IIIS Discussion Paper

No.134/April 2006

Looking far in the past: Revisiting the growth-returns nexus with non-parametric tests

Ekaterini Panopoulou
Department of Economics, National University of Ireland Maynooth

Nikitas Pittis
Department of Banking and Financial Management, University of Piraeus, Greece

Sarantis Kalyvitis
Department of International and European Economic Studies, Athens University of Economics and Business, Greece

IIIS Discussion Paper No. 134

Looking far in the past: Revisiting the growth-returns nexus with non-parametric tests

Ekaterini Panopoulou
Nikitas Pittis
Sarantis Kalyvitis

Looking far in the past: Revisiting the growth-returns nexus with non-parametric tests

Ekaterini Panopoulou* Nikitas Pittis† Sarantis Kalyvitis‡

March 2006

Abstract

In this paper we reexamine the linkages between output growth and real stock price changes for the G7 countries using a battery of non-parametric procedures to account for the impact of long-lagged observations. We find that correlation between growth and returns is detected at larger horizons than those typically employed in parametric studies. The major feedbacks emerge from stock price changes to growth within the first 6 to 12 months, but we show that significant feedbacks may last for up to two or three years. Our evidence also suggests that the correlation patterns differ substantially between the countries at hand when the sectoral share indices are considered.

JEL classification: C14, G10, O51.

Keywords: real stock price changes, output growth, long-run covariance matrix.

Acknowledgments: We are grateful to A. Antzoulatos, D. Malliaropulos, M. Michail, M. Roche and participants in the 2005 ASSET Conference and the 4th HFAA Conference for helpful comments and suggestions. Financial support under the "PYTHAGORAS II" project co-financed by the European Social Fund and the Greek Ministry of National Education and Religious Affairs is gratefully acknowledged. The usual disclaimer applies.

* *(corresponding author) Department of Economics, National University of Ireland Maynooth, Co.Kildare, Republic of Ireland. E-mail: apano@nuim.ie. Tel: 00353 1 7083793. Fax: 00353 1 7083934.*

† *Department of Banking and Financial Management, University of Piraeus, Karaoli & Dimitriou 80, Pireus, 18534, Greece. e-mail: npittis@unipi.gr*

‡ *Department of International and European Economic Studies, Athens University of Economics and Business, Patision Str 76, Athens 10434, Greece. e-mail: skalyvitis@aueb.gr*

1. Introduction

What is the interaction between the goods market and the stock market? This relationship has attracted considerable empirical research over the last thirty years.[1] Early contributions, beginning with the work by Goldsmith (1969), assessed the positive relationship between stock returns and economic growth. Subsequent studies by, among others, Bosworth (1975), Hall (1978), Fama (1981, 1990), Schwert (1990) and Estrella and Mishkin (1998), have focused on the US and strongly indicate that the stock market index can serve as a reliable leading indicator in the US economy. This conclusion reflects the view, put forward by Morck et al. (1990), that the stock market is largely a 'sideshow', which simply mirrors 'news' about anticipated developments in firms' future payouts and output growth. Moreover, some spotty evidence in the relevant literature suggests that there is also a negative -though weak- relationship between current output and future stock prices in the US (see Park, 1997, McQueen and Roley, 1993). This behavior might be triggered by the reaction of stock market participants to other macroeconomic variables closely linked to output, such as employment and inflation, which are negatively related to future earnings and business conditions.[2]

In general, the empirical studies have relied almost exlusively on single-equation or multivariate vector autoregressive (VAR) and panel models to investigate the relationship between output growth and stock price changes. However, single equations or finite-order multivariate models may be too restrictive to represent the true autocovariance structure of a given multiple time series for several reasons. First, although the process assumed may be wide sense stationary and purely non-deterministic, it will fail to have an autoregressive representation if some of

[1] The theoretical relationship between these sectors have been founded by Brainard and Tobin (1968) who pointed out that capital formation and, consequently, output growth are triggered when the market values new capital higher than its replacement cost (q-theory of investment). Hayashi (1982) has reinforced this finding by showing that under certain assumptions the stock market valuation of firms can be encapsulated in the neoclassical investment model with adjustment costs and serve as the main determinant for investment and output growth. Lettau and Ludvigson (2002) have shown that in the presence of a time-varying risk premium the q-theory implies that a change in expected returns alters future stock prices and the cost of capital, thus triggerring a change in investment over longer horizons. An alternative transmission channel involves consumption, and consequently wealth and output, which may rise after an increase in stock prices generated by optimistic expectations of future dividends or, alternatively, by a fall in interest rates (Parker and Julliard, 2005). These links may be more intense in the case of a financial crisis (Bosworth, 1975). From a fiscal policy point of view, Blanchard (1981) has shown that after an expansionary policy shock, asset prices change as a result of anticipated changes in real interest rates and profitability, thus affecting wealth and spending, and spurring a rise in supply and equilibrium output.

[2] Another possible explanation for this pattern may be that it reflects countercyclical macroeconomic policy through the reaction function of monetary authorities. For instance, in a period of unanticipated recession the Fed may react by reducing interest rates, thus inducing a rise in stock prices, as investors find the stock market more profitable. On the other hand, a rise in output growth is usually considered as a sign of future inflation, which affects negatively future growth and returns, and policymakers may respond by raising interest rates which, in turn reduces the future cash flows of firms.

the roots of the Laurent expansion of its moving average representation lie on the unit circle. Second, the process may admit a representation of infinite order, which implies that its finite approximation may give misleading results in common size samples.[3] Third, when parametric models are employed in which output growth is explained by lagged and contemporaneous stock price changes, as in Fama (1981, 1990) and Barro (1990), it is implicitly assumed that the latter are weakly exogenous to the parameters of interest, thus resulting in inconsistent and/or inefficient estimators if this assumption fails to hold. Finally, the problem of approximating the true data generation process by, say, a finite-order VAR may be particularly acute when data on stock returns are employed. The work by Fama and French (1988) and Poterba and Summers (1988) suggests the presence of transitory components in stock prices with returns showing positive autocorrelation over short periods (reflecting e.g. the well-known momentum effect, as in Jegadeesh, 1990), but negative autocorrelation over longer periods (due e.g. to mean reversion to fundamentals). In view of such an autocovariance structure the use of a finite-order VAR, or any other approximating parametric model, becomes questionable.[4]

The purpose of this study is to reinvestigate systematically this bivariate relationship by using non-parametric tests of long-run correlation between growth and stock returns for the G-7 countries. To remedy potential caveats associated with the use of standard parametric techniques in the empirical investigation of the growth-returns nexus, we estimate the long-run covariance matrix of the two series via kernel-based estimation techniques, which involve only the choice of a kernel and a bandwidth parameter to estimate the covariance matrix of the process that equals the spectral density of the process at frequency zero.[5] Based then

[3] Luetkepohl and Poskitt (1996) discuss the problems that arise in causality testing by fitting finite VAR models to infinite-order processes. The authors prove that the use of standard Wald tests for Granger-causality can indeed be justified under more general regularity conditions, but in small samples these tests tend to reject the null hypothesis of no causality more often than indicated by asymptotic significance levels. Additional reasons that may produce misleading inferences in testing for causality within VARs are related to the time heterogeneity properties of the vector process under consideration. For instance, if the process does admit a finite-order VAR representation, but contains unit roots and exhibits cointegration, then some estimated coefficients of the VAR(p) model converge to nonstandard limiting distributions with a faster rate than $T^{1/2}$. In such a case, testing for Granger causality requires prior knowledge of the number and location of unit roots in the system. See, for example, Sims et al. (1990), and Toda and Phillips (1993).

[4] To our knowledge, the only study that has attempted to tackle with this issue by use of a non-parametric technique is Hassapis (2003), who has applied the Andrews (1991) procedure to estimate the long-run covariance matrix of output growth and financial variables. The author investigates the relationship between Canadian and U.S. financial market variables and Canadian growth and finds that as the number of autocovariances that are assigned a non-zero weight increases, the feedback from selected Canadian or U.S. financial variables (including stock prices) to future Canadian output growth increases.

[5] These methods were first proposed by Parzen (1957) and Priestley (1962). Contributions to the covariance estimation literature include among others White (1984), Newey and West (1987, 1994), Andrews (1991), Robinson (1991) and B.E. Hansen (1992).

on the derivation of a normal asymptotic approximation of the spectral density matrix of the process, we are able to derive the asymptotic distribution of the long-run correlation coefficient between the series at hand and test for its significance. The aggregate correlation coefficient can be further decomposed into the contemporaneous and temporal cross correlation, in order to facilitate the analysis of the covariance pattern between growth and returns. We use the non-parametric methodology proposed by Hong (2001) to perform hypothesis testing. The test is based on the residual cross-correlation function of the series and is robust to distributional assumptions, which are likely to be important here since the variables at hand typically exhibit both autocorrelation and/or conditional volatility effects.

We utilize monthly data from the G-7 countries to investigate the bivariate relationship between stock price changes and industrial output growth in the context of these non-parametric methodologies. Until now, existing studies (including, among others, Barro, 1990, Fama, 1990, and Schwert, 1990), have focused in the impact of current and lagged stock prices on future output in the US, whereas fewer studies have investigated this pattern in other developed economies, like Canada (Barro, 1990), Japan, Germany and the UK (Mullins and Wadhwani, 1989), and the G-7 countries (Choi et al., 1999). In line with the empirical literature on the issue, our objective is not to test alternative theories on the determination of the growth-returns nexus, but rather to employ a recently developed general econometric framework to reinvestigate the direction of causality and the strength of the correlation patterns between real stock price changes and output growth for the G-7 countries.[6]

In contrast to the bulk of the literature that has established that the major feedbacks emerge from stock returns to growth within the first six to twelve months, our findings indicate that the effect may last for up to two or three years. In particular, our results indicate a positive correlation between stock returns and growth in the G-7 countries (with the exception of Italy). Decomposing this long-run correlation to allow for contemporaneous and temporal feedbacks, we

[6]There are several reasons why this relationship might be different between developed countries (Mauro, 2003, Binswanger, 2004). First, the size of some G-7 economies is relatively small compared to the US and the production of several large firms that are listed in domestic stock markets takes place abroad, which renders them less sensitive to anticipated developments in domestic real activity. Also, the degree of openess in European economies and in Canada is a lot higher than in Japan and the U.S. and, consequently, foreign disturbances may have weakened the association between domestic stock returns and the real sector of the economy. Moreover, in countries where the stock market regulations are of English origin the growth-returns link should be higher because managers are less protected from shareholders and, hence, less able to pursue e.g. investment strategies in the case of a negative market sentiment. In addition, these economies share some common characteristics, such as greater possibility of takeovers, lower gearing ratios, and smaller role of employees in decision making.

find that the long-run correlation is mainly triggered by the feedbacks from stock price changes to future output growth with the strongest feedbacks occurring for US, Japan, Germany, and the UK. The most interesting finding is that when the number of autocovariances that are assigned a non-zero weight increases, the feedback from stock price changes to output growth increases, reaching a peak at a range between eighteen to twenty-four months, whereas weaker effects may last up to thirty-six months. On the other hand, with the exception of the UK we do not find any evidence of substantial correlation running from output growth to stock returns. As regards the correlation patterns from sectoral indices we establish that there are large variations across sectors and countries with substantial information encountered in distant lags as well.

Our main contention is thus that there are valid grounds for expecting the growth-returns nexus to be one with long-term impacts. Hence, these findings complement and extend those reported by Fama (1990), Schwert (1990), Barro (1990), Choi et al. (1999) and other authors who have reported that there is a strong positive link between stock returns and future industrial production that reaches its maximum at a forecast interval of approximately 6 to 12 months, depending on the horizon of returns. Our approach suggests that stock prices are correlated with upward movements in industrial production at longer intervals as well, while useful information is also contained in the sectoral stock price indices. Hence, the non-parametric methodologies utilized here seem to provide additional information about the effect of the financial on the real sector of the economy that can be obtained by examining the past behavior of the stock price changes at horizons that are unlikely to be captured by parametric single-equation or multivariate regressions. Finally, our approach suggests that the finding of a negative correlation between output growth and future stock price changes, reported by Park (1997) and McQueen and Roley (1993) for the US economy, is mainly driven by the negative association of US output growth with future changes in the Basic Industries and the Consumer Goods share indices. However, with few exceptions this association is not broadly supported by aggregate or sectoral data from other developed economies.

The rest of the paper is structured as follows. Section 2 outlines the non-parametric procedures used for the empirical estimation of the growth-returns relationship and section 3 describes the data at hand. Sections 4 and 5 present and comment the empirical results for the G-7 countries. Section 6 concludes the paper.

2. Non-parametric tests for the growth-returns correlation

Consider the 'long-run' correlation coefficient between output growth, y_t, and real stock returns, x_t. The long-run covariance matrix Ω of the process $Z_t = [y_t, x_t]^\top$ is defined as:

$$\Omega \equiv \begin{bmatrix} \omega_{yy} & \omega_{xy} \\ \omega_{xy} & \omega_{xx} \end{bmatrix} = \lim_{T\to\infty} T^{-1} \sum_{i=1}^{T} \sum_{j=1}^{T} E(Z_i Z_j^\top) \tag{1}$$

In practice, only a fraction of the sample autocovariances is used to estimate the asymptotic variance Ω, by employing a class of kernel estimators and the selection of a bandwidth parameter, M, with the estimator of Ω given by:

$$\hat{\Omega}_T = \sum_{j=-T}^{T} k(j/M)\hat{\Gamma}(j) \tag{2}$$

where $\hat{\Gamma}(j) = \left\{ \begin{array}{l} \frac{1}{T} \sum\limits_{t=j+1}^{T} (Z_t Z_{t-j}^T) \text{ for } j \geq 0, \\ \frac{1}{T} \sum\limits_{t=-j+1}^{T} (Z_{t+j} Z_t^T) \text{ for } j < 0 \end{array} \right\}$, and $k(\cdot)$ is a real-valued kernel.[7] The estimator $\widehat{\Omega}$ is a consistent estimator of Ω for unconditionally fourth- or eighth-order stationary random variables, and for any given bandwidth $\{M\}$, such that $M \to \infty$ and $M/T^{1/2} \to 0$. More importantly, this long-run covariance matrix given by (2) is equal to 2π times the spectral density matrix evaluated at zero, an analogy which enables us to utilise the relevant asymptotic theory for spectral density estimation. Specifically, under certain regularity conditions, these nonparametric spectral density estimators have been shown to approximate the normal distribution.[8] The elements of $\widehat{\Omega}$ are jointly normally distributed and this joint distribution enables us to derive the asymptotic distribution for the long-run correlation coefficient estimate between the two series of interest, y_t and x_t, defined as $\hat{\rho}_{xy} \equiv \frac{\hat{\omega}_{xy}}{\sqrt{\hat{\omega}_{xx}\hat{\omega}_{yy}}}$, with $\hat{\rho}_{xy}$ normally distributed as

[7] Here, we employ the Quadratic Spectral (QS) kernel that gives a non-zero weight to all the sample cross correlations and is best with respect to an Asymptotic Truncated Mean Square Error (ATMSE) criterion in the class K as proved by Andrews (1991). The author, in an extensive Monte Carlo study, reports cases where the kernel estimators of Ω yield confidence intervals whose coverage probabilities are too low. This problem is not associated with a poor choice of a specific kernel or bandwidth parameter and is particularly severe when there is considerable temporal dependence in the data. In such a case, data filtering before estimating Ω may yield more accurately sized test statistics than standard kernel estimators; see Andrews and Monahan (1992). In the context of the present study, however, such a data prewhitening is unecessary since both stock price changes and output growth exhibit strong mean reverting properties.

[8] See Grenander and Rosenblatt (1953), Anderson (1971), and Priestley (1981). Sufficient regularity conditions for obtaining such a result is that $Z_t = \sum\limits_{j=0}^{\infty} \psi_j \varepsilon_{t-j}$, where ε_t is an i.i.d. process with $(E(\varepsilon_t) = 0, E(\varepsilon_t^2) < \infty, E(\varepsilon_t^4) < \infty$,and $\sum\limits_{j=0}^{\infty} |\psi_j| < \infty$.

follows (see the Appendix for the detailed derivation):

$$\sqrt{\frac{T}{M}}(\hat{\rho}_{xy} - \rho_{xy}) \sim N\left(0,\ \left(1-\rho_{xy}^2\right)^2\right) \tag{3}$$

An advantage of this methodology is that the long-run covariance matrix can be decomposed into the contemporaneous covariance matrix G and the temporal covariance matrix Λ (or $\Lambda^\top$), i.e. $\Omega = G + \Lambda + \Lambda^\top$where $G \equiv \begin{bmatrix} g_{yy} & g_{xy} \\ g_{xy} & g_{xx} \end{bmatrix} = E(Z_0 Z_0^\top)$ and $\Lambda \equiv \begin{bmatrix} \lambda_{yy} & \lambda_{yx} \\ \lambda_{xy} & \lambda_{xx} \end{bmatrix} = \sum_{k=1}^{\infty} E(Z_0 Z_k^\top)$. This, in turn, implies that the long-run correlation coefficient ρ_{xy} can be decomposed as:

$$\rho_{xy} = \left(\frac{g_{xy}}{\sqrt{\omega_{xx}\omega_{yy}}}\right) + \left(\frac{\lambda_{yx}}{\sqrt{\omega_{xx}\omega_{yy}}}\right) + \left(\frac{\lambda_{xy}}{\sqrt{\omega_{xx}\omega_{yy}}}\right) \equiv c_{xy} + r_{yx} + r_{xy} \tag{4}$$

Relationship (4) expresses the long-run coefficient, ρ_{xy}, as the sum of the contemporaneous correlation coefficient, c_{xy}, the temporal correlation coefficient, r_{yx}, describing feedbacks from past output growth to current real stock returns ($y_t \rightarrow x_t$), and the temporal correlation coefficient r_{xy} that describes feedbacks of the opposite direction ($x_t \rightarrow y_t$).

While we are able to exploit the asymptotic normality of the estimator of the two-sided long-run covariance matrix and derive the relevant distribution for the long-run correlation coefficient, formal hypothesis testing on the basis of the contemporaneous correlation coefficient, c_{xy}, and the temporal correlation coefficients, r_{xy} and r_{yx} is not feasible. The main reason is that asymptotic normal approximations for the respective components of the spectral density matrix are not available, since the off-diagonal elements of the one-sided long-run covariance matrix can not be expressed in terms of periodograms.

To circumvent the lack of formal hypothesis testing on the decomposed correlation coefficients, we indirectly investigate their significance by testing for the existence of causal relations in the mean of two series in the context of the non-parametric method put forward by Hong (2001). In particular, consider again the bivariate stationary and ergodic stochastic process $Z_t = [y_t, x_t]^\top$. The test is based on the sample cross-correlations function of the standardized residuals and involves two stages. In the first stage, we estimate univariate time-series models for both the series under scrutiny and in the second stage, we calculate the sample cross-correlations of the standardized residuals of output growth and real stock returns, $\widehat{u}_{yt}$ and

$\widehat{u}_{xt}$ respectively.[9] The sample cross-correlation function of u_{yt} and u_{xt} ($\widehat{\tau}_{x,y}(k)$) is given by:

$$\widehat{\tau}_{x,y}(k) \equiv \frac{\widehat{C}_{x,y}(k)}{\sqrt{\widehat{C}_{x,x}(0)\widehat{C}_{y,y}(0)}} \tag{5}$$

where $\widehat{C}_{x,y}(k) = \begin{cases} T^{-1}\sum_{t=k+1}^{T}[\widehat{u}_{yt}\widehat{u}_{xt-k}], & k \geqq 0 \\ T^{-1}\sum_{t=-k+1}^{T}[\widehat{u}_{yt+k}\widehat{u}_{xt}], & k < 0 \end{cases}$ is the sample cross-covariance, $\widehat{C}_{x,x}(0)$, $\widehat{C}_{y,y}(0)$ are the sample variances of the stock returns and output growth, respectively and T is the sample size. The test statistic, Q, proposed by Hong (2001) is given by the following formula:

$$Q = \frac{T\sum_{j=1}^{T-1} k^2(j/M) * \widehat{\tau}^2_{x,y}(j) - C_{1T}(k)}{\sqrt{2 * D_{1T}(k)}} \tag{6}$$

where $C_{1T}(k) = \sum_{j=1}^{T-1}(1 - \frac{j}{T}) * k^2(j/M)$, $D_{1T}(k) = \sum_{j=1}^{T-1}(1 - \frac{j}{T}) * (1 - \frac{j+1}{T}) * k^4(j/M)$ and $k(j/M)$ is a weighting function.[10] Under the null hypothesis of no causality and some appropriate regularity conditions, the Q-test follows asymptotically a $N(0,1)$ distribution.[11] This methodology allows for bivariate conditional mean specification and includes the case of infinite unconditional variance, which is often encountered in empirical studies on stock returns. Testing for the significance of the contemporaneous correlation coefficient between two series is performed by employing the typical sample correlation coefficient, which is also asymptotically normal (Anderson, 1971); assuming that the true value of the correlation coefficient is q, the correlation coefficient estimator is then distributed as $\widehat{q}_{x,y} \rightarrow N\left(q, \frac{(1-q^2)^2}{T}\right)$.

3. Data

To gauge this empirical relationship between output growth and stock returns, we use existing measures of output and real composite and sectoral stock price changes for the G-7 countries. Our data set is monthly and covers the period from January 1973 to August 2003. As a measure of the growth rate of output we use the industrial production index (seasonally adjusted) from Thomson Financial (obtained by Datastream). Following Fama (1990) and other authors, real stock price changes are obtained by use of Datastream-calculated composite and sectoral indices, appropriately adjusted for the inflation rate of the countries under consideration. So, apart from the total market aggregate index and the total non-financial market index,

[9] In our study, we employ the typical ARMA(p,q)-GARCH(1,1) models, the correct order of which is determined by means of the Akaike information criterion.

[10] In the present study, we use the QS kernel.

[11] Notice that the $Q-$test is an one-sided test and upper-tailed critical values should be used.

the following sectoral indices are employed: Financial, Basic Industries, General Industries, Cyclical Services, Non-Cyclical Services, Information Technologies, Cyclical Consumer Goods, Non-cyclical Consumer Goods, Utilities.[12]

4. Empirical evidence

In this section we apply the non-parametric techniques outlined above to examine the empirical relationship between growth and stock returns. We emphasize that, following Fama (1990), Schwert (1990) and others, we do not try to discriminate among various theoretical hypotheses. Instead, we implement the estimation and testing strategy outlined in section 2 to investigate non-parametrically the strength and the direction of correlation between real stock price changes and output growth for the G-7 countries.

4.1. Long-run correlation between growth and returns

We begin the empirical analysis with the estimates of the long-run correlation between growth and stock returns. The first column in the upper part of Table 1 reports the relevant figures for the aggregate market returns at the highest bandwidth examined (36 months). This choice of bandwidth, i.e. the number of autocovariances that are assigned a non-zero weight, represents one tenth of our sample and ensures that the majority of the effects have been taken into account. With the exception of Italy, estimates of the long-run correlation range from 0.488 (Japan) to 0.656 (UK). The second column reports the standard deviation of the point estimates of the long-run correlation based on (3). As was shown in the previous section, the variances of the point estimates are inversely related to the true value of the long-run correlation coefficients. Accordingly, Italy has the lower long-run correlation and thus exhibits the higher standard deviation of the respective estimate. The next column reports the respective figures for all the countries. In this respect, the long-run correlation of the rest of the countries is found to be significantly different from zero.[13] Not surprisingly, the only country for which we cannot reject the null hypothesis of zero long-run correlation is Italy.[14] In the same mode, we

[12] The Datastream codes for the corresponding stock market indices are the following: TOTMKXX, TOTLFXX, BASICXX, GENINXX, CYSERXX, NCYSRXX, ITECHXX, UTILSXX, CYCGDXX, NCYCGXX, where XX stands for the country code, i.e. CN (Canada), FR (France), BD(Germany), IT (Italy), JP (Japan), UK and US. In the same mode, the Consumer Price Index code is the XXI66...CE and the Industrial Production code is XXI64...F. All the reported results were obtained by programs written in E-views 4.1 and are available from the authors upon request.

[13] These tests are performed based on the asymptotic approximation of the distribution of the zero long-run correlation, which is shown to be standard normal.

[14] In principle, we could also calculate the range of bandwidths over which we reject the null hypothesis of a zero

can test whether the estimated long-run correlations are significantly different from any value of the correlation coefficient. The fourth column reports the results from such hypothesis tests for different imposed levels of the correlation coefficient for each country chosen on the basis of the estimated values. In all countries we can not reject the null, i.e. the estimated long-run correlation is not significantly different from the imposed value. The respective figures are 0.7 for the UK, 0.6 for Canada, France and the US, and 0.5 for Germany and Japan.

Our findings are not far from those derived by Choi et al. (1999) for the G-7 countries using in-sample cointegration techniques. These authors have established that there is strong evidence of short-run causality running from stock returns to growth in the cases of US, UK, Japan, Germany, and Canada, whereas weaker evidence is found for France and no causality is detected for Italy. In general, these results corroborate and extend the Fama (1990) and Schwert (1990) conclusions on the important correlation of lagged values of real stock price changes with output growth in six of the G-7 countries.

4.2. Temporal and contemporaneous feedbacks

Having established a significant long-run correlation between stock returns and growth, we move on to decompose it into the contemporaneous correlation coefficient, c_{xy}, and the temporal correlation coefficients, r_{xy} and r_{yx}, that describe feedbacks from past real stock price changes to current output growth ($x_t \rightarrow y_t$) and in the opposite direction ($y_t \rightarrow x_t$), respectively. The last three columns in the upper part of Table 1 report these correlation coefficients for the total market indices for the maximum value of bandwidth (36 months). Our findings suggest that the contemporaneous correlation is close to zero and, in fact, slightly negative for the majority of countries. The highest contemporaneous correlation is detected for France and the UK with estimates reaching 0.12. On the other hand, the estimates of the temporal correlation from stock returns to growth, r_{xy}, appear to be significant. Specifically, the respective estimates range from 0.50 (US) to 0.35 (Canada), whereas Italy fails to show any correlation with a low estimate of 0.19. The results from the temporal correlation from growth to stock returns paint the opposite picture with most estimates being close to zero (the largest coefficients are observed for Canada, UK, and the US and range between 0.12 and 0.16).

coefficient. However, the concave pattern of the relevant t-stat with respect to the bandwidth value M renders such an experiment uninformative for a given sample size. Typically, the null of a zero correlation coefficient is expected not to be rejected for low and high bandwidths due to a low correlation coefficient and a low T/M ratio, respectively.

As outlined in section 2, we can investigate the significance of the temporal correlation by testing for causal relations in the mean of the series following Hong (2001). Table 2A reports the results for causality-in-mean running from stock returns to growth, which indicate that there is a (positive) impact from stock returns to growth. Irrespective of the choice of bandwidth, the evidence is particularly strong for the US and Germany (in the latter case at bandwidths above 9). On the other hand, the test indicates that stock returns changes pass through Italy and Japan growth within 3 to 12 months as significant correlation is detected only at low bandwidths. As far as the UK is concerned, significant correlation is detected within 9 to 24 months. Canada paints the opposite picture as bandwidths exceeding 18 months are necessary for the detection of correlation. Interestingly, the only country for which our test fails to indicate any correlation from stock returns to growth is France.

Regarding the reverse pattern of correlation from growth to stock returns, our results reported in Table 2B do not provide any evidence of association for all the countries at hand, with the exception of the UK where correlation is detected for bandwidths above 12 months. This picture is somewhat against the evidence reported by Park (1997) and McQueen and Roley (1993), who have established a negative, although weak, correlation between output growth and future stock price changes for the US. Given this apparent discrepancy, we postpone any detailed discussion of these findings for the next subsection, where the presentation of the sectoral results from the non-parametric long-run correlation coefficient and its decomposed estimates may shed some further light.

Finally, turning to the contemporaneous part of the decomposed correlation coefficient, Table 3 displays the relevant values for the countries at hand.[15] Following the discussion in section 2, the Anderson (1971) test uses the original series and follows the standard normal distribution under the null of no correlation. The null of a zero coefficient can not be rejected in all countries though only marginally for Canada and France.

An open issue is whether these correlation patterns have been stable over the period under consideration or whether structural changes have induced shifts in the relationship between output growth and stock price changes. To explore this possibility, the second (lower) part of Table 1 presents the corresponding estimates for the post-1987 crash period covering the years

[15] Notice that the figures are different from the corresponding ones displayed in Table 1 as the latter are scaled by the related long-run variances.

1989-2003 for a bandwidth of 18 months (covering approximately ten percent of the sample). As can be readily seen, the point estimates do not display substantial differences, with the possible exceptions of Japan (0.27 compared to 0.49 for the whole sample) and Italy (0.37 compared to 0.19). This affects the tests on the null hypothesis of zero correlation, which is not rejected for Germany, Italy and Japan. As an informal test on the stability of the correlation coefficients, we also conduct tests of equality of the estimated values with the imposed values for the whole sample (see fourth column in the upper part of Table 1). In all cases the null cannot be rejected, which confirms that the correlation coefficients have not changed dramatically for the subsample investigated.[16] Hence, the contemporaneous and the temporal correlations do not display marked differences with those derived from the whole sample.

Now, to obtain a more in-depth picture of the pattern of the correlation estimates as the bandwidth increases, we depict in the top left plot of Figures 1 to 7 our estimates of the correlation coefficients, c_{xy}, r_{xy} and r_{yx}, under increasing values of the bandwidth parameter, M, for the total market index in the G-7 countries for the period 1973-2003. Specifically, we allow the bandwidth parameter (i.e. the number of autocovariances that are assigned a non-zero weight) to take values in the interval [1, 36] by steps of one. In general, the information content in these Figures shows that when the bandwidth parameter increases, the estimates of the temporal correlation coefficient r_{xy} describing the feedback from past stock price changes to output growth increase as well. On the other hand, the estimates of the contemporaneous correlation coefficient c_{xy} and the temporal correlation coefficient r_{yx}, remain close to zero for all values of the bandwidth parameter.

Interestingly, the rate of growth of the estimates of r_{xy} does not remain constant over the whole range of values of the bandwidth parameter M. Moreover, its pattern is not uniform across countries. In most cases, $\widehat{r}_{xy}$ increases with the correlation function having a concave form in terms of the bandwidth; this is cleary the case for France, Japan, UK and the US for bandwidth values below twenty-four. In these countries, $\widehat{r}_{xy}$ remains roughly constant beyond this point, indicating that it has reached its maximum value and no additional information can be gained by utilizing more lags of stock price changes. On the other hand, in the case of Germany, $\widehat{r}_{xy}$ yields additional information up to the point where the bandwidth parameter

[16] In fact, the point estimates derived from a bandwidth of 36 months are much closer to the estimates reported for the whole sample; these results are available upon request.

equals thirty-six, whereas it appears to be stable for values above twelve in Canada. Thus, although the general picture is consistent with the broad finding that the major feedbacks from stock price changes to output growth occur within the first six to twelve months, non-negligible feedbacks can be detected for periods lasting up to three years.

We close this section by noting that the earlier findings by Fama (1990), Schwert (1990) and other authors have pointed towards a strong positive relation between stock prices and future industrial production at a two to four quarter forecast interval, depending on the horizon of calculated returns. As has been shown by Fama (1990), the significance of lags tends to increase with the horizon of returns, due to their overlapping with future cash flows. These findings have been reinforced by the results in Estrella and Mishkin (1998) who have found that the stock market is a useful predictor of output in the US at a two quarter horizon. The evidence presented here suggests that in the G-7 countries (with the exception of Italy) stock prices anticipate upward movements in industrial production at longer intervals (lasting up to three years) as well. The overall picture from the estimates of long-run correlation coefficients and the relevant hypothesis testing suggests that, as pointed out by Mauro (2003), this long-term association is stronger in countries with high market capitalization (US, UK), but less weaker when capitalization is low (Italy).

5. Sectoral estimates

As mentioned in the Introduction, there are several theoretical channels through which output growth and stock price changes can be interrelated. In addition to the links between these variables at the aggregate level, which have been investigated extensively in the relevant literature via parametric methods, stock price indices of individual sectors may also be related with output. For instance, it is well known that profits tend to grow in line with output in the long run. So, if profits in certain sectors, and consequently sectoral indices, are highly procyclical, then useful information may be extracted from stock price changes in these sectors. Also, given that the stock market value of companies is related to investment projects (q-theory of investment), information from sectoral stock price changes may vary according to the sensitivity of sectors with different capital structure to the economic environment.[17]

We investigate the decomposed long-run correlation between output growth and sectoral

[17] For instance, Duffee and Prowse (1996) have shown that auto industry stock returns have higher explanatory power for future GDP than market returns.

share price changes in Figures 1 to 7. As a first observation, we note that the changes in the non-financial market share index appear more highly correlated with output growth compared to the changes in the financial index with the correlation appearing relatively stronger at lower bandwidths. The temporal correlation coefficient, r_{xy}, rises in a similar manner as the one obtained by use of the composite market index. Hence, the results derived earlier on are mainly driven by the changes in the non-financial index that yields a higher correlation with future output growth.[18] As expected, the temporal and the contemporaneous correlation coefficients, r_{yx} and c_{xy}, appear again insignificant.

Turning to the individual sectoral indices, we observe that their patterns vary across sectors and across countries. For instance, in the US the estimates of the temporal correlation coefficient, $\widehat{r}_{xy}$, take the largest values in the cases of the General Industries, the Cyclical Services, and the Cyclical Consumer Goods indices. As in the case of the aggregate indices, the bandwidths required range from eighteen to thirty-six months, which implies that the information content for future growth in these indices is present in distant lags as well. Looking at the other countries, the Cyclical Consumer Goods appears to take relatively large values too in the cases of Canada, France, Germany, and Japan. More importantly, the estimated coefficient increases with the bandwidth in Canada, and Japan indicating that, as in the US, the association becomes stronger when more lags are given a non-zero weight. Other noteworthy patterns appear in Germany for the General Industries and the Utilities indices, which increase substantially as the bandwidth widens, in Japan for the General Industries index, which takes its largest value when more than twenty lags are utilized, and in the UK where more than six lags are required for the long-run coefficient to start increasing. The contemporaneous correlation again is very close to zero confirming the results obtained from the aggregate indices.

Finally, an interesting feature is that output growth in the US is negatively correlated with future changes in the Basic Industries share index with the long-run correlation coefficient reaching its minimum value of -0.2 at a bandwidth of 20 months. A similar negative effect (though somewhat weaker) appears in the case of the Cyclical Consumer Goods share index in the US (and also in Canada and France). This evidence implies that a fall in output is associated with a future rise of US stock prices in these sectors, particularly in the capital-intensive sector

[18] In interpreting these results one should take into account that the industrial production index has been used as a measure of output.

of Basic Industries.[19]

Our finding of a negative coefficient only in the case of the US Basic Industries index explains the negative correlation between output growth and future stock price changes, reported by McQueen and Roley (1993) and Park (1997) for the US economy. Specifically, the capital-intensive Basic Industries index had a higher weight in the decades of the 70s and 80s and, thus, is likely to have been strongly affected by adverse developments in US monetary policy in a less open economic environment. This has driven the negative correlation during an era when manufacturing output and profits accounted for the largest portion of total output and profits, but the link has gradually evaporated as other sectoral indices became more heavily weighted in the total share market index.

6. Conclusions

The bulk of empirical evidence from parametric models has shown that stock price changes are useful in forecasting growth. However, inference within parametric models will be affected if some of the underlying assumptions are inappropriate for the dataset at hand. In particular, long-range dependence may call for a dynamic model with an unusually long lag-structure and, therefore, the usual practice of using parsimonious models may prove costly in terms of the desirable properties of estimators and related test-statistics. In this vein, we re-examined the correlation between stock price changes and output growth in the G-7 countries by employing non-parametric estimates of the long-run covariance matrix. The most important finding of the paper is that we have found non-negligible feedbacks from stock returns to growth lasting for up to three years, which implies that the underlying covariance structure of the two series evolves at a long-run level as well. Furthermore, we extended our analysis by including sectoral stock price indices, in order to investigate for possible links at a more disaggregate level, and we have established that the sectoral indices exhibit substantial variations across sectors and across countries.

Our results on the long-run links between these variables in the G-7 countries may shed some light in explaining the poor performance of stock price changes as predictors of future output growth despite their strong in-sample correlation (see Choi et al., 1999, and the survey

[19] To some extent, this result is to be anticipated as the growth rate of the industrial production index, used as a measure of output growth in this study, is more highly correlated with future growth rates of the industrial stock price index.

by Stock and Watson, 2003). It is likely that a subsantial portion of information is lost by the need to estimate parsimonious single-equation and multivariate parametric models, which in turn reduces their forecasting ability. Hence, although the evidence presented here can only be interpreted tentatively in terms of forecasting ability, there is some indication that some predictive content could be found if larger lags of stock price changes are utilized in parametric specifications aiming at predicting output in the G-7 countries.

The method employed here can also be applied to other cases in which parametric methods leave empirical questions open. For instance, Thoma and Gray (1998) claim that, contrary to the view popularly held in the literature, financial variables (money supply and interest rates) do not provide any predictive power for future industrial growth. The authors note that, given that the predictive power of parametric models should be evaluated in out-of-sample forecasting, much of their power is the outcome of specific outliers. The non-parametric empirical strategy used here can be extended to the estimation and hypothesis testing for the long-run covariance structure between monetary variables and real activity. Another promising route for further research involves the links between domestic and international stock portfolios and future output. Dumas et al. (2003) point out that an open question in the study of international financial markets is whether stock markets correlations across countries can be explained by economic fundamentals. Empirical findings on this issue have not been universally conclusive (see Smith, 1999) and the present methodology could shed some light on the links between variations in international aggregate or sectoral stock market links and underlying economic variables.

Appendix: Asymptotic distribution of the long-run correlation coefficient

Here we derive the asymptotic distribution of the long-run correlation coefficient $\hat{\rho}_{xy}$. Given that the covariance between any two elements of the spectral density matrix, for example (a, b) and (c, d), is equal to $f_{ac}f_{bd} + f_{ad}f_{bc}$, we obtain the following asymptotic distribution for the elements of $\widehat{\Omega}$:

$$\sqrt{\frac{T}{M}} \begin{bmatrix} \hat{\omega}_{xx} - \omega_{xx} \\ \hat{\omega}_{yy} - \omega_{yy} \\ \hat{\omega}_{xy} - \omega_{xy} \end{bmatrix} \sim N\left(\mathbf{0}, \begin{bmatrix} 2\omega_{xx}^2 & 2\omega_{xy}^2 & 2\omega_{xx}\omega_{xy} \\ 2\omega_{xy}^2 & 2\omega_{yy}^2 & 2\omega_{yy}\omega_{xy} \\ 2\omega_{xx}\omega_{xy} & 2\omega_{yy}\omega_{xy} & \omega_{xx}\omega_{xy} + \omega_{xy}^2 \end{bmatrix} \right) \tag{A1}$$

In order to derive the asymptotic distribution of the long-run correlation coefficient $\hat{\rho}_{xy} \equiv \frac{\hat{\omega}_{xy}}{\sqrt{\hat{\omega}_{xx}\hat{\omega}_{yy}}}$ we apply the delta method with the transformation vector J equal to the partial derivatives of ρ_{xy} with respect to ω_{xx}, ω_{yy} and ω_{xy}:

$$J = \begin{bmatrix} \frac{\partial \rho}{\vartheta \omega_{xx}} & \frac{\partial \rho}{\vartheta \omega_{yy}} & \frac{\partial \rho}{\vartheta \omega_{xy}} \end{bmatrix}$$

Specifically, we get that:

$$\frac{\partial \rho}{\vartheta \omega_{xx}} = \frac{\partial \left(\frac{\omega_{xy}}{\sqrt{\omega_{xx}\omega_{yy}}} \right)}{\vartheta \omega_{xx}} = \frac{-\omega_{xy}}{2\omega_{xx}^2 \sqrt{\omega_{xx}\omega_{yy}}}$$

$$\frac{\partial \rho}{\vartheta \omega_{yy}} = \frac{\partial \left(\frac{\omega_{xy}}{\sqrt{\omega_{xx}\omega_{yy}}} \right)}{\vartheta \omega_{yy}} = \frac{-\omega_{xy}}{2\omega_{yy}^2 \sqrt{\omega_{xx}\omega_{yy}}}$$

$$\frac{\partial \rho}{\vartheta \omega_{xy}} = \frac{\partial \left(\frac{\omega_{xy}}{\sqrt{\omega_{xx}\omega_{yy}}} \right)}{\vartheta \omega_{xy}} = \frac{1}{\sqrt{\omega_{xx}\omega_{yy}}}$$

Setting Q the asymptotic variance of the Ω matrix in (A1), the asymptotic variance of the long-run correlation coefficient is calculated as follows:

$$P = JQJ'$$

After some simple algebra, we have:

$$P = \frac{(\omega_{xy}^2 - \omega_{xx}\omega_{yy})^2}{\omega_{xx}^2\omega_{yy}^2} = (\rho_{xy}^4 + 1 - 2\rho_{xy}^2) = (\rho_{xy}^2 - 1)^2 \tag{A2}$$

It follows from (A1) and (A2) that:

$$\sqrt{\frac{T}{M}}\left[\hat{\rho}_{xy} - \rho_{xy}\right] \sim N\left(0,\ \left(1 - \rho_{xy}^2\right)^2\right)$$

which is equation (3) in the text.

References

Anderson T.W., 1971, *The Statistical Analysis of Time Series*, Wiley, New York.

Andrews D., 1991, 'Heteroskedasticity and autocorrelation consistent covariance matrix estimation', *Econometrica*, 59, 817-58.

Andrews D. and J. Monahan, 1992, 'An Improved Heteroskedasticity and Autocorrelation Consistent Covariance Matrix Estimator', *Econometrica,* 60, 953-966.

Barro R., 1990, 'The stock market and investment', *Review of Financial Studies*, 3, 115-131.

Binswanger M., 2004, 'Stock returns and real activity in the G-7 countries: Did the relationship change during the 1980s?', *Quarterly Review of Economics and Finance*, 44, 2, 237-252.

Blanchard O., 1981, 'Output, the stock market and interest rates', *American Economic Review*, 71, 132-143.

Bosworth B., 1975, 'The stock market and the economy', *Brookings Papers on Economic Activity*, 2, 257-290.

Brainard W. and J. Tobin, 1968, 'Pitfalls in financial model building', *American Economic Review*, 58, 99-122.

Choi J.J., S. Hauser and K.J. Kopecky, 1999, 'Does the stock market predict real economic activity? Time series evidence from the G-7 countries', *Journal of Banking and Finance*, 23, 1771-1792.

Duffee G. and S. Prowse, 1996, 'What's good for GM? Using auto industry stock returns to forecast business cycles and the q-theory of investment', *Board of Governors of the Federal Reserve System, Finance and Economics Discussion Paper Series No. 96-38.*

Dumas B., C. R. Harvey, P. Ruiz, 2003, 'Are correlations of stock returns justified by subsequent changes in national outputs?', *Journal of International Money and Finance*, 22, 777-811.

Estrella A. and F. Mishkin, 1998, 'Predicting US recessions: Financial variables as leading indicators', *Review of Economics and Statistics*, 80, 45-61.

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

Fama E., 1981, 'Stock returns, real activity, inflation and money', *American Economic Review*, 71, 545-565.

Fama E. and K. French, 1988, 'Permanent and temporary components of stock prices', *Journal of Political Economy*, 96, 2, 246-273.

Goldsmith R., 1969, *Financial Structure and Development*, Yale University Press, New Haven.

Grenander U. and M. Rosenblatt, 1953, 'Statistical spectral analysis arising from stationary stochastic processes', *Annals of Mathematical Statistics*, 24, 537-558.

Hall R., 1978, 'Stochastic implications of the life cycle-permanent income hypothesis: Theory and evidence', *Journal of Political Economy*, 86, 971-987.

Hansen B., 1992, 'Consistent covariance matrix estimation for dependent heterogeneous processes', *Econometrica*, 60, 967-72.

Hassapis C., 2003, 'Financial variables and real activity in Canada', *Canadian Journal of Economics*, 36, 2, 421-442.

Hayashi F., 1982, 'Tobin's marginal q and average q: A neoclassical interpretation', *Econometrica*, 50, 213-224.

Hong Y., 2001, 'A test for volatility spillover with application to exchange rates', *Journal of Econometrics*, 103, 183-224.

Jegadeesh N., 1990, 'Evidence of predictable behavior of security patterns', *Journal of Finance*, 45, 881-898.

Lettau M. and S. Ludvigson, 2002, 'Time-varying risk-premia and the cost of capital: An alternative implication of the q theory for investment', *Journal of Monetary Economics*, 49, 31-66.

Luetkepohl H. and D. Poskitt, 1996, 'Testing for causation using infinite order vector autoregressive processes', *Econometric Theory*, 12, 61-87.

Mauro P., 2003, 'Stock returns and output growth in emerging and advanced economies', *Journal of Development Economics*, 71, 129-153.

McQueen G. and V. Roley, 1993, 'Stock prices, news, and business conditions', *Review of Financial Studies*, 6, 3, 683-707.

Morck R., A. Shleifer and R. Vishny, 1990, 'The stock market and investment: Is the stock market a sideshow?', *Brookings Papers on Economic Activity*, 0, 2, 157-202.

Mullins M. and S.B. Wadhwani, 1989, 'The effect of stock market on investment: A comparative study', *European Economic Review*, 33, 931-961.

Newey W. and K. West, 1994, 'Automatic lag selection in covariance matrix estimation', *Review of Economic Studies*, 61, 631-53.

Newey W. and K. West, 1987, 'A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix', *Econometrica*, 55, 703-08.

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

Parker J. and C. Julliard, 2005, 'Consumption risk and the cross-section of expected returns' *Journal of Political Economy*, 113, 185-222.

Parzen E., 1957, 'On consistent estimates of the spectrum of a stationary time series', *Annals of Mathematical Statistics*, 28, 329-348.

Poterba J. and L. Summers, 1988, 'Mean reversion in stock prices: Evidence and implications', *Journal of Financial Economics*, 22, 27-59.

Priestley M.B., 1962, 'Basic considerations in the estimation of spectra', *Technometrics*, 4, 551-564.

Priestley M.B., 1981, *Spectral Analysis and Time Series*, Vols I and II, Academic Press, New York.

Robinson P.M., 1991, 'Automatic frequency domain infrence on semiparametric and non-parametric models', *Econometrica*, 59, 1329-1363.

Schwert W., 1990, 'Stock returns and real activity: A century of evidence', *Journal of Finance*, 45, 1237-1257.

Sims C., J. Stock and M. Watson, 1990, 'Inference in linear time series models with some unit roots', *Econometrica*, 58, 113-44.

Smith S., 1999, 'What do asset prices tell us about the future?', *Economic Review, Federal Reserve Bank of Atlanta*, 3, 4-13.

Stock J. and M. Watson, 2003, 'Forecasting output and inflation: The role of asset prices', *Journal of Economic Literature*, XLI, 788-829.

Thoma M. and J.A. Gray, 1998, 'Financial market variables do not predict real activity', *Economic Inquiry*, 36, 522-539.

Toda H. and P. Phillips, 1993, 'Vector autoregressions and causality', *Econometrica*, 61, 1367-93.

White H. 1984, *Asymptotic theory for econometricians,* New York: Academic Press.

Table 1. Long-run correlation estimates between output growth (y) and stock price changes (x)

Country	Long-Run Correlation	Standard Deviation	t-stat Ho: $\rho_{xy}=0$	t-stat Ho: $\rho_{xy}=\rho$	Contemporaneous correlation	Temporal correlation $x \rightarrow y$	Temporal correlation $y \rightarrow x$
			Sample period: 1973-2003				
Canada	0.556	0.221	2.536	-0.203 (ρ=0.6)	0.041	0.353	0.162
France	0.564	0.219	2.536	-0.201 (ρ=0.6)	0.116	0.362	0.086
Germany	0.491	0.243	2.219	-0.040 (ρ=0.5)	-0.021	0.451	0.061
Italy	0.194	0.309	0.862	-0.034 (ρ=0.2)	-0.033	0.190	0.037
Japan	0.488	0.244	2.216	-0.041 (ρ=0.5)	-0.022	0.476	0.034
UK	0.656	0.183	2.988	-0.158 (ρ=0.7)	0.116	0.422	0.118
US	0.583	0.211	2.641	-0.083 (ρ=0.6)	-0.018	0.498	0.103
			Sample period: 1989-2003				
Canada	0.575	0.210	2.005	-0.130 (ρ=0.6)	0.001	0.278	0.296
France	0.549	0.219	1.918	-0.254 (ρ=0.6)	0.090	0.321	0.138
Germany	0.412	0.260	1.439	-0.374 (ρ=0.5)	-0.131	0.424	0.119
Italy	0.371	0.271	1.296	0.562 (ρ=0.2)	0.084	0.285	0.002
Japan	0.275	0.289	0.961	-0.957 (ρ=0.5)	-0.030	0.348	-0.043
UK	0.565	0.214	1.974	-0.844 (ρ=0.7)	0.033	0.368	0.164
US	0.648	0.182	2.264	0.239 (ρ=0.6)	-0.020	0.395	0.273

Notes: The bandwidth for the 1973-2003 period is 36 months and for the 1989-2003 period is 18 months; see section 2 in text for details.

Table 2A. Hypothesis testing for temporal correlation: from stock price changes to output growth

	Q-test								
Country/Bandwidth	*3*	*6*	*9*	*12*	*18*	*24*	*30*	*36*	*48*
Canada	No	No	No	No	Yes**	Yes**	Yes**	Yes**	Yes**
France	No	No	No	No	No	No	No	No	No
Germany	No	No	Yes**	Yes**	Yes**	Yes**	Yes**	Yes**	Yes**
Italy	Yes*	Yes**	Yes*	No	No	No	No	No	No
Japan	Yes**	Yes**	Yes*	No	No	No	No	No	Yes*
UK	No	No	Yes*	Yes**	Yes**	Yes*	No	No	No
US	Yes**	Yes**	Yes**	Yes**	Yes**	Yes**	Yes**	Yes**	Yes**

Table 2B. Hypothesis testing for temporal correlation: from output growth to stock price changes

	Q-test								
Country/Bandwidth	*3*	*6*	*9*	*12*	*18*	*24*	*30*	*36*	*48*
Canada	No	No	No	No	No	No	No	No	No
France	No	No	No	No	No	No	No	No	No
Germany	No	No	No	No	No	No	No	No	No
Italy	No	No	No	No	No	No	No	No	No
Japan	No	No	No	No	No	No	No	No	No
UK	No	No	No	Yes**	Yes**	Yes**	Yes**	Yes**	Yes**
US	No	No	No	No	No	No	No	No	No

Notes: Q-test denotes the Hong (2001) test; see section 2 for details. denotes statistical significance at the 5% level and ** at the 1% level.*

Table 3. Hypothesis testing for contemporaneous correlation

Country	Contemporaneous correlation q_{xy}	t-stat Ho: $q_{xy}=0$
Canada	0.103	1.947
France	0.099	1.877
Germany	0.005	0.095
Italy	0.039	0.734
Japan	0.041	0.774
UK	0.059	1.128
US	-0.017	-0.317

Notes: q_{xy} denotes the Anderson (1971) test; see section 2 for details.

Figure 1
CANADA: Decomposed long-run correlation coefficient between output growth and stock price changes

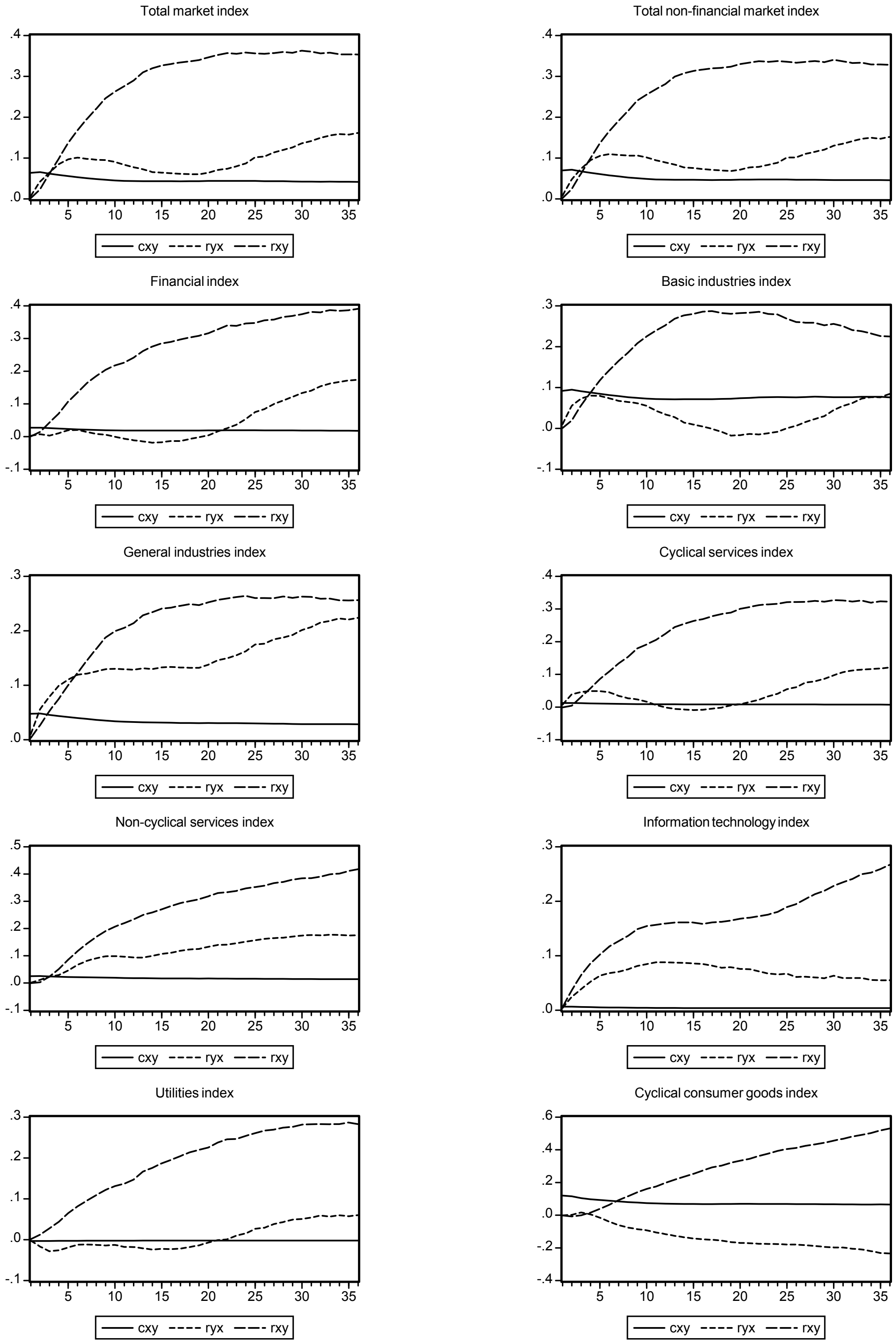


Figure 2

FRANCE: Decomposed long-run correlation coefficient between output growth and stock price changes

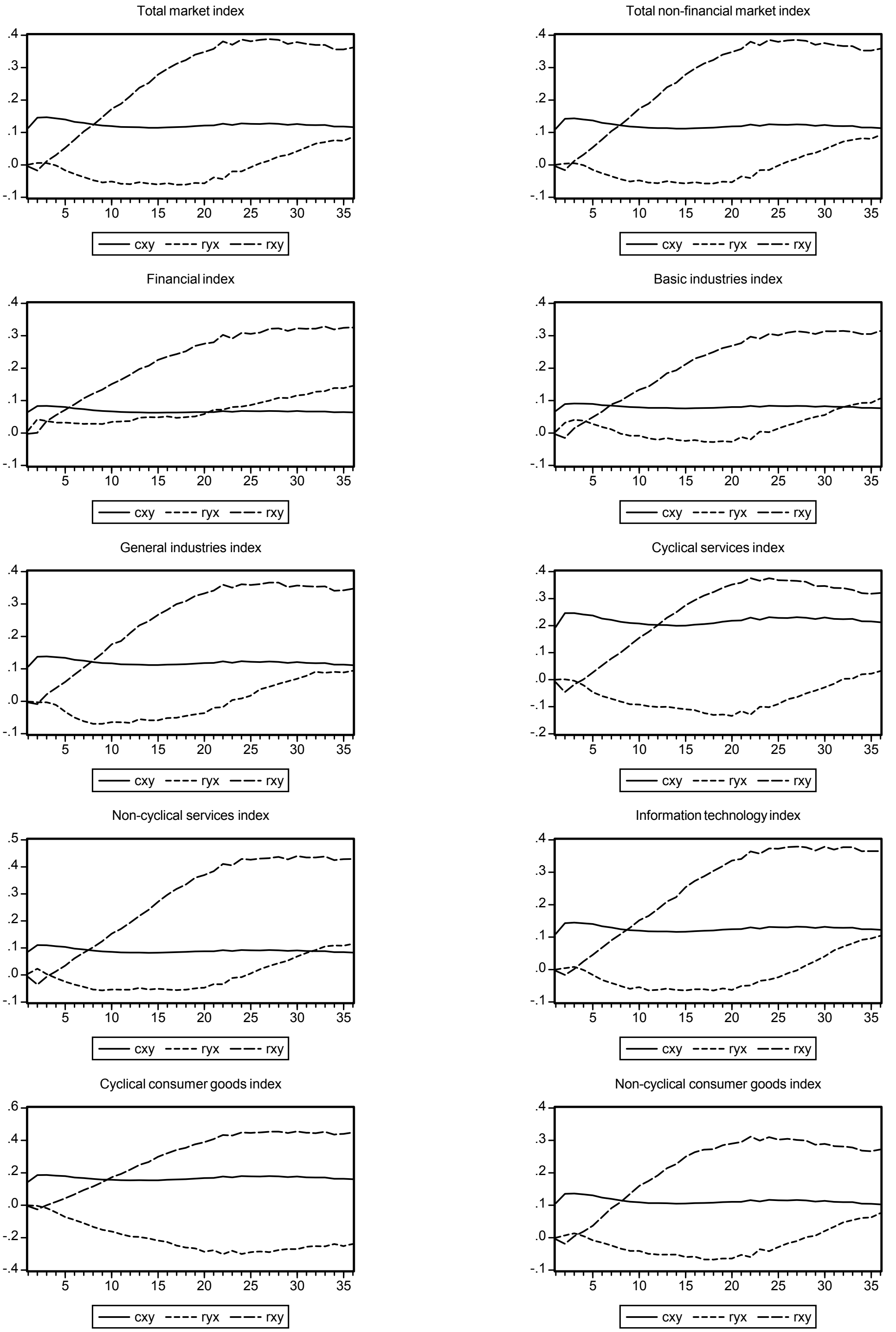


Figure 3

GERMANY: Decomposed long-run correlation coefficient between output growth and stock price changes

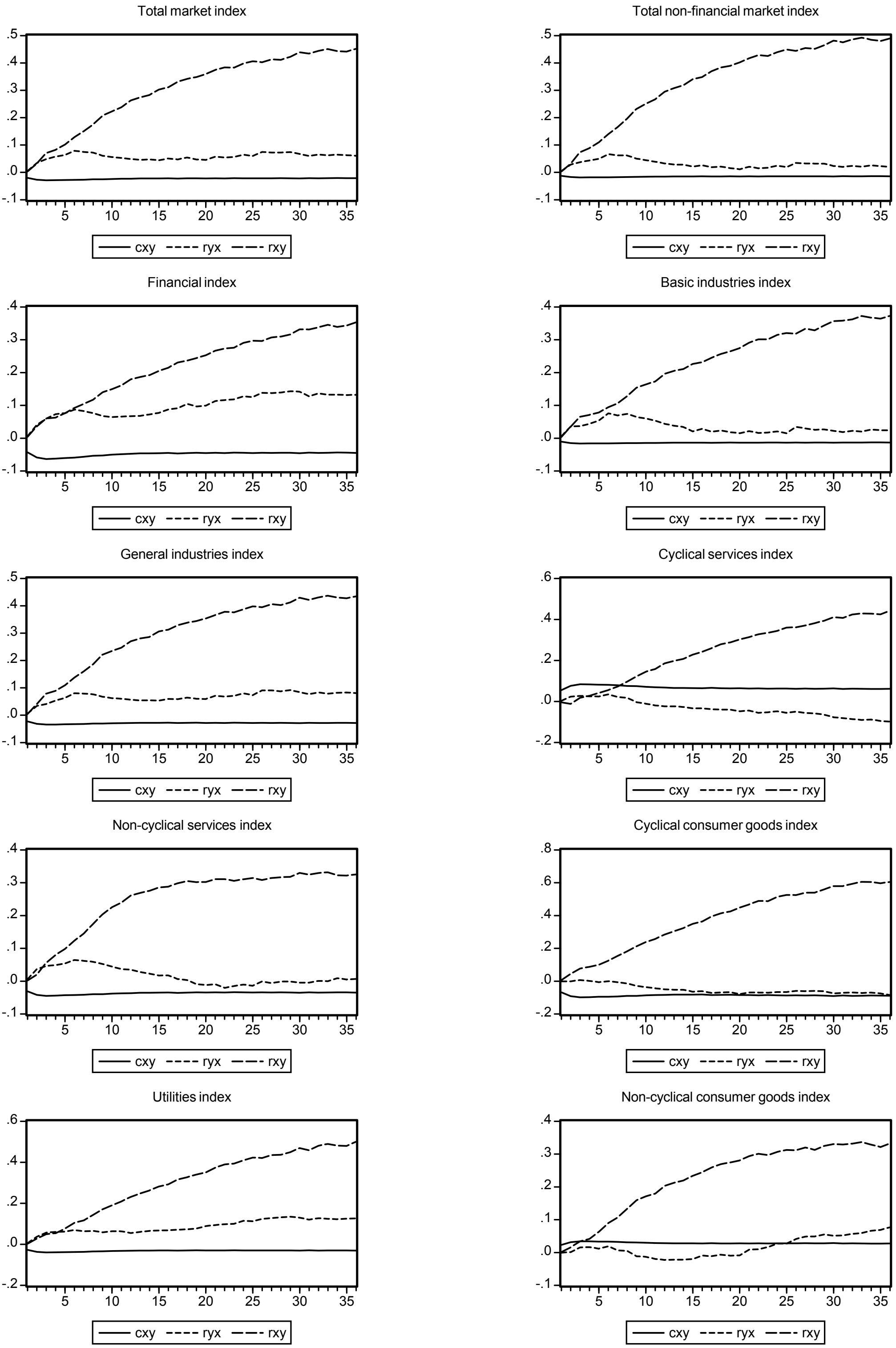


Figure 4
ITALY: Decomposed long-run correlation coefficient between output growth and stock price changes

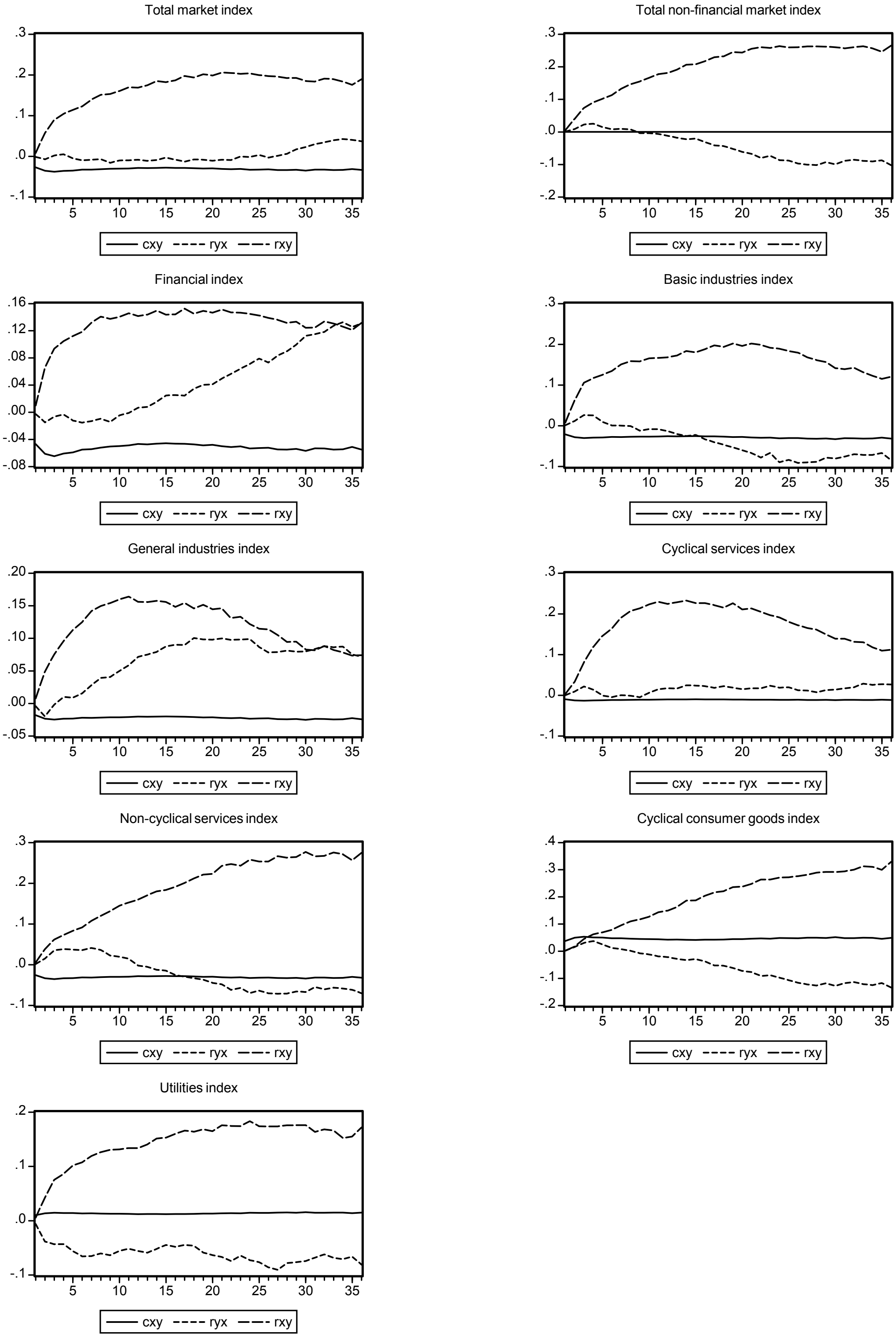


Figure 5

JAPAN: Decomposed long-run correlation coefficient between output growth and stock price changes

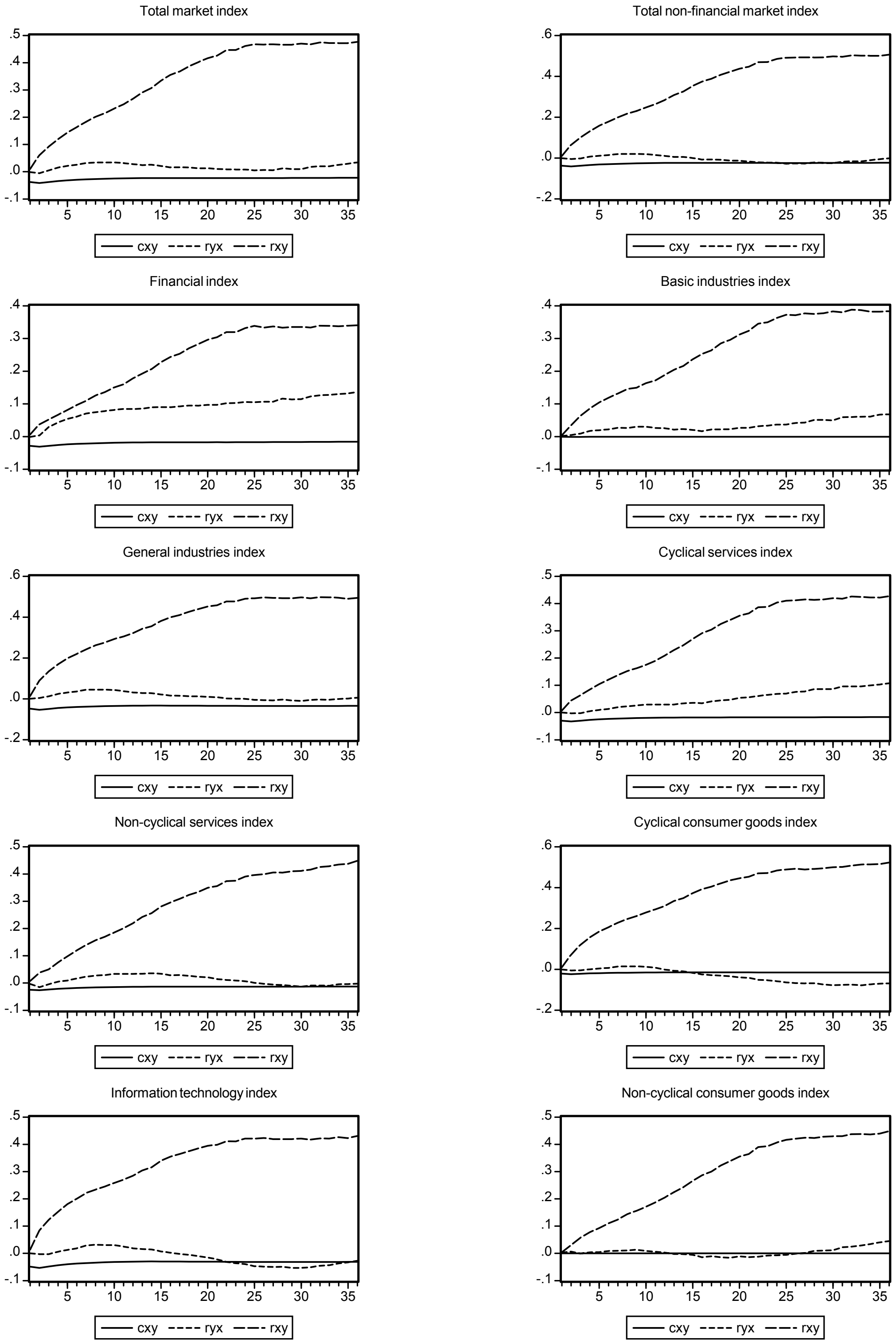


Figure 6
UK: Decomposed long-run correlation coefficient between output growth and stock price changes

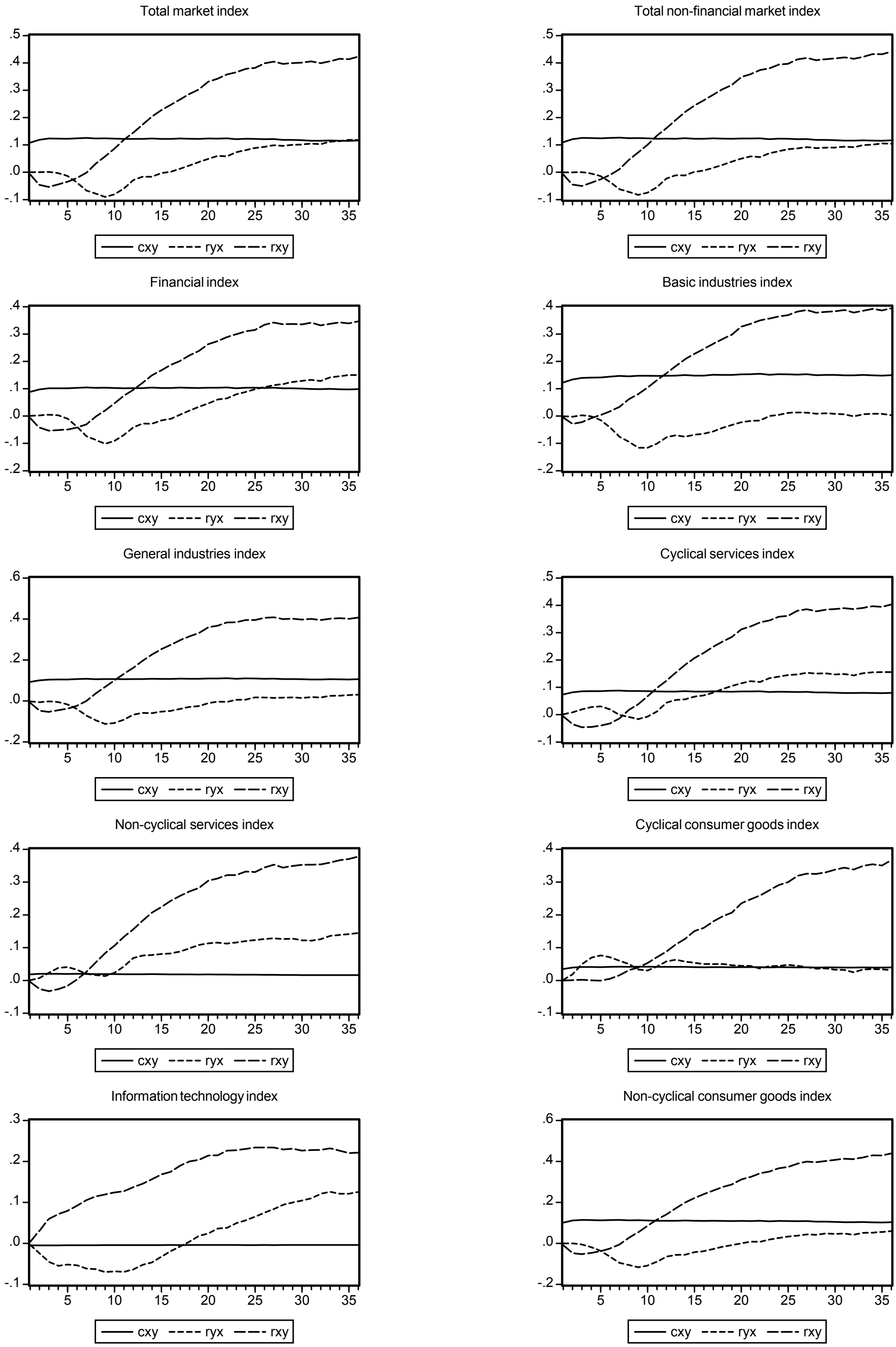
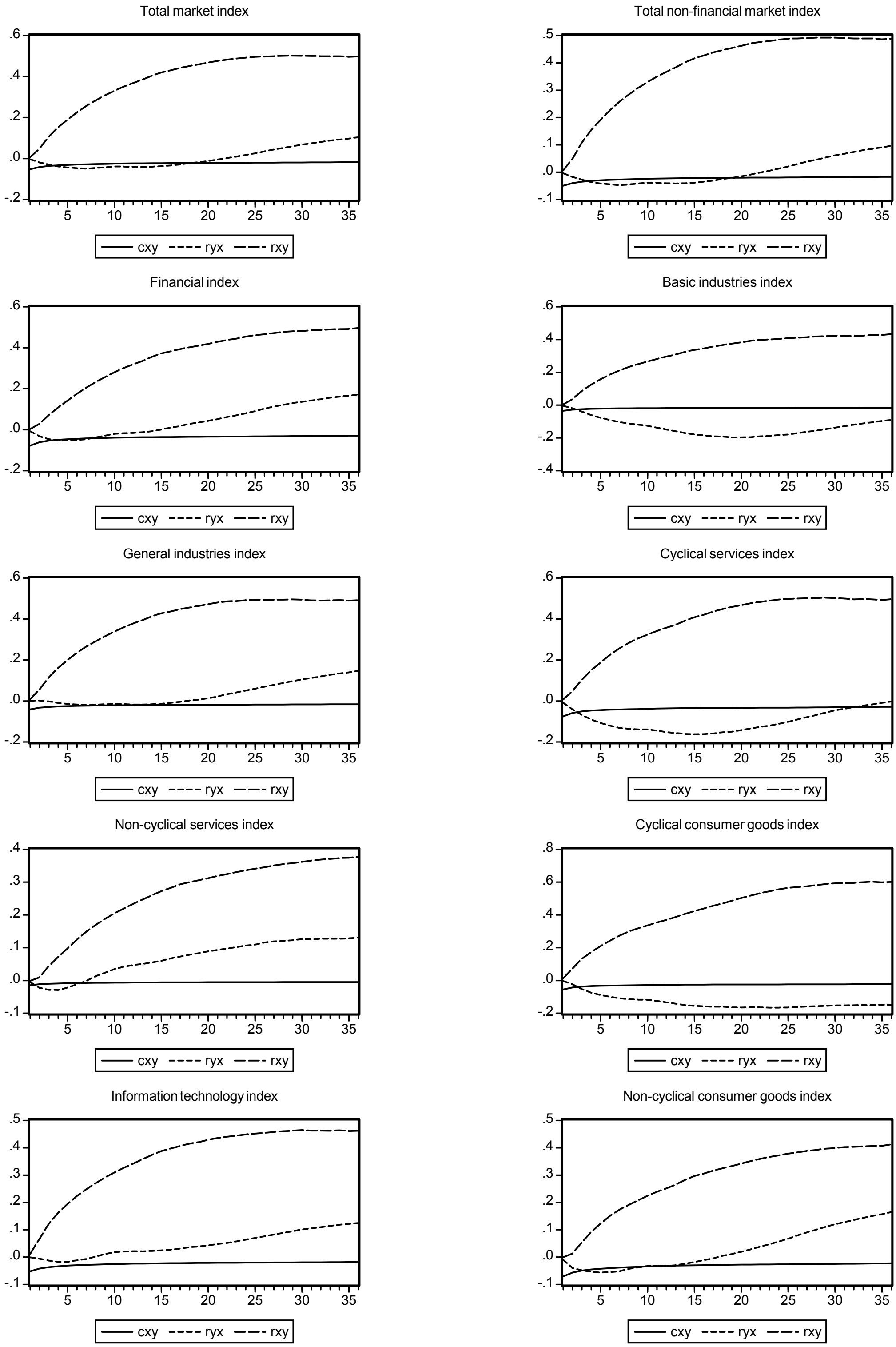


Figure 7
US: Decomposed long-run correlation coefficient between output growth and stock price changes



Institute for International Integration Studies
The Sutherland Centre, Trinity College Dublin, Dublin 2, Ireland