract

This paper investigates whether the stock returns of banks with different risk profiles exhibit different risk factor sensitivities over the business cycle. More specifically, we investigate whether or not capitalization, functional diversification, and geographical diversification provide banks with a structural hedge against a deterioration in the prevailing credit conditions. First, based on recent imperfect capital market theories, we offer some theoretical ground for the existence of asymmetries in systematic risk across various types of banks. Second, a regime-switching model is used to test the theoretical hypotheses empirically. We find that bank stock returns are strongly asymmetric: both the size of shocks and the conditional volatility is higher during business cycle troughs. Relatively poorly capitalized banks have a lower volatility than relatively highly capitalized banks, but react nevertheless stronger to bad news.

JEL: G12, G21, F34

Keywords: International Banking, Bank Strategy, Credit Risk, Regime Switching Models

1 Introduction

This paper investigates whether stock returns of banks with a different risk profile exhibit different risk factor sensitivities over the business cycle. While it is widely accepted that banks act as delegated monitors and manage risk, an important question is to what extent bank stock returns are sensitive to business cycle fluctuations. Theories of imperfect capital markets (see e.g. Bernanke and Gertler (1989) and Kiyotaki and Moore (1997)) argue that asymmetric information and agency costs are typically high during business cycle troughs and low during booms. The banking sector is especially vulnerable to adverse selection and moral hazard, both caused by asymmetric information. A recession will directly increase the overall riskiness of the outstanding loans through a reduction in the total value of collateral and a lower success rate of financed projects. Indirectly, moral hazard may increase loan riskiness if the lower firm value caused by worsening economic conditions leads to excessive risk taking behavior of borrowers ("gambling for resurrection"). Notice that also banks themselves will be more prone to gambling in an environment in which they have lower franchise value. These theories generally predict that banking becomes more risky in business cycle troughs. The aim of this paper is to provide some evidence about the empirical validity of these theoretical statements. More specifically, we test (1) whether or not bank stocks are sensitive to changes in the overall credit market conditions, and (2) whether or not these sensitivities vary asymmetrically over the business cycle.

A second question we want to address is whether the relationship between bank returns and credit conditions depends upon the risk profile of the bank. We investigate whether adequate capitalization, functional diversification (universal banking), and geographical diversification make banks less vulnerable to worsening credit market conditions. In addition, we test whether the asymmetry in business cycle sensitivity is different for banks with opposite risk profiles. Practically, we subdivide the sample of listed European banks in subsamples of relatively highly versus relatively poorly capitalized banks, functionally diversified versus specialized banks, and geographically diversified versus local banks. Similar to Perez-Quiros and Timmermann (2000), we compare the sensitivities of the stock returns of portfolios of banks with different risk profiles over the business cycle using a bivariate factor model with regime switches in both the factor sensitivities and the conditional volatility.

A thorough understanding of this issue is of obvious importance for national and international bank supervisors and regulators. A deterioration of bank health may be transmitted to the real economy and may raise questions about the systemic stability of the financial system. Following the capital account liberalization in various parts of the world, banks headquartered in industrialized countries are increasingly engaged in international lending, leaving them vulnerable to financial crises in both the home market and the borrowing countries. In addition, financial liberalization may have increased risk-taking behavior by banks through a negative effect on banks' franchise value (see Keeley (1990), Hellmann et al. (2000)). These considerations stress the importance of research concerning the sensitivity of banks to changes in the state of the business cycle. A related question is whether capital adequacy rules are the most optimal tool to counter adverse economic or financial shocks. Current efforts at the BIS level are aimed at strengthening the capital position of internationally operating banks. We investigate whether adequate capitalization is perceived by the stock market as a structural hedge against negative economic shocks. One of the pillars of the proposed new prudential strategy of Basel II is to introduce elements of market discipline in the supervisory process. Hence, it is important to determine whether bank stock prices are a potentially useful indicator of financial stress. The examination of the impact of functional diversification of banking institutions on their risk profile may provide useful information on the desirability of the gradual broadening of banking powers. In this respect, the European bank sector offers a broad scope for fertile research, since the Second Banking Directive (1989) has given banks a large degree of freedom to implement strategies of geographical and functional diversification. For bank managers, it is important to understand the potential implications of strategic choices for bank riskiness.

The remainder of the paper is organized as follows. Section 2 develops the theoretical framework for the existence of asymmetries in bank stock returns, both across the business cycle and across the various types of banks. Section 3 introduces the methodology that allows to incorporate these asymmetries in an empirical model. Section 4 describes the data, while section 5 presents the empirical results. Section 6 concludes.

2 Theoretical Foundations

The aim of this section is twofold. First, we want to provide a theoretical foundation for the hypothesis that bank stocks may depend asymmetrically on the business cycle. Second, we provide arguments for the claim that banks with a different risk profile may react differently to swings in the business cycle. More specifically, we develop hypotheses about the behavior of banks with a different degree of capital adequacy (highly versus poorly capitalized banks), functional specialization (diversified versus specialized banks) and geographical diversification (local versus global banks).

In their role as financial intermediaries, banks are inherently exposed to changes in the overall economic conditions. From a theoretical point of view, banks are commonly characterized as delegated monitors, because they obtain illiquid claims (loans) funded by short-term deposits with a relatively high degree of liquidity (Diamond, 1984). In their lending business, banks face problems of asymmetric information, both ex ante (adverse selection) and ex post (moral hazard). This feature exposes banks to different kinds of pervasive risk, of which market risk, interest rate risk and default risk are the most important ones. However, these risks are themselves influenced or even determined by business cycle conditions. In order to organize the discussion, we assume that banks are influenced by the business cycle through two main channels. The first is based on the association between the business cycle and the degree of asymmetric information. The second channel related to the role of banks in the transmission of monetary policy.

In economic downturns, it becomes more difficult for banks to assess the creditworthiness of corporate borrowers. Since adverse economic conditions have a negative impact on the cash flows of the most vulnerable borrowers, banks may suffer losses because some of their outstanding loans default. At the same time, the assessment of new loan applicants becomes more subject to type I errors because the net present value of new corporate investment becomes more uncertain. Moreover the net worth of companies and the value of their collateralizable assets decrease. Bernanke and Gertler (1989) argue that agency costs are inversely related to the borrower's net worth and collateral. Since the value of collateral is likely to be procyclical, asymmetric information will be relatively high in business cycle downturns and relatively low in booms. This implies that bank intermediation becomes riskier during downturns through a reduction in the value of collateral attached to outstanding loans and an increase in the degree of asymmetric information. These effects will especially increase the risk of illiquid and poorly capitalized banks with a specialization in traditional bank intermediation. Another possible asymmetric information effect is that potential entrants into a banking market are likely to suffer an adverse-selection effect stemming from their inability to determine whether applicant borrowers are new borrowers seeking financing for their untested projects or are in fact borrowers who have previously been rejected by an incumbent bank. This would raise the riskiness of entering banks, especially in an environment of worsening credit market conditions (Dell'Ariccia 2001, Dell'Ariccia, Friedman and Marquez 1999).

There is evidence of a bank lending channel in most developed economies, although its importance vis-à-vis other monetary policy transmission channels remains disputed (see, e.g., Angeloni et al., 2002). Faced with adverse business cycle conditions, banks may elect to ration credit. This happened in a number of periods, both in the US and in Europe. Peek and Rosengren (1995) argue that the recession of 1990-1991 in New England was partially caused by the reluctance of banks to lend. Also in the most recent business cycle downturn (2001-02), banks have been accused of being excessively restrictive, both in the US and in Europe (The Economist, 2002). However, banks will react differently to monetary policy actions, depending on their financial strength and their access to internally or externally generated liquidity. Kashyap and Stein (1995) conclude that small banks seem more prone than large banks to reduce their lending, with the effect greatest for small banks with relatively low buffer stocks of securities. On the other hand, well capitalized (or highly rated) banks should find it relatively easy to access the interbank or the securities markets to raise funds in the face of a deposit shock. This implies that a restrictive monetary policy will have less impact on the loan supply of well capitalized banks. Empirically, Kishan and Opiela (2000) show that the impact of monetary policy actions is different for banks with different sizes and capital ratios.

A shift in the risk profile of banks over the business cycle can also be caused by changing incentives on the part of banks. Economic downturns may produce the conditions in which banks have increased incentives to gamble and, hence, increase their riskiness. Hellman et al. (2000) show that, even with capital requirements, banks have an incentive to gamble when their franchise value is harmed. Since this effect will be stronger in economic downturns, bank riskiness may behave asymmetrically. Repullo (2002) and Schoors and Vander Vennet (2002) show that a gambling equilibrium may exist when the degree of asymmetric information increases. However, they also show that this risky behavior is less likely to occur when capital adequacy rules are binding. Hence, we expect that well capitalized banks will be less prone to excessive risk taking. These risk incentives may cause lending cycles and associated swings in the riskiness of banks (see, e.g., Kiyotaki and Moore 1997, Rajan 1994 or Asea and Blomberg 1998).

The conclusion of this selective literature review is that bank riskiness depends on the business cycle, but potentially in an asymmetric fashion. The central hypothesis of this paper is that banks with different risk strategies will be affected in a structurally different way by swings in credit market conditions. Banks know that shifts in credit market conditions, i.e. a deterioration of the creditworthiness of their borrowers, may be caused by reversals of the business cycle. Consequently, they will try to mitigate some of the associated risk, e.g. by hedging certain positions with credit or other types of derivatives. However, while the off balance sheet activities of commercial banks have increased substantially over the last decade, it is not clear if this trend has produced less risk. Hence, even a careful hedging strategy may not constitute an effective protection against unanticipated events. We consider three possible avenues for banks to adjust their risk profile in a more structural way: functional diversification, geographical diversification, and increased capital adequacy. We test whether or not the stock returns of these different types of banks exhibit a different sensitivity to changes in credit market conditions over the business cycle using a regime-switching methodology.

A first option for banks is to diversify their income sources by engaging in different types of financial services. Many countries allow universal banking or the formation of financial conglomerates in which commercial banking, insurance and securities-related activities can be integrated, although different organizational models of universal banking coexist (Saunders and Walter 1994). Typically, banks have tried to lessen their dependence on interest income (from loans and securities) and increase the proportion of non-interest income. The economic rationale refers to standard portfolio theory. If the non-interest income sources are imperfectly correlated with the traditional revenues from intermediation, the bundled income stream will be more stable. ECB (2000) reports an inverse correlation between interest income and non-interest income in several EU bank markets, suggesting a high potential for diversification benefits. The general conclusion of merger studies among different financial services providers is that the combination of banking and other activities, especially insurance, may have a positive impact on the overall riskiness of the conglomerate (Kwan and Laderman, 1999; Genetay and Molyneux, 1998). DeLong (2001), however, finds higher abnormal returns for focusing rather than diversifying US bank mergers. For US banks, Stiroh (2002) finds that interest income and non-interest income have become more correlated in recent years. In contrast to merger studies and correlation analyses, our approach allows a direct assessment of the sensitivity differences to economic shocks for diversified versus specialized banks.

Based on a different argumentation, a number of studies have provided evidence that universal banks could be less risky than their specialized peers. The closer ties with corporate borrowers and repeated lending may give universal banks access to private information which may improve the effectiveness of their monitoring efforts. The biggest advantage of universal banks may be in the ex post monitoring of firms facing financial distress because they can build up renegotiation reputation (Chemmanur and Fulghieri, 1994). If universal banks are better able to deal with financial distress, their cash flows will be less affected by adverse economic conditions. Specialized banks, on the other hand, are expected to be more vulnerable to economic fluctuations. Based on a large sample of European banks, Vander Vennet (2002) finds that the market betas of universal and specialized banks do not differ significantly in periods of economic expansion. In times of economic contraction, however, the market beta of universal banks is significantly lower than that of specialized banks. This finding is consistent with the conjecture that universal banks are better monitors and, hence, are less sensitive to shifts in the business cycle. The results are broadly in line with those reported by Dewenter and Hess (1998) for portfolios of relationship versus transactional banks in eight countries. Hence, our prediction is that (diversified) universal banks exhibit less sensitivity to shifts in credit market conditions than their specialized competitors and that universal banks are less vulnerable to adverse business cycle conditions.

The second option for banks to hedge their exposure to pervasive risks is to diversify geographically. Standard portfolio theory again implies that internationally operating banks will be less vulnerable to abrupt changes in local business cycle or credit market conditions. The underlying rationale is that a geographic diversification of credit and market risk exposures leads to more stable revenues due to the non-perfect correlation of market movements and asymmetric business cycles across different countries or world regions. Banks from industrialized countries have indeed expanded their involvement in international lending, including loans to emerging markets, often in the form of syndicated lending (Eichengreen and Mody (1999), see also BIS International Banking Statistics). Part of this movement may be explained by increased competition in their home markets, leading to eroding interest margins, and low domestic interest rates. Moreover, Western banks may also be induced to lend internationally because they enjoy deposit insurance, lender-of-last-resort services and implicit guarantees, along with the expectation that international institutions such as the IMF will organize bailouts when the borrowing countries are hit by adverse macroeconomic events. However, since borrower information in developing countries is more opaque, the net exposure of internationally operating banks to moral hazard may actually increase, as was evidenced during some of the financial crises in the 1990s (Asia, Russia, etc.). Moreover, cross-border entry may be associated with asymmetric information, increasing the riskiness of the entrants (DellArricia et al. 1999). Finally, the risk benefits of geographical diversification rely on the assumption of low cross-border correlations. When, on the other hand, adverse credit market conditions prevail across most regions, be it due to similarities in the causes or due to contagion, banks may experience little diversification benefits. Hence, the prediction that the stock returns of internationally diversified banks will be less sensitive to shifts in credit market conditions will probably only hold in cases of asymmetric regional shocks.

A third option for a bank to signal financial strength is to maintain a relatively high level of capital as a protection against possible losses. In all the countries under consideration in this paper, banks are required to maintain minimum capital levels as a proportion of their risky assets, calculated according to the current BIS standards. However, while the supervisory authorities impose a risk-based capital ratio of 8%, banks can signal their creditworthiness by holding levels of equity in excess of the required minimum. The excess capital serves as an additional buffer to cover unexpected future losses, thereby decreasing the risk of failure. In all standard models of banking, high capital levels are associated with a lower bankruptcy risk (see Freixas and Rochet, 1999). Hence, the prediction is that banks with a relatively high degree of capital coverage should be better able to alleviate adverse changes in the business cycle and, consequently, will be judged by the financial markets to be less sensitive to shifts in credit market conditions.

Next to this positive risk effect, well capitalized banks may also benefit from the potentially lower funding costs that this strategy may imply. This element of market discipline is expected to apply especially to the funds obtained in the professional and interbank markets, where competitive pricing based on perceived riskiness is standard practice. Berger (1995) documents a positive relationship between capital and earnings for US banks, a finding which he ascribes to the beneficial effect of capitalization on funding costs. Goldberg and Hudgins (2002) and Park and Peristiani (1998) show that uninsured deposits are exposed to market discipline. They find that riskier banks attract smaller amounts of uninsured deposits and pay higher interest rates on this type of funding than less risky competitors. This beneficial effect on bank profits may strengthen the positive risk effect of higher capital levels and, hence, affect the valuation of the bank by the stock market.

From this overview it is clear that banks with different risk profiles (functionally diversified versus specialized, geographically focused versus global and relatively high versus relatively low capital ratio) should exhibit different sensitivities to changes in credit market conditions over the business cycle. Since listed European banks have implemented different risk strategies, we can use their stock returns to assess the sensitivities to pervasive shifts in credit market conditions empirically. In the next section we outline the regime-switching methodology we use for this exercise.

3 The model

3.1 General Specification

Suppose we compare the return distribution of a portfolio of banks with a particular risk strategy with that of banks with the opposite strategy. Let $r_{1,t}$ be the return on a portfolio of banks[1] with strategy 1, and $r_{2,t}$ the return on a portfolio of banks with the opposite strategy. The current returns $r_t = [r_{1,t}, r_{2,t}]'$ contain an expected component $E_{t-1}[r_t]$ and an unexpected component $\varepsilon_t = [\varepsilon_{1,t}, \varepsilon_{2,t}]'$. The return innovations deviate from zero partly because of news and partly because of noise in the market. Suppose that the information that becomes available to investors at time t is contained in $X_t \in R^{n\times1}$, so that the time t information set is given by $\Omega_t = [X_t, X_{t-1}, ..., X_0]'$. We define news as innovations in the information set, or $\varepsilon_{x,t} = [X_t - E[X_t|\Omega_{t-1}]]$. Current returns are then described by the following system:

$$r_t = E[r_t|\Omega_{t-1}] + \varepsilon_t = E[r_t|\Omega_{t-1}] + \beta'(S_t)\,\varepsilon_{x,t} + u_t$$

where $\beta = \left[\beta^1, \beta^2\right]'$ is a n by 2 matrix of parameters that depends on a latent regime variable S_t. We suppose that S_t can take only two values, $S_t = 1$ or $S_t = 2$. u_t represents noise in the market. The matrix of parameters β governs the relationship between return innovations and news. Several authors (most recently, Flannery and Protopapadakis (2002)) have successfully demonstrated the link between return innovations and a large set of macroeconomic and financial news factors. Most of these studies however do not allow the relationship between returns and news to change over time. Perez-Quiros and Timmermann (2000, 2001) argue that the relationship between expected returns and information variables may depend on the state of the business cycle. They test their hypothesis on the Fama and French size-sorted decile portfolios, and find that asymmetries are especially strong for small firms. They argue that small firms typically have lower levels of collateral, which makes them especially vulnerable to tightening credit market conditions, typically observed in business cycle troughs. In the previous section, we argued that different types of banks are likely to react differently to changes in the prevailing credit market conditions. To test these hypotheses, we develop a regime-switching model similar to Perez-Quiros and Timmermann (2000, 2001) that makes the sensitivity of different types of banks to business cycle news dependent on a latent regime variable S_t.

[1] A number of studies have examined whether the stock market is able to differentiate among financial institutions with different financial and risk profiles. The evidence suggests that the stock market reacts efficiently to information concerning individual banks and to changes in the regulatory environment (see Flannery (1998) for the US and Brewer (1999) for Japan). The findings support the idea that stock markets are able to assess the quality of the bank's assets.

Recently, regime-switching volatility models have attracted considerable interest, for several reasons. First, as argued by, e.g., Diebold (1986) and Lamoureux and Lastrapes (1990), the near integrated behavior of the conditional variance might be due to the presence of structural breaks, which are not accounted for by standard GARCH-models. This persistence is shown to disappear when regime-switching volatility models, pioneered by Hamilton and Susmel (1994), Cai (1994), and Gray (1996), are used. Second, as discussed in Ang and Bekaert (2001), regime-switching volatility models do much better in modeling asymmetric correlations - this is the empirical regularity that correlations are larger when markets move downward than when they move upward - compared to even the fairly general GARCH models. Other studies have related conditional volatility to innovations in macroeconomic and financial variables. Stock return volatility is found to be substantially higher in business cycle troughs than in booms (see e.g. Campbell, Kim, and Lettau (1998)). Flannery and Protopapadakis (2002) find that a set of real and monetary variables significantly drive daily conditional US market volatility. In this paper, as in Perez-Quiros and Timmermann (2000), we take into account these findings by making the conditional variance-covariance matrix $\mathbf{H}_t$ dependent on the latent regime variable S_t and on a set of information variables y_{t-1},where $y_{t-1}$is a subset of Ω_{t-1}. To keep the number of parameters manageable, we start from the relatively simple constant correlation model of Bollerslev (1990):

$$u_t \sim i.i.d.N(0, \mathbf{H}(S_t, y_{t-1}))$$

where

$$\mathbf{H}(y_{t-1}, S_t) = \begin{bmatrix} h^1(y_{t-1}, S_t) & 0 \\ 0 & h^2(y_{t-1}, S_t) \end{bmatrix} \begin{bmatrix} 1 & \rho(S_t) \\ \rho(S_t) & 1 \end{bmatrix} \begin{bmatrix} h^1(y_{t-1}, S_t) & 0 \\ 0 & h^2(y_{t-1}, S_t) \end{bmatrix}$$

where $\rho(S_t)$ is the regime dependent correlation coefficient. The univariate conditional variance specifications $h^1$and h^2 are given by

$$\ln(h^z(y_{t-1}, S_t)) = \omega^z(S_t) + \Psi^z(S_t) y_{t-1}$$

where ω^z is an intercept, and Ψ^z is a $n \times 1$ vector of parameters[2], for $z = \{1, 2\}$.

As argued before, the sensitivity of return innovations and the variance-covariance matrix to news factors is conditional on a latent regime variable S_t that can take two values only, $S_t = 1$, or $S_t = 2$. This regime variable follows a two-state markov chain with a time varying transition probability matrix Π_t, defined as

$$\Pi_t = \begin{pmatrix} P_t & 1 - P_t \\ 1 - Q_t & Q_t \end{pmatrix} \tag{1}$$

where the transition probabilities are given by

$$\begin{aligned} P_t &= \Pr(S_t = 1 | S_{t-1} = 1, \phi_{t-1}) = p(\phi_{t-1}) \\ Q_t &= \Pr(S_t = 2 | S_{t-1} = 2, \phi_{t-1}) = q(\phi_{t-1}) \end{aligned} \tag{2}$$

[2]Given the relatively weak evidence of ARCH effects in monthly returns, we do not include an ARCH term.

where $\phi_{t-1}$is a subset of information variables that belong to the information set Ω_{t-1}.and influence the probability that there occurs a state switch between time $t-1$ and t. Because the states should more or less correspond with periods of booms and recessions, we let ϕ_{t-1} contain information about the state of the business cycle. We use a logistic function to guarantee that P_t and Q_t lie between zero and one at any time:

$$P = \frac{\exp(\xi_p + \zeta_p' \phi_{t-1})}{1 + \exp(\xi_p + \zeta_p' \phi_{t-1})}$$
$$Q = \frac{\exp(\xi_q + \zeta_q' \phi_{t-1})}{1 + \exp(\xi_q + \zeta_q' \phi_{t-1})}$$

The assumption that the return process of both bank series is driven by a single latent variable may look restrictive. However, the aim of this latent variable is to separate expansion from recession states, rather than discovering bank-specific states. Differences in exposure over the business cycle between banks will be determined by the bank-specific parameters within a state.

3.2 Testable Restrictions

The specification presented above allows for a large number of interesting tests. We first investigate whether the news variables have a significant influence on return innovations. More specifically, we test whether $\beta^1(S_t = 1) = \beta^1(S_t = 2) = 0$, whether $\beta^2(S_t = 1) = \beta^2(S_t = 2) = 0$, and whether they are jointly equal to zero. Similarly, the relevance of news for the conditional variance is investigated by testing, respectively, whether $\Psi^1(S_t = 1) = \Psi^1(S_t = 2) = 0$, $\Psi^2(S_t = 1) = \Psi^2(S_t = 2) = 0$, or both. Finally, we test whether the information variables contained in ϕ_t significantly drive the transition probabilities P_t and Q_t by testing whether ζ_p and ζ_q are significantly different from zero.

A second series of tests is designed to investigate whether different types of banks react differently to information. Suppose that state 1 and 2 broadly correspond to recession and expansion states, respectively. First of all, the reaction of bank stocks to news may only be statistically significant in one state, typically in the recession state. Therefore, the following hypotheses are tested: $\beta^1(S_t = 1) = \beta^2(S_t = 1)$, $\beta^1(S_t = 2) = \beta^2(S_t = 2)$, and both. To test whether the sensitivity of the conditional volatility to news differs significantly between banks across states, we test whether the hypothesis of $\Psi^1(S_t = 1) = \Psi^2(S_t = 1)$, $\Psi^1(S_t = 2) = \Psi^2(S_t = 2)$, or both, hold.

Finally, we investigate whether bank stock returns react asymmetrically over the business cycle. In the mean equation, we reject symmetry for bank z when the null hypothesis $\beta^z(S_t = 1) = \beta^z(S_t = 2)$ does not hold. Similarly, the hypothesis that bank 1 (2) reacts more asymmetrically to business cycle information than bank 2 (1) is investigated by testing the null that

$$\left|\beta^1(S_t = 1) - \beta^1(S_t = 2)\right| = \left|\beta^2(S_t = 1) - \beta^2(S_t = 2)\right|$$

against the alternative hypothesis that the sensitivity differential is largest for bank type 1 (2). In a similar fashion, we investigate whether the asymmetry of the conditional volatility is stronger for one type of banks, both with respect to the intercept ω and the sensitivities Ψ. Table 7 gives an overview of the various likelihood ratio tests calculated for this model.

4 Data Description

Our dataset includes a total number of 143 listed European banks[3] and covers the period January 1985-June 2002. This period encompasses markedly different states of the European business cycle and, hence, is particularly well suited to investigate the evolution of bank risk sensitivities over the business cycle. It contains the economic boom of the second half of the 1980s, the economic slowdown at the beginning of the 1990s, and the period of economic growth associated with the EMU-related convergence in the mid-1990s, interrupted by a number of financial crises (Mexican, Asian, and Russian crisis and the near-collapse of the Long Term Capital Management hedge fund). Finally, our sample also includes the period of global economic slowdown starting at the end of 2000 in which a lot of concerns were raised about the health of certain types of banks. Since most of the listed banks in Europe are the largest in terms of asset size, they cover the vast majority of their national banking systems. Consequently, our results reflect pervasive risk effects across European banking. These large banking institutions are also of particular concern for national and European regulators and supervisors.

The dependent variables in this study are the excess returns of portfolios of banks with specific characteristics. For 143 European banks, we download monthly stock returns (including dividends) from Datastream International. All returns are denominated in German marks. Next to the banks listed in June 2002, the sample includes 39 dead banks to alleviate the problem of survivorship bias.[4] We require that the banks display at least two years of return data in order to ensure that we estimate meaningful risk exposures. Furthermore, all banks have a balance sheet total of at least 850 million DEM.

4.1 Types of banks

All banks in the sample are ranked according to their degree of functional diversification, geographical diversification and capital adequacy. Balance sheet and income statement data are retrieved from Bankscope, a bank database maintained by the London-based rating agency Fitch/IBCA, on a yearly basis. In order to make a distinction between relatively highly and poorly capitalized

[3]More specifically, the sample includes 7 Austrian, 7 Belgian, 4 Danish, 6 Dutch, 3 Finnish, 6 French, 11 German, 4 Greek, 3 Irish, 24 Italian, 4 Luxemburg, 6 Norwegian, 7 Portugese, 20 Spanish, 6 Swedish, 8 Swiss and 17 UK banks.

[4]None of the banks included in the sample went bankrupt. After a merger, however, banks often change names. In that case, the 'old' stock becomes a dead stock.

banks, we make a ranking of banks based on the ratio 'equity-to-total customer loans'. To distinguish between functionally diversified and non-diversified banks, we make a ranking of banks based on the ratio 'non-interest income-to-total income'. Non-interest income includes commissions and fees, e.g., from insurance underwriting and distribution, investment banking activities and asset management. Since the Second Banking Directive (1989) allowed banks to engage freely in these types of financial service activities, a number of European banks have adopted strategies that eventually led to the creation of financial conglomerates. Others, however, elected to remain (or become) more focused on traditional intermediation. For the 143 European banks in our sample, there are on average 7 years of balance sheet data available, with a minimum of two years. As a result, we are not able to make a yearly ranking of banks from 1985 until 2002. Instead, we concentrate on the average 'equity-to-total customer loans' ratios, respectively 'non-interest income-to-total income' ratios for which data is available. Banks with the 30% (15%) highest ratios of 'total equity-to-total customer loans' are considered to be relatively well capitalized, whereas the group with the 30% (15%) lowest ratios is considered to be relatively poorly capitalized[5]. Diversified (specialized) banks are those with the 30% (15%) highest (lowest) ratio of 'non-interest income to total income'. Although both ratios vary over time, the probability that a bank changes from being classified as, for example, a diversified to a specialized bank is zero. Therefore, it also seems reasonable to take the average of both ratios.

Finally, we make a distinction between geographically diversified and local banks. Geographically diversified or global banks are those published in the list of global banks by the Banker once a year. The Banker makes a ranking of banks based on their percentage of assets overseas or outside the home country[6]. For ABN Amro, for example, total assets overseas means total assets outside the Netherlands. The global banks included in our analysis have on average 44.4% of their assets outside the home country, with a minimum of 20%. Banks that are not included in the list of global banks of the Banker are considered to be local banks.

Table 1 presents the summary statistics of the different portfolios of banks. For each portfolio (30% and 15% percentiles), we present the average, the standard deviation, the minimum and the maximum of the ratios 'Equity/ Total Customer Loans' and 'Non-interest Income/ Total Income'. The 30% portfolios consist of 43 banks whereas the 15% portfolios consist of 22 banks. Furthermore, 33 of the 143 European banks are classified as geographically diversified.

The summary statistics indicate that there is considerable cross-sectional variation between bank types for both ratios. For the relatively highly and poorly capitalized banks, the ratio 'Equity-to-Customer Loans' (30% percentiles)

[5]The capital and non-interest income ratios used to subdivide the sample are calculated based on the consolidated bank statements. For each bank we calculate the average ratio over the sample period, from the earliest possible year available in Bankscope to 2001

[6]We do not make a distinction based on the location of the geographical expansion, although this can be important to gauge the effect of geographically concentrated financial events or crises.

is 24.9% for the highly capitalized banks compared to 6.4% for the poorly capitalized banks. For the 15% portfolios, the difference is even more pronounced. The summary statistics indicate that highly capitalized banks are also more diversified compared to poorly capitalized banks. The percentage non-interest income is almost double for the highly capitalized banks. For both the 30% and the 15% percentiles, the minimum of the ratio 'Equity-to-customer loans' for the highly capitalized banks is much larger compared to the maximum ratio for the poorly capitalized banks. This shows that the equity ratio is significantly different for both types of banks. A similar observation can be made for the diversified versus specialized banks. The ratio 'Non-interest Income/ Total Income' for the 30% percentile is 8.8% for the specialized banks, compared to 27% for the diversified banks. The differences between the lowest and highest percentile become even more pronounced when we consider the 15% percentiles. For the diversified and specialized banks, the ratio 'Equity-to-Customer Loans' shows that both groups are equally capitalized. Since the difference between the different subcategories of banks is most pronounced for the 15% portfolios of banks, we will concentrate on the latter in the empirical analysis. Finally, we make a distinction between global and local banks. The results show that the functional diversification of both types of banks is comparable. The ratio 'Non-interest Income/ Total Income' is similar, 22% for global banks compared to 20% for local banks. The ratio 'Equity-to-Customer Loans' is higher for local banks. This is however due to three local banks that have an equity ratio above 100%.

To investigate whether there is not too a high overlap between the different portfolios, Table 2 presents the percentage of banks in each of the 15% portfolios that are also included in another portfolio of banks. The first part of table 2 shows that 30% of the banks that are relatively poorly capitalized are also functionally specialized. For the relatively highly capitalized banks, 20% are diversified, 39% specialized but only 4% are global. In the group of specialized banks, there are much more relatively poorly capitalized banks compared to relatively highly capitalized banks. According to our expectations, all of the specialized banks are local whereas 44% of the diversified banks are global. The last part of Table 2 confirms the previous results that a large part of the global banks are diversified. As a conclusion, this table indicates that there is some overlap between the different banking portfolios, but not to the extent that one is redundant with respect to the others.

Finally, Table 3 shows that none of the portfolios is overly dominated by banks from one specific country. The highest country percentages are observed for the UK and Spain, which represent respectively 21.2 percent of the global banks and 26.1 percent of the relatively highly capitalized banks. Overall, there is no evidence of a substantial country bias in any of the portfolios.

4.2 Bank Stock Returns

In table 4, we investigate whether the differences in risk profile are reflected in the (excess) return characteristics. On average, geographically diversified

European banks have produced higher excess returns than local banks (1.13% versus 0.95%), but were also more volatile (5.97% versus 4.34%). This results in a Sharpe Ratio, measuring the risk-return trade-off, that is higher for local than for geographically diversified banks[7].

For the other bank types, we first focus on the 30% percentile. Specialized banks in Europe yield an average return and volatility that is higher compared to diversified banks (1.08 versus 1.03 and 5.09 versus 4.78). Both types of banks produce similar Sharpe Ratios. Based on these summary statistics, the return distribution of specialized and diversified banks seems to be relatively similar. The average return of the relatively poorly capitalized banks is considerably lower than for the relatively highly capitalized banks, 0.83% versus 1.19%. The difference in return only partly compensates the difference in volatility. As a result, the Sharpe Ratio is higher for well capitalized banks (0.24 versus 0.18). While return characteristics are similar for the 15% percentile compared to the 30% percentile, differences are more pronounced. Therefore, we estimate the models outlined in the previous section on the 15% percentile portfolio returns[8]. The last three columns of table 4 report the Jarque-Bera test for normality, an ARCH test (with four lags) for heteroskedasticity, and a Q test (also with four lags) for autocorrelation. The Jarque-Bera rejects normality for all portfolios, mainly because of high excess kurtosis. In addition, the Q and ARCH test indicate that most series exhibit both (fourth order) autocorrelation and heteroskedasticity.

Table 5 reports average correlations between the returns on the different portfolios. All portfolios are highly correlated with the returns on a portfolio of all banks in sample. This suggests that all banks, independently of their risk profile, are to a large extent determined by common risk factors. Correlations are considerably lower between functionally diversified and specialized banks (66%), and between relatively poorly and well capitalized banks (72%). Geographically diversified and local banks however appear to be highly correlated (84%). This may be explained by the observation that the majority of the geographically diversified banks in our sample are European rather than true global banks.

Finally, Table 6 reports year-by-year average returns and volatility for the different bank portfolios. While both average returns and volatilities exhibit considerable variation over time, there is similarly strong evidence that the different bank types follow the same cycle. Banks returns are high and relatively stable during prosperous time, but low and volatility during recession years (e.g. during the periods 1987, 1990-1993, and 2001-2002).

[7]Notice that the higher volatility of geographically diversified banks may to some extent be explained by the larger number of banks contained in the local banks portfolio.

[8]The empirical findings for the 30% portfolios are very similar and are available from the authors.

4.3 Information Variables

Before estimating the model, we need to define the information variables in the information set Ω_{t-1}, and determine which instruments drive the factor innovations $\varepsilon_{x,t}$, the expected return μ_t, the conditional variance-covariance matrix $\mathbf{H}_t$, and the transition probabilities P_t and Q_t.

We relate excess bank stock returns to three instruments that were shown to have leading indicator properties for the business cycle, and hence for stock returns. The first variable is the short-term Interest Rate (IR), represented by the change in the one-month euro (or before the euro, ECU) interest rate. Fama (1981) argues that short-term nominal interest rates should be negatively related to stock returns. The author first shows that unobserved negative shocks to real economic activity induce a higher nominal short interest rate through an increase in the current and expected future inflation rate. Negative news about future economic activity reduces the demand for real money, which, given nominal money, has to be accommodated by a rise in the price level. Then he provides evidence that stock returns are positively related to a number of real variables. The combination of these two findings results in a negative relationship between nominal short-term interest rates and stock returns. This negative relation is also the result of the Present Value Models pioneered by Campbell and Shiller (1988). Recently, Ang and Bekaert (2001) compared the predictive power of the short rate to those of dividend and earnings yield, and find that, once corrected for small sample problems, the short-rate is the only robust predictor of stock returns. Moreover, banks may be especially prone to changes in the short-term interest rate because of a duration mismatch between their assets and liabilities structure. Among others, Flannery and James (1984b) and Aharony et al. (1986) find a negative relationship between bank returns and unexpected changes in the short-term interest rates.

We also include a measure for the overall liquidity of the economy, i.e. the growth in the Money Stock (M), here the money aggregate M1 for EMU plus UK. Fama (1981) argues that it is important to control for money supply when establishing the inflation - future real economic activity argument. Furthermore, Perez-Quiros and Timmermann (2001) find that the expected return of small firms reacts significantly positive to growth rates in the money base, especially so during business cycle downturns. One explanation for this may be that the central bank mainly expands the monetary base during recessions, and that small firms' risk and risk premium are highest in this state. Finally, there is some evidence that the increases in the economy's liquidity are partly explained by an increase in risk aversion, which gives rise to portfolio rebalancing from e.g. stocks and bonds to liquid assets like bank deposits.

A third information variable we consider is the Term Spread (TS), defined as the spread between the ten-year ECU benchmark bond rate and the 3-month euro (ECU) interest rate. This variable is consistently shown to be a leading indicator of real economic activity, and hence stock prices. Estrella and Hardouvelis (1991) and Estrella and Mishkin (1998) show that for the United States the yield spread significantly outperforms other financial and macroeconomic indicators in forecasting recessions. Bernard and Gerlach (1996), Estella and Mishkin (1997), and Ahrens (2002) represent similar results for other countries. Not surprisingly, a large literature Fama and French (1989) has successfully linked term structure variables to equity returns.

To extract the unexpected, or "news", component out of changes in these three instruments, we define $\mathbf{X}_t = [\Delta TS_t, \Delta IR_t, \Delta M_t]$, and estimate the following Vector-AutoRegressive (VAR) model of order n :

$$\mathbf{X}_t = \sum_{i=1}^{n} \mathbf{A}_i \mathbf{X}_{t-i} + \varepsilon_{x,t}$$

where n represents the number of autoregressive components, the $\mathbf{A}_i$'s are 3×3 matrices of parameters, and $\varepsilon_{x,t}$ a 3×1 vector of time t innovations. The Schwarz information criterion as well as a likelihood ratio test indicate that a lag of one, $n = 1$, is sufficient.

To determine the expected return component $\mu_t = [\mu_{1t}, \mu_{2t}]'$, we estimate the following set of equations:

$$\begin{aligned} r_{1t} &= \mu_{1t} + \varepsilon_{1,t} = \alpha_0^1 + \alpha_1^1 \Delta TS_{t-1} + \alpha_2^1 \Delta IR_{t-1} + \alpha_3^1 \Delta M_{t-1} + \varepsilon_{1,t} \\ r_{2t} &= \mu_{2t} + \varepsilon_{2,t} = \alpha_0^2 + \alpha_1^2 \Delta TS_{t-1} + \alpha_2^2 \Delta IR_{t-1} + \alpha_3^2 \Delta M_{t-1} + \varepsilon_{2,t} \end{aligned}$$

To keep the number of parameters in the regime-switching model manageable, we determine both the factor innovations and expected returns in a first step estimation.

The conditional variance-covariance matrix depends on a latent state variable S_t and on a set of information variables. Previous literature has documented a link between equity market volatility and the business cycle. Hamilton and Susmel (1994) estimate a regime-switching ARCH model for monthly US stock returns in which the probability of switching from a high to a low regime depends on the overall business cycle conditions. More specifically, the probability of staying in or switching to the high volatility state is higher during recessions. Errunza and Hogan (1998) investigate whether macroeconomic factors can predict stock market volatility. Over the period 1959-1993, they find that monetary instability - proxied by money supply volatility - Granger causes equity volatility in Germany and France, while the volatility of industrial production Granger causes equity volatility in Italy and the Netherlands. However, macroeconomic factors do not improve volatility forecasts in the U.K., Switzerland, and Belgium. Flannery and Protopapadakis (2002) relate US equity returns and their conditional variances to 17 series of macro announcements. They find that news about the balance of trade, employment, housing starts, and monetary aggregates affect volatility, while industrial production does not enter significantly. Finally, Glosten et al. (1993), Elyasiani and Mansur (1998), and Perez-Quiros and Timmermann (2000) find that lagged interest rates are important in modeling the conditional volatility of monthly stock returns. In this paper, we relate the conditional variance to a latent state variable S_t, which is supposed to separate recessions from booms, and on the lagged change in the three month interest rate IR_t. Short term interest rates are not only available at higher frequencies than macroeconomic data, there is also a direct link between bank performance and interest margins.

Finally, we have to choose the relevant drivers of the transition probabilities. The states should roughly correspond to business cycle booms and troughs. As many studies have successfully used the term spread in predicting recessions (see e.g. Ahrens (2002) and Ang et al.(2002) for recent contributions), we use this variable to model the transition between states:

$$P_t = \frac{\exp(\zeta'_{1p} + \zeta'_{2p} TS_{t-1})}{1 + \exp(\zeta'_{1p} + \zeta'_{2p} TS_{t-1})}$$
$$Q_t = \frac{\exp(\zeta'_{1q} + \zeta'_{2q} TS_{t-1})}{1 + \exp(\zeta'_{1q} + \zeta'_{2q} TS_{t-1})}$$

where TS_{t-1} is the one-month lagged value of the term spread, defined as the difference in yield between 10-year government bonds and 3-month treasury bills.

5 Estimation and Empirical Results

We estimate the expected return μ_t and the factor innovations $\varepsilon_{x,t}$ as outlined in the previous section in a first step regression[9], and impose these estimates in the second step. The model is then given by

$$\begin{aligned}
\varepsilon_{1,t} &= r_{1,t} - \mu_{1,t} = \beta_0^1(S_t) + \beta_1^1(S_t)\,\varepsilon_{\Delta TS,t} + \beta_2^1(S_t)\,\varepsilon_{\Delta IR,t} + \beta_3^1(S_t)\,\varepsilon_{\Delta M,t} + u_{1,t} \\
\varepsilon_{2,t} &= r_{2,t} - \mu_{2,t} = \beta_0^2(S_t) + \beta_1^2(S_t)\,\varepsilon_{\Delta TS,t} + \beta_2^2(S_t)\,\varepsilon_{\Delta IR,t} + \beta_3^2(S_t)\,\varepsilon_{\Delta M,t} + u_{2,t}
\end{aligned}$$

while the conditional variance-covariance matrix is specified as follows

$$u_t = [u_{1,t}, u_{2,t}]' \sim i.i.d.N(0, \mathbf{H}(\varepsilon_{\Delta IR,t}, S_t))$$
$$H(S_t, IR_{t-1}) = \begin{bmatrix} h^1(.)^2 & \rho(S_t)h^1(.)h^2(.) \\ \rho(S_t)h^1(.)h^2(.) & h^2(.)^2 \end{bmatrix}$$

and

$$\begin{aligned}
\ln(h^1(S_t, IR_{t-1})) &= \omega^1(S_t) + \Psi^1(S_t) IR_{t-1} \\
\ln(h^2(S_t, IR_{t-1})) &= \omega^2(S_t) + \Psi^2(S_t) IR_{t-1}
\end{aligned}$$

Finally, the time-varying transition probabilities are specified as

$$\begin{aligned}
P_t &= \Pr(S_t = 1 | S_{t-1} = 1, TS_{t-1}) = \frac{\exp(\zeta_{1p} + \zeta_{2p} TS_{t-1})}{1 + \exp(\zeta_{1p} + \zeta_{2p} TS_{t-1})} \\
Q_t &= \Pr(S_t = 2 | S_{t-1} = 2, TS_{t-1}) = \frac{\exp(\zeta_{1q} + \zeta_{2q} TS_{t-1})}{1 + \exp(\zeta_{1q} + \zeta_{2q} TS_{t-1})}
\end{aligned}$$

[9]Detailed results about the first step estimation are not reported, but are available upon request.

The parameters are estimated by maximum likelihood, assuming normally distributed errors. Given the highly nonlinear character of this model, the estimation procedure is started from 25 different starting values to avoid local maxima[10].

Panel A, B and C of table 8 present the estimated parameters and standard deviations of the mean equation. The dependent variables are unexpected excess portfolio returns of relatively poorly and relatively well capitalized banks (Panel A), global and local banks (Panel B), and functionally specialized and diversified banks (Panel C). Panel A, B and C of Table 9 report the corresponding likelihood ratio tests[11]. Part 1 of each panel investigates whether (combinations of) parameters are significantly different from zero and whether the mean and the conditional variance of the two types of banks react differently to information. In part 2 of each panel, we not only test for business cycle asymmetry, we also investigate whether this asymmetry is statistically different between banks. Figure 1 plots the filtered probability of being in state 1 for the different combinations of bank types. In Figure 2, the conditional volatility series are plotted for the different types of banks, while in Figure 3 we investigate to what extent shocks are different across bank types.

We first discuss the results of the transition probabilities. Then, we present the results of the mean equation followed by the variance equation.

5.1 Transition between States

The parameter estimates for the specification of the transition probabilities are given in the bottom part of Panels A, B, and C in Table 8. The corresponding Likelihood Ratio tests are presented in table 9 (part 1 of panels A, B and C). Figure 1 plots the filtered probabilities of being in state one for each combination of bank types.

The parameter estimates are similar for the different bank combinations. Under the assumption that $\zeta_{2p} = \zeta_{2q} = 0$, the estimates for the intercept would imply a constant probability of staying in state 1 between 0.92 and 0.96, a level of persistence often found in monthly data[12]. We do, however, also find evidence for time variation in the transition probabilities. A likelihood ratio test rejects the null hypothesis of no effect from the term structure on the transition probabilities at a 5% level for global and local banks, and at a 10% level for relatively poorly and highly capitalized banks, and for functionally diversified

[10]It is common knowledge that it is absolutely crucial to start estimation procedures for non-linear models from at least 10 different starting values. By doing so, one reduces the probability of being stuck in a local maximum, and hence use the wrong parameter estimates to draw conclusions. In this model, both the mean and variance equations are nonlinear, while the transition probabilities are allowed to vary over time. Because of the highly nonlinear character of this model, we increase the number of runs from 10 to 25.

[11]An overview of the likelihood ratio tests is given in Table 4.

[12]We could not reject the null hypothesis that the intercepts in the specification for the transition probabilities are equal ($\zeta_{1p} = \zeta_{1q}$). Consequently, to save parameters, we assume that $\zeta_{1p} = \zeta_{1q} = \zeta_1$.

and specialized banks. For all bank combinations, the probability of staying is positively related to the term structure in state 1, and negatively in state 2. As the term structure typically becomes steeper in (anticipation of) expansions and flatter (or negative) in recessions, this suggests that state 1 and 2 are boom and recession states respectively. The classification of states does not seem to depend a lot on the actual choice of bank portfolios. This suggest that the transition probabilities are determined by common rather than bank-specific factors. In addition, in all cases, the model switches from an expansion to a contraction state during the recession at the beginning of the 1990s, during the period of financial crises at the end of the 1990s, and during the global economic slowdown from the end of 2000 onwards. As can be seen in Table 6, the periods 1990-91 and 2001 are years characterized by higher volatility and lower mean bank stock returns for all types of banks. In 1990-91, the average yearly return is close to zero, whereas the volatility is above the average over the sample period. In 2001, the average yearly return is negative, whereas the volatility is almost double the average of the volatility over the sample period (7.09% versus 3.95%).

5.2 Mean Equation

In the mean equation, we find strong evidence that innovations in the term spread, the short rate, and the monetary base jointly influence realized bank returns. For each bank type, a likelihood ratio test rejects the null hypothesis of zero sensitivities (see Part 1 of panel A, B and C in Table 9) The sensitivities to innovations in the term spread are estimated with a high degree of precision and have the expected positive sign. While for 5 of the 6 bank types the sensitivity is higher in the recession state, suggesting asymmetry, we can reject the null hypothesis of equal sensitivities across states only in the case of relatively poorly capitalized banks. We find some evidence that bank types have different exposure to term spread innovations. While relatively poorly and highly capitalized banks have similar sensitivities to term spread innovations in the expansion state, relatively poorly capitalized banks have a much larger sensitivity in the recession state[13]. In addition, we find some evidence that the size of the asymmetry is larger for relatively poorly capitalized banks[14]. This evidence corroborates the hypothesis that well capitalized banks are less vulnerable to economic fluctuations and are perceived by the stock market to be less risky. Sensitivities to innovations in the short rate have the expected negative sign, but are often quite imprecisely estimated. Interestingly, while none of the interest rate sensitivities turns out to be different from zero in the expansion state, in 4 of the 6 cases we find a significant sensitivity in the recession state. Asymmetry is not only economically but also statistically significant for the

[13]More specifically, a likelihood ratio test rejects the null hypothesis that within the recession state relatively poorly and highly capitalized banks have equal sensitivities to innovations in the term spread (at a 10% level).

[14]We reject the null hypothesis that the difference in term spread sensitivity across states is equal across banks at a 10% level.

relatively poorly capitalized banks, geographically diversified banks, and local banks. However, we do not find evidence that interest rate sensitivities are different between bank types. A somehow similar result is found for innovations in the money base. Mostly, estimates have the expected negative sign, but are (marginally) significant in the recession state only. In all cases, sensitivities are (in absolute values) much larger in the recession state, even though this asymmetry is only statistically significant for the relatively poorly capitalized and local banks. In addition, we also find that the asymmetry is larger for relatively poorly capitalized banks than for banks with a higher capital buffer.

To further investigate how different types of banks react to changes in the prevailing credit market conditions, we compare the total shocks spillovers between different types of banks. The total shocks are calculated as follows:

$$\begin{aligned}\Lambda_t^1 &= \tilde{\beta}_0^1 + \tilde{\beta}_1^1 \varepsilon_{\Delta TS,t} + \tilde{\beta}_2^1 \varepsilon_{\Delta IR,t} + \tilde{\beta}_3^1 \varepsilon_{\Delta M,t} \\ \Lambda_t^2 &= \tilde{\beta}_0^2 + \tilde{\beta}_1^2 \varepsilon_{\Delta TS,t} + \tilde{\beta}_2^2 \varepsilon_{\Delta IR,t} + \tilde{\beta}_3^2 \varepsilon_{\Delta M,t}\end{aligned}$$

where Λ_t^1 and Λ_t^2 represent the total shocks for bank type 1 and 2 respectively, and $\tilde{\beta}$ the probability-weighted sensitivities. Because we are mainly interested in how banks with an opposite strategy react differently to information over the business cycle, Figure 3 plots the total shock difference, calculated as Λ_t^2-Λ_t^1. Panel A of Figure 3 plots the difference in shocks between relatively poorly and highly capitalized banks. While total shocks appear to very similar during most of the expansion period (difference close to zero), relatively poorly capitalized banks react much stronger to news in business cycle downturns. More specifically, relatively poorly capitalized banks perform worse compared to their better capitalized peers during the years 1997, 90-91, and 2001. The negative shock differences over the period 1997-2000, a period of strong equity market appreciation, are explained by the better performance of relatively well capitalized banks during this period. Panel B of Figure 3 plots the difference in shocks between geographically diversified and local banks. Overall, shock differences are relatively small, and are situated mostly within the [-0.5% 0.5%] interval. Geographically diversified banks tend to experience larger shocks during business cycle troughs, while the opposite occurs during expansions. This suggests that geographical expansion does not provide diversification benefits when they matter most, i.e. during periods of adverse economic performance. Shock differentials are considerably higher between functionally diversified and specialized banks. During recession periods, specialized banks receive considerably larger shocks than diversified banks. This suggests that specialized banks especially underperform diversified banks during business cycle troughs.

Finally, Table 10 reports a number of specification tests. We test whether there is evidence for fourth-order autocorrelation in the error (Mean) and squared error terms (Variance), as well as for skewness and excess kurtosis. We also calculate the Jarque-Bera test for normality and the R-squared measure for overall fit. We do not find evidence against the specification for both the mean and the variance. In addition, we cannot reject the null hypothesis of zero skewness and excess kurtosis. This is confirmed by the Jarque-bera test, even though normality is sometimes rejected at a 10% level. Finally, the R-squares range from 5.89% for the relatively highly capitalized banks to 16.46% for the geographically diversified banks.

5.3 Variance Equation

The level of volatility across states, time, and bank groupings, depends both on the time variation in the latent regime variable and on the actual estimates of the parameters in the conditional volatility specification. For all bank types, the intercepts are significant at the 1% level. In addition, there is clear evidence of volatility asymmetry, since the intercept is considerably larger in the recession state in all specifications of the variance equation. As can be seen in part 2 of Table 9, this asymmetry is not only economically important, but also statistically significant (at a 1% level). Overall, the parameter estimates in the recession state imply a level of conditional volatility that is between 6 and 9 times higher than in the expansion state. In all specifications, the estimates for the conditional correlations are higher in the recession state than in the expansion state, even though we can only reject the hypothesis of equal correlations in the case of global and local banks (see part 1 of panel A in table 9). We find that, except for diversified banks, the conditional volatility of the return series is significantly related to lagged changes in the short rate[15]. Moreover, in all specifications, interest rate sensitivities are considerably higher in the recession state (table 8). However, only for the returns of global, local, and specialized banks, we reject the hypothesis that the sensitivities to lagged changes in the short rate are equal across states. One of the advantages of the bivariate specification is that we can test whether banks with an opposite strategy react differently to information across states. In Part 1 of Panels A, B and C (Table 9), we test whether the parameter estimates are statistically different between bank types, both within a particular state, or jointly across states. The intercepts in the volatility specification for the relatively poorly and highly capitalized banks are statistically different in the recession state, but not in the expansion state. However, we do not find that the sensitivities of conditional variance to lagged changes in the short rate differ between these two types of banks. Panel A of Figure 2 plots the estimated conditional variances. While both bank types exhibit a comparable level of volatility during the expansion state, relatively well capitalized banks show a higher volatility intercept and appear to have higher levels of risk during recessions. This suggests that banks with a higher capital buffer not necessarily have a lower level of residual risk (not explained by the information variables) relative to their relatively less capitalized peers. A similar result is obtained for global and local banks (Panel B of Table 9, Panel B of Figure 2). Local banks have a lower volatility intercept in both states, even though this difference is only statistically significant in the recession state. This may to some extent be explained by the smaller number of banks in the global banks portfolio. In addition, since geographically diversified

[15] Notice that in most cases interest rate sensitivities are only significant at a 10% level.

banks are active in different markets, the frequency of news is higher, and this may have an impact on their total risk. Finally, the series of crises in the second part of the 1990s were global in nature, as well as the economic slowdown that started in 2000. While local banks may have been (temporarily) shielded, global banks were clearly exposed to those events. The conclusion is that investors do not perceive local banks to be more risky than global banks[16]. Apart from differences in the intercept, we cannot reject the null hypothesis of equal interest rate sensitivity in the recession state. Since the interest rate sensitivity is larger for global banks, these results indicate that banks that diversify their activities geographically are not necessarily rewarded with lower levels of stock volatility. For the case of functional diversification, we do find evidence that diversification of revenue sources is effective in lowering overall risk (see Panel C of Table 9, Panel C of Figure 2). The volatility intercept is higher for specialized banks, both in the expansion and in the recession state. Moreover, since we can reject the null of equal intercepts in both states, the difference appears not only economically, but also statistically relevant. In addition, there is some evidence that the specialized banks are more sensitive to lagged changes in the short rate, even though only while being in the recession state.

6 Conclusion

This study presents strong evidence that bank stock returns are sensitive to business cycle fluctuations. Furthermore, these sensitivities seem to vary asymmetrically over the business cycle. First, we find two states in the return-generating process of bank stock returns: a low volatility / high mean state (state 1), and a high volatility / low mean state (state 2) . The classification of states appears to be very similar across the various bank types. The high volatility / low mean state is observed around the 1987 stock market crisis, during the recession at the beginning of the 1990s, during the series of financial crises at the end of the 1990s, and in the period of global economic slowdown starting at the end of 2000. The link between the business cycle and the classification of states is further confirmed by the estimation results for the transition probability specification: the probability of staying is positively related to the term spread in state 1 and negatively in state 2, suggesting that state 1 and 2 are expansion and recession states, respectively. Second, we find strong evidence that innovations in the short rate, term spread, and money base jointly determine observed bank stock returns. The sharpest estimates are obtained for the sensitivities to the term spread. In economic terms, the sensitivities of most bank stock return series are substantially larger in the recession state. Because of relatively large standard errors, the statistical evidence for asymmetry is weaker. Innovations in the short rate and money base have a statistically relevant influence in the re-

[16]Even the local banks in the sample are quite large and operate nationwide networks within their home country. Apparently, diversification across sectors and regions within a country provides diversification benefits that cannot be improved by expanding abroad (see Danthine et al. 1999).

cession state only, but often only at a 10% level. Third, there is strong evidence for asymmetry in the conditional variance of all bank returns. The parameter estimates in the recession state imply a level of volatility that is between 6 and 9 times higher than in the expansion state. The conditional variance of most series seems to be significantly related to lagged changes in the short-term interest rate.

Making a distinction between groups of banks with different risk profiles, it seems that the asymmetric behavior of bank stock returns is more pronounced for certain types of banks. The sensitivities of stock returns of relatively poorly capitalized and local banks is larger in the recession state. Symmetry is rejected for all three information variables for the relatively poorly capitalized banks, and for two of the instruments in the case of local banks. For the other bank types, there is no evidence of asymmetry in the mean equation. Furthermore, the conditional variance of bank stock returns of relatively poorly capitalized banks, geographically diversified banks, and local banks is significantly larger in the recession state.

In the expansion and recession state, the difference between bank stock sensitivities for groups of banks with opposite strategies is relatively weak. With only one exception, sensitivities are not different in the expansion state. In the recession state, however, we find some evidence that sensitivities are different for relatively poorly versus highly capitalized banks and functionally diversified versus specialized banks. Plotting the difference in shock size between banks with apposite strategies shows that relatively poorly capitalized and specialized banks are harder hit during business cycle downturns than their better capitalized and functionally diversified peers. Maintaining relatively high capital levels and functional diversification are therefore identified as useful strategies for banks to decrease their overall risk profile.

Although, the difference between bank stock sensitivities for groups of banks with opposite strategies is relatively weak, the behavior of their conditional volatility can be substantially different. First, while relatively poorly and highly capitalized banks have similar levels of volatility in the expansion state, the level of residual volatility in the recession state is higher for the better capitalized banks. This is only partly compensated by the higher sensitivity of the relatively poorly capitalized banks to lagged changes in the short rate. Second, geographically diversified banks exhibit higher levels of volatility both in expansions and recessions. This contradicts the hypothesis that diversification across regions reduces overall risk. The fact that a series of financial crises over the sample period were global in nature may constitute a partial explanation for the lack of diversification benefits from geographical bank expansion. Third, in accordance with ex ante expectations, we find evidence that functionally diversified banks have lower levels of volatility than specialized banks. This finding offers support to the claim that the formation of financial conglomerates may be beneficial for the stability of the banking system.

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Table 1: Summary Statistics of Balance Sheet Variables for Portfolios of Banks

		Mean	stdev	min	max
15% ratios (22 banks)					
Rel. High Cap.	TECL	34.2	28.2	16.2	119.4
	NIITI	22.8	16.7	1.6	73.0
Rel. Poor Cap.	TECL	5.7	1.1	2.2	6.8
	NIITI	13.3	7.6	0.4	32.5
Funct. Divers.	TECL	10.6	4.7	5.9	27.4
	NIITI	31.7	9.4	23.0	53.6
Funct. Special.	TECL	11.5	11.3	2.2	53.1
	NIITI	5.4	3.5	0.4	10.0
30% ratios (43 banks)					
Rel. High Cap.	TECL	24.9	22.8	13.0	119.4
	NIITI	20.3	13.4	1.3	73.0
Rel. Poor Cap.	TECL	6.4	1.2	2.2	7.9
	NIITI	14.7	7.5	0.4	32.5
Funct. Diver.	TECL	11.9	6.6	5.9	45.4
	NIITI	27.0	8.5	20.5	53.6
Funct. Special.	TECL	10.4	8.7	2.2	53.1
	NIITI	8.8	4.5	0.4	14.6
Geogr. Divers. (33 banks) versus Geogr. Special. (110 banks)					
Geogr. Divers.	TECL	10.2	6.1	5.0	40.4
	NIITI	22.1	9.9	11.4	53.6
Geogr. Special.	TECL	16.3	19.4	2.2	119.4
	NIITI	19.7	15.0	0.4	86.2

Note: A distinction is made between local and geographically diversified banks, specialized and diversified banks, and relatively poorly and highly capitalized banks. Geographically diversified banks are those published in The Banker's list of global banks. The division between relatively highly and lowly capitalized banks is based on the ratio "Total Equity to Customer Loans (TECL)". Similarly, specialized and diversified banks are separated by the ratio "Non-Interest Income over Total income (NIITI)". This table reports averages of both ratios for the lowest and highest 30% and 15% percentiles. The balance sheet data used to calculate these ratios is taken from Bankscope.

Table 2: Percentage of Banks of one type also included in other types

	Specialized	Diversified	Global	Local
Rel. poor. Cap.	30.4%	8.7%	17.4%	82.6%
Rel. high. Cap.	39.1%	21.7%	4.3%	95.7%

	Rel. poor. Cap.	Rel. high. Cap.	Global	Local
Funct. Special.	34.8%	17.4%	0.0%	100%
Funct. Divers..	8.7%	4.3%	43.5%	56.5%

	Rel. poor. Cap.	Rel. high. Cap.	Specialized	Diversified
Geogr. Divers.	15.2%	3.0%	0.0%	33.3%

Note: This table reports how many of the banks that are allocate to one bank type (relatively highly / lowly capitalized, functionally diversified or sepcialized, or global / local banks) are also part of the portfolio of banks of another type.

Table 3: Geographical Representation of Banks in different portfolios

	GLOBAL	LOCAL	SPECIAL.	DIVERS.	LOW CAP.	HIGH CAP.
Austria	9.1%	3.6%	4.3%	4.3%	4.3%	-
Belgium	15.2%	1.8%	4.3%	8.7%	8.7%	-
Denmark	3.0%	2.7%	4.3%	-	-	4.3%
Finland	-	2.7%	-	8.7%	-	4.3%
France	6.1%	3.6%	-	8.7%	8.7%	4.3%
Germany	9.1%	7.3%	13.0%	4.3%	17.4%	4.3%
Greece	-	3.6%	17.4%	-	4.3%	13.0%
Ireland	6.1%	0.9%	8.7%	-	-	-
Italy	9.1%	19.1%	17.4%	17.4%	17.4%	8.7%
Luxembourg	-	3.6%	4.3%	-	-	13.0%
Netherlands	3.0%	4.5%	-	-	-	8.7%
Norway	-	5.5%	8.7%	-	8.7%	-
Portugal	-	6.4%	-	17.4%	-	8.7%
Spain	9.1%	15.5%	-	-	-	26.1%
Sweden	-	5.5%	8.7%	4.3%	4.3%	-
Switzerland	9.1%	4.5%	-	8.7%	8.7%	4.3%
UK	21.2%	9.1%	8.7%	17.4%	17.4%	-

Note: This table reports the percentage each country represents in the respective portfolios. GLOBAL refers to the portfolio of geographically diversified banks, SPECIAL. and DIVERS. to the functionally specialized and diversified banks, and LOW CAP. and HIGH CAP. to the relatively poor and well capitalized banks.

Table 4: Summary Statistics of Portfolio Returns

	Mean	Volatility	Sharpe Ratio	Jarque-Bera	ARCH(4)	Q(4)-Test
All European Banks	0.978	4.543	0.215	91.7***	5.37	10.19**
Geogr. Divers. Banks	1.126	5.969	0.189	167.9***	12.36**	7.91*
Local Banks	0.954	4.338	0.220	72.1***	3.46	12.93**
30% indices						
Funct. Special. Banks	1.082	5.091	0.212	52.2***	9.24*	8.20*
Funct. Divers. Banks	1.028	4.779	0.215	92.9***	3.10	6.99
Rel. Poor Capital	0.833	4.672	0.178	69.3***	9.73**	6.32
Rel. High Capital	1.191	5.078	0.235	47.5***	12.29**	17.71***
15% indices						
Funct. Special. Banks	1.192	6.284	0.190	38.9***	9.67**	9.31**
Funct. Divers. Banks	0.972	4.845	0.201	68.1***	3.24	6.88
Rel. Poor Capital	0.894	5.086	0.176	26.5***	14.71***	3.34
Rel. High Capital	1.393	5.988	0.233	140.0***	15.08***	25.62**

Note: This table reports summary statistics of portfolio excess returns of European banks, both for the total sample, and for the different portfolios of banks. We calculated the mean, volatility (standard deviation), Sharpe Ratio, the Jarque-Bera test for normality, an ARCH(4) test for heteroskedasticity, and a Q(4) test for autocorrelation. All returns are monthly, total returns obtained from Datastream International. All returns are denominated in deutschemarks. *** indicates that the parameter is significant at a 1% level, ** at a 5% level and * at a 10% level.

Table 5: Correlation Matrix of Portfolio Returns

	EU	GLOBAL	LOCAL	SPECIAL.	DIVERS.	LOW CAP.	HIGH CAP.
EU	1.00						
GLOBAL	0.93	1.00					
LOCAL	0.98	0.84	1.00				
SPECIAL.	0.81	0.68	0.84	1.00			
DIVERS.	0.92	0.93	0.86	0.66	1.00		
LOW CAP.	0.89	0.85	0.87	0.83	0.82	1.00	
HIGH CAP.	0.81	0.67	0.84	0.82	0.66	0.72	1.00

Table 6: Mean Return and Variance per Year

Panel A: Mean Return per Year

	EU	GLOBAL	LOCAL	SPECIAL.	DIVERS.	LOW CAP.	HIGH CAP.
1985	3.47	3.29	3.65	3.56	3.73	3.45	3.28
1986	1.48	1.23	1.77	1.87	0.91	0.42	4.74
1987	-1.12	-1.59	-0.90	-1.42	-1.22	-1.37	-2.39
1988	1.26	1.78	1.05	1.04	1.26	0.90	1.37
1989	1.45	1.81	1.31	2.85	2.09	2.25	2.47
1990	-0.42	-1.60	0.01	4.05	-1.67	0.58	2.37
1991	-0.56	0.61	-0.97	-0.91	-0.23	-0.33	-0.71
1992	-1.21	0.30	-1.73	-1.73	-0.52	-1.33	-0.72
1993	2.83	2.78	2.85	2.42	2.72	2.38	2.58
1994	-0.74	-1.28	-0.55	-0.51	-0.70	-0.60	-0.79
1995	0.44	0.92	0.29	-0.31	0.34	-0.35	0.31
1996	1.77	1.32	1.91	2.28	1.62	1.59	2.27
1997	4.12	4.66	3.96	4.21	4.57	4.35	4.92
1998	2.92	3.23	2.83	4.09	2.11	1.93	5.72
1999	1.40	1.94	1.25	1.21	2.17	2.31	0.84
2000	0.68	0.84	0.64	-1.13	0.90	-0.08	0.54
2001	-0.77	-0.29	-0.90	-1.19	-0.76	-0.02	-1.83
2002	-0.97	-1.29	-0.88	-1.14	-1.55	-1.48	-1.70

Note: Panel A and B of this table report respectively the average return and standard deviation of stock returns on the different bank stock portfolios over the different years. All returns are in percentages, and are calculated as $(index_{i,t+12} - index_{i,t})/index_{i,t}$, where $index_{i,t}$ represents the stock index calculated on the basis of the portfolio returns of bank grouping i. GLOBAL refers to the portfolio of geographically diversified banks, SPECIAL. and DIVERS. to the functionally specialized and diversified banks, and LOW CAP. and HIGH CAP. to the relatively poor and well capitalized banks.

Panel B: Standard Deviation per Year

	EU	GLOBAL	LOCAL	SPECIAL.	DIVERS.	LOW CAP.	HIGH CAP.
1985	2.76	3.12	2.87	4.18	3.18	2.95	3.76
1986	5.02	5.57	5.21	7.69	5.10	5.58	6.17
1987	5.55	5.54	5.78	7.18	4.89	5.12	8.37
1988	2.42	3.14	2.54	3.75	2.36	3.26	3.43
1989	3.16	4.02	3.00	4.16	4.27	3.70	2.97
1990	5.85	6.62	5.72	10.29	5.38	7.78	10.13
1991	4.86	6.31	4.37	7.81	4.90	5.52	6.40
1992	3.55	5.14	3.56	3.95	3.73	3.19	4.42
1993	3.28	3.33	3.34	3.52	3.34	3.60	3.10
1994	2.75	3.08	2.84	4.59	3.27	2.87	3.77
1995	3.18	4.10	3.01	3.90	2.92	3.39	3.37
1996	1.76	2.52	1.67	3.51	2.09	4.92	2.58
1997	4.47	6.44	3.97	7.76	5.53	5.62	6.32
1998	8.80	12.79	7.87	10.54	9.14	8.87	9.97
1999	2.04	4.59	1.63	3.86	3.13	3.09	3.59
2000	1.78	4.98	1.17	2.80	2.96	3.86	3.67
2001	6.90	10.02	6.12	8.00	7.47	6.79	7.76
2002	6.11	10.45	5.11	6.87	7.99	7.26	5.31

Table 7: Overview of the different Likelihood Ratio Tests

Part 1: Zero and Equality Restrictions

Sensitivities, Zero constraints	JOINT	Type 1	Type 2
MEAN EQUATION			
All sensitivities = 0	$\beta^1(z) = \beta^2(z) = 0$	$\beta^1(z) = 0$	$\beta^2(z) = 0$
Term Spread	$\beta_1^1(z) = \beta_1^2(z) = 0$	$\beta_1^1(z) = 0$	$\beta_1^2(z) = 0$
Short Rate	$\beta_2^1(z) = \beta_2^2(z) = 0$	$\beta_2^1(z) = 0$	$\beta_2^2(z) = 0$
Money Base (M3)	$\beta_3^1(z) = \beta_3^2(z) = 0$	$\beta_3^1(z) = 0$	$\beta_3^2(z) = 0$
VARIANCE EQUATION			
Interest Rate Effect	$\Psi^1(z) = \Psi^2(z) = 0$	$\Psi^1(z) = 0$	$\Psi^2(z) = 0$
LEADING INDICATOR			
Term Spread	$\zeta_{2p} = \zeta_{2q} = 0$	$\zeta_{2p} = 0$	$\zeta_{2q} = 0$

Sensitivities, Equality Constraints	JOINT	STATE 1	STATE 2
MEAN EQUATION			
All Sensitivities Equal	$\beta^1(z) = \beta^2(z)$	$\beta^1(1) = \beta^2(1)$	$\beta^1(2) = \beta^2(2)$
Term Structure	$\beta_1^1(z) = \beta_1^2(z)$	$\beta_1^1(1) = \beta_1^2(1)$	$\beta_1^1(2) = \beta_1^2(2)$
Return 3 Month Interest Rate	$\beta_2^1(z) = \beta_2^2(z)$	$\beta_2^1(1) = \beta_2^2(1)$	$\beta_2^1(2) = \beta_2^2(2)$
Change Monetary Base (M3)	$\beta_3^1(z) = \beta_3^2(z)$	$\beta_3^1(1) = \beta_3^2(1)$	$\beta_3^1(2) = \beta_3^2(2)$
VARIANCE EQUATION			
Equal Intercepts, across states	$\omega^1(z) = \omega^2(z)$	$\omega^1(1) = \omega^2(1)$	$\omega^1(2) = \omega^2(2)$
Equal IR Sensitiv., across states	$\Psi^1(z) = \Psi^2(z)$	$\Psi^1(1) = \Psi^2(1)$	$\Psi^1(2) = \Psi^2(2)$
Joint	$\omega^1(z) = \omega^2(z)$ $\Psi^1(z) = \Psi^2(z)$	$\omega^1(1) = \omega^2(1)$ $\Psi^1(1) = \Psi^2(1)$	$\omega^1(2) = \omega^2(2)$ $\Psi^1(2) = \Psi^2(2)$
Equal Correlation	$\rho(1) = \rho(2)$		

Part 2: Test for Asymmetry

	Type 1 vs. Type 2	Type 1	Type 2
MEAN EQUATION			
Business Cycle Asymmetry	$\left\|\beta^1(2)-\beta^1(1)\right\| = \left\|\beta^2(2)-\beta^2(1)\right\|$	$\beta^1(2)=\beta^1(1)$	$\beta^2(2)=\beta^2(1)$
Intercept	$\left\|\beta_0^1(2)-\beta_0^1(1)\right\| = \left\|\beta_0^2(2)-\beta_0^2(1)\right\|$	$\beta_0^1(2)=\beta_0^1(1)$	$\beta_0^2(2)=\beta_0^2(1)$
Term Spread	$\left\|\beta_1^1(2)-\beta_1^1(1)\right\| = \left\|\beta_1^2(2)-\beta_1^2(1)\right\|$	$\beta_1^1(2)=\beta_1^1(1)$	$\beta_1^2(2)=\beta_1^2(1)$
Short Rate	$\left\|\beta_2^1(2)-\beta_2^1(1)\right\| = \left\|\beta_2^2(2)-\beta_2^2(1)\right\|$	$\beta_2^1(2)=\beta_2^1(1)$	$\beta_2^2(2)=\beta_2^2(1)$
Money Base (M3)	$\left\|\beta_3^1(2)-\beta_3^1(1)\right\| = \left\|\beta_3^2(2)-\beta_3^2(1)\right\|$	$\beta_3^1(2)=\beta_3^1(1)$	$\beta_3^2(2)=\beta_3^2(1)$
VARIANCE EQUATION			
Equal Intercepts	$\left\|\omega^1(2)-\omega^1(1)\right\| = \left\|\beta^2(2)-\beta^2(1)\right\|$	$\omega^1(2)=\omega^1(1)$	$\omega^2(2)=\omega^2(1)$
Equal Interest Rate Sensitiv.	$\left\|\mathbf{\Psi}^1(2)-\mathbf{\Psi}^1(1)\right\| = \left\|\mathbf{\Psi}^2(2)-\mathbf{\Psi}^2(1)\right\|$	$\mathbf{\Psi}^1(2)=\mathbf{\Psi}^1(1)$	$\mathbf{\Psi}^2(2)=\mathbf{\Psi}^2(1)$
Joint	$\left\|\omega^1(2)-\omega^1(1)\right\| = \left\|\beta^2(2)-\beta^2(1)\right\|$	$\omega^1(2)=\omega^1(1)$	$\omega^2(2)=\omega^2(1)$
	$\left\|\mathbf{\Psi}^1(2)-\mathbf{\Psi}^1(1)\right\| = \left\|\mathbf{\Psi}^2(2)-\mathbf{\Psi}^2(1)\right\|$	$\mathbf{\Psi}^1(2)=\mathbf{\Psi}^1(1)$	$\mathbf{\Psi}^2(2)=\mathbf{\Psi}^2(1)$

Table 8: Estimation Results for European Banks

Panel A: Relatively Poorly versus Relatively Well Capitalized Banks

	LOW CAPITAL		HIGH CAPITAL	
	Estim.	*s.e.*	*Estim.*	*s.e.*
MEAN EQUATION				
Constant, state 1	0.002	0.003	-0.007**	0.003
Constant, state 2	-0.001	0.008	0.01	0.01
Term Spread, State 1	0.69***	0.18	0.77***	0.18
Term Spread, State 2	1.21**	0.50	0.84*	0.46
Short Rate, State 1	-1.47	5.52	-0.44	0.58
Short Rate, State 2	-14.91**	6.50	-18.93	15.19
Money Base, state 1	3.56	9.05	-0.06	8.82
Money Base, state 2	-16.70**	7.81	-3.54	6.07
VARIANCE EQUATION				
Constant, state 1	-7.04***	0.18	-7.12***	0.24
Constant, state 2	-5.49***	0.20	-4.98***	0.26
Short Rate, State 1	64.84*	36.01	54.87*	31.76
Short Rate, State 2	102.10*	55.73	88.25	72.55
Correlation, State 1	0.78***	0.12		
Correlation, State 2	0.83***	0.15		
TRANSITION PROBABILITY				
Intercept	2.84	0.45		
Term Spread, state 1	0.39	0.28		
Term Spread, state 2	-0.84**	0.32		

Note: Panel A presents the results of the regime switching model for the 15% poorly versus 15% highly capitalized European banks. The dependent variables are the unexpected excess returns for both types of banks. The parameter estimations (Estim.) and the standard deviations (s.e.) in both states of the mean equations are presented in the upper part of the table. The middle part gives the results of the variance equation and the correlation (ρ) in both states. The lower part of the table presents the results of the transition probability. ***, **,* indicate significance at a 1%, 5% and 10% level respectively.

Panel B: Global versus Local Banks

	GLOBAL		LOCAL	
	Estim.	*s.e.*	*Estim.*	*s.e.*
MEAN EQUATION				
Constant, state 1	0.003	0.005	0.005	0.005
Constant, state 2	-0.004	0.01	-0.01*	0.01
Term Spread, State 1	0.13***	0.03	0.09***	0.03
Term Spread, State 2	0.14*	0.08	0.10*	0.06
Short Rate, State 1	-0.42	1.04	-0.28	0.92
Short Rate, State 2	-3.42*	1.76	-2.75*	1.48
Money Base, state 1	0.66	1.58	0.40	1.1554
Money Base, state 2	-3.87	3.74	-3.04*	1.69
VARIANCE EQUATION				
Constant, state 1	-6.82***	0.25	-7.01***	0.22
Constant, state 2	-4.60***	0.29	-5.55***	0.29
Short Rate, State 1	71.12	73.99	14.15	30.49
Short Rate, State 2	167.32**	68.86	295.60***	52.75
Correlation, State 1	0.77***	0.09		
Correlation, State 2	0.95***	0.15		
TRANSITION PROBABILITY				
Intercept	3.11***	1.39		
Term Spread, state 1	0.57*	0.32		
Term Spread, state 2	-2.78*	1.56		

Note: Panel B presents the results of the regime switching model for the global versus local European banks. The dependent variables are the unexpected excess returns for both types of banks. The parameter estimations (Estim.) and the standard deviations (s.e.) in both states of the mean equations are presented in the upper part of the table. The middle part gives the results of the variance equation and the correlation (ρ) in both states. The lower part of the table presents the results of the transition probability ***, **,* indicate significance at a 1%, 5% and 10% level respectively.

Panel C: Specialized versus Diversified Banks

	SPECIALIZED		DIVERSIFIED	
	Estim.	*s.e.*	*Estim.*	*s.e.*
MEAN EQUATION				
Constant, state 1	0.02*	0.01	-0.001	0.003
Constant, state 2	-0.02	0.03	-0.002	0.02
Term Spread, State 1	0.84**	0.35	0.91***	0.24
Term Spread, State 2	1.22*	0.70	-0.37	0.92
Short Rate, State 1	-3.65	5.98	-4.38	5.58
Short Rate, State 2	-6.13***	1.47	-15.85	14.42
Money Base, state 1	-1.32	1.78	1.06	0.93
Money Base, state 2	-5.67*	2.97	-0.79	1.20
VARIANCE EQUATION				
Constant, state 1	-6.18***	0.28	-7.03***	0.27
Constant, state 2	-4.35***	0.37	-4.91***	0.56
Short Rate, State 1	12.90	59.53	8.77	38.45
Short Rate, State 2	195.16**	90.32	70.92	62.95
Correlation, State 1	0.68***	0.10		
Correlation, State 2	0.83**	0.32		
TRANSITION PROBABILITY				
Intercept	2.43*	1.41		
Term Spread, state 1	0.01	0.76		
Term Spread, state 2	-1.01**	0.47		

Note: Panel C presents the results of the regime switching model for the 15% most specialized and diversified European banks. The dependent variables are the unexpected excess returns for both types of banks. The parameter estimations (Estim.) and the standard deviations (s.e.) in both states of the mean equations are presented in the upper part of the table. The middle part gives the results of the variance equation and the correlation (ρ) in both states. The lower part of the table presents the results of the transition probability. ***, **,* indicate significance at a 1%, 5% and 10% level respectively.

Table 9: Likelihood Ratio Tests for European Banks

Panel A: Relatively Poorly versus Highly Capitalized

Part 1: Zero and Equality Restrictions

Sensitivities, Zero constraints	JOINT		LOW CAPITAL		HIGH CAPITAL	
	Estim.	Prob.	Estim.	Prob.	Estim.	Prob.
MEAN EQUATION						
All sensitivities = 0	36.78	[0.00]	28.79	[0.00]	19.35	[0.004]
Term Spread	26.95	[0.00]	22.99	[0.00]	14.49	[0.00]
Short Rate	3.09	[0.54]	2.99	[0.23]	1.39	[0.50]
Money Base (M3)	6.05	[0.20]	4.68	[0.10]	0.02	[0.99]
VARIANCE EQUATION						
Interest Rate Effect	8.93	[0.06]	7.31	[0.03]	5.49	[0.06]
LEADING INDICATOR						
Term Spread	5.67	[0.06]				

Sensitivities, Equality Constraints	JOINT		STATE 1		STATE 2	
	Estim.	Prob.	Estim.	Prob.	Estim.	Prob.
MEAN EQUATION						
All Sensitivities Equal	23.72	[0.02]				
Term Spread	4.27	[0.12]	1.18	[0.28]	3.02	[0.08]
Short Rate	0.96	[0.62]	0.76	[0.39]	0.64	[0.42]
Money Base (M3)	3.11	[0.21]	0.17	[0.68]	2.91	[0.09]
VARIANCE EQUATION						
Equal Intercepts, across states	5.01	[0.08]	0.33	[0.56]	4.41	[0.04]
Equal IR Sensitiv., across states	1.19	[0.55]	0.04	[0.83]	0.63	[0.43]
Joint	6.96	[0.14]	0.77	[0.68]	4.82	[0.09]
Equal Correlation	0.58	[0.45]				

Part 2: Test for Asymmetry

	Low vs. High		Low Capital		High Capital	
	Estim.	Prob.	Estim.	Prob.	Estim.	Prob.
MEAN EQUATION						
Business Cycle Asymmetry	8.77	[0.07]	13.55	[0.01]	4.29	[0.37]
Intercept	0.18	[0.67]	0.11	[0.74]	1.66	[0.20]
Term Spread	2.90	[0.09]	6.75	[0.01]	1.62	[0.20]
Short Rate	0.78	[0.38]	3.18	[0.08]	0.90	[0.34]
Money Base (M3)	3.26	[0.07]	3.71	[0.05]	0.83	[0.36]
VARIANCE EQUATION						
Equal Intercepts	3.65	[0.06]	21.51	[0.00]	19.65	[0.00]
Equal IR Sensitiv.	0.58	[0.45]	0.60	[0.44]	0.61	[0.44]
Joint	3.66	[0.16]	22.31	[0.00]	20.98	[0.00]

Panel B: Global versus Local European Banks

Part 1: Zero and Equality Restrictions

Sensitivities, Zero constraints	JOINT		GLOBAL		LOCAL	
	Estim.	Prob.	Estim.	Prob.	Estim.	Prob.
MEAN EQUATION						
All sensitivities = 0	34.07	[0.00]	17.00	[0.01]	25.07	[0.00]
Term Spread	17.76	[0.00]	9.76	[0.01]	11.91	[0.00]
Short Rate	8.59	[0.07]	4.75	[0.09]	5.15	[0.08]
Money Base (M3)	7.28	[0.12]	3.77	[0.15]	4.10	[0.13]
VARIANCE EQUATION						
Interest Rate Effect	8.91	[0.06]	6.11	[0.05]	5.83	[0.05]
LEADING INDICATOR						
Term Spread	6.90	[0.03]				

Sensitivities, Equality Constraints	JOINT		STATE 1		STATE 2	
	Estim.	Prob.	Estim.	Prob.	Estim.	Prob.
MEAN EQUATION						
All Sensitivities Equal	18.87	[0.09]				
Term Spread	4.71	[0.10]	3.88	[0.05]	1.41	[0.24]
Short Rate	3.50	[0.17]	0.60	[0.44]	2.39	[0.12]
Money Base (M3)	2.98	[0.23]	0.95	[0.33]	1.12	[0.29]
VARIANCE EQUATION						
Equal Intercepts, across states	8.02	[0.02]	2.03	[0.16]	6.97	[0.01]
Equal IR Sensitiv., across states	9.37	[0.01]	2.41	[0.12]	5.64	[0.02]
Joint	13.72	[0.01]	3.42	[0.18]	8.59	[0.01]
Equal Correlation	5.61	[0.02]				

Part 2: Test for Asymmetry

	Global. vs. Local		Global		Local	
	Estim.	Prob.	Estim.	Prob.	Estim.	Prob.
MEAN EQUATION						
Business Cycle Asymmetry	6.00	[0.20]	6.99	[0.14]	8.21	[0.08]
Intercept	1.71	[0.19]	1.11	[0.29]	1.94	[0.16]
Term Spread	1.39	[0.24]	0.98	[0.32]	1.19	[0.28]
Short Rate	2.45	[0.12]	3.76	[0.05]	3.41	[0.07]
Money Base (M3)	0.99	[0.32]	2.34	[0.13]	3.39	[0.07]
VARIANCE EQUATION						
Equal Intercepts	5.09	[0.02]	12.19	[0.00]	15.55	[0.00]
Equal Interest Rate Sensitiv.	4.75	[0.03]	3.89	[0.05]	7.62	[0.01]
Joint	6.72	[0.04]	17.99	[0.00]	25.90	[0.00]

Panel C: Functionally Specialized versus Diversified Banks

Part 1: Zero and Equality Restrictions

Sensitivities, Zero constraints	JOINT		SPECIALIZED		DIVERSIFIED	
	Estim.	Prob.	Estim.	Prob.	Estim.	Prob.
MEAN EQUATION						
All sensitivities = 0	45.39	[0.00]	15.38	[0.02]	14.98	[0.02]
Term Spread	15.81	[0.00]	10.64	[0.01]	12.31	[0.00]
Short Rate	4.99	[0.29]	1.25	[0.54]	2.56	0.28
Money Base (M3)	6.51	[0.16]	4.90	[0.09]	1.90	[0.39]
VARIANCE EQUATION						
Interest Rate Effect	4.04	[0.40]	5.51	[0.06]	0.49	[0.78]
LEADING INDICATOR						
Term Spread	5.15	[0.08]				

Sensitivities, Equality Constraints	JOINT		STATE 1		STATE 2	
	Estim.	Prob.	Estim.	Prob.	Estim.	Prob.
MEAN EQUATION						
All Sensitivities Equal	12.08	[0.06]				
Term Spread	4.17	[0.13]	0.96	[0.33]	2.81	[0.09]
Short Rate	1.81	[0.18]	0.09	[0.77]	1.72	[0.19]
Money Base (M3)	3.81	[0.15]	0.79	[0.38]	3.19	[0.07]
VARIANCE EQUATION						
Equal Intercepts, across states	6.09	[0.05]	2.92	[0.09]	3.88	[0.05]
Equal IR Sensitiv., across states	5.11	[0.08]	0.41	[0.52]	4.61	[0.03]
Joint						
Equal Correlation	1.09	[0.30]				

Part 2: Test for Asymmetry

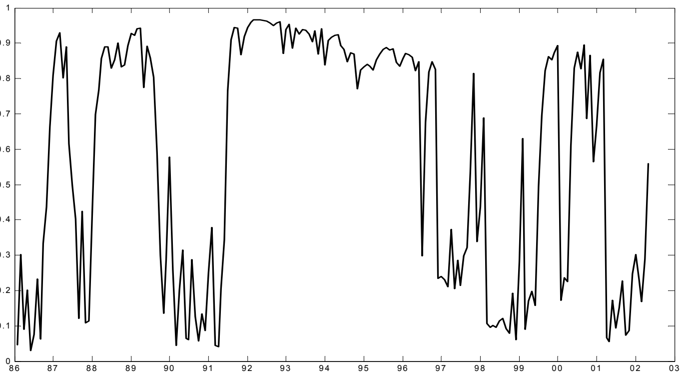
	DIV. vs. SPEC.		SPECIALIZED		DIVERSIFIED	
	Estim.	Prob.	Estim.	Prob.	Estim.	Prob.
MEAN EQUATION						
Business Cycle Asymmetry	8.37	[0.08]	10.18	[0.04]	2.39	[0.67]
Intercept	3.30	[0.07]	7.49	[0.01]	0.79	[0.37]
Term Spread	0.50	[0.48]	0.30	[0.58]	2.06	[0.15]
Short Rate	5.60	[0.02]	3.59	[0.06]	3.90	[0.05]
Money Base (M3)	0.66	[0.42]	0.79	[0.37]	0.27	[0.60]
VARIANCE EQUATION						
Equal Intercepts	0.97	[0.33]	33.83	[0.00]	40.98	[0.00]
Equal IR Sensit.	1.69	[0.19]	3.53	[0.06]	0.48	[0.49]
Joint	2.89	[0.09]	34.53	[0.00]	6.28	[0.00]

Table 10: Specification Tests

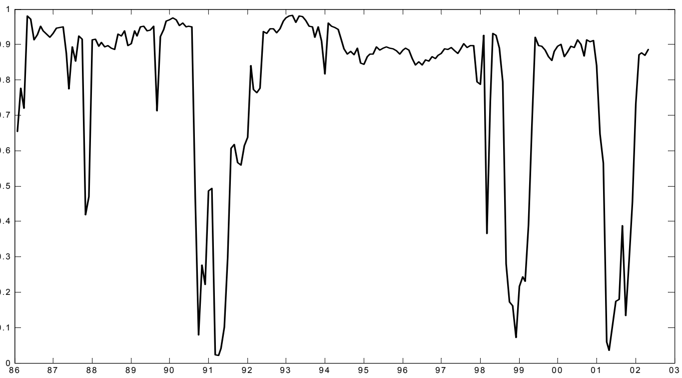
	Mean	Variance	Skewness	Kurtosis	Joint	Jarque-Bera	R^2
Rel. Poorly Capit. Banks	0.44	4.22	0.03	2.24	19.04	4.20	10.67%
	[0.98]	[0.38]	[0.87]	0.14	0.16	[0.12]	
Rel. Highly Capit. Banks	0.51	3.77	0.01	0.003	21.01	5.31	5.89%
	[0.97]	[0.44]	[0.93]	0.96	0.10	[0.07]	
Global Banks	0.69	2.64	0.38	0.70	17.52	5.82	16.46%
	[0.95]	[0.62]	[0.54]	[0.40]	[0.23]	[0.06]	
Local Banks	0.91	4.07	0.51	2.02	18.16	3.91	15.39%
	[0.92]	[0.40]	[0.47]	[0.16]	[0.20]	[0.14]	
Specialized Banks	7.18	3.77	1.29	1.55	18.82	3.00	6.93%
	[0.13]	[0.44]	[0.86]	0.21	[0.17]	[0.23]	
Funct. Diversified Banks	6.89	3.29	0.89	2.55	19.89	5.02	8.50%
	[0.14]	[0.51]	[0.93]	[0.11]	[0.13]	[0.08]	

Figure 1 : Probability of being in state 1

Relatively Highly versus Poorly Capitalized Banks



Geographically Diversified versus Local Banks



Functionally Diversified versus Specialized Banks

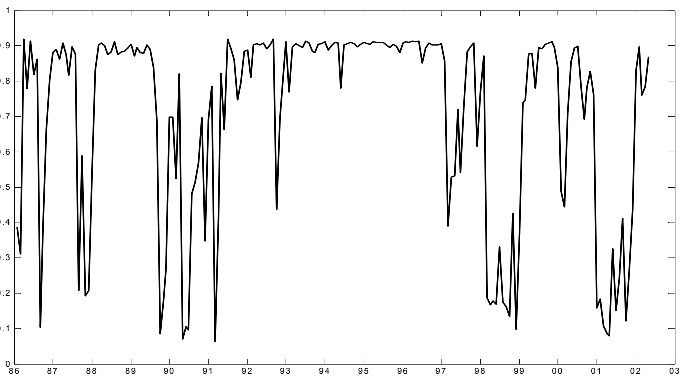
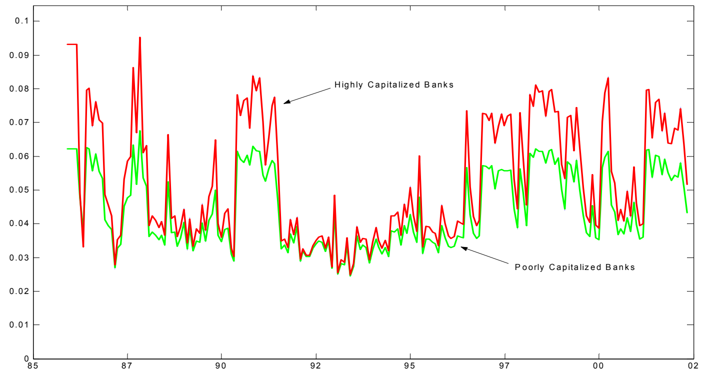
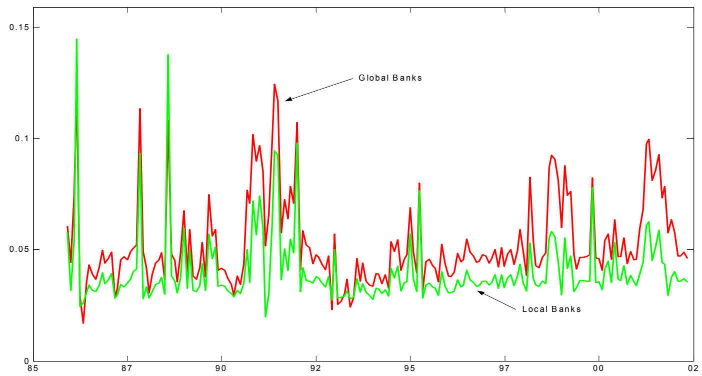


Figure 2 : Individual Conditional Standard Deviations

Relatively Highly versus Poorly Capitalized Banks



Geographically Diversified versus Local Banks



Functionally Diversified versus Specialized Banks

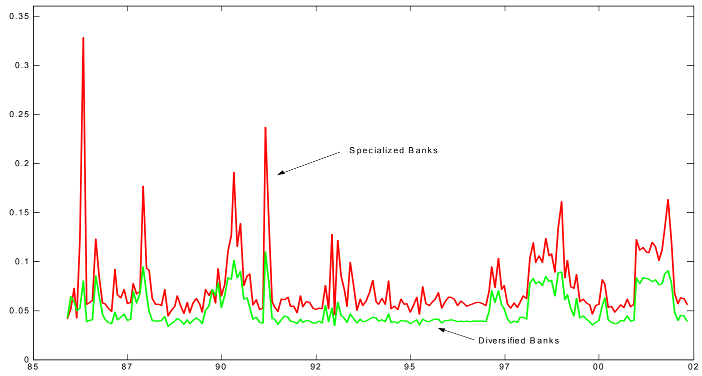
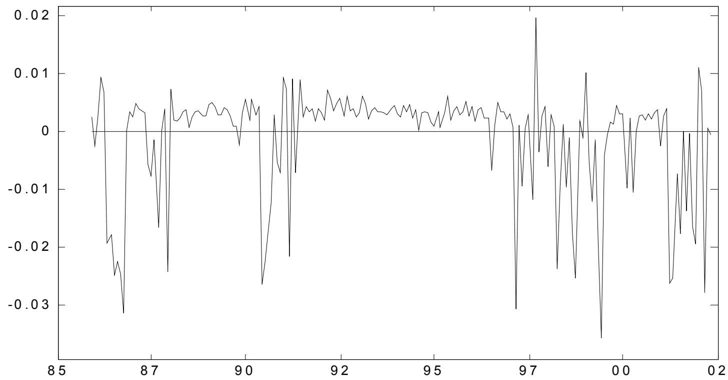
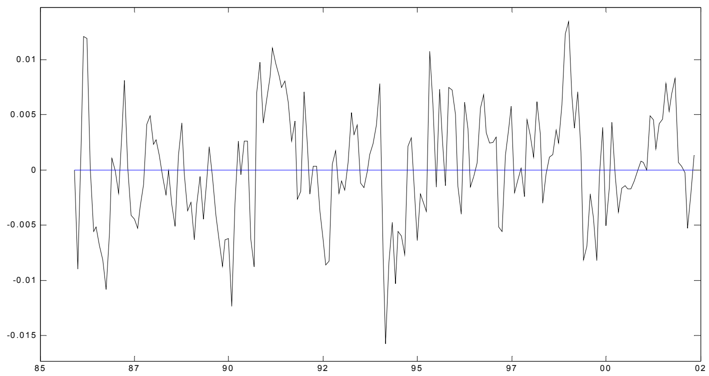


Figure 3 : Differences in Shocks

Shock Differential between poorly and highly capitalized banks



Shock Differential between Geographically diversified and local banks



Shock Differential between specialized and diversified banks