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Stock Return Volatility on Scandinavian Stock Markets and the Banking Industry

Evidence from the Years of Financial Liberalisation and Banking Crisis

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Abstract

This paper investigates the evolution of the (conditional) volatility of returns on three Scandinavian markets (Finland, Norway and Sweden) over the turbulent period of the past decade, namely the overlapping periods of financial liberalisation, drastically changing macroeconomic conditions and banking crisis. We find that even over this relatively turbulent period volatility is in most cases successfully captured by past volatility and shocks to past volatility, ie by a (symmetric) GARCH process. In each country banking crisis has induced regime shifts in (unconditional) volatility. We also find evidence for cross-country volatility spillovers during the banking crisis episodes. The estimated volatility patterns suggest that even though the volatility of returns was of very high magnitude during the years of banking crisis, developments within the banking industry were not reflected in market uncertainty until all the damage had been done and the severe problems afflicting banks began to be realised in full.

Key words: GARCH, conditional volatility, banking crisis, volatility spillovers

Osaketuottojen volatiliteetti pohjoismaisilla osakemarkkinoilla

Rahoitusmarkkinoiden sääntelyn purkamisen ja pankkikriisin vuosilta saatuja tuloksia

Suomen Pankin keskustelualoitteita 19/99

Ari Hyytinen
Rahoitusmarkkinaosasto

Tiivistelmä

Tässä tutkimuksessa analysoidaan kolmen Pohjoismaan (Suomi, Ruotsi ja Norja) osakemarkkinatuottojen (ehdollista) volatiliteettia menneen vuosikymmenen aikana, joka ajanjakso kattaa näissä maissa osin rahoitusmarkkinoiden vapauttamisen eri vaiheet, voimakkaasti muuttuneet makrotaloudelliset suhdanteet sekä pankkikriisin. Huolimatta ajanjakson erityisluonteesta niin koko markkinoiden kuin erityisesti pankkitoimialan tuottojen vaihtelua voidaan useimmiten parhaiten selittää vaihtelun omalla historialla sekä vaihtelussa aikaisemmin tapahtuneilla yllättävillä muutoksilla, so. (symmetrisellä) GARCH-prosessilla. Pankkikriisit ovat aiheuttaneet regiiminmuutoksen (ei-ehdollisessa) varianssissa. Siitä huolimatta, että tuotot olivat estimoitujen volatiliteettirakenteiden mukaan hyvin vaihtelevia koko pankkikriisin ajan, pankkitoimialan tapahtumat eivät yleisesti ottaen heijastuneet volatiliteettiin ennen kuin pankkien ongelmat todella realisoituivat ja pankkikriisi saavutti huippunsa.

Asiasanat: GARCH, ehdollinen volatiliteetti, pankkikriisi

Contents

1 Introduction

Over the last two decades, there has been a plethora of research examining the volatility of asset returns in general and its changing nature and predictability in particular; see Bollerslev et al. (1992), and Bera and Higgins (1993) for detailed literature reviews. Taking these features into account is crucial not only for understanding the behaviour of speculative markets, for most asset pricing theories and risk management, but also from a wider economic viewpoint. The stability and proper functioning of financial markets are nowadays regarded as a self-evident necessary condition for balanced overall economic performance and steady economic growth.

The objective of this study is provide additional insights into the dynamics of modern asset markets by investigating and comparing the evolution and statistical properties of the variance of three Scandinavian stock markets, namely those of Finland, Norway and Sweden. Besides being relatively small market places and, therefore, thin markets, these three markets provide an unusual and challenging testing environment for the widely used parametric volatility models. The reason is that the data of the past decade on these markets is generated in a highly special economic environment, i.e., over the overlapping periods of financial liberalisation, exchange rate turbulence, drastically changing macroeconomic conditions and banking crisis. We examine whether, how and when the developments within banking industries were reflected in the (conditional) volatility of the Scandinavian stock returns during this turbulent period. Besides documenting the historical time profile of risk, the present study has two specific objectives: we evaluate whether banking crises have induced regime shifts in the volatility and whether there have been cross-country spillovers in the volatility during the banking crisis episodes.

To investigate these issues, we examine stock returns at the market and banking industry levels and apply to them a particular class of volatility models, namely autoregressive conditional heteroscedasticity (ARCH) models.[1] These models have proven useful for empirically modelling the evolution of return volatility over time. As a comparison of different ARCH models is beyond the scope of the paper, we take as our basic model the Generalized ARCH(p,q) model of Bollerslev (1986), and augment it as follows. Firstly, we extend it by utilising a version of Zakoian's (1994) TGARCH-model to allow for potential asymmetry in volatility. Asymmetry may well be present in our banking data as banks are highly levered and therefore so-called leverage effect may show up as an asymmetric response to shocks. Moreover, Zakonian's model is nearly identical to that of Glosten, Jagannathan and Runkle (1993), which Kim and Kon (1994) document to be the best alternative for empirical stock market studies drawing on one model specification. Second, we follow Lastrapes (1990) by considering the possibility of regime shifts in the volatility. To this end, the possible non-stationary of the unconditional variance due to the banking crisis episodes is accounted for. Finally, the basic GARCH-model is augmented in the spirit of Engle et al. (1990) to allow for volatility spillovers.

The rest of the paper is organised as follows: in the next section we present the econometric specification of the volatility models to be used in this paper. Section 3 describes the data, and in Section 4 the empirical results are presented. Section 5 concludes by briefly summarising the main results.

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[1] The ARCH-models build on the seminal work of Engle (1982).

2 Basic Econometric Specification and Estimation

Let R_t be the continuously compounded rate of return on a portfolio of stocks, measured from $(t-1)$ to t and I_{t-1} the information available to investors at time $(t-1)$. Denote the conditional mean $x_t = E(R_t \mid I_{t-1})$ and conditional variance $h_t = Var(R_t \mid I_{t-1})$. The unexpected return at time t is $\varepsilon_t = R_t - x_t$, which can be regarded as a collective measure of news at time t (Engle and Ng 1993). An unexpected increase in returns is an indication of the arrival of good news whereas bad news is associated with an unexpected decrease in returns. A high absolute value of ε_t signals the importance of incoming news.

In the present study, we take as our basic conditional variance specification the following GARCH(q,p) model:

$$\mathrm{h}_{\mathrm{t}} = \omega + \sum\nolimits_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum\nolimits_{j=1}^{p} \beta_j h_{t-j} \tag{1a}$$

where α, β, and γ are constant parameters. As noted in Bollerslev et al. (1992), very low order specifications have been found to be successful in most empirical implementations of GARCH models. Even over very long sample periods, such parsimonious models as GARCH(1,1), GARCH(2,1) and GARCH(1,2) seem to be sufficient.

To allow for asymmetry in volatility, the basic model (1a) is augmented by including a dummy variable, d_{t-1}, that takes the value of unity if $\varepsilon_{t-1} < 0$ and zero otherwise:

$$\mathrm{h}_{\mathrm{t}} = \omega + \sum\nolimits_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} + \sum\nolimits_{j=1}^{p} \beta_j h_{t-j} \tag{1b}$$

This is Zakoian's (1994) threshold GARCH. In model (1b), asymmetry in volatility is inferred if $\gamma \neq 0$; leverage effect is present in the data if the estimated value of γ is positive.

GARCH models are typically estimated using maximum likelihood methods. Let the conditional mean be modelled as $r_t = \varepsilon_t$. Then, after conditioning on initial values, the log likelihood for a sample of N observations is proportional to

$$\mathrm{L}(\psi) = \sum\nolimits_{t=1}^{N} \left\{ -\log\left|h_t\right| - \frac{\varepsilon_t^2}{h_t} \right\} \tag{2}$$

where ψ is a vector of model parameters and where conditional normality of forecast errors is assumed. A common empirical finding for financial time series data is that the normality of conditional distributions is rejected. In such an environment, Quasi-Maximum Likelihood Estimates (QMLE) are still consistent under the assumption that the first and second moments of the standardised residuals can be obtained (see Weiss 1986 and Bollarslev and Woldridge 1992). The result carries also over to finite samples and valid inference regarding the QMLE of ψ (ψ^*, say) may be based on the robust variance-covariance estimator $A(\psi^*)^{-1}B(\psi^*)A(\psi^*)^{-1}$, where $A(\psi^*)$ and $B(\psi^*)$ are the Hessian and the outer product of the gradients, evaluated at ψ^*. Assuming a correct specification for h_t and the conditional mean, this variance-covariance estimator leads to a Wald statistic that has an asymptotic chi-square distribution under the null hypothesis, irrespective of whether or not the conditional density is normal.

3 Data

The data set includes for each country a weekly value-weighted price index series for the entire stock market and the banking sector. Due to data availability constraints, the Finnish data do not cover years when its financial markets were still regulated but rather begin from the middle of the liberalisation process, i.e., from the first week of January 1987. For Sweden and Norway the sample is from the first week of January 1983 and therefore includes a sub-period of regulated capital markets and the liberalisation period. The sample ends in the 22nd week of 1997 for each country. For further details of the data, see Table 1.

A caveat regarding the data is in order. The composition of banking indexes (i.e., the particular institutions included in it) has changed during the sample period due to the severe banking problems and industry restructuring. Moreover, government interventions aimed at handling banking crises were extensive in each country, and in Norway, for instance, the state became a major owner of the banking sector. These have affected the stock market data, and one should interpret the reported results with these facts (among other things) in mind. A brief account of the data environment and macroeconomic conditions is given in Appendix 1.

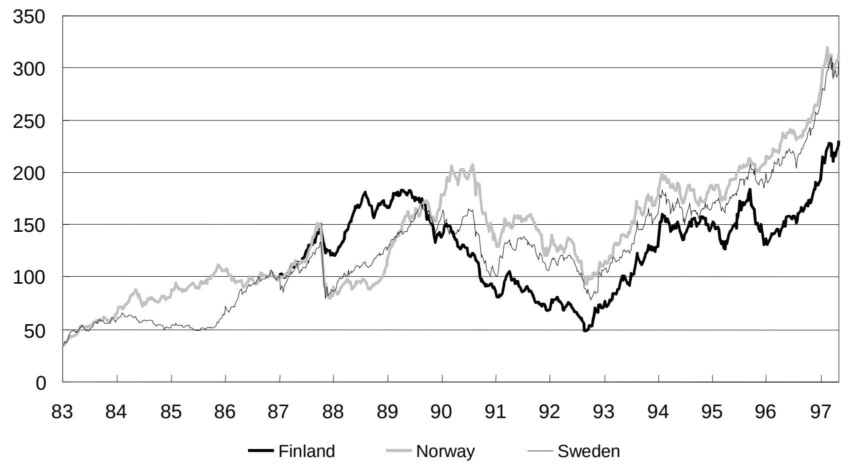
Table 1. **The Data (weekly)**

	Finland	Sweden	Norway
Sample	1987(1)–1997(22)	1983(1)–1997(22)	1983(1)–1997(22)
Market Index	HEX General Price Index	Veckans Affarer (VA) Weighted All Share Price Index	Oslo Stock Exchange (OSE) General Price Index
Banking Index	HEX Bank & Finance Price Index	VA Banks Price Index	OSE Banking Price Index

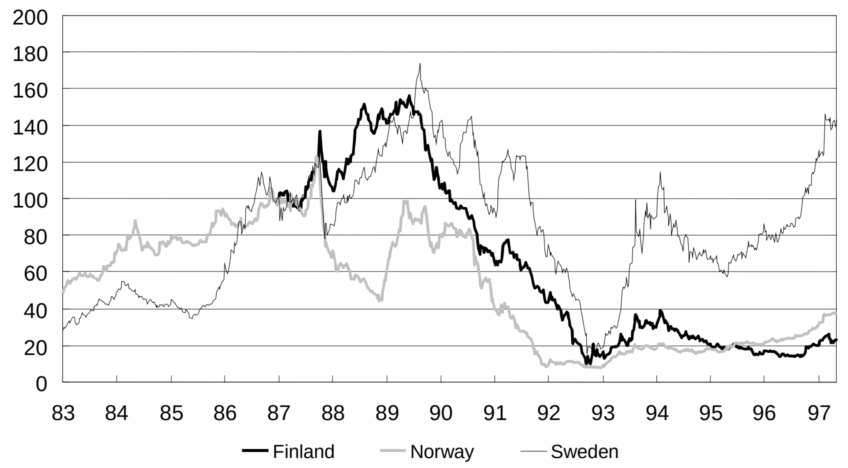
The price indices for the entire market and the banking industry are displayed in Figure 1. The price developments during the sample period are quite drastic. Even though price changes for the banking sector differ (during post-crisis period) from those for the entire market, a general pattern emerges. First, towards the end of 1980s, the prices boomed and then, at the beginning of the 1990s, they began to decline (as macroeconomic conditions deteriorated and risks and problems begun to materialise). The stock prices in Finland and Sweden began to decrease at least two years before they reached their lowest level in 1992, which probably is the darkest crisis year in these countries. For Norway, a somewhat different pattern emerges. There stock prices did not recover from October ’87 crash until at the beginning of 1989. During the latter half of year 1990, they then began to decrease again so as to hit their lowest value in 1991. During the latter half of the 1990s, i.e. during the post-crisis period, the markets have recovered and a new all-time-high has been reached in each country.

Figure 1. **Stock Prices: General Market Index and Banking Industry Index**

a) Stock Prices, Market (1987(1)=100)



b) Stock Prices, Banking Sector (1987(1)=100)



4 Empirical Results

We study the behaviour of weekly stock returns computed as a first logarithmic difference from the relevant stock price index and measured in percentages. That is, R_t = 100*ln(P_t/P_{t-1}) where P_t is the level of a price index at time t. We utilise the procedure of Pagan and Schwert (1990) when constructing a measure of the unpredictable element of stock returns. To filter out any predictability e.g. due to non-synchronous trading, in the mean return, the raw return data, R_t, is regressed on a constant and $\{R_{t-j}\}$ with j = 1, 2,… ,8 (a two-month period). The residuals from this regression, r_t, are then the unpredictable part of stock returns.

We report descriptive statistics for these unpredictable returns in Appendix 2. Several features of the pre-filtered return data stand out. First, by construction, the unconditional mean of r_t is zero and there is no evidence of autocorrelation in these pre-whitened series. Second, the unconditional standard deviation of banking sector has in each country been higher than that of the whole market. A visual inspection of the series reveal volatility clustering so that large (small) changes in r_t tend to be followed by large (small) changes of either sign. This is also confirmed by the high values Ljung-Box statistics for the squared r_t, indicating that there are strong second moment dependencies. Finally, under the null of normally distributed data the estimators of skewness and excess kurtosis are asymptotically normally distributed with mean zero and variances 6/N and 24/N, respectively (N = number of observations). The return distributions are strongly leptokurtic, meaning that they have thicker tails than would be compatible with a normal distribution. Unsurprisingly, then, normality is strongly rejected in all cases. These findings are fully in line with the turbulent nature of the sample period.

4.1 Estimation Results

In the estimation of (T)GARCH models, we started with the general specification for the conditional variance as given by equation (1a) and (1b). When identifying the final specifications, three criteria were considered. First, the properties of standardised residuals were checked. As is well known, these should exhibit no systematic patterns (i.e., they should be independent and identically distributed with mean zero and variance one), if the model is not mis-specified. To this end, the Ljung-Box statistics for the standardised residual and squared standardised residuals of the models were, among others, computed. Second, if a nested version of (T)GARCH -model seemed to be a successful candidate, the more constrained model was tested against the general model by means of the log-likelihood ratio test. Third, the Schwarz Information Criterion (SIC) was used to trade off a better fit of a model for a more parsimonious model.[2]

Table 2 presents the estimates of various GARCH models for the pre-filtered market return and bank industry return series estimated using the entire sample period. Interestingly, the best and most parsimonious specification for market returns in each country is GARCH(1,1). The estimates of these models

[2] Estimations were performed using Shazam version 7.0 and Eviews version 3.0. Different starting values for parameters were used in all volatility estimations so as to ensure that a global maximum was achieved.

show that, using Bollerslev-Wooldridge robust covariance matrix, most of the parameters of the variance equation are statistically significant at 5 % level. Thus, even over this relatively turbulent period, stock market volatility is in these Scandinavian countries successfully captured by a symmetric process and as a function of past volatility shocks and of past conditional variances from the previous week.

As to bank return series, we find that for Sweden TGARCH(1,1) model appears to be more appropriate than any constrained version nested within it. Though the coefficient of the asymmetry term is not statistically significant if judged using its t-value, the likelihood ratio statistic rejected the null hypothesis of symmetry of response. Also SIC suggested that TGARCH(1,1) should be preferred to GARCH(1,1). For the Finnish bank returns, the null hypothesis of symmetric volatility and constant mean cannot be rejected. The same applies to the Norwegian bank returns. Thus, perhaps a bit surprisingly, a simple GARCH(1,1) model appears to be the best specification for the Finnish and Norwegian banking sectors.[3]

To evaluate the fit of these estimated models, several tests were performed. Squared standardised residuals of all these models pass standard Ljung-Box tests at 5 % significance levels. The Engle-type Lagrange multiplier tests for ARCH effects in the standardised residuals did not reject the null of no such effects. Except those of the Finnish banking sector[4], standardised residuals pass standard Ljung-Box autocorrelation tests at 5 % significance level. The null hypothesis of normally distributed standardised residuals is, however, rejected at 5 % level for Swedish and Norwegian models. Given the turbulent nature of the episode, this is not surprising. It is perhaps worth mentioning that the departures from normality are mainly due to few extreme outliers and thus removable, say, by a small number of dummies. For instance, the models were not particularly sensitive to the exclusion of October 1987 crash; the parameter values changed only slightly when a dummy controlling for this event was included in the models.[5]

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[3] To check the robustness of the reported results regarding asymmetry, the exponential GARCH (EGARCH) of Nelson (1991) was also fitted to the return data. The estimated volatility exhibited similar patterns as those reported in this paper with the exception that the null hypothesis of symmetric process was marginally *not* rejected in these estimations for the Swedish banking sector. Whether markets as a rule respond differently to negative shocks than to positive shocks is a somewhat open question. Following Black's (1976) and Christie's (1982) seminal studies on leverage effect, Nelson (1991), Rabemananjara and Zakoian (1993), Zakoian (1994) and Koutmos (1998) report evidence supporting the view that in large and developed stock markets negative shocks to the market lead to larger return volatility than positive shocks of a same magnitude. There is, however, some evidence that a duality between developed and not so developed stock markets exists. In Shields (1997), for instance, no asymmetry in the volatility of returns was found in the emerging markets of two East-European countries. Neither is there evidence for asymmetry in the Chinese stock markets (Song et al. 1998). Interestingly enough, the asymmetry seems again to be present in the Hong Kong stock market, according to the results reported in Henry (1998).

[4] As to autocorrelation in the standardised residuals of the Finnish banking sector we make the following remarks. First, the reported model was clearly the most parsimonious one, i.e., it minimised SIC. Secondly, more complex volatility models (higher degree GARCH-models and the like) did not remove the autocorrelation. Finally, the autocorrelation was removed when we adopted a more complex pre-filtering process, that is, when a new set of unexpected returns was generated and then its volatility estimated. Our conclusions remained qualitatively unchanged when this other series was used.

[5] To control for kurtosis, one could use t-distribution instead of the normal distribution. However, in the present case the benefits from doing so are perhaps questionable, as it is likely that the kurtosis is due to a small number of extreme events and not a more general property of the return distribution.

Table 2. **The Estimates of Conditional Variance Models**

	Finland		Norway		Sweden	
Estimation Period	1987:9–1997:21		1983:9–1997:21		1983:9–1997:21	
Param. Estimates	Market	Bank	Market	Bank	Market	Bank
ω	0.2503 [2.1309]	0.2258 [1.6741]	0.3845 [2.5599]	0.2395 [2.0784]	0.7102 [1.9772]	0.5050 [1.4649]
α	0.1175 [3.3610]	0.1873 [4.5948]	0.0919 [2.7630]	0.1028 [4.5281]	0.1167 [2.7264]	0.0431 [1.3843]
γ	–	–	–	–	–	0.0811 [1.0131]
β	0.8527 [21.066]	–0.8194 [21.7833]	0.8531 [20.9913]	0.8807 [37.4168]	0.7897 [10.0464]	0.8913 [25.8206]
LogL	–1256.122	–1469.456	–1711.395	–1886.022	–1756.760	–2064.394
L-B Q(16)	20.349	38.367	8.873	8.107	11.043	20.743
L-B $Q^2(16)$	13.384	20.215	2.708	8.350	4.934	9.604
ARCH(16)	14.671	23.241	2.445	8.920	7.057	9.825
Skewness	–0.060	0.009	–0.970	0.377	–0.347	0.420
Kurtosis	3.376	3.448	11.072	5.2874	6.979	7.189
J-B	3.464	4.4690	2127.493	179.134	503.820	563.878
Wald test: H_0: $\alpha+\beta=1$	2.597	0.1166	5.694	1.239	2.693	–

Note: Robust t-ratios are given in the square-brackets [.]. ARCH(16) is the standard Engle-type Lagrange multiplier test for conditional heteroscedasticity. J-B is the Jarque-Bera test for normality. L-B is the Ljung–Box portmanteau statistic testing for autocorrelation in the stand. residuals (Q(16)) and in the squared stand. residuals ($Q^2(16)$), distributed as $\chi^2(16)$. The 5% and 10% critical values for these tests are 26.269 and 23.542, respectively. Wald-tests are computed using the robust Bollerslev-Wooldridge covariance matrix.

As Engle and Bollerslev (1986) note, GARCH models can be used to test whether a time series is integrated in variance (IGARCH). In brief, this amounts to evaluating whether the null hypothesis $\alpha + \beta = 1$ can be rejected. To test for this null hypothesis of variance non-stationary, a robustified Wald test is computed. This procedure is justified by the results of Lee and Hansen (1994), which show that even in the case of IGARCH, the QML estimator for GARCH(1,1) models has an asymptotically normal distribution, provided that certain fairly loose conditions hold. The results of this exercise are reported in the last row of Table 2. Clearly, the results are mixed, and for instance at 10% significance level, the null of infinite persistence in the estimated models cannot be rejected in two cases of six.

4.2 Accounting for Banking Crisis Regimes

Given the turbulent nature of the sample period, it is somewhat restrictive to suppose that the constant in the (T)GARCH equation would not be subject to structural breaks. Lastrapes (1989) has for instance documented that the ARCH process for exchange rates is not independent of U.S monetary policy. As past experience suggests that there is a relationship between the episodes of financial distress and the level of asset price volatility, we now examine the possibility that the banking crisis period shows up as a regime shift, i.e., as non-stationary of the unconditional variance.

An obvious empirical strategy to investigate this contention is to consider three non-overlapping sub-samples defined as pre-crisis, crisis and post-crisis periods.[6] As to define the time lapse of banking crisis is somewhat arbitrary, we rely on earlier literature when defining these sub-samples: according to IMF (see, e.g. Lindgren et al. 1996 and Demirguc-Kunt and Detragiache 1998), the banking crisis period was 1991-1994 in Finland, 1987-1993 in Norway and 1990-1993 in Sweden. These choices are in line with other interpretations/descriptions of the peaks of these crisis periods (see, e.g., Kaen and Michelsen 1993, and Davis 1995, 1999). They also include the years when loan losses peaked in each country and when a bulk of government interventions took place.

To allow for shifts in the variance constant and thereby in unconditional variance, we estimate a more general variance model:

$$h_t = \omega + \delta_c D_{ct} + \delta_{pc} D_{pct} + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \gamma \varepsilon_{t-1}^2 d_{t-1} + \sum_{j=1}^{p} \beta_j h_{t-j} \qquad (3)$$

where D_{ct} = 1 for observations in the crisis period and 0 otherwise and where D_{pct} = 1 for observations in the post-crisis period and 0 otherwise. Note that equation (3) amounts to (1) if $\delta_c = \delta_{pc} = 0$. The coefficients of the two dummies measure therefore the change in the variance constant relative to that of the pre-crisis period (ω). The asymmetry term was included in the specification for the Swedish bank returns only.

As the estimation results do not differ significantly from those reported in Table 2, we focus on the constants, dummy-variables and likelihood ratio statistics; they are reported in Table 3. In Table 3 we also report Wald tests for the null hypothesis of infinite persistence in variance in the general variance model of (3). These are of interest since previous literature (see e.g. Lastrapes 1989) suggests that the findings of infinite persistence in the conditional variance may be due to structural shifts in the unconditional variance.

The results are implicative: the joint hypothesis that both during the crisis and the post-crisis periods variance constant equals to that of the pre-crisis period is rejected for the banking sector returns and the returns of the entire market. Though not reported in the table, LR-tests rejected the hypothesis that the crisis period variance constant does not by itself differ from the pre-crisis period, given that the post-crisis period does; we were able to reject H_0: $\delta_c = 0 \mid \delta_{pc} \neq 0$ at 1 % significance level.[7] The coefficient of D_{ct} is in all cases positive suggesting significantly increased unconditional variance during the crisis phase; for the market returns the unconditional variances over the pre-crisis, crisis and post-crisis phases are as follows: Finland 4.435, 9.446, 8.923; Norway 4.560, 8.955, 2.847 and Sweden 6.871, 10.413, 4.956. A similar pattern emerged for banking industry returns. We also experimented by inserting crisis and post-crisis dummies into mean equations; these turned out not to gain significance. Finally, in all cases except one the Wald test for H_0: $\alpha+\beta=1$ obtained higher values than in the case of no-dummies in the model. This is in line with the findings of earlier studies.

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[6] In a recent paper, Kim and Kon (1999) however discuss the problems associated with using calendar dates of economic events when modeling structural breaks. The danger is that the structural change-points in variance are not detected accurately enough. They suggest a statistical detection procedure should be used instead, which indeed might be a useful avenue for future research in the present context.

[7] LR-test statistics were 32.364, 16.100 and 50.456 for banking industry returns in Finland, Norway and Sweden; for the entire market they were 38.690, 33.292 and 43.868, respectively.

Table 3. **The Case of Non-stationary of the Unconditional Variance**

	Finland	Norway	Sweden
Market (coefficients)			
ω	0.4083	0.61126	0.9174
δ_c	0.4616	0.5899	0.4729
δ_{pc}	0.4129	-0.2295	-0.2757
Bank (coefficients)			
ω	0.3455	0.4612	0.5646
δ_c	1.1213	1.1670	0.9555
δ_{pc}	1.1274	-0.0725	0.4178
LR –test: H_0: $\delta_c = \delta_{pc} = 0$			
Market	5.652	35.278	9.284
Bank	8.360	28.356	9.908
Wald test: H_0: $\alpha+\beta=1$			
Market	2.623	2.340	4.944
Bank	1.433	2.712	–

Notes: LR-test is distributed as $\chi^2(2)$. The 1 %, 5 % and 10 % critical values for the test are 9.21, 5.99 and 4.61, respectively.

4.3 Volatility Spillovers and Banking Crisis

In this sub-section, we briefly examine whether there has been volatility spillovers between the three Scandinavian stock markets during the IMF-defined banking crisis episodes. The existence of spillovers would imply that shocks to the banking industry returns during a country's banking crisis episode are transmitted to the stock market of its neighboring countries. To test for spillovers, we adopt the empirical strategy of Engle et al. (1990) in which the variance equation is augmented by a predetermined intervening variable (see also Song et al. 1998):

$$h_{s,t} = \omega_s + \delta_{s,c} D_{s,ct} + \delta_{s,pc} D_{s,pct} + \sum\nolimits_{i=1}^{q} \alpha_{s,i} \varepsilon_{s,t-i}^2 + \sum\nolimits_{j=1}^{p} \beta_{s,j} h_{s,t-j} + \eta_k D_{k,ct} \times \varepsilon(bank)_{k,t-1}^2 \tag{4}$$

where subscripts s and k refer to country, i.e., $s, k \in$ {Finland, Sweden, Norway}, $s \neq k$, and where $D_{k,ct} \times \varepsilon(bank)^2_{k,t-1}$ is the intervening variable of interest, i.e., the IMF banking crisis dummy times the lagged squared banking industry residual (error) of country k (at time $t-1$).[8] Though not explicitly indexed, specification (4) is used to model both the conditional volatility of the entire market as well as that of the banking industry. When constructing equation (4), the banking industry volatility of the previous week in the neighboring country has been treated as a predetermined variable.

In this framework, a significant estimate of coefficient η would suggest a spill-over effect of the banking crisis volatility in country k on the volatility of country s. In other words, the coefficient η measures the impact of past banking crisis shocks (to the banking industry returns) of country k on the conditional stock market volatility of country s. Notice, however, that when evaluating the

[8] Notice that asymmetry is not allowed for in this specification; as the null hypothesis of symmetry was rejected only for the Swedish bank returns, this restriction should not be of serious concern. The results (regarding spillovers) for the Swedish banking sector are similar even if the asymmetry term is included in the specification.

Finnish market and its relationship between the Norwegian and Swedish market, the sample period needs to be restricted to 1987-1997. In other words, only the overlapping parts of the sample periods can be considered.

What's more, there are several other ways to evaluate spillovers.[9] The one adopted here should thus considered as an indicative exercise providing potentially 'stylized facts' regarding spillovers and ideas for further research.

As the estimation results do not provide new insights when compared to those obtainable from Table 2, only the LR-tests for the η coefficients are reported in Table 4. At 5 % significance level, the results suggest on the one hand that both the Norwegian and Swedish banking crisis shocks were transmitted to the conditional volatility of the Finnish stock markets. The same applies to the Swedish market, as shocks to the Finnish and Norwegian bank returns during their respective crisis episodes were transmitted to it. The results hence imply that there may have been a bi-directional causal relationship between the volatility of the Finnish and Swedish stock markets during the banking crisis episodes. The Norwegian market shows hardly any signs of responding to shocks in the Finnish or Swedish market.

Table 4. **LR-tests for Volatility Spillovers**

	Finland	Norway	Sweden
i) h_t(market):			
$\eta_{Finland}$	–	0.244	13.072
η_{Norway}	16.762	–	6.016
η_{Sweden}	19.512	3.716	–
ii) h_t(banking industry):			
$\eta_{Finland}$	–	1.330	58.754
η_{Norway}	16.572	–	4.588
η_{Sweden}	11.584	3.944	–

Note: LR-test is distributed as $\chi^2(1)$. The 1 %, 5 % and 10 % critical values for the test are 6.63, 3.84 and 2.71, respectively. In the estimations including the Finnish market, the overlapping part of the sample is used, i.e. 1987–1997.

4.4 Estimated Volatility Patterns

The aim of this sub-section is to highlight whether, when and how the developments within banking industries were reflected in the conditional volatility of the

[9] For instance, we evaluated causality (and spillovers) between the banking industry volatility and the volatility for the entire market within each country. In such exercise it is important to recognize that banks included in the banking industry index *are* constituents of the index for the entire market. This implies a certain degree of "endogeneity" between the market index and the banking industry index *within* a country. We found a bi-directional relationship, which is likely due to the described "endogeneity" problem. In addition to these tests, we performed standard Granger causality -tests using the estimated volatility series. The results suggested that no unidirectional relationship between the volatility of the entire stock market and the banking industry volatility could be uncovered within a given country. This confirms the earlier finding (obtained using specification (4)). Using Granger -tests and estimated volatility series, we also evaluated the nature of the relationship between bank return volatility and return volatility of *a* real sector of the economy (as opposed to financial firms). The indices in this experiment were metal and engineering sector (Finland), engineering sector (Sweden) and industry (Norway). The results suggested that at 1% significance level, both in Finland and Sweden the volatility of bank returns cause the volatility of the representative real sector index but not the other way around. For Norway no such effects were detected.

Scandinavian stock returns over the turbulent period under scrutiny.[10] A question of obvious interest is, for instance, is it the case that bank prices produced early (and predictable) warning signals in the form of extreme volatility relative to the entire market which banking regulators, among others, might have used when assessing the health of the banking industry before the crisis actually hit?

Though the analysis of section 4.2 to some extent already addressed these issues, we wish to shed additional insights by computing the ratio of the estimated conditional standard deviation of bank returns to that of the entire market. Such a "deflated" volatility series might reveal patterns that are specific to banking industry as it accounts for changes in general uncertainty. This is so because whenever the banking problems arise due to external shocks, then such surprises would be observed in the general market index, too. These relative volatility series are displayed in the Figure set of Appendix 3, together with vertical lines representing for each country the IMF-defined crisis years.

As expected, clear evidence for drastically time-varying volatility is found for all three markets. However, the timing of the periods of the most extreme volatility (volatility peaks) seem to be relatively late, if judged on the basis that they roughly coincide with the peak years of the crisis, i.e. with the years when all the damage had been done and severe problems begun to realise on their full scale.[11] As price levels had been strongly declining already during the earlier years and as they were still declining during the volatility peaks, it seems that during the periods of the most extreme volatility, there was a bulk of news suggesting overpricing (negative returns). Apparently, the deepness of the banking problems was to some extent a surprise. As we see it, the results from the analysis of section 4.2 are in line with this interpretation. From this perspective, then, the markets did not produce early warning signals in the form of high volatility but rather adjusted only after hard news on realised risks came into the market.[12]

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[10] Literature, which would utilise stock market data when examining the developments within the Scandinavian banking industries over the liberalisation process and crisis episode, is almost non-existent. The only study we are aware of is the one by Kaen and Michalsen (1993). In that study, Norwegian stock market data are used, and the authors' main interest is in detecting whether there were market and industry wide contagion effects associated with financial distress announcements of banking firms. A further question they address is whether investors recognised potential and developing problems and valued bank stocks prior to the distress accordingly. The main results of the paper are, firstly, that there indeed were contagion effects from commercial bank failures and, secondly, that the severe problems of the industry were reflected in the stock market data only after a number of banks had failed.

[11] In the case of Finland and Sweden, foreign exchange market regime shifts, which were related to more general economic pressures that these countries experienced at the time, seem to coincide with the periods of the most extreme volatility of bank returns. Relative volatility series suggest that even after controlling for market level reactions, bank returns were extremely volatile at the time. At least in Finland, this could be regarded as a rational market response to the fact that during the years of rapid lending expansions, many of the loans were dominated in a foreign currency. This exposes bank customers, and thereby banks and even the whole economy, to exchange rate risks since borrowers' ability to repay the loans is at risk if a large devaluation of the home currency occurs.

[12] At least two alternative standpoints can be taken on this result. On the one hand, a conventional rational expectations explanation for asset pricing suggests that the most extreme pricing volatility should occur during the years when most of the problem loans were incorporated into banks' balance sheets (i.e. during the years of most rapid lending growth and booming economy). Or, at the very least, it should occur before risks begun to realise on their full scale and before major interventions by regulators took place. On the other hand, there are at least two explanations why the most extreme bank price volatility might not anticipate developing and forthcoming banking problems. Firstly, there is evidence that modern banks are opaque business entities (Morgan 1999; see also Pong et al. 1999). This may imply that market participants experience difficulties in interpreting and understanding the behaviour and risks of these firms. Secondly, structural breaks and investors learning processes provide a reason why the most extreme volatility does not necessarily precede the major events within the banking sector (Timmermann 1998).

5 Conclusions

In this paper, we have applied standard GARCH model and augmented it in various ways to investigate the conditional volatility on Finnish, Norwegian and Swedish stock markets. In summary, the empirical results are as follows: First, a relatively simple (T)GARCH model seems to be flexible enough to serve as a general model for modelling conditional volatility even in turbulent markets. Second, bank crisis seems to have induced regime shifts in volatility. Third, we find evidence for cross-country volatility spillovers during the banking crisis episodes. Finally, the analysis suggested that though the volatility of bank returns was found to be of high magnitude during the years of the largest problems, the timing of the periods of the most extreme volatility (volatility peaks) seems to be relatively late, if judged on the basis that they roughly coincide with the periods when severe problems begun to realise on their full scale.

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Appendix 1. Data Environment

The purpose of this section is to briefly highlight the developments at macroeconomic level and within the banking industries in the three countries under scrutiny. The description that follows borrows rather freely from Dahlheim et al. (1992), Kaen and Michalsen (1993), Koskenkylä (1994) and Murto (1996) to which the reader is referred for further details and references.

In Figures 1–3 three central economic variables (GDP growth, consumer price inflation and short interest rates) confirm the drastic nature of the changes that each country during the sample faced. Three phases can roughly be distinguished for each economy: first, during the1980s, growth was rapid and interest rates remained at relatively high levels. Second, for each country there were signs of accelerated inflation and overheating. In Norway, this occurred somewhat earlier than in Finland and Sweden; in these two countries consumer prices rose relatively rapidly towards the end of the 1980s and GDP growth reached its peak about at the same time. Third, the economic problems of Finland and Sweden began in the early 1990s; inflatory pressures disappeared and growth rates shrank. Finally, as economies began to recover, interest rates started a steady decline.

A view on banking sector developments during the sample period can be based on Figures 4–6. The figures for lending growth, bank profitability (ratio of operating profits to average assets) and asset quality (ratio of loan losses to average assets) portray a clear picture on the developments within the sector. After the liberalisation process, lending increased rapidly and in each country, there were years when lending growth exceeded 25 %. Then, during the crisis years, aggregate lending diminished and lending growth rates became negative. Profitability remained relatively stable until the beginning of 1990s when the largest problems and risks finally realised and the crisis hit. The severity of banks' problems is evident from the time-series of loan losses. The ratio of loan losses to average assets reached its peak in 1991 in Norway and in 1992 in Finland and Sweden.

At a general level, the background of the crises had certain parallels of which the two most important ones were as follows. First, financial markets were de-regulated in each country fairly rapidly, which, together with increased competition on the part of other financial institutions, lead to competition for market shares and, as we just observed from Figures 4–6, to very fast lending growth. In Norway the financial markets were liberalised by the end of 1984 while in Finland and Sweden this occurred a year or two later. A characteristic feature of the years of rapid credit expansion was, as we now with the benefit of hindsight know, 'bad' credit screening practises within banks and, to some extent, 'bad policies' (almost no attempts to control the expansion were made). Second, macroeconomic conditions contributed to the development of the crisis in each country; in Norway, perhaps the most important factor affecting the economy was the decline in oil prices in 1985–1986, whereas in Finland the collapse of the trade with Soviet Union during the last years of 1980s provided the start for deteriorating economic performance. In Sweden no single factor has been identified even though the general decline in the growth of export markets and a tax reform (leading to higher post-tax interest rates) have been mentioned as contributing factors.

The problems that had been accumulating for years started to emerge on their full scale in 1987 in Norway and achieved their climax in 1991. In fact, early evidence on the potential problems appeared as early as in 1986 when commercial bank loan losses rose by 75 per cent. In Finland and Sweden the problems begun to materialise later and 1991 is the year when banks' financial problems became truly apparent. In Finland, however, one of the first signs of the developing problems was perhaps the restructuring programme of the Skopbank (initiated by the Finnish banking authorities) in October 1989. In Sweden, the large increase in credit losses of deposit banks in 1990 could be regarded as one of the first unambiguous signals about the condition of the banking sector.

In each country, not only were the commercial banks involved in the process but the savings banks encountered, if possible, even more severe problems. Also in each country, the role of government intervention was important as the crisis unfolded. Murto (1996) reports that the total amount of the bank support granted by the governments in 1989-1993 was 14.7 % in Finland, 4.5 % in Norway and 6.2 % in Sweden as a percentage of GDP. In Finland and Sweden most of the banks remained in the private hands while in Norway the government effectively took over all the major commercial banks. Both in Sweden and in Finland the governments made it more or less clear that a) the state had no incentives to become an owner of the banks and that b) the stability of the banking system was guaranteed under all circumstances.[1] In Norway, the policy was different and for instance in October 1989 a commercial bank was taken under state control for the first time since 1928. In October 1991, the Norwegian state became the sole owner of the second and third largest banks and the major owner of the largest bank.

To complete the description, a very selective list of certain major events related to banking crisis and foreign exchange market turbulence is given:

Finland: i)"Autumn 1990" = the incident of drawing up a restructuring programme (by the authorities) for a large commercial bank (Skopbank) in October 1990; ii) "Autumn 1991" = the third week of September 1991 was the week when the market confidence on Skopbank finally collapsed and when the consequent take-over of the bank by the Bank of Finland took place; the devaluation of markka in October 1991; iii) "Autumn 1992" = the event of letting the markka float in September 1992.

Sweden: i) "Spring 1990" = Swedish commercial paper crisis, i.e. collapse of market liquidity and issuance; ii) "Spring 1991" = (roughly) the first announcements of very large credit losses for the accounting year 1990 by Swedish banks in April 1991; iii) "Autumn 1992" = the nullification of the share capital of the smallest of Sweden's large commercial banks (Gota Bank) in September 1992; The event of letting the Krona float at the end of November 1992.

Norway: i) "Autumn 1988" = the announcement that two Norwegian savings banks (Sparebanken Nord and Tromso Sparebank) were found to have lost their equity capital and that their administration was taken over by the authorities in October 1988; ii) "Autumn 1991" = the event of government taking over the second largest Norwegian commercial bank (Kreditkassen) on 14th October 1991; iii) "Winter 1991" = the event of writing down the original share capital of two major Norwegian commercial banks (Fokus Bank and Den Norske Bank) during the first week of December 1991.

[1] This was explicitly announced in February 1993 in Finland. In Sweden the parliament gave quarantine for all the liabilities of banks and certain credit institutions except for the share capital in December 1992.

Figure 1. **Growth in Nominal GDP (%)**

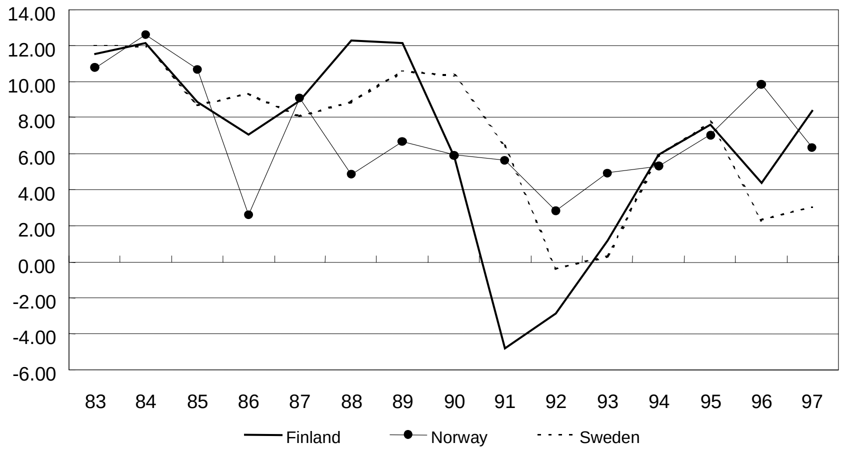


Figure 2. **Consumer Price Inflation (%)**

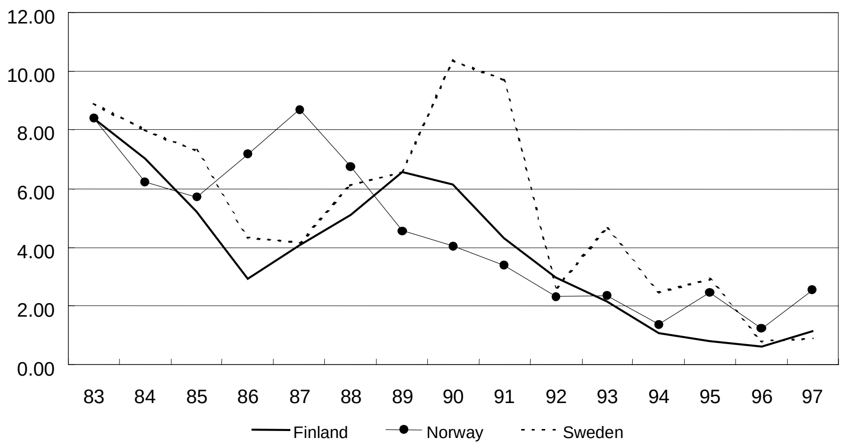


Figure 3. **Short Interest Rates (3 month, %)**

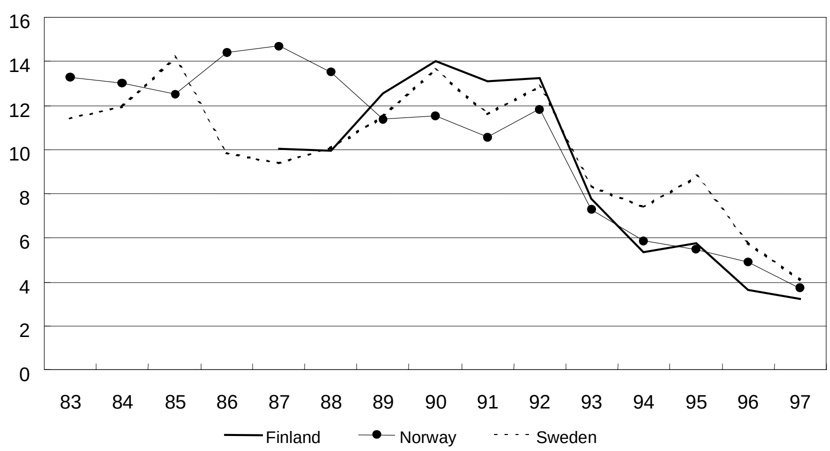


Figure 4. **Lending Growth (%)**

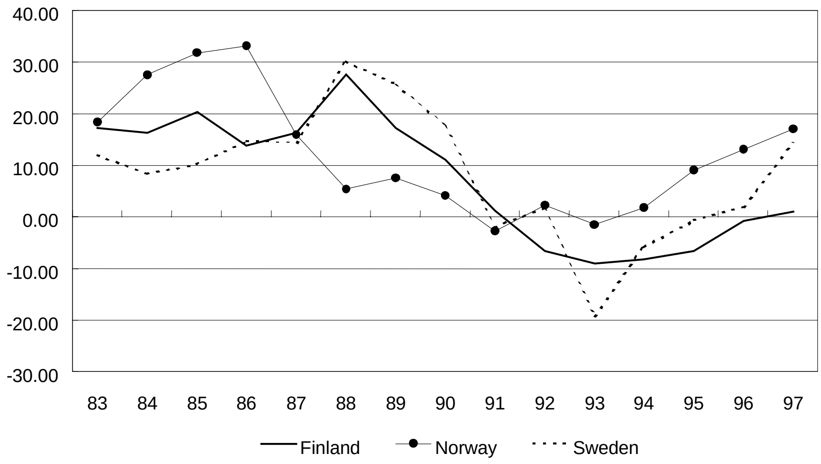


Figure 5. **Ratio of Loan Losses to Average Assets**

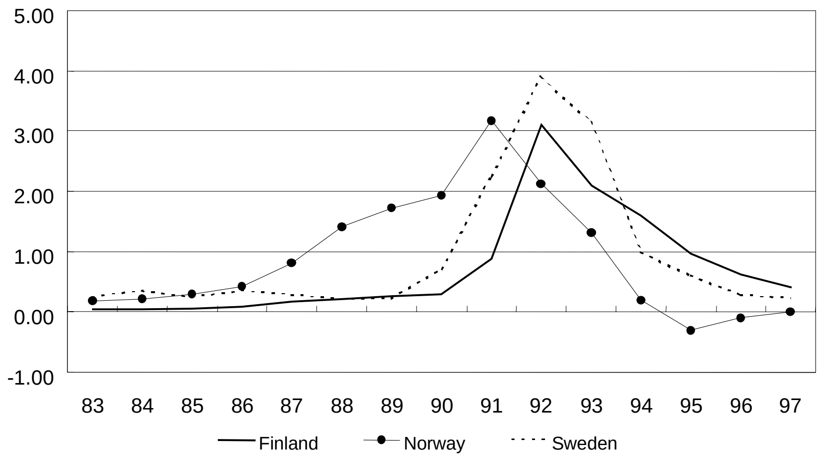
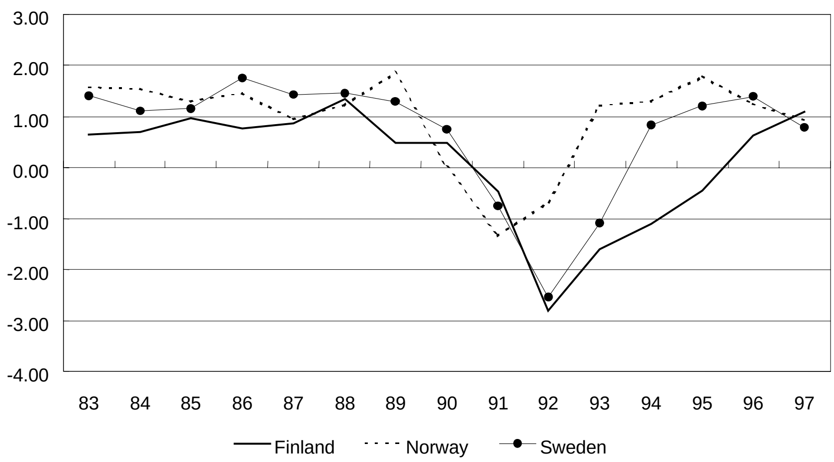


Figure 6. **Ratio of Operating Profit to Average Assets**



Appendix 2. Descriptive Statistics for Unexpected Stock Return (r_t)

	Finland	Norway	Sweden
Sample size	532	741	741
Mean			
Market return	0.000	0.000	0.000
Bank return	0.000	0.000	0.000
Control return	0.000	0.000	0.000
Std. Devn.			
Market return	2.720	2.549	2.765
Bank return	5.231	3.537	4.679
Control return	2.872	3.022	3.109
Skewness			
Market return	0.217	-0.791	-0.163
Bank return	0.310	0.328	0.401
Control return	0.595	-1.820	0.002
Kurtosis			
Market return	4.091	10.006	8.541
Bank return	9.338	7.244	16.519
Control return	4.057	22.575	6.884
J-B (p-value)			
Market return	0.000	0.000	0.000
Bank return	0.000	0.000	0.000
Control return	0.000	0.000	0.000
L-B (Q(16)| Q^2(16))			
Market return	11.874 | 171.49	8.701 | 72.755	7.046 | 145.28
Bank return	9.486 | 877.01	8.400 | 340.26	11.900 | 217.08
Control return	8.139 | 23.742	3.964 | 117.45	6.260 | 92.787

Note: The entries in the table are computed for unexpected weekly returns. J-B is the Jarque-Bera test for normality. L-B is the Ljung–Box portmanteau statistic testing for autocorrelation in the returns (Q(16)) and in the squared returns (Q^2(16)), distributed as $\chi^2(16)$. The 5% and 10 % critical values for these tests are 26.269 and 23.542, respectively.

Appendix 3. Relative Conditional Standard Deviation (Bank/Market)