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Economic Activity and the Stock Market: The Asymmetric Impact of Fundamental and Non-Fundamental News

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Economic Activity and the Stock Market: The Asymmetric Impact of Fundamental and Non-Fundamental News [*]

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Abstract

In this paper, we present a general model of the joint data generating process underlying economic activity and stock market returns allowing for complex nonlinear feedbacks and interdependencies between the conditional means and conditional volatilities of the variables. We propose statistics that capture the long and short run responses of the system to the arrival of fundamental and non-fundamental news, conditioning on the sign and time of arrival of the news. The model is applied to US data. We find that there are significant differences between the short and long run responses of economic activity and stock returns to the arrival of news. Moreover, for certain classifications of news, the respective responses of economic activity and stock returns vary according to the nature of the news and the phase of the business cycle at which the news arrives.

Keywords: **Nonlinearity, Asymmetry, Stochastic Simulation, Business Cycle**

J.E.L. Codes: **E44, E47**

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1. Introduction

There is an extensive empirical literature that investigates the market impact of new information about the economy. This literature is often in the context of the stock market (see, inter alia Chen, Roll and Ross, 1986, Sun and Tong 2000, Boyd et al, 2005, Anderson et al, 2007), the foreign exchange market (see inter alia DeGennaro and Shreives, 1997, Almeida, Goodhart and Payne, 1998, Anderson et al, 2007), and the bond market (see inter alia, Fleming and Remolona, 1999, Kim et al, 2007, Faust et al, 2007). The literature focuses on both how, and to what extent, scheduled and unscheduled news (i.e. information that becomes available after taking into account expectations) on macroeconomic fundamentals is incorporated in prices in these markets.

Underlying these studies is the view that in an efficient market, and in the absence of speculative bubbles, asset returns reflect the range of factors associated with investors' exposure to state variables that characterise the economy (see, for example, Chen, Roll and Ross (1986), Campbell and Shiller (1988) and Cox *et al* (1985) *inter alia*). Support for the efficient markets hypothesis exists in the empirical literature; for example, variables that are likely to be informative about future corporate cash flows such as real GNP, industrial production and investment, have been found to influence stock prices (see Fama (1981), Geske and Roll (1983), Kaul (1987) and Barro (1990) *inter alia*). An alternative school of thought, motivated predominately by Shiller (1981), suggests that the link between prices and macroeconomic fundamentals is more tenuous and that there might be long periods of divergence. Indeed, there are a number of empirical studies suggesting that the potential speculative bubbles in US stock markets in the 1980s and 1990s served to dilute the links between macroeconomic fundamentals and asset returns (see inter alia, Mandelkar and Tandon (1985), Gjerde and Saettem (1999), Chaudhuri and Smiles (2004), Binswanger (2004)).

A variety of approaches have been adopted to resolve the question of the nature of a link between asset returns and macroeconomic fundamentals; for instance, the effect of the business cycle on the response of financial market indicators; the asymmetric effect of 'good' news and 'bad' news on market returns and volatility; and the comparative response to macroeconomic news by various asset classes, markets and countries (see Anderson et al, 2007, for further details). These studies share a common feature; whether the modelling framework is univariate (the dependent variable of interest being returns), or multivariate (so that the various returns of the assets or financial markets of interest are jointly modelled to allow for their contemporaneous determination), there is generally assumed to be one-way causality from news on macroeconomic fundamentals to market prices. This assumption is consistent with prices changing in response to new information. Further, it is possible (albeit with slight modifications) to accommodate the impact on returns of the *uncertainty* with which news arrives on macroeconomic fundamentals. This might be important if, for instance, uncertainty in macroeconomic news causes changes in the investment opportunity set due to changes in expectations of future market returns or in the risk-return trade-off.[1]

In our view, there are two important considerations when formulating an empirical model to shed light on this issue that are not often addressed in the literature. Firstly, there need not be a simple one-way causal structure flowing from economic activity to stock returns; for instance, there may be a common news component that causes revisions to both activity and returns. Secondly, and typical of speculative markets, is that *market uncertainty* has implications for economic decisions and hence potentially for the real economy.

A far more general modelling framework than that usually adopted is required to accommodate these considerations. This framework would need to allow (i) for movements in market returns which are *not* due to economic fundamentals, to have an impact on the real economy; (ii) for the joint determination of market returns and economic fundamentals and therefore the accommodation of news which arrives and which impacts on both market prices and economic activity contemporaneously; and (iii) the conditional volatility (i.e. uncertainty) of both economic fundamentals and market returns to affect the conditional means of, respectively, asset returns and economic activity.

In light of these considerations, this paper makes the following contributions to the literature.

[1] Most notably, Black (1987), for example, suggests that, during periods of growth uncertainty, the riskiest investment projects may become more profitable, and hence there will be a positive feedback between macroeconomic uncertainty and the real economy. On the other hand, Woodford (1990) hypothesizes a negative feedback based on the increased riskiness of investment when output is volatile. Both effects will be reflected in the market's pricing of risk and hence also the return to investment.

Firstly, the paper presents a general model of the joint data generating process underlying a measure of economic activity, namely, industrial production, and stock market returns. The modelling framework allows for the joint determination of market returns and economic activity, accommodates inter-linkages between uncertainty in stock market returns and uncertainty in the macroeconomy, and allows volatility associated with the market and economic activity each to feedback into the levels of these variables. Specifically, the characterization of the joint data generating process is a bivariate, asymmetric GARCH-in-mean specification in which allowance is made for a possible asymmetric response of the conditional variance-covariance process to good and bad news. This empirical specification allows for a greater deal of generality in the underlying dynamics than has previously been the case.

Secondly, using stochastic simulation techniques, the paper quantifies the extent to which 'innovations' impact on the conditional means of economic activity and stock returns and develops a measure of the relative persistence of these impacts. The computed innovations for each variable have the property that they are orthogonal to each other. Hence, the innovations to stock returns can be thought of the innovations that cause changes in stock prices which are not due to innovations in economic activity. In a loose sense, these can be thought of innovations that occur due to factors such as changes in opinion, investor psychology or speculative behaviour. On the other hand, the dynamic response of market returns to innovations in economic activity can be thought of reflecting news on fundamentals that causes prices to change. Therefore, in contrast to the existing literature, the impacts of, and dynamic responses to, innovations on the conditional means and volatilities of *both* variables are considered.

Thirdly, the paper develops a simulation methodology and associated metrics to investigate the short and long run responses of stock returns and economic activity to innovations sourced from, respectively, the real economy and from the stock market.

Finally, the paper explicitly addresses the questions of whether these short run impact and long run persistence effects differ (i) according to the sign of the innovation (sign asymmetry), and (ii) across the phases of the business cycle (phase asymmetry).

Our paper proceeds as follows. In the next section we present a general nonlinear bivariate modelling framework and introduce the concepts of sign and phase asymmetry. The third section provides a data description for our empirical application. The empirical model and the results are presented in the fourth section. The fifth section describes the stochastic simulation of the empirical model and the associated results. The final section then provides a summary and some concluding comments.

2. Modelling Framework and Measures of Asymmetry

Consider the general, bivariate, nonlinear model for growth, y_t, and stock returns r_t,

$$\begin{aligned} Y_t &= \phi_0 + f\left(\phi_1, Y_{t-i}\right) + \varepsilon_t \\ \{Y_{t-i}\} &= Y_{t-1},\ Y_{t-2},\ \ldots, Y_{t-p}, \end{aligned} \tag{1}$$

where *f(.)* is a nonlinear function, $Y_t = \left(y_t, r_t\right)'$, ϕ_0 is a vector of intercepts, ϕ_1 is a matrix of parameters and ε_t is a vector of innovations. This framework is sufficiently general that it allows for a range of interdependencies and feedbacks between the conditional means and volatilities of both growth and returns.

The focus in this paper is in the investigation of the dynamic system-response to an impulse acting on (1) which would lead agents to revise their expectations of future growth and/or returns. Analysis of the dynamic impact of an innovation upon this system may be performed using the generalized impulse response function (*GIRF*) developed by Koop, Peseran and Potter (1996) and obtained by stochastic simulation of (1). *GIRF*s are the appropriate analytical tool in this instance, given the nonlinear nature of equation (1). Unlike conventional impulse responses obtained from vector autoregressions, *GIRF*s make allowance for the effects of the sign, size and timing of impulses on the estimated dynamic responses derived from (1). The *GIRF* derived from (1) following a specific innovation υ_t and history ω_{t-1} can be written as,

$$GIRF_Y(n, \upsilon_t, \omega_{t-1}) = E\left[Y_{t+n} \mid \upsilon_t, \omega_{t-1}\right] - E\left[Y_{t+n} \mid \omega_{t-1}\right], \tag{2}$$

for n = 1, 2, ….. Hence, the *GIRF* is conditional on υ_t and ω_{t-1} and constructs the response by averaging out future innovations given the past and present. Given this, a natural reference point for the impulse response function is the conditional expectation of Y_{t+n} given only the history ω_{t-1}, and, in this benchmark response, the current innovation is also averaged out. Assuming that υ_t and ω_{t-1} are realisations of the random variables V_t and Ω_{t-1}, respectively, that generate realisations of $\{Y_t\}$, then (following the ideas proposed in Koop *et al*, 1996) the *GIRF* defined in (2) can be considered to be a realisation of a random variable given by,

$$GIRF_Y(n,V_t,\Omega_{t-1}) = E\left[Y_{t+n} \mid V_t,\Omega_{t-1}\right] - E\left[Y_{t+n} \mid \Omega_{t-1}\right]. \tag{3}$$

By conditioning on the sign or timing of the impulse when constructing the *GIRF*s, it is possible to quantify asymmetric reactions to the arrival of new information.[2]

2.1 Sign Asymmetry

Let $GIRF_Y(n,V_t^+,\Omega_{t-1})$ denote the G*IRF* from conditioning on the set of all possible positive innovations, where $V_t^+ = \{\upsilon_t \mid \upsilon_t > 0\}$ and $GIRF_Y(n,V_t^-,\Omega_{t-1})$ denote the *GIRF* from conditioning on the set of all possible negative innovations. It follows that if the response to innovations is symmetric, then $GIRF_Y(n,V_t^+,\Omega_{t-1}) = GIRF_Y(n,V_t^-,\Omega_{t-1})$ for all horizons *n*.

Denoting the cumulative generalised impulse function, *CGIRF*, for horizon *N=1,2,3,…*, as

$$CGIRF_Y(N,V_t,\Omega_{t-1}) = \sum_{n=1}^{N} GIRF_Y(n,V_t,\Omega_{t-1}), \tag{4}$$

it is possible to construct a measure of sign asymmetry as a random variable, $R_S(N,V_t,\Omega_{t-1})$, capturing the relative persistence in the response of the system to positive against negative impulses. In more detail, the measure can be expressed as:

$$R_S(N,V_t,\Omega_{t-1}) = \left(\frac{\left|CGIRF_Y(N,V_t^+,\Omega_{t-1})\right|}{\left|CGIRF_Y(N,V_t^-,\Omega_{t-1})\right|} \right). \tag{5}$$

Analogous to the construction of the $GIRF_Y(n,\upsilon_t,\omega_t)$ in expression (2), assuming that υ_t^+, υ_t^- and ω_{t-1} are realisations of the random variables V_t^+, V_t^- and Ω_{t-1}, respectively, then $R_S(N,\upsilon_t,\omega_{t-1})$ can be considered to be a realisation of the random variable given in expression (5). This measure is centered on unity under the null hypothesis of symmetry. In the event of sign asymmetry, the reaction of the system to a positive (negative) innovation exceeds that to a negative (positive) innovation of equal magnitude and the $R_S(N,V_t,\Omega_{t-1})$ statistic will on average be significantly

[2] There are other asymmetries that could also be considered within this framework, such as those associated with the size of innovations. We leave investigation of these asymmetries for future research.

different from one in absolute value. This statistic and its associated standard error can be obtained using a model based bootstrap, thereby providing a statistical test for sign asymmetry and an estimate of the relative importance of the sign of the innovation at horizon N.

2.2 Phase Asymmetry

Sign asymmetry relates to the distinction between positive and negative innovations. Another potentially important source of asymmetry relates to the timing of the innovation. As outlined above, information about the macroeconomy could have an effect on asset markets. Given the strong pro-cyclicality of investment (Blanchard and Fisher, 1989 pp19-20, *inter alia*), this effect may vary according to the particular phase of the business cycle in which the information arrives. Furthermore, new information arriving to asset markets will cause revisions to expected returns and lead to changes in asset prices, resulting in changes in the cost of capital, impacting upon investment and growth. Again, given the pro-cyclicality of investment, it can be hypothesised that the effect of this information may differ according to the phase of the business cycle.

We use the term *phase asymmetry* to denote the possibility that the dynamic response to an impulse affecting (1) differs according to the phase of the business cycle. To the best of our knowledge, phase asymmetry has not been investigated previously in this context.

To make the concept of phase asymmetry operational, there are issues to be resolved concerning the taxonomy of business cycle phases. Consider the representation of the business cycle in Figure 1. Such a representation may be based on a business cycle chronology, such as that used by the NBER for the United States. For our purposes, it is useful to break up the cycle into regular intervals, enabling an investigation of phase asymmetry across all stages of the business cycle, not just peaks and troughs. The difficulty here is that, in the data, the phase of the cycle can vary with time, most notably, expansions being longer than contractions, and expansions and contractions being of varying lengths across cycles. A business cycle chronology, however, allows the identification of points that are fixed in relation to the peak and trough; in Figure 1, for example, Mid-Phase^C is half-way between Peak$_1$ and the trough. Dividing the cycle into similar fixed points for each successive phase allows a structured stochastic simulation to be performed based on the entire span of the sample data and hence allows the construction of metrics to measure the degree to which the effect of impulses varies across fixed reference points on the cycle.

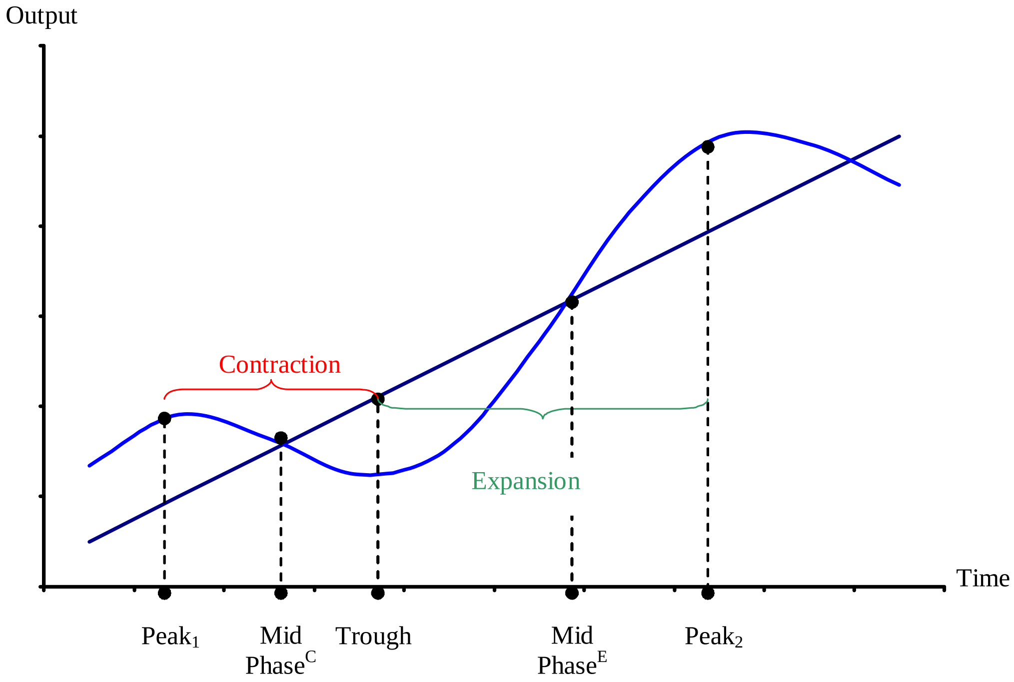

Figure 1: Phases of the Business Cycle

In detail, GIRFs can be calculated according to $GIRF_Y(n,V_t,\Omega^{ph}) = E\left[Y_{t+n} \mid V_t,\Omega^{ph}\right] - E\left[Y_{t+n} \mid \Omega^{ph}\right]$ where *ph* represents the particular fixed reference point of interest. For example, GIRFs can be constructed for peak or trough histories; histories that relate to the mid-point between peaks and troughs; histories relating to the mid-point between troughs and peaks, or indeed any fixed reference point across the cycle.

Analogous to the measure for sign asymmetry, a random variable $R_{ph}(N,V_t,\Omega^{ph})$ measuring phase asymmetry can also be constructed. To illustrate the form of this measure, we can write,

$$R_{ph}(N,V_t,\Omega^{ph}) = \left(\frac{CGIRF_Y(N,V_t\ ,\Omega^{i})}{CGIRF_Y(N,V_t\ ,\Omega^{j})}\right) \tag{6}$$

where Ω^i and Ω^j, for $i \neq j$, denote specific histories relating to phase i and phase j over the cycle. For instance, Ω^i and Ω^j could relate to the fixed histories associated with all peaks and all troughs, respectively. Assuming that υ_t and ω^{ph} are realisations of the random variables V_t and Ω^{ph}, respectively, then $R_{ph}(N, \upsilon_t, \omega^{ph})$ can be considered to be a realisation of the random variable (6). Under the null of no phase asymmetry, this measure will be centered on unity. In the event of phase asymmetry, the reaction of the system to a shock in one given phase relative to another given phase implies that the $RP_{ph}(N, V_t, \Omega^{ph})$ statistic will on average be significantly different from one. Both the statistic and its associated standard error can be obtained using a model based bootstrap.

These approaches to the detection and quantification of sign and phase asymmetry bear some relation to the long tradition of papers that study patterns and magnitudes of variations in the mean and volatility of stock returns over the course of the business cycle (Perez-Quiros and Timmermann 2000 *inter alia*). In general, these papers find that risk premia and stock return volatility are negatively correlated with the business cycle.[3] It is important to recognise, however, that the approaches in this paper are quite distinct from those taken in this previous literature. Rather than examining how the first and second moments of stock returns vary across the business cycle, we address the issue of how *new information* impacts on asset returns *and* economic activity, accommodating inter-linkages and feedbacks, and whether this reaction is correlated with the business cycle. These methods to deal with the asymmetric effect of new information in the context of both sign and phase asymmetries are novel to the literature.

[3] Consumption based asset pricing models (see Breeden 1979) would ascribe these fluctuations in the mean and variance of return to changes in the marginal utility of wealth over the course of the business cycle. Cochrane (2006) argues that given the relative smoothness in consumption, and that macroeconomic shocks occur in product and labour markets, the link between asset prices and production is likely to be of more relevance. Cochrane (1991) develops a link between asset prices and production through firm first order conditions, revealing that investment returns are highly correlated with stock returns.

3. Data Description

The industrial production data used in this study were obtained from the FRED database at the Federal Reserve Bank of Saint Louis. The sample comprises monthly data over the period July 1946 to June 2004. We measure real activity, y_t, as

$$y_t = \log\left(I_t \big/ I_{t-1} \right) \times 100 . \qquad (7)$$

where I_t represents the index of industrial production.

We measure stock returns, r_t, as the, monthly difference of the logarithm of P_t, the Standard and Poor's 500 index sourced from Datastream,

$$r_t = \log\left(P_t \big/ P_{t-1} \right) \times 100 . \qquad (8)$$

Note that P_t is adjusted for dividend payments, so r_t represents a measure of total return for period *t*. The growth and return data are plotted in Figure 1 and appear to display the volatility clustering associated with ARCH processes.

-Figure 1 about here-

Table 1 presents summary statistics for the data. Both real activity and stock returns fail to satisfy the null hypothesis of the Bera-Jarque (1980) test for normality. While y_t is positively skewed, r_t displays negative skewness and excess kurtosis. Augmented Dickey-Fuller (1979) unit root tests and Kwiatkowski, Phillips, Schmidt and Shin (1992) tests for stationarity suggest that both y_t and r_t are I(0) series[4]. However, a series of Ljung-Box tests for serial correlation suggests that there is a significant amount of serial dependence in the growth data.

-Table 1 about here-

Also reported in Table 1 are Engle's (1982) LM test for ARCH and Engle and Ng's (1993) test for asymmetry in volatility. Engle and Ng's approach facilitates a test of *sign bias*; whether positive and negative shocks to volatility affect future volatility differently. *Size* bias, where not only the sign, but also the magnitude of the innovation in volatility is important, can also be tested. Given the evidence of serial correlation in the growth data, the Engle (1982) LM test for ARCH and the Engle and

[4] The lag orders for the ADF tests reported in Table 1 were chosen using the Schwarz (1978) information criterion. The Akaike (1974) criterion selects higher orders of augmentation without qualitatively affecting the results of the tests.

Ng (1993) tests for sign and sign bias were performed on the residuals from a fourth order autoregression, which was sufficient to ensure that the residuals were free from serial correlation. Choosing the order of the autoregression using either the Schwarz (1978) or Akaike (1974) criteria does not qualitatively affect the evidence reported in Table 1.

The results in Table 1 suggest that the data display strong evidence of conditional heteroscedasticity. Furthermore, it appears that the conditional volatility of real activity may be sensitive to the size and sign of the innovation. There is strong evidence of negative size bias, some evidence of positive size bias, and the joint test for both sign and size bias in variance is highly significant at all usual levels of confidence. Likewise, the tests suggest that the sign of innovations to equity returns influences returns volatility with r_t displaying negative sign and size bias. The joint test for r_t is also significant at all usual levels of confidence.

3. The Empirical Model

Given the evidence of conditional heteroscedasticity and asymmetry in the conditional second moment of the data, we characterise the joint data generating process underlying equity returns and real activity as a Multivariate Asymmetric GARCH-in-Mean model.

The conditional mean equations of the model are specified a k^{th} order augmented Vector Autoregression[5],

$$Y_t = \mu + \sum_{i=1}^{k} \Gamma_i Y_{t-i} + \Psi \sqrt{h_t} + \varepsilon_t \qquad (9)$$

where

$$Y_t = \begin{bmatrix} y_t \\ r_t \end{bmatrix} ; \ \mu = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix} ; \ \Gamma_i = \begin{bmatrix} \Gamma_{11}^i & \Gamma_{12}^i \\ \Gamma_{21}^i & \Gamma_{22}^i \end{bmatrix} ; \ \Psi = \begin{bmatrix} \psi_{11} & \psi_{12} \\ \psi_{21} & \psi_{22} \end{bmatrix}; \ \sqrt{h_t} = \begin{bmatrix} \sqrt{h_{y,t}} \\ \sqrt{h_{r,t}} \end{bmatrix}; \ \varepsilon_t = \begin{bmatrix} \varepsilon_{y,t} \\ \varepsilon_{r,t} \end{bmatrix};$$

Under the assumption $\varepsilon_t \mid \Omega_t \sim N(0, H_t)$, the model may be estimated using Maximum Likelihood methods, subject to the requirement that H_t be positive definite for all values of ε_t in the sample.

[5] We choose the value of k that minimises the Schwartz information criteria. In the results below, k=2.

To allow for the possibility of asymmetry in volatility we follow Henry and Sharma (1999) and Brooks et al (2002), *inter alia*, who extend the BEKK approach of Engle and Kroner (1995), using

$$H_t = C_0^{*'}C_0^{*} + A_{11}^{*'}\varepsilon_{t-1}\varepsilon_{t-1}^{'}A_{11}^{*} + B_{11}^{*'}H_{t-1}B_{11}^{*} + D_{11}^{*'}\xi_{t-1}\xi_{t-1}^{'}D_{11}^{*} \qquad (10)$$

where $C_0^{*} = \begin{bmatrix} c_{11}^{*} & c_{12}^{*} \\ 0 & c_{22}^{*} \end{bmatrix}; A_{11}^{*} = \begin{bmatrix} \alpha_{11}^{*} & \alpha_{12}^{*} \\ \alpha_{21}^{*} & \alpha_{22}^{*} \end{bmatrix}; B_{11}^{*} = \begin{bmatrix} \beta_{11}^{*} & \beta_{12}^{*} \\ \beta_{21}^{*} & \beta_{22}^{*} \end{bmatrix}; D_{11}^{*} = \begin{bmatrix} \delta_{11}^{*} & \delta_{12}^{*} \\ \delta_{21}^{*} & \delta_{22}^{*} \end{bmatrix}$ and

$$\xi_t = \begin{bmatrix} \xi_{y,t} \\ \xi_{r,t} \end{bmatrix} = \begin{bmatrix} \min\{\varepsilon_{y,t}, 0\} \\ \min\{\varepsilon_{r,t}, 0\} \end{bmatrix}.$$

Note that $\xi_{y,t}$ and $\xi_{r,t}$ allow for the observed negative sign and size bias in real activity and equity returns. The inclusion of these variables allows for different relative responses to positive and negative shocks in the time-varying variance-covariance matrix, relaxing the assumption of symmetry in the BEKK model.

4. Results and Specification Tests

Maximum likelihood techniques were used to obtain estimates of parameters for equations (9) and (10) assuming a Student's-*t* distribution with unknown degrees of freedom, η, for the errors. The parameter estimates for the conditional mean and variance equations are displayed in Table 2.

- Table 2 about here -

The estimates of the conditional mean equations suggest that the data strongly reject the null hypothesis of no linear Granger causality. The null hypothesis that the companion matrices of the VAR are diagonal, $H_0 : \Gamma_{12}^{(1)} = \Gamma_{21}^{(1)} = \Gamma_{12}^{(2)} = \Gamma_{21}^{(2)} = 0$, distributed as $\chi^2(4)$ is strongly significant (Wald statistic = 20.1691, marginal significance level = 0.0005). This relationship is consistent with one-way linear causality from returns to growth because the null hypothesis that equity returns do not cause growth, $H_0 : \Gamma_{12}^{(1)} = \Gamma_{12}^{(2)} = 0$, distributed as $\chi^2(2)$ is strongly rejected by the data (Wald statistic = 18.5316, marginal significance level = 0.0001). On the other hand, the hypothesis that growth does not cause equity returns, $H_0 : \Gamma_{21}^{(1)} = \Gamma_{21}^{(2)} = 0$, distributed as $\chi^2(2)$, is satisfied for the data. (Wald statistic = 0.4909, marginal significance level = 0.7824).

We note that not all the elements of the Ψ matrix are statistically significant at the 5% level. The null hypothesis $H_0 : \psi_{21} = \psi_{22} = 0$, that is, that the GARCH-M parameters in the equity returns equation are insignificantly different from zero, is satisfied for the data.

The estimates confirm that the equity return-real activity process is strongly conditionally heteroscedastic. The hypothesis $H_0 : \alpha_{ij} = \beta_{ij} = \delta_{ij} = 0$, for $i, j = 1, 2$, distributed as $\chi^2(12)$ is overwhelmingly rejected by the data (Wald statistic = 24407.7625, marginal significance level = 0.0000). There is a lack of statistical significance in the case of the estimated off-diagonal elements of the A_{11}^*, B_{11}^* and D_{11}^* matrices. Individually, only $\hat{\delta}_{21}$ is significant at the 5% level. A test of the null hypothesis, $H_0 : \alpha_{12} = \alpha_{21} = \beta_{12} = \beta_{21} = \delta_{12} = \delta_{21} = 0$, distributed as $\chi^2(6)$ is satisfied for the data (Wald statistic = 4.3041, marginal significance level 0.6355). Lagged squared innovations to equity returns (real activity) do not significantly influence the conditional variance of real activity (equity returns). However, there is some evidence that negative innovations to growth spill over into equity volatility since $\hat{\delta}_{21}$ is individually significant at the 5% level. Given the insignificance of $\hat{\delta}_{12}$, there is no evidence that negative return innovations influence growth volatility. This implies that the evidence for non-linear Granger causality is very weak and hinges on the significance of one coefficient, $\hat{\delta}_{21}$.

Shocks to volatility appear highly persistent. Estimates of the main diagonal elements of B_{11}^* are, in general, close to unity. There is also some evidence of own variance, cross variance and covariance asymmetry in the data. This is highlighted by the significance of the parameters in the D_{11}^* matrix. The hypothesis $H_0 : \delta_{11} = \delta_{12} = \delta_{21} = \delta_{22} = 0$, distributed as $\chi^2(4)$ is strongly rejected by the data (Wald statistic = 43.1548, marginal significance level 0.0000).

-Figure 2 about here-

Figure 2 displays the estimated elements of H_t. Visual inspection of this figure suggests that the volatility of output growth is highest in the early part of the sample.

Returns volatility is at its highest in 1987, but also peaks in the 1970s. The conditional covariance between returns and growth is largely positive, but displays a negative spike at the time of the 1987 equity market crash.

The evidence in Table 2 suggests that the model is well specified. The standardised residuals, $z_{it} = \varepsilon_{it}/\sqrt{h_{it}}$ for $i = y, r$, and their corresponding squares, satisfy the null of no twelfth order linear dependence of the $Q(12)$ and $Q^2(12)$ tests at the 1% level. For a well-specified model, $E(z_{it}) = 0$ and $E(z_{it}^2) = 1$. These conditions are not rejected at any standard level of significance. The model also reduces the degree of skewness and kurtosis in the standardised residuals when compared with the raw data. Similarly, the model predicts that $E\left(\varepsilon_{i,t}^2\right) = h_{i,t}$ for $i = y, r$ and $E\left(\varepsilon_{y,t}\varepsilon_{r,t}\right) = h_{yr,t}$. These conditions are not rejected at the 5% level.

Table 3 reports the results of applying robust conditional moment bias tests to the estimated model (Kroner and Ng 1998). These tests are based on a comparison of the cross-product matrix of the residuals from the estimated model with the estimated covariance matrix. One indication that the estimated model provides a good characterization of the data is the absence of systematic patterns in the vertical distance between the elements of $\varepsilon_{y,t}\varepsilon_{r,t}$ and $h_{yr,t}$. This distance is measured by the generalized residual $u_{yr,t} = \varepsilon_{y,t}\varepsilon_{r,t} - h_{yr,t}$. A correctly specified model would imply $E_{t-1}(u_{yr,t}) = 0$; this means that $u_{yr,t}$ should be orthogonal to any variable known in period *t*-1. Similar generalized residuals $u_{i,t} = \varepsilon_{i,t}\varepsilon_{i,t} - h_{i,t}$ can be defined for $i = y, r$.

We check for three types of systematic biases in the generalized residuals. For *sign* bias, we define indicator variables $m_1^i = I(\varepsilon_{i,t-1} < 0)$ for $i = y, r$, where $I(\cdot)$=1 if the argument is true. A test for *quadrant* bias can be based on a partition of $\varepsilon_{y,t-1}\varepsilon_{r,t-1}$ according to $\left(\varepsilon_{y,t-1} < 0,\ \varepsilon_{r,t-1} < 0\right)$, $\left(\varepsilon_{y,t-1} > 0,\ \varepsilon_{r,t-1} < 0\right)$, $\left(\varepsilon_{y,t-1} < 0,\ \varepsilon_{r,t-1} > 0\right)$ and $\left(\varepsilon_{y,t-1} > 0,\ \varepsilon_{r,t-1} > 0\right)$. The indicator variables m_2^i relate to these respective quadrants. Finally, a set of indicators, m_3^i, can be defined that scale the sign bias indicators by the magnitude of the innovations. These variables can be used to detect sensitivity to the *sign and size* of the innovations.

-Table 3 about here-

Table 3 shows that, in the main, the model is well specified. Only six of the thirty generalised residual test statistics are significant at the 5% level.

5. Stochastic Simulations

In this section, we investigate the dynamics implied by the model by perturbing the system with orthogonal innovations to real activity and returns. We use the NBER recession chronology to impose structure on our simulation experiments and employ a bootstrap-on-bootstrap approach to construct our measures of sign and phase asymmetry.

Specifically, we trace the effects of innovations on the elements of the state vector Y_t in (9). It is important to distinguish between shocks and impulses or innovations. We reserve the term shocks for the contemporaneously correlated vector of disturbances ε_t, while we treat impulses as a vector of i.i.d. innovations. These i.i.d. innovations, υ_t, may be referred to as the *underlying* innovations obtained via a Jordan decomposition of the conditional variance-covariance matrix H_t. If λ_{ts}, s=1,2, denote the eigenvalues of H_t with corresponding eigenvectors ξ_{ts}, s=1,2, then the symmetric matrix $H_t^{1/2}$ is defined as $H_t^{1/2} = \Xi_t \Lambda_t^{1/2} \Xi_t^{'}$, with $\Xi_t = (\xi_{t1}, \xi_{t2})$ and $\Lambda_t = diag(\lambda_{t1}, \lambda_{t2})$. Therefore, $\hat{\upsilon}_t$ is drawn from the vector of standardized residuals $\hat{z}_t$. This atheoretic approach ensures identification and uniqueness if, as found in this analysis, the elements of $\hat{z}_t$ are not normally distributed.[6]

Despite their statistical construct, the innovations are nevertheless meaningful. By construction, they are uncorrelated with each other. This implies that the innovations to returns, for instance, can be thought of as news unrelated to real economic activity which cause stock prices to change. News with this type of property would be exhibited by innovations in investor opinion or psychology, for instance, or by innovations originating from the financial sector such as those underlying the recent subprime mortgage crisis. These innovations not only cause stock prices to change but

[6] This approach to the definition of news can also be found in Hafner and Herwartz (2001). Note that our approach differs from that of Gallant, Rossi and Tauchen (1993), who directly set $\hat{\upsilon}_t = \hat{\varepsilon}_t$; however, in this case the shocks would be contemporaneously correlated and so would fail our definition for innovations.

could also potentially affect the real economy. Analogously, the innovations in economic activity can be thought of as being the part of news that relates to the 'fundamentals' in the economy. It is the stock market response to this type of news (although distinctly defined here) that is typically investigated in the literature.

In order to investigate the dynamic response of the variables to these innovations, Monte Carlo methods of stochastic simulation need to be used since analytical expressions for the conditional expectations cannot be constructed for the non-linear structure proposed in this paper.[7] The algorithm essentially follows that described in Koop *et al* (1996), but allows for time-varying composition dependence. To allow for the observed time-varying dependence, the estimated residuals $\hat{\varepsilon}_t$ are first transformed to obtain $\hat{z}_t = \hat{\varepsilon}_t \hat{H}_t^{-1/2}$, using $\hat{H}_t^{-1/2}$, the Jordan decomposition of the variance-covariance matrix $\hat{H}_t$. Next, 2000 innovations are drawn randomly with replacement from the joint distribution of the underlying innovations at each of the 696 histories. These innovations are identically and independently distributed over time. Recovering the time-varying contemporaneous dependence, 1,392,000 realisations of the impulse responses are therefore computed for horizons *n*=1,…,15. Finally, *R*=20 replications are used to average out the effects of the impulses.

5.1 Sign Asymmetry

Table 4 presents evidence of how the cumulative responses of returns and growth (or equivalently the response of the level of stock prices and industrial production) to innovations to returns and growth vary with the sign of the innovation. The Table reports t-ratios relating to $CGIRF_Y(N, V_t^{+}, \Omega_{t-1})$, the cumulative impulse response functions conditioning on positive shocks, and $CGIRF_Y(N, V_t^{-}, \Omega_{t-1})$, the cumulative impulse response functions conditioning on negative shocks. These cumulative generalised impulse response functions, which underlie the measure of sign asymmetry, $R_S(N, \upsilon_t, \omega_{t-1})$, capture the system response to positive and negative innovations of $\hat{\upsilon}_{y,t}$ and $\hat{\upsilon}_{r,t}$, which respectively denote orthogonal innovations in economic activity and stock returns. In each panel of Table 4, impulses are drawn

[7] See Granger and Teräsvirta (1993, Ch. 8), Koop *et al* (1996) and Pesaran and Shin (1998) for a background to the methods employed here.

with replacement from the set of all innovations, $\hat{\upsilon}_t$. Measures are reported in the upper panel by averaging over all histories and then, in the lower panels, conditioning, respectively, on expansions and contractions as defined by the NBER's reference dates. We refer to the horizon *N=1* as the initial impact and *N=15* as the final effect.[8]

There are two findings worth noting. First, with the exception of the initial response of economic activity to an innovation to stock returns, all the responses are statistically significant from zero, whether the economy is in an expansionary or contractionary phase. The finding that innovations in stock returns have no initial impact on economic growth is not surprising. It is interesting to note however, that there is a significant long run effect on the real economy of these 'non-fundamental' innovations. This may reflect that our modeling framework allows transmission through feedbacks of the conditional means, the conditional volatilities, or both.[9] The second finding worth noting is that negative innovations in economic activity cause a positive response in stock market returns, both on impact and at the final horizon. In other words, 'bad' news about fundamentals is 'good' news for the stock market.

Table 5 displays the measures for sign asymmetry $R_S(N, \upsilon_t, \omega_{t-1})$, as defined by expression (5), and associated standard errors and t-ratios for the hypothesis, $H_0 : R_S = 1$. The R_S measures are constructed as the average values of 1000 random comparisons of the simulated realisations of the *CGIRF*'s in the numerator relative to the denominator.

In the upper panel of Table 5 the R_S measures relate to an information set which consists of all histories, while the middle and lower panels average across expansionary and contractionary histories, respectively.

There is weak evidence of sign asymmetry in the impact effect of an innovation to growth on growth when averaging over all histories. On the other hand, there is strong evidence of sign asymmetry in the final effect of a growth innovation on growth. The relevant R_S measure is greater than one in magnitude, implying that positive growth innovations elicit a more persistent response from growth than negative impulses of equal magnitude at the long horizon.

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[8] The dynamic response of the system to the innovations has dissipated by the 15th period and hence the final or long-run effect is measured at this horizon.

[9] It may be the case that this effect reflects the role that the conditional volatility of growth has in affecting returns; for example, in times of uncertainty about the real economy, the proportion of wealth held as stocks might increase. This is the subject of future research.

Averaging over all histories, returns appear to display statistically significant asymmetry to growth innovations in the long run. In this case negative growth innovations have relatively greater long run persistence. However, the evidence for sign asymmetry in the impact effect of a growth innovation on returns (or stock prices) is weak.

There is no evidence of asymmetric response by growth to purely returns innovations upon impact, when averaging over all histories. However, in the long run, positive shocks are significantly more persistent than negative shocks of equal magnitude.

Looking at the effects of a return innovation on returns, we note that the impact and final effects are significantly different from unity where a positive return innovation has a relatively greater effect than a negative return innovation. We also note that they are almost identical in magnitude, when averaging over all histories. This suggests that the majority of the response to news which arises purely from the financial market, and is not associated with news on the fundamentals in the economy, occurs upon impact.[10] One implication of this is that the market quickly assesses the information content of this news and immediately impounds this into prices.[11]

Using the NBER recession chronology we are able to examine whether this pattern of asymmetric response is consistent across this definition of expansions and contractions[12]. Averaging over all expansions, the results are qualitatively unchanged from those obtained by averaging over all histories. In contrast, averaging over all contractions, there is far less evidence of significant asymmetry in response. In fact, the only evidence of asymmetry occurs in the final effect for a growth innovation on returns where the effect of a negative growth innovation generates a more persistent response from returns than an impulse of equal magnitude but opposite sign. Interestingly, whether the economy is in an expansionary phase or a contractionary phase, the impact response of market returns does not differ whether the innovations represent ‘good news’ or ‘bad news’. However, once the system accounts for the fairly complicated feedbacks and interactions between the conditional moments of the

[10] Note that innovations associated with macroeconomic fundamentals will be correlated with the growth innovations.

[11] Visual inspection of the respective cumulative impulse response functions is consistent with this interpretation. These are available on request from the authors.

[12] These are available on http://www.nber.org/cycles.html/.

variables, both in mean and volatility, the long-run effect shows a significantly larger response to negative innovations. This highlights the usefulness of impulse responses as a tool to investigate both the short run and long run dynamics of a system once potentially non-linear feedback and inter-dependencies are considered to be important.

5.2 Phase Asymmetry

In this section, we consider whether the cumulative responses of returns and growth to innovations to returns and growth vary with the phase of the business cycle. Note that here, we condition on all innovations, making no distinction between innovations which are positive or negative. Our interest is in whether there is an asymmetric effect that arises purely from the timing of innovations. Our approach fixes specific histories, Ω^{ph}, at various points over the cycle. The phases we consider are based on the NBER chronology which identifies business cycle reference dates.

In more detail, the histories considered over the time interval between the peak and the trough, T^{PT}, are given by Ω_{PT}^{ph} for *ph* = 1, 25, 50, 75, 100; *ph* = 1 refers to one month after the peak; *ph* = 25, 50, 75, are respectively one-quarter, one-half and three-quarters of T^{PT}; *ph* = 100 denotes the trough. Analogously, let T^{TP} be the time interval between the trough and peak, with relevant histories given by Ω_{TP}^{ph} for *ph* = 1, 25, 50, 75, 100; *ph* = 1 refers to one month after the trough; *ph* = 25, 50, 75, are respectively one-quarter, one-half and three-quarters of T^{TP}; *ph* = 100 denotes the peak.

The *GIRF*s for each phase are calculated by drawing from the joint distribution of the innovations as described above according to the expression $GIRF_Y(n, V_t, \Omega_\kappa^{ph}) = E\left[Y_{t+n} \mid V_t, \Omega_\kappa^{ph}\right] - E\left[Y_{t+n} \mid \Omega_\kappa^{ph}\right]$ for κ = PT and TP. We draw 20000 realizations at each Ω_κ^{ph} and repeat this experiment 50 times to obtain each *GIRF*. These *GIRF*s are then cumulated according to expression (4) to obtain $CGIRF_Y(N, V_t, \Omega_\kappa^{ph})$.

We consider the following two questions. First, are the cumulative impulse responses significantly different from zero? Second, is there phase asymmetry? In other words, are there significant differences in the *CGIRF*s across the histories Ω_{κ}^{ph}, for κ = PT and TP, for given forecast horizons?

To answer the first question, we use standard errors obtained from the simulation experiments to derive confidence intervals around the *CGIRF*s for each respective history. The resulting t-ratios of the *CGIRF*s for horizons *N*=1 and *N*=15 for each phase history are presented in Table A1 of the Appendix to this paper.

To address the second question, we calculate measures for phase asymmetry, R_{ph}. Expression (6) shows that the numerator and denominator of this measure of phase asymmetry differ in that they relate to cumulative impulse response functions, each respectively corresponding to a different phase. These R_{ph} measures are constructed as the average values of 1000 random comparisons of the simulated realisations of the *CGIRF*s in the numerator relative to the denominator of expression (6). Tables A2-A5 in the Appendix present evidence regarding phase asymmetry based on these R_{ph} statistics across the histories Ω_{κ}^{ph}, for κ = PT and TP, for *N*=1 and *N*=15.

Figures 3 – 6 present the $CGIRF_Y(N, V_t, \Omega_{\kappa}^{ph})$ following innovations to returns and growth. The respective *CGIRF*s are scaled such that the innovation driving the impulse causes average growth over all histories to increase by one percent on impact. The units of measurement on the respective *x*-axes are the various histories defined by Ω_{κ}^{ph} for κ = PT and TP. These are one period after the average peak [1], 25% to the average trough [2], 50% to the average trough [3], 75% to the average trough [4], at the average trough [5], one period after the average trough [6], 25% to the average peak [7], 50% to the average peak [8], 75% to the average peak [9], at the average peak [10]. The vertical axis of each diagram plots the cumulative response of variable *i* in the system to innovations in variable *j*. The *z*-axis plots the horizon of the cumulative impulse response.[13] For a given forecast horizon, *N*, the absence of phase asymmetry would imply that the level of the surface in each figure be invariant to the phase of the cycle.

-Figure 3 here -

[13] We take a graphical approach rather than calculate relative persistence measures across each of our 10 reference points on the cycle. For a given impulse horizon there are P[P-1]/2 necessary relative persistence measures, where P measures the number of fixed reference points. In our case P=10 so we would need 45 such measures for each horizon. We consider a maximum of 15 horizons in this analysis.

Figure 3 presents the cumulative impulse responses for growth following an innovation to growth over the specific histories described above. The t-ratios in Table A1 in the Appendix suggest that neither the impact nor final effects are significantly different from zero at each history, Ω_{κ}^{ph}. Further, although visual inspection of Figure 3 might suggest phase asymmetry on impact and at the final horizon, the t-ratios of the $R_{ph}(N, V_t, \Omega^{ph})$ statistics in Table A2 suggest that there is no such evidence.[14] In other words, there is no statistical evidence to suggest that the response of economic activity to innovations about the real economy varies systematically across the phases of the business cycle.

-Figure 4 here -

The cumulative impulse responses for stock returns following an innovation to growth across the histories Ω_{κ}^{ph} are displayed in Figure 4. The relevant t-ratios in Table A1 suggest that innovations in macroeconomic fundamentals are statistically important for both the impact and final effects on stock returns, at each respective history, Ω_{κ}^{ph}. The observed variation in the height of the surface plotted in Figure 4 also suggests phase asymmetry on impact, whilst the long run effect is unclear from the Figure. Table A3 provides statistical evidence for this where significant t-ratios suggest phase asymmetry at the initial horizon. More specifically. there is strong evidence that innovations to growth arriving in the contractionary histories of the cycle, Ω_{PT}^{ph} for *ph* = 1, 25, 50, 75, 100, elicit a systematically different initial response in returns relative to innovations arriving in the expansionary histories considered, Ω_{TP}^{ph}, for *ph* = 1, 25, 50, 75, 100. This finding that the time of arrival of an innovation to the real economy is important for the short run response of stock returns is consistent with the literature – for instance, see Boyd et al (2005) who find that the stock market's short run response to news about the real economy depends on whether the economy is expanding or contracting. However, after allowing for feedback within, as well as between, the conditional means and volatilities of both variables, any observed initial phase asymmetry disappears in the long-run response of stock returns.

-Figure 5 here -

[14] For instance, in Figure 3, there is the minimum initial impact occurring at point [6] on impact, one period after the average trough, whilst at the final horizon, there also appears to be visual evidence of variation in the height of the surface.

Figure 5 presents the cumulative impulse responses for growth following an innovation to stock returns over the histories Ω_{κ}^{ph}. It is an open question whether news causing stock prices to change, which is unrelated to economic activity, would have any real effects on the economy – regardless of it's time of arrival. In fact, the t-ratios for the relevant *CGIRF*s at horizon N=1 in Table A1 suggest that none of the impact effects are significantly different from zero. However, once system feedbacks and inter-linkages are accommodated, Table A1 shows that, in the case where the stock return (or 'non-fundamental') innovation arrives at Ω_{PT}^{1}, one period after the average peak, the long-run response of economic activity is statistically different from zero. This statistical significance at this history implies that there will also be evidence of phase asymmetry only at the long horizon. This is suggested by Figure 5 and confirmed in Table 5 where the t-ratios show that the final responses of economic activity to stock return innovations arriving immediately after the peak, Ω_{PT}^{1}, are significantly different at the 10% level or better when compared to the growth response to innovations arriving during expansionary histories, Ω_{TP}^{ph}, for ph = 1, 75 and 100. This is consistent with a view that a peak in the business cycle is an important event in this context.

-Figure 6 here -

Finally, cumulated generalized impulse responses for returns following a innovation purely associated with stock returns are presented in Figure 6. The evidence in Table A1 suggests that this news is not important for the stock market since none of the initial or final responses are statistically different from zero, over the Ω_{κ}^{ph}. Whilst there is some suggestion of variation in the height of the surface in the figure across histories, Ω_{κ}^{ph}, and horizons, N in the figure, as expected from the results in Table A1, Table A5 suggests an absence of phase asymmetry. There is no evidence that the time of arrival of a return innovation has a significant impact on equity prices. Together with the results from Table 4, these findings are consistent with the efficient markets hypothesis for the type of innovation arising from 'non-fundamentals'.

6. Conclusions

This paper examines the nature of the link between stock returns and real economic activity. The contributions of this research are at least four-fold.

First, our approach uses an empirical specification that allows for a greater deal of generality in the underlying dynamics than has previously been the case. The modelling framework allows for the joint determination of equity returns and growth in industrial production whilst accommodating complex feedbacks and interdependencies between the conditional means and conditional volatilities of these variables. Further, the framework, while nesting the linear VAR framework, captures a range of possible non-linearities in the dynamic response of the system to shocks.

Second, the approach taken in this paper allows for the statistical characterisation of two types of innovations which can, to some extent, be thought of as economically meaningful. We distinguish between (i) innovations that can be thought of as being representative of those purely associated with macroeconomic fundamentals and (ii) innovations that cause stock prices to change which are not associated with the real economy. This second type of innovation can be thought of as being due to changes in speculative behaviour, investor opinion, or due to a financial market shock, for example.

Third, we develop metrics to quantify the significance of these non-linear interactions based upon stochastic simulations from the proposed multivariate, non-linear model. In more detail, the simulation framework and the associated metrics enable investigation of the long-run response of both stock returns and economic activity to the different types of innovation accounting for potentially important interactions and feedbacks. This is in addition to the short run response, which is typically examined in research examining the link between stock returns and announcements on the real economy. It should be noted that the design of our simulation experiment is quite general and, with the use of the proposed metrics, lends itself to quantifying the potentially non-linear impacts of any innovations on the economy.

Fourth, the non-linear nature of the modelling framework allows stock returns and economic activity to respond asymmetrically to the sign, magnitude and timing of an innovation. In our simulation experiments we hold the magnitude of the average innovation constant and use our proposed metrics to quantify the effects of differences in the sign of the innovation (sign asymmetry) and its time of arrival (phase asymmetry). In more detail, we investigate whether there is sign asymmetry once we condition on all histories and whether sign asymmetry itself varies over business cycle expansions and contractions. In the case of phase asymmetry, we hold the sign and average size of the innovation constant and assess the possibility that the dynamic response to an impulse differs according to the phase of the business cycle.

The main findings of this paper are as follows.

The first is that there is a clear rejection of a linear conditional characterization of the joint data generating process underlying stock returns and growth. Hence, inference based on a linear representation would be potentially misleading.

With respect to the impact of an innovation derived from macroeconomic fundamentals (as represented by the index of industrial production), we find that the time horizon over which the analysis is undertaken is crucial. If we look first at how innovations to industrial production impact on industrial production itself, we find that there is no asymmetry in terms of the response to good or bad news on impact. There is, however, sign asymmetry at the long horizon, where we find that in expansions, good news on growth has a more persistent long run impact on growth than bad news. The results suggest sign asymmetry is of fundamental importance in this context since we find no evidence of phase asymmetry once we condition on all possible innovations. In other words, timing of itself is not a source of asymmetry; instead, it is timing in conjunction with the sign of the innovation that causes a relative differential in the response of economic activity.

The picture that emerges once we examine how innovations from macroeconomic fundamentals affect stock returns also depends on the time horizon but is slightly more complicated. Once again, there is no sign asymmetry apparent on impact. However, significant sign asymmetry is present at long horizons, with bad news being relatively more persistent, and this is true in both economic expansions and contractions. Here, however, there is some evidence of a pure phase asymmetry effect with the results suggesting that the effect on impact, conditioning on all possible innovations, differs between expansions and contractions.

We now summarise our findings with regard to innovations that originate in the stock market, and which are unrelated to industrial production. As before, the time horizon is critical. There is an asymmetric effect on industrial production but this exists only in the long run. This is apparent from the results on sign asymmetry which shows positive innovations to be more persistent in the long run in expansions (there is no asymmetric effect in contractions). There is also a pure phase effect detectable in the long run when the innovation arrives at the turning point immediately after a peak in economic activity.

There is also an asymmetric effect in terms of how these innovations impact on stock returns themselves but, consistent with the efficient markets hypothesis, this occurs only on impact. Interestingly, the asymmetry is only apparent in economic expansions. Of itself, the time of arrival of the innovations seems unimportant; conditioning on all histories, there is no evidence whatsoever of phase asymmetry.

The analysis in this paper highlights the potential benefits of adopting a very general modelling specification, one that allows for non-linear interactions between variables that derive from interdependencies between the conditional first and second moments of the data, and a simulation framework that identifies asymmetries at the short and long time horizons. Of interest is the question of the channels through which these effects are transmitted. For example, to what extent are the long run asymmetries that we identify the result of the effect of innovations on the conditional means or the conditional volatilities or some combination of both? To the extent that conditional volatility reflects uncertainty, this investigation will provide further economic insights into the transmission mechanism by which variables respond to news. This is the subject of future research.

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Tables and Figures

Table 1: Summary Statistics

	Mean	**Variance**	**Skewness**	**Excess Kurtosis**	**Normality**
y_t	0.3077 [0.0000]	1.2010	1.3550 [0.0000]	12.4106 [0.0000]	4706.7855 [0.0000]
r_t	0.5874 [0.0002]	17.5284	-0.5751 [0.0000]	2.1817 [0.0000]	177.6692 [0.0000]
Time Series Properties					
	ADF(μ)	**KPSS(μ)**	***Q*(4)**	***Q*(12)**	**ARCH(4)**
y_t	-12.9857	0.3299	197.1891 [0.0000]	228.0106 [0.0000]	69.3836 [0.0000]
r_t	-25.7742	0.0763	1.4020 [0.8438]	12.1742 [0.4317]	141.3775 [0.0000]
5 % C.V.	-2.8661	0.463			
Tests for Size and Sign Bias in Variance					
	Sign	**Neg. Size**	**Pos. Size**	**Joint**	
y_t	1.9313 [0.0539]	-6.9538 [0.0000]	4.2287 [0.0000]	90.8586 [0.0000]	
r_t	4.1049 [0.0000]	-4.1473 [0.0003]	-3.0629 [0.0023]	20.5976 [0.0000]	

Notes: P-values displayed as [.]. The ARCH(4) tests and the tests for size and sign bias are based on residuals from a 4th order autoregression.

Table 2: The Multivariate Asymmetric GARCH-in-Mean Model

$$Y_t = \mu + \sum_{i=1}^{k} \Gamma_i Y_{t-i} + \Psi\sqrt{h_t} + \varepsilon_t$$

$$Y_t = \begin{bmatrix} y_t \\ r_t \end{bmatrix};\ \mu = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix};\ \Gamma_i = \begin{bmatrix} \Gamma_{11}^i & \Gamma_{12}^i \\ \Gamma_{21}^i & \Gamma_{22}^i \end{bmatrix};\ \Psi = \begin{bmatrix} \psi_{11} & \psi_{12} \\ \psi_{21} & \psi_{22} \end{bmatrix};\ \sqrt{h_t} = \begin{bmatrix} \sqrt{h_{y,t}} \\ \sqrt{h_{r,t}} \end{bmatrix};\ \varepsilon_t = \begin{bmatrix} \varepsilon_{y,t} \\ \varepsilon_{r,t} \end{bmatrix};$$

μ	Element	Γ_1	Γ_2	Ψ
μ_1	1,1	0.2811 (0.0344)	0.1609 (0.0311)	0.1280 (0.0978)
0.4909 (0.2229)	1,2	0.0133 (0.0060)	0.0184 (0.0054)	-0.1082 (0.0557)
μ_2	2,1	-0.0176 (0.1328)	-0.1062 (0.1522)	0.4219 (0.3629)
-0.9967 (1.2366)	2,2	-0.0137 (0.0381)	-0.0152 (0.0373)	0.3674 (0.2955)

$$H_t = C_0^{*'}C_0^* + A_{11}^{*'}\varepsilon_{t-1}\varepsilon_{t-1}^{'}A_{11}^* + B_{11}^{*'}H_{t-1}B_{11}^* + D_{11}^{*'}\xi_{t-1}\xi_{t-1}^{'}D_{11}^*$$

$$C_0^* = \begin{bmatrix} c_{11}^* & c_{12}^* \\ 0 & c_{22}^* \end{bmatrix}; A_{11}^* = \begin{bmatrix} \alpha_{11}^* & \alpha_{12}^* \\ \alpha_{21}^* & \alpha_{22}^* \end{bmatrix}; B_{11}^* = \begin{bmatrix} \beta_{11}^* & \beta_{12}^* \\ \beta_{21}^* & \beta_{22}^* \end{bmatrix}; D_{11}^* = \begin{bmatrix} \delta_{11}^* & \delta_{12}^* \\ \delta_{21}^* & \delta_{22}^* \end{bmatrix}; \xi_t = \begin{bmatrix} \min\{\varepsilon_{y,t}, 0\} \\ \min\{\varepsilon_{r,t}, 0\} \end{bmatrix}$$

Element	C_0^*	B_{11}^*	A_{11}^*	D_{11}^*
1,1	0.1285 (0.0415)	0.9151 ((0.0271)	-0.0698 (0.0508)	0.5259 (0.0917)
1,2	-1.4457 (0.8394)	0.1285 (0.0790)	0.1446 (0.1899)	-0.1835 (0.2091)
2,1	0	0.0144 (0.0088)	-0.0055 (0.0074)	-0.0283 (0.0148)
2,2	0.8211 (1.0317)	0.8610 (0.0358)	0.2457 (0.0715)	0.2730 (0.1129)

η
7.6219
(1.3373)

Table 2 (continued)

Diagnostic Tests

	Mean	Variance	Skew	Ex. Kurt	$Q(12)$	$Q^2(12)$
$z_{y,t}$	-0.0083	1.1392	0.3249	5.6538	21.9710	11.3156
	[0.8375]	[0.9649]	[0.0000]	[0.0000]	[0.0378]	[0.5021]
$z_{r,t}$	-0.0518	0.9813	-0.7272	2.8115	13.9120	6.2898
	[0.1671]	[.9701]	[0.0000]	[0.0000]	[0.3063]	[0.9008]

Moment Conditions

$E(\varepsilon_{y,t}^2) = h_{y,t}$	$E(\varepsilon_{y,t}\varepsilon_{r,t}) = h_{yr,t}$	$E\left(\varepsilon_{r,t}^2\right) = h_{r,t}$
0.0629	1.5788	1.0364
[0.8020]	[0.2089]	[0.3087]

Notes: Asymptotic standard errors displayed as (.).$Q(12)$ and $Q^2(12)$ are Ljung-Box tests for 12*th* order serial correlation in $z_{j,t}$ and $z_{j,t}^2$ respectively for $j = y,r$. P-values for for the Ljung-Box tests and moment conditions $E(z_{it}) = 0$, $E(z_{it}^2) = 1$, zero skewness, zero excess kurtosis and for the elements of $\hat{H}_t$ are displayed as [.].

Table 3: Robust Conditional Moment Tests

Indicator	$u_{y,t}=\varepsilon^2_{y,t}-h_{y,t}$	$u_{yr,t}=\varepsilon_{y,t}\varepsilon_{r,t}-h_{yr,t}$	$u_{r,t}=\varepsilon^2_{r,t}-h_{r,t}$
m_1^y	0.0629	1.0461	0.5019
	[0.8020]	[0.3064]	[0.4787]
m_1^r	0.7635	0.0867	14.5076
	[0.3822]	[0.7684]	[0.0001]
$m_2^{-,-}$	8.0138	2.5781	0.0091
	[0.0044]	[0.1083]	[0.5845]
$m_2^{-,+}$	0.2442	5.9797	1.5677
	[0.6212]	[0.0145]	[0.2105]
$m_2^{+,-}$	0.7115	2.6656	3.7623
	[0.3989]	[0.1025]	[0.0524]
$m_2^{+,+}$	0.2379	4.9422	3.3838
	[0.6257]	[0.0262]	[0.0658]
$m_3^{y,y}$	0.3083	0.0915	6.5625
	[0.5787]	[0.7623]	[0.0104]
$m_3^{y,r}$	0.2109	0.0014	3.4520
	[0.6461]	[0.9701]	[0.0632]
$m_3^{r,y}$	1.9648	2.2442	3.1197
	[0.1610]	[0.1341]	[0.0773]
$m_3^{r,r}$	0.1385	1.2565	6.728
	[0.7097]	[0.2623]	[0.0095]

Sign Misspecification	Quadrant	Size/ Sign
$m_1^y=I\left(\varepsilon_{y,t-1}<0\right)$	$m_2^{-,-}=I\left(\varepsilon_{y,t-1}<0,\varepsilon_{r,t-1}<0\right)$	$m_3^{y,y}=\varepsilon^2_{y,t-1}I\left(\varepsilon_{y,t-1}<0\right)$
$m_1^r=I\left(\varepsilon_{r,t-1}<0\right)$	$m_2^{+,-}=I\left(\varepsilon_{y,t-1}>0,\varepsilon_{r,t-1}<0\right)$	$m_3^{y,r}=\varepsilon^2_{y,t-1}I\left(\varepsilon_{r,t-1}<0\right)$
	$m_2^{-,+}=I\left(\varepsilon_{y,t-1}<0,\varepsilon_{r,t-1}>0\right)$	$m_3^{r,y}=\varepsilon^2_{r,t-1}I\left(\varepsilon_{y,t-1}<0\right)$
	$m_2^{+,+}=I\left(\varepsilon_{y,t-1}>0,\varepsilon_{r,t-1}>0\right)$	$m_3^{r,r}=\varepsilon^2_{r,t-1}I\left(\varepsilon_{r,t-1}<0\right)$

Notes: P-values are displayed as [.].

Table 4: Significance of Positive and Negative Innovations

	$\hat{\upsilon}_{y,t}$ on y_t		$\hat{\upsilon}_{y,t}$ on r_t		$\hat{\upsilon}_{r,t}$ on y_t		$\hat{\upsilon}_{r,t}$ on r_t	
	+	-	+	-	+	-	+	-
All histories								
Impact	14.432	-18.347	27.519	23.587	7.160	-1.318	21.126	-9.834
Final	15.911	-15.021	18.301	32.269	19.249	-3.954	20.957	-9.983
Expansions								
Impact	11.758	-13.594	22.075	19.926	6.092	-1.658	22.782	-8.751
Final	13.218	-11.467	17.717	25.203	16.921	-3.512	22.671	-8.912
Contractions								
Impact	6.975	-4.691	25.733	20.116	7.812	-1.424	8.480	-4.713
Final	7.630	-4.167	12.258	22.433	14.540	-3.080	8.373	-4.747

Notes: The statistics represent the t-ratios of $CGIRF_Y(N, V_t^+, \Omega_{t-1})$ and $CGIRF_Y(N, V_t^-, \Omega_{t-1})$ as measured on impact and at the final horizon. These cumulative generalised impulse response functions capture the system response to positive and negative innovations of $\hat{\upsilon}_{y,t}$ and $\hat{\upsilon}_{r,t}$, which respectively denote innovations in growth and returns.

Table 5: Measures of Sign Asymmetry R_S

	$\hat{\upsilon}_{y,t}$ on y_t	$\hat{\upsilon}_{y,t}$ on r_t	$\hat{\upsilon}_{r,t}$ on y_t	$\hat{\upsilon}_{r,t}$ on r_t
		All histories		
Impact Effect	1.179	1.187	15.043	1.456
Standard Error	0.101	0.060	29.921	0.157
$H_0 : R_s = 1$	1.831	1.813	0.0647	2.970
Final Effect	1.594	0.597	2.638	1.441
Standard Error	0.142	0.037	0.657	0.154
$H_0 : R_s = 1$	4.300	-11.370	2.569	2.937
		Expansions		
Impact Effect	1.103	1.106	8.286	1.433
Standard Error	0.120	0.072	10.951	0.165
$H_0 : R_s = 1$	0.879	1.510	0.720	2.682
Final Effect	1.515	0.605	2.603	1.420
Standard Error	0.169	0.041	0.855	0.161
$H_0 : R_s = 1$	3.109	-9.940	2.033	2.660
		Contractions		
Impact Effect	1.192	1.114	12.816	1.375
Standard Error	0.360	0.069	24.586	0.359
$H_0 : R_s = 1$	0.537	1.692	0.703	1.067
Final Effect	1.512	0.597	1.844	1.368
Standard Error	0.522	0.054	0.679	0.356
$H_0 : R_s = 1$	1.038	-7.699	1.279	1.057

Notes: $\hat{\upsilon}_{y,t}$ and $\hat{\upsilon}_{r,t}$ denote innovations in growth and returns, respectively.

Figures

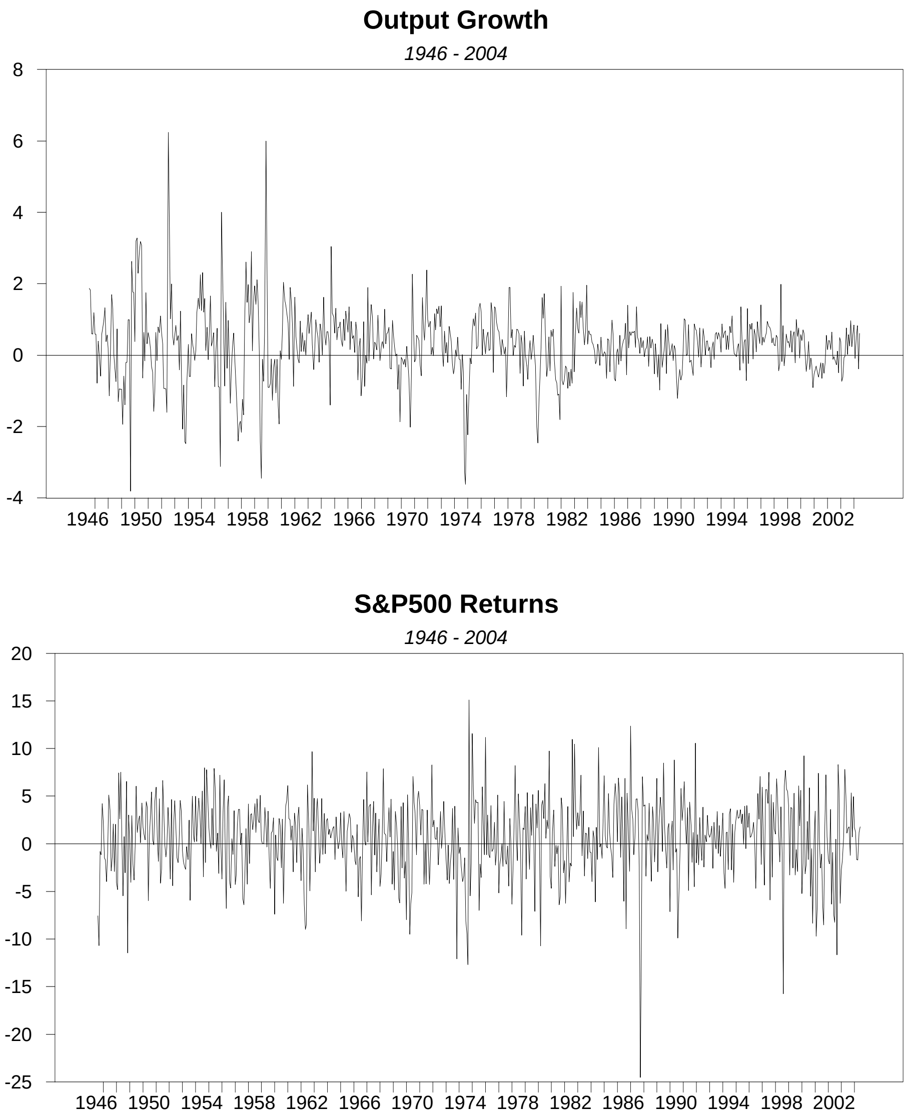

Figure 1: The data

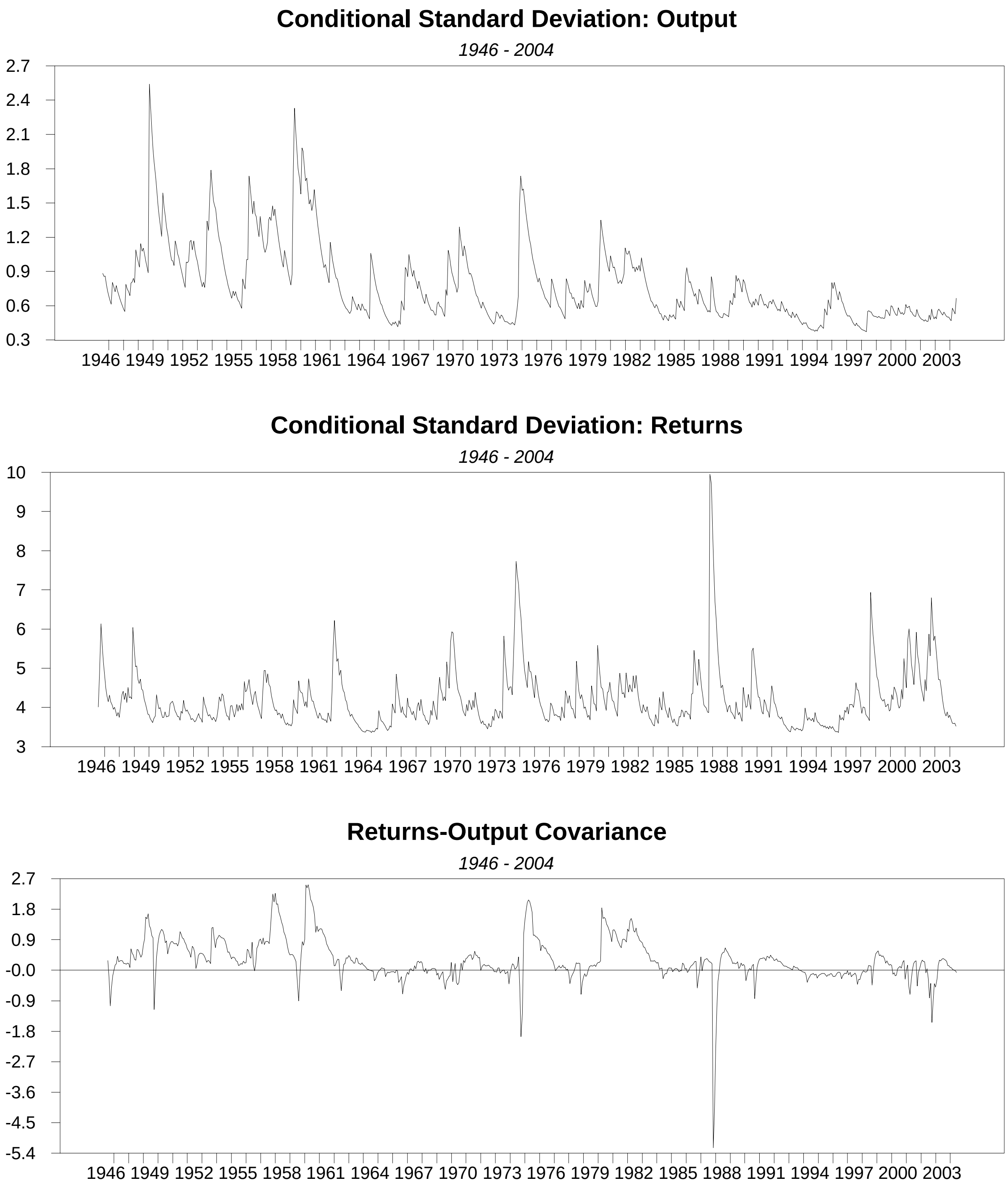

Figure 2: Estimated elements of H_t

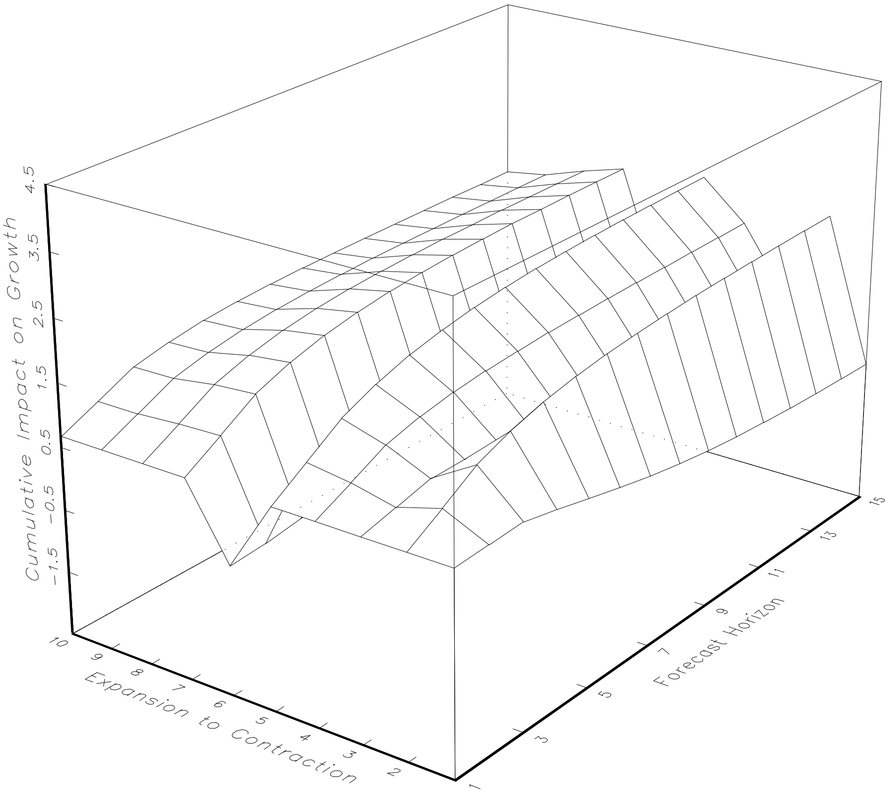

Figure 3: Cumulative Impulse Responses of an Innovation to Growth on Growth over the Phase of the Business Cycle

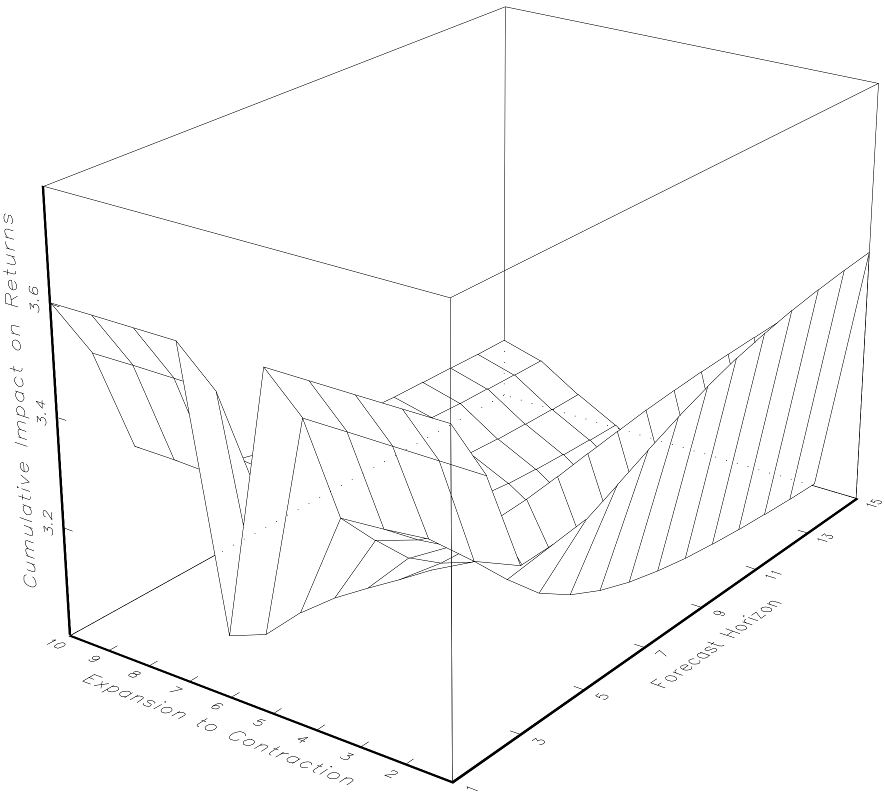

Figure 4: Cumulative Impulse Responses of an Innovation to Growth on Returns over the Phase of the Business Cycle

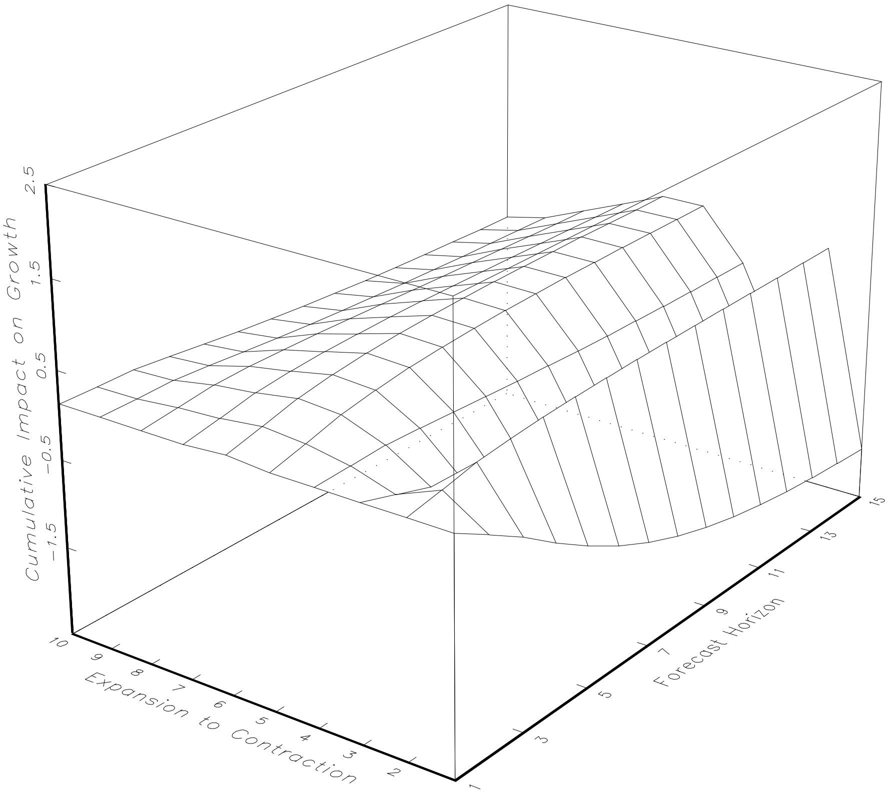

Figure 5: Cumulative Impulse Responses of an Innovation to Returns on Growth over the Phase of the Business Cycle

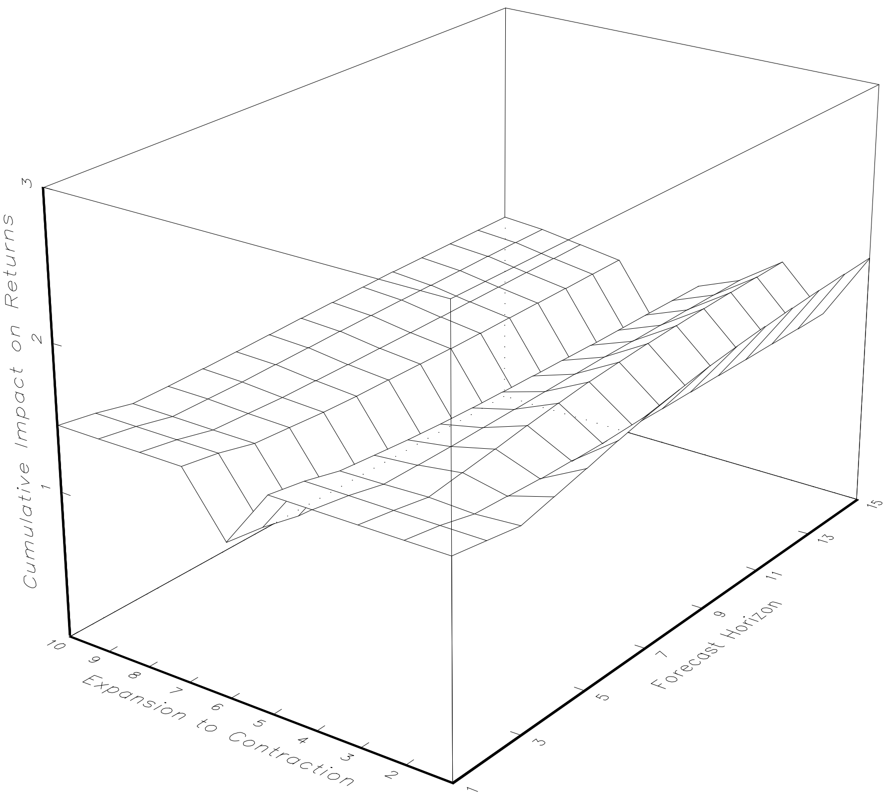

Figure 6: Cumulative Impulse Responses of an Innovation to Return on Returns over the Phase of the Business Cycle

Appendix: Phase asymmetry

Table A1: Significance of $CGIRF_Y(N, V_t, \Omega_K^{ph})$

	$\hat{\upsilon}_{y,t}$ on y_t		$\hat{\upsilon}_{y,t}$ on r_t		$\hat{\upsilon}_{r,t}$ on y_t		$\hat{\upsilon}_{r,t}$ on r_t	
	N=1	*N*=15	*N=1*	*N*=15	*N=1*	*N*=15	*N=1*	*N*=15
Ω_{TP}^{1}	0.039682	0.26546	8.868752	3.690155	0.296621	0.127915	-0.20163	-0.20792
Ω_{TP}^{25}	-0.25715	-0.07947	11.29764	4.443811	0.258565	0.070113	0.014133	0.012693
Ω_{TP}^{50}	-0.14854	-0.00779	11.61541	4.30199	0.391491	-0.08212	0.095202	0.099431
Ω_{TP}^{75}	0.152413	0.201654	15.37928	5.863271	0.279998	-0.43158	0.048481	0.06051
Ω_{TP}^{100}	0.306099	0.517901	8.480966	3.149904	0.342794	0.207743	0.127766	0.125242
Ω_{PT}^{1}	-0.03921	-0.44551	9.810599	4.099415	-0.03724	-2.04254	0.003831	0.062836
Ω_{PT}^{25}	0.236378	0.355569	12.35176	5.011712	0.365707	0.048475	0.297982	0.302221
Ω_{PT}^{50}	0.106515	0.056265	8.418738	4.20152	0.416288	-0.64637	0.20633	0.222394
Ω_{PT}^{75}	-0.16293	0.065165	8.234967	6.176936	0.138152	0.155085	0.087575	0.085372
Ω_{PT}^{100}	-0.24325	-0.08004	5.601557	3.964044	-0.53395	-0.20765	-0.06336	-0.05903

Notes: $\hat{\upsilon}_{y,t}$ and $\hat{\upsilon}_{r,t}$ denote innovations in growth and returns, respectively. Figures are bootstrap t-ratios for the significance of $CGIRF_Y(N, V_t, \Omega_K^{ph})$ for horizons *N=1* (impact effect) and *N*=15 (final effect) for phase histories Ω_{κ}^{ph}, κ = PT and TP.

Table A2: Asymmetry measures R_{ph} **-** $\hat{\upsilon}_{y,t}$ on y_t

		Impact Effect, *N=1*									
		Ω^{1}_{TP}	Ω^{25}_{TP}	Ω^{50}_{TP}	Ω^{75}_{TP}	Ω^{100}_{TP}	Ω^{1}_{PT}	Ω^{25}_{PT}	Ω^{50}_{PT}	Ω^{75}_{PT}	Ω^{100}_{PT}
	Ω^{1}_{TP}		-0.22002	-0.17474	-0.05968	-0.27856	-0.12347	0.00817	-0.09477	-0.01313	-0.1217
	Ω^{25}_{TP}	-0.18155		-0.19164	-0.08482	-0.2306	-0.12212	-0.01298	-0.06669	-0.03191	-0.10984
Final	Ω^{50}_{TP}	-0.11187	-0.11236		-0.08662	-0.34462	-0.15951	-0.0026	-0.10039	-0.01834	-0.1511
Effect	Ω^{75}_{TP}	-0.10086	-0.09565	-0.15536		-0.38229	-0.27352	-0.14223	-0.02396	-0.1169	-0.23719
N=15	Ω^{100}_{TP}	-0.17351	-0.15142	-0.22074	-0.24948		-0.25783	-0.11234	-0.03147	-0.09853	-0.22755
	Ω^{1}_{PT}	-0.05936	-0.06055	-0.10013	-0.06615	-0.05279		-0.03263	-0.07999	-0.05314	-0.16418
	Ω^{25}_{PT}	-0.09643	-0.07446	-0.13251	-0.04342	0.009724	-0.1999		-0.06751	-0.14066	-0.32802
	Ω^{50}_{PT}	-0.04594	-0.03634	-0.06317	-0.10563	-0.10395	-0.00487	-0.14522		-0.08769	-0.26048
	Ω^{75}_{PT}	-0.08876	-0.07113	-0.11669	-0.08153	-0.05742	-0.14039	-0.13169	-0.16363		-0.30329
	Ω^{100}_{PT}	-0.13683	-0.11455	-0.17722	-0.17826	-0.16033	-0.14056	-0.24876	-0.23765	-0.33606	

Notes: The Table presents t-ratios for the null hypothesis $H_0 : E\left[RP_{ph}(N, V_t, \Omega^{ph}_{\kappa})\right] = 1$ across the histories Ω^{ph}_{κ} for κ = PT and TP. $\hat{\upsilon}_{y,t}$ denotes a growth innovation. Figures above and below the diagonal relate to the impact and final effects, respectively. For instance the figure -0.22002 in cell 1,2 is the test statistic for the null hypothesis $H_0 : E\left[RP_{ph}(N, V_t, \Omega^{ph}_{\kappa})\right] = 1$ comparing an impulse arriving at history Ω^{1}_{TP} to one arriving at history Ω^{25}_{TP} on impact. Cell 2,1 shows the test statistic for the corresponding final impact.

Table A3: Asymmetry measures R_{ph} **-** $\hat{\upsilon}_{y,t}$ on r_t

		Initial Effect, *N=1*									
		Ω^{1}_{TP}	Ω^{25}_{TP}	Ω^{50}_{TP}	Ω^{75}_{TP}	Ω^{100}_{TP}	Ω^{1}_{PT}	Ω^{25}_{PT}	Ω^{50}_{PT}	Ω^{75}_{PT}	Ω^{100}_{PT}
	Ω^{1}_{TP}		-1.31395	-0.73072	-0.43705	-0.12885	1.220975	1.940216	1.938416	1.399973	1.662159
	Ω^{25}_{TP}	-0.57375		0.722749	1.209382	1.049279	2.443817	3.385601	3.049066	2.443072	2.280231
Final	Ω^{50}_{TP}	-0.18176	0.368967		0.303717	0.438315	2.030734	3.076929	2.770427	2.102557	2.068638
Effect	Ω^{75}_{TP}	-0.03831	0.619028	0.390605		0.275395	1.937522	3.054637	2.728405	2.023288	2.018574
N=15	Ω^{100}_{TP}	0.313731	0.522124	0.438312	0.338033		1.863307	2.772442	2.563572	1.975913	1.998989
	Ω^{1}_{PT}	0.236211	0.632336	0.490192	0.282857	0.211565		0.839822	1.050095	0.43547	1.082048
	Ω^{25}_{PT}	0.880749	1.25524	1.23661	1.064936	0.927933	0.780231		0.468209	-0.20131	0.720106
	Ω^{50}_{PT}	0.250095	0.461346	0.489155	0.374916	0.290598	0.192056	-0.2495		-0.77804	0.30334
	Ω^{75}_{PT}	0.766364	1.286853	1.303886	1.016397	0.83141	0.624775	-0.5034	-0.44629		1.033646
	Ω^{100}_{PT}	0.933549	1.283871	1.282422	1.11925	0.987593	0.840564	0.153026	0.133518	0.696869	

Notes: See notes to Table A2.

Table A4: Asymmetry measures R_{ph} **-** $\hat{\upsilon}_{r,t}$ on y_t

		Initial Effect, *N=1*									
		Ω^{1}_{TP}	Ω^{25}_{TP}	Ω^{50}_{TP}	Ω^{75}_{TP}	Ω^{100}_{TP}	Ω^{1}_{PT}	Ω^{25}_{PT}	Ω^{50}_{PT}	Ω^{75}_{PT}	Ω^{100}_{PT}
	Ω^{1}_{TP}		-0.27787	-0.25551	-0.1298	-0.10487	-0.03294	-0.07276	-0.15689	-0.07213	-0.16983
	Ω^{25}_{TP}	-0.27303		-0.26139	-0.13653	-0.09699	-0.0425	-0.08195	-0.1606	-0.07776	-0.16183
Final	Ω^{50}_{TP}	-0.24173	-0.21671		-0.13001	0.025711	0.061969	0.011114	-0.14729	-0.0091	-0.28318
Effect	Ω^{75}_{TP}	-0.36674	-0.33779	-0.35098		-0.17394	-0.06195	-0.11429	-0.19527	-0.09384	-0.15648
N=15	Ω^{100}_{TP}	-0.28369	-0.2685	-0.26853	-0.41616		-0.00059	-0.07846	-0.26962	-0.09367	-0.34736
	Ω^{1}_{PT}	-1.67243	-1.4965	-1.46244	-1.68337	-2.84072		-0.11947	-0.18721	-0.1179	-0.10564
	Ω^{25}_{PT}	-0.06738	-0.05571	-0.00131	-0.16174	0.048534	-0.23317		-0.2418	-0.07066	-0.29961
	Ω^{50}_{PT}	-0.20435	-0.17938	-0.17677	-0.15595	-0.34155	0.096321	-0.26223		-0.10924	-0.25422
	Ω^{75}_{PT}	-0.17175	-0.16534	-0.12802	-0.37998	-0.06073	-0.38152	-0.16242	-0.48176		-0.35078
	Ω^{100}_{PT}	-0.05616	-0.03327	0.013628	-0.12894	0.058792	-0.19673	0.033042	-0.16656	0.031341	

Notes: $\hat{\upsilon}_{r,t}$ denotes a returns innovation. See notes to Table A2.

Table A5: Asymmetry measures R_{ph} **-** $\hat{\upsilon}_{r,t}$ on r_t

		Initial Effect, *N=1*									
		Ω^{1}_{TP}	Ω^{25}_{TP}	Ω^{50}_{TP}	Ω^{75}_{TP}	Ω^{100}_{TP}	Ω^{1}_{PT}	Ω^{25}_{PT}	Ω^{50}_{PT}	Ω^{75}_{PT}	Ω^{100}_{PT}
	Ω^{1}_{TP}		-0.27046	-0.09303	-0.26411	-0.1415	-0.33285	-0.10698	-0.12182	-0.05863	-0.08035
	Ω^{25}_{TP}	-0.27533		-0.08826	-0.24384	-0.13739	-0.31363	-0.09339	-0.10013	-0.05355	-0.08473
Final	Ω^{50}_{TP}	-0.06908	-0.06008		-0.28492	-0.10082	-0.37636	-0.06533	-0.03967	-0.03365	-0.15252
Effect	Ω^{75}_{TP}	-0.26304	-0.24507	-0.29591		-0.15266	-0.50025	-0.09686	-0.07013	-0.0555	-0.19394
N=15	Ω^{100}_{TP}	-0.15371	-0.14349	-0.1065	-0.16139		-0.54571	-0.07336	-0.04333	-0.04077	-0.22553
	Ω^{1}_{PT}	-0.30652	-0.29531	-0.38748	-0.501	-0.56374		-0.05225	-0.03417	-0.03101	-0.19453
	Ω^{25}_{PT}	-0.10624	-0.09287	-0.06627	-0.09418	-0.07544	-0.04297		0.048423	0.012338	-0.2136
	Ω^{50}_{PT}	-0.12484	-0.10109	-0.05024	-0.08053	-0.06508	-0.03519	0.02717		-0.06299	-0.21866
	Ω^{75}_{PT}	-0.05155	-0.04723	-0.02991	-0.04605	-0.03687	-0.02084	0.012512	-0.05294		-0.25541
	Ω^{100}_{PT}	-0.09909	-0.09061	-0.08894	-0.10815	-0.10199	-0.06599	-0.03783	-0.10665	-0.12931	

Notes: $\hat{\upsilon}_{r,t}$ denotes a returns innovation. See notes to Table A2.