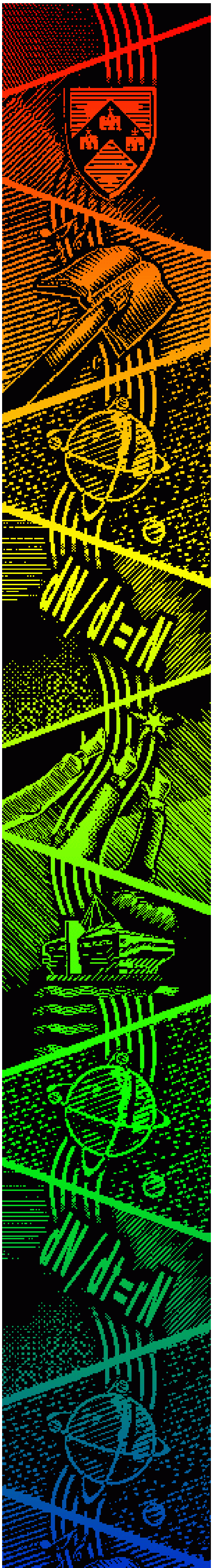

THE UNIVERSITY of York

Discussion Papers in Economics

No. 2008/09

Firm Level Volatility-Return Analysis using Dynamic Panels
By

L. Vanessa Smith and Takashi Yamagata

Department of Economics and Related Studies
University of York
Heslington
York, YO10 5DD

Firm Level Volatility-Return Analysis using Dynamic Panels*

L. Vanessa Smith
CFAP, University of Cambridge

Takashi Yamagata
University of York

May 2008

Abstract

This paper examines "leverage" and volatility feedback effects at the firm level by considering both market effects and firm level effects, using 242 individual firm stock data in the US market. We adopt a panel vector autoregressive framework which allows us to control simultaneously for common business cycle effects, unobserved cross correlation effects in return and volatility via industry effects, and heterogeneity across firms. Our results suggest that volatility feedback effects at the firm level are present due to both market effects and firm effects, though the market volatility feedback effect is stronger than the corresponding firm level effect. We also find that the leverage effect at the firm level is persistent, significant and negative, while the effect of market return on firm volatility is persistent, significant and positive. The presence of these effects is further explored through the responses of the model's variables to market-wide return and volatility shocks.

JEL-Classification:

Keywords: Volatility Feedback; Stock Return; Leverage Effects; Panel Vector Autoregression

*A preliminary version of this paper was presented at the Third Cambridge-Princeton Conference, September 21-22, 2007, University of Princeton. We are grateful for useful comments by the discussant Mark Watson and conference participants. We would further like to thank Mardi Dungey, John Eatwell, Tom Flavin, Ólan Henry, Stewart Myers, Denise Osborn, Hashem Pesaran, Peter Smith, Nicos Savva, Peter Spencer, Mike Wickens and Paolo Zaffaroni for useful comments and discussions. Thanks are also due to Tugrul Vehbi for data collection and processing. Financial support from Cambridge Endowment for Research in Finance (CERF) is gratefully acknowledged.

†Corresponding author. Address: CFAP, Judge Business School, University of Cambridge, Trumpington Street, Cambridge CB2 1AG UK. Tel.: +44 (0)1223-760 578; Fax: +44 (0)1223-760 576. E-mail address: lvs21@cam.ac.uk.

1 Introduction

Traditionally in finance, stock return volatility is modelled as negatively correlated with stock returns, with Black (1976) and Christie (1982) putting forth the explanation of the leverage effect hypothesis for such a relation: A drop in the value of the stock increases financial leverage, which makes the stock riskier and increases its volatility.[1] Another explanation for the negative relation between returns and volatility is that it could simply reflect the existence of time-varying risk premiums (Schwert and Stambaugh, 1987). If volatility is priced, an anticipated increase in volatility raises the required return on equity, leading to an immediate stock price decline. This is often referred to as the volatility feedback effect. While both of these effects could be at work, which of these effects is the main determinant of the stock return-volatility relation remains an open question.

The empirical results on the leverage effect and the volatility feedback effect are rather mixed and inconlusive. Black (1976), Christie (1982) and Duffee (1995) find negative leverage effects. French, Schwert and Stambaugh (1987) and Campbell and Hentschel (1992) find weak evidence of a positive effect of the conditional volatility on the return, while, Turner, Startz and Nelson (1989), Glosten, Jagannathan and Runkle (1993) and Nelson (1991) find a negative volatility feedback effect. Figlewski and Wang (2000) find strong evidence of a leverage effect, while Bekaert and Wu (2000) reject the pure leverage model of Christie (1982) and find support for a volatility feedback effect story.

This paper contributes to return-volatility analysis, by addressing a number of important issues that have either been largely underexplored or overlooked in the existing literature.

Firstly, both volatility feedback and leverage effects are examined at the firm level, while considering both market effects - that is the effects of market return (volatility) on firm volatility (return) - and corresponding firm effects. We define the former as market level volatility or leverage effects and the latter as firm level volatility or leverage effects. The majority of studies focus either on the leverage effect or the volatility feedback effect, while the latter is typically explored at the market level.

Secondly, most existing studies based on firm or industry data control for market variables only. However, the literature has found evidence that stock prices of firms in the same industry exhibit a common movement that goes beyond the market effect see King (1966), Meyers (1973) and Livingston (1977) and more recently Hong, Torous and Valkanov (2007). We explicitly control for industry return and industry volatility effects.

Thirdly, we identify the contemporaneous effects and lagged effects separately, in

[1] Although it can be argued whether the "leverage effect" is the correct terminology, following the extant literature we remain with this term.

order to investigate their dynamic behaviour. The volatility feedback story suggests that, because volatility is priced, after the immediate price drop following an anticipated increase in volatility, persistently high volatility is expected to lead to higher return, unless the firm goes bankrupt. On the other hand, leverage effects are expected to die out over time, given that returns are not as persistent as volatility. We will empirically examine this conjecture.

Fourthly, we control for the effect of business cycle variables on firm return and volatility. Most existing studies ignore this effect, even though the relationship between business cycle variables and the stock market is well documented in the literature. Chen, Roll, and Ross (1986), Keim and Stambaugh (1986), Campbell (1987), Fama and French (1989), Fama (1990) among others document a significant relationship between macroeconomic variables and stock returns, while evidence of a similar relationship with stock return volatility can be found in Schwert (1989) and more recently in Engel, Ghysels and Sohn, (2006) and Fornari and Mele (2006). The main mechanisms linking returns volatility to macroeconomic factors are in fact highlighted in the equilibrium models of Campbell and Hentschel (1992), Bansal and Yaron (2004) and Tauchen (2005), that attempt to formally explain the relation between return volatility and returns.

To address the above issues, we develop a panel vector autoregressive framework that allows us to control simultaneously for common business cycle effects, unobserved cross correlation effects in return and volatility, and heterogeneity across firms.[2] After estimation of the individual firm models, the system of the entire set of firm returns and volatilities and business cycle variables is obtained by linking the firm specific models in a consistent and cohesive manner. This enables us to study the impulse response functions of our large system and to visualize the significant leverage and volatility feedback effects that we uncover.

The rest of this paper is organized as follows. Section 2 lays out the econometric model. Section 3 describes the data. Section 4 summarizes the estimation results. Section 5 further examines the dynamic interrelation between return and volatility as well as business cycle variables by means of impulse response analysis and discusses the results. Finally Section 6 contains some concluding remarks.

[2]Specifically, we extend the methodology of Whitelaw (1994), and Brandt and Kang (2004), Pesaran, Schuermann and Weiner (2004) and Dees, Di Mauro, Pesaran, and Smith (2007).

2 Firm Specific Models of Return and Volatility

Define r_{ijt} and $\ln \sigma_{ijt}$ as the monthly return and the log of volatility of the i^{th} firm in the j^{th} industrial sector[3] at month t, respectively. Suppressing the subscript j for notational conciseness, the return and volatility equations of firm i are given by

$$\begin{aligned} r_{it} &= \alpha_{ri} + \sum_{\ell=1}^{p} \left(\phi_{11i\ell} r_{i,t-\ell} + \phi_{12i\ell} \ln \sigma_{i,t-\ell}\right) + \sum_{z=1}^{S} \sum_{\ell=0}^{q} \left(\gamma_{11i,z\ell} r^*_{iz,t-\ell} + \gamma_{12i,z\ell} \ln \sigma^*_{iz,t-\ell}\right) \\ &\quad + \sum_{\ell=0}^{q} \boldsymbol{\gamma}'_{dr,i\ell} \mathbf{d}_{t-\ell} + v_{rit}, \qquad (1) \end{aligned}$$

and

$$\begin{aligned} \ln \sigma_{it} &= \alpha_{\sigma i} + \sum_{\ell=1}^{p} \left(\phi_{21i\ell} r_{i,t-\ell} + \phi_{22i\ell} \ln \sigma_{i,t-\ell}\right) + \sum_{z=1}^{S} \sum_{\ell=0}^{q} \left(\gamma_{21i,z\ell} r^*_{iz,t-\ell} + \gamma_{22iz\ell} \ln \sigma^*_{iz,t-\ell}\right) \\ &\quad + \sum_{\ell=0}^{q} \boldsymbol{\gamma}'_{d\sigma,i\ell} \mathbf{d}_{t-\ell} + v_{\sigma it}, \qquad (2) \end{aligned}$$

where r^*_{izt} $(\ln \sigma^*_{izt})$ is the z^{th} industrial sector return (volatility), which is a weighted average of the firm return (volatility) in industrial sector $z(= 1, ..., S)$[4] *excluding firm i itself*, and $\mathbf{d}_t$ is a $n \times 1$ vector of business cycle variables.[5]

Some remarks are in order. Firstly, it should be noted that for each equation, the contemporaneous firm level return and volatility do not enter as a right hand side variable, to avoid the simultaneity problem. However, contemporaneous industry sector variables,

[3] An industrial sector is a group of industries to be specified below.

[4] The firm specific industrial sector return, without suppressing subscript j, is defined as $r^*_{ij,zt} = \sum_{r=1}^{N_z} w_{ij,rz} r_{rzt}$, with

$$w_{ij,rz} = \begin{cases} 0, & \text{when } r = i \text{ and } z = j \\ \frac{\omega_{rz}}{\sum_{v=1}^{N_z} \omega_{vz} - \omega_{iz}}, & \text{when } r \neq i \text{ and } z = j \\ \frac{\omega_{rz}}{\sum_{v=1}^{N_z} \omega_{vz}}, & \text{when } z \neq j \end{cases},$$

so that $\sum_{r=1}^{N_z} w_{ij,rz} = 1$ for $z = 1, 2, ..., S$, with ω_{ij} the value-weight (of the S&P500) for the i^{th} firm of the j^{th} industrial sector, such that $\sum_{j=1}^{S} \sum_{i=1}^{N_j} \omega_{ij} = 1$.

[5] Note that the return equations given in (1) allow to capture the temporary component of Fama and French's (1988) model in which stock prices are governed by a random walk and a stationary autoregressive process, respectively, encompassing also the model of Lamoureux and Zhou (1996) for $\phi_{12ij\ell} = 0$ for all j and ℓ and in the absence of the industrial sectors and business cycle variables. The volatility equations in (2) incorporate the standard stochastic volatility model, as well as that considered by Wiggins (1987) and Andersen and Sørensen (1996) among others, for $\phi_{21ij\ell} = 0$ for all j and ℓ and in the absence of the industrial sectors and business cycle variables. The difference in the latter equations being that we consider realised volatility rather than a latent variable.

$(r^*_{iz,t}, \ln \sigma^*_{iz,t})$, and contemporaneous busyness cycle variables, $\mathbf{d}_t$, are present as regressors, as they are assumed to be weakly exogenous: that is, $E\left[(r^*_{iz,t}, \ln \sigma^*_{iz,t})\mathbf{v}'_{is}\right] = \mathbf{0}$ and $E\left[\mathbf{d}_t \mathbf{v}'_{is}\right] = \mathbf{0}$ for $s \geq t$ and all i. This imposes the restriction that a single firm does not affect the market, business cycle variables or industrial sectors contemporaneously. Secondly, 'market' return and volatility are not included separately in our model specification, as they are perfectly multicollinear with the industrial sector variables. Therefore, the sum of the coefficients over the industrial sectors, $\sum_{z=1}^{S} \gamma_{i,z\ell}$, can be thought of as the 'market' effect. Finally, the error terms v_{rit} and $v_{\sigma it}$ are assumed to be contemporaneously correlated and serially uncorrelated. More precisely, it is assumed that the errors $\mathbf{v}_{it} = (v_{rit}, v_{\sigma it})'$ follow

$$\mathbf{v}_{it} \sim iid \left[\mathbf{0}, \begin{pmatrix} \sigma^2_{11i} & \sigma_{12i} \\ \sigma_{21i} & \sigma^2_{22i} \end{pmatrix}\right].$$

Equations (1) and (2) are estimated separately for each firm using ordinary least squares (OLS).[6]

2.1 Reparametarization

We next illustrate the reparametarization of models (1) and (2) in line with Brandt and Kang (2004), so that the contemporaneous firm level effects can be identified. For notational simplification, we suppress subscript j as before, abstract from busyness cycle variables, assume one industry sector ($S = 1$), and set the lags $p = q = 1$.

Firstly, to see the connection to volatility in the mean models, the firm return equations (1) and (2) are written as

$$\begin{aligned} r_{it} &= \alpha_{ir} + \phi_{11i} r_{i,t-1} + \phi_{12i} \ln \sigma_{i,t-1} \\ &\quad + \gamma_{11i} r^*_{i,t} + \gamma_{12i} \ln \sigma^*_{i,t} + \gamma_{11i1} r^*_{i,t-1} + \gamma_{12i1} \ln \sigma^*_{i,t-1} + v_{irt}, \end{aligned} \tag{3}$$

$$\begin{aligned} \ln \sigma_{it} &= \alpha_{i\sigma} + \phi_{21i} r_{i,t-1} + \phi_{22i} \ln \sigma_{i,t-1} \\ &\quad + \gamma_{21i} r^*_{i,t} + \gamma_{22i} \ln \sigma^*_{i,t} + \gamma_{21i1} r^*_{i,t-1} + \gamma_{22i1} \ln \sigma^*_{i,t-1} + v_{i\sigma t}. \end{aligned} \tag{4}$$

Assume

$$v_{irt} = \pi_{i\sigma} v_{i\sigma t} + \varpi_{irt} \tag{5}$$

[6] Including an intercept dummy for the October 1987 crash gave very similar results.

where $E(v_{i\sigma t}\varpi_{irt}) = 0$. From (3)-(5), (3) can be rewritten as

$$\begin{aligned} r_{it} &= (\alpha_{ir} - \pi_{i\sigma}\alpha_{i\sigma}) + \pi_{i\sigma}\ln\sigma_{it} \\ &+ (\phi_{11i} - \pi_{i\sigma}\phi_{21i})\, r_{i,t-1} + (\phi_{12i} - \pi_{i\sigma}\phi_{22i})\ln\sigma_{i,t-1} \\ &+ (\gamma_{11i} - \pi_{i\sigma}\gamma_{21i})\, r^*_{it} + (\gamma_{12i} - \pi_{i\sigma}\gamma_{22i})\ln\sigma^*_{it} \\ &+ (\gamma_{11i1} - \pi_{i\sigma}\gamma_{21i1})\, r^*_{i,t-1} + (\gamma_{12i1} - \pi_{i\sigma}\gamma_{22i1})\ln\sigma^*_{i,t-1} + \varpi_{irt}. \end{aligned} \tag{6}$$

The estimator of $\pi_{i\sigma}$ is obtained by regressing v_{irt} on $v_{i\sigma t}$. Clearly, $\pi_{i\sigma}$ is the firm level contemporaneous volatility feedback effect, and $(\phi_{12i} - \pi_{i\sigma}\phi_{22i})$ is the lagged firm level volatility feedback effects. Also $(\gamma_{12i} - \pi_{i\sigma}\gamma_{22i})$ and $(\gamma_{12i1} - \pi_{i\sigma}\gamma_{22i1})$ are the contemporaneous and lagged market volatility effects on the firm return, respectively.

Similarly, for the volatility equation, assume

$$v_{i\sigma t} = \pi_{ir}v_{irt} + \varpi_{i\sigma t} \tag{7}$$

where $E(v_{i\sigma t}\varpi_{irt}) = 0$, so that

$$\begin{aligned} \ln\sigma_{it} &= (\alpha_{i\sigma} - \pi_{ir}\alpha_{ir}) + \pi_{ir}r_{it} \\ &+ (\phi_{21i} - \pi_{ir}\phi_{11i})\, r_{i,t-1} + (\phi_{22i} - \pi_{ir}\phi_{12i})\ln\sigma_{i,t-1} \\ &+ (\gamma_{21i} - \pi_{ir}\gamma_{11i})\, r^*_{i,t} + (\gamma_{22i} - \pi_{ir}\gamma_{12i})\ln\sigma^*_{i,t} \\ &+ (\gamma_{21i1} - \pi_{ir}\gamma_{11i1})\, r^*_{i,t-1} + (\gamma_{22i1} - \pi_{ir}\gamma_{12i1})\ln\sigma^*_{i,t-1} + \varpi_{i\sigma t}. \end{aligned} \tag{8}$$

Now π_{ir} is the contemporaneous firm level leverage effect, and $(\phi_{21i} - \pi_{ir}\phi_{11i})$ is the lagged firm level leverage effects. Also $(\gamma_{21i} - \pi_{ir}\gamma_{11i})$ and $(\gamma_{21i1} - \pi_{ir}\gamma_{11i1})$ are the contemporaneous and lagged market return effects on firm volatility, respectively. Our investigation of the volatility feedback effects and leverage effects in what follows will be based on these reparametarised coefficients.

2.2 Mean Group Estimator and Fraction of Rejections

To quantify the overall effects of regressors across firms, we will use two measures. The first measure is the mean group estimator also used in Duffee (1995). Pesaran and Smith (1995) show that under mild assumptions on the heterogeneity of the parameters as given below, the pooled estimator under heterogeneity can be estimated consistently. Suppressing the index j for industrial sectors as before, consider a parameter vector of the firm i, $\boldsymbol{\theta}_i$. Assume the random coefficient specification $\boldsymbol{\theta}_i = \boldsymbol{\theta} + \boldsymbol{\nu}_i$, where $\boldsymbol{\varpi}_i \sim iid(\mathbf{0}, \boldsymbol{\Omega}_\nu)$ so that $E(\boldsymbol{\theta}_i) = \boldsymbol{\theta}$. Now define the mean group estimator over all firms as

$$\bar{\hat{\boldsymbol{\theta}}}_{MG} = N^{-1}\sum_{i=1}^{N}\hat{\boldsymbol{\theta}}_i, \tag{9}$$

where N is the total number of firms. In the context of our model and estimation methods specified above, $\bar{\hat{\boldsymbol{\theta}}}_{MG}$ is consistent for the centred value $\boldsymbol{\theta}$, as N and T goes to infinity.[7] The t-ratio of the mean group estimator is based on the non-parametric variance covariance estimator defined as

$$\hat{\boldsymbol{\Sigma}}_{MG} = \frac{1}{N(N-1)} \sum_{i=1}^{N} \left(\hat{\boldsymbol{\theta}}_i - \bar{\hat{\boldsymbol{\theta}}}_{MG} \right) \left(\hat{\boldsymbol{\theta}}_i - \bar{\hat{\boldsymbol{\theta}}}_{MG} \right)'. \tag{10}$$

The second measure is the fraction of rejections of the t-ratio of each equation across firms, at the 10% significance level. Namely,

$$\frac{1}{N} \sum_{i=1}^{N} I\left(|t_{v,i}| > 1.645\right),$$

where $t_{v,i}$ is the t-ratio of the $\hat{\theta}_{v,i}$, which is the v^{th} element of the coefficient of $\hat{\boldsymbol{\theta}}_i$, based on the Newey-West heteroskedasticity and autocorrelation robust variance covariance estimator, and $I(A)$ is the indicator function which is unity if A is true, and zero otherwise. One might expect the fraction of rejections to be less than or equal to 10%, if a regressor is actually not important in the model. We also report the cross average of the coefficient estimates which are significant, namely,

$$\frac{\sum_{i=1}^{N} \hat{\theta}_{v,i} \times I\left(|t_{v,i}| > 1.645\right)}{\sum_{i=1}^{N} I\left(|t_{v,i}| > 1.645\right)}.$$

2.3 Long-Run Coefficients

Returning to the basic models, (1) and (2), to compactly summarize the impact of the right hand side variables on return and volatility, their long-run effects will be reported. The long-run effects of these variables in the return equation and the volatility equations, $\boldsymbol{\theta}_{ir}$ and $\boldsymbol{\theta}_{i\sigma}$, respectively, are defined in Table 1. Observe that λ_{ijr} and $\lambda_{ij\sigma}$ are not long-run parameters, but the sum of the coefficients of lagged variables. The standard errors of $\boldsymbol{\theta}_{ir}$ and $\boldsymbol{\theta}_{i\sigma}$ are obtained by the delta-method.

[7] See Hsiao and Pesaran (2007) for more details about mean group estimation in dynamic panel models.

Table 1: Definitions of the Long-Run Effects

Return Equation		Volatility Equation	
Long-Run Effects on r_{it} of	Components of Long-Run Parameter $\boldsymbol{\theta}_{ir}$	Long-Run Effects on $\ln \sigma_{it}$ of	Components of Long-Run Parameter $\boldsymbol{\theta}_{i\sigma}$
–	$\lambda_{ir} = \sum_{\ell=1}^{p} \phi_{11i\ell}$	–	$\lambda_{i\sigma} = \sum_{\ell=1}^{p} \phi_{22i\ell}$
μ_{ir}	$\frac{\alpha_{ir}}{1-\lambda_{ir}}$	$\mu_{i\sigma}$	$\frac{\alpha_{i\sigma}}{1-\lambda_{i\sigma}}$
$\mathbf{d}$	$\frac{\sum_{\ell=0}^{q} \gamma_{idr\ell}}{1-\lambda_{ir}}$	$\mathbf{d}$	$\frac{\sum_{\ell=0}^{q} \gamma_{id\sigma\ell}}{1-\lambda_{i\sigma}}$

Notes: $\boldsymbol{\theta}_{ir}$ and $\boldsymbol{\theta}_{i\sigma}$ are the long-run effects of the right hand side variables in the return and volatility equation, respectively. The parameters of the second and third columns are defined by (1) and (2).

3 Data

Monthly returns and volatilities are constructed using dividend adjusted daily stock price data from *Datastream* for $N = 242$ firms of the S&P500, which survived over the period January 1973 to April 2007.[8] The return of the i^{th} firm belonging to the j^{th} sector at month t is defined as

$$r_{ijt} = \frac{P_{ijD_t} - P_{ijD_{t-1}}}{P_{ijD_{t-1}}}, \; i = 1, 2, ..., N_j; j = 1, 2, ..., S; t = 1, 2, ..., T,$$

where P_{ijD_t} is the price at D_t, the final date of the month t. The volatility measure is defined as

$$\sigma_{ijt}^2 = \sum_{d=2}^{D_t} \left[\frac{P_{ijtd} - P_{ijtd-1}}{P_{ijtd-1}} \right]^2 .$$

This amounts to 412 monthly data points. A theoretical motivation for using the sum of high-frequency squared returns to compute measures of volatility at lower frequencies is provided by Merton (1980). Examples of this practice using daily volatility to construct estimates of monthly volatility include the work of French, Schwert and Stambaugh (1987) and Schwert (1989,1990) among others.

The individual firm weights, ω_{ij}, are fixed over time and are the average of monthly value-weights for the S&P500 over the period January 2003 to December 2004.[9]

Table 2 illustrates the four industrial sectors in terms of the industrial groups. Based on the Global Industry Classification Standard (GICS, provided by Datastream, effective after April 28, 2006), the 242 firms are classified into nine industries. Given that there are only 412 data points for each stock, including nine industries in models (1) and (2) would

[8] As documented in Duffee (1995), survivorship bias is likely using such data. Therefore, the results we obtain should be interpreted as those conditioning upon long term survived firms.

[9] S&P500 firm specific weights are only available monthly post January 2003.

give rise to an inadmissible numbers of parameters to be estimated. For instance, if we have eight business cycle variables, as will be the case in what follows, and choosing the lag orders $p = q = 4$ lags, the number of parameters to be estimated in a single equation is 139, which is clearly too large. To avoid this, the nine GICS industries are further classified into four industrial sectors as reported in Table 2. The sector classification is based on the correlation matrices of the industry returns and volatilities and a visual inspection of the monthly time plot of the stock price average over firms for each industry category.[10]

Table 2: Definition of Four Industrial Sectors

Industrial Sector (j or z)	Number of Firms (weights) in Sector j or z		**Industry**^{a}	Number of Firms (weights) in Industry
1	26 (0.04)	1	Utilities	26 (0.04)
2	104 (0.42)	2	Energy	13 (0.08)
		3	Materials	25 (0.04)
		4	Industrials	35 (0.13)
		5	Financials	31 (0.17)
3	87 (0.43)	6	Consumer Discretionary	45 (0.12)
		7	Consumer Staples	26 (0.14)
		8	Health Care	16 (0.18)
4	22 (0.11)	9	IT&Telecom^b	22 (0.11)

Notes:

a. The category 'industry' corresponds to the two digits in the Global Industry Classification Standard (GICS).

b. The IT&Telecom industry is the Information Technology and Telecommunication Services in GICS merged.

The macroeconomic and financial market variables considered are those typically used in studies that examine the relation of business cycle variables with the stock market such as Chen, Roll, and Ross (1986), Keim and Stambaugh (1986), Campbell (1987), Fama and French (1989), Fama (1990), Schwert (1989) and Glosten et al (1993) among others, and include

$$\mathbf{d}_t = \left(\Delta p_t, \Delta ip_t, \Delta p_t^{oil}, \Delta ue_t, \Delta m2_t, \Delta DS_t, \Delta TS_t, \Delta TB_t\right)'$$

where Δ signifies the change in the variables (or first differences), $p_t = \ln(CPI_t)$ where CPI_t is the US Consumer Price Index at time t, $ip_t = \ln(IP_t)$ where IP_t is US Industrial Production, $p_t^{oil} = \ln(POIL)$ where $POIL$ is the price of West Texas Intermediate Crude oil, $ue_t = \ln(UE_t)$ where UE_t is the number of unemployed in the US, $m2_t = \ln(M2_t)$ where $M2_t$ is the US money stock, the Default Spread (DS_t), the Term Spread (TS_t) and the 3 month Treasury bill (TB_t), at an annual rate. The default spread is calculated as the difference between the yield on BAA- and AAA-rated corporate bonds. The term spread is calculated as the difference between the yield on the US long-term government bond

[10] See Appendix for more details.

(10 year) and the US 3 month Treasury bill rate. Monthly CPI, IP, UE, M2, DS, 3 month TB are obtained from the Federal Reserve Economic Data (FRED) database. Monthly POIL is obtained from the International Financial Statistics, IMF and the monthly US long-term government bond (10 year) is obtained from the European Central Bank.[11]

We proceed with our model specification which contains sixteen 'common' factors, consisting of eight industrial sector variables and eight business cycle variables. The question that arises here is whether this number is sufficient to capture the unobserved cross correlation effects in return and volatility. To partially answer this question, the number of factors in r_{ijt} and $\ln \sigma_{ijt}$ are estimated using the information criteria proposed by Bai and Ng (2002), the results of which are reported in Table 3. The evidence suggests the likely presence of five to eleven factors, which is well below sixteen. In what follows we assess the effectiveness of the industrial sector variables in capturing the unobserved common factors and reducing the cross-section correlation of the variables, by examining residual correlation matrices in Section 4.4.

Table 3: Estimated Number of Factors using Information Criteron proposed by Bai and Ng (2002)

Information Criterion	Return	Log of Volatility
PC1	7	8
PC2	7	6
PC3	10	11
IC1	6	6
IC2	5	5
IC3	8	10

Notes: All six information criterion are proposed by Bai and Ng (2002). The maximum number of factors is set to 16.

4 Estimation Results

In this section we report the firm specific estimation results.[12] We begin by discussing the volatility feedback effect and leverage effects in subsection 4.1, using the estimation results of the reparametarised models (6) and (8). Next we consider the long-run industrial sector effects based on models (1) and (2). The estimation results of the long-run effects of the business cycle variables follow in subsection 4.2.

[11] We also considered the dividend yield and the price-earning ratio, however, we dropped these variables due to high correlation with r^*_{ijt} and $\ln \sigma^*_{ijt}$, to avoid multi-collinearity problems.

[12] We have chosen the lag-orders $p = q = 4$ in the models (1) and (2), based on joint consideration of the multivariate Akaike Information Criterion (MAIC) and test results for error serial correlation. For detailed test results, see Appendix A.1.

4.1 The Volatility Feedback Effect and Leverage Effect

To shed light on the time dimension of the volatility effects, Table 4 reports the mean group estimators of the contemporaneous and lagged coefficients on the volatilities of the industrial sectors as well as the individual firms. A noteworthy feature of these results is the large negative contemporaneous market volatility effect which is strongly significant. The contemporaneous firm level volatility feedback effect is also negative, though not significant. Turning our attention to the lagged effects, the average effects of lagged 'market' volatility and the lagged firm level volatility effects are predominantly positive. The former are much larger and strongly significant at the first two lags compared to the latter, which are significant at the second and fourth lags. These results suggest that volatility feedback effects at the firm level are present due to both market effects and firm effects, and that the market volatility feedback effect is stronger than the firm level volatility feedback effect. This is an interesting finding and also quite intuitive if one considers that it is market risk which cannot be diversified away, contrary to idiosyncratic risk, and is therefore expected to have a greater bearing on stock returns. At the same time, the lagged firm level volatility results are consistent with the earlier work by Merton (1987) who suggests that in an information-segmented market, firms with higher idiosyncratic volatility or firm specific risk may require higher returns to compensate for imperfect diversification.

Table 4: Mean Group Estimates of the Contemporaneous and Lagged Market and Firm Volatility Effects on Stock Returns

Return Equation			
Coefficients on Market Variables		Coefficients on Firm Variables	
	Mean Group Estimates of Sum over Four Sectors (t-ratio)		Mean Group Estimates (t-ratio)
$\ln \sigma^*_{it}$	**-0.212 (-9.764)**	$\ln \sigma_{i,t}$	-0.024 (1.264)
$\ln \sigma^*_{i,t-1}$	**0.133 (6.302)**	$\ln \sigma_{i,t-1}$	0.005 (0.535)
$\ln \sigma^*_{i,t-2}$	**0.104 (4.581)**	$\ln \sigma_{i,t-2}$	**0.021 (1.996)**
$\ln \sigma^*_{i,t-3}$	-0.027 (-1.318)	$\ln \sigma_{i,t-3}$	-0.005 (-0.488)
$\ln \sigma^*_{i,t-4}$	**-0.076 (4.173)**	$\ln \sigma_{i,t-4}$	**0.036 (3.661)**

Notes: Reported figures are average of reparametarised coefficients shown in (6) over firms, The t-ratios are reported in parenthesis, which are based on the variance estimator defined by (10). The estimates which are significant at the 10% level are in bold face.

Table 5: Mean Group Estimates of the Contemporaneous and Lagged Market and Firm Return Effects on Stock Volatility

Volatility Equation			
Coefficients on Market Variables		Coefficients on Firm Variables	
	Mean Group Estimates of Sum over Four Sectors (t-ratio)		Mean Group Estimates (t-ratio)
r^*_{it}	0.002 (0.693)	$r_{i,t}$	**-0.005 (-1.750)**
$r^*_{i,t-1}$	**0.026 (7.706)**	$r_{i,t-1}$	**-0.030 (-15.558)**
$r^*_{i,t-2}$	**0.013 (4.023)**	$r_{i,t-2}$	**-0.014 (-7.611)**
$r^*_{i,t-3}$	**0.008 (2.593)**	$r_{i,t-3}$	**-0.009 (-4.998)**
$r^*_{i,t-4}$	**-0.006 (-1.824)**	$r_{i,t-4}$	0.001 (0.824)

Notes: Reported figures are average of reparametarised coefficients shown in (8) over firms. The t-ratios are reported in parenthesis, which are based on the variance estimator defined by (10). The estimates which are significant at the 10% level are in bold face.

We now turn to Table 5 to examine the leverage effects. The contemporaneous firm return effect on volatility is negative and significant. It appears though that lagged firm return effects on volatility are far more negative and significant. The most significant effect is observed for the one month lagged return with a t-ratio of -15.558. By lag four the firm return effect coefficient becomes non significant. Thus, the leverage effect appears to last three to four months. This is consistent with the finding of Figlewski and Wang (2000). Interestingly the lagged 'market' return effect is predominantly positive and significant. This can be interpreted as follows. Recall that the 'market' return of the i^{th} firm, r^*_{izt}, is a weighted average of all firms except itself. Thus, *ceteris paribus*, a decrease (increase) in the market return will result in the return of firm i being regarded (viewed) as relatively large (small), and therefore the firm's leverage will be regarded as relatively low (high), compared to other firms, on average. Consequently, positive effects are expected.

So far we have focused on the 'market' effects. We now examine the effects of each industrial sector separately, rather than jointly. The estimation results of the effects of the four industrial sectors returns and volatilities are reported in Table 6. Initially we consider the return equation results. Regarding industrial volatility effects, we find that all four industrial volatilities have significant negative effects on firm returns, with the exception of the fourth industrial sector, IT & Telecom. In addition, in the volatility equation, the effect of the first lag of all industrial sector returns is significant and positive, except for IT & Telecom, which is insignificant and negative. Overall, it appears that the IT & Telecom industrial sector behaves rather differently compared to the rest of the sectors, a phenomenon that could be related to the steep growth observed for these two industries over the period under investigation. We would not be able to observe this, had only a single market variable been included in the analysis.

Table 6: Mean Group Estimators of Effects of Four Industrial Sectors Returns and Voatilities

Return Equation (t-ratio)				
	$\ln\sigma^*_{i1t}$ (sector 1)	$\ln\sigma^*_{i2t}$ (sector 2)	$\ln\sigma^*_{i3t}$ (sector 3)	$\ln\sigma^*_{i4t}$ (sector 4)
lag0	**-0.037 (-1.975)**	**-0.136 (-4.375)**	**-0.091 (-3.068)**	**0.051 (2.552)**
lag1	**0.071 (3.395)**	**0.067 (1.899)**	0.017 (0.506)	-0.022 (-0.956)
lag2	**-0.041 (-2.040)**	**0.127 (3.628)**	0.051 (1.500)	-0.033 (-1.518)
lag3	**0.034 (1.754)**	**-0.099 (-2.896)**	-0.013 (-0.423)	**0.051 (2.273)**
lag4	**-0.049 (-2.445)**	0.041 (1.323)	**-0.129 (-4.212)**	**0.061 (2.824)**
Volatility Equation (t-ratio)				
	r^*_{i1t} (sector 1)	r^*_{i2t} (sector 2)	r^*_{i3t} (sector 3)	r^*_{i4t} (sector 4)
lag0	**0.005 (1.884)**	-0.003 (-0.631)	-0.004 (-1.069)	**0.004 (2.073)**
lag1	**0.006 (1.882)**	**0.014 (3.178)**	**0.009 (2.294)**	-0.003 (-1.442)
lag2	**0.007 (2.416)**	0.001 (0.316)	0.003 (0.876)	0.001 (0.853)
lag3	**0.007 (2.209)**	-0.003 (-0.774)	0.002 (0.568)	0.002 (1.233)
lag4	0.001 (0.309)	**-0.008 (-1.906)**	-0.002 (-0.493)	**0.003 (1.725)**

Notes: The return and volatility equations are defined by (6)) and (8), respectively. The t-ratios are reported in parenthesis, which are based on the variance estimator defined by (10). The estimates which are significant at the 10% level are in bold face. The z^{th} sector return (volatility), r^*_{iz} ($\ln\sigma^*_{iz}$), are weighted averages of returns (volatilities) of the firms belonging to z^{th} industrial sector, defined in Table 2. The Sectors contain: Sector 1: Utility; Sector 2: Energy, Materials, Industrials and Financials; Sector 3: Consumer Discretionary, Consumer Staples and Health Care; Section 4: IT & Telecom.

4.2 Long-Run Effects of Business Cycle Variables

As our main focus is on the return-volatility relation, it is necessary to control for the effects of the business cycle variables. However, we also consider the estimation results of these variables *per se* to be of interest, particularly in view of the revived interest of the literature in the relationship between the stock market and economic activity referred to in the introduction. Table 7 reports the mean group estimators of the long-run business cycle variable effects across firms classified as in Table 2. In the return equation, the mean group estimate of the long-run intercept is significantly negative. The firm-average of the sum of the coefficients of the lagged dependent variables is -0.175, which is highly significant, and almost half of the firms have significant lagged effects. Next, in the volatility equation, the firm-average of the sum of the coefficients of the lagged dependent variables is 0.532, which is highly significant, with almost all firm coefficients being significant.

Table 7: Mean Group Estimators Across of the 242 Firms based on the Firm Specific Model Results

Return Equation			Volatility Equation		
	$\overline{\hat{\boldsymbol{\theta}}}_{r,MG}$ (t-ratio)	Mean among Significants (fraction)		$\overline{\hat{\boldsymbol{\theta}}}_{\sigma,MG}$ (t-ratio)	Mean among Significants (fraction)
μ_{ir}	**-0.016 (-3.890)**	-0.062 (0.149)	$\mu_{i\sigma}$	**-0.017 (-3.832)**	-0.061 (0.219)
λ_{ir}	**-0.175 (-15.596)**	-0.285 (0.521)	$\lambda_{i\sigma}$	**0.532 (65.351)**	0.534 (0.996)
Δp	**0.700 (5.099)**	2.205 (0.161)	Δp	-0.196 (-0.895)	0.342 (0.314)
Δip	**-0.268 (-2.706)**	-0.955 (0.169)	Δip	0.029 (0.298)	-0.556 (0.103)
Δue	**-0.105 (-3.273)**	-0.512 (0.149)	Δue	**0.087 (2.248)**	0.319 (0.149)
Δp^{oil}	**-0.024 (-2.589)**	-0.038 (0.256)	Δp^{oil}	**0.016 (2.363)**	0.053 (0.186)
$\Delta m2$	0.137 (1.181)	0.897 (0.202)	$\Delta m2$	0.024 (0.139)	-0.149 (0.326)
ΔDS	**-1.169 (-2.081)**	-0.628 (0.140)	ΔDS	-0.997 (-1.547)	-6.168 (0.165)
ΔTS	0.005 (0.021)	-0.019 (0.223)	ΔTS	0.257 (1.266)	0.971 (0.120)
ΔTB	**-0.435 (-2.008)**	-1.637 (0.202)	ΔTB	0.030 (0.160)	0.301 (0.161)

Notes: The return and volatility equations are defined by (1) and (2), respectively. These equations are estimated by ordinary least squares (OLS) for each firm separately. The mean group estimates of the long-run effects, which are defined in Table 1, are computed and reported as $\overline{\hat{\boldsymbol{\theta}}}_{r,MG}$ and $\overline{\hat{\boldsymbol{\theta}}}_{\sigma,MG}$. The t-ratios of $\overline{\hat{\boldsymbol{\theta}}}_{r,MG}$ and $\overline{\hat{\boldsymbol{\theta}}}_{\sigma,MG}$, reported in parenthesis, are based on the variance estimator defined by (10). The estimates which are significant at the 10% level are in bold face. The third and sixth columns report the averages of long-run effects across firms for which the long-run coefficient is significant at the 10% level (based on Newey-West heteroskedasticity and serial correlation robust variance-covariance estimator with three month lag-window). The fractions of firms for which the coefficient is significant are shown in parenthesis.

4.2.1 Return Equation

Initially we concentrate on the return equation results, namely, the long-run effect of the macro and financial variables on firm returns. As argued by Fama (1981) equity prices reflect main macroeconomic variables such as real economic growth, industrial production and employment. In accordance, Table 7 shows the growth of industrial production to have a significant long-run effect on return.While this effect is negative, not what one would typically expect, this finding is similar to the results of Hassapis and Kalyvitis

(2002) and Park (1997).[13] For unemployment, our results indicate that an increase in growth of this variable has a significant negative effect on stock returns on average. As an indicator of the business cycle and as a measure of the economy's growth potential, an increase in unemployment would be demonstrative of a period of slow down, leading to potential and eventual drops in the value of stocks. On average, inflation has a significant positive effect on stock returns, a result which is in line with the Fisher hypothesis that states a positive relationship between stock returns and inflation contrary to most past empirical literature that shows stock returns are negatively correlated with inflation; see Nelson (1976), Fama and Schwert (1977), Schwert (1981) and Barnes et al. (1999). As in Fama (1990) we find a negative relationship between stock returns and the default spread. On the basis of the work by Fama and French (1989) and Fama (1990) the literature concurs that default spread is a leading indicator of business cycle conditions. Keim and Stambaugh (1986) demonstrate that the default spread together with the term spread are pro-cyclical and capture future developments of the real side of the economy and are consequently able to serve as proxies for macroeconomic shocks to expected cash flows.

The growth of the three month Treasury Bill has a significant negative effect on return, on average. The impact of the short term interest rate on stock returns derives from the well known valuation theory. From the point of view of valuation theory, the fundamental value of a firm's stock is the expected present value of future dividends. Therefore, an increase in future discount rates, should other things being equal, cause stock prices to fall; see also Choi, Elyasiani and Kopecky (1992) and references therein.

We find a significant negative effect of changes in oil prices on stock returns. Increases in oil price depress aggregate stock prices by lowering expected earnings. In fact, Chen et al. (1986) suggest oil prices as a measure of economic risk in the U.S. stock market. Our results corroborate the findings of Jones and Kaul (1996) and Sadorsky (1999) that oil price hikes have a significant and detrimental effect, on average, on the stock market of the US and other countries, with both current and lagged oil price variables affecting stock returns negatively.

On average there appears to be no significant effect of the money market on the stock market supporting the view that if the stock market is efficient, it would already have incorporated all the current and anticipated changes in money supply. A non-significant effect on stock returns is also found for the term spread variable.

[13] In the impulse response analysis that follows, a positive association between these two variables is found, that is a decrease in stock returns is followed by downward movements in growth in industrial production.

4.2.2 Volatility Equation

We now turn to the volatility equation results, focusing on the long-run effect of the business cycle variables. Fornari and Mele (2006) report on the connection between equity return volatility and macroeconomic conditions. In particular, they offer economic explanations of why we should expect financial volatility to be related to future economic developments including certain types of agents' preferences and beliefs, restricted stock-market participation, and even behavioral biases in the human perception of risk. Such a connection dates back to the work of Schwert (1989) who finds evidence that stock market volatility is related to the general health of the economy. One interpretation of this evidence as he posits is caused by financial leverage. Leverage increases during recessions, causing an increase in the volatility of leveraged stocks.

We find that an increase in the growth of unemployment has a significant positive effect, on average, on stock market volatility. This result appears to be in line with the findings in the study by Hamilton and Lin (1996) that arrives at the conclusion that economic recessions are the single largest factors causing increased stock market volatility, accounting for more than 60 % of the variance of stock returns. In fact, these authors observe that a model for stock market volatility that lacks macroeconomic factors is insufficient and that macroeconomic factors are key determinants in explaining stock market volatility and returns. Hamilton and Susmel (1994) also find that equity volatility is more likely to become (remain) high during a recession, which link to the recent findings of Fornari and Mele (2006) who observe that all recession episodes are associated with an increase in volatility and that stock-market volatility anticipates positive turning points in a remarkable manner.

An increase in the growth of oil prices whichs adds to the uncertainty in the economy, also displays a significant positive effect, on average, on stock market volatility. There is no significant effect of the rest of the business cycle variables on stock market volatility. However, it is interesting to note that while inflation on average has no significant effect on volatility, the proportion of individual firms that have significant inflation effects on volatility is quite high 31.4% with the average effect among significant firms equal to 0.342. The same is true for money growth yielding 32.6% and -0.149, respectively. This is in contrast to the growth of industrial production, the default spread, the term spread and three month Treasury bill rate for which a much lower number, roughly half of individual firms, exhibit significant effects on volatility.

4.3 Structural Stability

In this section we undertake individual equation stability tests of our firm specific models to examine the structural stability of the parameter coefficients and error variances. We consider the test for parameter constancy against non-stationary alternatives proposed by Nyblom (1989) together with the heteroskedasticity-robust version of this test, as well as Ploberger and Krämer's (1992) maximal OLS cumulative sum statistic (PK_{sup}) and mean square variant (PK_{msq}). The PK_{sup} test statistic is similar to the CUSUM test suggested by Brown et al (1975), although the latter is based on recursive rather than OLS residuals.[14]

Table 8 below presents the results of the alternative tests per variable at the 5% significance level.

Table 8: Number of Firm Equations of which the Null of Parameter Constancy is Rejected

Alternative test statistics	Return	Volatility
$\mathcal{N}$	58(24.0)	15(6.2)
Robust-$\mathcal{N}$	29(12.0)	22(9.1)
PK_{sup}	5(2.1)	22(9.1)
PK_{msq}	1(0.4)	11(4.5)

Note: The reported numbers are the number of firm return and volatility equations, of which the null of parameter constancy is rejected. The fraction is reported in the parenthesis. $\mathcal{N}$ is the Nyblom (1989) test for time-varying parameters and Robust-$\mathcal{N}$ denotes its heteroskedasticity robust version. The test statistics PK_{sup} and PK_{msq} are Ploberger and Krämer's (1992) maximal OLS cumulative sum statistic and mean square variant respectively, and are based on the cumulative sums of *OLS* residuals. All tests are implemented at the 5% significance level, based on bootstrap critical values.

For the Nyblom test the null hypothesis of parameter stability is rejected for 15.1% of the return and volatility equations, and once possible changes in error variances are allowed for, this number drops to 10.5%. Using the PK tests the null hypothesis of parameter stability is rejected for 5.6% of the return and volatility equations for the PK_{sup} test, and 2.5% for the PK_{msq} statistic.

Overall the above test results show that the parameter coefficients of the majority of firm equations appear to have been reasonably stable. This is evidence that our models are rich enough to successfully capture the structural changes in the parameter coefficients

[14] The critical values of the structural stability tests for the individual firm equations, computed under the null of parameter stability, were calculated using the sieve bootstrap samples obtained from the system of the entire 242 firm returns and volatilities including the business cycle variables, given by (11). Detailed results of the structural breaks tests and of the bootstrap procedure are available upon request.

over the time span of the data considered by inclusion of the industrial sector variables and business cycle variables. In view of the robust Nyblom test results a fair portion of the number of rejections noted appears to be attributed to changes in error variances, rather than the parameter coefficients. This is dealt with by considering heteroskedasticity robust standard errors when reporting the estimation results.

4.4 Residual Correlation Matrix

We next consider the cross section correlation matrix of the residuals, which is expected to measure how well the systematic risks are captured. Table 9 reports the average correlation of residuals of the return equations within the nine industries, for both the specifications of four and one sectors.[15] In the case of the four sector specification, given in Tables 6& 7, the average of the within industry residual correlations is 0.07. There are only two industries for which the average of the within industry correlation coefficients exceeds 0.10, while there are six such industries for the one sector model. In the case of the one sector model, the average of the within industry residual correlation is 0.16, which is more than double that of the four sector case. These results confirm that the four sector specification captures systematic risks much better than the one sector specification.[16]

[15] In order to check the robustness of the estimation results reported above, we considered alternative specifications. The first specification differs from that described above only in that the estimation includes solely 'market' return and volatility, r_i^* and $\ln \sigma_i^*$, which are weighted averages of return and volatility across firms, that is the number of sectors is one instead of four. Another specification adopted differs from that given above only in that the default spread, term spread and three month treasury bills are all in levels, rather than in changes. The results were qualitatively similar to those presented earlier. Detailed results are available upon request.

[16] In the volatility equation similar findings emerge as in the case of the return equations when comparing the four sector and one sector specifications. Full residual correlation matrices are available upon request from the authors.

Table 9: Average Correlation of Residuals of Return and Volatility Equations, within and between Nine Industries

Industries	**Four Sectors**	**One Sector**
Utilities	-0.02	**0.38**
Energy	**0.23**	**0.28**
Materials	**0.11**	**0.13**
Industrials	0.08	**0.11**
Financials	0.09	**0.14**
Consumer Discretionary	0.08	0.08
Consumer Staples	0.04	0.09
Health Care	0.04	0.07
IT&Telecom	0.02	**0.14**
Average	0.07	0.16

Notes: The figures are average residual correlation coefficient between the pairs of firms in the same industry. The figures in bold face are more than or equal to 0.10 in absolute value.

5 Impulse Response Analysis

To further understand the dynamic behaviour of the interrelation between return and volatility we consider generalised impulse response analysis advanced by Pesaran and Shin (1998). To this end, we rewrite the bivariate firm specific models consisting of equations (1) and (2), as a large system comprising the entire disaggregated set of firm returns, volatilities and business cycle variables. Generalised impulse response analysis allows for the interdependence of shocks and is invariant to the ordering of the firms/industries and variables in our model, given that no natural ordering of firms and variables is apparent.

5.1 Solving for Firm Returns,Firm Volatilities and Business Cycle Variables

Having estimated consistently the individual firm models given by (1) and (2), we now combine them in such a manner as to yield a large system of the entire set of firm returns, firm volatilities and business cycle variables, preserving all complicated dynamic interrelationships between and across firms. This is achieved by using the fact that the industrial sector variables, $(r^*_{izt}, \ln \sigma^*_{izt})$, are weighted averages of the firm variables, $(r_{it}, \ln \sigma_{it})$.

Defining the collection of all firm returns, firm volatilities and busyness cycle variables as $\mathbf{y}_t = (\mathbf{x}'_t, \mathbf{d}'_t)'$, with dimension $2{\times}242{+}8 = 452$, where $\mathbf{x}_t = \{(r_{1t}, \ln \sigma_{2t})\,; ...; (r_{Nt}, \ln \sigma_{Nt})\}'$, following Pesaran, Schuermann and Weiner (2004) the models (1) and (2) can be combined in such a way as to yield a vector autoregression of the form,[17]

$$\mathbf{y}_t = \boldsymbol{\alpha} + \sum_{\ell=1}^{\max(p,q,g)} \boldsymbol{\Lambda}_\ell \mathbf{y}_{t-\ell} + \mathbf{C}\boldsymbol{\zeta}_t \tag{11}$$

where the coefficients of (11) embody the cross-firm interdependencies and are determined by the parameters of the underlying firm specific models. The error term consists of two components, $\boldsymbol{\zeta}_t = (\mathbf{v}_t', \boldsymbol{\eta}_{dt}')'$, corresponding to the firm variables, $\mathbf{x}_t$, and the busyness cycle variables, $\mathbf{d}_t$, respectively. Apart from the assumption that $\mathbf{v}_t$ and $\boldsymbol{\eta}_{dt}$ are uncorrelated due to the weak exogeneity assumption of the business cycle variables, there are no other restrictions on the covariance matrix $\boldsymbol{\Omega}_\zeta = E(\boldsymbol{\zeta}_t\boldsymbol{\zeta}_t')$. Hence, a natural estimator of $\boldsymbol{\Omega}_\zeta$ is $\hat{\Omega}_\zeta = \sum_{t=1}^{T} \boldsymbol{\zeta}_t\boldsymbol{\zeta}_t'/T$. The VAR model given by (11) is stable in that all its roots lie inside the unit circle.[18]

5.2 Impulse Response Functions

Let $\mathbf{y}_t = \boldsymbol{\mu} + \sum_{\ell=0}^{\infty} \boldsymbol{\Xi}_\ell \boldsymbol{\epsilon}_{t-\ell}$ be the infinite moving average representation of (11) where $\boldsymbol{\epsilon}_t = \mathbf{C}\boldsymbol{\zeta}_t$ and $\boldsymbol{\Xi}_\ell$ can be derived recursively as $\boldsymbol{\Xi}_\ell = \boldsymbol{\Lambda}_1\boldsymbol{\Xi}_{\ell-1} + \boldsymbol{\Lambda}_2\boldsymbol{\Xi}_{\ell-2} + ... + \boldsymbol{\Lambda}_{\max(p,q,g)}\boldsymbol{\Xi}_{\ell-\max(p,q,g)}$, $\ell = 1, 2, ...$with $\boldsymbol{\Xi}_0 = \mathbf{I}_{Nk+n}$, $\boldsymbol{\Xi}_\ell = \mathbf{0}$ for $\ell < 0$. The generalised impulse response function (GIRF) to a one standard deviation shock at time t over the horizon $h = 0, 1, 2, ...$ is defined by

$$\boldsymbol{\psi}(h) = E\left(\mathbf{y}_{t+h} | \zeta_t^g = \sqrt{\mathbf{g}'\boldsymbol{\Omega}_\zeta\mathbf{g}}, \mathcal{I}_{t-1}\right) - E\left(\mathbf{y}_{t+h} | \mathcal{I}_{t-1}\right),$$

where $\mathbf{g}$ is a $(kN + n \times 1)$ selection vector, whose corresponding element to be shocked is one and zero otherwise, and $\mathcal{I}_{t-1}$ is the inf ormation set up to time $t-1$. Under the assumption that $\boldsymbol{\zeta}_t$ has a multivariate normal distribution or the conditional expectations can be assumed linear, the GIRF can be derived as

$$\boldsymbol{\psi}(h) = \frac{\boldsymbol{\Xi}_h \mathbf{C}\boldsymbol{\Omega}_\zeta\mathbf{g}}{\sqrt{\mathbf{g}'\boldsymbol{\Omega}_\zeta\mathbf{g}}}, \quad h = 0, 1, 2, ... \tag{12}$$

Our model allows us to assess the time profile of the effects of a variety of shocks, which are determined by the selection vector, $\mathbf{g}$.[19] Given the focus of the paper, and considering the importance of (unexpected) news effects on the stock market, we are interested in

[17] A detailed derivation of (11) can be found in the Appendix A.2.

[18] This is supported by the eigenvalues of the model. The eigenvalues with the largest complex part are $0.121 \pm 0.767i$, $0.018 \pm 0.765i$ and $-0.320 \pm 0.758i$, where $i = \sqrt{-1}$. The three largest eigenvalues (in moduli) are 0.934, 0.930 and 0.923.

[19] For example, shock to the return/volatility of a particular firm, shock to an industry return/volatility, market-wide shocks to return, and shock to a macro/financial variable.

market-wide shocks to return and volatility and their effects on the individual industries as classified in Table 2. It is these shocks that we focus on in the discussion of the impulse response functions that follows, while as a by product we also refer to the effect of such shocks on the business cycle variables.

5.3 Empirical Results of Impulse Response Functions

Figures 1-6 show the impulse response bootstrap mean estimates arising from market-wide shocks to the return and volatility equations and their effects on the individual industries and business cycle variables in the system, together with the 90 per cent bootstrap error bands. Note that market-wide shocks refer to a simultaneous value weighted shock across all individual firms/industries, while all effects on business cycles variables, excluding inflation, are for the growth rates of the variables under consideration. All references to volatility, including shocks and responses, are to the standard deviation of equity volatility.

Figure 1 shows the effect of a market-wide negative one standard error shock to industrial returns on industrial returns themselves. Such a shock is equivalent to a 4.5% average fall, on impact, in returns across industries. The largest drop corresponds to the IT & Telecom services, 6.9%, and the lowest to the Utilities industry, 1.7%, reflecting the importance of the former in the S&P index. Returns stabilize reasonably quickly, after exhibiting some jittery behaviour, roughly by the end of the first year.

Figure 2 shows the effect of a market-wide negative one standard error shock to industrial returns on industrial realized volatilities. The transmission of such a shock to volatility across industries appears to be rather rapid and in most cases significant. The standard deviation of equity volatility of Utilities, Consumer Staples and Energy displays a significant increase of 0.35% , 0.34% and 0.36%, respectively, on impact for the former two industries, and in the first month for the latter. The rest of the industries, excluding Materials for which no significant effect is observed, exhibit a significant increase in realized volatility both on impact and in the first month, by 0.37% on average for Industrials, 0.40% for Financials, 0.33% for Consumer Discretionary, 0.39% for Health Care and 0.40% for IT & Telecom services. In all cases the effect of such a shock dies out roughly by the end of the first year.

Figure 3 reports on the effect of a market-wide negative one standard error shock to industrial returns on the business cycle variables. In particular, inflation exhibits a significant decline of 0.02% in the first month. For industrial production, the negative market-wide return shock is accompanied by a minor, though insignificant, increase the first month followed by a significant decline of 0.08% on average over the subsequent three months, with the decline peeking in the third month at 0.12%. For the oil price there appears to be a significant increase in the second (0.18%) and fourth (0.2%) months. Unemployment displays a significant positive response at 0.68% in the first month and 0.38% in the seven month. A significant positive increase is observed for the default spread over the first three months, equal to 0.009% on average, while there is a significant decrease in the relative T-Bill over the first two months of 0.06% on average. There is no significant effect on M2 or the Term Spread.

Turning to volatility, Figure 4 depicts the effect of a market-wide positive unit one standard error shock to industrial realized volatility and its effect on industrial returns. Such a shock displays a significant decrease on impact, only, for all Industries, excluding Energy, Financials and Health Care for which no significant effect is observed. For the industries that exhibit significant responses, these range from 0.67% for Utilities to 1.33% for Materials.

Figure 5 shows the effect of a market-wide positive unit one standard error shock to industrial realized volatility on industrial realized volatility itself. Reflecting the persistence nature of volatility, for Industrials, Financials and IT & Telecom Services the effect of such a shock is significant for a one year period. For the rest of the industries it is significant for just over half a year. A market-wide positive unit one standard error shock to industrial realized volatility is equivalent to a 1.7% average fall, on impact, in realized volatility across industries. The largest drop is noted for Health Care and Consumer Staples followed by Industrials, Financials, IT&Telecom Services and Consumer Discretionary. For those months over which significant responses are observed, realized volatility ranges from 0.53% to 0.91% on average across the different industries, the lowest average value observed for Utilities and the highest for Health Care, Consumer Staples and Consumer Discretionary.

Figure 6 shows the responses of an market-wide positive unit one standard error shock to industrial realized volatility on the business cycle variables. In particular, inflation exhibits a significant decrease of 0.03% on average over the first two months. A slight increase in industrial production is observed in the first month, though insignificant, followed by a significant decrease of 0.06% on average in the two subsequent months. The oil price exhibits a positive significant increase of 0.38% in the second month. There is a significant positive effect of 0.009% on average for the default spread over the first three months. The term spread exhibits a significant decrease of 0.03% in the first month. M2 shows a significant positive increase of 0.02% both in the fourth and sixth month. A significant negative effect on unemployment of 0.6% is noted in the third month. There is no significant effect on the relative T-Bill.

On the whole, the above results indicate that after controlling for business cycle effects, unobserved cross sectional correlations in return and volatility, as well as heterogeneity across firms, responses of firm volatility to an adverse market-wide return shock reveal significant evidence of the leverage effect for the majority of industries. These findings are in line with the estimation results of the firm specific volatility equations. Responses of firm equity returns to a rise in market-wide volatility further highlight the presence of significant volatility feedback effects on impact, at the industry level. These effects however do not appear to significantly persist thereafter, which was the case for the individual firm return equations in the estimation results reported earlier. As for the business cycle variables, we find that the majority of the variables considered are significantly affected by market-wide return and volatility shocks.

6 Concluding Remarks

This paper has examined "leverage" and volatility feedback effects at the firm level by considering both market effects and firm level effects, for 242 individual firm stock data in the US market. We adopt a panel vector autoregressive framework which allows us to control simultaneously for common business cycle effects, unobserved cross correlation effects in return and volatility via industry effects, and heterogeneity across firms.

Based on estimates of the individual firm models, we find strong evidence of a large negative contemporaneous market volatility effect, though this is not the case for the contemporaneous negative firm level volatility feedback effect which is not significant. Lagged volatility feedback effects, on the other hand, appear significant for both 'market' volatility and firm level volatility and are predominantly positive. Our results therefore suggest that volatility feedback effects at the firm level are present due to both market effects and firm effects, though the market volatility feedback effect is stronger than the firm level volatility feedback effect. These findings can be linked to the non-diversifiable nature of market risk and the need of firms with higher idiosyncratic volatility or firm specific risk to require higher returns to compensate for imperfect diversification. We also find that negative and significant firm leverage effects are at work, which appear to last three to four months. Interestingly significant lagged 'market' return effects are also detected and are predominantly positive. This would be expected based on a relativety argument and given that the 'market' return of the the individual firm is a weighted average of all firms except itself.

The decomposition of the 'market' effects into industrial return and volatility effects, contrary to most existing studies that control for market variables only, highlights a rather distinct behaviour of the IT&Telecom industrial sector over the period under examination, in comparison to the rest of the sectors. In addition, the correlation matrices of residuals reveal that our four industrial sector model captures unobserved common factors much better than the one market factor model.

Our approach enables us to combine the firm specific equations to form a large system of the entire disaggregated set of firm returns and volatilities including the business cycle variables, preserving all complicated dynamic interrelationships between and across firms. This in turn allows us to conduct impulse response analysis to obtain a better understanding of the dynamic behaviour of the interrelation between return and volatility. Results indicate that after controlling for business cycle effects, unobserved cross sectional correlations in return and volatility, as well as heterogeneity across firms, responses of firm volatility to an adverse market-wide return shock reveal significant evidence of the leverage effect for the majority of industries. These findings are in line with the estimation results of the firm specific volatility equations. Responses of firm equity returns to a rise in market-wide volatility further highlight the presence of significant volatility feedback effects on impact, at the industry level. These effects however do not appear to significantly persist thereafter, which was the case for the individual firm return equations in the estimation results.

With regard to the business cycle variables, based on estimates of the firm specific models, we find most of these variables to have significant effects, on average, on stock returns with the expected signs. In particular, we find inflation to have a significant positive effect on stock returns, a result which is in line with the Fisher hypothesis though contrary to most past empirical literature that finds stock returns to be negatively correlated with inflation. The growth rate of the number of unemployed and of oil prices are the only variables to have a significant effect, on average, on firm volatility. In terms of the impulse response estimates, we find that the majority of the business cycle variables considered are significantly affected by market-wide return and volatility shocks.

Our approach can clearly be extended to the analysis of stock market indices across countries rather than focussing solely on S&P500 stocks, while it would also be of interest to examine the forecasting ability of the proposed model. These avenues remain to be explored in future research.

Appendix

A.1 Choice of Lag-Orders p, q

The choice of the lag orders p and q in the models (1) and (2) is based on joint consideration of the multivariate Akaike Information Criterion (MAIC) and test results for error serial correlation. The fraction of firms for which the lag orders (p_{ij}, q_{ij}) are chosen based on the MAIC is given in Table 10 for (max$p$,max$q$)=(12,4).

The highest fraction is given for $q = 1$, $p = 3$, while it gradually decreases as p increases. We select $p = 4$, since for $q = 1$ and p up to 4 covers 60.3% of firms. The fraction of rejections of the error serial correlation test statistics over all firms, for each return and volatility equation are shown in Table 11. As expected, the return equation displays little evidence of residual serial correlation with $p = 4$. Only around 5.0-7.4% of firms reject the null of no serial correlation. The volatility equation shows more evidence of residual serial correlation. When $p = 4$ and $q = 1$, the fraction of rejections of no serial correlation is 29.3%, while only 9.5% when $p = 4$ and $q = 4$. Based on the above, we adopt the VARX*$(4, 4)$ specification as the most preferable, which covers 65.7% of the specifications of firms chosen by MAIC, while gives the smallest number of firms suffering from error serial correlation.[20]

Table 10: Fraction of Firms for which the lag-order p,q are Chosen by AIC

(p, q)	$q = 1$	$q = 2$	$q = 3$	$q = 4$
$p = 1$	0.062	0.000	0.000	0.000
$p = 2$	0.157	0.017	0.000	0.000
$p = 3$	0.260	0.025	0.004	0.000
$p = 4$	0.124	0.008	0.000	0.000
$p = 5$	0.091	0.004	0.000	0.000
$p = 6$	0.087	0.004	0.000	0.000
$p = 7$	0.029	0.000	0.000	0.008
$p = 8$	0.029	0.000	0.000	0.000
$p = 9$	0.021	0.004	0.004	0.000
$p = 10$	0.025	0.000	0.004	0.000
$p = 11$	0.004	0.000	0.000	0.000
$p = 12$	0.017	0.012	0.000	0.000

Notes: The choice is based on the multivariate version of the Akaike Information Criteria (MAIC), for the firm specific return-volatility variables with (max$p$,max$q$)=(12,4).

[20]This specification requires 89 parameters to be estimated in each equation with 408 observations. The number of parameters and observations, and the frequency of the data specified here (monthly) are similar to influential VAR studies, such as Bernanke and Mihov (1998) and Hanson (2006).

Table 11: Fraction of Firms for which the hypothesis of No Error Serial Correlation is Rejected

VARX*(p,q)	(4,1)	(4,2)	(4,3)	(4,4)
Fractions of Rejections in r_{ijt} Equation				
	0.070	0.062	0.050	0.074
Fractions of Rejections in $\ln \sigma_{ijt}$ Equation				
	0.326	0.174	0.153	0.095

A.2 Derivation of Equation (11)

Defining

$$\mathbf{x}_{ijt} = (r_{ijt}, \ln \sigma_{ijt})', \; i = 1, 2, ..., N_j; j = 1, 2, ..., S; t = 1, 2, ..., T$$

the models (1) and (2) are compactly expressed in a vector autoregressive VARX*(p, q) model of the form

$$\mathbf{x}_{ijt} = \boldsymbol{\alpha}_{ijx} + \sum_{\ell=1}^{p} \boldsymbol{\Phi}_{ij\ell} \mathbf{x}_{ij,t-\ell} + \sum_{z=1}^{S} \sum_{\ell=0}^{q} \boldsymbol{\Gamma}_{ijz\ell} \mathbf{x}^{*}_{ijz,t-\ell} + \sum_{\ell=0}^{q} \boldsymbol{\Gamma}_{ijd\ell} \mathbf{d}_{t-\ell} + \mathbf{v}_{ijt}. \tag{A.2}$$

While the individual firm specific models are estimated separately, they are combined in a consistent manner along the lines of the global VAR modelling framework proposed by Pesaran, Schuermann and Weiner (2004) and further developed by Dees, di Mauro, Pesaran and Smith (2007), to form a model in terms of $\mathbf{x}_t = (\mathbf{x}'_{11t}, \mathbf{x}'_{21t}, ..., \mathbf{x}'_{N_1 1t}; \mathbf{x}'_{12t}, ...; \mathbf{x}'_{1St}, \mathbf{x}'_{2St}, ..., \mathbf{x}'_{N_s St})'$. The key to solving the model is to note that the link between x_t and the variables in the i^{th} firm specific model, which can be expressed in terms of $(\mathbf{x}'_{ijt}; \mathbf{x}^{*\prime}_{ij1t}, ..., \mathbf{x}^{*\prime}_{ijSt})'$, is given by the identity

$$(\mathbf{x}'_{ijt}; \mathbf{x}^{*\prime}_{ij1t}, ..., \mathbf{x}^{*\prime}_{ijSt})' = \underset{(k(S+1)\times kN)}{\mathbf{W}_{ij}} \underset{(kN\times 1)}{\mathbf{x}_t} \tag{A.3}$$

where $\mathbf{W}_{ij} = (\mathcal{W}_{ij,11}; ...; \mathcal{W}_{ij,rz}; ...; \mathcal{W}_{ij,N_s S})$ is a $(k(S+1) \times kN)$ 'link' matrix defined by the value weights with

$$\mathcal{W}_{ij,rz} = \begin{cases} \begin{pmatrix} \mathbf{I}_k \\ \mathbf{e}_{S,z} \otimes \omega_{ij,rz} \mathbf{I}_k \end{pmatrix} & \text{for } i = r \text{ and } j = z \\ \begin{pmatrix} \mathbf{0}_{k\times k} \\ \mathbf{e}_{S,z} \otimes \omega_{ij,rz} \mathbf{I}_k \end{pmatrix} & \text{otherwise,} \end{cases}$$

where $\mathbf{0}_{k\times k}$ is a $(k \times k)$ matrix of zeros and $\mathbf{e}_{S,z}$ is an $(S \times 1)$ elementary vector with z^{th} element equal to one and zero otherwise.

For the purpose of impulse response analysis the process for the observed common components $\mathbf{d}_t$ needs to be defined, which was not required during the estimation stage of the firm specific models. We consider the following model for $\mathbf{d}_t$ given by

$$\mathbf{d}_t = \boldsymbol{\alpha}_d + \sum_{j=1}^{S} \sum_{\ell=1}^{g} \mathbf{D}_{1dj\ell} \bar{\mathbf{x}}_{j,t-\ell} + \sum_{\ell=1}^{g} \mathbf{D}_{2d\ell} \mathbf{d}_{t-\ell} + \boldsymbol{\eta}_{dt}, \tag{A.4}$$

where

$$\bar{\mathbf{x}}_{jt} = \sum_{i=1}^{N_j} \omega_{ij} \mathbf{x}_{ijt}. \tag{A.5}$$

The $\boldsymbol{\eta}_{dt}$ and $\mathbf{v}_{ijt}$ innovations are assumed to be uncorrelated, so that $\mathbf{d}_t$ is weakly exogenous for $\mathbf{x}_{ijt}$. This is reasonable, as we do not expect that a single firm can affect the market or macro/financial variables, conditioning on its industry and/or market. The multivariate AIC with a maximum lag-order of 6 selects $g = 1$, however, the null of no error serial correlation is rejected for seven equations out of eight. Increasing the g to 2,3,4 the number of rejected equations becomes 4, 4 and 1, respectively. Therefore, $g = 4$ is chosen.[21]

Using the identity

$$(\mathbf{x}'_{ijt};\mathbf{x}^{*\prime}_{ij1t},...,\mathbf{x}^{*\prime}_{ijSt})' = \underset{(k(S+1)\times kN)}{\mathbf{W}_{ij}} \underset{(kN\times 1)}{\mathbf{x}_t}$$

(A.2) can be written as

$$\mathbf{A}_{ij}\mathbf{x}_t = \boldsymbol{\alpha}_{ijx} + \sum_{\ell=1}^{\max(p,q,g)} \mathbf{B}_{ij\ell}\mathbf{x}_{t-\ell} + \sum_{\ell=0}^{\max(p,q,g)} \boldsymbol{\Gamma}_{ijd\ell}\mathbf{d}_{t-\ell} + \mathbf{v}_{ijt},$$

where

$$\begin{aligned} \underset{(k\times kN)}{\mathbf{A}_{ij}} &= [\mathbf{I}_k; -\boldsymbol{\Gamma}_{ij10}; -\boldsymbol{\Gamma}_{ij20}; ...; -\boldsymbol{\Gamma}_{ijS0}]\,\mathbf{W}_{ij}, \\ \underset{(k\times kN)}{\mathbf{B}_{ij\ell}} &= \left[\boldsymbol{\Phi}_{ij\ell}; \boldsymbol{\Gamma}_{ij1\ell}; \boldsymbol{\Gamma}_{ij2\ell}; ...; \boldsymbol{\Gamma}_{ijS\ell}\right]\mathbf{W}_{ij}. \end{aligned}$$

Stacking the above equations for all i and j we obtain

$$\mathbf{G}\mathbf{x}_t = \boldsymbol{\alpha}_x + \sum_{\ell=1}^{\max(p,q,g)} \mathbf{H}_\ell\mathbf{x}_{t-\ell} + \sum_{\ell=0}^{\max(p,q,g)} \boldsymbol{\Pi}_{d\ell}\mathbf{d}_{t-\ell} + \mathbf{v}_t,$$

where

$$\begin{aligned} \underset{(kN\times kN)}{\mathbf{G}} &= \left(\mathbf{A}'_{11}, \mathbf{A}'_{21}, ..., \mathbf{A}'_{N_sS}\right)', \quad \underset{(kN\times kN)}{\mathbf{H}_\ell} = \left(\mathbf{B}'_{11\ell}, \mathbf{B}'_{21\ell}, ..., \mathbf{B}'_{N_sS\ell}\right)' \\ \underset{(kN\times n)}{\boldsymbol{\Pi}_{d\ell}} &= \left(\boldsymbol{\Gamma}'_{11d\ell}, \boldsymbol{\Gamma}'_{21d\ell}, ..., \boldsymbol{\Gamma}'_{N_sSd\ell}\right)', \quad \underset{(kN\times 1)}{\mathbf{v}_t} = \left(\mathbf{v}'_{11t}, \mathbf{v}'_{21t}, ..., \mathbf{v}'_{N_sSt}\right)'. \end{aligned}$$

Assuming that $\mathbf{G}$ is invertible, we have

$$\mathbf{x}_t = \mathbf{G}^{-1}\boldsymbol{\alpha}_x + \sum_{\ell=1}^{\max(p,q,g)} \mathbf{G}^{-1}\mathbf{H}_\ell\mathbf{x}_{t-\ell} + \sum_{\ell=0}^{\max(p,q,g)} \mathbf{G}^{-1}\boldsymbol{\Pi}_{d\ell}\mathbf{d}_{t-\ell} + \mathbf{G}^{-1}\mathbf{v}_t. \tag{A.6}$$

Now define

$$\bar{\mathbf{W}}_j = \left(\bar{\mathcal{W}}_{j1}; \bar{\mathcal{W}}_{j2}; ...; \bar{\mathcal{W}}_{jS}\right)(k\times kN)$$

with

$$\bar{\mathcal{W}}_{jz} = \begin{cases} \left(\frac{\omega_{1j}}{\sum_{i=1}^{N_j}\omega_{ij}}, \frac{\omega_{2j}}{\sum_{i=1}^{N_j}\omega_{ij}}, ..., \frac{\omega_{N_jj}}{\sum_{i=1}^{N_j}\omega_{ij}}\right)\otimes\mathbf{I}_k & \text{for } j = z \\ \mathbf{0}'_{N_z}\otimes\mathbf{I}_k & \text{otherwise,} \end{cases}$$

so that

$$\bar{\mathbf{x}}_{j,t-\ell} = \bar{\mathbf{W}}_j\mathbf{x}_{t-\ell}.$$

Further, define $\mathbf{D}_{1d\ell} = [\mathbf{D}_{1d1\ell}, \mathbf{D}_{1d2\ell}, ..., \mathbf{D}_{1dS\ell}]$ $(n\times Sk)$ and $\bar{\mathbf{W}} = [\bar{\mathbf{W}}'_1, \bar{\mathbf{W}}'_2, ..., \bar{\mathbf{W}}'_S]'$ $(Sk\times kN)$, so that (A.4) can be written as[22]

$$\mathbf{d}_t = \boldsymbol{\alpha}_d + \sum_{\ell=1}^{\max(p,q,g)} \mathbf{D}_{1d\ell}\bar{\mathbf{W}}\mathbf{x}_{t-\ell} + \sum_{\ell=1}^{\max(p,q,g)} \mathbf{D}_{2d\ell}\mathbf{d}_{t-\ell} + \boldsymbol{\eta}_{dt}. \tag{A.7}$$

[21] The estimation results of equation (A.4) are not reported here, but are available upon request from the authors.

[22] Note that the coefficients for ℓ such that $p, q, g < \ell \leq \max(p, q, g)$, are set to matrices of zeros.

Defining $\mathbf{y}_t = (\mathbf{x}'_t, \mathbf{d}'_t)'$, equations (A.6) and (A.7) can be written as

$$\mathbf{y}_t = \boldsymbol{\alpha} + \sum_{\ell=1}^{\max(p,q,g)} \boldsymbol{\Lambda}_\ell \mathbf{y}_{t-\ell} + \mathbf{C}\boldsymbol{\zeta}_t$$

where

$$\underset{(kN+n\times 1)}{\boldsymbol{\alpha}} = \begin{bmatrix} \mathbf{G}^{-1}\left(\boldsymbol{\alpha}_x + \boldsymbol{\Pi}_{d0}\boldsymbol{\alpha}_d\right) \\ \hat{\boldsymbol{\alpha}}_d \end{bmatrix},$$

$$\underset{(kN+n\times kN+n)}{\boldsymbol{\Lambda}_\ell} = \begin{bmatrix} \mathbf{G}^{-1}\left[\mathbf{H}_\ell + \boldsymbol{\Pi}_{d0}\mathbf{D}_{1d\ell}\bar{\mathbf{W}}\right] & \mathbf{G}^{-1}\left[\boldsymbol{\Pi}_{d\ell} + \boldsymbol{\Pi}_{d0}\mathbf{D}_{2d\ell}\right] \\ \mathbf{D}_{1d\ell}\bar{\mathbf{W}} & \mathbf{D}_{2d\ell} \end{bmatrix},$$

and

$$\mathbf{C} = \begin{bmatrix} \mathbf{G}^{-1} & \mathbf{G}^{-1}\boldsymbol{\Pi}_{d0} \\ \mathbf{0} & \mathbf{I}_n \end{bmatrix}, \underset{(kN+n\times 1)}{\boldsymbol{\zeta}_t} = \begin{bmatrix} \mathbf{v}_t \\ \boldsymbol{\eta}_{dt} \end{bmatrix}, \boldsymbol{\zeta}_t \sim iid(\mathbf{0}, \boldsymbol{\Omega}_\zeta).$$

Note that $\mathbf{v}_t$ and $\boldsymbol{\eta}_{dt}$ are assumed to be uncorrelated.

References

Andersen, T. G. and B. Sørensen (1996). GMM estimation of a stochastic volatility model: a Monte Carlo study. *Journal of Business and Economic Statistics*, 14, 328-352.

Bai, J. and S. Ng (2002). Determining the number of factors in approximate factor models. *Econometrica*, 70, 191-221.

Bansal, R. and A. Yaron (2004). Risks for the long run: a potential resolution of asset pricing puzzles. *Journal of Finance,* 59, 1481-1509.

Barnes, M., Boyd, J.H. and B.D. Smith (1999). Inflation and asset returns. *European Economic Review,* 43, 737–754.

Bekaert, G. and G. Wu (2000). Asymmetric volatility and risk in equity markets. *Review of Financial Studies*, 13, 1–42.

Bernanke, B. S. and I. Mihov (1998). Measuring monetary policy. *Quarterly Journal of Economics*, 113, 869–902.

Black, F. (1976). Studies of stock market volatility changes. Proceedings of the American Statistical Association, Business and Economic Statistics Section, 177-181.

Brandt, M.W. and Q. Kang (2004). On the relationship between the conditional mean and volatility of stock returns: A latent VAR approach. *Journal of Financial Economics*, 72, 217-257.

Brown, R.L., Durbin, J. and J.M. Evans (1975). Techniques for testing the constancy of regression relationships over time. *Journal of the Royal Statistical Society Series B*, 37, 149–192.

Campbell, J.Y. (1987). Stock Returns and the term structure. *Journal of Financial Economics*, 373- 99.

Campbell, J. and L. Hentschel (1992). No news is good news: an asymmetric model of changing volatility in stock returns. *Journal of Financial Economics*, 31, 281–318.

Choi, J. J., Elyasiani, E. and K. J. Kopecky (1992). The sensitivity of bank stock returns to market, interest and exchange rate risks. *Journal of Banking and Finance*, 16, 983-1004.

Chen, N., Roll, R. and S. Ross (1986). Economic forces and the stock market. *Journal of Business*, 59, 383-403.

Christie, A.A. (1982). The stochastic behavior of common stock variances: value, leverage and interest rate effects. *Journal of Financial Economics*, 10, 407-432.

Dees, S., Di Mauro, F., Pesaran, M.H. and L.V. Smith (2007). Exploring the international linkages of the euro area: a global VAR analysis. *Journal of Applied Econometrics*, 22, 1-38.

Duffee, G.R. (1995). Stock return and volatility: a firm-level analysis. *Journal of Financial Economics*, 37, 399-420.

Engle, R.F., Ghysels, E. and B. Sohn (2006). On the economic sources of stock market volatility, *mimeo.*

Fama, E.F. (1981). Stock returns, real activity, inflation and money. *American Economic Review,* 71, 545–565.

Fama, E.F. (1990). Stock returns, expected returns, and real activity. *Journal of Finance*, 45, 1089-1108.

Fama, E.F. and K.R. French (1988). Permanent and Temporary Components of Stock Prices. *The Journal of Political Economy*, 96, 246-273.

Fama, E.F. and K.R. French (1989). Business Conditions and Expected Returns on Stocks and Bonds. *Journal of Financial Economics*, 25, 23-49.

Fama, E.F. and G.W. Schwert (1977). Stock market returns and inflation. *Journal of Financial Economics*, 5, 115–146.

Figlewski, S. and X. Wang, (2001). Is the "Leverage Effect" a Leverage Effect?, working paper, Department of Finance, New York University.

Fornari, F. and A. Mele (2006). Financial volatility and real economic activity, *mimeo.*

French, K. R., Schwert, G. W. and R. F. Stambaugh (1987). Expected Stock Returns and Volatility. *Journal of Financial Economics*, 19, 3-29. 106.

Glosten, L.R., Jagannathan, R. and D.E. Runkle (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *Journal of Finance*, 48, 1779-1801.

Hamilton, J.D. and R. Susmel (1994). Autoregressive conditional heteroskedasticity and changes in regime. *Journal of Econometrics*, 64, 307–333.

Hamilton, J. D. and G. Lin (1996). Stock Market Volatility and The Business Cycle. *Journal of Applied Econometrics*, 11, 573–593.

Hanson, M.S. (2006). Do industries lead stock markets?. *Journal of Financial Economics*, 83, 367–396.

Hassapis, C. and S. Kalyvitis (2002). Investigating the links between growth and real stock price changes with empirical evidence from the G-7 economies. *The Quarterly Review of Economics and Finance*, 42, 543-575.

Hong, H., Torous, W. and R. Valkanov (2007). Do industries lead stock markets?. *Journal of Financial Economics*, 83, 367–396.

Hsiao, C. and M.H. Pesaran (2007). Random coefficient panel data models, in Matyas, L., and P. Sevestre *The Econometrics of Panel Data (Third Edition)*, Kluwer Academic Publishers, forthcoming.

Jones, C.M. and Kaul, G. (1996). Oil and the stock markets. *Journal of Finance*, 51, 463–491.

Kein, D. B. and R. F. Stambaugh (1986). Predicting returns in the stock and bond markets. *Journal of Financial Economics*, 17, 357-390.

King, B. F. (1966). Market and industry factors in stock price behavior. *Journal of Business,* 39, 139-190.

Krämer, W. (1992), The CUSUM test with OLS residuals. *Econometrica*, 60, 271-85.

Lamoureux, C. and G. Zhou (1996). Temporary components of stock returns: what do the data tell us?. *Review of Financial Studies,* 9, 1033–1059.

Linton, O.; Connor, G.and R. Korajczyk (2006). The common and specific components of dynamic volatility. *Journal of Econometrics*, 132, 231-255.

Livingston, M. (1977). Industry movements of common stocks. *Journal of Finance*, 32, 861-874.

Merton, R.C. (1980). On estimating the expected return on the market: an exploratory investigation. *Journal of Financial Economics*, 8, 323-361.

Merton, R.C. (1987). A Simple model of capital market equilibrium with incomplete information. *Journal of Finance*, 42, 483-510.

Meyers, S.L. (1973). A re-examination of market and industry factors in stock price behavior. *Journal of Finance*, 28, 695-705.

Nelson, C. (1976). Inflation and rates of return on common stock. *Journal of Finance*, 31, 471-483.

Nelson, D.B. (1991). Conditional heteroskedasticity in asset returns: a new approach. *Econometrica*, 59, 347-370.

Nyblom, J. (1989). Testing the constancy of parameters over time. *Journal of the American Statistical Association*, 84, 223-230.

Park, S. (1997). Rationality of negative stock-price responses to strong economic activity. *Financial Analysts Journal*, 53, 52-56.

Pesaran, M.H. and R.P. Smith (1995). Estimating long-run relationships from dynamic heterogenous panels. *Journal of Econometrics*, 68, 79-113.

Pesaran, M.H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica*, 74, 967-1012.

Pesaran, M.H., Schuermann, T. and S. Weiner (2004). Modelling regional interdependencies using a global error-correcting macroeconometric model. *Journal of Business and Economics Statistics*, 22, 129-162.

Pesaran, M.H. and Y. Shin (1998). Generalised impulse response analysis in linear multivariate models. *Economic Letters*, 58, 17-29.

Sadorsky, P. (1999). Oil price shocks and stock market activity. *Energy Economics,* 2, 449-469.

Schwert, G.W. (1981). The adjustment of stock prices to information about inflation. *Journal of Finance,* 36, 15-29.

Schwert, G.W. (1989). Why does stock market volatility change over time?. *Journal of Finance*, 64, 1115-1153.

Schwert, G.W. (1990). Stock volatility and the crash of '87?. *Review of Financial Studies*, 3, 77-102.

Tauchen, G. (2005). Stochastic volatility in general equilibrium, *mimeo.*

Turner, C.M., Startz R. and C.R. Nelson (1989). A Markov model of heteroskedasticity, risk, and learning in the stock market. *Journal of Financial Economics*, 25, 3-22.

Whitelaw, R. F. (1994). Time variations and covariations in the expectation and volatility of stock market returns. *Journal of Finance*, 49, 515-541.

Wiggins, J. B. (1987). Option values under stochastic volatilities. *Journal of Financial Economics*, 19, 351-372.

Figure 1: Generalised Impulse Responses of a Market-Wide Negative Unit (1 s.e.) Shock to Industrial Returns and its Effect on Industrial Returns
(Bootstrap Mean Estimates with 90 per cent Bootstrap Error Bounds)

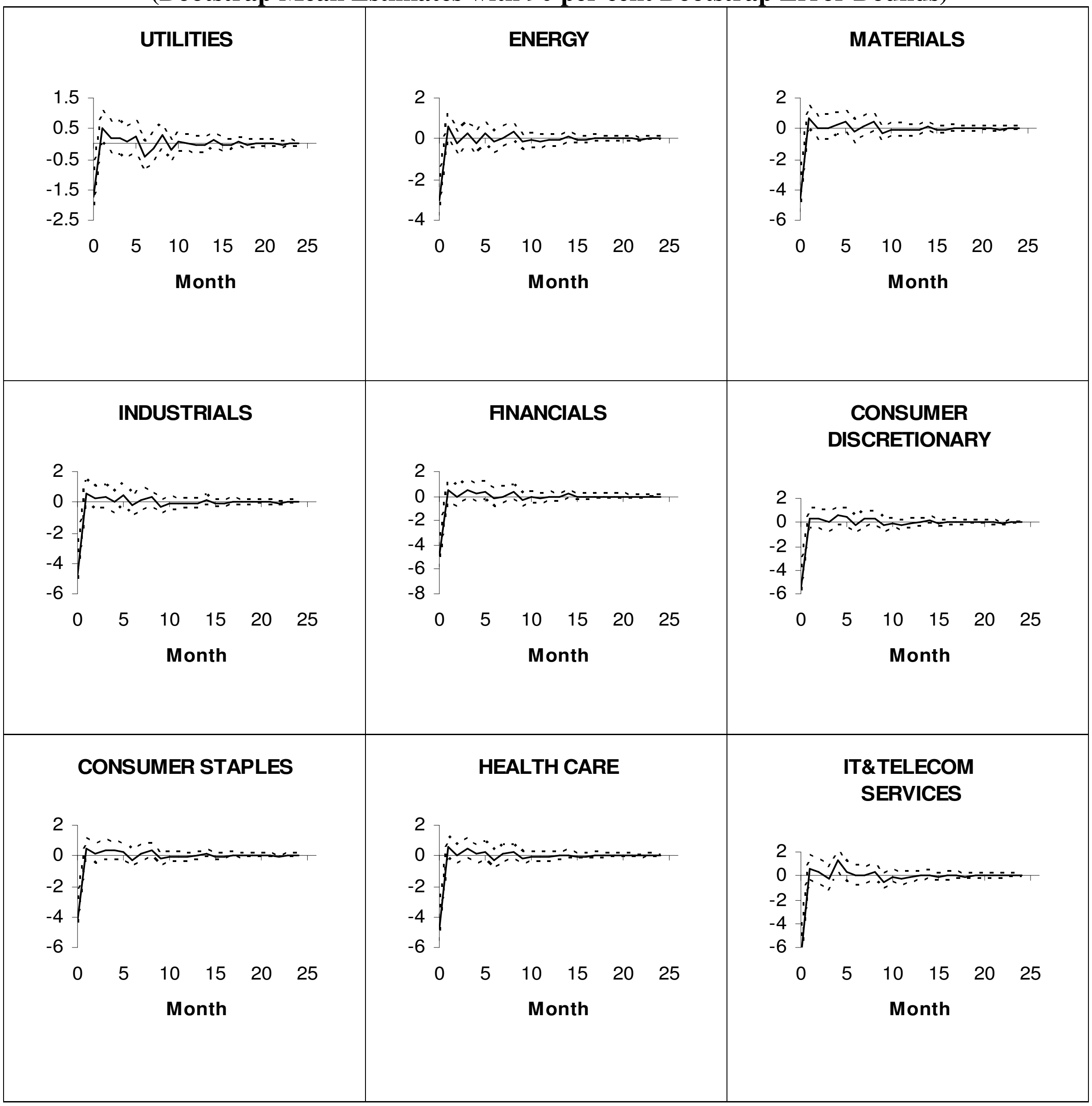

Figure 2: Generalised Impulse Responses of a Market-Wide Negative Unit (1 s.e.) Shock to Industrial Returns and its Effect on Industrial Realised Volatily
(Bootstrap Mean Estimates with 90 per cent Bootstrap Error Bounds)

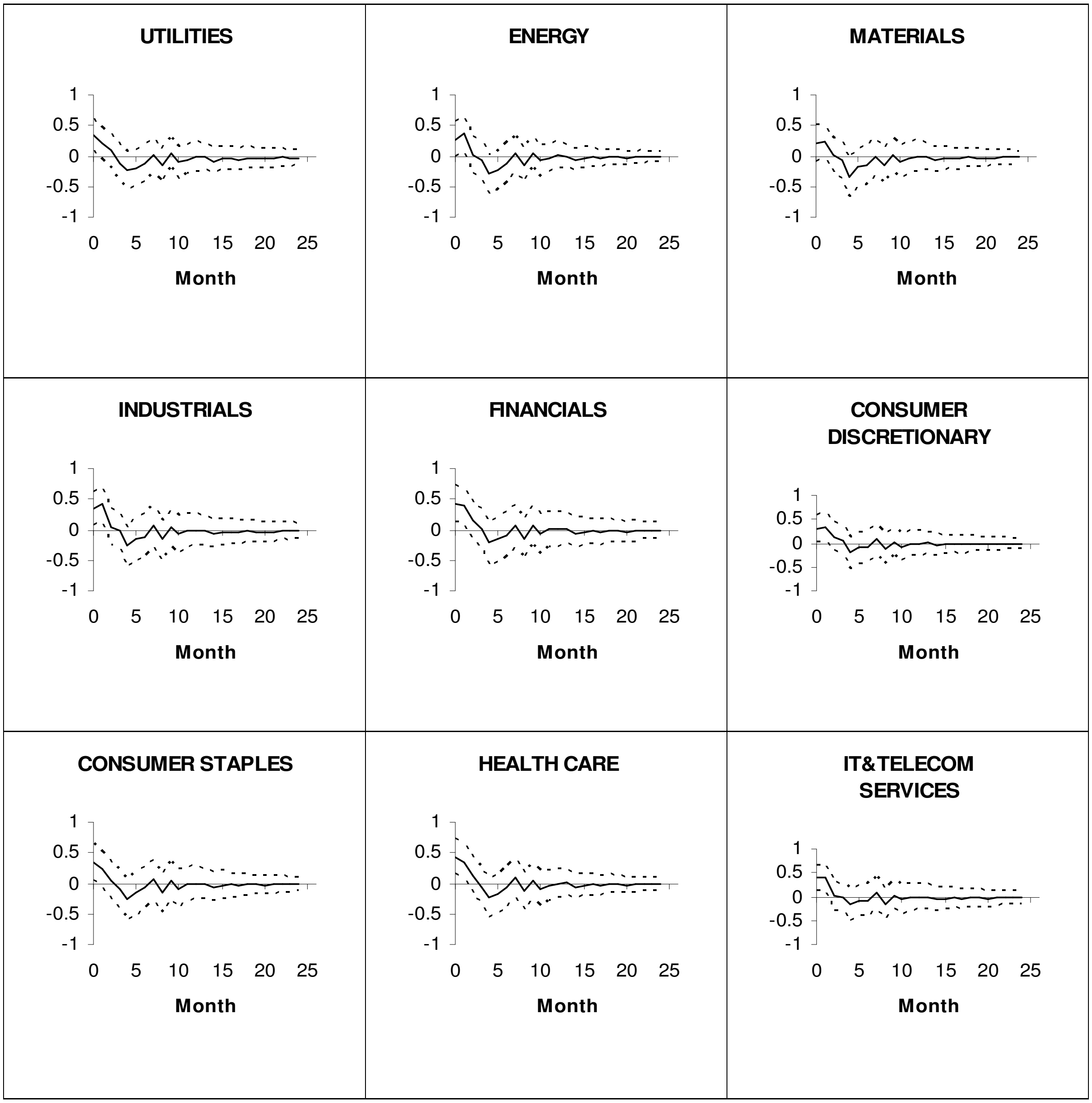

Figure 3: Generalised Impulse Responses of a Market-Wide Negative Unit (1 s.e.) Shock to Industrial Returns and its Effect on Macro and Financial Variables
(Bootstrap Mean Estimates with 90 per cent Bootstrap Error Bounds)

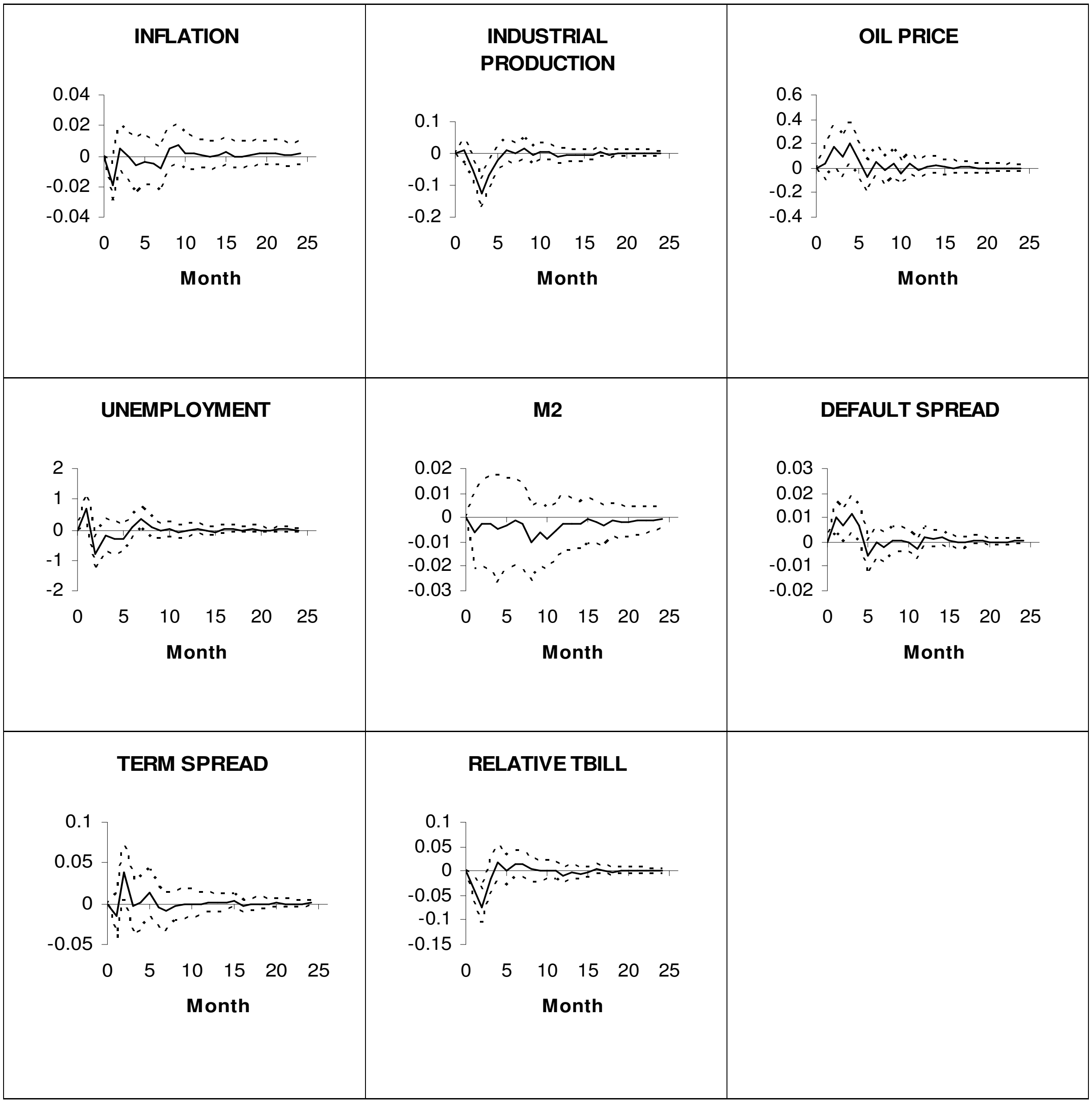

Figure 4: Generalised Impulse Responses of a Market-Wide Positive Unit (1 s.e.) Shock to Industrial Realised Volatility and its Effect on Industrial Returns

(Bootstrap Mean Estimates with 90 per cent Bootstrap Error Bounds)

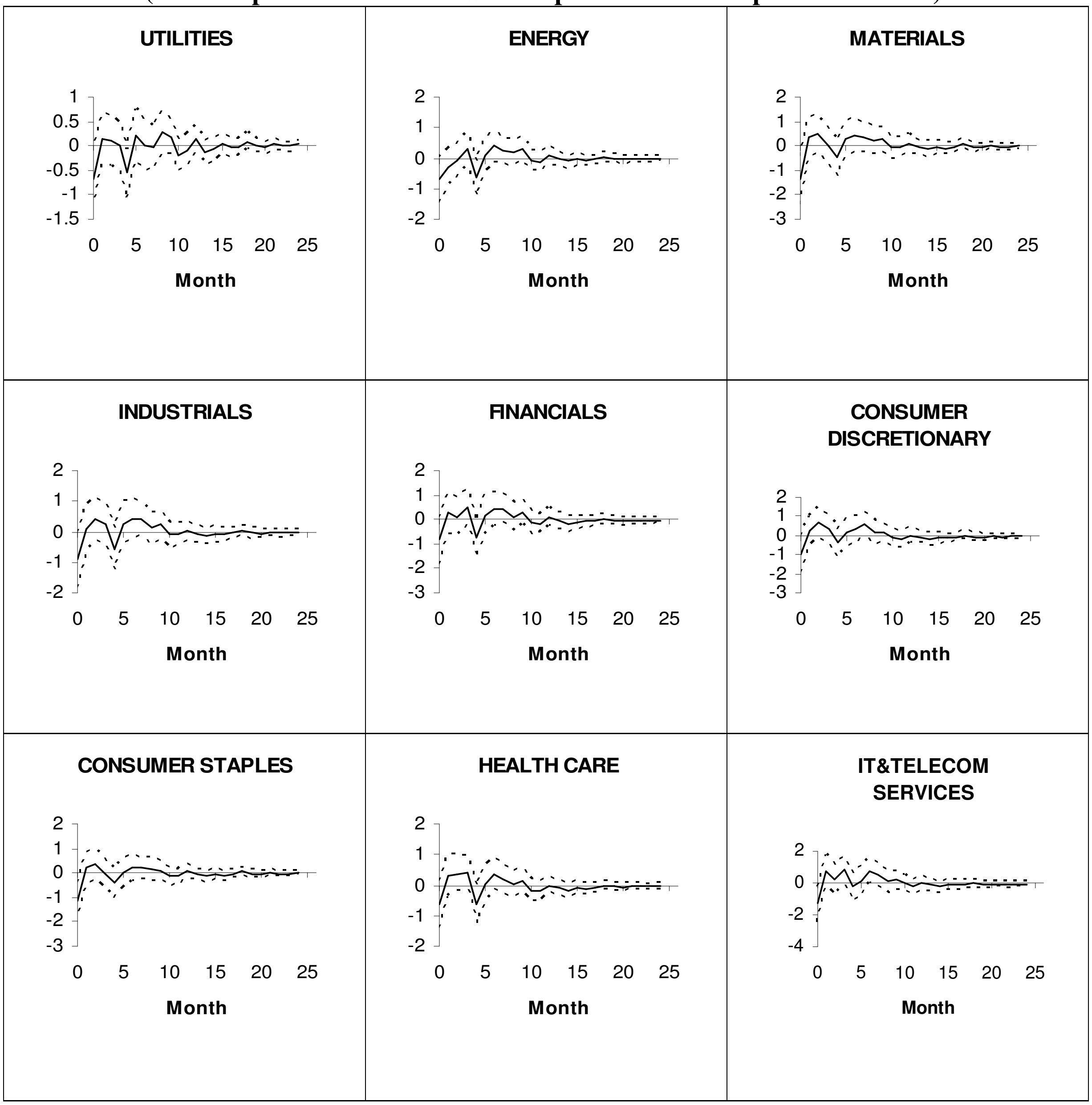

Figure 5: Generalised Impulse Responses of a Market-Wide Positive Unit (1 s.e.) Shock to Industrial Realised Volatility and its Effect on Industrial Realised Volatily
(Bootstrap Mean Estimates with 90 per cent Bootstrap Error Bounds)

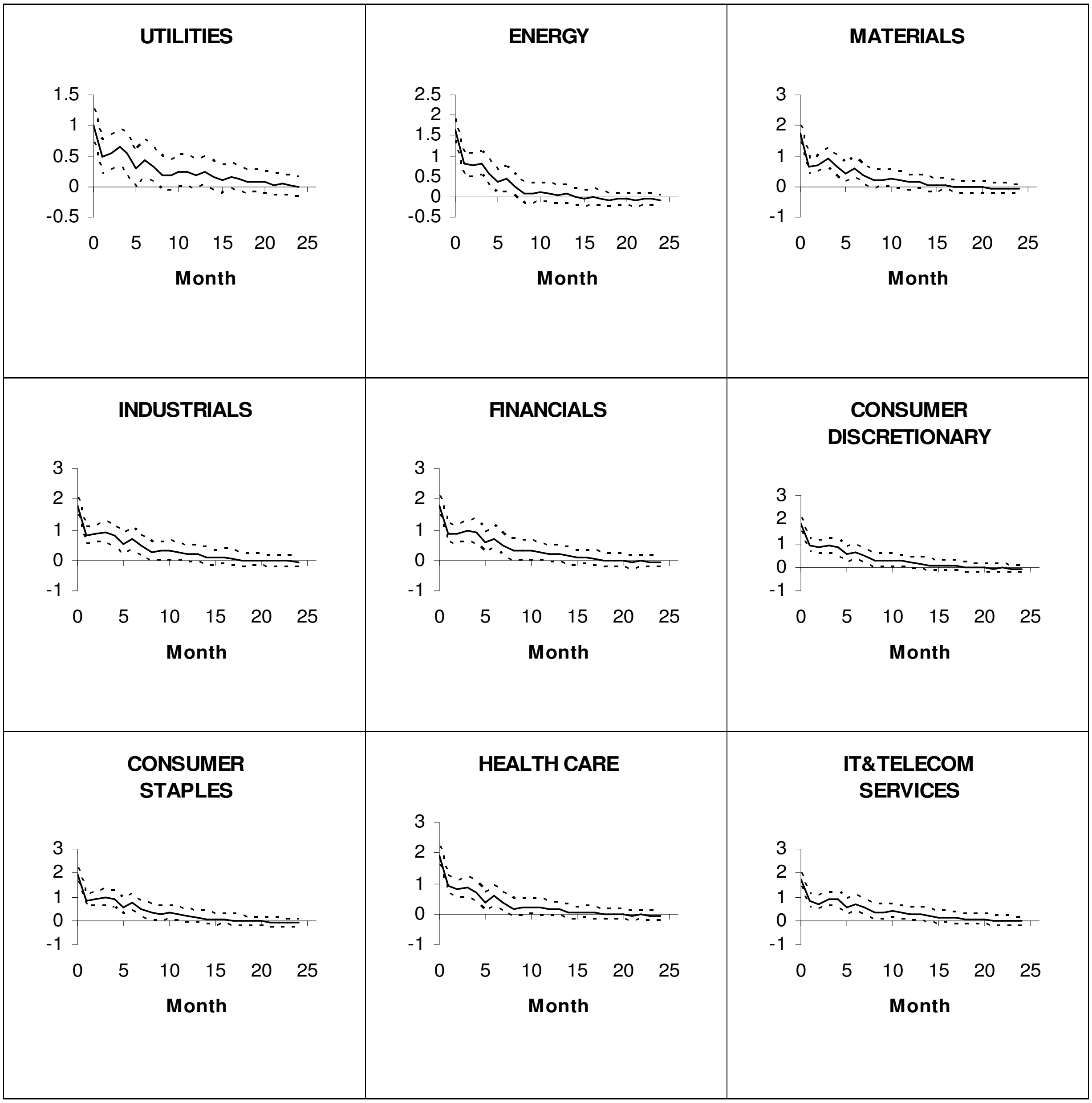

Figure 6: Generalised Impulse Responses of a Market-Wide Positive Unit (1 s.e.) Shock to Industrial Realised Volatility and its Effect on Macro and Financial Variables

(Bootstrap Mean Estimates with 90 per cent Bootstrap Error Bounds)