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

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Abstract In this paper we reexamine the linkages between output growth and real stock price changes for the G7 countries using 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.

Keywords: Real stock price changes, Output growth, Long-run covariance matrix.

JEL classification : C14, G10, O51.

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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. Early contributions, beginning with the work by Goldsmith (1969), assessed the positive relationship between stock returns and economic growth with the prevalent explanation being that an efficient asset market will immediately reflect 'news' about the macroeconomy, like productivity and policy shocks. In contrast, these developments will appear with some delay in the product markets, due for instance to menu costs and other frictions, and will thus generate a positive correlation of stock returns with future output growth in the data. This conclusion reflects in turn 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. In this vein, a series of empirical 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. 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.[1]

In general, the empirical studies on the relationship between output growth and stock price changes have relied almost exclusively on single-equation or multivariate vector autoregressive (VAR) and panel models. However, parametric models may be too restrictive to represent the true autocovariance structure of the growth-returns nexus. 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). This 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.[2]

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[1]A possible explanation for this pattern may be that it reflects countercyclical monetary policy through the reaction function of authorities. For instance, in a period of unanticipated recession the central bank may react by reducing interest rates, thus triggering 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.

[2]Luetkepohl and Poskitt (1996) discuss the problems that arise in causality testing by fitting finite VAR models

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.[3] Based on 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; Schwert 1990), have focused on 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; Binswanger 2004). 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.[4]

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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.

[3]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 Hansen (1992).

[4]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

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 linkages 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 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 included in the estimation of the long-run covariance matrix increases, the feedback from stock price changes to output growth also increases, reaching a peak at a range between eighteen to twenty-four months, whereas weaker effects may last up to thirty-six months. We also establish that these linkages can improve in-sample and out-of-sample forecasting in the context of parametric models. 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. A by-product of our approach is that the finding of a negative correlation between output growth and future stock price changes 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 studies closest in spirit to ours are the papers by Choi et al. (1999) and Hassapis (2003). In particular, Choi et al. (1999) examine the growth-returns relationship for the G-7 countries using in-sample cointegration techniques and establish 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. Their findings complement and extend those reported by Fama (1990), Schwert (1990), Barro (1990), and other authors who have reported that there is a strong

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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 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 links between the financial and the real sector of the economy compare with those obtained by examining the past behavior of the stock price changes at horizons based on parametric single-equation or multivariate regressions. Using a similar approach as the one adopted here, Hassapis (2003) estimates the long-run covariance matrix 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. Our paper corroborates and extends these findings by employing a richer dataset by covering the G-7 countries in order to analyze and compare both aggregate and sectoral stock market indices. Moreover, we are able to test the significance of the long-run correlation coefficient by deriving its asymptotic distribution and also the significance of the temporal feedbacks calculated from the long-run correlation coefficient through appropriate bivariate non-parametric causality tests.

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

We are interested in estimating the 'long-run' correlation coefficient, ρ_{xy}, between output growth, y_t, and real stock returns, x_t. The long-run covariance matrix Ω of the process $Z_t = [y_t, x_t]^T$ is defined as:

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

For a given sample size, T, the estimand Ω_T of Ω can be written as the sum of the sample

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employees in decision making.

estimates of the variances of output growth and stock returns and the respective cross-covariances between these series, i.e.

$$\Omega_T = \sum_{j=-T}^{T} \Gamma_T(j)$$

where $\Gamma_T(j) = \begin{Bmatrix} \frac{1}{T} \sum_{t=j+1}^{T} [Z_t Z_{t-j}], j \geq 0 \\ \frac{1}{T} \sum_{t=-j+1}^{T} [Z_{t+j} Z_t], j < 0 \end{Bmatrix}, t = 1,2,....T.$ In practice, only a fraction of the sample autocovariances is used to estimate the asymptotic variance $\Omega,$ by employing a class of kernel estimators and the selection of a bandwidth parameter, M , with the estimator of Ω given by:

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

where $k(\cdot)$ is a real-valued kernel.[5] The kernel is a function that determines the scheme with which past cross covariances enter the estimation of the long-run covariance matrix, while the bandwidth determines the number of lags employed in the estimation. The estimator $\hat{\Omega},$ 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 utilize 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.[6] The elements of $\hat{\Omega}$ are jointly normally distributed and this joint

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[5]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.

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

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 follows (see the Appendix for the detailed derivation)[7]:

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

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 Λ^T), i.e. $\Omega = G + \Lambda + \Lambda^T$ where $G \equiv \begin{bmatrix} g_{yy} & g_{xy} \\ g_{xy} & g_{xx} \end{bmatrix} = E(Z_0 Z_0^T)$ and $\Lambda \equiv \begin{bmatrix} \lambda_{yy} & \lambda_{yx} \\ \lambda_{xy} & \lambda_{xx} \end{bmatrix} = \sum_{k=1}^{\infty} E(Z_0 Z_k^T)$. 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 ($y_t \to x_t$), and the temporal correlation coefficient r_{xy} that describes feedbacks of the opposite direction $(x_t \to y_t)$. Since our aim is to decompose the long-run coefficient into its constituents, the common denominator employed, i.e. the square root of the product of the long-run variances of the series at hand, reflects our goal to measure the contribution of each of the three components to the long-run correlation coefficient. In this respect, these three components add to the long-run coefficient value.[8]

While we are able to exploit the asymptotic normality of the estimator of the two-sided

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$E(\varepsilon_t) = 0, E(\varepsilon_t^2) < \infty, E(\varepsilon_t^4) < \infty$, and $\sum_{j=0}^{\infty} \left|\psi_j\right| < \infty$.

[7]Before calculating the long-run correlation coefficient, the data are demeaned so as to avoid inducing bias to our estimates through the means of the series.

[8] This modification does not affect the properties of the three components that can be interpreted as correlation coefficients since they always lie in the interval [-1,1].

long-run covariance matrix and derive the relevant distribution for the long-run correlation coefficient, ρ_{xy}, 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).[9] In particular, consider again the bivariate stationary and ergodic stochastic process $Z_t = [y_t, x_t]^T$. 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 so as to avoid detecting a significant relationship due to autocorrelation or heteroskedasticity and in the second stage, we calculate the sample cross-correlations of the standardized residuals of output growth and real stock returns, $\hat{u}_{yt}$ and $\hat{u}_{xt}$ respectively.[10] The sample cross-correlation function of u_{yt} and u_{xt} ($\hat{\tau}_{x,y}(k)$) is given by:

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

where $\hat{C}_{x,y}(k) = \begin{Bmatrix} T^{-1} \sum_{t=k+1}^{T} [\hat{u}_{yt}\hat{u}_{xt-k}], k \geq 0 \\ T^{-1} \sum_{t=-k+1}^{T} [\hat{u}_{yt+k}\hat{u}_{xt}], k < 0 \end{Bmatrix}$ is the sample cross-covariance, $\hat{C}_{x,x}(0), \hat{C}_{y,y}(0)$ 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:

[9]The methodology developed by Hong (2001) accommodates testing for causality in mean although it was primarily aimed at detecting volatility spillovers, i.e. causality in variance.

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

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

where $k(j/M)$ is a weighting function, $C_{1T}(k) = \sum_{j=1}^{T-1}(1-\frac{j}{T}) * k^2(j/M)$, and $D_{1T}(k) = \sum_{j=1}^{T-1}(1-\frac{j}{T}) * (1-\frac{j+1}{T}) * k^4(j/M)$.[11] Under the null hypothesis of no causality and some appropriate regularity conditions, the Q-test follows asymptotically a $N(0,1)$ distribution.[12] 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 $\hat{q}_{x,y} \sim N(q, \frac{(1-q^2)^2}{T}$.

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 February 2008.[13] 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, the following sectoral indices are employed: Financial, Basic Industries, General Industries, Cyclical Services, Non-Cyclical Services, Information

[11]In the present study, we use the *QS* kernel. Employing other kernels such as the Bartlett and the Parzen one yields qualitatively similar results. We do not report these results for brevity but they are available from the authors upon request.

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

[13]The estimation of the long-run correlation along with the in-sample parametric tests employs the sample up to December 2003, while the out-of sample forecasting experiment (Section 4.3) employs the remaining 50 observations up to February 2008.

Technologies, Cyclical Consumer Goods, Non-cyclical Consumer Goods, Utilities.[14]

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. We then assess our findings in the context of standard parametric techniques, which can also accommodate asymmetric responses of output growth to stock returns and out-of-sample forecasting of long-horizon growth.

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 lag length of the cross-covariances employed, represents one tenth of our sample and ensures that the majority of the effects have been taken into account.[15] With the exception of Italy, estimates of the long-run correlation range from 0.49 (Japan) to 0.66 (UK). The second column reports the standard deviation of the point estimates of the long-run correlation based on (3). As was shown in section 2, 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

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[14]The Datastream codes for the corresponding stock market indices are the following: TOTMKXX, TOTLFXX, TOTLIXX, 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.

[15]Alternatively, we could employ the automatic bandwidth selection procedures put forward by Andrews (1991) and Newey and West (1987). The Andrews procedure is parametric and relies on the estimates of univariate autoregressive models. Applying this procedure to our dataset yields bandwidths that range from 3 months to 6 months for the countries at hand. This low value of the bandwidth is expected since the series under inspection exhibit low autocorrelation. On the other hand, the non-parametric procedure of Newey and West yields bandwidths that range from 11 to 19 months.

different from zero.[16] Not surprisingly, the only country for which we cannot reject the null hypothesis of zero long-run correlation is Italy and marginally Germany and Japan. In principle, we could also calculate the range of bandwidths over which we reject the null hypothesis of a zero coefficient. Given the concave pattern of the relevant t-stat with respect to the bandwidth value M, 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. This is true for Germany and Japan for which we cannot reject the null of a zero correlation coefficient when the bandwidth is in the range of 17 to 32 and 16 to 28, respectively. More importantly, we 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. that 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.

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, for which the Anderson (1971) test rejects the null of a zero correlation. 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

[16]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.

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 0.10 and 0.16).

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.[17] 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. 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 9 months.

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 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 (0.28 compared to 0.49 for the whole sample) and Italy (0.38 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

[17] Hong (2001) reports Monte Carlo simulations on the size and power of the *Q*-test (along with some variations of it) employing sample sizes *T* equal to 300, 500 and 800, and finds that it performs equally well for all sample sizes considered. Specifically, the test performs well at the 10% level, but tends to overreject at the 5% level. With respect to its power, the best results are achieved when employing a non-uniform weighting scheme such as the *QS* kernel employed in the present study.

coefficients have not changed dramatically for the subsample investigated.[18] Hence, the contemporaneous and the temporal correlations do not display marked differences with those derived from the whole sample. This finding is in contrast with Binswanger (2004) who finds that a significant relationship between lagged stock market growth rates and current output growth exists only for the US and Germany when the subsample 1989 onwards is considered.

Now, to obtain a more in-depth picture of the pattern of the correlation estimates as the bandwidth increases we depict in Figure 1 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 employed in the estimation) to take values in the interval [1, 36] by steps of one. In general, the information content in this Figure 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. However, a bandwidth, M^*, exists after which marginal increases in r_{xy} are prevalent. Interestingly, this point coincides with the optimal bandwidth as determined by the data dependent procedure of Newey and West (1987); according to this procedure the bandwidths selected are 11 months for Canada, 16 for Japan and the UK, 18 for Italy and 19 months for France, Germany and the US. 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.

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, $\hat{r}_{xy}$ increases with the correlation function having a concave form in terms of the bandwidth; this is clearly the case for France, Japan, UK and the US for bandwidth values below twenty-four. In these countries, $\hat{r}_{xy}$ 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, $\hat{r}_{xy}$ yields additional information up to the point where the bandwidth parameter equals thirty-six, whereas it appears to be stable for values above twelve in Canada.

[18] In fact, the point estimates derived from a bandwidth of 36 months are much closer to the estimates reported

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 weak when capitalization is low (Italy).[19] In countries with high market capitalization, stocks constitute a larger proportion of consumer's portfolios and consequently stock price developments can have a major impact on consumption through their impact on wealth. A similar impact is expected on investment through the 'financing hypothesis' that argues that when stock prices are high compared to the replacement cost of capital, investment is more likely to happen through new physical capital such as the issuance of new shares rather than the purchase of existing firms on the stock market. In this respect, financially developed countries are expected to display a stronger link between stock returns and growth.

4.3 Alternative methodologies, conditioning and forecasting

In light of our evidence on the long-run nature of the linkages between returns and growth, in this section we re-address the issue in the context of a parametric methodology suitable for addressing these impacts, which has been employed by, among others, Stock and Watson (2003) and Rapach and Weber (2004). This methodology can accommodate both the in-

for the whole sample; these results are available upon request.

[19] Mauro (2003) finds that the magnitude of a country's slope coefficient in the returns-growth regressions would approximately double if a country were to double its market capitalization to GDP ratio.

sample predictability that is directly compared to our non-parametric methodology and the out-of-sample predictability of stock returns for future growth at various horizons.

Specifically, we estimate the following Autoregressive Distributed Lag (ADL) model for each country:

$$y_{t+h}^{h} = c + a(L)y_t + b(L)x_t + \varepsilon_{t+h}^{h} \tag{7}$$

where c is a constant, $a(L)$, $b(L)$ are scalar lag polynomials, y_t is output growth, x_t is stock returns and y_{t+h}^{h} is the growth of output over the next h periods, i.e. is equal to $\Sigma_{s=t+1}^{t+h} y_s$. The number of lags for both y_t and x_t is selected by the Schwartz Bayesian information criterion (SIC). We set the maximum lag length at 12 to avoid estimating any models with low degrees of freedom and focus on forecast horizons (h) of 1, 2, 3, 6, 9, 12, 15 and 18 months. To conduct an in-sample test of forecasting ability of stock returns (x_t), we just estimate equation (7) and carry out a Wald test of the null hypothesis that all the coefficients of the lag polynomial $b(L)$ are equal to zero. If the null hypothesis is rejected, then stock returns have in-sample predictive ability for future output growth at various horizons.[20]

The results (reported in Table 3) suggest that stock returns contain in-sample information with respect to future growth. In the case of Japan and US, this result is evident for any horizon considered, ranging from the short-run (next month's growth) to the long-run (growth over the next 18 months). Similarly, significant in-sample predictability is found for Germany at horizons greater than 2 months, while for France and UK stock returns contain information for future growth at horizons exceeding 6 months. For Canada, the horizon is further extended to over 12 months. On the other hand, for Italy this predictability is significant only at the short-run horizons of 1 and 3 months.

A series of papers (see e.g. McQueen and Roley 1993; Park, 1997; Boyd et al. 2006) have suggested that when the economy is weak, the correlation between current returns and future growth is positive and stronger than the case of a strong economy.[21] To accommodate the effect of a conditional correlation in our model, we augment (7) by including a dummy

[20]Notice that for horizons greater than one we have an overlapping samples problem that generates autocorrelation in the disturbance term. We account for this problem by employing a heteroscedasticity and autocorrelation consistent covariance matrix as the one suggested by Newey and West (1987).
[21]We thank a referee for pointing out to us this issue.

variable taking the value of 1 in cases of recession, as follows:[22]

$$y_{t+h}^{h} = c + a(L)y_t + b(L)x_t + dDUM_t + \varepsilon_{t+h}^{h} \quad (8)$$

We then contact a likelihood ratio (LR) test between the unrestricted model, given by (8), and the restricted one, given by (7), and test whether the exclusion of the parameter d from (8) is a valid restriction.[23]

Table 4 reports our results of conditional in sample forecasting for the countries at hand. In general we find evidence of a significant asymmetric response of stock returns to growth for all the countries with the exception of Italy albeit at various horizons. Specifically, for Canada, this effect is significant at the horizons of 1 month and 6-12 months, while for France is only a medium term phenomenon for horizons of 6 to 12 months. For Germany, our results suggest that the correlation is stronger at horizons exceeding one year, while for Japan and the UK a positive effect is evident at the 2-quarters horizons and the 1-quarter horizon, respectively.[24] This effect is stronger in the US as the unrestricted model is preferred to the restricted in most time horizons.

Next, we turn to the out-of sample forecasting experiment conducted for the period of January 2004 to February 2008 (50 observations). Since evaluating the forecasting accuracy of the candidate models is of equal importance as constructing the forecasts, the estimation procedure is designed to allow us to implement formal statistical tests for the comparison of the forecasts provided by two different models. Specifically, we first estimate an AR model for each country by setting $b(L)$ in (7) equal to zero. Our simulated out-of-sample forecasting experiment proceeds recursively in the following manner. In each date of the out-of-sample forecast period, the AR model is re-estimated by keeping the lag-order fixed providing us with a sequence of forecasts. We then add stock returns, x_t, to our model. We keep the order of $a(L)$ fixed and once more use SIC to select the order of $b(L)$.[25] Consequently, the AR model, which is used as a benchmark when evaluating forecasts, is always nested within the alternative model.

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[22]Periods of recessions are defined as periods of at least two consecutive negative growth instances. See Candelon and Gil-Alana (2004) for a more detailed analysis of the issue.

[23]The test follows asymptotically the chi-squared distribution with one degree of freedom. To ensure that there is no change in the lag structure of the models invalidating the nested properties of the models at hand, we estimate (8) keeping the lag orders of the polynomials $a(L), b(L)$ fixed at the respective lags of (7).

[24]Please note that the coefficient d is found to be positive, so the relationship between current returns/future growth actually becomes stronger in periods of weak growth.

[25]The lag structure of the models is allowed to vary across countries.

The forecasting performance of the model containing stock returns is assessed by the simulated out-of-sample mean squared forecast error (*MSFE*) relative to the *MSFE* of the benchmark AR model (Theil's U). To establish the statistical significance of this ratio, one has to test the hypothesis that the population relative *MSFE* is equal to one, against the alternative of a ratio less than one. Techniques for comparing the forecasting performance of two nested models, since the AR model is always nested within the remaining models considered, were only recently developed. In this study, we use the following F-statistic proposed by McCracken (2004):

$$MSE-F=\frac{\sum_{t=1}^{P}[\varepsilon_{1,t}^{2}-\varepsilon_{2,t}^{2}]}{P^{-1}\sum_{t=1}^{P}\varepsilon_{2,t}^{2}} \tag{9}$$

where $\varepsilon_{i,t}, i=1,2$ are the forecast errors of the restricted and the unrestricted model, respectively and P is the number of out-of-sample observations. Under the null hypothesis, the two models have equal *MSFE*, while under the alternative the *MSFE* of the unrestricted model is less than that of the restricted one.

We also consider testing the forecasting ability of the stock returns for future growth by employing the notion of forecast encompassing, i.e. testing whether an optimal composite forecast can be derived utilizing information from both the restricted and the unrestricted model. We use here the following test statistic proposed by Clark and McCracken (2001):

$$ENC-NEW=\frac{\sum_{t=1}^{P}\varepsilon_{1,t}[\varepsilon_{1,t}-\varepsilon_{2,t}]}{P^{-1}\sum_{t=1}^{P}\varepsilon_{2,t}^{2}} \tag{10}$$

where $\varepsilon_{i,t}, i=1,2$ are the forecast errors of the restricted and the unrestricted model, respectively and P is the number of out-of-sample observations. Under the null hypothesis, the restricted model forecasts encompass the unrestricted ones.

The limiting distributions of the aforementioned test-statistics are non-standard and numerical estimates of the asymptotic critical values for valid inference depend on the ratio of in sample and out-of-sample observations and the number of parameter restrictions. While the asymptotic critical values of the aforementioned test are valid for one-step ahead horizons, these values cannot be employed for horizons greater than one. For these cases, Clark and Mc Cracken (2001, 2005) recommend basing inference on a bootstrap procedure along the lines of Kilian (1999). Following this recommendation, we base our inferences on this bootstrap procedure for all the forecast horizons considered.[26]

The results from the tests based on (9) and (10) with respect to the out-of sample forecasts of stock returns for future growth are reported in Table 5. As can be readily seen, Canadian stock returns do not contain any information about future growth at any horizon, while the opposite is true for the US. In this case, both tests suggest significant out-of-sample predictability of stock returns to output growth. The same is true for the UK albeit at horizons greater than 6 months. Forecast encompassing of the restricted model is rejected for the remaining countries almost for the majority of horizons considered. In this respect, the long-term information content of stock returns for future growth can be useful when constructing growth forecasts.[27]

Overall, our results corroborate the findings of Choi et al. (1999) with respect to the out-of sample forecasting ability of monthly output growth.[28] Specifically, the authors provide evidence of a significant stock market effect on monthly forecasts of IP growth for three of the G-7 countries, namely Japan, the UK and the US. Their findings also suggest that predictability in the remaining countries is probably at a shorter horizon than 12 months, which coincides with our MSE-F results for Germany, Italy and perhaps France.

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.[29]

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[26]A detailed description of this procedure can be found in Clark and McCracken (2005). The programs written in GAUSS are available from David Rapach's website (http://pages.slu.edu/faculty/ rapachde/Research.htm).

[27]Notice however that the *MSE-F* test of equal forecasting ability displays significant heterogeneity among this set of countries. For example, for France equal forecasting ability is rejected for periods up to 3 months and for the long- horizon of 18 months.

[28] Our results are not fully comparable to Choi et al. (1999) due to the different data sample and the ratio of in-sample/out-of sample observations.

[29]For instance, Duffee and Prowse (1996) have shown that auto industry stock returns have higher explanatory

We investigate the decomposed long-run correlation between output growth and sectoral share price changes in Table 6 (Panels A to C).[30] 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.[31] As expected, the temporal and the contemporaneous correlation coefficients, r_{yx} and c_{xy}, appear again insignificant.[32]

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, $\hat{r}_{xy}$, 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

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power for future GDP than market returns.

[30]We also considered sectoral industrial production indices where available and our results are qualitatively similar. The results (available from the authors upon request) are not reported here due to the limited availability of these indices across the G-7 countries coupled with the lack of a direct mapping between the respective sectoral industrial production index and the stock market.

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

[32]Similar figures to Figure 1 were produced for each sector and countrry at hand, but we do not report these to

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 of Basic Industries.[33]

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. 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 by Stock and Watson 2003). The method employed here can also be applied to other cases in which parametric methods leave empirical questions open. For instance, Thoma and

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save space. The reader is referred to the working paper version for the full set of results (Panopoulou et al. 2006).

[33]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.

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 a more in-depth analysis of the links between sectoral stock portfolios and future sectoral output growth. As data on cash flows at the plant or sectoral level become available, unraveling the link between firm-specific returns and future output is of importance. Depending on the nature of the sector (firm) one could expect to find differences in this firm-specific correlation, for instance across services and industries. Finally following Hong et al. (2000), who indicate an asymmetry between good and bad news on firm returns, one could go one step further and test for the stock returns/growth link across financial states, i.e. across negative and positive shocks to returns.

Appendix: Asymptotic distribution of the long-run correlation coefficient

In the Appendix 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 $\hat{\Omega}$:

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

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} :

$$J = \left[\frac{\partial \rho}{\partial \omega_{xx}} \quad \frac{\partial \rho}{\partial \omega_{yy}} \quad \frac{\partial \rho}{\partial \omega_{xy}} \right]$$

Specifically, we get that:

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

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

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

Setting Q the asymptotic variance of the Ω matrix in (A1), the asymptotic variance of the long-run correlation coefficient is calculated by setting $P = JQJ'$ where:

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

From (A1) and (A2) it follows directly that we can get equation (3) in the text.

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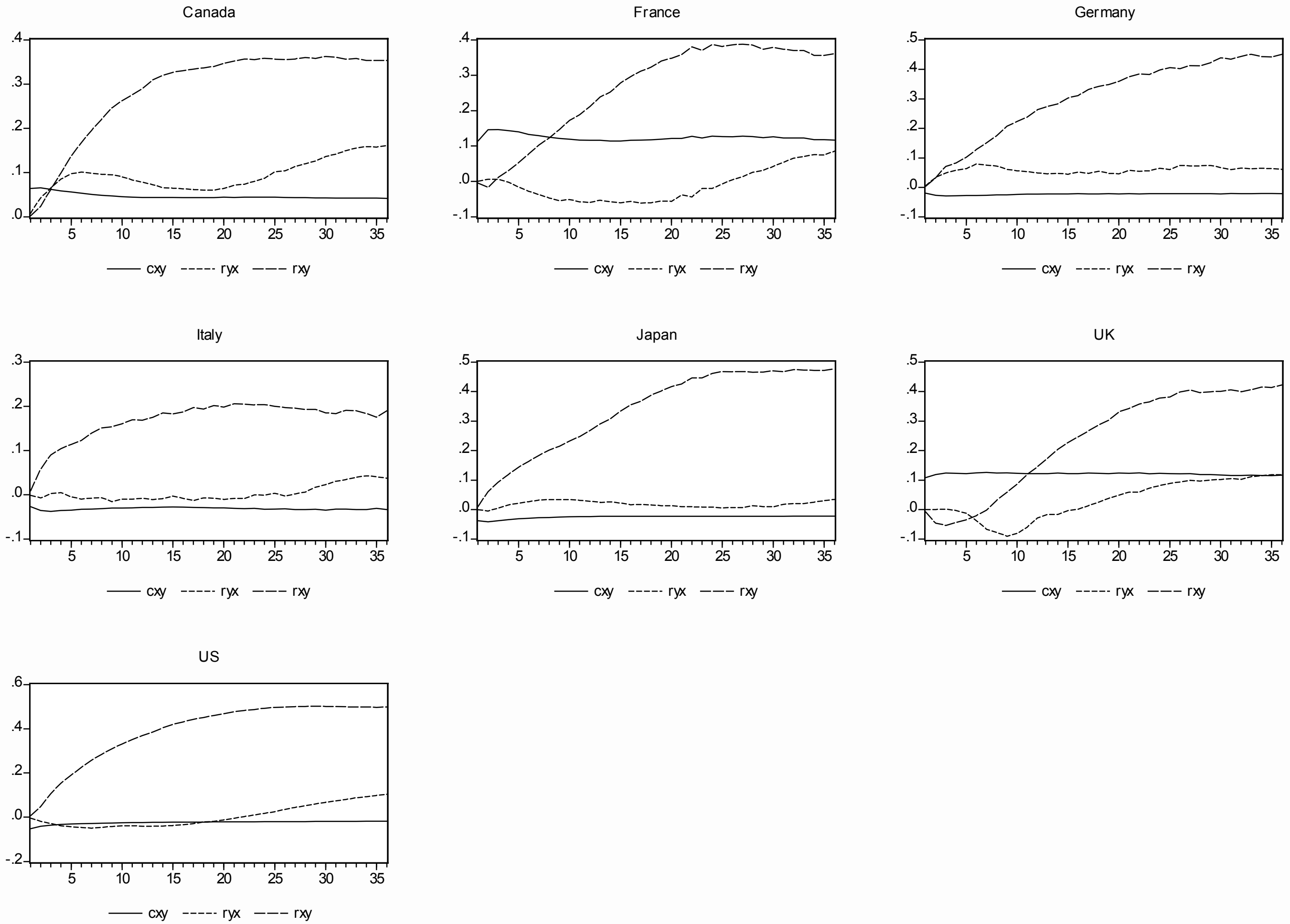
Fig. 1 Decomposed long-run correlation coefficient between output growth and stock returns



Notes: The bandwidth parameter *M* is on the horizontal axis. Stock returns are calculated from the Total Market index.

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	0.215	**1.789**	-0.219 (ρ=0.6)	0.041	0.353	0.162
France	0.564	0.212	**1.812**	-0.183 (ρ=0.6)	**0.116**	0.362	0.086
Germany	0.491	0.236	1.578	-0.040 (ρ=0.5)	-0.021	0.451	0.061
Italy	0.195	0.299	0.627	-0.017 (ρ=0.2)	-0.032	0.190	0.037
Japan	0.489	0.237	1.572	-0.047 (ρ=0.5)	-0.022	0.477	0.034
UK	0.658	0.176	**2.115**	-0.265 (ρ=0.7)	**0.116**	0.423	0.119
US	0.582	0.206	**1.871**	-0.090 (ρ=0.6)	-0.018	0.497	0.103
				Sample period: 1989-2003			
Canada	0.578	0.211	**1.828**	-0.109 (ρ=0.6)	0.002	0.279	0.297
France	0.549	0.221	**1.736**	-0.252 (ρ=0.6)	**0.090**	0.321	0.138
Germany	0.416	0.262	1.316	-0.354 (ρ=0.5)	**-0.131**	0.428	0.119
Italy	0.378	0.271	1.195	0.586 (ρ=0.2)	0.085	0.289	0.004
Japan	0.278	0.292	0.879	-0.936 (ρ=0.5)	-0.030	0.348	-0.040
UK	0.568	0.214	**1.796**	-0.818 (ρ=0.7)	0.036	0.368	0.164
US	0.647	0.184	**2.046**	0.232 (ρ=0.6)	-0.020	0.394	0.273

Notes: The bandwidth for the period 1973-2003 is 36 months and for the period 1989-2003 is 18 months; see section 2 in text for details. Bold denotes statistical significance at the 10% level.

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

Country/Bandwidth	*3*	*6*	*9*	*12*	*18*	*24*	*30*	*36*
Canada	0.57	0.26	0.18	0.12	**0.04**	**0.03**	**0.04**	**0.04**
France	0.46	0.47	0.58	0.63	0.64	0.67	0.72	0.75
Germany	0.39	0.17	**0.04**	**0.01**	**0.00**	**0.00**	**0.01**	**0.01**
Italy	**0.09**	**0.05**	**0.08**	0.12	0.23	0.33	0.38	0.41
Japan	**0.04**	**0.03**	**0.09**	0.15	0.18	0.18	0.16	0.13
UK	0.55	0.16	**0.07**	**0.04**	**0.05**	**0.08**	0.15	0.20
US	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**	**0.00**

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

Country/Bandwidth	*3*	*6*	*9*	*12*	*18*	*24*	*30*	*36*
Canada	0.12	0.18	0.30	0.40	0.56	0.63	0.60	0.51
France	0.81	0.82	0.85	0.88	0.91	0.88	0.83	0.78
Germany	0.52	0.73	0.65	0.59	0.61	0.56	0.49	0.39
Italy	0.79	0.77	0.76	0.77	0.80	0.82	0.84	0.86
Japan	0.81	0.79	0.78	0.80	0.79	0.79	0.78	0.76
UK	0.38	0.54	**0.09**	**0.05**	**0.05**	**0.02**	**0.01**	**0.02**
US	0.74	0.82	0.82	0.77	0.71	0.71	0.74	0.77

Notes: P-values for the Q-test (Hong,2001) reported (see section 2 for details). Bold denotes statistical significance at the 10% level.

Table 3 In-sample forecasting from stock price changes to output growth

Country/Bandwidth		*1*	*2*	*3*	*6*	*9*	*12*	*15*	*18*
Canada	*Wald-test*	0.081	1.568	0.802	0.337	0.880	**6.745**	**4.779**	**8.686**
	p-value	0.780	0.260	0.406	0.562	0.408	**0.056**	**0.090**	**0.008**
	R-square	0.061	0.139	0.152	0.273	0.341	0.420	0.417	0.451
France	*Wald-test*	0.100	0.745	0.426	**7.506**	**10.421**	**12.326**	**7.387**	**4.506**
	p-value	0.770	0.406	0.516	**0.022**	**0.014**	**0.002**	**0.036**	**0.058**
	R-square	0.145	0.058	0.029	0.088	0.115	0.113	0.089	0.021
Germany	*Wald-test*	0.363	**4.108**	**3.603**	**20.782**	**18.745**	**20.482**	**11.664**	**12.111**
	p-value	0.594	**0.058**	**0.082**	**0.004**	**0.002**	**0.004**	**0.022**	**0.006**
	R-square	0.163	0.115	0.065	0.199	0.157	0.125	0.115	0.116
Italy	*Wald-test*	**3.588**	2.639	**5.085**	2.682	1.999	2.492	2.328	1.250
	p-value	**0.078**	0.118	**0.042**	0.154	0.216	0.160	0.188	0.290
	R-square	0.172	0.110	0.057	0.014	0.020	0.010	0.019	0.030
Japan	*Wald-test*	**3.680**	**8.506**	**9.130**	**8.399**	**20.386**	**27.847**	**26.886**	**28.073**
	p-value	**0.076**	**0.012**	**0.006**	**0.020**	**0.006**	**0.004**	**0.000**	**0.000**
	R-square	0.209	0.234	0.236	0.203	0.277	0.238	0.229	0.199
UK	*Wald-test*	2.031	0.737	0.074	**23.555**	**28.772**	**62.371**	**53.807**	**53.427**
	p-value	0.194	0.466	0.802	**0.006**	**0.000**	**0.000**	**0.000**	**0.000**
	R-square	0.041	0.028	0.000	0.168	0.198	0.211	0.216	0.191
US	*Wald-test*	**31.222**	**19.066**	**15.723**	**35.169**	**29.153**	**24.952**	**25.619**	**23.038**
	p-value	**0.000**	**0.000**	**0.002**	**0.000**	**0.000**	**0.000**	**0.000**	**0.004**
	R-square	0.264	0.337	0.330	0.367	0.349	0.303	0.256	0.196

Notes: Bold indicates significance at the 10% level.

Table 4 Conditional in-sample forecasting from stock price changes to output growth

Country/Bandwidth		*1*	*2*	*3*	*6*	*9*	*12*	*15*	*18*
Canada	*LR -test*	**3.857**	1.263	2.213	**4.898**	**6.142**	**3.005**	2.534	2.775
	p-value	**0.050**	0.261	0.137	**0.027**	**0.013**	**0.083**	0.111	0.948
France	*LR -test*	0.234	2.310	0.013	**10.937**	**11.256**	**3.189**	3.010	1.157
	p-value	0.628	0.129	0.908	**0.053**	**0.047**	**0.074**	0.390	0.282
Germany	*LR -test*	1.687	0.979	0.426	2.125	1.737	**5.122**	**3.606**	7.477
	p-value	0.194	0.322	0.514	0.977	0.884	**0.077**	**0.058**	0.187
Italy	*LR -test*	0.076	0.256	0.019	0.309	0.011	0.218	0.054	0.008
	p-value	0.783	0.613	0.889	0.579	0.916	0.641	0.816	0.929
Japan	*LR -test*	3.133	2.392	2.604	**6.597**	7.344	4.936	1.797	2.181
	p-value	0.077	0.122	0.107	**0.010**	0.500	0.764	0.987	0.975
UK	*LR -test*	0.039	1.967	**3.095**	5.000	4.634	5.786	4.734	2.979
	p-value	0.844	0.161	**0.079**	0.758	0.796	0.671	0.786	0.936
US	*LR -test*	**12.020**	**14.805**	**11.183**	9.707	**16.361**	**20.783**	**19.497**	**11.823**
	p-value	**0.002**	**0.001**	**0.004**	0.286	**0.038**	**0.004**	**0.007**	**0.037**

Notes: Bold indicates significance at the 10% level.

Table 5 Out-of-sample forecasting from stock price changes to output growth

Country/Bandwidth		*1*	*2*	*3*	*6*	*9*	*12*	*15*	*18*
Canada	*MSE-F*	-0.020	-0.129	-0.079	-0.479	-1.361	-15.605	-17.334	-19.585
	p-value	0.356	0.462	0.416	0.606	0.834	0.998	0.996	1.000
	ENC-NEW	-0.009	-0.010	-0.006	-0.202	-0.513	-5.955	-6.607	-6.844
	p-value	0.432	0.446	0.424	0.648	0.834	1.000	0.998	1.000
France	*MSE-F*	**2.479**	**2.340**	**1.037**	-7.967	-8.218	-8.402	-0.782	**2.479**
	p-value	**0.008**	**0.010**	**0.062**	1.000	1.000	0.994	0.852	**0.008**
	ENC-NEW	**2.973**	**1.489**	**0.738**	**8.218**	**10.332**	**9.802**	**9.862**	**2.973**
	p-value	**0.002**	**0.016**	**0.054**	**0.000**	**0.000**	**0.000**	**0.004**	**0.002**
Germany	*MSE-F*	-0.691	**3.324**	**2.023**	-3.012	-1.179	**1.288**	-0.356	-2.743
	p-value	0.778	**0.004**	**0.018**	0.978	0.904	**0.034**	0.680	0.974
	ENC-NEW	-0.094	**2.408**	**1.900**	**14.287**	**10.734**	**10.198**	**7.912**	**5.219**
	p-value	0.596	**0.002**	**0.012**	**0.000**	**0.000**	**0.000**	**0.004**	**0.002**
Italy	*MSE-F*	**0.641**	**4.715**	**6.573**	**3.643**	**1.772**	**1.154**	0.705	0.339
	p-value	**0.088**	**0.000**	**0.000**	**0.004**	**0.012**	**0.064**	0.112	0.178
	ENC-NEW	**2.108**	**3.472**	**4.896**	**2.830**	**1.402**	**1.184**	**0.858**	0.344
	p-value	**0.002**	**0.000**	**0.000**	**0.008**	**0.018**	**0.026**	**0.044**	0.142
Japan	*MSE-F*	**0.877**	**1.547**	**2.655**	0.276	**4.009**	**4.870**	-0.403	-8.281
	p-value	**0.060**	**0.032**	**0.002**	0.204	**0.004**	**0.002**	0.720	0.992
	ENC-NEW	**0.753**	**1.500**	**2.284**	**1.187**	**6.910**	**11.540**	**7.453**	**1.345**
	p-value	**0.048**	**0.016**	**0.000**	**0.026**	**0.004**	**0.002**	**0.002**	**0.010**
UK	*MSE-F*	-2.773	-2.974	-2.040	**3.140**	**6.459**	**10.662**	**10.526**	**6.234**
	p-value	0.990	0.972	0.952	**0.004**	**0.000**	**0.002**	**0.000**	**0.000**
	ENC-NEW	-0.944	-1.105	-0.925	**5.814**	**7.454**	**9.339**	**8.242**	**4.836**
	p-value	0.988	0.978	0.974	**0.002**	**0.000**	**0.002**	**0.000**	**0.000**
US	*MSE-F*	**5.281**	**11.212**	**5.982**	**13.435**	**23.352**	**16.671**	**10.087**	**6.381**
	p-value	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.002**
	ENC-NEW	**9.257**	**20.358**	**18.088**	**30.119**	**32.896**	**22.991**	**15.267**	**9.518**
	p-value	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**

Notes: Bold indicates significance at the 10% level.

Table 6 Sectoral estimates

Panel A. Temporal correlation from stock price changes to output growth

Country/Sector	*TOTLI*	*TOTLF*	*BASIC*	*GENIN*	*CYSER*	*NCYSR*	*CYCGD*	*NCYCG*	*UTILS*	*ITECH*
Canada	0.328	0.391	0.225	0.256	0.322	0.417	0.530	---	0.283	0.267
France	0.358	0.325	0.314	0.347	0.321	0.429	0.449	0.272	---	0.365
Germany	0.490	0.353	0.372	0.434	0.442	0.325	0.605	0.332	0.500	---
Italy	0.265	0.132	0.120	0.074	0.112	0.275	0.329	---	0.172	---
Japan	0.506	0.341	0.383	0.494	0.427	0.448	0.523	0.448	---	0.430
UK	0.441	0.346	0.394	0.407	0.403	0.377	0.366	0.438	---	0.221
US	0.488	0.496	0.433	0.491	0.496	0.377	0.601	0.412	---	0.462

Panel B. Temporal correlation from output growth to stock price changes

Country/Sector	*TOTLI*	*TOTLF*	*BASIC*	*GENIN*	*CYSER*	*NCYSR*	*CYCGD*	*NCYCG*	*UTILS*	*ITECH*
Canada	0.152	0.173	0.084	0.224	0.121	0.175	-0.235	---	0.060	0.055
France	0.092	0.145	0.106	0.094	0.032	0.115	-0.239	0.075	---	0.104
Germany	0.020	0.132	0.024	0.081	-0.099	0.007	-0.084	0.077	0.126	---
Italy	-0.103	0.131	-0.085	0.072	0.027	-0.070	-0.134	---	-0.081	---
Japan	-0.001	0.137	0.068	0.005	0.107	-0.002	-0.069	0.045	---	-0.028
UK	0.104	0.150	0.002	0.031	0.155	0.144	0.031	0.060	---	0.125
US	0.096	0.171	-0.091	0.146	-0.003	0.130	-0.148	0.165	---	0.125

Panel C. Contemporaneous correlation between output growth and stock price changes

Country/Sector	*TOTLI*	*TOTLF*	*BASIC*	*GENIN*	*CYSER*	*NCYSR*	*CYCGD*	*NCYCG*	*UTILS*	*ITECH*
Canada	0.046	0.018	0.076	0.029	0.008	0.014	0.066	---	-0.002	0.004
France	0.114	0.064	0.077	0.112	0.212	0.083	0.160	0.103	---	0.123
Germany	-0.014	-0.045	-0.013	-0.028	0.062	-0.035	-0.088	0.028	-0.030	---
Italy	0.000	-0.055	-0.031	-0.024	-0.011	-0.032	0.049	---	0.015	---
Japan	-0.023	-0.016	0.000	-0.034	-0.017	-0.013	-0.015	0.000	---	-0.031
UK	0.117	0.098	0.150	0.106	0.080	0.016	0.040	0.103	---	-0.004
US	-0.017	-0.029	-0.016	-0.016	-0.028	-0.005	-0.023	-0.023	---	-0.018

Notes: Correlations are calculated at a bandwidth, M=36. TOTLI=total market excluding financial, TOTLF=financial BASIC= Basic Industries, GENIN= General Industries, CYSER= Cyclical Services, NCYSR= Non-Cyclical Services, ITECH= Information Technologies, UTILS= Utilities, CYCGD=Cyclical Consumer Goods, NCYCG=Non-cyclical Consumer Goods.