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FINANCIAL VARIABLES AND REAL ECONOMIC ACTIVITY

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1. Introduction

Our purpose in this paper is to non-parametrically estimate the temporal correlations between financial variables and output growth in two different groups of countries and then to compare this non-parametric method with the VAR model. These two groups of countries are the emerging and the developed counties, respectively. Financial variables examined are those that are very often associated with future output growth (industrial production), such as stock prices, interest rates, interest rate spreads, and monetary aggregates. The monthly data on the financial we use are available and obtained from DataStream.

In most empirical studies the lead-lag relationship between output growth and financial variables is examined by testing for Granger causality within the context of an appropriate parametric vector autoregressive (VAR) model. However, finite order VAR models may be too restrictive to represent the true autocovariance structure of a given multiple time series for two reasons. First, although the process may be wide sense stationary and purely non-deterministic, it will fail to have an autoregressive representation if some of the roots of the Laurent expansion of its moving average representation lie on the unit circle. Second, the process may admit a VAR representation of infinite order.[1] This implies that its approximation by a finite order VAR may give misleading results in common size samples.[2]

The problem of approximating the true data generation process by a finite order VAR may be particularly acute when data on stock returns are

[1] This case has been analyzed by Luetkepohl and Poskitt (1996) who 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.

[2] 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).

employed. The work of Fama and French (1988) and Poterba and Summers (1988) suggest the presence of transitory components in stock prices with returns showing positive autocorrelation over short periods but negative autocorrelation over longer periods. In view of such an autocovariance structure the use of finite order VARs as approximating models becomes questionable.

A VAR model can be written as: $\begin{pmatrix} Y_t \\ X_t \end{pmatrix} = \begin{pmatrix} a_{11} \\ a_{21} \end{pmatrix} + \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \begin{pmatrix} Y_{t-1} \\ X_{t-1} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$ if we have one lag, and two variables, and it is a VAR (1) model. If $Z_t = \begin{pmatrix} Y_t \\ X_t \end{pmatrix}$ then the above equation is equivalent with $Z_t = A + BZ_{t-1} + U_t$, where $A = \begin{pmatrix} a_{11} \\ a_{21} \end{pmatrix}$, $B = \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix}$ and $U_t = \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$. More generally a VAR (p) model has the form:

$$Z_t = A + B_1 Z_{t-1} + B_2 Z_{t-2} + \ldots\ldots\ldots\ldots + B_p Z_{t-p} + U_t = A + \sum_{i=1}^{p} B_i + U_t$$

The optimal lag length k for all variables is based on the Akaike information criterion and the Scwartz test also.

The causality is tested by making a hypothesis test on the coefficients of X_t and Y_t respectively. For example if the optimal lag is k=2 then:

$$\begin{pmatrix} Y_t \\ X_t \end{pmatrix} = \begin{pmatrix} a_{11} \\ a_{21} \end{pmatrix} + \begin{pmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{pmatrix} \begin{pmatrix} Y_{t-1} \\ X_{t-1} \end{pmatrix} + \begin{pmatrix} b_{11}^* & b_{12}^* \\ b_{21}^* & b_{22}^* \end{pmatrix} \begin{pmatrix} Y_{t-2} \\ X_{t-2} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \end{pmatrix}$$

$$Y_t = a_{11} + b_{11} Y_{t-1} + b_{12} X_{t-1} + b_{11}^* Y_{t-2} + b_{12}^* X_{t-2} + u_{1t}$$

H_0: $b_{12} = b_{12}^* = 0$ if the null hypothesis is accepted then X_t do not Granger causes Y_t. By making the same thing with the equation of X_t we are testing the opposite direction causality.

As an alternative to the use of VAR models, Fama (1981, 1990) and Barro (1990) have employed single-equation models where output growth is explained by lagged and contemporaneous stock price changes. However, these models implicitly assume that price changes are weakly exogenous to the parameters of interest, and may thus result in inconsistent and/or inefficient estimators if the exogeneity status of stock price changes does not hold.

In this paper, instead of employing typical single-equation or VAR models to analyze the relationship between various financial variables and output growth, we investigate the temporal and contemporaneous correlation between these variables by using a non-parametric technique. This technique has been proposed by Andrews (1991) to estimate the long-run covariance matrix, between alternative financial variables and output growth and is based on a kernel estimation procedure involving only the choice of a kernel and a bandwidth parameter for the representation of the second order moments (autocovariance structure) of the process. The bandwidth parameter can be determined by means of data-dependent methods, which in turn implies that the non-parametric procedure is fully 'automatic' and does not require further assumptions on the data generating process of the series at hand. Thus, we are able to analyze the detailed contemporaneous and temporal cross correlation pattern between various financial variables and output growth. Moreover, as the size of included lags increases we can locate a nearly 'optimal' bandwidth and the associated correlation coefficient. The kernel estimator of the long-run covariance matrix is consistent under very general conditions, which permit globally non-stationary (including unconditionally heteroskedastic) data process, requiring the existence of only (2+δ) order moments, for δ>0. Moreover, recent consistency proofs require the bandwidth parameter to be $o(T^{1/2})$ (Hansen, 1992), or even $o(T)$ (Andrews,1991), as opposed to the required order of the approximating VAR process, which is $o(T^{1/3})$ (Luetkepohl and Poskitt, 1996). This non-parametric method is more general and robust than the Granger causality concept in the sense that it also accounts for non-linear relationships among the variables involved, whereas Granger causality assumes only the existence of a linear relationship. Of course, before employing our method and because this non-parametric method demands stationarity we will test for unit roots.

2. A review of related work

Many studies over the past thirty years have examined the extent to which financial variables, namely, stock prices, interest rates, interest rate spreads, and monetary aggregates, can be used to forecast future economic activity. Beckett (1961), Goldsmith (1969), Bosworth (1975), Hall (1978), Fama (1981), Geske and Roll (1983), as well as more recent studies by Barro (1990), Estrella and Mishkin (1998), and Hassapis and Kalyvitis (2002), are among the many studies that strongly show that the stock market index can serve as a reliable leading indicator. It is found in all these studies that stock returns are highly correlated with future real activity, for various data frequencies covering very long periods, and are robust to alternative definitions of the data series.

There are several theoretical channels through which the stock market rationally signals (leads) changes in real activity. For example optimistic expectations of future profits may cause a rise in stock prices, which is an increase in wealth, which has the likely effect of an increase in demand for consumption and/or investment goods. Similarly, in the case of an expansionary policy shock, asset prices change as a result of anticipated changes in real interest rates and profitability. This in turn affects wealth and spending and fuels a rise in supply and equilibrium output, which justifies the original rise in stock prices; therefore, asset prices will tend to predict future output (see Blanchard 1981).

The above channels can be broadly thought of as self-fulfilling in nature. There are other channels, more informational in nature that can also provide explanations for the relationship between stock returns and real activity. For example, stock market valuation plays a key role in q-type models of investment determination. When the market value of an additional unit of capital is higher than its replacement cost, then a firm can raise its profit by investing. Information asymmetry in financial markets is another possible link between investment and share prices. For example, a rise in share improves the balance sheet position of a firm, thereby increasing its ability to directly fund projects or to provide collateral for external finance (see, e.g., Blanchard, Rhee, and Summers 1993).

Stock price indices may also be linked with future output. In the absence of bubbles, stock prices tend to reflect future corporate earnings, which in turn may reflect future economic conditions. Thus, if profits are highly pro-cyclical, then useful information may be extracted from stock price changes. A change in interest rate is another possible link, which can cause changes in stock prices and in the production of investment goods. Especially in the case of an interest rate rise, which maybe due to a financial crisis, the link may be even more intense, since the stock market crash and the fall of the firm's net worth may ultimately lead to decreased lending and a fall of output (see e.g. Bosworth 1975).

In a large strand of this literature other variables that can be used to predict economic activity has also been examines. In particular, interest rates, interest rate spread, and monetary aggregates have attracted considerable attention from academics as well as market analysts and policy makers. Over the last years many researchers have discovered that the yield spread has been correlated with movements of future economic activity. In general, a positive yield spread is associated with future economic expansion, whereas a negative yield spread is associated with future economic contraction. In addition, the magnitude of the spread is related to the level of economic growth; that is, the larger the spread, the faster will be the rate of economic growth in the future.

Stock and Watson (1989), Harvey (1988, 1997), Estrella and Hardouvelis (1991), Cozier and Tkacz (1994), Plosser and Rouwenhorst (1994), as well as more recent papers by Haubrich and Dombrosky (1996), Ducker (1997), Estrella and Mishkin (1997,1998), Atta-Mensah and Tkacz (1998), Dotsey (1998), Thoma and Gray (1998), Hassapis, Pittis, and Prodromides (1999), Black, Corrigan, and Dowd (2000), Galbraith and Tkacz (2000), and Hamilton and Kim (2000) are among the many studies in which the term structure and monetary aggregates are found to be associated with future economic activity. In particular, in most of these studies the yield spread is found to be an excellent predictor of future economic growth. Moreover, it is established that the yield spread outperforms many other leading indicators, among them interest rate levels, money stocks, and stock prices as predictors of output.

There are several theoretical channels through which the term “structure” rationally signals changes in real activity with a positive relationship between interest rate spreads and real activity. Two main explanations have been offered in the literature for this empirical relationship. First, the yield spread may reflect the stance of monetary policy. For example, a tightening of monetary policy will cause short-term interest rates to rise. This causes the yield spread to narrow. The higher interest rates will cause reduced spending in those sectors of the economy that are interest rate sensitive. As a result of the monetary policy action, the narrowing of the yield spread is associated with slower future economic growth.

The second explanation of the apparent link between the yield spread and future economic growth has to do with the assertion that the yield spread reflects market expectations for future economic growth. Let us assume, for example, that the market participants have reason to expect a rise in real income in the future. This will imply that bond participants will reduce today’s demand for long-term bonds that pay off in the future. The decrease in the demand for long-term bonds will cause their to fall, or their yields to rise. Thus, the yield curve steepens as long-term interest rates rise. If the expectations for economic are then realized, the steepening of the yield curve will be associated with a future increase in economic activity. (see, e.g. Harvey 1989).

A related explanation for the relationship between the slope of the yield curve and future economic activity is the following: The expected increase in future real income implies an increase in profitable investment opportunities today. Businesses, in order to take advantage of these opportunities, will increase their borrowing and thus issue more bonds. Typically, these will be longer-term bonds, since the investments sought will be longer term. The subsequent increase in the supply oflonger-term bonds will reduce their price and increase their yield. This will cause the yield curve to steepen as long-term rates rise relative to short-term rates. As long as these expectations for future growth materialize, even partially, a steepening of the yield curve will be associated with future increase in real economic activity (see also Bonser-Neal and Morley 1997).

Another important issue that is examined, is the influence of inflation on the stability of real output growth. A number of considerations suggest a positive relationship between higher average rates of inflation and greater variability of inflation, which in turn leads to greater uncertainty in production, investment, and marketing decisions, and greater variability in real growth. One leading candidate (suggested by Okun) is that at a high average rate of price change, a country is likely to be less consistent in its application of fiscal and financial policies as it tries various approaches to control inflation and bring it within a politically tolerable range while simultaneously attempting not to violate other political constrains-for example, low nominal interest rates on home mortgages. Judging by recent U.S. experience, high average rates of inflation are more likely to elicit stop-go policies than more moderate rates. In addition to this macro conjecture, recent empirical work by Parks and others has shown that high inflation tends to produce large variations in relative prices. Such large variations may themselves lead to higher variability in real; growth. One simple explanation of the connection between the two follows.

Producers operating in a highly inflationary economy receive distorted signals concerning demand for their goods and hence distorted signals concerning whether new plants ought to be opened and the expansion of production economically justified. With a surge in nominal income, a producer may experience a rise product demand. Whether the increase in demand is a consequence of the producer's failure to raise prices relative to new inflation bloated nominal income or a result of a real shift in consumer demand preferences may indistinguishable to any given producer. Some producers may guess the former and raise prices; others may guess the latter and build additional capacity. To the extent that such guesses are wrong, abnormally large fluctuations in relative prices may follow. More importantly, to the extent relative price variation creates additional producer uncertainty, it is highly likely that the inability to distinguish real shifts in demand from 'nominal' shifts, real growth in investment, and all other economic activity for that matter will be more variable than it would be in an environment where less guessing as to the source of an increase in nominal demand was necessary.

Apart from the relative price change phenomenon, there are other reasons to suspect a relationship between inflation and the variability of real growth. For example, models with a stable inflation-unemployment trade-off imply a positive relationship between the variability of inflation and the variability of real activity.[3] Additionally, any increase in uncertainty is likely to induce sufficient ebbs and flows in consumer/investor confidence to hamper smooth decision making.

The rate of inflation and its variability has an uncertain effect on the average rate of growth of real output in the long run[4]. On the one hand, one might argue that the only operative constraints on long run growth are really long-run supplies of factors. If the economy' s factor supplies grow at 3 percent per annum then over the longer run the economy will grow at 3 percent, whatever the inflation rate. On the other hand, the level and variability of inflation rate may have strong effects on the average level of factor use-the time path of the natural logarithm of real output will shift down with an increase in average inflation. High inflation could lead to a prolonged reduction in the rate of growth as a result of an induced reluctance to invest with highly uncertain real returns. Alternatively, the growth rate may not be noticeably affected, but the economy could always operate at a lower level of activity than it may otherwise achieve. This question, unfortunately, remains open.[5]

Finally, about the understanding of how monetary policy transmitted to the economy by affecting the stock market and other macroeconomic magnitudes simply the answer is that, the transmission of monetary policy, via changes in the short-term interest rates, influences asset prices which, in turn, affect borrowing costs, private wealth and ultimately the real economic activity.

This consensus, that financial variables are associated with future economic activity, is reflected in their inclusion, in one form or another, as explanatory

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[3] Suppose $\left(\frac{\Delta \mathrm{P}}{\mathrm{P}}\right)_t = a - bNu_t + e_t$, *a, b >0,* where ΔP/P is the inflation rate, Nu the unemployment rate, and e an error term independent of Nu. Then, $s\,^2\Delta\mathrm{P}/\mathrm{P} = b^2 sNu^2 + se^2$, $\left[(ds\,^2\mathrm{N}u)/(ds\,^2\Delta P/P)\right]$>0.

[4] Since countries can be expected to have different underline growth potentials even at equal inflation rates, the results shown are unlikely to shed much light on the effect of inflation on the average growth rate; average inflation, however, is unlikely to be the dominant influence on a country's trend growth rate.

[5] Recent work by Fama shows a negative relationship between inflation and real economic activity in the U.S. But further confirmation of the innovative work is necessary before a strong judgment can be maid.

variables in the consumption and investment equations of many large-scale macroeconomic models. Estrella and Mishkin (1998) argue that even though large-scale macroeconomic models are very useful for forecasting future economic activity, policy makers and market participants could benefit by looking at a few well-chosen financial indicators. First, they argue, these indicators can be used to double check econometric and judgmental predictions. For example, a quick look at a financial indicator may be used to flag potential problems of more involved approaches. If the model and the indicator agree, then our confidence in the model's results is enhanced. If, however the indicator gives a different signal, this may lead to a review of the assumptions and relationships of the more complicated model that led to the prediction. The second reason that one should look at simple financial indicators is the potential for ever-fitting econometric models. Carefully, chosen financial indicators could help us to avoid this problem. Thirdly, financial indicators provide quick and simple signs of future economic activity.
Making a similar argument, Harvey (1997) also argues that one of the advantages of using simple financial indicators is their simplicity, since a simple variable is used to forecast economic activity. In fact, he finds that the forecasts obtained by this simple yield model are not dominated by the forecasts generated by one of the leading econometric services (Data Resources Inc. (DRI) Canada), which uses a large macroeconomic model of the Canadian economy, involving a large number of equations and identities.
Some of the most interesting studies which refer to the relationship between financial variables and real economic activity are presented below:

C. Hassapis (2003) estimated non-parametrically (as we will do as well) the temporal correlations between Canadian financial variables and Canadian output growth. As it is often argued that the U.S. economy has a large, maybe even dominant, influence on the Canadian economy, Hassapis investigated this proposition by also estimating the temporal correlations between selected U.S. financial variables and Canadian output growth. To gauge these empirical relationships Hassapis used measures of output, real stock price changes, interest rates, interest rate spreads and monetary aggregates for Canada and the U.S. The monthly data sample covers the period from

January 1966 to September 2000. As a measure of the growth rate of output used the industrial production index, seasonally adjusted, from IMF, International Financial Statistics, CD-ROM edition. Following Fama (1990), Barro (1990), Atta-Mensah and Tkacz (1998), Estrella and Mishkin (1998), and other authors, Hassapis calculated real stock returns by using the TSE (Toronto Stock Exchange) and NYSE (New York Stock Exchange) composite indices appropriately adjusted for the inflation rate of Canada and the United States, respectively. The interest rates used are as follows: Over 10-Year Government of Canada Marketable Bonds, 90-day Commercial Paper Rate - Canada, the Prime Corporate Paper Rate - 1 Month - Canada, the Prime Corporate Paper Rate - 3 Months - Canada, U.S. 10-Year Treasury bonds, U.S. 3-Month Treasury Bills, as well as the yield spreads between the 10-Year Bonds (Canada and U.S.) and various short term rates from above. The Canadian monetary aggregates used are real M1, M2, and M3.

The results that Hassapis concluded using the non-parametric method, and we will use as well, showed that stock prices, yield spreads (the difference between long-term and short-term interest rates) and monetary aggregates are useful predictors of Canadian growth. This is in line with earlier parametric studies in the literature, usually for the United States, which find these variables to be good predictors of economic activity.

More specifically, his results show that there is a strong positive relationship (temporal correlation) between current Canadian (and U.S.) financial variables and future Canadian output growth. The evidence suggests that for the case of Canadian and U.S. stock price changes the major effect on future Canadian output growth is within the first nine and sixteen months, although weaker effects may last for up to 26 and 36 months, respectively. This basically implies that current Canadian and U.S. stock price changes anticipate upward movements in Canadian output up to about 26 and 36 months into the future respectively, and therefore can be used as useful predictors of Canadian output growth. The relationship between the Canadian output growth and future U.S. stock price changes is found to be not significantly different from zero (as expected), as is the relationship between the Canadian output growth and future Canadian stock price changes. These findings for Canada are consistent with all the theoretical explanations, cited earlier, that show a strong positive link between stock prices and future real activity. These results also reinforce the recent results by Estrella and Mishkin (1998), who find, for the case of the United States, that the stock market is a useful predictor of output at a horizon of about one to three quarters. However, their results, consistent with our results, indicate that for horizons of more than one quarter, the slope of the yield curve emerges as the clear individual choice, since it outperforms all their other indicators. In particular, they found that the steepness of the yield curve seems to be an accurate predictor of real activity, especially between two and six quarters ahead. These findings are also similar to earlier findings by Fama (1990), Schwert (1990), and other authors who also point towards a strong positive relation between past stock prices and industrial production. In all these papers, depending on the horizons of returns, the relationship appears at a two to four quarter forecast interval. However these results contradict those of Atta-Mensah and Tkacz (1998), who, even though they originally argue that the TSE index is closely linked with economic activity in Canada, find, contrary to these findings that their results do not support the hypothesis that the stock market is a good predictor of economic activity.

With regard to the various Canadian yield spreads and future Canadian output growth, the relationship is again positive, and the evidence suggests that the major effect on future Canadian output growth is within the first eleven months, although weaker effects may also last up to about three years. Again, this basically implies that the yield spread is a useful predictor of Canadian output up to a three-year horizon. The relationship between Canadian output growth and future yield spread is also found to be not significantly different from zero. Similar results are also obtained for the case of the U.S.- Canadian yield spread (i.e., the differential between the U.S. ten-year bond yield and the Canadian three-month bond yield) and the Canadian output growth. Again these results are consistent with all off the earlier theoretical explanations and many studies that find that the term structure, and, in particular, the yield spread are excellent predictors of future economic growth. In a paper similar to that of Estrella and Mishkin (1998),Atta-Mensah and Tkacz (1998) examine the Canadian case and also find that the Canadian yield curve is best predicting real activity up to five quarters ahead, among several alternatives examined.

More specifically they have also found that the differential between yields on 10-Year plus government of Canada bonds and the 90-day commercial paper is best at predicting Canadian output growth up to five (5) quarters ahead.

With regard to the Canadian monetary aggregates, the evidence suggests that the relationship is again positive. The major effect of Canadian monetary aggregates on future Canadian output growth is found to be strongest within the first three months, although weaker effects may last up to about 27 months. Again, these results are consistent with the earlier theoretical explanations as well as with the Estrella and Mishkin (1998) results, which show that that real monetary base predicts real activity well within the first year, as well as, the Atta -Mensah and Tkacz (1998) results that show that the growth of real M1 over one quarter in Canada performs reasonably well in predicting Canadian output in the short run (less than four quarters).

The results when Hassapis used U.S. financial variables are:

- Contrary to the case where Canadian stock prices used, the evidence suggests that the major feedbacks from the U.S. stock price change to Canadian output growth occur within the first 16 months and weaker feedbacks last up to 36 months. This in conjunction with the earlier results for Canada implies that Canadian output reacts to both the Canadian as well as the U.S. stock market changes.
- Contrary to the Canadian yield case, the evidence in this case suggests that the major feedbacks from the U.S. - Canadian yield to Canadian output growth occurs within the first six months and weaker feedbacks last up to about 36 months.

Eugene F. Fama (1981) attempted to explain the anomalous stock return-inflation relation (puzzling results) working in two steps. The first step is to document the negative relations between inflation and real activity because the negative stock return-inflation relations are induced by negative relations between inflation and real activity. A simple rational expectations version of the quantity theory of money predicted negative partial correlations between inflation and real activity are observed consistently in monthly, quarterly, and annual data for the post-1953 period. The second step is to study the relations among the real variables presumed to be the fundamental determinants of stock returns. In the theory of finance, the quantity of investments available to firms with expected rates of return in excess of costs of capital is central in the determination of equity values. Fama studied empirically a simple model of the capital expenditures process, similar in spirit to the 'flexible accelerator' models summarized by Dale Jorgenson, in which increases in output raise average real rates of return on capital, which in turn induce increased capital expenditures. The last set of tests involve relating real common stock returns first to other real variables, then to inflation measures, and finally to combinations of real variables and inflation measures. Real common stock returns are positively related to real variables like capital expenditures, the real rate of return on capital, and output. More interesting stock returns lead all of the real variables, which suggest that the market makes rational forecasts of the real sector. As in the earlier studies referenced above, stock returns also show strong negative simple correlations with measures of expected and unexpected inflation. However in multiple regressions of stock returns on real variables and inflation measures, the most anomalous of the stock return-inflation relations, that between the ex post stock return and the ex ante expected inflation rate, always disappears. In the annual data, the unexpected component of inflation also has no marginal explanatory power. In sum the story proposed is a union of rational expectations models for the monetary and real sectors.

Fama first used two types of models for expected inflation. One is based on decomposition of interest rates into expected inflation rates and expected real returns. Since the interest rates are observed at the beginning of the time intervals of interest, this approach estimates the ex ante expected inflation rates which eventually allow as to document the negative relations between ex ante expected stock returns and expected inflation rates.

$\mathrm{I}_t = a_{t-1} + b\mathrm{T}B_{t-1} + h_t$, where $a_{t-1} = -\mathrm{E}R_{t-1}$ the expected real return follows a random walk and the one period interest rate $\mathrm{TB}_{t-1} = \mathrm{E}R_{t-1} + \mathrm{EI}_{t-1}$,

EI_{t-1} is an expected inflation rate. The 'wandering intercept' regressions estimated from monthly and quarterly inflation and interest rates and with interest rate coefficients constrained to equal 1.0. The inflation rates are calculated from the U. S. Consumer Price Index. The interest rates, taken from the quote sheets of Salomon Brothers, are those for one- and three-month Treasury bills observed at the end of the month or quarter preceding the inflation rates with which they are paired. Inflation and interest rates are continuously compounded, and the data are for successive non-overlapping months or quarters. Regressions indicate that the annualized $EITB_{t-1}$, which corresponds to the sum $a_{t-1} + TB_{t-1}$ and are the estimates of ex ante monthly and quarterly expected inflation rates, has good properties as an estimate of the annual ex ante expected rate, and we henceforth use it as such. The second approach based on money demand theory and the quantity theory of money, estimates conditional expected inflation rates as functions of money and real activity growth rates. Since measures of current money and current and future real activity growth rates are major explanatory variables, these conditional expected inflation rates are not ex ante measures. However, the money demand-quantity theory models of inflation provide the empirical economic story which explains why the ex ante expected inflation rates extracted from interest rates are also strongly related to current and future real activity. For empirical purposes the demand for money function is represented, in differenced form, as: $\Delta \ln m_t = \Delta \ln M_t - \Delta \ln P_t$

$$= b_0 + b_1 \Delta \ln A_t + b_2 \Delta \ln R_t + e_t \qquad (1)$$

Where m_t and M_t are the quantities of real and nominal money, P_t is the price level, A_t is a measure of anticipated real activity, R_t is one plus the nominal interest rate, e_t is a random disturbance, and Δ indicates the difference of the relevant variable. The theory postulates that $b_2 < 0.0$ and $b_1 > 0.0$. In a fully rational bond market, the interest rate set at time t is 'largely' exogenous with respect to the price level set at t. With real activity, money and the interest rate exogenous, the money demand equation becomes a model for inflation. From (1) $\Rightarrow$

$\Delta \ln \mathrm{P}_t = -b_0 - b_1 \Delta \ln \mathrm{A}_t - b_2 \Delta \ln R_t + b_3 \Delta \ln \mathrm{M}_t + h_t$, (2) where $h_t = -e_t$, b_3=1.0 and the other parameters are as before. Controlling for variation in other variables, a positive relation between money and anticipated real activity in the money demand equation (b_1>0 in (1)) implies a negative relation between the inflation rate and the anticipated growth rate of real activity in (2).
In the annual regression (1), the real activity measures are current, future, and past annual growth rates of industrial production. Money growth is measured by base (currency plus reserves held against deposits) growth rates, since these always have
more power in explaining inflation than other monetary measures like demand deposit growth rates or M1 growth rates. In the annual regression (1) both the current base growth rate and the lagged growth rate are included as explanatory variables. None of the inflation regressions contain the change in interest rate as an explanatory variable, reflecting the finding of Famas' 1980 paper that interest changes never have variable marginal explanatory power. The explanatory variables in the monthly and quarterly regressions are annual growth rates of the base and industrial production. As predicted by money demand theory, all estimated coefficients of real activity growth rates are reliably negative, while the estimated coefficients of base growth rates are reliably positive. The coefficients in the monthly and quarterly regressions are much smaller than those in the annual regression (1). The cross correlations show that measures of current and future real activity have negative simple correlations both with the annual inflation rate I_t observed for year t and with the estimated ex ante annual expected inflation rate EITB_{t-1} extracted from interest rate observed at the beginning of the year. The results above establish that inflation for month, quarter, or year t is related to the growth rate of real activity for the following year.
The hypothesis that Fama studied next is that forecasts of real activity are also the important determinants of common stock returns. The more limited goal here is the study of relations proposed by a bare-bones model of investments in order to identify real variables which are potentially important in the determination of stock returns. These real variables can then put against measures of expected and unexpected inflation in stock return regressions.

The model proposed for the capital expenditures process captures the spirit of the 'flexible accelerator' models summarized by Jorgenson. In brief an increase in the general level of real activity puts pressure on the existing capital stock, raising the average return on the existing stock and thus inducing increased capital expenditures. The measure of general real activity used is the rate of change of industrial production. The rate of change of GNP yields similar results. The dependent variables in the regressions are the change in the rate of capital expenditures of non-financial corporations, and the change in the after tax average real rate of return on their capital stock. Evidence shows that capital expenditures are led by both the average real rate of return on capital and industrial production, while the average real rate of return on capital is led by industrial production. Industrial production is always the leading variable in the investment process, and capital investment is the lagging variable. Measures of expected and unexpected inflation do not seem to be direct determinants of either capital expenditures or the average real rate of return on capital. Finally the absence of any marginal effect of expected or unexpected inflation in the change in the after tax average real rate of return on their capital stock, is evidence against the popular hypothesis that negative stock return-inflation relations are the consequence of over taxation of corporate profits during inflation.

Fama next offers the relation between stock returns and the real variables. The evidence here suggests that there is a strong positive relation between a measure of annual real common stock returns and the real variables from the capital investment process.[6] Preliminary tests showed that the stock return is never led by any of the real variables, and as indicated by the choice of explanatory variables in the regressions, the growth rate of industrial production is the only real variable that shows a strong contemporaneous relation with the stock return.

At the end Fama tests whether the stock return-inflation relations observed during the post-1953 period proxy for more fundamental relations between stock returns and real activity. The results from the regressions document

[6] The real stock return is the annual continuously compounded nominal return on a value weighted portfolio of all New York Stock Exchange common stocks less the annual continuously compounded inflation rate calculated from the U. S .Consumer Price Index. The nominal stock return is from the Center for Research in Security Prices of the University of Chicago.

statistically reliable negative relations between real stock returns and measures of expected and unexpected inflation. Furthermore expected inflation rates never have marginal explanatory power in stock return regressions that also include base and future real activity growth rates as explanatory variables, but the evidence on the relations between real common stock returns and unexpected inflation is less consistent. In the annual data, the explanatory power of the annual unexpected inflation rate disappears when placed in competition with base and future real activity growth rates. On the other hand, the reliable negative relations between monthly and quarterly real stock returns and unexpected inflation are undisturbed, in terms of magnitudes of estimated regression coefficients and t-statistics. Finally the results show that using base and future real activity growth rates to explain real stock returns kills the explanatory power of expected inflation. However, the fact that the variation in expected stock returns cannot be attributed to expected inflation does not erase the implication that the two variables move in opposite directions during the post-1953 period; in short that expected real stock returns are reliably lower later in the period. Although the base growth rate seems to dominate the expected inflation rate, the two variables have a similar role.

In short, the hypothesis for both common stocks and bonds is that expected real returns are determined in the real sector. Spurious negative relations between inflation and expected real returns are often induced by a somewhat unexpected characteristic of the money supply process during the post-1953 period, in particular, the fact that most of the variation in real money demanded in response to variation in real activity has been accommodated through offsetting variation in inflation rather than through nominal money growth.

Eugene F. Fama (1990) tried to study the combined explanatory power of the three sources of return variation. Standard Valuation Models posit three sources of variation in stock returns: (a) shocks to expected cash flows, (b) predictable return variation due to variation through time in the discount rates that price expected cash flows, and (c) shocks to discount rates.

The model says that, if information about the production of a given month evolves over many previous months, the production of a given month will affect the stock returns of many previous months. A given monthly return then has information about many future production growth rates, but adjacent returns have additional information about the same production growth rates. The R^2 from regressions of monthly returns on future production growth rates will then understate the information about production in the sequence of returns. Consistent with the evidence, the model says that the proportion of the variation in returns due to information about production is captured better when longer-horizon returns are regressed on future production growth rates.

The tests attempt to explain real returns on the value-weighted portfolio of NYSE stocks. Real returns are nominal returns, from the Center for Research in Security Prices, adjusted for the inflation rate of the U. S. Consumer Price Index (CPI). The tests use continuously compounded real returns, R (t, t + T), for return horizons, T, of one month, one quarter, and one year.

Three time-t variables are used by Fama to track the expected value of R (t, t + T):

(a) D(t)/V(t)- the dividend yield on the value-weighted NYSE portfolio, computed by summing monthly dividends on the portfolio for the year preceding t and dividing by the value of the portfolio at t.

(b) DEF (t)- the default spread, defined as the difference between the time-t yield on a portfolio of 100 corporate bonds, sampled to approximate a value-weighted portfolio of all corporate bonds, and the time-t yield on a portfolio of bonds with Aaa (Moody's) ratings.

(c) TERM (t) – the term spread, defined as the time-t difference between the yield on the Aaa corporate bond portfolio and the one-month Treasury bill rate. The corporate bond yields in TERM (t) and DEF (t) are from Ibbotson Associates and are made available through the sponsorship of Dimensional Fund Advisors.

The results of regressions of returns, R (t, t + T), on D(t) / V(t), DEF (t), and TERM (t) are robust to changes in the definitions of the forecasting variables. Fama used a market-portfolio bond yield because it is less subject to changes through time in the meaning of bond ratings. The hypothesis that dividend yields forecast stock returns is old. The intuition of the efficient-markets version of the hypothesis is that stock prices are low relative to dividends when discount rates and expected returns are high, and vice versa, so D(t) / V(t) varies with expected returns. In short, the view adopted here is that the variation in returns forecast by the dividend yield, the default spread, and the term spread is rational variation in expected returns in response to business conditions. Shocks to monthly and quarterly expected returns are measured by the residuals from first-order autoregressions (AR1's) fit to monthly and quarterly observations on the default spread and the term spread. Shocks to annual expected returns are measured by the sums of the four relevant residuals from the AR1's fit to quarterly observations on DEF (t) and TERM (t). Because contemporaneous shocks to the dividend yield and stock returns are almost necessarily negatively correlated, the tests only use expected-return shocks estimated from the expected-return variables, DEF (t) and TERM (t) that do not involve stock prices. Finally, variation in stock returns due to expectations of future cash flows are estimated by regressing returns on future growth rates of real activity. Preliminary tests showed that industrial production explains as much or more return variation as other real-activity variables, but growth rates of real GNP and Gross Private Investment are close competitors. Quarterly growth rates of seasonally adjusted production up to four quarters ahead are used to explain monthly, quarterly, and annual returns. The relations between stock returns and future production surely in part reflect the information about cash flows in production, there are at least two other possibilities (Barro (1990)): (1) stock prices and production can respond together to other variables. (2) stock returns might also cause changes in real activity. The test period is 1953-1987. Starting in 1953 avoids the weak war-time relations between stock returns and real activity reported by Kaul (1987) and Shah (1989). The 1953-1987 period also avoids any unusual behavior of the default spread and term spread. During the interest rate pegging period prior to the 1991 Treasury- Federal Reserve accord. Fama focuses on 1953-1987, but the results for other periods examined (1948-1987, 1948-1978, 1953-1978) are similar. A puzzling result in Fama (1981) and Kaul (1987) is that real activity explains larger fractions of return variation for longer return horizons. In brief, suppose that information about

the production of a given period is spread over many previous periods and so affects the stock returns of many previous periods. A given short-horizon return then has information about the production growth rates of many future periods, but adjacent returns have additional information about the same production growth rates.
As a result, regressions of long-horizon returns on future production growth rates (or regressions of long-horizon production growth rates on passed returns) give a better picture of the cumulative information about production in returns.
The general hypothesis underlining the analysis above is that information about the production of a given period is spread across preceding periods and so affects the stock returns of preceding periods. The hypothesis predicts that, in regressions of
P (t, t+1), the production growth rate for the month from t to t+1, on lags of monthly returns, more than one past return should have explanatory power.
The estimated regression of the monthly production growth rates of 1953-1987 on 12 lags of the monthly NYSE value-weighted return is

P (t, t+1) = 0,001+0,009 R (t-1, t) + 0,027 R (t-2, t-1)
+ 0,028 R (t-3, t-2) + 0,042 R (t-4, t-3)
+ 0,033 R (t-5, t-4) + 0,038 R (t-6, t-5)
+ 0,020 R (t-7, t-6) + 0,019 R (t-8, t-7)
+ 0,025 R (t-9, t-8) + 0,028 R (t-10, t-9)
+ 0,011 E (t-11, t-10) + 0,013 R (t-12, t-11) + e (t, t+1)

In short, up to 10 lags of the one-month return have power to forecast the one-month production growth rate. The explanatory power, as measured by R^2, is about the same when quarterly rather than monthly returns are used to forecast monthly production. The analysis suggests that the noise can be reduced, and forecast power increased, with regressions of longer-horizon production growth rates on the relevant returns. The regression R^2 rises from 0,14 for monthly production growth rates to 0,30 for quarterly growth rates and 0,44 for annual growth rates. The fact that R^2 increases with the forecast horizon but does not approach 1 suggest that information about production is not the sole determinant of returns, or vice versa. The symmetry between the return regressions is apparent. Leads of quarterly production up to three or four quarters ahead help to explain monthly, quarterly, annual stock returns, and three or four lugs of quarterly returns help to forecast monthly, quarterly and annual production growth. The model says that the higher R^2 for annual returns is relevant for judging how much return variation is explained by information real activity.

Fama next examines the multiple regressions of the real stock return, R (t, t + T), on the time – t terms spread, TERM (t), and either the dividend yield, D (t)/V (t), or the defaults spread, DEF (t). The regression also include the estimates shocks to DEF (t) and TERM (t), meant to capture return variation caused by shocks to expected returns. The dividend yield, the default spread, and the term spread forecast stock returns. The default spread and the term spread track expected returns, but the evidence that shocks to DEF (t) and TERM (t) produce a discount-rate effect in returns is weak. The discount-rate effect predicts that the slope in regressions of R(t, t+T) on the contemporaneous shocks to the default and term spreads is negative. The evidence that D (t)/V (t) and DEF (t) track expected returns is more reliable when production growth rates are used to explain returns.

Similarly to the other regressions three or four leads of quarterly production growth help to explain monthly, quarterly and annual returns. Annual returns are also in part explained by contemporaneous production growth for the last three quarters of the year. The losers in this situation are the term spread and shocks to the default spreads. The decline in the explanatory power of the term spread and shocks to the default spread that occurs when production growth rates are included in the return regressions suggests co-linearity. The correlation matrix for the regressions variables shows some relevant evidence. The correlation matrix confirms that TERM (t) is positively correlated with quarterly growth rates of production for at least five quarters ahead. Fama and French (1989) show that the term spread has a business-cycle pattern. TERM (t) is low around business peaks when future recession growth rates of production will be low, and is high around troughs, preceding the strong growth rates of production observed during the early phases of business expansions. The dividend yield and the default spread are also negatively correlated with production growth one and perhaps two quarters ahead. High values of the variables signal lower than average near-term production growth, and vice versa.

The fact that the dividend yield and the default spread are mostly backward looking with respect to output, but the term spread is strongly forward looking, can explain, in mechanical terms, why future production growth absorbs the forecast power of

TERM (t), but not of D(t)/ V (t) and DEF (t).

Finally, the general message about expected returns that comes out of the regressions is that they vary opposite to business conditions; expected returns are high when times have been poor (D(t)/ V (t) and DEF (t)) and when times are poor but improvement is anticipated (TERM (t)).

In conclusion, the tests suggest that a large fraction of the variation of stock returns can be explained, primarily by time-varying expected returns and forecasts of real activity. It is possible that, with fresh data, the explanatory power of the variables used here would be lower than that measured for 1953-1987. it is also possible that some explained return variation is not rational. On the other hand, it is possible that, if the variables and functional forms that drive the rational variation in stock prices were somehow revealed, we would find that the in-sample R^2 values obtained here understate the rational proportion of the variation on returns.

Arturo Estrella and Frederic Mishkin (1998) examined the usefulness of various financial variables[7] in out-of-sample predictions of whether or not the U.S. economy will be in a recession anywhere between one and eight quarters in the future. Variables with potential predictive content- interest rate spreads, stock price indexes, and monetary aggregates- are selected from a broad array of candidates and are examined by themselves and in some plausible combinations. The results are compared with similar exercises

[7] Financial variables, such as the prices of financial instruments are commonly associated with expectations of future economic events. Long –term interest rates, for example, are frequently analysed as weighted averages of expected future short-term interest rates. In this framework spreads between rates of different maturities are interpreted as expectations of future rates of corresponding to the period between the two maturities. Stock prices are similarly interpreted as expected discounted values of future dividend payments, and so incorporate views regarding both the future profitability of the firm and future interest or discounting rates.

involving more traditional macroeconomic indicators, including widely used indexes of leading indicators and their component variables. Their analysis differs in three important respects from much of the earlier research examining the usefulness of financial variables in predicting future macroeconomic outcomes. First, in contrast to most of the literature, with the exception of Stock and Watson (1993), they focus simply on predicting recessions rather than on quantitative measures of future economic activity.

Second, the principal criterion of predictive accuracy in their paper is out- of-sample performance, which is accuracy in predictions for quarters beyond the period over which the model is estimated.[8]

Third, new econometric techniques are brought to bear on this question.

In order to quantify the predictive power of the variables examined with respect to future recessions they use a probit model. The probit form is dictated by the fact that the variable being predicted takes on only two possible values-whether the economy is or is not in a recession. The model is defined in reference to a theoretical linear relationship if the form:

$y^*_{t+k} = b'x_t + e_t$, where y^*_t is an unobservable that determines the occurrence of a recession at time t, k is the length of the forecast horizon, e_t is a normally distributed error term, b is a vector of coefficients, and x_t is a vector of values of the independent variables, including a constant. The observable recession indicator R_t is related to this model by:

$$R_t = \begin{cases} 1, if & y^*_t > 0 \\ 0, & otherwise \end{cases}$$

The form of the estimated equation is: $P(R_{t+k} = 1) = F(b'x_t)$ (1)

Where F is the cumulative normal distribution function corresponding to -e .

The model is estimated by maximum likelihood, with the likelihood function defined as

$$L = \prod_{[R_{t+k}=1]} F(b'x_t) \prod_{[R_{t+k}=0]} [1 - F(b'x_t)].$$

In practice, the recession indicator is obtained from the standard National Bureau of Economic Research (NBER) recession dates that is:

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8 In- sample performance can always be improved by introducing additional variables, but in the out-of-sample performance context more is not necessarily better.

$$R_t = \begin{cases} 1, if \quad the \quad economy is \quad in \\ recession \quad in \quad quarter(t) \\ 0, \quad otherwise \end{cases}$$

In their paper, they examined many variables with potential predictive power for recessions, and they considered each variable with predictive horizons ranging from one to eight quarters ahead. The volume of output generated by this type of analysis makes it important to summarize the results in a meaningful way.

The principal measure is a pseudo R^2, that is, a simple measure of goodness of fit that corresponds intuitively to the widely used coefficient of determination in a standard linear regression. The measure of fit is defined by:

Pseudo R^2 =1- $\left(\frac{\log L_u}{\log L_c} \right)^{-(2/n)\log L_c}$,

Where L_u is the unconstrained maximum value of the likelihood function *L* and L_c is its maximum value under the constrained all coefficient are zero except for the constant, while *n* is the number of observations.

The form of this function ensures that the values 0 and 1 correspond to "no fit" and "perfect fit", respectively, and that intermediate values have roughly the same interpretations as their analogous in the linear case.

As in the linear regression case the pseudo, R^2 is a useful measure fit, but is not sufficient for statistical hypothesis testing. For predicting horizons of two or more quarters, they had an overlapping data problem in that the forecast horizon is longer than the observation interval. As a result, forecast errors are likely to be serially correlated, raising the possibility that the estimates of the significance of individual variables using conventional test statistics may be misstated.

Therefore, they calculated t-statistics using standard errors adjusted for the overlapping data problem by applying the Newey-West (1987) technique to the first- order conditions of the maximum-likelihood estimates.

$$F_t = F(b' x_t) \text{ , } f_t = F'(b' x_t) \text{ and } h_t = \frac{y_t - F_t}{F_t(1-F_t)} f_t x_t \text{, } \quad h \equiv \sum_{i=1}^{T} h_t \text{ .}$$

The first-order condition for the probit estimates may then be expressed as h=0. Further, computed the sample autocovariances of h_t,

$$\hat{\Omega}_j = \frac{1}{T}\sum_{t=j+1}^{T} h_t h_{t-j}^{'}$$ and constructed an estimator of the covariance of h from

$$\hat{S} = \hat{\Omega}_0 + \sum_{J=1}^{m} l_j \left(\hat{\Omega}_j + \hat{\Omega}_j^{'} \right),$$ where $l_j = 1 - j/(m+1)$. Using the notation $\mathrm{H} \equiv (1/T)(\partial h/\partial b)$, the variance-covariance matrix of the coefficient estimates is given by:

$$V=\frac{1}{T}\left(H^{'}H\right)^{-1} H^{'}\,\hat{S}\,H\left(H^{'}H\right)^{-1}$$

Estrella and Rodrigues (1997) show that coefficient estimates are consistent even in the presence of serial correlation and that, therefore, this variance estimator is consistent.

Of particular interest in their paper are the out-of-sample results. They again use the pseudo R^2 measure to assess the out-of-sample accuracy of the forecasts. However, when applied to out-of-sample results, there is no guarantee that the value of the pseudo R^2 will lie between 0 and 1, as is also true in the standard linear regression. Nevertheless, the pseudo R^2 for out-of-sample results is useful as a simple measure of fit and is comparable to the root-mean-square error or R^2 measures in the linear regression case.[9]

The primary focus of their paper is to test whether simple financial variables are useful predictors of future recession. Thus they examined such variables as interest rates, interest rate spreads, stock price indexes, and monetary aggregates, both nominal and real. To establish the usefulness of their results it was necessary for them to compare their results with models based on

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[9] In the standard linear regression model within sample and with a constant term, the variance of the dependent variable decomposes exactly into the variance of the fitted values and the variance of the errors. Thus the ratio of the mean-squared error to the variance of the dependent variable may be subtracted from 1 to obtain an R^2 that is always between 0 and 1. Out-of –sample, the mean-squared error may exceed the variance of the dependent variable, and the resulting pseudo R^2 may be less than zero. Nevertheless, the mean-squared error (or its square root) is frequently used as a measure of out-of-sample fit. A negative R^2 simply indicates a very poor out-of-sample fit. The explanatory variables do such a poor job that they are worse than a constant term by itself. The interpretation of negative values for the pseudo R^2 in their paper is completely analogous. In this case, the likelihood function plays a role similar to that of the mean-squared error in the linear case.

traditional macroeconomic indicators. They therefore also include as explanatory variables the Commerce Department's index of leading economic indicator and several of its component series, two experimental indexes of leading indicators constructed by Stock and Watson (1989, 1993) in conjunction with the NBER, and also lagged growth in real GDP.

Another important consideration is the possible lag in the availability of the data for the explanatory variables. Some variables, such as interest rates and stock prices, are available on a continuous basis with no information data. In contrast, many monthly macroeconomic series are only available one or two months after the period covered by the data, and GDP has a lag of almost one full quarter. To place all the variables on an equal footing, only observations actually available as of the end of a given quarter are assigned to that quarter. The recession variable is constructed using the standard NBER dates.

The equations are estimated using quarterly data from the first quarter of 1959 to the first quarter of 1995. Even though most series are available on a monthly basis the estimates in their paper are derived from quarterly data for two basic reasons, as they claim: monthly data are generally too noisy and produce somewhat weaker results, whereas the use of quarterly data guarantees comparability of all series. However, they have found that results derived from monthly data lead to similar conclusions on the usefulness of the financial indicators.

In-sample results are based on equations estimated over the entire sample period. Their predictions or fitted values are then compared with the actual recession dates. Three types of results are provided: a pseudo R^2, a t-statistic, and indicators of significance at the 5 and 1 % levels. Because the focus of their paper is out-of- sample prediction, only a few selected in-sample results are presented with the text.

The general strategy of the analysis is the following. The probit equation is estimated using its series. Because the yield curve spread variable (SPREAD) produce consistently strong results across all horizons, equations are also run containing the SPREAD variable and each of the other variables in term.

Among the non-financial (or not strictly financial) variables, the leading indicators[10] and the GDP are clearly strong predictors in the very short run, with the significance generally declining within a year. The results they obtain are consistent with those of Koenig and Emery (1991), who show that the predictive horizon for these indicators tends to be short. Among the indexes of leading indicators the strongest performers is the original Stock- Watson indicator.

Among the financial variables, stock prices and the commercial paper spread exhibit a pattern similar to the indexes, although the fit is generally not as good, particularly for the commercial paper spread. Because the commercial paper spread is the difference between two six-month rates, which are presumably forward looking over that horizon, it's not surprising that the predictive power of this variable appears at the very short end. The one-quarter projection is significant at the 5% level.

Stock prices should be more forward looking than the commercial paper spread, at least in principle. This expectation is confirmed empirically by the results for the New York Stock Exchange (NYSE) index, which are significant up to four quarters.[11]

The evidence about the real monetary base, as the two authors present shows that, the real monetary base performs very well within the first year, and its fit is remarkably consistent over quarters one through four. In contrast, the predictive performance of the nominal monetary aggregates is uniformly poor.

Some of the most significant results in their paper are associated with the yield curve spread variable SPREAD. The steepness of the yield curve seems to be an accurate predictor of real activity, especially between two and six quarters ahead. For quarters two and beyond, the SPREAD variable produces a better fit than the other variables, with the exception of the Stock-Watson (1989) indicator (XLI) in quarter two. Note, however, that the Stock-Watson

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[10] The leading indicators are constructed from variables that have historically been correlated with future activity.

[11] They use quarterly growth rate of the stock index as a predictor, but, other equity-related variables such as the dividend yield or the price-earnings ratio could also be used. In this context, the latter two variables underperform the S&P 500 index growth both in sample (pseudo R^2 at least three percentage points lower) and out of sample. Predictive performance exists only for the price earnings ratio with a one-quarter horizon.

XLI variable includes a yield curve spread as one of its constituent variables, from which it seems to derive much of its out-of-sample predictive power.

When the yield curve spread is combined with the other variables in the probit model, the results of the single-variable analysis are generally confirmed, although some interesting combinations result. On the one hand, the significance of the SPREAD variable is basically undiminished beyond the first two to three quarters. Even within that range, only the real monetary base undoes the significance of the spread at the 5% level, and then only one quarter ahead. On the other hand, the other variables remain strong within two to three quarters, with two exceptions. By including SPREAD, both the commercial paper spread and the real base become insignificant beyond one quarter.

The results of their model that combines the yield curve spread with stock prices suggest that these two financial variables, which are readily and continuously available, form a very strong combination across all the horizons examined. The significance at the short end is enhanced by including the stock index, and the significance at the long end is driven largely by SPREAD.

The out-of-sample results were obtained in the following way. First, a given model is estimated using data from the beginning of the sample up to a particular quarter; say the first quarter of 1970. Then these estimates are used to form projections, say four quarters ahead. In this case, the projection would apply to the first quarter of 1971. After adding one more quarter to the estimation period, the procedure was repeated. That is, data up to the second quarter of 1970 were used to make a projection for the second quarter of 1971.In this way, the procedure mimics what a statistical model would have predicted with the information available at any point in the past. Data that become available subsequent to the prediction data are not used to estimate or to predict recessions.

As they assume this type of procedure leads ta a fairer and more realistic test of the predictive abilities of the various models than the in-sample results, but it nevertheless has several drawbacks.

The first data point for which predictions are made is the first quarter of 1971, because they needed to capture some recession observations to arrive at accurate parameter estimates as they support. Predictions are computed through the first quarter of 1995.

The evidence show that, variables that perform well, confirming expectations are the yield curve spread, the real monetary base, stock prices, and the indexes of the leading indicators. Compared with the in-sample results the performance of these variables shows some deterioration, in terms of both accuracy and length of the predictive horizon. For a few variables the deterioration in performance is substantial. For example, the commercial paper spread, which was highly significant for one and two quarters in sample, has a negative pseudo R^2 for every predictive horizon out of sample. The Commerce Department's leading indicators also have significantly diminished predictive power compared with in sample results. The original Stock-Watson XLI index outperforms the other leading indicators, particularly one quarter ahead.

As in the in-sample results, the SPREAD variable tends to dominate the results starting with the two-quarter ahead predictions. Although predictive power at seven and eight quarters is absent, the results for two and three quarters are actually stronger than in sample. No other single variable exhibits this kind of performance, including the traditional macroeconomic indicators. They also note that the model with SPREAD is relatively over time.

When the yield curve spread is included in the model with each of the variables, the effects are quite dramatic. With very few exceptions, additional predictive power is absent beyond one quarter when other variables are combined with the yield curve spread. What is noteworthy, however, is that some variables that do extremely well by themselves, such as the real monetary base and the original Stock-Watson index, are almost completely overshadowed by the spread.

It is clear from evidence that the only variables that truly and consistently enhance the out-of-sample predictive power of the yield curve beyond one quarter are the stock price indexes. With horizons of one, two, three, and five quarters, the results are better with either of the broader market indexes, namely, NYSE and the Standard and Poor's 500. Even for four and six quarters, the reduction in predictive fit is not that large. Some additional conclusions that can be drawn are: (1) stock prices provide information that is not contained in the yield curve spread and which is useful in predicting future recessions. (2) a simple model containing these two variables is about the best that can be constructed from financial variables for out-of sample prediction. Again it generally pays to be parsimonious.

Finally Estrella and Mishkin present a case study where they examine the performance of two parsimonious models-using SPREAD only and using SPREAD with NYSE- in forecasting the 1990-1991 recession out of sample and compare the results with those from the Commerce and Stock-Watson leading indicators. They examine forecasting horizons of two and four quarters ahead.

Before turning to the 1990-1991 results, consider the earlier performance of the series. For a forecasting horizon of two quarters, all four variables were fairly reliable until the late 1980s. When they used the yield curve spread (SPREAD) and the combined spread and stock index (NYSE) models the results were again fairly accurate, with the exception in 1988 of the model using both SPREAD and NYSE variables, when the stock market crash of 1987 produces a false recession signal.

In the 1990-1991 recession the models using the financial indicators forecast better the recession than the both leading indicators. When they looked at the longer four-quarter forecasting horizon, the dominance of the forecasting models using financial indicators is far more clear-cut.

Arturo Estrella and Gikas A. Hardouvelis (1991) examined the predictability of the term structure of interest rates in real economic activity.

They begin their study by documenting the empirical relation between future rates of growth in real GNP and its components with the current slope of the yield curve.

Real GNP is observed quarterly, and thus their sample is quarterly from 1955 through the end of 1988. The dependent variable in their basic regression is the annualized cumulative percentage change in the seasonally adjusted finally revised real GNP number based on 1982 dollars:

$$Y_{t,t+k} \equiv (400/k)[\log(y_{t+k}/y_t)] \ , \qquad (1)$$

where k denotes the forecasting horizon in quarters, and y_{t+k} denotes the level of real GNP during quarter t + k, and Y_{t+k} denotes the percentage change from current quarter t to future quarter t + k. They also examine the predictability of the annualized marginal percentage change in real GNP from future quarter t + k – j to future quarter t + k, defined as:

$$Y_{t+k-j,t+k} \equiv (400/j)\left[\log\left(y_{t+k} / y_{t+k-j}\right)\right] . \quad (2)$$

The cumulative percentage change $Y_{t,t+k}$ is the average of consecutive marginal percentage changes $Y_{t+i-1,t+i}$ for i=1, 2, 3 ….k. Hence, each $Y_{t+i-1,t+1}$ provides more precise information on how far into the future the term structure can predict.

For simplicity, they use only two interest rates to construct the slope of the yield curve, the 10-year government bond rate R^L, and the 3-month T-bill rate R^S. Both R^L and R^S are annualized bond equivalent yields. Their measure of the slope of the yield curve is the difference between the two rates.

$$SPREAD_t \equiv R_t^L - R_t^S . \quad (3)$$

In computing the two rates, they use average quarterly data as opposed to point-in- time data. There, they concern is predicting real GNP, and point-in-time data are not essential. On the contrary, it seems that GNP would be more closely associated with average interest rates over the quarter. Furthermore, averaged data provide an opportunity to check the robustness of previous results on the predictive power of the term structure that used only point-in-time data. There is evidence (for Treasury bills) that point-in-time data at the term of the calendar month contain systematic biases (Park and Reinganum (1986)).

Their basic regression equations have the following general form:

$$Y_{t,t+k} = a_0 + a_1 SPREAD_t + \sum_{i=1}^{N} b_i X_{it} + e_t , \quad (4)$$

Where $Y_{t,t+k}$ and $SPREAD_t$ are defined by equations (1) and (3) above, and X_{it} represents other information variables available during quarter *t*. Their sampling period is quarterly, but the forecasting horizon *k* varies from 1 to 20 quarters ahead. The overlapping of forecasting horizons creates special econometric problems. The data overlapping generates a moving average error term of order *k-1*, where *k* is the forecasting horizon. The moving average does not affect the consistency of the OLS regression coefficients but does affect the consistency of the OLS standard errors. For correct inferences, the OLS standard errors have to be adjusted. They use the Newey and West (1987) method of adjustment. Given that the non-overlapping data may have autocorrelated errors, they allow for a moving average of order length longer than *k-1*. They choose the lag length of each Newey and West correction after observing the estimated autocorrelation function of the OLS residuals, but the corrected standard errors are not very sensitive to the choice of the lag length.

Consistent with current thinking the evidence shows that a steeper (flatter) slope implies faster (slower) future growth in real activity. All constant terms a_0 and b_0 are positive. The positive constant terms imply that a negative slope does not necessarily predict negative future real GNP growth.

As expected, cumulative changes in real output are more predictable than marginal changes. The predictive power for cumulative changes lasts for about 4 years, while the predictive power of consecutive marginal changes in real output lasts for about 6 to 7 quarters. The marginal predictive power results indicate that financial market participants are able to predict events that will occur 6 to 7 quarters ahead. The results for marginal changes can be used to calculate how low the slope of the yield curve would have to be in order to predict a future recession.

The coefficients of determination, R^2, provides a measure of in-sample forecasting accuracy, while the statistical significance of the SPREAD coefficient provides information on the reliability of the equation in predicting the direction of a future change in output. The forecasting accuracy in predicting cumulative changes is highest 5 to 7 quarters ahead: SPREAD explains more than one-third of the variation in future output changes. From the visual representation of the predictive power of the slope of the yield curve, where the figure plots the annualized rate of growth of real GNP from quarter t-4 to quarter t and the slope of the yield curve during quarter t-4, they showed that the slope of the yield curve tracks the future realization in output growth impressively well, especially in the 1970s and early 1980s. However from 1985 through 1988 the association between the two variables is not very precise. The yield curve also has predictive power for all private sector components of real GNP as the evidence show.

Estrella and Hardouvelis next are trying to answer the question of, whether the yield curve may be a better predictor of, a binary variable X_t that simply indicates the presence $(X_t = 1)$ or absence $(X_t = 0)$ of a recession. In order to explore this question, they estimate a model that relates the indicator variable X_t to the slope of the yield curve 4 quarters earlier, $SPREAD_{t-4}$. The model is nonlinear and relates the probability of a recession as dated by the National Bureau of Economic Research (NBER) during current quarter t to the slope of the yield curve of quarter t-4:

$\Pr[X_t = 1 \setminus SPREAD_{t-4}] = F(a + bSPREAD_{t-4})$, where Pr denotes probability, F is the cumulative normal distribution, and X_t equals unity during those quarters considered as official recessions by NBER.[12] The model above is the usual probit model, and its log-likelihood function is as follows:

$$\log L = \sum_{X_t=1} \log F(a + bSPREAD_{t-4}) + \sum_{X_t=0} \log F(1 - a - bSPREAD_{t-4}) \qquad (6)$$

Maximizing the log-likelihood function (6) with respect to the unknown parameters a and b over the quarterly sample period from 1956:1 through 1988:4 they showed that an increase in the spread between the long and short-term interest rates implies a decrease in the probability of a recession 4 quarters later. The relation between the probability of a recession and the spread is statistically significant, but because the relation is nonlinear it is difficult to assess the quantitative significance of the association.

The figure that plots the estimated probability of a recession derived from the historical data on SPREAD lagged 4 quarters, and the cumulative normal distribution shows that all peaks in the estimated probability were associated with a recession except for the peak of 40 % in 1966-1967 when a slowdown occurred instead of a recession. Notice that in the recent 1985-1988 period

[12] The NBER definition of a recession corresponds essentially to two consecutive quarters of negative real GNP growth.

the estimated probability of a recession was close to zero. Also, the yield curve of the last quarter of 1988 does not predict a recession, but the yield curve of the first quarter of 1989 produces a probability of 20%. While this probability exceeds the levels observed in most non-recessionary quarters, it is still substantially lower than the recession predictions of 70 and 90 % of the last three recessions and is far from a firm prediction.

The hypothesis they take, that the causal variable behind the predictive power of the yield curve is expected future monetary policy appears to be in conflict with very basic sample correlations in the data.

Furthermore, only if monetary policy is neutral with respect to real output and the historical correlations reflect 'deep' parameters in the optimal plans of private agents would the yield curve continue to be a useful indicator after the monetary authorities become aware of its historical usefulness.

In the final step of their study they examine more closely the comparative value of the information in the yield curve. They add to the basic regression equation a number of information variables that are widely thought to predict future economic activity and examine whether or not the slope of the yield curve continues to have extra predictive power. The information variables that they choose are the recent growth in the index of leading indicators, the lagged growth in real output, and the lagged rate of inflation. The index of leading indicators is the first obvious choice and consists of twelve macroeconomic variables.

The evidence shows that: (1) first, SPREAD, continues to have explanatory over the entire forecasting horizon. Its regression coefficients are statistically significant up to 3 years into the future. (2) Second, an increase in the real federal funds rate predicts a drop in real GNP for about 6 quarters into the future. (3) Third, an increase in the index of leading indicators predicts a future increase in real GNP. However, the predictive power lasts for only up to 3 quarters ahead. This is very weak predictive power when compared to the predictive power of the slope of the yield curve. (4) Fourth, the lagged growth in output has a negative coefficient showing a slight mean reversion. (5) Fifth, the lagged rate of inflation also shows a negative coefficient, which is statistically significant at all, horizons beyond two quarters.

In the case of the probit equation for predicting recessions, the supplementary information variables are strikingly devoid of additional explanatory power- singly or jointly- in the presence of SPREAD.

Another way to assess the quality of the information in the slope of the yield curve is to compare its forecasting performance with the forecasting performance of survey evidence. They used data from mid-quarter surveys conducted by the American Statistical Association and the NBER since the beginning of 1970. The data are median forecasts of current real GNP and the real GNP of the next 2 quarters. They also have data for the median forecast of 3 quarters ahead since 1981.

The evidence shows that SPREAD is a better predictor of future output growth than the median survey forecast. They regressed the realized percentage change in real GNP on the predicted change by the survey and on the slope of the yield curve. The survey forecasts have predictive power for one and 2 quarters ahead but not for 3 quarters ahead. Also the predictive ability of the slope of the yield curve is better than that of the median survey forecast as evidenced by uniformly larger R^2's. Furthermore, adding the survey forecast as an additional regressor in the $SPREAD_t$ regressions does not increase the R^2.

Regarding the results of out-of-sample forecasts the evidence is interesting. For all three forecasting horizons, the root mean squared error (RMSE) of the forecast based on all the information variables is the smallest, followed by the RMSE of the forecasts based on the slope of the yield curve alone. Thus, simple econometric models that include more variables in addition to *SPREAD* outperform *SPREAD* alone as a forecasting tool. Both predictors perform better than the median forecast of the survey. For the forecasting horizon of 3 quarters, the econometric model that includes only the slope of the yield curve produces a higher correlation (r^2) with the actual values than the econometric model that includes additional information variables. However, the higher correlation of the former model is offset by a larger bias over the sample period 1982-1988.

A comparison of the RMSE of *SPREAD* with the standard deviation of the actual growth in real GNP provides a rough idea of the out-of-sample forecasting accuracy of the slope of the yield curve.

Nikiforos T. Laopodis (2004) examined whether significant dynamic interdependencies existed among stock returns, inflation, real activity and monetary policy since the 1970s, decade by decade. Their paper also novels on the grounds that it is the first study, that examines all four magnitudes within a multivariate setting.

Laopodis is trying to answer the below questions: (1) the first concerns the role of monetary policy. (2) the second issue deals with the relationship between equity returns and inflation (3) the last issue relates to the relationship between real activity and equity returns.

He addressed these questions by exploiting the latest advances in econometric methodology which include cointegration , causality and error-correction methods via the means of Multivariate Vector Autoregressive (MVAR) or Multivariate Vector Error-Correction (MVEC) models.

His paper novels on the idea that the empirical analysis is done decade by decade and in the sense that it considers the ever-interesting issue of dynamic interdependencies between monetary policy and the stock market that manifests itself through inflation or real economic activity.

He used monthly data on the federal funds rate, the S&P500 index, the Consumer Price Index (CPI), and the industrial production index which were collected from DataStream and the Federal Reserve's FRED database for the period of January 1, 1970 to January 31, 2001. As he claimed, the choice for the federal funds rate as the monetary policy instrument in his study stems from the fact that almost all past studies have used this instrument to examine the effects of monetary policy actions on other financial variables such as interest rates, foreign exchange rates and, of course, stock prices. The S&P500 calculates continuous nominal monthly returns as measured by the following expression, $\ln\left(S\,\&\,P500_t / S\,\&\,P500_{t-1}\right)$, and real monthly returns when the S&P500 is deflated by the CPI. The industrial production index variable is the Federal Reserve's Board Index of Industrial Production as the proxy for real economic activity.

Laopodis, began his study with the preliminary statistical investigation of the data which includes the descriptive statistics, unit roots and cointegration. At this point it is important to note that the sample period he used, has been split into three sub-periods (decades) for the sole purpose of detecting any changes in the underlying characteristics of the dynamic linkages between any two variables.

The results from the descriptive statistics of the data for the three sub-periods, 1970-1980, 1981-1990, and 1991-2001, and the entire period, 1970-2001 shows that:

- First, the risk-return characteristics of the stock market have varied during each decade with a more favorable outcome during the 1980s. During that decade, there existed greater returns with modest increases in risk, compared to the first or the third sub-periods.
- Second, during that same decade the federal funds rate had the highest value and the highest average value compared to the other decades.
- Third, both variables exhibited serious departures from normally (especially in the first two sub-periods) as seen by the significant values of skewness, kurtosis and the Jarque-Bera statistic (which tests for presence or absence of normality).

Regarding the descriptives for the inflation rate and the industrial production, one must notice the sharp reduction in the rate of inflation during the third sub-period, in between its highest level in the seventies and its lowest level in the eighties.

The univariate results from the unit root tests using the monthly series provide strong evidence in favor of the presence of a unit root in each series.

The above evidence of non-stationarity suggests that the federal funds rate, the S&P500, the rate of inflation and the industrial production index share similar intertemporal properties, that is, they are non-stationary in their (log) level form and contain a unit root, but stationary in their first-difference form.

The next step in Laopodis study is to check for cointegration, and then follows error-correction representations and causality tests of the relationships among the cointegrated series.
The results from the Johansen cointegration procedure for the monthly series shows that, the real returns-real activity pair does not exhibit any cointegration in any of the three sub-periods under each of the three null hypotheses set forth above. The real returns-interest rate pair does not reveal any cointegration in the first or the second sub-period but in the third one cointegration surfaces under the third hypothesis (of an intercept but no trend) at the 5% level. Finally, the third variable pair real returns-inflation-displays bivariate cointegration in the first decade under the first null hypothesis (of no intercept and no trend) and in the third sub-period under the third hypothesis both at the 5% level of significance. From the multivariate cointegration results, it is evident that during the 1970s and the 1990s the consistent result is that there is a single common stochastic trend that bounded the four variables together in the long-run under the three null hypotheses. During the 1980s however, no common trends have surfaced corresponding to either one of the three null hypotheses. Consequently, the estimation of the dynamic linkages among these variables will have to include an error-correction term in the first and third sub-periods so that the previous period's disequilibrium relationship is explicitly modeled.
He now turns to the construction and interpretation of the (multivariate) vector error-correction (VEC) or VAR models. The error-correction framework can capture the short and the long-run equilibrium dynamics among these time series and provides a convenient way for examining the Granger-causality among the variables. This causality (or lead/lag relationship) provides the short-run dynamic adjustments required by the levels of the variables to equilibrate in the long run.
Following the Granger representation theorem, the four cointegrated variables have the following joint VEC representation as Laopodis writes:

$$\Delta FFR_{i,t} = a_1 + g_1 e_{t-1} + \sum_{i=1}^{n_1} b_{1,i} \Delta FFR_{i,t} + \sum_{i=1}^{n_2} b_{2,i} \Delta S\,\&\,P_{j,t} + \sum_{i=1}^{n_3} b_{3,i} \Delta INF_{i,t} + \sum_{i=1}^{n_4} b_{4,i} \Delta IP_{j,t} + e_{1,t}$$

$$\Delta S\&P_{j,t} = a_2 + g_2 e_{t-1} + \sum_{i=1}^{m_1} d_{1,i}\Delta FFR_{i,t} + \sum_{i=1}^{m_2} d_{2,i}\Delta S\&P_{j,t} + \sum_{i=1}^{m_3} d_{3,i}\Delta INF_{i,t} + \sum_{i=1}^{m_4} d_{4,i}\Delta IP_{j,t} + e_{2,t}$$

$$\Delta INF_{i,t} = a_3 + g_3 e_{t-1} + \sum_{i=1}^{l_1} j_{1,i}\Delta FFR_{i,t} + \sum_{i=1}^{l_2} j_{2,i}\Delta S\&P_{j,t} + \sum_{i=1}^{l_3} f_{3,i}\Delta INF_{i,t} + \sum_{i=1}^{l_4} f_{4,i}\Delta IP_{j,t} + e_{3,t}$$

$$\Delta IP_{j,t} = a_4 + g_4 e_{t-1} + \sum_{i=1}^{p_1} q_{1,i}\Delta FFR_{i,t} + \sum_{i=1}^{p_2} q_{2,i}\Delta S\&P_{j,t} + \sum_{i=1}^{p_3} q_{3,i}\Delta INF_{i,t} + \sum_{i=1}^{p_4} q_{4,i}\Delta IP_{j,t} + e_{4,t}$$

where FFR_t, denotes the federal funds rate, S&P is the S&P500, INF is the inflation rate, and IP the industrial production index, Δ is the difference operator, and $e_{1,t}$,.....,$e_{4,t}$ are stationary random processes describing the error terms. The n_i's, m_i's, l_i's and p_i's, (i=1,……T) are the optimal orders of the autoregressive process for a given variable. Finally, the e_{t-1} magnitudes are the error-correction terms obtained from the cointegrating equations, so that changes in the FFR, S&P, INF and IP variables are partly driven by the past values of e_t.

Under cointegration, the above equations serve as an appropriate framework for evaluating the dynamic short and long-run interactions among the four variables. Specifically, the short-run dynamics between two variables, say the FFR and the S&P, are captured by the $b_{2,i}$ and $d_{1,i}$ coefficients. On the other hand, existence of a long-run relationship between the federal funds rate and the stock market depends upon the statistical significance of g_1 and g_2 coefficients. Given that the FFR and S&P are cointegrated, the e_t term that represents the divergence from the long-run relation must incorporate both variables and either g_1 or g_2 are expected to surface as negative and statistically significant. Nonetheless, Laopodis also examines the lagged influences of each by estimating coefficients of $b_{1,i}$ and $d_{2,i}$. Since determining the optimal lag structure of the above equations is a concern that needs to be addressed, for if the lag structure is misspecified, the empirical results may be biased, the use of Akaike's (1969) Final Prediction Error (FPE) criterion will be employed. The values of the criterion will determine the optimal lag structure of the n_i's. In essence, Akaike's criterion balances the bias from choosing too small a lag order with the increased variance (inefficiency) of a higher lag-order specification.

Before he moves to the estimation of the multivariate VAR/VEC models among the four variables, Laopodis presents some bivariate estimates for the pairs among the variables. For the first sub-period (1970:01-1979:12), the only significant relationship surfaces in the case of the federal funds rate (FFR) as 'Granger-causing' the real stock returns (SP). This significance holds at lower and higher lags as well. Other notable uni-directional causal relations are those between the FFR and the CPI and between the CPI and the S&P. The second sub-period (1980:01-1989:12) reveals one strongly significant reciprocal 'Granger-causality' relationship, for the pair of IP-FFR, and four uni-directional ones, albeit marginal, for the following pairs: FFR-CPI, S&P-IP, S&P-CPI, and CPI-IP. Finally, the third sub-period (1990:01-1999:12) has shown two significant mutual causality results, one between the IP-FFR pair and the other between the CPI-IP pair. Also, some significant uni-directional causal patterns, such as the FFR-CPI, S&P-IP and S&P-CPI variable pairs exist.

Regarding the bivariate correlations, the pairs SP-FFR, SP-CPI and CPI-IP exhibit negative but weak correlations, while all others possible pairs among these four variables exhibit positive and also weak correlations in the first sub-period. The nature of correlations has stayed the same in the second sub-period but became much weaker. In the third sub-period, the pairwise correlations again remained the same with the exception of the CPI-FFR pair which became negative. Although some of the correlations became stronger during that decade, relative to the previous two, a notable result is the stronger correlation for each of the SP-CPI and CPI-IP pairs in this decade.

Laopodis observed both short-run and long run interdependencies among all four magnitudes in the 1970s and 1990s but only short-run interdependencies in the 1980s. His bivariate results (but not the multivariate results, except perhaps for the 1990s) for the linkages between real stock returns and inflation confirm the surprising result of a negative correlation between the two magnitudes found by other researchers. This was in contrast to the widely held view that stock returns were a hedge to inflation since they were supposed to be positively correlated with (expected and unexpected) inflation, in the short-run.

In regards to the relationship between real returns and the federal funds rate, his bivariate and multivariate findings suggest a weak negative relationship for every decade. Furthermore, the federal funds rate surfaces as the only variable (compared to the other variables in the multivariate setting) that adjusted to disequilibria in the long run.

Lastly, the bivariate results for the real stock returns-real activity (or industrial production) pair uncover a weak and negative relationship in the 1970s and1990s, a positive in the 1980s, but no significant relationship within the multivariate framework (in fact, industrial production has emerged as the most exogenous variable of all in each decade). These conflicting findings do not support the view that real stock returns signal changes in future real activity as earlier research has noted. As Laopodis supported, a suggested interpretation could be that each decade, and particularly the 1970s and 1990s, has produced different economic fundamentals (structure) such as high inflationary periods with supply shocks and speculative bubbles that loosened the link between the stock market and economic activity.

Last, but not least, focusing on the important relationship, that is, between monetary policy (via the federal funds rate) and the stock market, his results seem to suggest that there is no concrete and consistent dynamic relationship between the two magnitudes since the nature of such dynamics has been different in each decade. Perhaps this implies as Laopodis claim, that the Fed has never intended to influence the stock market in the long-run or has taken the risk to increase the federal funds markedly in order to avert excessive speculation in the market.

DALE L. DOMIAN and DAVID A. LOUTON (1997) investigate the effect of business cycle asymmetries on the relation between stock returns and real economic activity. They use monthly time series over the period January 1947 to December 1992. Real stock returns are obtained by adjusting nominal returns from the Center for Research in Security Prices (CRSP) for the inflation rate of the U. S. Consumer Price Index. Both value weighted and equally weighted CRSP indices are used. Seasonally adjusted industrial production data are obtained from Citibase. They use production growth rates computed as percentage changes in industrial production.

Stationarity is required for the time series methods used throughout in their paper. From the augmented Dickey-Fuller (1979) stationary tests they figured out that the series are stationary, consistent with the Nelson and Plosser (1982) results for annual data. Non-stationarities in monthly stock returns reported by Pagan and Schwert (1990) were primarily due to high volatility during the Great Depression, which does not affect their sample period.

They first examine the relationship between real stock returns and industrial production in the context of a conventional linear autoregressive model. This model forces a symmetric response to stock increases and decreases, so it serves as a benchmark for later results. Their initial test equation takes the following form:

$$\mathrm{IP}_t = a_0 + \sum_{j=1}^{J} a_j \mathrm{IP}_{t-j} + \sum_{k=1}^{K} b_k STOCK_{t-k} + m_t \qquad (1)$$

Model selection is carried out using Akaike's (1973) information criterion (AIC) technique. The AIC selects lag lengths to minimize a function of the residual sum of squares which includes a penalty term that increases with the number of estimated parameters. They estimated (1) by ordinary least squares using all combinations of lag lengths from 1 to 24. The AIC-selected lag lengths are (J, K) = (14, 6) for both value weighted and equally weighted stock returns. The AIC rises as the lag lengths are either increased or decreased from (14, 6).

For both value weighted and equally weighted stock returns, every individual $\hat{b}_k$ is positive throughout all of the lag length combinations. Most of these test statistics are significant at the 1 percent level, with the others significant at 5 percent. These results are consistent with previous findings that stock returns are positively correlated with future production growth rates.

They next examine whether business cycle asymmetry results in industrial production response magnitudes which depend on the signs of the stock returns. Define two series STOCKPOS and STOCKNEG containing only positive and negative returns, respectively:

$$STOCKPOS_t = \begin{cases} STOCK_t, if \quad STOCK_t \geq 0 \\ 0.0, \quad if \quad STOCK_t < 0 \end{cases}$$

$$STOCKNEG_t = \begin{cases} 0.0, \quad if \quad STOCK_t \geq 0 \\ STOCK_t, if \quad STOCK_t < 0 \end{cases}$$

Then consider the model:

$$\mathrm{IP}_t = a_0 + \sum_{j=1}^{J} a_j \mathrm{IP}_{t-j} + \sum_{k=1}^{K} (b_k STOCKPOS_{t-k} + g_k STOCKNEG_{t-k}) + m_t \qquad (2)$$

This “asymmetric response model” is estimated for lag lengths from 1 to 24, and exclusion tests are performed on the $\hat{b}_k s$ and $\hat{g}_k s$. The AIC selects J=14 as before, but now the optimal stock lags are reduced to K=3. These results show a marked contrast between the responses to stock increases and decreases. The STOCKPOS coefficients have mixed signs, so that their sums are negative in some regressions and positive in others. Exclusion tests of the STOCKPOS coefficients are always insignificants. On the other hand, each STOCKNEG coefficient has a positive sign in every regression. The magnitudes of their sums are greater than those of the STOCKPOS coefficients, and the STOCKNEG exclusion tests are always significant at the 1 per cent level.

After that they tried to measure the cumulative change in industrial production over several months after a positive or negative stock return. They define cumulative change variables $\Delta\mathrm{IP}_{1,t}$ from the IP_t growth rates as follows:

$$\Delta\mathrm{IP}_{1,t} = \mathrm{IP}_{t+1}$$

$$\Delta\mathrm{IP}_{2,t} = (1 + \mathrm{IP}_{t+2})(1 + \Delta\mathrm{IP}_{1,t}) - 1$$

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$$\Delta\mathrm{IP}_{14,t} = (1 + \mathrm{IP}_{t+14})(1 + \Delta\mathrm{IP}_{13,t}) - 1$$

Each $\Delta \mathrm{IP}_{k,t}$ measures the percentage change over months t+1 through t+k. These variables are used in the following model:

$$\Delta \mathrm{IP}_{k,t} = a + b_1 STOCKPOS_t + b_2 STOCKNEG_t + e_t, \quad \text{for} \quad k=1, \quad \ldots\ldots,14$$

(3)

This model measures the industrial production response over k months after a month t stock return. In the context of the ordinary linear model these methods can be used to adjust standard errors for autocorrelation induced by overlapping forecast horizons. However, the efficacy of these adjustments in the presence of threshold effects is not well understood, and thus it may be inappropriate to relay on asymptotic statistics for assessing significance. They avoid this problem by using a randomization experiment.

The results confirm that the industrial productions responses to stock returns are highly asymmetrical. The $\hat{b}_1 STOCKPOS_t$ coefficients are small and insignificant, while the $\hat{b}_2 STOCKNEG_t$ coefficients are large and highly significant over all forecast horizons considered. This method is not applicable for assessing the significance of the constants. Note also that the $STOCKNEG_t$ coefficients increase systematically over the first ten months, with uniformly strong significance. In contrast, the $STOCKPOS_t$ coefficients are small and insignificant for at least eight months. That is, negative stock returns are followed by sharp decreases in the growth rate of industrial production. While only slight, often faltering, increases in real activity follow positive stock returns.

Robert J. Barro (1990) in his paper examines the relation between stock market and investment. Initially he gives the notion of q and the theory which is behind it. A literature initiated by Tobin (1969) relates investment to q, which is the ratio of the market's valuation of capital to the cost of acquiring new capital. An increase in the prospective return on capital or a decrease in the market's discount rate raises q and thereby increases investment. The growth rate of investment relates to current and lagged values of proportionate changes in q. An important source of variation in the numerator of q-the market value of capital- is the change in stock in stock market prices. Therefore, q theory can rationalize a positive relation between investment and current and lagged changes in stock market prices, as estimated by Fama (1981) and Barro (1989), among others.

Barro uses in his regressions annual U.S. data for DI_t, the growth rate of real fixed, non-residential, private domestic investment. He does not consider broader definitions of investment, which would include expenditures on residential housing and other consumer durables, and perhaps outlays on human capital, since these flows do not relate directly to stock market prices or other variables that measure the market value of business capital. As he underlines, the results for the corporate component of investment, which relates naturally to the stock market and to corporate profits, are similar to those for his broader concept of business investment.

The sample periods considered, which exclude dates around World Wars I and II, 1891-1914, 1921-1940, 1948-1987; 1921-1940, 1948-1987; and 1948-1987. The variables, he considered, were:

- DI_t : Growth rate of investment (year t relative to year t-1).
- $Stock_t$: Growth rate for year t of the real stock market price. For 1926-1985, Barro used the value-weighted return on stocks, exclusive of dividends[13], from the Center for Research in Securities Prices (CRSP) of the University of Chicago. For 1986-1987, he used the returns based on the NYSE index, as reported by Data Resources, Inc. (DRI). For 1871-1925, he used the returns based on the Cowles Commission (1939) index for the value of all stocks. The inflation rate for the GNP deflator (year t relative to year t-1) was subtracted from the change in nominal stock prices to compute real changes. Although the timing of inflation and stock returns is off slightly, the adjustment of the nominal returns for inflation has, in any event, only a minor effect on the results.
- $D\Pr of_t$: The first difference of the ratio of after-tax corporate profits to GNP (the value for year t less that for year t-1). For 1929-1987, corporate

[13] From the standpoint of q theory, the change in investment depends on the change in the market value of capital. Therefore, it is appropriate to measure stock returns exclusive of dividends. Conceptually, it would also be desirable to adjust for retained earnings. However, the measurement of retained earnings is problematic because it requires an estimate of depreciation.

profits are the standard national accounts' numbers, which adjust for capital consumption and inventory revaluation. Numbers for 1919-1928 (provided by Changyong Rhee) are after-tax corporate profits as reported in issues of Internal Revenue Service Statistics of Income.

- Dq_t : Growth rate of q (year t relative to year t-1), where q_t is an annual average for year t. the measure of q_t, is an estimate of the ratio of total nominal market value of non-financial corporations (equity plus net debt) to capital stock at nominal reproduction cost. The figure on the capital stock includes standard estimates of depreciation. The variable used makes no separate adjustment for taxes. The underlying data are annual averages for 1900-1958 and quarterly averages for 1952-1987. In order to obtain a series that was comparable to the earlier data, annual averages of the quarterly figures were used to construct q_t, for 1958-1987 and Dq_t for 1959-1987.
- DY_t : Growth rate of real GNP (year t relative to year t-1).

The results for the regressions which apply to the period 1891-1914, 1921-1940, 1948-1987, suggest that some disturbance-such as a shift in the prospective real return on capital-shows up as a shift in stock market valuation and, with about a one year lag, as an increase in investment expenditures. The use of nominal stock price changes, rather than real changes, makes only a minor difference, as Barro estimated. As theory predicts and Barro confirms, the data indicate that investment relates to the change in real market value, rather than nominal market value.

The results of the regressions which deal with the period 1921-1940, 1948-1987 are surprising in that the q-variable takes account of stock market valuation and also consider the market value of net debt. In addition, the variable allows for changes in the stock of capital at reproduction cost. Thus, q measures total market value per unit of physical capital. In contrast, even without changes in the market value of debt, stock price indices err in not adjusting for retained earnings. Furthermore the regression with $Stock_{t-1}$ and Dq_{t-1} omitted, shows that the lagged profit variable, $D\mathrm{Pr}of_{t-1}$, has significant explanatory power for DI_t and another regression which adds contemporaneous values of the change in stock prices and the profit ratio shows that the current stock market variable, $Stock_t$, is insignificant, but the current change in the profit ratio, $D\Pr of_t$, is highly significant. Barro says about this regression that he would interpret it by thinking about an exogenous disturbance, such as a change in the prospective return on capital. The results suggest that as he claims that this kind of shock has an immediate reflection in stock market valuation and some contemporaneous effect on the ratio of corporate profits to GNP. The principal effect on investment expenditures and the larger impact on the profit ratio show up with a one-year lag. As would be expected, there is no lagged effect on stock prices-that is, the full adjustment of financial prices is contemporaneous with the disturbance.

Results for the 1948-1987 sample are similar to those for the period 1921-1940, 1948-1987.[14] One difference is that the estimated coefficients on the lagged stock market variable, $Stock_{t-1}$, and the current change in the profit ratio, $D\Pr of_t$, are smaller than before. The regressions with the dependent variable changed to the growth rate of real GNP have results similar to those shown before, although the estimated coefficients on the Stock and DProf tend to be smaller in this situation. These results are in accordance with the much greater volatility of investment than of GNP.

Barro's next step was to check the forecasts which were associated with the stock market crashes of 1987 and 1929 and his first observation was that the stock market crash lowered the annual rate of change of real stock prices for 1987 by 0.254.

The decrease in real stock prices in 1987 corresponds to a reduced forecast of growth in investment and GNP for 1988. In any event, the crash corresponded to a revision from a forecast of a strong boom for 1988 to a prediction of below average growth. The actual economic performance for 1988 turned out to be strong. Although the actual growth rates exceed the

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[14] Results are also similar for the period 1954-1987. for the period 1953-1987, it is possible to compute Dq_t ,based on fourth-quarter-to-fourth-quarters values. The correlation of Dq_t ,with $Stock_t$ is then 0.88 versus 0.64 when Dq_t is a first difference of annual averages. When the fourth-quarter values are used there is no longer much difference between Dq_{t-1} and $Stock_{t-1}$ in the regression for DI_t over the period 1954-1987.

projected values in each case, the gap is never statistically significant at the 5 percent level. Thus as Barro concludes, while the stock market did not predict well for 1988, one cannot conclude with any confidence from this observation that the economy has shifted to a new regime where the stock market is generally unreliable. In other words, given the typical margin of error for the sample, the incorrect forecasts for 1988 are not very unusual. In the case of the stock market crash of 1929, the regressions for the growth of investment and GNP were estimated over the period 1891-1914, 1921-1929. While the plunge in stock prices accurately predicted a decline in economic activity after 1929, the forecasts substantially understate the extent of the decline in this case. Putting 1987 and 1929 together Barro claims that, there is no indication that stock market crashes are systematically ignored in terms of the response of economic activity.

The results for the annual growth of investment and GNP over the long-term sample (1891-1914, 1921-1940, 1948-1987), using monthly changes in real stock prices as regressors follow next. Each monthly term is the logarithm of stock prices at the end of the month less the logarithm of stock prices at the end of the previous month. To get a rough estimate of the change in real stock prices, Barro subtracted the inflation rate for the year (expressed on a monthly basis), calculated from the annual GNP deflator. In other words, the inflation rate used is the same for all 12 months within a given year.

The regression for investment shows that this year's growth rate (annual average of investment for year t relative to that for year t-1) relates especially to real stock price changes between May and December of the previous year. Estimated coefficients for monthly stock price changes in the current year turn out to be insignificant, as do those for changes prior to December two years previous. The standard error of each coefficient on monthly stock price movements is fairly high, which allows for a good deal of random variation in point estimates from month to month. Nevertheless, there is some indication of a distributed lag pattern for the coefficients that rises between December and September of the previous year and then gradually diminishes to reach close to zero within about 15 months. The results for GNP reveal a similar pattern.

Barro's final step is the comparison of results for Canada and the United States. In the regressions for Canada he uses the growth rate of real fixed, non-residential, private domestic investment in Canada for the period 1928-1940, 1948-1987. The growth rate of real stock prices is based on the Toronto 300 composite index. Values of q for Canada were unavailable.

The regressions which use data on investment, real stock prices, and after-tax corporate profits as a ratio to GNP have comparable results with those for the United States. Other results are: (1) as with the United States, the lagged change in the corporate profit ratio has some additional explanatory power for the growth of investment. (2) the contemporaneous stock price change is again insignificant for the growth of investment. The current change in the corporate profits ratio is significant; but-unlike for the United States- the lagged value has a larger coefficient than the contemporaneous value.

It is often argued that the U.S. economy has a large, perhaps dominant, influence on the Canadian economy. Therefore, it is natural to consider U.S. variables as regressors for Canadian investment growth and that is what Barro does next. In the regressions he adds the U.S. lagged variables that he used before to explain U.S. investment growth - $D\mathrm{I}_{t-1}, Stock_{t-1}$ and $D\,\mathrm{Pr}\,of_{t-1}$ - to explain an equation for Canadian investment growth. This equation also includes the Canadian lagged variables as regressors. The results of these regressions show that changes in U.S. stock prices predict growth in Canadian investment, but-holding fixed the behavior of the U.S. stock market-the change in Canadian stock prices has no predictive value for growth in Canadian investment. The apparent predictive role for the Canadian stock market in some regressions can be attributed to the strong positive correlation between the changes in Canadian and U.S. real stock prices over the sample period.

Instead of entering the three lagged U.S. variables separately, one can combine them into the implied forecast for U.S. investment growth. Barro did that and found that, the usual likelihood test accepts the hypothesis that the U.S. variables matter for Canadian investment growth only to the extent that these variables predict U.S. investment growth. The results from the regressions suggest that the conclusion about the insignificance of Canadian stock price changes for Canadian investment growth still holds if one includes the contemporaneous values, $D\Pr of_{t-1}$ or $Stock_t$, for Canada.

The results for the 1948-1987 period are consistent with the idea that Canadian investment relates more to the U.S. stock market than to the Canadian market. But the results also indicate that Canadian investment is only weakly related to developments on either stock market over this period. The main evidence for a link between the U.S. stock market and the Canadian investment comes when the data from 1928-1940 are added to the sample. Thus, the behavior during the depressed 1930s plays a major role in the findings. Assuming that the Canadian stock market is a good measure of the market value of capital in Canada, the results are puzzling.

James D. Hamilton and Dong Heon Kim in their study, revisit the yield spread's usefulness for predicting future real GDP growth. They use the 10-year T-bond rate, 3-month T-bill rate, and real GDP from 1953:Q2 to 1998:Q2. the source of interest rates is the Statistical Release H.15 of the Federal Reserve Board of Governors, while real GDP is taken from the DRI Economic Database (formerly Citibase Economic Database). Based on historical data Hamilton and Kim concluded initially that the yield curve has flattened or become inverted prior to all seven recessions and these episodes illustrated when the gap between two interest rates became negative. Many researchers have identified the extent to which the yield curve is tilted away from its normal slope as a useful leading indicator of recessions. Of course, the yield curve does not have to become inverted to signal that recession is imminent; it may simply flatten relative to normal.

Many previous studies, such as Estrella and Hardouvelis(1991), Estrella and Mishkin (1997), Haubrich and Dombrosky (1996), Bonser-Neal and Morley (1997), Kozicki (1997) and Dotsey (1998), used the following regression to examine the predictability of the yield spread for real activity:

$$y_t^k = a_0 + a_1 Spread_t + e_t \ , \qquad (2.1)$$

$$y_t^k = (400/k)^* (\ln Y_{t+k} - \ln Y_t) \ ,$$

$$Spread_t = i_t^n - i_t^1 ,$$

where Y_{t+k} is real GDP in quarter t + k , y_t^k is the annualized real GDP growth over the next k quarters, and i_t^n, i_t^1 are the 10-year Treasury bond rate and the 3-month Treasury bill rate at time t. The estimation of equation (2.1) using OLS as the authors present show that these estimates are qualitatively similar to those obtained by previous researchers, confirming that the yield spread helps predict real GDP growth up to 8 quarters ahead.

Although equation (2.1) follows most of the literature in trying to predict the cumulative GDP growth over the next k quarters, it is also of interest as in Estrella and Hardouvelis (1991), Plosser and Rouwenhorst (1994), Kozicki (1997), and Dotsey (1998) to measure the marginal effect on year-to-year GDP growth for a horizon k quarters in the future. Evidence presented by Hamilton and Kim confirms that the spread makes a contribution to year-to-year growth rates for up to seven quarters in the future, though interestingly makes a negative contribution as one looks to a four-year horizon.

Following Haubrich and Dombrosky (1996), Bonser-Neal and Morley (1997), Kozicki (1997), and Dotsey (1998) Hamilton and Kim estimated the following equation:

$$y_t^k = b_0 + b_1 Spread_t + b_2 y_{t-1}^1 + b_3 y_{t-2}^1 + b_4 y_{t-3}^1 + b_5 y_{t-4}^1 + e_t \qquad (2.2)$$

where y_{t-i}^1 is quarterly real GDP growth beginning in quarter t-i. Because current and lagged rates of growth of real GDP may be useful for forecasting future GDP, these real growth rates are included in the estimated equation (2.2). The results from equation (2.2) again are qualitatively similar to previous studies as the authors claim. More specifically the values of the estimated coefficient on the spread are slightly smaller than the estimated coefficients without including lagged real GDP growth, but remain statistically significant at conventional levels up to 8 quarters ahead. Thus, the yield spread, they conclude, provides additional information beyond that contained in current and lagged growth rates. The statistical significance of the estimated coefficient on the spread shows a similar pattern with that of the estimated coefficient on the spread without lagged real GDP growth as explanatory variables.

Estrella and Hardouvelis (1991), Ploser and Rouwenhorst (1994), Estrella and Mishkin (1997), and Dotsey (1998) have investigated whether the yield spread has additional information beyond that contained in monetary policy. The following regression as Hamilton and Kim assume, allow them to take a look at whether there is predictive power of the yield spread over and above that provided by other variables that reflect the stance of monetary policy:

$$y_t^k = b_0 + b_1 Spread_t + b_2 X_t + e_t \qquad (2.3)$$

where X_t is the contemporaneous measure of monetary policy. They used the federal funds rate and two monetary aggregates as measures of monetary policy X_t. The source of federal funds rate and narrow (M1) and broad (M2) monetary aggregates is the Statistical Release H.15 and H.6 of the Federal Reserve Board of Governors.

The results as the two authors indicate show that, even when they include the change in the Federal funds rate or either monetary aggregate, the coefficient on the spread remains statistically significant at the 5% level up to 8 quarters ahead. It is interesting that although the coefficient on the change in the Federal funds rate 1 quarter ahead is statistically significant and positive; the coefficients from 8 quarters ahead are statistically significant and negative. The positive value of the coefficient on the change in Federal funds rate suggests that the Fed tries to raise the Federal funds rate to hold down the inflation pressure in an economic expansion. In the monetary aggregate case, the coefficient on the spread is statistically significant at the 1% level up to 8 quarters ahead conditioning on either M1 or M2. These results confirm the finding of previous studies that the yield spread provides additional information beyond that contained in monetary policy.

The yield spread is determined by the financial market's expectation of future short rates and a term premium. The relationship between the yield spread and future economic activity could be explained either in terms of the spread's role as a signal of the future expected short rates (the expectation effect) or as a signal of the change in the term premium (the term premium effect). It would be useful as Hamilton and Kim argue, to be able to decompose the spread's forecasting contribution into an expectations effect and a term premium effect, to see which mechanism accounts for the historical correlation.

So, the authors working on that direction are doing the below:

As before, let i_t^n, i_t^1 denote the n-period interest rate (long-term rate) and one-period interest rate (short-term rate) respectively. Consider the following definition of the time-varying term premium TP_t :

$$i_t^n = \frac{1}{n}\sum_{j=0}^{n-1} \mathrm{E}_t i_{t+j}^1 + \mathrm{TP}_t \,,$$

(2.5)

where $\mathrm{E}_t\left(i_{t+j}^1\right)$denotes the market's expectation at time t of the value ofi_{t+j}^1. The term premium TP_t could be viewed, for example, as the sum of a liquidity premium (h_t) and risk premium$(q_t): \mathrm{TP}_t = h_t + q_t$. Equation (2.5) can alternatively be written:

$$i_t^n - i_t^1 = \left(\frac{1}{n}\sum_{j=0}^{n-1} \mathrm{E}_t i_{t+j}^1 - i_t^1\right) + \mathrm{TP}_t \,.$$

(2.6)

Equation (2.6) implies that the spread can be decomposed into two terms. The first term on the right-hand side of equation (2.6) is the difference between short-term interest rates expected over the next n periods and the current rate. The second term is the time-varying term premium. To the question of, to what extent each term contributes to the rise of the short rate relative to the long rate prior to a recession, Hamilton and Kim answer that both the expected change of the short-term rate over n periods and the time-varying term premium help predict real GDP growth up to 8 quarters ahead. Which factor contributes more to predicting real GDP growth? The results of a Wald test of the null hypothesis that the coefficient on the expected change of short-term rates over n-periods is equal to that of the term premium show that, even though the estimated coefficients are similar, the null hypothesis is rejected in all cases where both estimated coefficients are statistically significant. The contribution of the future expected change of short-term rates to prediction of real GDP growth is statistically significantly bigger than that of the term premium. Hence the most important reason that a negative yield spread predicts slower real GDP growth is that a low spread implies falling future short-term interest rates.

One factor that should matter for the term premium is the volatility of interest rates. Higher interest rate volatility is associated with a decrease in the spread and an expected drop in interest rates. However, higher volatility appears to increase the term premium, rather than decrease.

Finally, Hamilton and Kim conclude that although interest rate volatility is an important determinant of the term structure of interest rates and an a priori plausible explanation for why the term premium helps predict GDP growth, in practice it appears that the explanation for why the interest spread helps forecast economic activity must be sought elsewhere.

In sum, the authors have confirmed earlier results on the usefulness of the spread between long-term and short-term interest rates for forecasting GDP growth. They have shown how to decompose this effect into an expectation effect and a term premium effect. Both effects are statistically significant-a forecast of falling short-term interest rates is associated with a forecast of slower GDP growth, and an increase in the expected return from rolling over 1-period bonds relative to an n-period bond is also associated with a forecast of slower GDP growth –though the first effect (the expectation effect) is slightly more important quantitatively and statistically. They proposed a simple model for interpreting the second effect (the term premium effect) based on time-variation in the variance of short-term interest rates. According to the model, an increase in interest rate volatility at the end of an expansion could explain why the spread and term premium fall at the end of the expansion. They found that volatility is an empirically important determinant of the spread and the term premium and a useful predictor of future interest rates. However, cyclical movements in volatility appear to be able to account for the usefulness of the spread and term premium for forecasting GDP.

David A. Peel and Mark P. Taylor (1998) in this paper explore the transmission mechanism from nominal interest rate spreads to real activity empirically. Using a variant of an econometric technique originally developed by Blanchard and Quah (1989) they investigate whether nominal spreads are more closely correlated with permanent or temporary movements in real output. In the aggregate supply and demand framework employed by Blanchard and Quah, permanent and temporary shocks to output may be associated with, respectively, supply and demand shocks to the economy so that, under this interpretation, their investigation as they claim, is tantamount to examining whether the slope of the yield curve affects real activity through the supply or the demand side of the economy.

Quarterly data for the period 1957i-1994iv were obtained for the UK and the US on real and nominal GDP, three-month treasury bill rates and ten-year government bond yields from the International Monetary Fund's International Financial Statistics data base. The first two series were used to construct a series for the implicit GDP deflator. For the US, only seasonally adjusted data on GDP were available. For the UK, seasonally unadjusted series were used. In both cases, however, all regressions were performed with and without seasonal dummies (in the US case in order to take care of any seasonality still present in the data). Since the results were qualitatively identical and qualitatively similar whether or not seasonal were included, the results presented below are using seasonal dummies in all regressions for the UK but not for the US.

The dependent variable in the basic regressions is the annualized cumulative percentage change in real GDP:

$$\nabla_k y_{t+k} = (400/k)(y_{t+k} - y_t), \qquad (1)$$

where k denotes the forecasting horizon in quarters, y_t is the logarithm of the level of real GDP at time t. The slope of the nominal yield curve is measured by the difference between the long bond yield (r_t) and the Treasury bill rate (i_t). The basic regression equations are therefore of the form:

$$\nabla_k y_{t+k} = a + b(r_t - i_t) + h_{t+k},$$

where h_{t+k} is the forecast error. As is well known, even under the assumption of rational expectations, the fact that the sampling interval may be smaller than the forecasting horizon generates a moving average forecast error of order one less than the number of sampling periods in the forecast horizon. Hence, h_{t+k} may be assumed to have a moving average representation of order *k-1*.

For the U.S., the results accord closely with those of Estrella and Hardouvelis (1991). A strongly significant slope coefficient is found for horizons up to twelve quarters which, for horizons up to eight quarters, is insignificantly different from unity. Again according with the results of Estrella and Hardouvelis, greatest predictive power is recorded in the five- and six-quarters horizons, where twenty eight per cent of the variation in the cumulative GDP growth is explained by the slope of the yield curve.

These results are also echoed for the U.K, although the percentage of variation explained is somewhat lower- around sixteen per cent at the five-and six-quarter horizons and the slope coefficient is more often closer to 0.5 than unity. Nevertheless, the estimated U.K. slope coefficient is strongly significant for all horizons are to six quarters.

In the traditional aggregate demand-aggregate supply (ADAS) model with a long run vertical supply curve, for example, aggregate demand disturbances result in a temporary rise output, while aggregate supply disturbances permanently affect the level of aggregate output. The authors follow Blanchard and Quah (1989) who use an ADAS framework in their analysis, and associate aggregate supply shocks with permanent shocks and aggregate demand shocks with temporary shocks. While it is possible that demand disturbances may have permanent effects on the real side of the economy, they concur with Blanchard and Quah that shocks having a permanent effect on output are likely to be due mostly if not wholly to supply-side factors, while those having only a temporary effect are likely to be due mostly if not wholly to demand- side. This allows them to investigate whether movements in the slope of the nominal yield curve affect real economic activity predominantly through the supply side or the demand side of the economy.

Given this taxonomy of permanent and temporary shocks to output, supply and demand shocks to real economic activity can be identified by imposing appropriate restrictions on the Wold representation of time series for real and nominal macroeconomic variables. In particular, consider the Wold representation for changes in output and prices,

$\begin{bmatrix} \Delta y_t \\ \Delta p_t \end{bmatrix} = \sum_{i=0}^{\infty} L^i \begin{bmatrix} f_{11i} & f_{12i} \\ f_{21i} & f_{22i} \end{bmatrix} \begin{bmatrix} e_{1t} \\ e_{2t} \end{bmatrix}$, where the f_{jki} represent the parameters of the multivariate moving average representation and e_{1t} and e_{2t} represent white noise innovations. They identify e_{1t} and e_{2t} as demand and supply innovations in the following way. Write $e_t = (e_{1t} e_{2t})'$, and denote the bivariate vector of innovations recovered from the vector autoregressive representation for $(\Delta y_t \Delta p_t)'$ by u_t. Since the VAR representation is simply an inversion of the Wold representation u_t will in general be a linear function of $e_t, u_t = Ae_t$ say, where A is a 2X2 matrix of constants. To recover the underlined demand and supply innovations from the VAR residuals then requires that the four elements of A be identified, which requires four identifying restrictions. Three restrictions can be obtained by normalizing the variances of e_{1t} and e_{2t} to unity and setting their covariances to zero. The fourth, crucial, identifying restriction which effectively identifies e_{1t} as the demand innovation, is the requirement that e_{1t} has no long-run-effect on the level of real output, although it may affect the long-run price level. The latter restriction on the Wold representation may be written: $\sum_{i=0}^{\infty} f_{11i} = 0$. These four restrictions are then sufficient to recover the underlying temporary and permanent innovations to output, which as we discussed above, maybe interpreted as underlying demand and supply innovations respectively.

After identifying the supply and demand innovations they then partition the moving average representation for GDP growth to construct counterfactual series, corresponding to the path that would have obtained the absence of demand innovations and the path that would have obtained in the absence of supply innovations over the estimation period. By utilizing these counterfactual series in tests of the predictive power of the slope of the yield curve, they can then investigate whether; the transmission mechanism from interest rates to real activity is operating through the demand side or the supply side of the economy, or both.

Preliminary unit root tests on the data showed the quarterly change in the logarithm of real GDP, and in the logarithm of the implicit GDP deflator to be stationary processes for both the U.K. and the U.S. There was also no evidence of cointegration between real GDP and prices for either country. They therefore proceeded to estimate a vector autoregressive representation for the vector time series $(\Delta y_t \Delta p_t)'$ for each of the two countries. The order of the VAR was chosen by sequentially excluding the highest lags of both series, starting from a twelfth-order VAR, and testing the exclusion restrictions on the system using a likelihood ratio test. For both the UK and the US this led to a choice of lag depth of eight.

They denote the series for GDP growth due to entirely to demand innovations over the sample period by a superscript d(Δy_t^d) while the corresponding series for GDP growth due entirely to supply innovations over the period is denoted by a superscript $s(\Delta y_t^s)$. The annualized cumulative percentage growth in these series for each of the forecasting horizons can then be constructed using the relation:

$$\nabla_k y_{t+k}^x = (400/k)\sum_{j=0}^{k} \Delta y_{t+j}^x \text{, x=d,s.}$$

The corresponding OLS projections of these series onto the nominal yield curve slope are given by:

$$\nabla_k y_{t+k}^d = a + b(r_t - i_t) + h'_{t+k},$$

$$\nabla_k y_{t+k}^s = a + b(r_t - i_t) + h_k.$$

Using the GDP series purged of supply innovations, there is little qualitative difference in these results compared to those obtained using the unadjusted GDP series for either country. Although there is some slight reduction in the size of the estimated slope coefficients, they are strongly significantly different from zero at horizons up to eight quarters ahead in both cases. Compared to the previous results, there is a slight reduction in the degree of variation in $\nabla_k y_{t+k}^d$ explained by the nominal yield curve slope for the US, while for the UK there is a slight increase. Turning to the results for $\nabla_k y_{t+k}^s$- the cumulative percentage change in the component of GDP purged of demand innovations- they see, however, that there is a very marked reduction in the amount of variation explained and, for both, countries at every forecasting horizon, the slope coefficients are insignificantly different from zero at the five per cent level. Thus, stripping real GDP movements of the component due to demand innovations over the sample period eliminates the correlation with the slope of the nominal yield curve.

Laurence G. Kantor (1986) in his study reexamines the effect of inflation uncertainty on real economic activity by including inflation hedging in the analysis. Previous research suggests that increased inflation uncertainty reduces real economic activity. The basic hypothesis of Kantor is that increased inflation uncertainty creates an incentive for adjustments to hedge inflation that mitigate the costs of inflation uncertainty. His paper focuses on a particular category of adjustments: portfolio reallocations that are designed to insulate real rates of return from unexpected changes in inflation. His evidence suggests that portfolio adjustments to increased inflation uncertainty in the early and mid-seventies consisted of a reallocation of wealth out of stocks and long-term financial assets and into real estate and short-term financial assets.

He formalize and test his theory by employing the Capital Asset Pricing Model (CAPM) to derive expressions for two components of inflation risk : unsystematic inflation risk and systematic inflation risk.

The (CAPM) can be used to derive measures of inflation risk that incorporate inflation hedging.[15] This model derives that the equilibrium expected real rate of return on an asset, E(r), is determined as follows:

$$\mathrm{E}(r) = r_f + l\,Cov(r, r_m), \qquad (1)$$

where

r_f = the real rate of return on an asset whose real return is uncertain ex ante (i.e., the real, risk-free rate of return),

r_m = the uncertain real rate of return on the market portfolio, which consists of all investment assets weighted by their respective outstanding market values, and

λ= $\left(\mathrm{E}(r_m) - r_f\right)/Var(r_m)$= the market price for the risk-bearing services.

[15] An alternative to the standard CAPM is the consumption based CAPM developed by Breeden (1979), which would render different measures of systematic and unsystematic inflation risk.

Let R_n denote the nominal rate of return on an asset whose nominal return is certain ex ante. Then the real rate of return on this asset, r_n, is uncertain since the inflation rate, P, is uncertain: $r_n = R_n - \mathrm{P}$ (2)

In principle, the only factor that distinguishes r_n from r_f is inflation risk.

Substituting r_n for r in equation (1), and making use of equation (2), he obtains:

$$\mathrm{E}(r_n) = r_f + l\,Cov(-P, r_m). \tag{3}$$

Thus, the market valuation of systematic inflation risk, $\mathrm{E}(r_m) - r_f$, is equal to $l\,Cov(-P, r_m)$.

A comparison of systematic inflation risk with the most commonly employed measure of inflation uncertainty in previous studies of its macroeconomic effects-the variance of inflation (or inflation forecasts)-clarifies the difference between Kantor's approach and that taken by others. The relationship between systematic inflation risk and the variance of inflation is:

$$Cov(-P, r_m) = Var(\mathrm{P}) - Cov(\mathrm{P}, R_m), \tag{4}$$

where R_m = the nominal rate of return on the market portfolio. Thus, the variance of inflation can be split into a systematic component $(Cov(-P, r_m))$ and an unsystematic component $(Cov(\mathrm{P}, R_m))$.

The results that Kantor derived using this portfolio-theory framework reveal that inflation hedging offsets the effect of inflation uncertainty on the riskiness of real returns. Equation (3) shows that the market's valuation of inflation risk reflects only systematic inflation risk. Equation (4) indicates that the variance of inflation is comprised of systematic inflation risk and unsystematic inflation risk, where the latter is a measure of the degree to which nominal returns and inflation are associated. If this association increases in response to increased inflation uncertainty, then the effect of inflation uncertainty on systematic inflation risk and hence on the riskiness of real rates of return will be smaller.

Kantor's next step is to calculate measures of systematic, unsystematic, and total inflation risk. To construct empirical counterparts to the theoretical expressions for inflation risk derived above, a market portfolio return index must be compiled. The return index used Kantor here consists of the holding-period yields on a market-value-weighted portfolio of 23 categories of assets including real estate, stock, and numerous debt instruments.[16] All returns are calculated on a calendar-year basis. Market values used to weight these returns are calculated as the end of the previous year.

Evidence about the nominal rate of return on the market portfolio and the rate of inflation shows that, the rate of inflation was relatively low and stable until the late sixties. When inflation became significantly greater and more volatile, its association with the nominal rate of return on the market portfolio appears contemporaneously negative, although it seems that the market return adjusted with a lag. However, over the 1977-1981 period, the rate of inflation and the rate of return on the market portfolio seem very highly and positively correlated.

These observations are supported by calculations for inflation volatility and systematic and unsystematic inflation risk. Inflation volatility is calculated by a moving variance of the annual rate of inflation (using the CPI). Systematic inflation risk is measured by the negative of a moving covariance between the real rate of return on a market portfolio and the rate of inflation. Unsystematic inflation risk is calculated by the moving covariance between the nominal rate of return on the market portfolio and the rate of inflation.

When inflation became substantially more volatile, systematic inflation risk at first increased along with it (and unsystematic decreased).However, after an adjustment period of several years, the market managed to hedge inflation quite well, as indicated by a sharp increase in the association between inflation and the nominal market rate of return (unsystematic or hedged

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[16] The 23 categories of assets are : New York Stock Exchange common stock, American Stock Exchange common stock, over-the-counter stock, preferred stock, farm real estate, residential real estate, long-term corporate bonds, intermediate-term corporate bonds, U.S. Treasury bills, Treasury notes, U.S. Treasury bonds, U.S. government agency securities, U.S. savings bonds, short-term municipal bonds, long-term municipal bonds, M1, commercial paper, bankers' acceptances, Eurodollars, overnight repurchase agreements, term repurchase agreements large certificates of deposits, and small savings and time deposits at commercial banks and thrifts. Ibbotson and Fall (1979) and Ibbotson and Siegel (1983) are major sources of data for this rate-of-return index. Other sources are Musgave (1981), Chase Econometrics Inc., the Federal Reserve Bulletin, a table provided by the U.S. Savings Bond Division, the Federal Home Loan Bank Board Financing Sourcebook, and Winningham and Hagan (1980). The methods used to calculate the market values and returns for each asset category as well as the data are available upon request from the author.

inflation risk). This coincides with a sharp decrease in systematic inflation risk, despite continued high inflation volatility.
To gain some insight into whether inflation hedging has reduced the macroeconomic costs associated with inflation uncertainty, Kantor extend previous tests of the effect of inflation uncertainty on real economic activity. Levi and Makin (1980), using the standard deviation of inflation forecasts across respondents to the Livingston survey to proxy inflation uncertainty , find that inflation uncertainty significantly reduced employment growth over the 1965-1975 period. To test whether the effect of inflation uncertainty on employment growth is different in the latter sub-period, he adds a regressor that consists of σ (the Livingston inflation uncertainty proxy) multiplied by a dummy variable which equals 1 for 1976-1981 and zero otherwise. Using either the 6-month or 12-month forecast horizon, the estimated coefficient associated with this dummy variable is positive and statistically significant. This implies that the estimated effect of inflation uncertainty on employment growth is significantly smaller in the 1976-1981 period than in the 1965-1975 period.
Mullineaux (1980), using a similar specification, finds that inflation uncertainty increases the unemployment rate. He reports the sum of the coefficients for lagged values of the same inflation uncertainty proxy. The results indicate that the sums of the coefficients for lagged values of inflation uncertainty fall substantially when the sample is extended, as do the coefficients of determination. In addition, most of the estimated coefficients for the individual lags of inflation uncertainty are statistically insignificant, and may have a negative sign.
The results presented here indicate that when the sample periods for tests that have reported deleterious macroeconomic effects of inflation uncertainty are extended through 1981, the size of these effects is reduced.
Finally Kantor directly tests the components of inflation risk-systematic and unsystematic- as determinants of real economic activity. He performs his tests using Makin's (1982) specification, which also includes expected and unexpected money growth as determinants. Makin (1982) finds that inflation uncertainty has a significantly negative effect on real output growth. Using the same data and sample period (1953-1975) as Makin (1982), Kantor

replicates his test except that he include systematic and unsystematic inflation risk as determinants.

The evidence indicate that when diversifiable and systematic inflation risk are both included as determinants, diversifiable inflation risk is insignificant while systematic inflation risk has a significantly negative effect on real output growth. When diversifiable inflation risk is omitted (equation 2.2), the regression's explanatory power and the statistical significance of systematic inflation risk increases. These results suggest that only that portion of inflation risk that cannot be eliminated by diversification reduces real output growth. While there are transactions costs associated with hedging, they are apparently either not substantial enough to significantly affect output growth or perhaps they are offset by a reduction in costs associated with a more efficient allocation or resources. The results also suggest that systematic inflation risk explains real output growth slightly better than the proxy for total inflation uncertainty used in previous studies. The explanatory power of the equation that uses systematic inflation risk (equation 2.2) is slightly greater than that of the equation that uses total inflation uncertainty. When both of these measures are included, systematic inflation risk is statistically significant while total inflation uncertainty is not. However, the explanatory power of this last regression is greater than all of the others and the hypothesis that total inflation uncertainty is statistically significant fails by a relatively small margin.

Dennis E. Logue (1981) is his study examines the relationship between inflation and real economic growth. He has chosen cross-sectional tests using data from countries that are members of the OECD. Three simple empirical tests were carried out. Annual data on the rate of consumer price change (CPI) and the rate of real growth in industrial production (RGIP) for twenty-four countries[17] for the period 1950 through 1971 were obtained from the Data Resources Incorporated (DRI0 data bank. The period was truncated so that confounding effects of floating exchange rates and the world energy situation

[17] Countries included were the United States, the United Kingdom, Austria, Belgium, Denmark, France, Germany, Italy, Luxembourg, the Netherlands, Norway, Sweden, Canada, Japan, Greece, Iceland, Portugal, Australia, Finland, Switzerland, Ireland, Spain, New Zealand, and Turkey.

would be eliminated. From these rates of change, means (-) and standard deviations (σ) were computed.

The following quite simple cross-sectional relationships are implied by our view of the inflation process.[18]

$$sCPI_i = a_0 + a_1\overline{CPI_i} + e_i \quad (1)$$

$$\overline{RGIP_i} = b_0 + b_1\overline{CPI_i} + e_i \quad (2)$$

$$\overline{RGIP_i} = c_0 + c_1 sCPI_i + e_i \quad (3)$$

$$^{s}RGIP_i = d_0 + d_1\overline{CPI_i} + e_i \quad (4)$$

$$^{s}RGIP_i = e_0 + e_1 sCPI_i + e_i \quad (5)$$

Where $a_1 > 0$ and the coefficients b_1 and c_1 should equal zero, in view of the fact that the average long-run growth rate should be unaffected by inflation.

As the author claims, although this study is merely suggestive, two new empirical regularities emerged. First, the mean rate of inflation has little influence on the average growth rate of real output. Hence, there may have been insufficient variation in the variables to yield definite conclusions about the influence of inflation on growth. Second, and quite significant, the variability in real growth seems to be strongly related to the rate of inflation. Finally, a subsidiary finding is further empirical confirmation that there tends to be a strong positive association between the average rate of inflation and its variability.

Maria Carkovic and Ross Levine (2002) in their study examine the relationship between foreign direct investment and real economic growth. This study uses new statistical techniques and two new databases to reassess the relationship between economic growth and FDI. First based on a recent World Bank dataset, they construct a panel dataset with data averaged over each of the seven 5-year periods between 1960 and 1995. They also confirm the results using new FDI data from the International Monetary Fund's (IMF).

[18] The specifications of these cross-section regressions can be derived from a number of models. For example if Phillips curve slope coefficients are equal across countries, these regressions follow. While this assumption is unlikely to be exactly valid, note that random variations in these parameters across countries will bias our estimates downward and will understate the significance of the relationship.

Methodologically, they use the Generalized Method of Moments (GMM) panel estimator designed by Arellano and Bover (1995) and Blundell and Bond (1997) to extract consistent and efficient estimates of the impact of FDI flows on economic growth. Unlike past work, the GMM panel estimator exploits the time-series variation in the data, accounts for unobserved country-specific effects, allows for the inclusion of lagged dependent variables as regressors, and controls for endogeneity of all the explanatory variables, including international capital flows.

They do not discuss the determinants of FDI. Instead, they extract the exogenous component of FDI using system panel techniques. Also, they do not examine any particular country in depth. They use data on 72 countries over the period 1960-95. Thus, their investigation provides evidence based on a cross-section of countries.

Carkovic and Levine use two econometric methods to assess the relationship between FDI inflows and economic growth. They first use simple ordinary least squares (OLS) regressions with one observation per country over the 1960-1995 period. Second, they use a dynamic panel procedure with data averaged over five-year periods, so that there are seven possible observations per country over the 1960-95 period.

The pure cross-sectional, OLS analysis uses data averaged over 1960-95, such that there is one observation per country, and heteroskedasticity-consistent standard errors. The basic regression takes the form:

$$GROWTH_i = a + bFDI_i + g\left[CONDITIONING \quad SET\right]_i + e_i \quad (1)$$

where the dependent variable, GROWTH, equals real per capita GDP growth, FDI is gross private capital inflows to a country, and CONDITIONING SET represents a vector of conditioning information.

The Generalized-Method-of-moments (GMM) estimators developed for dynamic panel data. The authors' panel consists of data for a maximum of 72 countries over the period 1960-1995, though capital flow data does not begin until 1970 for many countries. They average data over non-overlapping, five-year periods, so that data permitting there are seven observations per country (1961-65; 1966-70; etc.). The subscript 't' designates one of these five-year averages. Consider the following regression equation:

$$y_{i,t} - y_{i,t-1} = (a - 1)y_{i,t-1} + b^{'} X_{i,t} + h_i + e_{i,t} \tag{2}$$

where y is the logarithm of real per capita GDP, X represents the set of explanatory variables (other than lagged per capita GDP), η is an unobserved country-specific effect, ε is the error term, and the subscripts i and t represent country and time period, respectively. Specifically, X includes FDI inflows to a country as well as other possible growth determinants. They also use time dummies to account for period-specific effects, though these are omitted from the equations in the text. They can rewrite equation (2):

$$y_{i,t} = a y_{i,t-1} + b^{'} \mathrm{X}_{i,t} + h_i + e_{i,t} \tag{3}$$

To eliminate the country-specific effect, they take first-differences of equation (3).

Under the assumptions that (a) the error term is not serially correlated, and (b) the explanatory variables are weakly exogenous, the GMM dynamic panel estimator uses the following moment conditions.

$$\mathrm{E}\left[y_{i,t-s} \cdot \left(e_{i,t} - e_{i,t-1}\right)\right] = 0, \text{ for s≥2; t=3,……,T} \tag{4}$$

$$\mathrm{E}\left[\mathrm{X}_{i,t-s} \cdot \left(e_{i,t} - e_{i,t-1}\right)\right] = 0, \text{ for s≥2; t=3,……,T} \tag{5}$$

The authors refer to the GMM estimator based on these conditions as the difference estimator. There are, however, conceptual and statistical shortcomings with the difference estimator. Conceptually, as they argue, they would like to study the cross-country relationship between financial development and per capita GDP growth, which is eliminated in the difference estimator.

To reduce the potential biases and imprecision associated with the usual estimator, they use a new estimator that combines in a system the regression in differences with the regression in levels. The instruments for the regression in difference are the same as above. The instruments for the regression in levels are the lagged differences of the corresponding variables. These are appropriate instruments under the following additional assumption: although there may be correlation between the levels of the right-hand side variables and the country specific effect in equation (3), there is no correlation between the differences of these variables and the country-specific effect, i.e., $\mathrm{E}\left[y_{i,t+p} \cdot h_i\right] = \mathrm{E}\left[y_{i,t+q} \cdot h_i\right]$ and ., $\mathrm{E}\left[X_{i,t+p} \cdot h_i\right] = \mathrm{E}\left[X_{i,t+q} \cdot h_i\right]$ for all p and q

The additional moment conditions for the second part of the system (the regression in levels) are:

$$\mathrm{E}\left[\left(y_{i,t-s} - y_{i,t-s-1}\right) \cdot \left(h_i + e_{i,t}\right)\right] = 0 \qquad \text{for} \qquad s=1 \qquad (7)$$

$$\mathrm{E}\left[\left(\mathrm{X}_{i,t-s} - \mathrm{X}_{i,t-s-1}\right) \cdot \left(h_i + e_{i,t}\right)\right] = 0 \qquad \text{for} \qquad s=1 \qquad (8)$$

Thus, they use the moment conditions presented in equations (4), (5), (7) and (8), use instruments lagged two period (t-2) and employ a GMM procedure to generate consistent and efficient parameter estimates.

They collected data on FDI from two sources. First, they use data from the World Bank's ongoing project to improve the accuracy, breadth, and length of national accounts data. Second they confirm the findings using the IMF's World Economic Output (2001) data on openness.

Evidence shows that the exogenous component of FDI does not exert a reliable, positive impact on economic growth, and the regressions do not reject the null hypothesis that FDI does not exert an independent influence on economic growth. Furthermore the lack of an impact of FDI on growth does not depend on the stock of human capital. In the OLS regressions, FDI and the interaction term do not enter significantly in any of the regressions. In the panel regressions, FDI and the interaction term occasionally enter significantly, but even here, the results do not conform to theory. Namely, when FDI and the interaction do not enter significantly the term on FDI is significant and the coefficient on the interaction term is negative. They re-ran the regression using the interaction term, FDI * income per capita and found that there is not a reliable link between growth and FDI when allowing for the impact of FDI on growth to depend on the level of income per capita. Although the OLS regressions suggest that FDI has a positive growth effect, especially in financially developed economies, the panel evidence does not confirm this finding. On net, these results do not provide much support for the view that FDI flows to financially developed economies exert an exogenous impact on growth. In sum, they do not find a robust link between FDI and growth even when allowing these relationships to vary with trade openness. While, FDI flows may go hand-in-hand with economic success, they do not tend to exert an independent growth effect. Thus, by correcting statistical shortcoming with past work this paper reconciles the broad-cross country evidence with microeconomic studies.

Finally, they find that FDI inflows do not exert an independent influence on economic growth. Thus, while sound economic policies may spur both growth and FDI, the results are inconsistent with the view the FDI exerts a positive impact on growth that is independent of other growth determinants.

Benjamin M.Friedman (1995) examines the real effect of monetary policy on real economic growth. The predominant weight of the existing evidence, assembled using each of three different empirical methodologies--partial equilibrium structural models, vector autoregressions based on observed prices and quantities, and vector autoregressions incorporating non-quantitative information—suggests that the real effects of monetary policy are systematic, significant, and sizeable. Yet, questions remain, both about individual empirical results and about each methodological approach more broadly. In all likelihood, such questions will always remain. Just as earlier research produced findings that new research questioned, only to have yet further research challenge these answers, the progressive interplay of empirical findings and subsequent questions is an ongoing process. It is a sign of the development of economics as an empirical science. Importantly, however, the process is progressive, not merely circular. We may not yet satisfactorily “know” whether the monetary policy affects real economic activity, but as a result of the research summarized we do know more than we knew. And what we have learned mostly buttresses what we “knew”-in a different sense-before. Monetary policy does have systematic real effects, and they are both statistically significant and economically important.

3. Kernel-based estimators of the long-run covariance matrix

We are interested in estimating the 'long-run' correlation coefficient between output growth, u_{1t}, and real stock returns, u_{2t}. The long-run covariance matrix Ω of the process $u_t = [u_{1t}, u_{2t}]^T$ is defined as:

$$\Omega = \begin{bmatrix} w_{11} & w_{12} \\ w_{12} & w_{22} \end{bmatrix} = \lim_{T\to\infty} T^{-1} \sum_{i=1}^{T}\sum_{j=1}^{T} E(u_i\, u_j^T) \qquad (1)$$

This, under stationarity, reduces to:

$$\Omega = G + \Lambda + \Lambda^{\mathrm{T}}$$

Where $G = \begin{bmatrix} g_{11} & g_{12} \\ g_{12} & g_{22} \end{bmatrix} = E\left(u_0 u_0^{\mathrm{T}}\right)$ and $\Lambda = \begin{bmatrix} l_{11} & l_{12} \\ l_{21} & l_{22} \end{bmatrix} = \sum_{k=1}^{\infty} E\left(u_0 u_k^{\mathrm{T}}\right)$ (2)

Equation (2) decomposes the long-run covariance matrix Ω into the contempora-neous covariance matrix G and the temporal covariance matrix Λ (or Λ^{T}). This, in turn, implies that the long-run correlation coefficient:

$$r_{12} = \left(\frac{w_{12}}{\sqrt{w_{11} w_{22}}} \right) \qquad (3)$$

can be decomposed:

$$r_{12} = \left(\frac{g_{12}}{\sqrt{w_{11} w_{22}}} \right) + \left(\frac{l_{12}}{\sqrt{w_{11} w_{22}}} \right) + \left(\frac{l_{21}}{\sqrt{w_{11} w_{22}}} \right) = c_{12} + t_{12} + t_{21} \qquad (4)$$

This relationship expresses the long-run coefficient, ρ_{12}, as the sum of the contemporaneous correlation coefficient c_{12} , the temporal correlation coefficient τ_{12} that our case describes feedbacks from past output growth to current real stock returns ($u_1 \to u_2$), and the temporal correlation coefficient τ_{21} that describes feedbacks of the opposite direction ($u_2 \to u_1$).

Our goal is to estimate Ω, G and Λ non-parametrically. In this vein, Newey and West (1987) and Andrews (1991) suggest estimating Ω, G and Λ by means of the following kernel estimator:

$$\hat{\Omega} = \hat{G} + \hat{\Lambda} + \hat{\Lambda}^{\mathrm{T}} \qquad (5)$$

where $\hat{G} = \left(\frac{1}{\mathrm{T}-1}\right)\sum_{t=2}^{\mathrm{T}} \hat{u}_t \hat{u}_t^{T}$ and $\hat{\Lambda} = \sum_{j=1}^{T-2} k\left(\frac{j}{S_T}\right)\hat{\Gamma}(j)$, with $\hat{\Gamma}(j) = \left(\frac{1}{\mathrm{T}-1}\right)\sum_{t=2}^{T-j} \hat{u}_t \hat{u}_{t+j}^{\mathrm{T}}$ for j > 0, and $\hat{\Gamma}(j) = \hat{\Gamma}(-j)^{\mathrm{T}}$ for j < 0. The kernel weights $k(\cdot)$ belong to the following set:

K= $\left\{ k(\cdot): R \to [-1,1] / k(0) = 1, k(x) = k(-x); \int_R |x| dx < 0; K(l) \geq 0 \forall\, l \in R \right\}$,

where $K(l) = \frac{1}{2p}\int_{-\infty}^{\infty} k(x) e^{-ixl}\, dx$.

Andrews (1991) shows that the set K contains kernels that necessarily generate positive semi-definite (psd) estimators of Ω in finite samples. This set includes the following kernels, employed in the present study:

Bartlett: $k_B(x) = \begin{cases} 1-|x|, for |x| \leq 1 \\ 0, \quad otherwise \end{cases}$

Parzen: $k_p(x) = \begin{cases} 1-6x^2+6|x|^3, for 0 \leq |x| \leq 1/2 \\ 2(1-|x|)^3, \quad for \quad 1/2 \leq |x| \leq 1 \\ 0, \quad otherwise \end{cases}$

Quadratic Spectral (QS): $k_Q(x) = \frac{25}{12p^2x^2}\left(\frac{\sin(6px/5}{6px/5} - \cos(6px/5)\right)$

The estimator $\hat{\Omega}$, as defined above, is a consistent estimator of Ω for unconditionally fourth or eighth order stationary random variables and for any given bandwidth sequence $\{S_T\}$, such that $S_T \to \infty$ and $S_T / T^{1/2} \to 0$ (Andrews, 1991). Consistency and rate of convergence results have also been established, for more general cases, including unconditional heteroskedasticity and trending moments.[19] Moreover, the QS, kernel is best with respect to Asymptotic Truncated Mean Square Error (ATMSE) in the class K. As far as the choice of S_T is concerned, Andrews (1991) provides sequences of fixed bandwidth parameters that are optimal in the sense of minimizing the ATMSE. Specifically, for the kernels discussed above, the optimal bandwidth parameters $\{S_T^+\}$ are:

Bartlett: $S_T^+ = 1.1447[a(1)\mathrm{T}]^{1/3}$

Parzen: $S_T^+ = 2.6614[a(2)\mathrm{T}]^{1/5}$

Q.S: $S_T^+ = 1.3221[a(2)\mathrm{T}]^{1/5}$

where α(q), (q = 1,2) is a function of the unknown spectral density matrix of u_t at frequency zero, along with its q-th generalized derivative, and a 4x4 weighting matrix of known constants. This means that a(1), a(2) and hence S_T^+ are also unknown in practice. Estimates of a(1), and a(2) may be obtained either by estimating simple parametric models, as suggested by Andrews (1991), or non-parametrically as suggested by Newey and West (1994). Once these estimates are obtained, they may

be used into the formulas given above, to yield an estimator $\hat{S}_T^+$ of S_T^+. The latter is usually referred to as the 'automatic bandwidth estimator'. If each element of u_t is approximated by an AR (1) model, i.e.,

$$u_{1t} = r_1 u_{1t-1} + e_{1t}\ ,\quad e_{1t} \sim \mathrm{IID}(0, s_1^2)$$

$$u_{2t} = r_2 u_{2t-1} + e_{2t}\ ,\quad e_{2t} \sim \mathrm{IID}(0, s_2^2)$$

Then the estimates of $\hat{a}(1)$ and $\hat{a}(2)$ are given by:

[19] See Andrews (1991), Hansen (1992), de Jong and Davidson (1996).

$$\hat{a}(1) = \sum_{i=1}^{2} w_i \frac{4\hat{r}_i}{\left(1-\hat{r}_i\right)^6} \frac{\hat{s}_i^4}{\left(1+\hat{r}_i\right)^2} \Bigg/ \sum_{i=1}^{2} w_i \frac{\hat{s}_i^4}{\left(1-\hat{r}_i\right)^4} \qquad (6)$$

$$\hat{a}(2) = \sum_{i=1}^{2} w_i \frac{4\hat{r}_i}{\left(1-\hat{r}_i\right)^8} \hat{s}_i^4 \Bigg/ \sum_{i=1}^{2} w_i \frac{\hat{s}_i^4}{\left(1-\hat{r}_i\right)^4} \qquad (7)$$

where w_i, i=1,2 denote the weights assigned to the two diagonal elements of Ω. Alternatively, Newey and West (1994) propose a non-parametric method for the estimation of S_T^+ that does not assume a specific structure for u_t. Estimates of α(1) and α(2) are obtained by utilizing truncated sums of the sample autocovariances:

$$\hat{a}(q) = \left(\frac{w^T \hat{\Omega}^{(q)} w}{w^T \hat{\Omega}^{(0)} w} \right)^2, \text{ q=1,2} \qquad (8)$$

where $\hat{\Omega}^{(q)} = \sum_{j=-l}^{l} |j|^q \, \hat{\Gamma}(j)$, q=0,1,2 and l is equal to $c_1(T/100)^{2/9}$, $c_2(T/100)^{4/25}$ and $c_3(T/100)^{2/25}$ for the Bartlett, Parzen and QS kernels respectively. The choice of l depends on the choice of c_i, i=1, 2, 3 which in turn, implies that an element of subjective choice is built in this procedure as well. Newey and West (1994) consider the values 4 and 12 for c_1 and c_2 and the values 3 and 4 for c_3. They also consider weight vectors ω which are more general than those of Andrews (1991) in the sense that they assign positive (instead of zero) weights to the off-diagonal elements of $\hat{\Omega}^{(0)}$ and $\hat{\Omega}^{(q)}$ [20].

[20] In an extensive Monte Carlo study, Andrews (1991) reports cases where the kernel estimators of Ω yield confidence internals 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 a case , data filtering before estimating Ω may yield more accurately sized test statistics than standard kernel estimators; see Andrews and Monahan (1992).

4. Data and empirical results

To gauge these empirical relationships we use existing measures of output, real stock price changes, interest rates, interest rate spreads and monetary aggregates for G7 countries (United States, United Kingdom, Japan, Canada, Italy, Germany, France) and for a group of emerging countries (India, Korea, South Africa, Taiwan, Malaysia, Portugal, Greece). Our monthly data sample for the G7 countries covers the period, from 3/1980 to 1/2005 for Canada, from 2/1981 to 1/2005 for United States, from 11/1986 to 1/2005 for United Kingdom, from 11/1987 to 1/2005 for France, from 12/1990 to 1/2005 for Germany, from 6/1993 to 1/2005 for Italy and finally from 12/1995 to 1/2005 for Japan. Respectively our monthly data sample for the group of the emerging countries covers the period, from 7/1981 to 1/2005 for South Africa, from 2/1991 to 11/2004 for Korea, from 5/1994 to 2/2005 for Greece, from 2/1995 to 2/2005 for Taiwan, from 2/1996 to 2/2005 for Malaysia, from 6/1997 to 1/2005 for India and finally from 3/1999 to 2/2005 for Portugal. As a measure of the growth rate of output we used the industrial production index, seasonally adjusted, from DataStream. We calculated real stock returns appropriately adjusted for the inflation rate of each country respectively. The interest rates used are as follows: Over 10-Year Government Bonds, 3-month Treasury Bills or Interbank 3- month rates, 1-month interest rates, 1-year interest rates, as well as the yield spreads between the 10-Year Bonds and the short term interest rates (3 and 1-month) respectively for each country. The monetary aggregates used are real M1, M2, and M3.

As we mentioned earlier, there are several theoretical channels through which financial market variables rationally signal (lead) changes in real activity. In what follows we do not try to discriminate among these various hypotheses. Instead, we employ the non-parametric technique of section 3 to investigate the correlation pattern between various financials variables for a number of countries with respect to their output growth.

4. A.1. Canadian financial variables and output growth

Table A1 presents the estimated temporal correlation for all the financial variables that were examined in this paper. Among the various groups of Canadian financial variables examined, the Toronto Stock Exchange

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In the context of the present study, however, such data prewhitening is unnecessary since both stock price changes and output growth exhibit strong mean reverting properties

Composite Index (TSE), the Canadian yield (Can10Y-Can3M), and real M2 (RM2) were found to exhibit the strongest temporal correlations (t_{21}) with respect to Canadian output growth and are analyzed in greater detail below.
Our estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to the value of the current financial variable at hand ($u_{1,t-i} \rightarrow u_{2,t}$), and the temporal correlation coefficient t_{21}, which describes feedbacks from past values of the financial variable at hand to current output growth (i.e., in the opposite direction ($u_{2,t-i} \rightarrow u_{1,t}$), for alternative values of the bandwidth parameter S_T are reported in figures 1-9 for the Bartlett kernel.[21] The bandwidth parameter takes values in the interval [1, 45] by steps of one.
What figure 1 shows, for the Canadian composite stock price (TSE) and the Canadian output growth is that when the bandwidth parameter (i.e., the number of autocovariances that are assigned a non-zero weight) increases, our estimates of the temporal correlation coefficient t_{21}, that describes feedbacks from past real stock returns to current output growth ($u_{2,t-i} \rightarrow u_{1,t}$), increase as well. Similarly, the estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to current real stock returns ($u_{1,t-i} \rightarrow u_{2,t}$), are positive and increase as well as with the bandwidth parameter too.

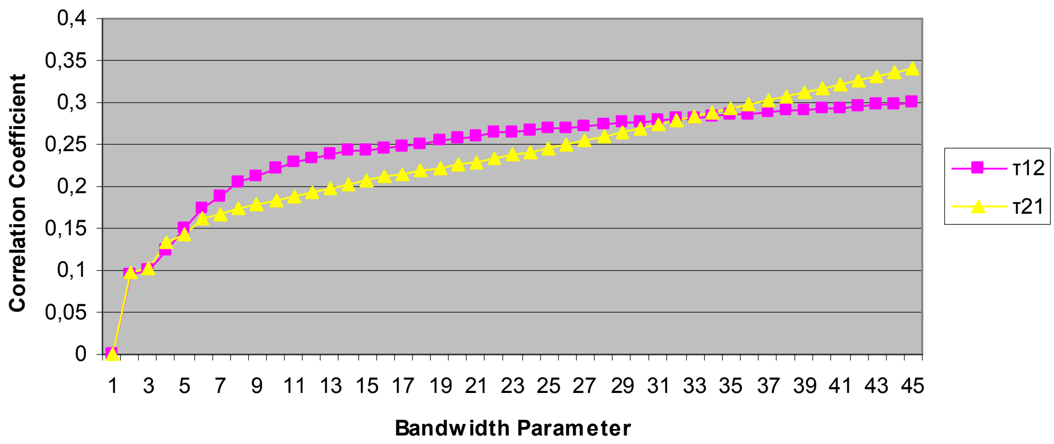

Figure 1: Estimated correlation coefficients: Canadian output growth and returns from the Canadian Stock price index (TSE)

It is interesting that the rate of growth of the estimates of t_{21} does not remain constant over the whole range of values of the bandwidth parameter S_T. When $S_T \in$ [1, 6], $\hat{t}_{21}$ increases at an increasing rate. For S_T=6, the estimate of t_{21} is equal to 0.16 for the Bartlett kernel. Beyond this point, $\hat{t}_{21}$ increases at a decreasing rate thus reaching its maximum value of 0.34 for S_T=45. What the evidence here suggests is that the major feedbacks, from past stock price

[21] Similar results for all cases under consideration, are reported at the appendix B, are also found with respect to the Parzen and QS kernels.

changes to output growth, occur within the first six months, with a maximum feedback of around 45 months. The relationship between past Canadian output growth and stock price changes is found to be significantly different from zero. The estimate of t_{12} follows an increasing rate when $S_T \in [1, 8]$ with $\hat{t}_{12}$ =0.20 when S_T=8 and reaches its maximum value of 0.29 for S_T=45.
What our results show is that there is a strong positive relationship (temporal correlation) between past stock price changes and current Canadian output growth, as expected. Our evidence here suggests that the major effect on the Canadian output growth is within the first six months, although weaker effects may last for up to 45 months. Basically, this implies that, for Canada, stock prices are useful predictors of output for a horizon of up to 45 months. The results from the Granger causality test for the Canadian industrial production and the stock index are:

GRANGER CAUSALITY	CHI-SQ	DF
IND $\longrightarrow$ IP	20.42622 [0.0010]	5
IP $\not\longrightarrow$ IND	4.666265 [0.4580]	5

Our findings for Canada are consistent with all the theoretical explanations, cited earlier, that show a strong positive link between stock prices and future activity. Our results also reinforce the recent results by Estrella and Mishkin (1998), who find, for the case of the United States, that the stock market is a useful predictor of output at a horizon of about one to three quarters. They also find stock prices, as well as the real monetary base, to be useful predictors, particularly for one through three quarters ahead. However, their results, consistent with our results, indicate that for horizons of more than one quarter, the slope of the yield curve emerges as the clear individual choice, since it outperforms all their other indicators. In particular, they find that the steepness of the yield curve seems to be an accurate predictor of real activity, especially between two and six quarters ahead.
Our findings are also similar to earlier findings by Fama (1990), Schwert (1990), and other authors who also point towards a strong positive relation between past stock prices and industrial production. These authors find that the strong positive link between these two variables reaches its maximum at a forecast interval of approximately six to twelve months, depending on the horizon of returns. It is interesting to note that our approach and results suggests that stock prices anticipate upward movements in industrial production at longer intervals as well.
In all these papers, depending on the horizon of returns, the relationship appears at a two to four quarters forecast interval. Fama (1990) has shown that the significance of lags will tend to increase, with the horizon of returns, owing to their overlapping with future cash flows. What our evidence presented here suggests is that stock prices anticipate upward movements in industrial production at longer intervals, up to about 60 months as well. Our results are also in line with those of Cozier and Tkacz (1994), who find for the case of Canada that stock prices predict output growth at short horizons: one to two quarters. However these results contradict those of Atta-Mensah and Tkacz (1998), who even though they originally argue that the TSE index is closely linked with economic activity in Canada, find, contrary to our findings,

that their results do not support the hypothesis that the stock market is a good predictor of economic activity.

Figure 2 shows the results for the Canadian yield spread (Can10Y-Can3M) and the Canadian output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{31} increase as well. The estimates of the temporal correlation coefficient t_{13} are again positive and they also increase as the bandwidth parameter increases as well. The rate of growth of the estimates of t_{31} again does not remain constant over the whole range of values of the bandwidth parameter S_T.

For S_T=5, the estimate of t_{31} is equal to 0.15, for the Bartlett kernel. Beyond this point, $\hat{t}_{31}$ increases at a decreasing rate, with a value of $\hat{t}_{31}$=0.26 for S_T=11 and reaching its maximum value of 0.45 for S_T=45. What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 11 months, although weaker feedbacks may last up to 45 months. What these results show, with regards to the Canadian yield spread (Can10Y-Can3M) and the future Canadian output

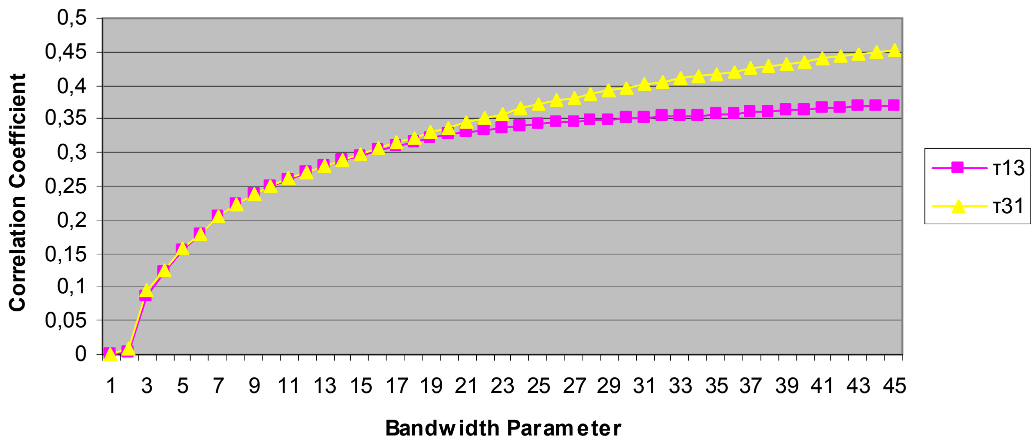

Figure 2: Estimated correlation coefficients: Canadian output growth and Canadian Yield (Can10Y-Can3M)

growth is that their relationship is positive, as expected. Our evidence suggests that the major effect on the future Canadian output growth is within the first eleven months, although weaker effects may also last up to four years. This basically implies that the yield spread is a useful predictor of Canadian output up to a four-year horizon. The relationship between the Canadian output growth and the future yield spread is found to be significantly different from zero. The estimate of t_{13} follows an increasing rate when $S_T \in$ [1, 11] with $\hat{t}_{13}$=0.25 when S_T=11 and reaches its maximum value of 0.37 for S_T=45. So, our evidence here suggests a strong positive relationship and between the opposite direction, with major effects reaching the first 11 months, but weaker effects may last for up to 45 months as well.

The results from the Granger causality test for the Canadian industrial production and the yield spread (Can10Y-Can3M) are:

GRANGER CAUSALITY	CHI-SQ	DF
$S3 \longrightarrow IP$	16.46709 [0.0009]	3
$IP \longrightarrow S3$	8.956574 [0.0299]	3

Again these results are consistent with all of our earlier theoretical explanations and with many studies, cited earlier, that find that the term structure and, in particular, the yield spread are excellent predictors of future economic growth. In a paper similar to that of Estrella and Mishkin (1998), Atta-Mensah and Tkacz (1998) examine the Canadian case and also find that the Canadian yield curve is best at predicting real activity up to five quarters ahead, among several alternatives examined. More specifically they have also found that differential between yields on 10-year plus government of Canada bonds and the 90-day commercial paper is best at predicting Canadian output up to five quarters ahead. Similar results are obtained by Estrella and Mishkin (1988), who also find that the steepness of the yield curve seems to be an accurate predictor of real activity in the United States, especially between two and six quarters ahead.

Changes in monetary aggregates are also among the variables that have the potential to affect real activity in the short run. This is also confirmed by our results, shown in figure 3, which show that real M1 (RM1) has an estimated temporal correlation coefficient t_{91} that increases at a decreasing rate.

For S_T=4, the estimate of t_{91} is equal to 0.10 for the Bartlett kernel. Beyond this point $\hat{t}_{91}$ increases at a decreasing rate and reaching its maximum value

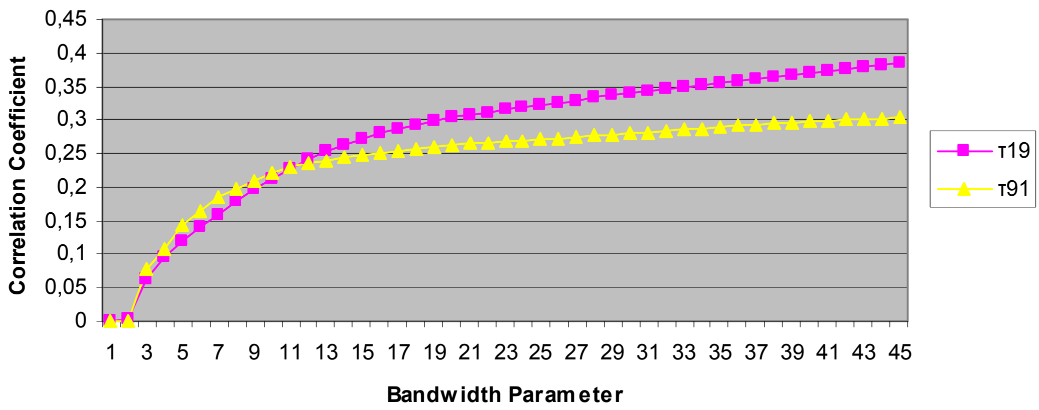

Figure 3: Estimated correlation coefficients: Canadian output growth and Canadian real money (M1)

of 0.30 for S_T=45. What the evidence here suggests is that the major feedbacks from real M1 to output growth occur within the first four months with a maximum feedback of around 45 months. Again, these results are consistent with our earlier theoretical explanations as well as with the Estrella and Mishkin (1988) results, which show that real monetary base predicts real activity well within the first year, as well as the Atta-Mensah and Tkacz (1998) results that show that the growth of real M1 over one quarter in Canada performs reasonably well in predicting Canadian output in the short run (less than four quarters). The relationship between the Canadian output growth and the future real M1 is found to be significantly different from zero. The estimate of t_{19} follows an increasing rate when $S_T \in$ [1, 3] with $\hat{t}_{19}$ =0.061 when S_T =3 and reaches its maximum value of 0.38 for S_T =45. So, our evidence here suggests a strong positive relationship and between the Canadian output growth and the future real M1, with major effects reaching the first 3 months, but weaker effects may last for up to 45 months as well.

The results from the Granger causality test for the Canadian industrial production and the real M1 (RM1) are:

GRANGER CAUSALITY	CHI-SQ	DF
RM1 $\longrightarrow$ IP	13.68678 [0.0084]	4
IP $\not\longrightarrow$ RM1	0.305158 [0.9895]	4

Similarly with the case of the spread (Can10Y-Can3M) in the case of the spread (Can10Y-Can1M) the results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{41} increase as well. The estimates of the temporal correlation coefficient t_{14} are again positive and they also increase as the bandwidth parameter increases as well. The rate of growth of the estimates of t_{41} again does not remain constant over the whole range of values of the bandwidth parameter S_T.

Figure 4 shows the results for the Canadian yield spread (Can10Y-Can1M) and the Canadian output growth.

For S_T =4, the estimate of t_{41} is equal to 0.20, for the Bartlett kernel. Beyond this point, $\hat{t}_{41}$ increases at a decreasing rate, with a value of $\hat{t}_{41}$ =0.25 for S_T =6 and reaching its maximum value of 0.38 for S_T =45. What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 6 months, although weaker feedbacks may last up to 45 months.

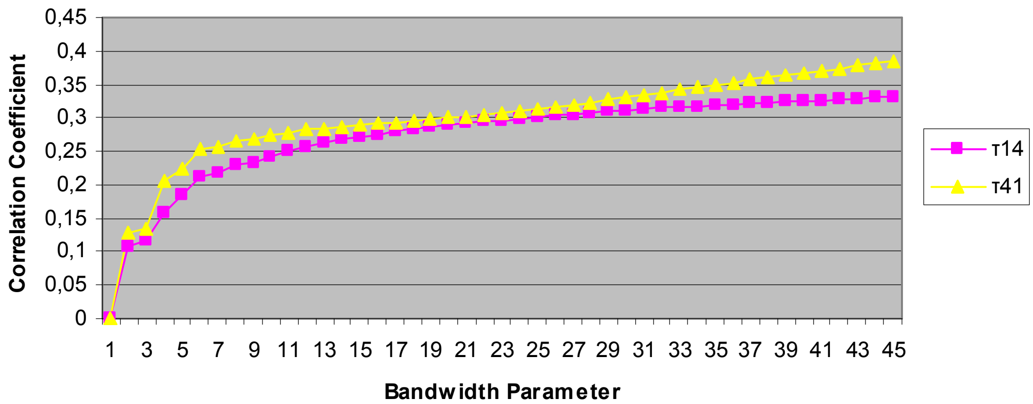

Figure 4: Estimated correlation coefficients: Canadian output growth and Canadian Yield (Can10Y-Can1M)

What these results show, with regards to the Canadian yield spread (Can10Y-Can1M) and the future Canadian output growth is that their relationship is positive, as expected. Our evidence suggests that the major effect on the future Canadian output growth is within the first six months, although weaker effects may also last up to four years. The relationship between the Canadian output growth and the future yield spread is found to be significantly different from zero. The estimate of t_{14} follows an increasing rate when $S_T \in$ [1, 6] with $\hat{t}_{14}$ =0.21 when S_T =6 and reaches its maximum value of 0.33 for S_T =45. So, our evidence here suggests a strong positive relationship and between the opposite direction, with major effects reaching the first 6 months, but weaker effects may last for up to 45 months as well.

The results from the Granger causality test for the Canadian industrial production and the yield spread (Can10Y-Can1M) are:

GRANGER CAUSALITY	CHI-SQ	DF
$S1 \longrightarrow IP$	22.24720 [0.0000]	1
$IP \not\longrightarrow S1$	0.197426 [0.6568]	1

Also real M2 (RM2) show similar pattern with RM1. This is also confirmed by our results, shown in figure 5, which show that real M2 (RM2) has an estimated temporal correlation coefficient t_{101} that increases at a decreasing rate. For S_T =4, the estimate of t_{101} is equal to 0.33 for the Bartlett kernel. Beyond this point $\hat{t}_{101}$ increases at a decreasing rate and reaching its maximum value of 0.3937 for S_T =29.

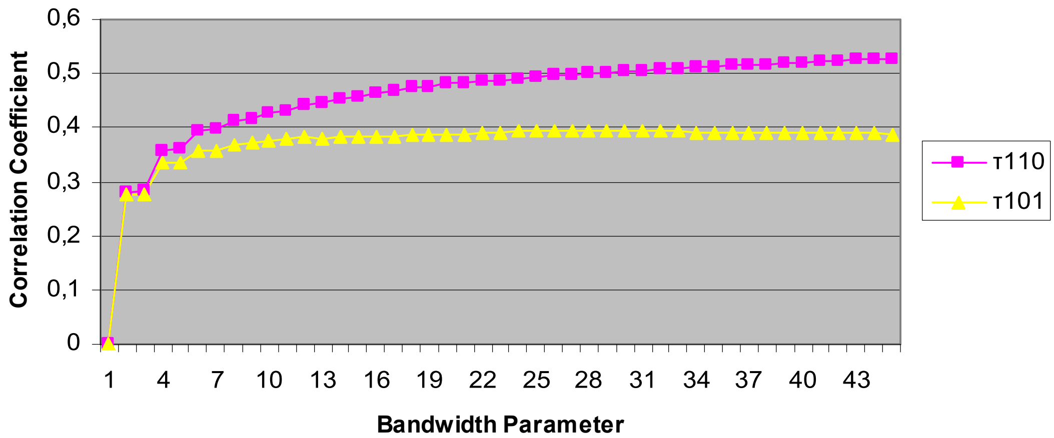

Figure 5: Estimated correlation coefficients: Canadian output growth and Canadian real money (M2)

What the evidence here suggests is that the major feedbacks from real M2 to output growth occur within the first four months with a maximum feedback of around 29 months. The relationship between the Canadian output growth and the future real M2 is found to be significantly different from zero. The estimate of t_{110} follows an increasing rate when $S_T \in$ [1, 4] with $\hat{t}_{110}$ =0.35 when S_T =4

and reaches its maximum value of 0.52 for S_T=45. So, our evidence here suggests a strong positive relationship and between the Canadian output growth and the future real M2, with major effects reaching the first 4 months, but weaker effects may last for up to 45 months as well.
The results from the Granger causality test for the Canadian industrial production and the real M2 (RM2) are:

GRANGER CAUSALITY	CHI-SQ	DF
RM2 $\not\longrightarrow$ IP	2.194492 [0.5330]	3
IP $\not\longrightarrow$ RM2	2.480447 [0.4788]	3

Also for the various interest rates (10–year government bond, 1-month, 3-month and 1-year interest rates) which we examined, the results are robust again and similar with that of the other variables.
Figure 6 shows the results for the Canadian 10–year government bond and the Canadian output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{51} increase as well. The estimates of the temporal correlation coefficient t_{15} are again positive and they also increase as the bandwidth parameter increases as well. The rate of growth of the estimates of t_{51} does not remain constant over the whole range of values of the bandwidth parameter S_T.
For S_T=3, the estimate of t_{51} is equal to 0.064, for the Bartlett kernel. Beyond this point, $\hat{t}_{51}$ increases at a decreasing rate, with a value of $\hat{t}_{51}$=0.19 for S_T=8 and reaching its maximum value of 0.39 for S_T=45. What the evidence here suggests is that the major feedbacks from the 10–year government bond to output growth occur approximately within the first 8 months, although weaker feedbacks may last up to 45 months. What these results show, for the Canadian 10–year government bond and the future Canadian output growth is that their relationship is positive.

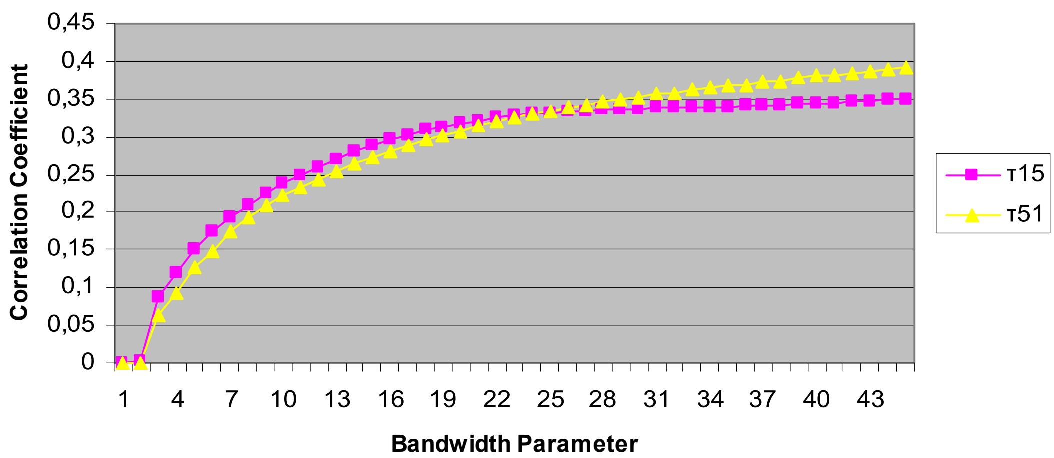

Figure 6: Estimated correlation coefficients: Canadian output growth and Canadian 10–year government bond

Our evidence suggests that the major effect on the future Canadian output growth is within the first eight months, although weaker effects may also last up to four years. This basically implies that the 10–year government bond is a useful predictor of Canadian output up to a four-year horizon. The relationship between the Canadian output growth and the future 10–year government bond is found to be significantly different from zero. The estimate of t_{15} follows an increasing rate when $S_T \in$ [1, 9] with $\hat{t}_{15}$ =0.22 when S_T =9 and reaches its maximum value of 0.35 for S_T =45. So, our evidence here suggests a strong positive relationship and between the Canadian output growth and the future 10–year government bond, with major effects reaching the first 9 months, but weaker effects may last for up to 45 months as well.
The results from the Granger causality test for the Canadian industrial production and the 10-year government bond are:

GRANGER CAUSALITY	CHI-SQ	DF
$10Y \longrightarrow IP$	17.27909 [0.0040]	5
$IP \not\longrightarrow 10Y$	6.239009 [0.2837]	5

Familiar results are exported and for the other interest rates. Figures 7, 8 and 9 also show the correlation coefficients for the 3-month, 1-month and 1-year Canadian interest rates with respect with the Canadian output growth.[22]

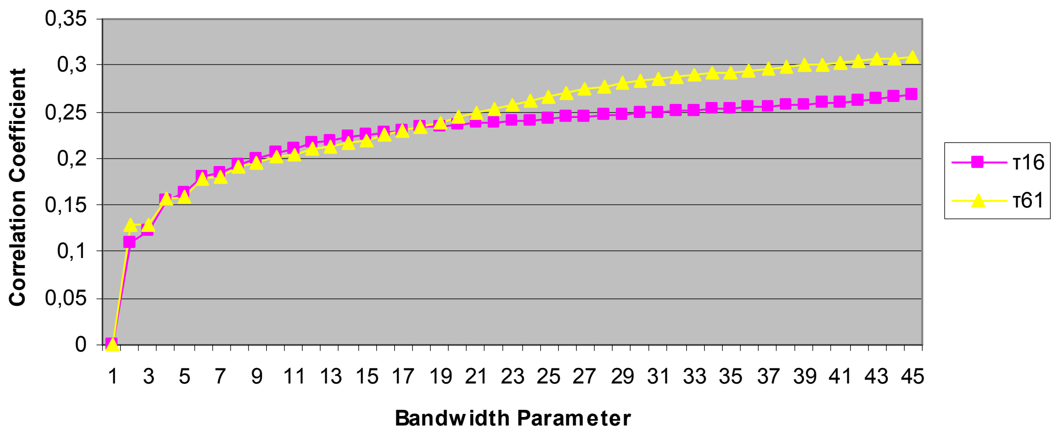

Figure 7: Estimated correlation coefficients: Canadian output growth and Canadian 1–month interest rate

The results from the Granger causality test for the Canadian industrial production and the 1-month interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
$1M \not\longrightarrow IP$	4.372561 [0.2239]	3
$IP \longrightarrow 1M$	11.28425 [0.0103]	3

[22] Appendix B contains the results for these variables for the Bartlett and the Parzen kernel as well as with all other variables for all countries.

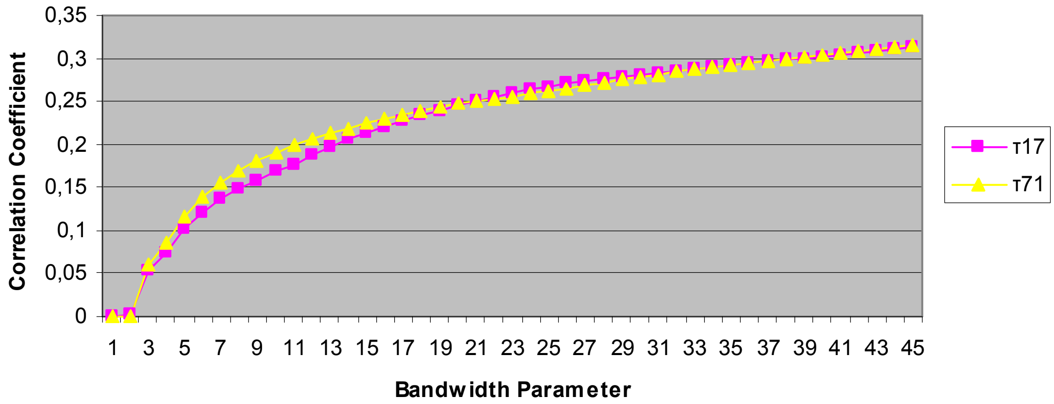

Figure 8: Estimated correlation coefficients: Canadian output growth and Canadian 3–month interest rate

The results from the Granger causality test for the Canadian industrial production and the 3-month interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
$3M \nrightarrow IP$	6.087752 [0.5295]	7
$IP \longrightarrow 3M$	15.06478 [0.0352]	7

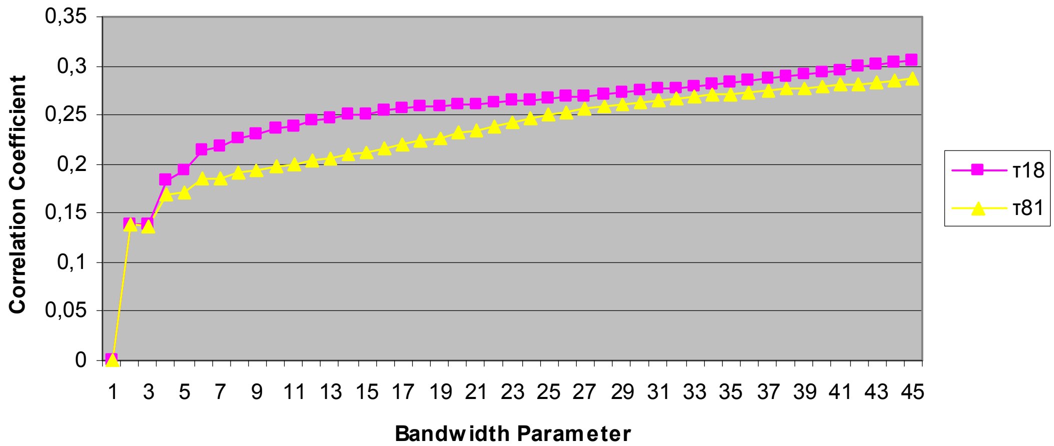

Figure 9: Estimated correlation coefficients: Canadian output growth and Canadian 1–year interest rate

The results from the Granger causality test for the Canadian industrial production and the 1-year interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
$1Y \nrightarrow IP$	6.756277 [0.2394]	5
$IP \longrightarrow 1Y$ (10%)	10.13610 [0.0715]	5

4. A.2. U.S. financial variables and output growth

Table A2 presents the estimated temporal correlation for all the financial variables that were examined in this paper. Among the various groups of the United States financial variables examined, the Dow Jones industrial share price index, the United States yield (US10Y-US3M), and real M2 (RM2) were found to exhibit the strongest temporal correlations (t_{21}) with respect to United States output growth and are analyzed in greater detail below.
Our estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to the value of the current financial variable at hand ($u_{1,t-i} \rightarrow u_{2,t}$), and the temporal correlation coefficient t_{21}, which describes feedbacks from past values of the financial variable at hand to current output growth (i.e., in the opposite direction ($u_{2,t-i} \rightarrow u_{1,t}$), for alternative values of the bandwidth parameter S_T are reported in figures 1-9 for the Bartlett kernel.
Figure 1 shows, for the United States industrial stock price index and the United States output growth, that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{21}, that describes feedbacks from past real stock returns to current output growth ($u_{2,t-i} \rightarrow u_{1,t}$), increase as well. Similarly, the estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to current real stock returns ($u_{1,t-i} \rightarrow u_{2,t}$), are positive and increase as well as with the bandwidth parameter too.

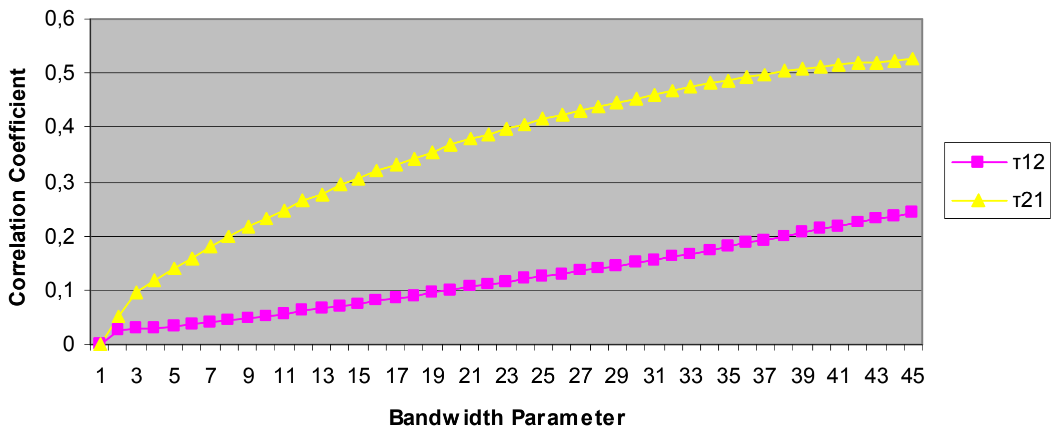

Figure 1: Estimated correlation coefficients: U.S. output growth and returns from the U.S. Stock price index

The rate of growth of the estimates of t_{21} does not remain constant over the whole range of values of the bandwidth parameter S_T. When $S_T \in$ [1, 11], $\hat{t}_{21}$ increases at an increasing rate. For S_T=11, the estimate of t_{21} is equal to 0.24 for the Bartlett kernel. Beyond this point, $\hat{t}_{21}$ increases at a decreasing rate thus reaching its maximum value of 0.52 for S_T=45. What the evidence here suggests is that the major feedbacks, from past stock price changes to

output growth, occur within the first eleven months, with a maximum feedback of around 45 months. The relationship between past U.S. output growth and stock price changes is found to be significantly different from zero. The estimate of t_{12} follows a decreasing rate when $S_T \in$ [1, 2] with $\hat{t}_{12}$ =0.02 when S_T=2 and reaches its maximum value of 0.24 for S_T=45.
What our results show is that there is a strong positive relationship (temporal correlation) between past stock price changes and current U.S. output growth, as expected. Basically, this implies that, and for the United States, stock prices are useful predictors of output for a horizon of up to 45 months.
The results from the Granger causality test for the United States industrial production and the stock index are:

GRANGER CAUSALITY	CHI-SQ	DF
IND $\longrightarrow$ IP	28.35436 [0.0000]	4
IP $\not\longrightarrow$ IND	1.670724 [0.7960]	4

Figure 2 shows the results for the United States yield spread (U.S.10Y-U.S.3M) and the United States output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{31} increase as well. The estimates of the temporal correlation coefficient t_{13} are again positive and they also increase as the bandwidth parameter increases as well. The rate of growth of the estimates of t_{31} again does not remain constant over the whole range of values of the bandwidth parameter S_T.

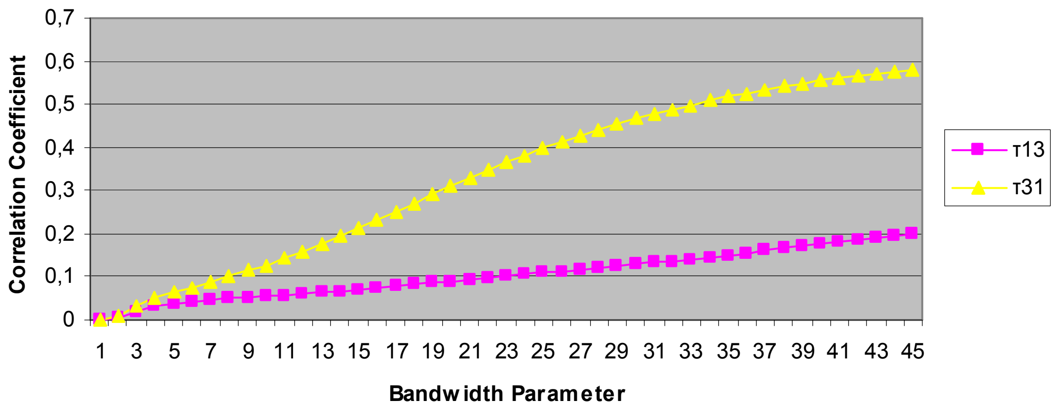

Figure 2: Estimated correlation coefficients: U.S. output growth and U.S. Yield (U.S.10Y-U.S.3M)

For S_T=4, the estimate of t_{31} is equal to 0.049, for the Bartlett kernel. Beyond this point, $\hat{t}_{31}$ increases at a decreasing rate, with a value of $\hat{t}_{31}$ =0.17 for S_T=13 and reaching its maximum value of 0.58 for S_T=45. What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 13 months, although weaker feedbacks may last up to 45 months. These results show, with regards to the

United States yield spread (U.S.10Y-U.S.3M) and the future United States output growth that their relationship is positive, as expected. Our evidence suggests that the major effect on the future U.S. output growth is within the first 13 months, although weaker effects may also last up to four years. This basically implies that the yield spread is a useful predictor of U.S. output up to a four-year horizon. The relationship between the U.S. output growth and the future yield spread is found to be significantly different from zero. The estimate of t_{13} follows an increasing rate when $S_T \in$[1, 4] with $\hat{t}_{13}$ =0.030 when S_T =4 and reaches its maximum value of 0.20 for S_T =45. So, our evidence here suggests a positive relationship, with major effects reaching the first four months, but weaker effects may last for up to 45 months as well.
The results from the Granger causality test for the United States industrial production and the yield spread (U.S.10Y-U.S.3M) are:

GRANGER CAUSALITY	CHI-SQ	DF
$S3 \longrightarrow IP$	13.61493 [0.0086]	4
$IP \not\longrightarrow S3$	4.619205 [0.3286]	4

Real M1 (RM1) has an estimated temporal correlation coefficient t_{91} that increases at a decreasing rate as we can see from figure 3.

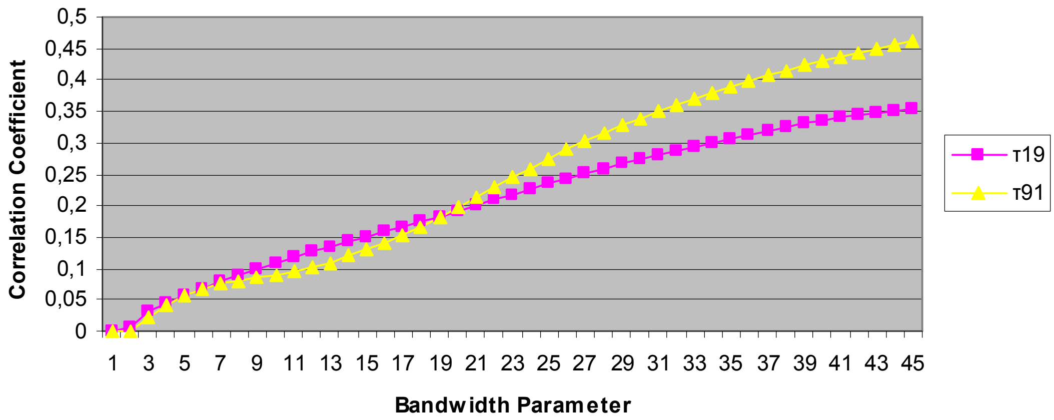

Figure 3: Estimated correlation coefficients: U.S. output growth and U.S. real money (M1)

For S_T =9, the estimate of t_{91} is equal to 0.085 for the Bartlett kernel. Beyond this point $\hat{t}_{91}$ increases at a decreasing rate and reaching its maximum value of 0.46 for S_T =45. What the evidence here suggests is that the major feedbacks from real M1 to output growth occur within the first nine months with a maximum feedback of around 45 months. The relationship between the U.S. output growth and the future real M1 is found to be significantly different from zero. The estimate of t_{19} follows an increasing rate when $S_T \in$[1, 9] with $\hat{t}_{19}$ =0.099 when S_T =9 and reaches its maximum value of 0.35 for S_T =45. So, our evidence here suggests a strong positive relationship and between the

U.S. output growth and the future real M1, with major effects reaching the first nine months, but weaker effects may last for up to 45 months as well.
The results from the Granger causality test for the United States industrial production and the real M1 (RM1) are:

GRANGER CAUSALITY	CHI-SQ	DF
RM1 $\longrightarrow$ IP	12.74967 [0.0126]	4
IP $\longrightarrow$ RM1	14.25563 [0.0065]	4

In the case of the spread (U.S.10Y-U.S.1M) the results do not differentiate at all and show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{41} increase as well. The estimates of the temporal correlation coefficient t_{14} are again positive and they also increase as the bandwidth parameter increases. The rate of growth of the estimates of t_{41} again does not remain constant over the whole range of values of the bandwidth parameter S_T.
Figure 4 shows the results for the U.S. yield spread (U.S.10Y-U.S.1M) and the U.S. output growth.

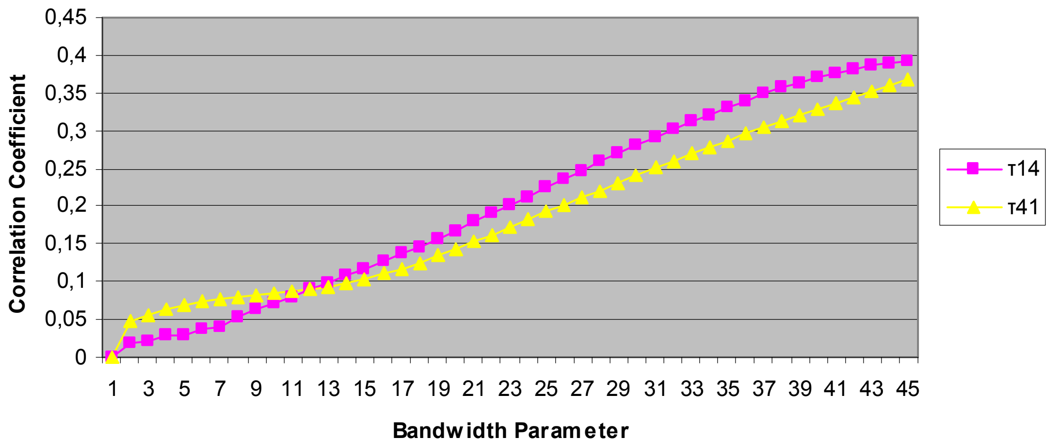

Figure 4: Estimated correlation coefficients: U.S. output growth and U.S. Yield (U.S.10Y-U.S.1M)

For S_T=4, the estimate of t_{41} is equal to 0.063, for the Bartlett kernel. Beyond this point, $\hat{t}_{41}$ increases at a decreasing rate, with a value of $\hat{t}_{41}$=0.073 for S_T=6 and reaching its maximum value of 0.36 for S_T=45. What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 6 months, although weaker feedbacks may last up to 45 months. What these results show, with regards to the U.S. yield spread (U.S.10Y-U.S.1M) and the future U.S. output growth is that their relationship is positive, as expected. The relationship between the U.S. output growth and the future yield spread is found to be significantly different from zero. The estimate of t_{14} follows an increasing rate when

$S_T \in$ [1, 9] with $\hat{t}_{14}$ =0.062 when S_T =9 and reaches its maximum value of 0.39 for S_T =45. So, our evidence here suggests a strong positive relationship, with major effects reaching the first 9 months, but weaker effects may last for up to 45 months as well.
The results from the Granger causality test for the United States industrial production and the yield spread (U.S.10Y-U.S.1M) are:

GRANGER CAUSALITY	CHI-SQ	DF
$S1 \longrightarrow IP$	10.09067 [0.0389]	4
$IP \not\longrightarrow S1$	4.184766 [0.3816]	4

Real M2 (RM2) show similar pattern with RM1 but the relationship is not as strong as RM1. This is confirmed by our results, shown in figure 5, which show that real M2 (RM2) has an estimated temporal correlation coefficient t_{101} that increases at a decreasing rate.

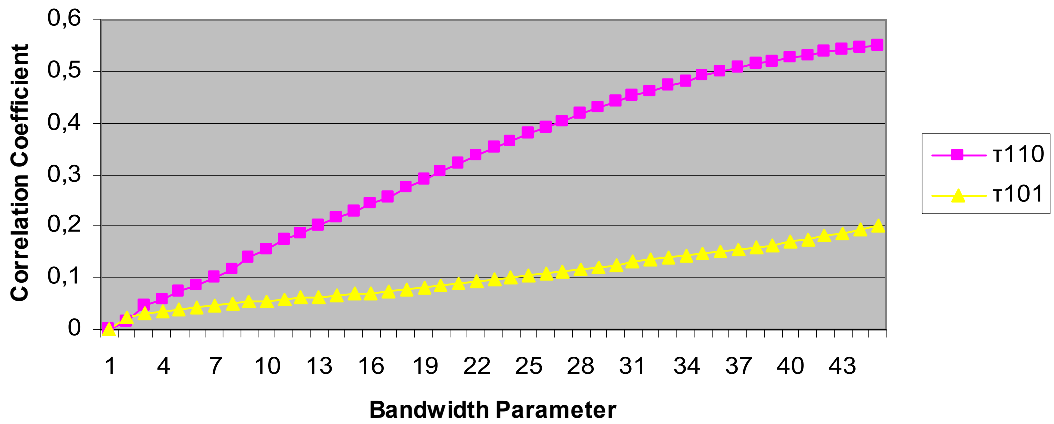

Figure 5: Estimated correlation coefficients: U.S. output growth and U.S. real money (M2)

For S_T =4, the estimate of t_{101} is equal to 0.035 for the Bartlett kernel. Beyond this point $\hat{t}_{101}$ increases at a decreasing rate and reaching its maximum value of 0.20 for S_T =45. What the evidence here suggests is that the major feedbacks from real M2 to output growth occur within the first four months with a maximum feedback of around 45 months. The relationship between the U.S. output growth and the future real M2 is found to be significantly different from zero. The estimate of t_{110} follows an increasing rate when $S_T \in$ [1, 11] with $\hat{t}_{110}$ =0.17 when S_T =11 and reaches its maximum value of 0.55 for S_T =45. So, our evidence here suggests a strong positive relationship between the U.S. output growth and the future real M2, with major effects reaching the first 11 months, but weaker effects may last for up to 45 months as well.

The results from the Granger causality test for the United States industrial production and the real M2 (RM2) are:

GRANGER CAUSALITY	CHI-SQ	DF
RM2 $\longrightarrow$ IP	11.37673 [0.0226]	4
IP $\longrightarrow$ RM2	14.22016 [0.0066]	4

The various interest rates (10–year government bond, 1-month, 3-month and 1-year interest rates) which we examined have results that are similar with that of the other variables.

Figure 6 shows the results for the U.S. 10–year government bond and the U.S. output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{51} increase as well. The estimates of the temporal correlation coefficient t_{15} are again positive and they also increase as the bandwidth parameter increases. The rate of growth of the estimates of t_{51} does not remain constant over the whole range of values of the bandwidth parameter S_T.

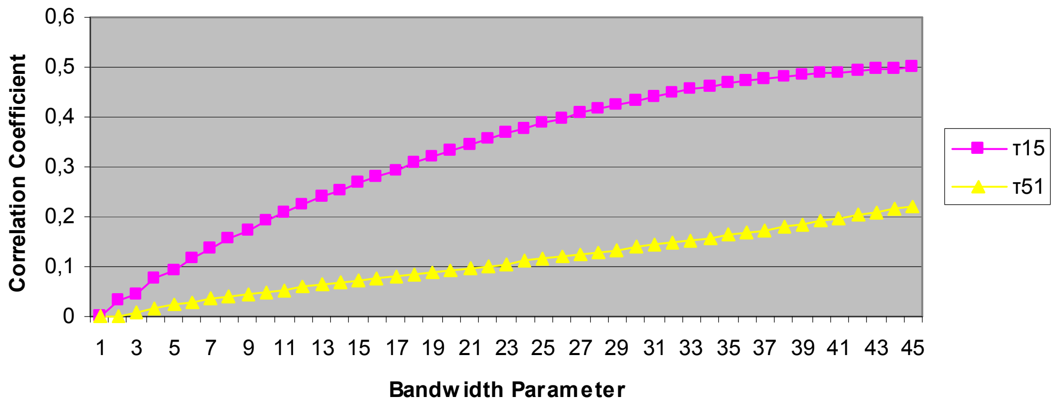

Figure 6: Estimated correlation coefficients: U.S. output growth and U.S. 10–year government bond

For S_T=3, the estimate of t_{51} is equal to 0.0075, for the Bartlett kernel. Beyond this point, $\hat{t}_{51}$ increases at a decreasing rate, and reaching its maximum value of 0.22 for S_T=45. What the evidence here suggests is that the major feedbacks from the 10–year government bond to output growth occur approximately within the first 3 months, although weaker feedbacks may last up to 45 months. What the results showed, for the U.S. 10–year government bond and the future U.S. output growth is that their relationship is not as strong as in the case of Canada.

Our evidence suggests that the major effect on the future U.S. output growth is within the first three months, although weaker effects may also last up to four years. This basically implies that the 10–year government bond is a useful predictor of U.S. output up to a four-year horizon. The relationship between the U.S. output growth and the future 10–year government bond is found to be significantly different from zero and stronger than that of the opposite direction. The estimate of t_{15} follows an increasing rate when $S_T \in$ [1, 12] with $\hat{t}_{15}$ =0.22 when S_T =12 and reaches its maximum value of 0.50 for S_T =45. So, our evidence here suggests a strong positive relationship between the U.S. output growth and the future 10–year government bond, with major effects reaching the first 12 months, but weaker effects may last for up to 45 months as well.

The results from the Granger causality test for the United States industrial production and the 10-year government bond are:

GRANGER CAUSALITY	CHI-SQ	DF
$10Y \longrightarrow IP$	10.71953 [0.0299]	4
$IP \longrightarrow 10Y$	22.85692 [0.0001]	4

Familiar results are exported and for the other interest rates. Figures 7, 8 and 9 also show the correlation coefficients for the 3-month, 1-month and 1-year U.S. interest rates with respect with the United States output growth.

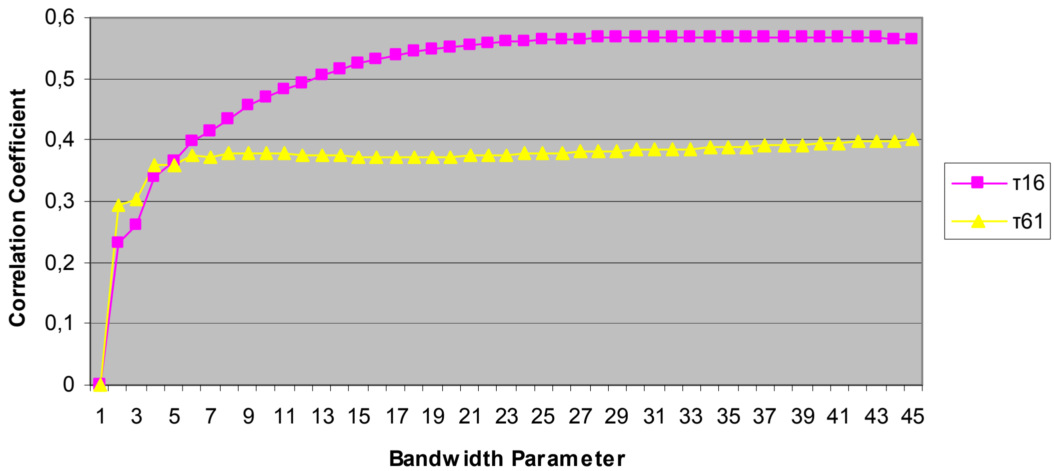

Figure 7: Estimated correlation coefficients: U.S. output growth and U.S. 1–month interest rate

The results from the Granger causality test for the United States industrial production and the 1-month interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
$1M \longrightarrow IP$	20.21973 [0.0005]	4
$IP \longrightarrow 1M$	10.85229 [0.0283]	4

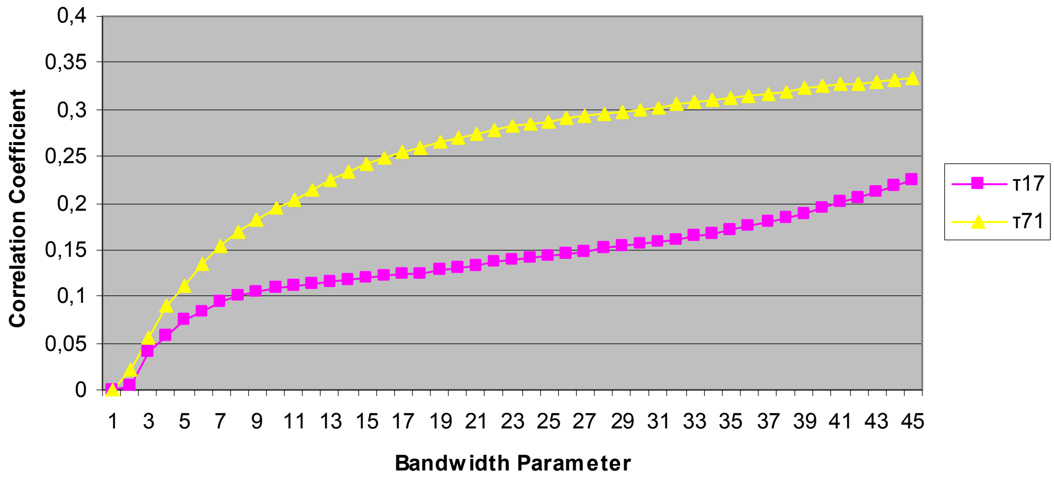

Figure 8: Estimated correlation coefficients: U.S. output growth and U.S. 3–month interest rate

The results from the Granger causality test for the United States industrial production and the 3-month interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
3M ⟶ IP	31.64673 [0.0000]	4
IP ⟶ 3M	17.50162 [0.0015]	4

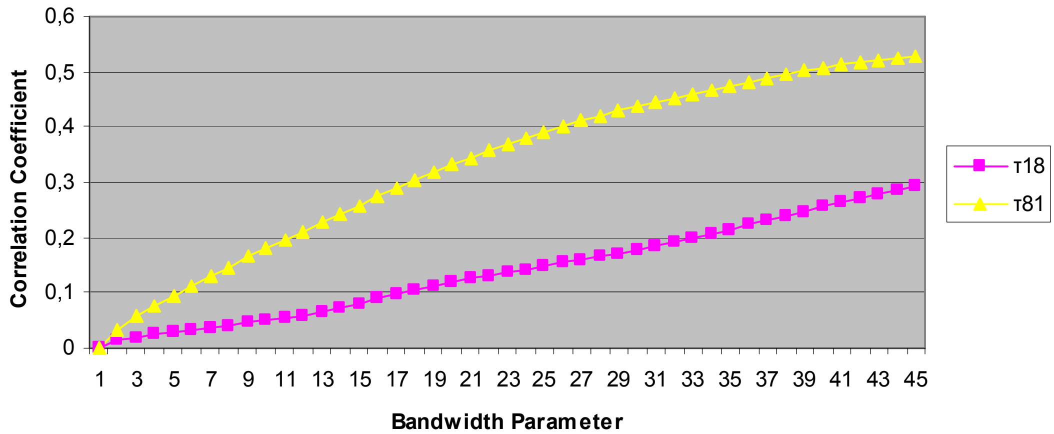

Figure 9: Estimated correlation coefficients: U.S. output growth and U.S. 1–year interest rate

The results from the Granger causality test for the United States industrial production and the 1-year interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
1Y ⟶ IP	19.73894 [0.0006]	4
IP ⟶ 1Y	16.88395 [0.0020]	4

4. A.3. Japanese financial variables and output growth

Table A3 presents the estimated temporal correlation for all the financial variables that were examined in this paper. Among the various groups of the Japan financial variables examined, the Tokyo Stock Exchange share price index, the Japan yield (JP10Y-JP3M), and real M1 (RM1) were found to exhibit the strongest temporal correlations (t_{21}) with respect to Japan output growth as expected and from the other previous countries.

Our estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to the value of the current financial variable at hand ($u_{1,t-i} \rightarrow u_{2,t}$), and the temporal correlation coefficient t_{21}, which describes feedbacks from past values of the financial variable at hand to current output growth (i.e., in the opposite direction ($u_{2,t-i} \rightarrow u_{1,t}$), for alternative values of the bandwidth parameter S_T are reported in figures 1-8 for the Bartlett kernel. The bandwidth parameter takes values in the interval [1, 30] by steps of one.

Figure 1 shows, for the Japan stock price index and the Japan output growth, that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{21}, that describes feedbacks from past real stock returns to current output growth ($u_{2,t-i} \rightarrow u_{1,t}$), increase as well. Similarly, the estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to current real stock returns ($u_{1,t-i} \rightarrow u_{2,t}$), are positive and increase as well as with the bandwidth parameter too.

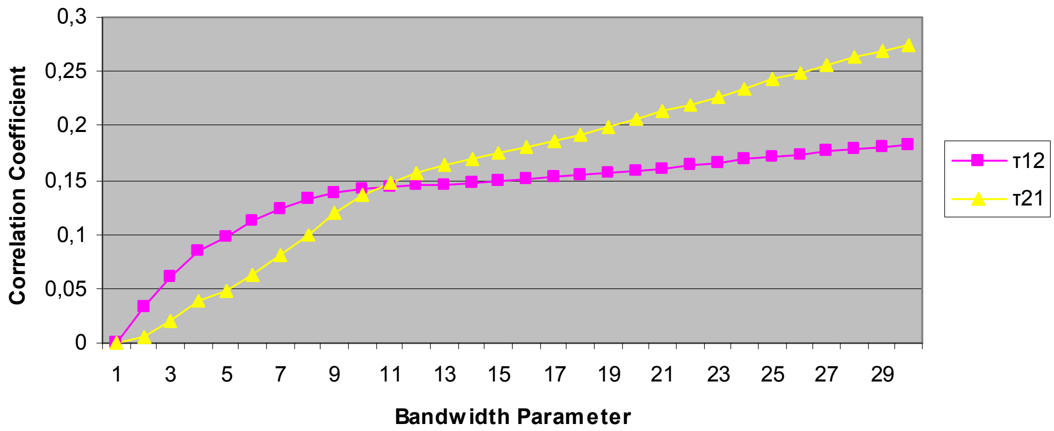

Figure 1: Estimated correlation coefficients: Japan output growth and returns from the Japan Stock price index

The rate of growth of the estimates of t_{21} does not remain constant over the whole range of values of the bandwidth parameter S_T. When $S_T \in$ [1, 12], $\hat{t}_{21}$ increases at an increasing rate. For S_T=12, the estimate of t_{21} is equal to 0.15 for the Bartlett kernel. Beyond this point, $\hat{t}_{21}$ increases at a decreasing rate thus reaching its maximum value of 0.27 for S_T=30. What the evidence here suggests is that the major feedbacks, from past stock price changes to output growth, occur within the first twelve months, with a maximum feedback of around 30 months. The relationship between past Japan output growth and stock price changes is found to be significantly different from zero. The estimate of t_{12} follows a decreasing rate when $S_T \in$ [1, 8] with $\hat{t}_{12}$ =0.13 when S_T=8 and reaches its maximum value of 0.18 for S_T=30.

What our results show is that there is a strong positive relationship (temporal correlation) between past stock price changes and current Japan output growth, as expected, but and for the opposite direction as well. Basically, this implies that, and for the Japan, stock prices are useful predictors of output for a horizon of up to 30 months.

The results from the Granger causality test for the Japan industrial production and the stock index are:

GRANGER CAUSALITY	CHI-SQ	DF
IND $\not\longrightarrow$ IP	6.721379 [0.1514]	4
IP $\not\longrightarrow$ IND	0.648110 [0.9576]	4

Figure 2 shows the results for the Japan yield spread (J.P.10Y-J.P.3M) and the Japan output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{31} increase as well. The rate of growth of the estimates of t_{31} again does not remain constant over the whole range of values of the bandwidth parameter S_T.

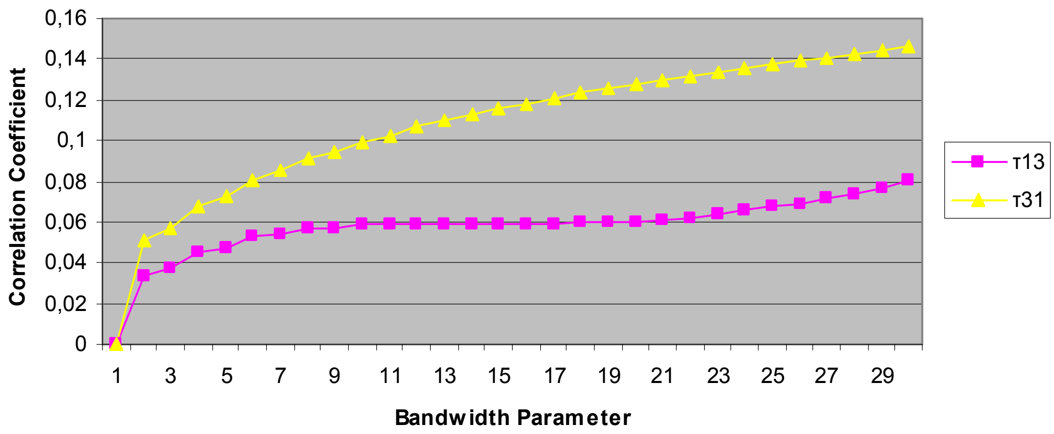

Figure 2: Estimated correlation coefficients: Japan output growth and Japan Yield (J.P.10Y-J.P.3M)

For S_T=4, the estimate of t_{31} is equal to 0.068, for the Bartlett kernel. Beyond this point, $\hat{t}_{31}$ increases at a decreasing rate, with a value of $\hat{t}_{31}$ =0.091 for S_T=8 and reaching its maximum value of 0.1466 for S_T=30. What the evidence here suggests is that the major feedbacks from the yield spread to

output growth occur approximately within the first 8 months, although weaker feedbacks may last up to 30 months. These results show, with regards to the Japan yield spread (J.P.10Y-J.P.3M) and the future Japan output growth that their relationship is positive, as expected. Our evidence suggests that the major effect on the future Japan output growth is within the first 8 months, although weaker effects may also last up to three years. This basically implies that the yield spread is a useful predictor of Japan output up to a three-year horizon. The relationship between the J.P. output growth and the future yield spread is found to be not significantly different from zero.
The results from the Granger causality test for the Japan industrial production and the yield spread (J.P.10Y-J.P.3M) are:

GRANGER CAUSALITY	CHI-SQ	DF
$S3 \not\rightarrow IP$	6.022982 [0.1974]	4
$IP \not\rightarrow S3$	0.844190 [0.9324]	4

Real M1 (RM1) has an estimated temporal correlation coefficient t_{91} that increases at a decreasing rate as we can see from figure 3.

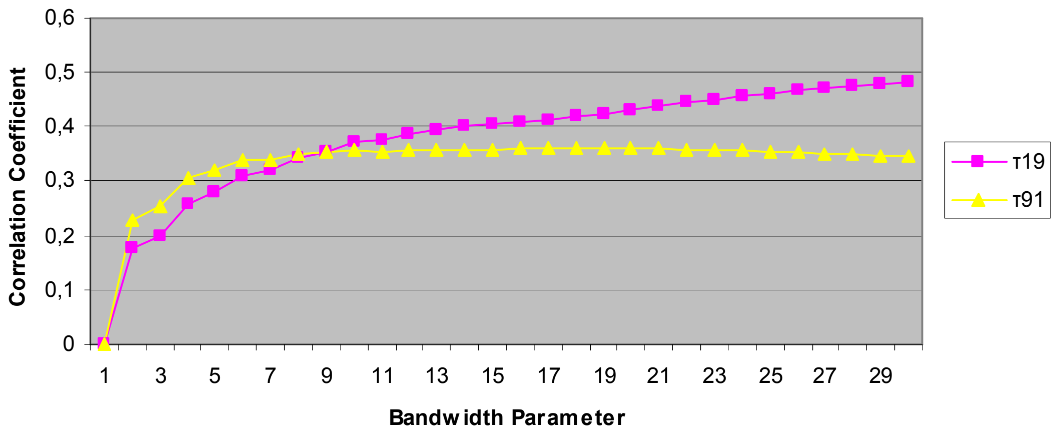

Figure 3: Estimated correlation coefficients: Japan output growth and Japan real money (M1)

For S_T=8, the estimate of t_{91} is equal to 0.35 for the Bartlett kernel. Beyond this point $\hat{t}_{91}$ increases at a decreasing rate and reaching its maximum value of 0.36 for S_T=18. What the evidence here suggests is that the major feedbacks from real M1 to output growth occur within the first eight months with a maximum feedback of around 18 months. The relationship between the Japan output growth and the future real M1 is found to be significantly different from zero. The estimate of t_{19} follows an increasing rate when $S_T \in$ [1, 6] with $\hat{t}_{19}$ =0.30 when S_T=6 and reaches its maximum value of 0.48 for S_T=30. So, our evidence here suggests a strong positive relationship and between the Japan output growth and the future real M1, with major effects

reaching the first six months, but weaker effects may last for up to 30 months as well.
The results from the Granger causality test for the Japan industrial production and the real M1 (RM1) are:

GRANGER CAUSALITY	CHI-SQ	DF
RM1 $\not\rightarrow$ IP	7.331787 [0.8843]	13
IP $\not\rightarrow$ RM1	13.56764 [0.4050]	13

In the case of the spread (J.P.10Y-J.P.1M) the results do not differentiate at all and show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{41} increase as well. The estimates of the temporal correlation coefficient t_{14} are positive and they also increase as the bandwidth parameter increases. The rate of growth of the estimates of t_{41} again does not remain constant over the whole range of values of the bandwidth parameter S_T.
Figure 4 shows the results for the Japan yield spread (J.P.10Y-J.P.1M) and the Japan output growth.
For S_T=2, the estimate of t_{41} is equal to 0.0021, for the Bartlett kernel. Beyond this point, $\hat{t}_{41}$ increases at a decreasing rate, with a value of $\hat{t}_{41}$ =0.018 for S_T=8 and reaching its maximum value of 0.19 for S_T=30.

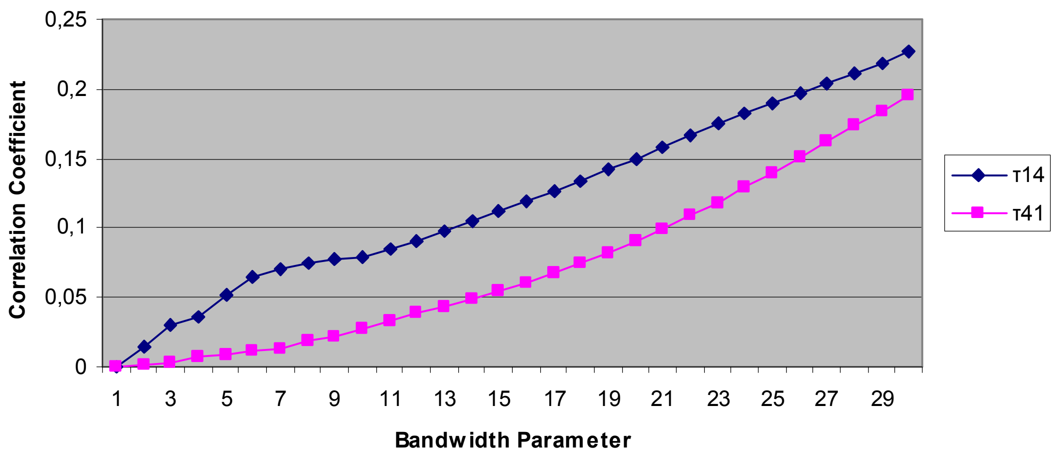

Figure 4: Estimated correlation coefficients: Japan output growth and Japan Yield (J.P.10Y-J.P.1M)

What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 8 months, although weaker feedbacks may last up to 30 months. What these results show, with regards to the Japan yield spread (J.P.10Y-J.P.1M) and the future Japan output growth is that their relationship is positive, as expected. The relationship between the Japan output growth and the future yield spread is found to be significantly different from zero. The estimate of t_{14} follows an increasing rate when $S_T \in$ [1, 13] with $\hat{t}_{14}$ =0.098 when S_T=13 and reaches its

maximum value of 0.22 for S_T=30. So, our evidence here suggests a strong positive relationship, with major effects reaching the first 13 months, but weaker effects may last for up to 30 months as well.
The results from the Granger causality test for the Japan industrial production and the yield spread (J.P.10Y-J.P.1M) are:

GRANGER CAUSALITY	CHI-SQ	DF
S1 $\longrightarrow$ IP (10%)	8.057936 [0.0895]	4
IP $\not\longrightarrow$ S1	0.387355 [0.9835]	4

The various interest rates (10–year government bond, 1-month, 3-month and 1-year interest rates) which we examined have results that are similar with that of the other variables.
Figure 5 shows the results for the Japan 10–year government bond and the Japan output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{51} increase as well. The estimates of the temporal correlation coefficient t_{15} are again positive and they also increase as the bandwidth parameter increases. The rate of growth of the estimates of t_{51} does not remain constant over the whole range of values of the bandwidth parameter S_T.
For S_T=7, the estimate of t_{51} is equal to 0.2383, for the Bartlett kernel. Beyond this point, $\hat{t}_{51}$ increases at a decreasing rate, and reaching its maximum value of 0.32 for S_T=30. What the evidence here suggests is that the major feedbacks from the 10–year government bond to output growth occur approximately within the first 7 months, although weaker feedbacks may last up to 30 months. What the results showed, for the Japan 10–year government bond and the future Japan output growth is that their relationship is strong as expected.

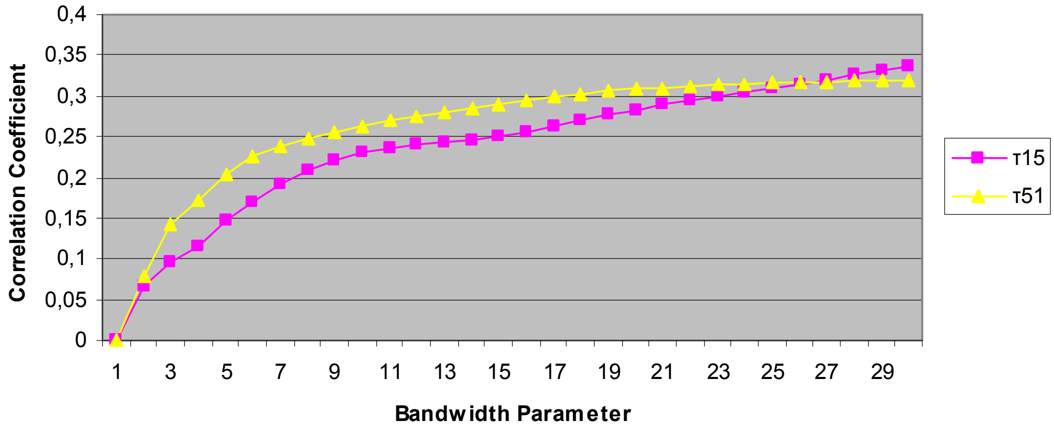

Figure 5: Estimated correlation coefficients: Japan output growth and Japan 10–year government bond

Our evidence suggests that the major effect on the future Japan output growth is within the first seven months, although weaker effects may also last up to three years. This basically implies that the 10–year government bond is a useful predictor of Japan output up to a three-year horizon. The relationship between the Japan output growth and the future 10–year government bond is found to be significantly different from zero. The estimate of t_{15} follows an increasing rate when $S_T \in [1, 9]$ with $\hat{t}_{15}$=0.22 when S_T=9 and reaches its maximum value of 0.33 for S_T=30. So, our evidence here suggests a strong positive relationship between the Japan output growth and the future 10–year government bond, with major effects reaching the first 9 months, but weaker effects may last for up to 30 months.

The results from the Granger causality test for the Japan industrial production and the 10-year government bond are:

GRANGER CAUSALITY	CHI-SQ	DF
$10Y \longrightarrow IP$ (10%)	9.079551 [0.0591]	4
$IP \not\longrightarrow 10Y$	1.572848 [0.8137]	4

Familiar results are exported and for the other interest rates. Figures 6, 7 and 8 also show also the correlation coefficients for the 3-month, 1-month and 1-year Japans interest rates with respect with the Japan output growth.

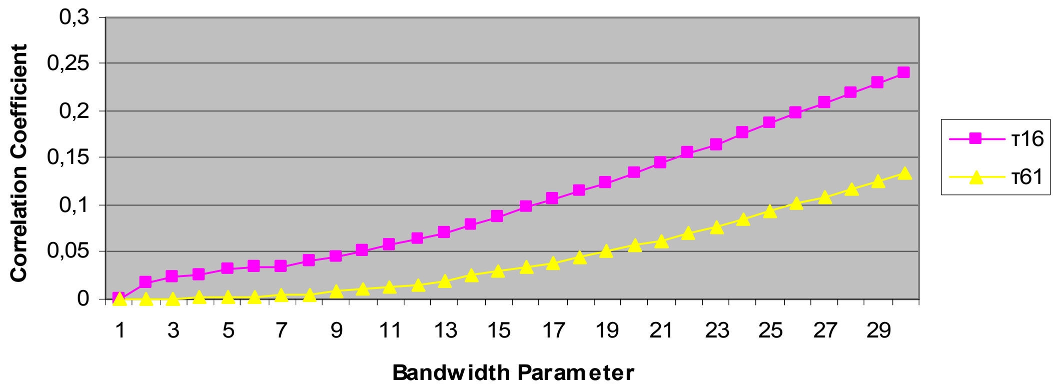

Figure 6: Estimated correlation coefficients: Japan output growth and Japan 1–month interest rate

The results from the Granger causality test for the Japan industrial production and the 1-month interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
$1M \longrightarrow IP$ (10%)	3.190009 [0.0741]	1
$IP \not\longrightarrow 1M$	0.084332 [0.7715]	1

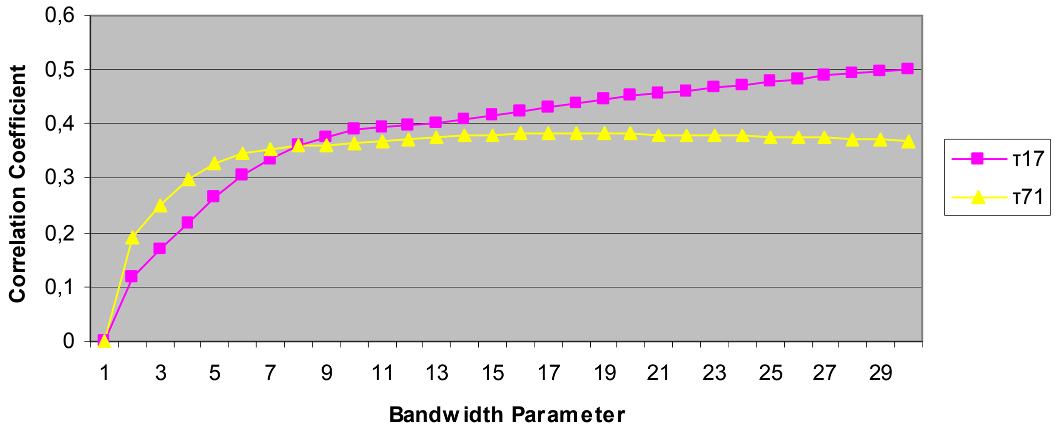

Figure 7: Estimated correlation coefficients: Japan output growth and Japan 3–month interest rate

The results from the Granger causality test for the Japan industrial production and the 3-month interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
3M $\longrightarrow$ IP	1565.450 [0.0000]	36
IP $\not\longrightarrow$ 3M	10.97304 [1.0000]	36

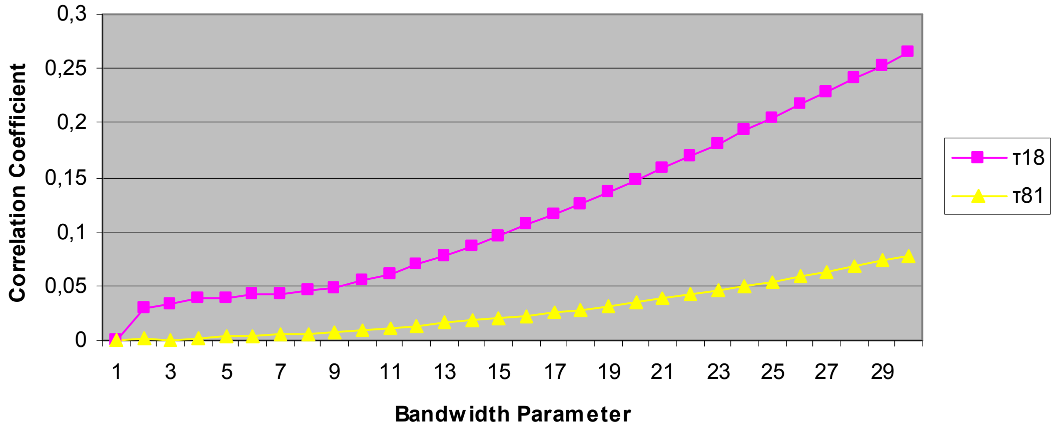

Figure 8: Estimated correlation coefficients: Japan output growth and Japan 1–year interest rate

The results from the Granger causality test for the Japan industrial production and the 1-year interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
1Y $\longrightarrow$ IP	4.680124 [0.0305]	1
IP $\not\longrightarrow$ 1Y	0.361876 [0.5475]	1

4. A.4. United Kingdom financial variables and output growth

Table A4 presents the estimated temporal correlation for all the financial variables that were examined in this paper. Among the various groups of the United Kingdom financial variables examined, the U.K. FT all share index, the U.K. yield (UK10Y-UK3M), and real M2 (RM2) were found to exhibit the strongest temporal correlations (t_{21}) with respect to United Kingdom output growth.

Our estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to the value of the current financial variable at hand ($u_{1,t-i} \rightarrow u_{2,t}$), and the temporal correlation coefficient t_{21}, which describes feedbacks from past values of the financial variable at hand to current output growth (i.e., in the opposite direction ($u_{2,t-i} \rightarrow u_{1,t}$), for alternative values of the bandwidth parameter S_T are reported in figures 1-8 for the Bartlett kernel. The bandwidth parameter takes values in the interval [1, 45] by steps of one.

Figure 1 shows, for the U.K. stock price index and the U.K. output growth, that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{21}, that describes feedbacks from past real stock returns to current output growth ($u_{2,t-i} \rightarrow u_{1,t}$), increase as well. The estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to current real stock returns ($u_{1,t-i} \rightarrow u_{2,t}$), are mainly positive and remain close to zero for all values of the bandwidth parameter.

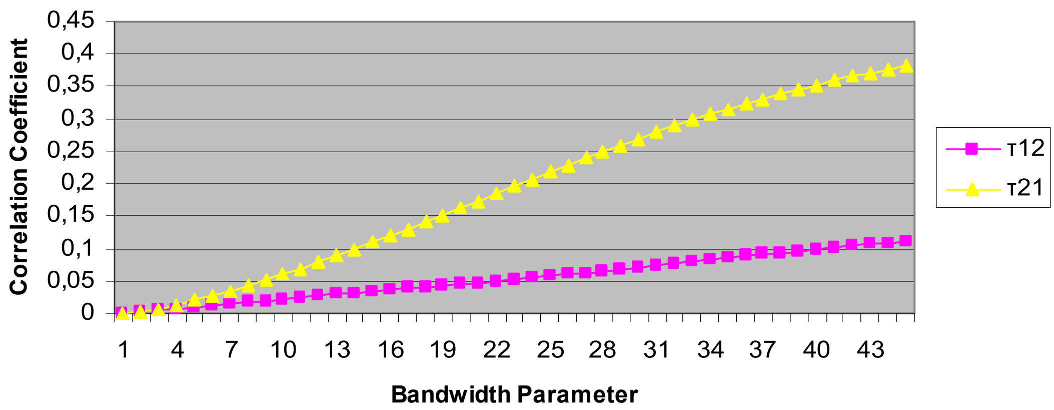

Figure 1: Estimated correlation coefficients: U.K. output growth and returns from the U.K. Stock price index

The rate of growth of the estimates of t_{21} does not remain constant over the whole range of values of the bandwidth parameter S_T. When $S_T \in [1, 13]$, $\hat{t}_{21}$ increases at an increasing rate. For S_T=13, the estimate of t_{21} is equal to 0.09 for the Bartlett kernel. Beyond this point, $\hat{t}_{21}$ increases at a decreasing rate thus reaching its maximum value of 0.38 for S_T=45. What the evidence

here suggests is that the major feedbacks, from past stock price changes to current output growth, occur within the first 13 months, with a maximum feedback of around 45 months. The relationship between past U.K. output growth and stock price changes is found to be not significantly different from zero. What our results show is that there is a strong positive relationship (temporal correlation) between past stock price changes and current U.K. output growth. Basically, this implies that, and for the United Kingdom, stock prices are useful predictors of output for a horizon of up to 45 months.
The results from the Granger causality test for the United Kingdom industrial production and the stock index are:

GRANGER CAUSALITY	CHI-SQ	DF
IND $\longrightarrow$ IP (10%)	8.997605 [0.0612]	4
IP $\not\longrightarrow$ IND	2.618218 [0.6236]	4

Figure 2 shows the results for the U.K. yield spread (U.K.10Y-U.K.3M) and the U.K. output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{31} increase as well. The rate of growth of the estimates of t_{31} again does not remain constant over the whole range of values of the bandwidth parameter S_T.
For S_T=6, the estimate of t_{31} is equal to 0.18, for the Bartlett kernel. Beyond this point, $\hat{t}_{31}$ increases at a decreasing rate, with a value of $\hat{t}_{31}$=0.26 for S_T=11 and reaching its maximum value of 0.36 for S_T=45.

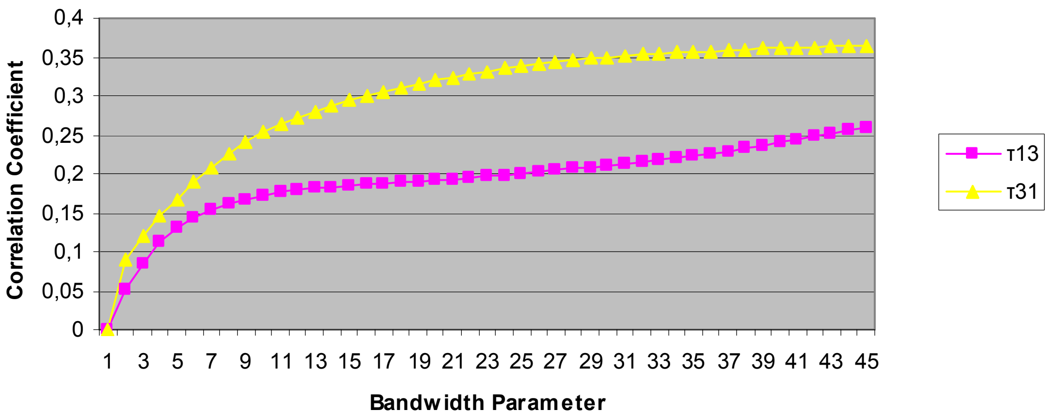

Figure 2: Estimated correlation coefficients: U.K. output growth and U.K. Yield (U.K.10Y-U.K.3M)

What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 11 months, although weaker feedbacks may last up to 45 months. These results show, with regards to the U.K. yield spread (U.K.10Y-U.K.3M) and the future U.K. output growth that their relationship is positive, as expected. Our evidence suggests that the major effect on the future U.K. output growth is within the

first 11 months, although weaker effects may also last up to four years. This basically implies that the yield spread is a useful predictor of United Kingdom output up to a four-year horizon. The relationship between the United Kingdom output growth and the future yield spread is found to be significantly different from zero. The estimate of t_{13} follows an increasing rate when $S_T \in$ [1, 6] with $\hat{t}_{13}$ =0.14 when S_T =6 and reaches its maximum value of 0.25 for S_T =45. So, our evidence here suggests a positive relationship, with major effects reaching the first six months, but weaker effects may last for up to 45 months as well.
The results from the Granger causality test for the United Kingdom industrial production and the yield spread (U.K.10Y-U.K.3M) are:

GRANGER CAUSALITY	CHI-SQ	DF
S3 $\longrightarrow$ IP (10%)	5.395140 [0.0674]	2
IP $\nrightarrow$ S3	2.193154 [0.3340]	2

Real M2 (RM2) has an estimated temporal correlation coefficient t_{91} that increases at a decreasing rate as we can see from figure 3.

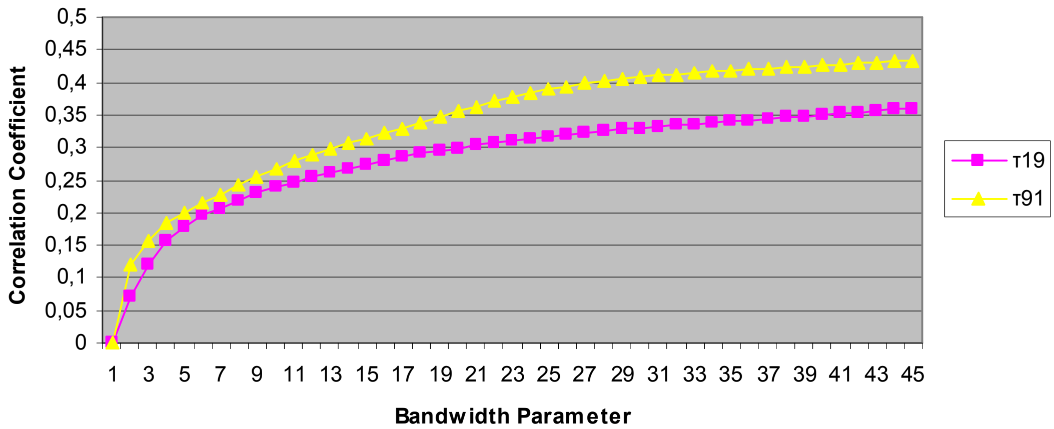

Figure 3: Estimated correlation coefficients: U.K. output growth and U.K. real money (M2)

For S_T =6, the estimate of t_{91} is equal to 0.21 for the Bartlett kernel. Beyond this point $\hat{t}_{91}$ increases at a decreasing rate and reaching its maximum value of 0.43 for S_T =45. What the evidence here suggests is that the major feedbacks from real M2 to output growth occur within the first six months with a maximum feedback of around 45 months. The relationship between the U.K. output growth and the future real M2 is found to be significantly different from zero. The estimate of t_{19} follows an increasing rate when $S_T \in$ [1, 6] with $\hat{t}_{19}$ =0.19 when S_T =6 and reaches its maximum value of 0.35 for S_T =45. So, our evidence here suggests a strong positive relationship and between the U.K. output growth and the future real M2, with major effects reaching the first six months, but weaker effects may last for up to 45 months as well.

The results from the Granger causality test for the United Kingdom industrial production and the real M2 (RM2) are:

GRANGER CAUSALITY	CHI-SQ	DF
RM2 $\longrightarrow$ IP (10%)	5.945233 [0.0512]	2
IP $\not\longrightarrow$ RM2	2.061022 [0.3568]	2

In the case of the spread (U.K.10Y-U.K.1M) the results do not differentiate at all and show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{41} increase as well. The estimates of the temporal correlation coefficient t_{14} are positive and they also increase as the bandwidth parameter increases. The rate of growth of the estimates of t_{41} again does not remain constant over the whole range of values of the bandwidth parameter S_T.

Figure 4 shows the results for the United Kingdom yield spread (U.K.10Y-U.K.1M) and the United Kingdom output growth.

For S_T=4, the estimate of t_{41} is equal to 0.010, for the Bartlett kernel. Beyond this point, $\hat{t}_{41}$ increases at a decreasing rate, with a value of $\hat{t}_{41}$=0.096 for S_T=14 and reaching its maximum value of 0.33 for S_T=45.

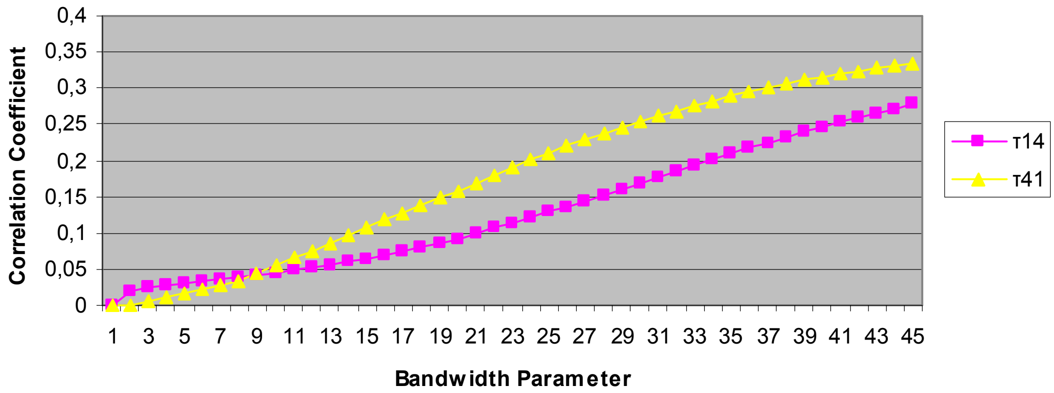

Figure 4: Estimated correlation coefficients: U.K. output growth and U.K. Yield (U.K.10Y-U.K.1M)

What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 14 months, although weaker feedbacks may last up to 45 months. What these results show, with regards to the U.K. yield spread (U.K.10Y-U.K.1M) and the future U.K. output growth is that their relationship is positive, as expected. The relationship between the U.K. output growth and the future yield spread is found to be significantly different from zero. The estimate of t_{14} follows an increasing rate when $S_T \in$ [1, 6] with $\hat{t}_{14}$=0.033 when S_T=6 and reaches its maximum value of 0.27 for S_T=45. So, our evidence here suggests a strong positive relationship, with major effects reaching the first 6 months, but weaker effects may last for up to 45 months as well.

The results from the Granger causality test for the United Kingdom industrial production and the yield spread (U.K.10Y-U.K.1M) are:

GRANGER CAUSALITY	CHI-SQ	DF
S1 $\nrightarrow$ IP	7.027459 [0.1344]	4
IP $\nrightarrow$ S1	0.353691 [0.9861]	4

The various interest rates (10–year government bond, 1-month, 3-month and 1-year interest rates) which we examined have results that are similar with that of the other variables.

Figure 5 shows the results for the United Kingdom 10–year government bond and the United Kingdom output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{51} increase as well. The estimates of the temporal correlation coefficient t_{15} are again positive and they also increase as the bandwidth parameter increases. The rate of growth of the estimates of t_{51} does not remain constant over the whole range of values of the bandwidth parameter S_T.

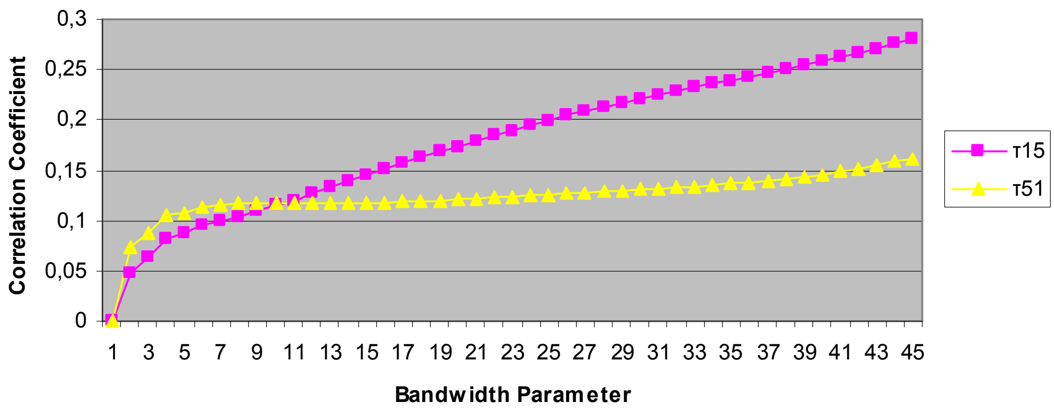

Figure 5: Estimated correlation coefficients: U.K. output growth and U.K. 10–year government bond

For S_T=4, the estimate of t_{51} is equal to 0.10, for the Bartlett kernel. Beyond this point, $\hat{t}_{51}$ increases at a decreasing rate, and reaching its maximum value of 0.16 for S_T=45. What the evidence here suggests is that the major feedbacks from the 10–year government bond to output growth occur approximately within the first 4 months, although weaker feedbacks may last up to 45 months. What the results showed, for the U.K. 10–year government bond and the future U.K. output growth is that their relationship is positive.

Our evidence suggests that the major effect on the future U.K. output growth is within the first four months, although weaker effects may also last up to four years. The relationship between the U.K. output growth and the future 10–year government bond is found to be significantly different from zero. The

estimate of t_{15} follows an increasing rate when $S_T \in$ [1, 8] with $\hat{t}_{15}$ =0.10 when S_T =8 and reaches its maximum value of 0.28 for S_T =45. So, our evidence here suggests a strong positive relationship between the U.K. output growth and the future 10–year government bond, with major effects reaching the first 8 months, but weaker effects may last for up to 45 months.
The results from the Granger causality test for the United Kingdom industrial production and the 10-year government bond are:

GRANGER CAUSALITY	CHI-SQ	DF
10Y $\nrightarrow$ IP	4.502973 [0.2120]	3
IP $\nrightarrow$ 10Y	5.740245 [0.1250]	3

Familiar results are exported and for the other interest rates. Figures 6, 7 and 8 also show the correlation coefficients for the 3-month, 1-month and 1-year United Kingdom interest rates with respect with the United Kingdom output growth.

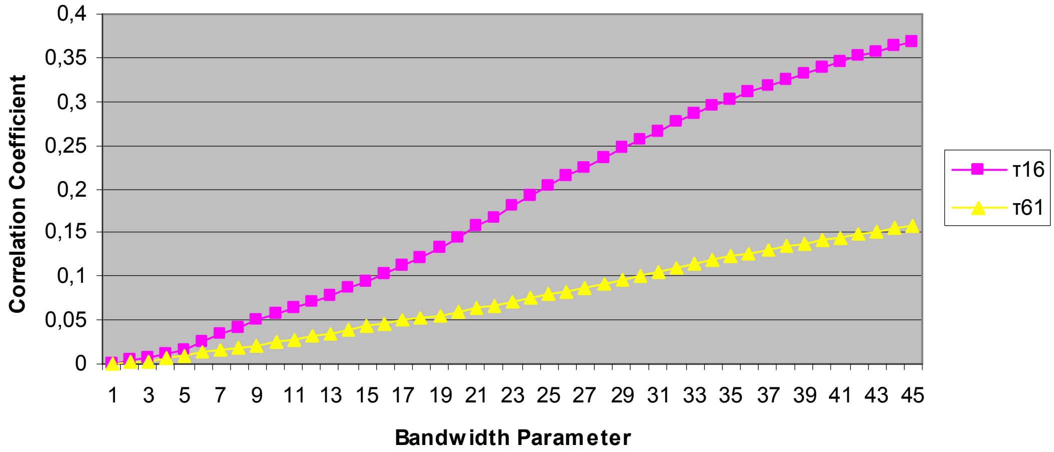

Figure 6: Estimated correlation coefficients: U.K. output growth and U.K. 1–month interest rate

The results from the Granger causality test for the United Kingdom industrial production and the 1-month interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
1M $\nrightarrow$ IP	2.083099 [0.5553]	3
IP $\nrightarrow$ 1M	3.643596 [0.3026]	3

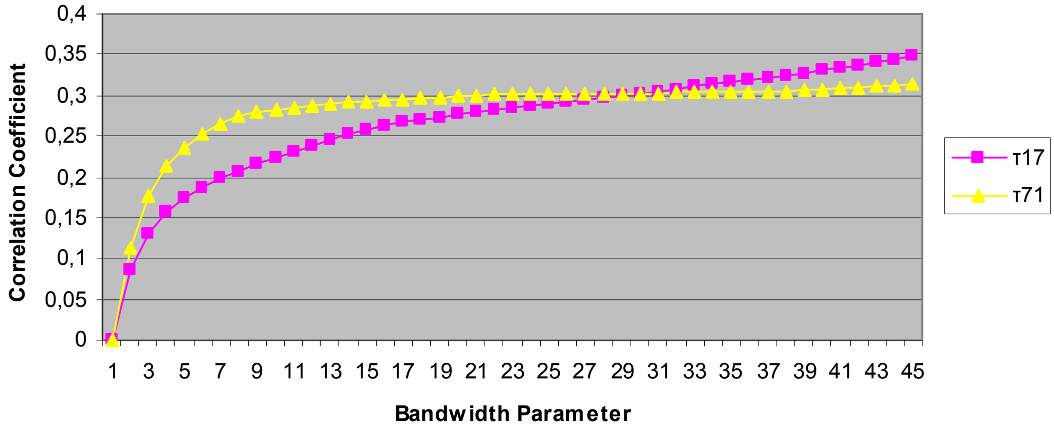

Figure 7: Estimated correlation coefficients: U.K. output growth and U.K. 3–month interest rate

The results from the Granger causality test for the United Kingdom industrial production and the 3-month interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
3M $\not\rightarrow$ IP	1.418145 [0.4921]	2
IP $\not\rightarrow$ 3M	4.17494 [0.1240]	2

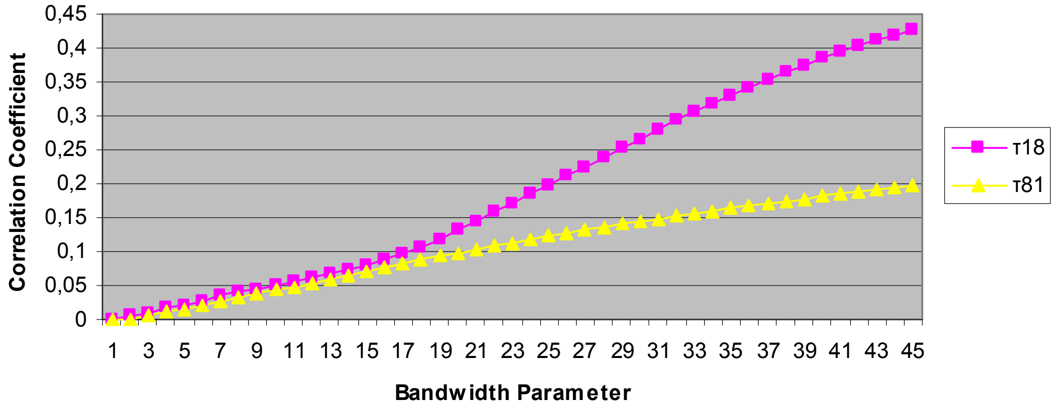

Figure 8: Estimated correlation coefficients: U.K. output growth and U.K. 1–year interest rate

The results from the Granger causality test for the United Kingdom industrial production and the 1-year interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
1Y $\not\rightarrow$ IP	5.348169 [0.1480]	3
IP $\rightarrow$ 1Y (10%)	7.674580 [0.0532]	3

4. A.5. German financial variables and output growth

Table A5 presents the estimated temporal correlation for all the financial variables that were examined for this country. Among the various groups of the Germany financial variables examined, the DAX share price index, the Germany yield (BD10Y-BD3M), and real M1 (RM1) were found to exhibit the strongest temporal correlations (t_{21}) with respect to Germany output growth.
Our estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to the value of the current financial variable at hand ($u_{1,t-i} \to u_{2,t}$), and the temporal correlation coefficient t_{21}, which describes feedbacks from past values of the financial variable at hand to current output growth (i.e., in the opposite direction ($u_{2,t-i} \to u_{1,t}$), for alternative values of the bandwidth parameter S_T are reported in figures 1-9 for the Bartlett kernel. The bandwidth parameter takes values in the interval [1, 30] by steps of one.
Figure 1 shows, for the Germany stock price index and the Germany output growth, that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{21}, that describes feedbacks from past real stock returns to current output growth ($u_{2,t-i} \to u_{1,t}$), increase as well. The estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to current real stock returns ($u_{1,t-i} \to u_{2,t}$), are mainly positive and remain close to zero for all values of the bandwidth parameter.

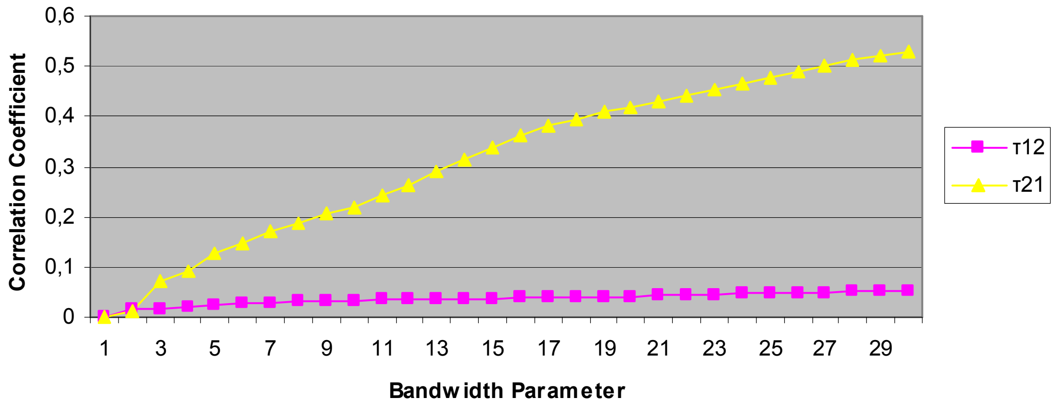

Figure 1: Estimated correlation coefficients: Germany output growth and returns from the Germany Stock price index

The rate of growth of the estimates of t_{21} does not remain constant over the whole range of values of the bandwidth parameter S_T. When $S_T \in$ [1, 15], $\hat{t}_{21}$ increases at an increasing rate and for S_T=15, the estimate of t_{21} is equal to 0.34 for the Bartlett kernel. Beyond this point, $\hat{t}_{21}$ increases at a decreasing rate thus reaching its maximum value of 0.52 for S_T=30. What the evidence here suggests is that the major feedbacks, from past stock price changes to

current output growth, occur within the first 15 months, with a maximum feedback of around 30 months. The relationship between past Germany output growth and stock price changes is found to be not significantly different from zero. What our results show is that there is a strong positive relationship (temporal correlation) between past stock price changes and current Germany output growth. Basically, this implies that, and for the Germany, stock prices are useful predictors of output for a horizon of up to 30 months.
The results from the Granger causality test for the Germany industrial production and the stock index are:

GRANGER CAUSALITY	CHI-SQ	DF
IND $\not\longrightarrow$ IP	8.546800 [0.7411]	12
IP $\longrightarrow$ IND	24.97625 [0.0149]	12

Figure 2 shows the results for the Germany yield spread (BD10Y-BD3M) and the Germany output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{31} increase as well. The rate of growth of the estimates of t_{31} again does not remain constant over the whole range of values of the bandwidth parameter S_T.

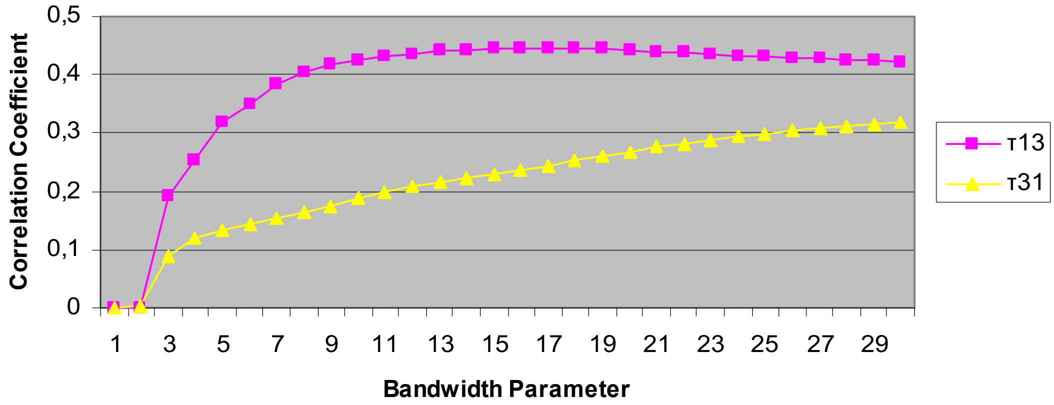

Figure 2: Estimated correlation coefficients: Germany output growth and Germany Yield (BD10Y-BD3M)

For S_T=3, the estimate of t_{31} is equal to 0.087, for the Bartlett kernel. Beyond this point, $\hat{t}_{31}$ increases at a decreasing rate, with a value of $\hat{t}_{31}$=0.19 for S_T=11 and reaching its maximum value of 0.30 for S_T=30.
What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 11 months, although weaker feedbacks may last up to 30 months. These results show, with regards to the Germany yield spread (BD10Y-BD3M) and the future Germany output growth that their relationship is positive, as expected. Our evidence suggests that the major effect on the future Germany output growth is within the first 11 months, although weaker effects may also last up to three

years. This basically implies that the yield spread is a useful predictor of Germany output up to a three-year horizon. The relationship between the Germany output growth and the future yield spread is found to be significantly different from zero. The estimate of t_{13} follows an increasing rate when $S_T \in$ [1, 6] with $\hat{t}_{13}$ =0.35 when S_T =6 and reaches its maximum value of 0.445 for S_T =17. So, our evidence here suggests a positive relationship, with major effects reaching the first six months, but weaker effects may last for up to 17 months as well.

The results from the Granger causality test for the Germany industrial production and the yield spread (BD10Y-BD3M) are:

GRANGER CAUSALITY	CHI-SQ	DF
$S3 \not\rightarrow IP$	6.143391 [0.9408]	13
$IP \not\rightarrow S3$	16.04693 [0.2466]	13

Real M1 RM1 has an estimated temporal correlation coefficient t_{91} that increases at a decreasing rate as we can see from figure 3.

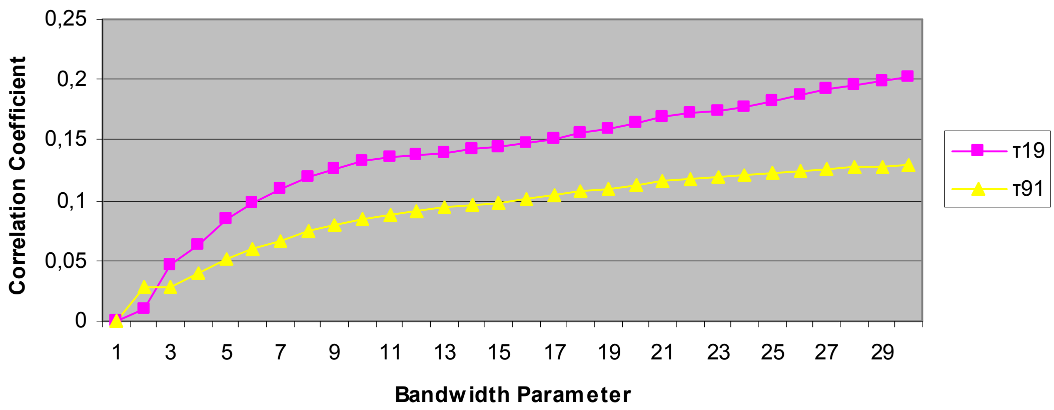

Figure 3: Estimated correlation coefficients: Germany output growth and Germany real money (M1)

For S_T =6, the estimate of t_{91} is equal to 0.060 for the Bartlett kernel. Beyond this point $\hat{t}_{91}$ increases at a decreasing rate and reaching its maximum value of 0.13 for S_T =30. What the evidence here suggests is that the major feedbacks from real M1 to output growth occur within the first six months with a maximum feedback of around 30 months. The relationship between the Germany output growth and the future real M1 is found to be significantly different from zero. The estimate of t_{19} follows an increasing rate when $S_T \in$ [1, 8] with $\hat{t}_{19}$ =0.12 when S_T =8 and reaches its maximum value of 0.20 for S_T =30. So, our evidence here suggests a strong positive relationship and between the Germany output growth and the future real M1, with major effects

reaching the first eight months, but weaker effects may last for up to 30 months as well.
The results from the Granger causality test for the Germany industrial production and the real M1 (RM1) are:

GRANGER CAUSALITY	CHI-SQ	DF
RM1 $\longrightarrow$ IP	26.63536 [0.0215]	14
IP $\not\longrightarrow$ RM1	10.23338 [0.7449]	14

In the case of the spread (BD10Y-BD1M) the results do not differentiate at all and show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{41} increase as well. The estimates of the temporal correlation coefficient t_{14} are mainly positive and remain close to zero for all values of the bandwidth parameter. The rate of growth of the estimates of t_{41} again does not remain constant over the whole range of values of the bandwidth parameter S_T.
Figure 4 shows the results for the Germany yield spread (BD10Y-BD1M) and the Germany output growth.
For S_T=3, the estimate of t_{41} is equal to 0.11, for the Bartlett kernel. Beyond this point, $\hat{t}_{41}$ increases at a decreasing rate, with a value of $\hat{t}_{41}$ =0.42 for S_T=11 and reaching its maximum value of 0.63 for S_T=30.

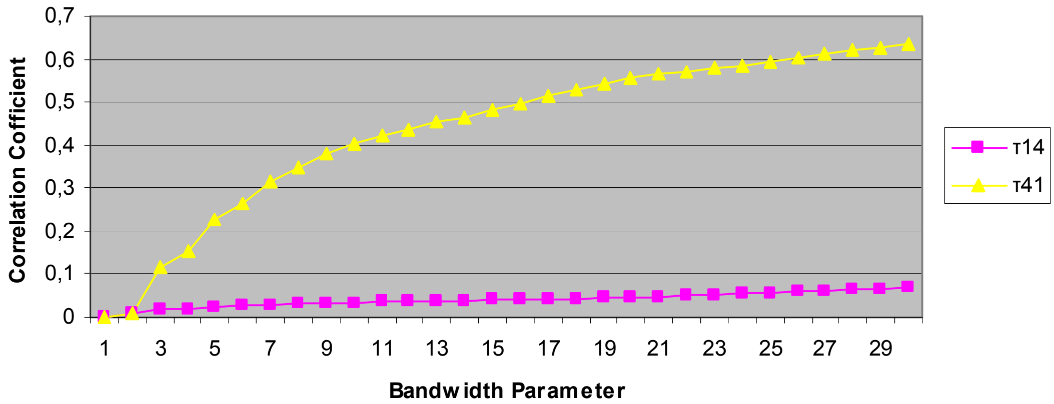

Figure 4: Estimated correlation coefficients: Germany output growth and Germany Yield (BD10Y-BD1M)

What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 11 months, although weaker feedbacks may last up to 30 months. What these results show, with regards to the Germany yield spread (BD10Y-BD1M) and the future Germany output growth is that their relationship is positive, as expected. The relationship between the Germany output growth and the future yield spread is found to be not significantly different from zero.

The results from the Granger causality test for the Germany industrial production and the yield spread (BD10Y-BD1M) are:

GRANGER CAUSALITY	CHI-SQ	DF
$S1 \nrightarrow IP$	9.469258 [0.7367]	13
$IP \nrightarrow S1$	15.11610 [0.3002]	13

Real M2 (RM2) show similar pattern with RM1 but the relationship is stronger than RM1. This is confirmed by our results, shown in figure 5, which show that real M2 (RM2) has an estimated temporal correlation coefficient t_{101} that increases at a decreasing rate.

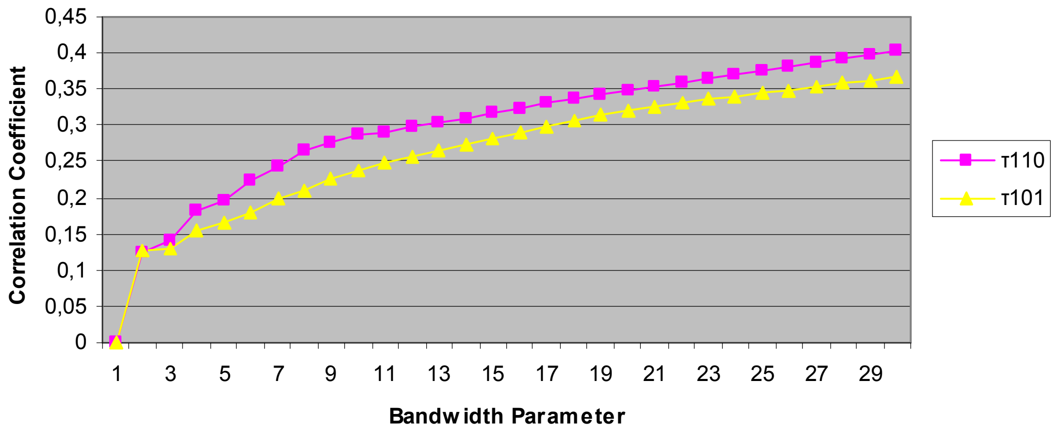

Figure 5: Estimated correlation coefficients: Germany output growth and Germany real money (M2)

For S_T=11, the estimate of t_{101} is equal to 0.25 for the Bartlett kernel. Beyond this point $\hat{t}_{101}$ increases at a decreasing rate and reaching its maximum value of 0.36 for S_T=30. What the evidence here suggests is that the major feedbacks from real M2 to output growth occur within the first eleven months with a maximum feedback of around 30 months. The relationship between the Germany output growth and the future real M2 is found to be significantly different from zero. The estimate of t_{110} follows an increasing rate when $S_T \in [1, 10]$ with $\hat{t}_{110}$ =0.28 when S_T=10 and reaches its maximum value of 0.40 for S_T=30. So, our evidence here suggests a strong positive relationship and between the Germany output growth and the future real M2, with major effects reaching the first 10 months, but weaker effects may last for up to 30 months as well.

The results from the Granger causality test for the Germany industrial production and the real M2 (RM2) are:

GRANGER CAUSALITY	CHI-SQ	DF
$RM2 \longrightarrow IP$	80.22309 [0.0000]	12
$IP \nrightarrow RM2$	1.411934 [0.9999]	12

The various interest rates (10–year government bond, 1-month, 3-month and 1-year interest rates) which we examined have results that are similar with that of the other variables.

Figure 6 shows the results for the Germany 10–year government bond and the Germany output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{51} increase as well. The estimates of the temporal correlation coefficient t_{15} are positive and they also increase as the bandwidth parameter increases. The rate of growth of the estimates of t_{51} does not remain constant over the whole range of values of the bandwidth parameter S_T.

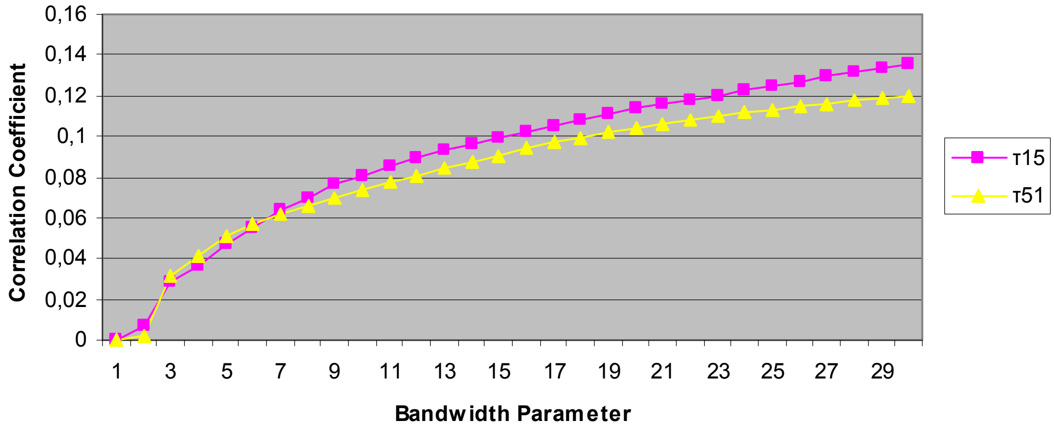

Figure 6: Estimated correlation coefficients: Germany output growth and Germany 10–year government bond

For S_T=5, the estimate of t_{51} is equal to 0.05, for the Bartlett kernel. Beyond this point, $\hat{t}_{51}$ increases at a decreasing rate, and reaching its maximum value of 0.12 for S_T=30. What the evidence here suggests is that the major feedbacks from the 10–year government bond to output growth occur approximately within the first 5 months, although weaker feedbacks may last up to 30 months. What the results showed, for the Germany 10–year government bond and the future Germany output growth is that their relationship is not as strong as in the case of Canada.

Our evidence suggests that the major effect on the future Germany output growth is within the first five months, although weaker effects may also last up to three years. This basically implies that the 10–year government bond is a useful predictor of Germany output up to a three-year horizon. The relationship between the Germany output growth and the future 10–year government bond is found to be significantly different from zero and stronger than that of the opposite direction. The estimate of t_{15} follows an increasing rate when $S_T \in$ [1, 9] with $\hat{t}_{15}$ =0.076 when S_T=9 and reaches its maximum value of 0.13 for S_T=30. So, our evidence here suggests a strong positive relationship between the Germany output growth and the future 10–year

government bond, with major effects reaching the first 9 months, but weaker effects may last for up to 30 months as well.
The results from the Granger causality test for the Germany industrial production and the 10-year government bond are:

GRANGER CAUSALITY	CHI-SQ	DF
10Y $\longrightarrow$ IP (10%)	20.20982 [0.0901]	13
IP $\not\longrightarrow$ 10Y	15.15468 [0.2978]	13

Familiar results are exported and for the other interest rates. Figures 7, 8 and 9 also show the correlation coefficients for the 3-month, 1-month and 1-year Germany interest rates with respect with the Germany output growth.

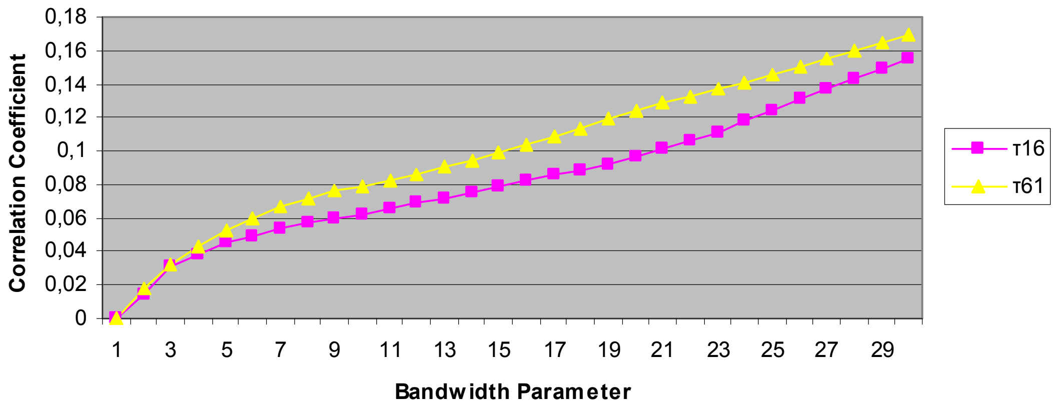

Figure 7: Estimated correlation coefficients: Germany output growth and Germany 1–month interest rate

The results from the Granger causality test for the Germany industrial production and the 1-month interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
1M $\longrightarrow$ IP	23.81367 [0.0216]	12
IP $\longrightarrow$ 1M	26.85584 [0.0081]	12

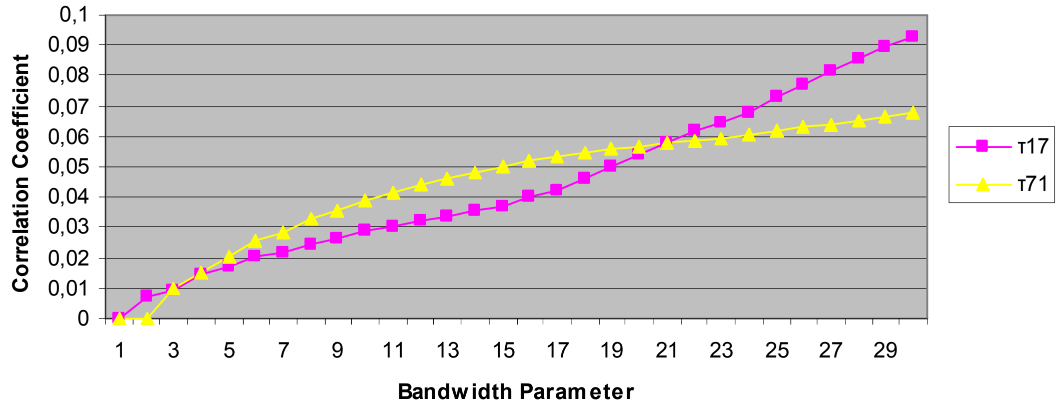

Figure 8: Estimated correlation coefficients: Germany output growth and Germany 3–month interest rate

The results from the Granger causality test for the Germany industrial production and the 3-month interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
3M $\nrightarrow$ IP	11.91420 [0.5347]	13
IP $\nrightarrow$ 3M	20.16137 [0.0913]	13

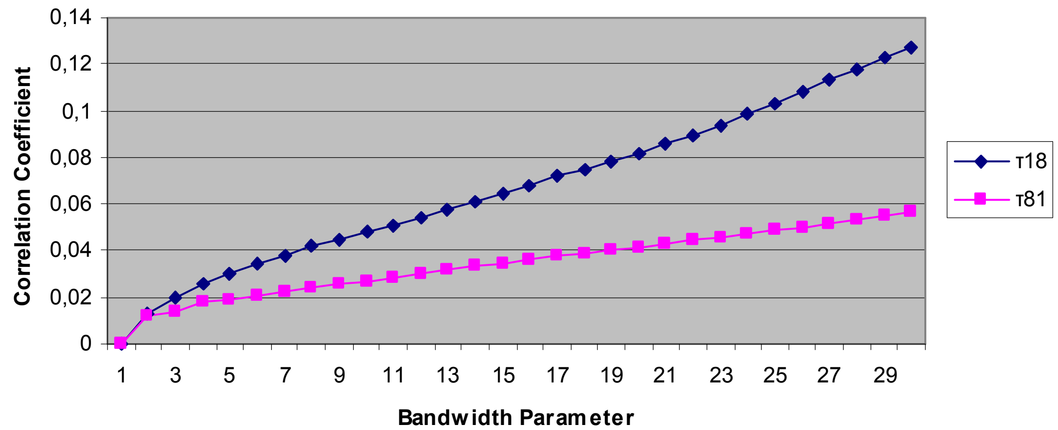

Figure 9: Estimated correlation coefficients: Germany output growth and Germany 1–year interest rate

The results from the Granger causality test for the Germany industrial production and the 1-year interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
1Y $\longrightarrow$ IP	44.29605 [0.0000]	13
IP $\nrightarrow$ 1Y	10.65418 [0.6398]	13

4. A.6. France financial variables and output growth

Table A6 presents the estimated temporal correlation for all the financial variables that were examined for this country. Among the various groups of the France financial variables examined, the FR share price index, the France yield (FR10Y-FR3M), and real M1 (RM1) were found to exhibit the strongest temporal correlations (t_{21}) with respect to France output growth.

Our estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to the value of the current financial variable at hand ($u_{1,t-i} \rightarrow u_{2,t}$), and the temporal correlation coefficient t_{21}, which describes feedbacks from past values of the financial variable at hand to current output growth (i.e., in the opposite direction ($u_{2,t-i} \rightarrow u_{1,t}$), for alternative values of the bandwidth parameter S_T are reported in figures 1-9 for the Bartlett kernel. The bandwidth parameter takes values in the interval [1, 30] by steps of one.

Figure 1 shows, for the France stock price index and the France output growth, that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{21}, that describes feedbacks from past real stock returns to current output growth ($u_{2,t-i} \rightarrow u_{1,t}$), increase as well. Similarly the estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to current real stock returns ($u_{1,t-i} \rightarrow u_{2,t}$), are positive and increase as the bandwidth parameter increases too.

The rate of growth of the estimates of t_{21} does not remain constant over the whole range of values of the bandwidth parameter S_T. When $S_T \in$ [1, 12], $\hat{t}_{21}$ increases at an increasing rate and for S_T=12, the estimate of t_{21} is equal to 0.23 for the Bartlett kernel.

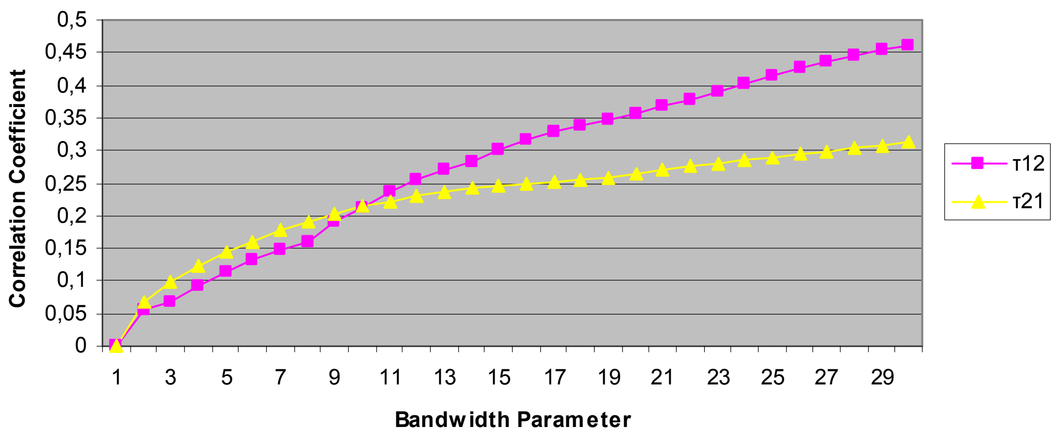

Figure 1: Estimated correlation coefficients: France output growth and returns from the France Stock price index

Beyond this point, $\hat{t}_{21}$ increases at a decreasing rate thus reaching its maximum value of 0.31 for S_T=30. What the evidence here suggests is that the major feedbacks, from past stock price changes to output growth, occur within the first twelve months, with a maximum feedback of around 30 months. The relationship between past France output growth and stock price changes is found to be significantly different from zero. The estimate of t_{12} follows a decreasing rate when $S_T \in$ [1, 15] with $\hat{t}_{12}$ =0.30 when S_T=15 and reaches its maximum value of 0.46 for S_T=30.

What our results show is that there is a strong positive relationship (temporal correlation) between past stock price changes and current France output growth, as expected. Basically, this implies that, and for the France, stock prices are useful predictors of output for a horizon of up to 30 months.

The results from the Granger causality test for the France industrial production and the stock index are:

GRANGER CAUSALITY	CHI-SQ	DF
IND $\nrightarrow$ IP	0.020768 [0.8854]	1
IP $\nrightarrow$ IND	0.024329 [0.8760]	1

Figure 2 shows the results for the France yield spread (FR10Y-FR3M) and the France output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{31} increase as well. The estimates of the temporal correlation coefficient t_{13} are again positive and they also increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{31} does not remain constant over the whole range of values of the bandwidth parameter S_T.

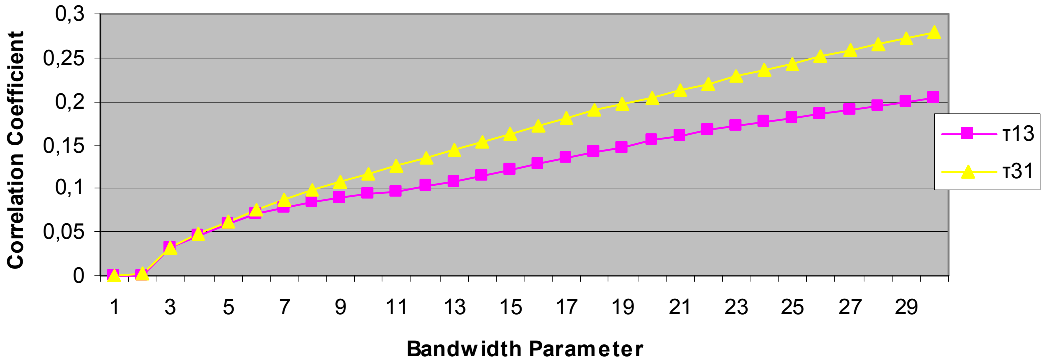

Figure 2: Estimated correlation coefficients: France output growth and France Yield (FR10Y-FR3M)

For S_T=4, the estimate of t_{31} is equal to 0.047, for the Bartlett kernel. Beyond this point, $\hat{t}_{31}$ increases at a decreasing rate, with a value of $\hat{t}_{31}$=0.12 for S_T=11 and reaching its maximum value of 0.28 for S_T=30. What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 11 months, although weaker feedbacks may last up to 30 months. These results show, with regards to the France yield spread (FR10Y-FR3M) and the future France output growth that their relationship is positive, as expected. Our evidence suggests that the major effect on the future France output growth is within the first 11 months,

although weaker effects may also last up to three years. This basically implies that the yield spread is a useful predictor of France output up to a three-year horizon. The relationship between the France output growth and the future yield spread is found to be significantly different from zero. The estimate of t_{13} follows an increasing rate when $S_T \in$ [1, 11] with $\hat{t}_{13}$ =0.097 when S_T =11 and reaches its maximum value of 0.20 for S_T =30. So, our evidence here suggests a positive relationship, with major effects reaching the first eleven months, but weaker effects may last for up to 30 months as well.
The results from the Granger causality test for the France industrial production and the yield spread (FR10Y-FR3M) are:

GRANGER CAUSALITY	CHI-SQ	DF
S3 $\not\longrightarrow$ IP	1.192130 [0.5510]	2
IP $\longrightarrow$ S3	31.46266 [0.0000]	2

Real M1 (RM1) has an estimated temporal correlation coefficient t_{91} that increases at a decreasing rate as we can see from figure 3.

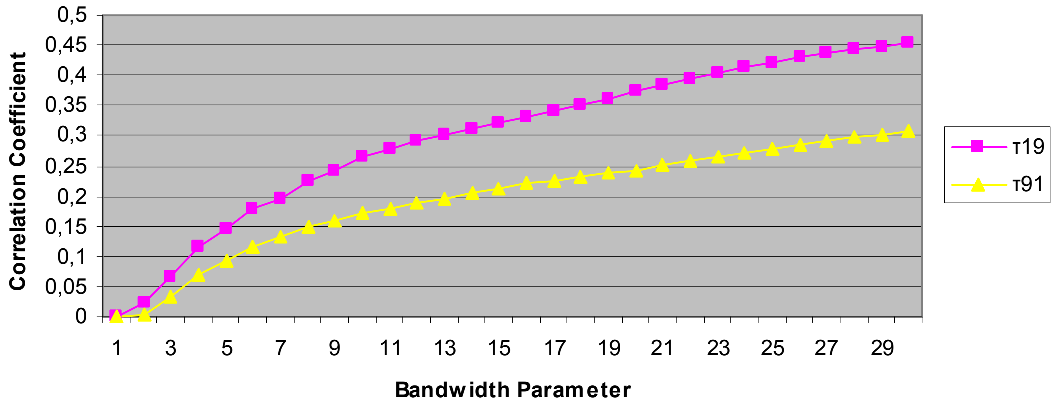

Figure 3: Estimated correlation coefficients: France output growth and France real money (M1)

For S_T =10, the estimate of t_{91} is equal to 0.17 for the Bartlett kernel. Beyond this point $\hat{t}_{91}$ increases at a decreasing rate and reaching its maximum value of 0.30 for S_T =30. What the evidence here suggests is that the major feedbacks from real M1 to output growth occur within the first ten months with a maximum feedback of around 30 months. The relationship between the France output growth and the future real M1 is found to be significantly different from zero. The estimate of t_{19} follows an increasing rate when $S_T \in$ [1, 11] with $\hat{t}_{19}$ =0.27 when S_T =11 and reaches its maximum value of 0.45 for S_T =30. So, our evidence here suggests a strong positive relationship and between the France output growth and the future real M1, with major effects reaching the first eleven months, but weaker effects may last for up to 30 months as well.

The results from the Granger causality test for the France industrial production and the real M1 (RM1) are:

GRANGER CAUSALITY	CHI-SQ	DF
RM1 $\not\rightarrow$ IP	8.116611 [0.8100]	12
IP $\not\rightarrow$ RM1	22.37711 [0.1602]	12

In the case of the spread (FR10Y-FR1M) the results do not differentiate at all and show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{41} increase as well. The estimates of the temporal correlation coefficient t_{14} are again positive and they also increase as the bandwidth parameter increases. The rate of growth of the estimates of t_{41} again does not remain constant over the whole range of values of the bandwidth parameter S_T.

Figure 4 shows the results for the France yield spread (FR10Y-FR1M) and the France output growth.

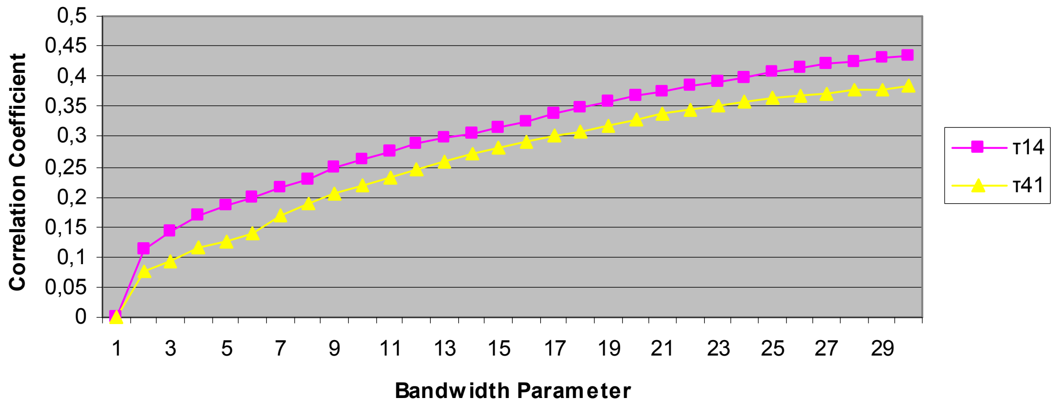

Figure 4: Estimated correlation coefficients: France output growth and France Yield (FR10Y-FR1M)

For S_T=3, the estimate of t_{41} is equal to 0.09, for the Bartlett kernel. Beyond this point, $\hat{t}_{41}$ increases at a decreasing rate, with a value of $\hat{t}_{41}$=0.22 for S_T=10 and reaching its maximum value of 0.38 for S_T=30. What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 10 months, although weaker feedbacks may last up to 30 months. What these results show, with regards to the France yield spread (FR10Y-FR1M) and the future France output growth is that their relationship is positive, as expected. The relationship between the France output growth and the future yield spread is found to be significantly different from zero. The estimate of t_{14} follows an increasing rate when $S_T \in$ [1, 12] with $\hat{t}_{14}$=0.28 when S_T=12 and reaches its maximum value of 0.43 for S_T=30. So, our evidence here suggests a strong positive relationship, with major effects reaching the first 12 months, but weaker effects may last for up to 30 months as well.

The results from the Granger causality test for the France industrial production and the yield spread (FR10Y-FR1M) are:

GRANGER CAUSALITY	CHI-SQ	DF
$S1 \nrightarrow IP$	0.706312 [0.7025]	2
$IP \longrightarrow S1$	25.10465 [0.0000]	2

Real M2 (RM2) show similar pattern with RM1 and the relationship is as strong as RM1. This is confirmed by our results, shown in figure 5, which show that real M2 (RM2) has an estimated temporal correlation coefficient t_{101} that increases at a decreasing rate.

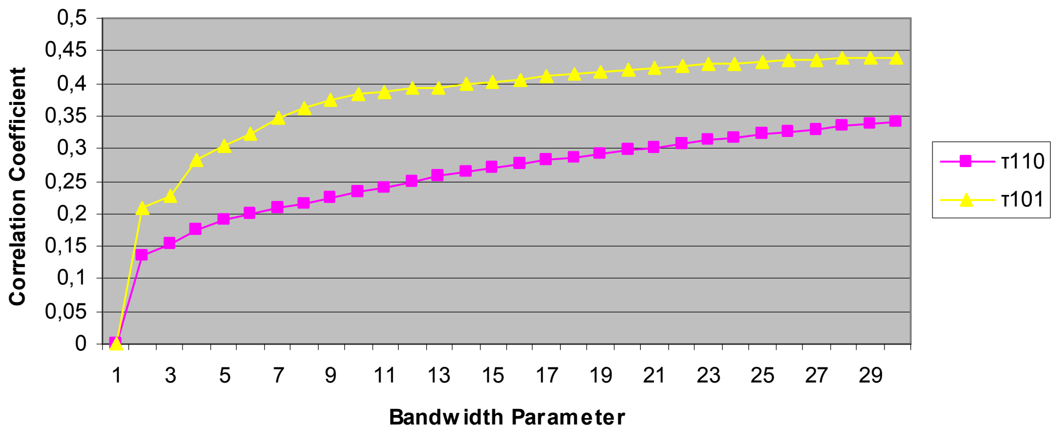

Figure 5: Estimated correlation coefficients: France output growth and France real money (M2)

For S_T=9, the estimate of t_{101} is equal to 0.37 for the Bartlett kernel. Beyond this point $\hat{t}_{101}$ increases at a decreasing rate and reaching its maximum value of 0.43 for S_T=30. What the evidence here suggests is that the major feedbacks from real M2 to output growth occur within the first nine months with a maximum feedback of around 30 months. The relationship between the France output growth and the future real M2 is found to be significantly different from zero. The estimate of t_{110} follows an increasing rate when $S_T \in$ [1, 5] with $\hat{t}_{110}$ =0.19 when S_T=5 and reaches its maximum value of 0.33 for S_T=30. So, our evidence here suggests a strong positive relationship between the France output growth and the future real M2, with major effects reaching the first 5 months, but weaker effects may last for up to 30 months as well.
The results from the Granger causality test for the France industrial production and the real M2 (RM2) are:

GRANGER CAUSALITY	CHI-SQ	DF
$RM2 \nrightarrow IP$	8.342052 [0.8206]	13
$IP \longrightarrow RM2$ (10%)	20.16006 [0.0913]	13

The various interest rates (10–year government bond, 1-month, 3-month and 1-year interest rates) which we examined have results that are similar with that of the other variables.
Figure 6 shows the results for the France 10–year government bond and the France output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{51} increase as well.

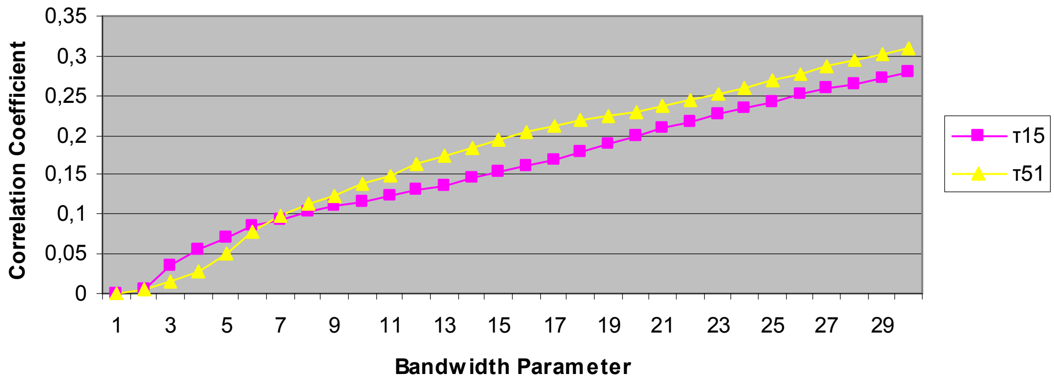

Figure 6: Estimated correlation coefficients: France output growth and France 10–year government bond

The estimates of the temporal correlation coefficient t_{15} are again positive and they also increase as the bandwidth parameter increases. The rate of growth of the estimates of t_{51} does not remain constant over the whole range of values of the bandwidth parameter S_T.
For S_T=12, the estimate of t_{51} is equal to 0.16, for the Bartlett kernel. Beyond this point, $\hat{t}_{51}$ increases at a decreasing rate, and reaching its maximum value of 0.31 for S_T=30. What the evidence here suggests is that the major feedbacks from the 10–year government bond to output growth occur approximately within the first 12 months, although weaker feedbacks may last up to 30 months. What the results showed, for the France 10–year government bond and the future France output growth is that their relationship is strong.
Our evidence suggests that the major effect on the future France output growth is within the first twelve months, although weaker effects may also last up to three years. This basically implies that the 10–year government bond is a useful predictor of France output up to a three-year horizon. The relationship between the France output growth and the future 10–year government bond is found to be significantly different from zero and as strong as that of the opposite direction. The estimate of t_{15} follows an increasing rate when $S_T \in [1, 8]$ with $\hat{t}_{15}$ =0.10 when S_T=8 and reaches its maximum value of 0.28 for S_T=30. So, our evidence here suggests a strong positive relationship between the France output growth and the future 10–year government bond, with major effects reaching the first 8 months, but weaker effects may last for up to 30 months as well.

The results from the Granger causality test for the France industrial production and the 10-year government bond are:

GRANGER CAUSALITY	CHI-SQ	DF
10Y $\nrightarrow$ IP	6.667749 [0.6717]	9
IP $\nrightarrow$ 10Y	1.971095 [0.9919]	9

Familiar results are exported and for the other interest rates. Figures 7, 8 and 9 also show the correlation coefficients for the 3-month, 1-month and 1-year France interest rates with respect with the France output growth.

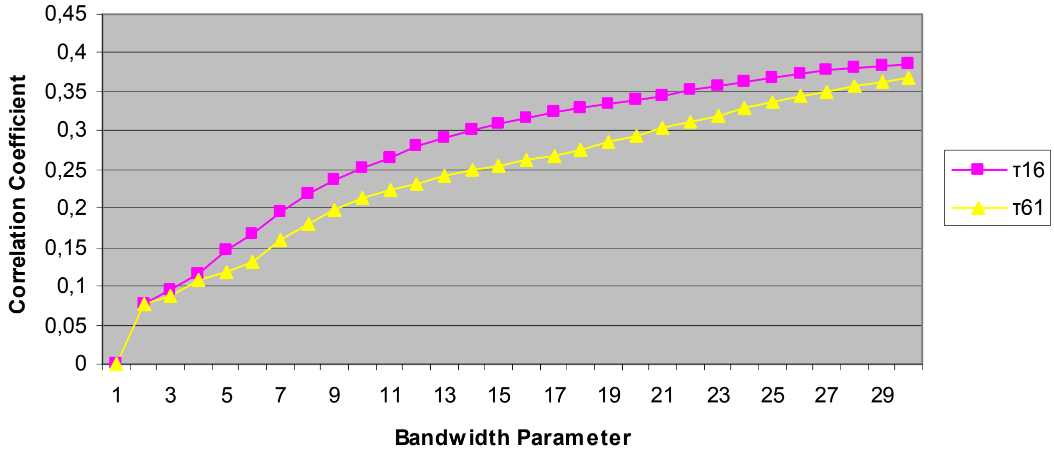

Figure 7: Estimated correlation coefficients: France output growth and France 1–month interest rate

The results from the Granger causality test for the France industrial production and the 1-month interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
1M $\nrightarrow$ IP	0.397479 [0.8198]	2
IP $\longrightarrow$ 1M	31.96160 [0.0000]	2

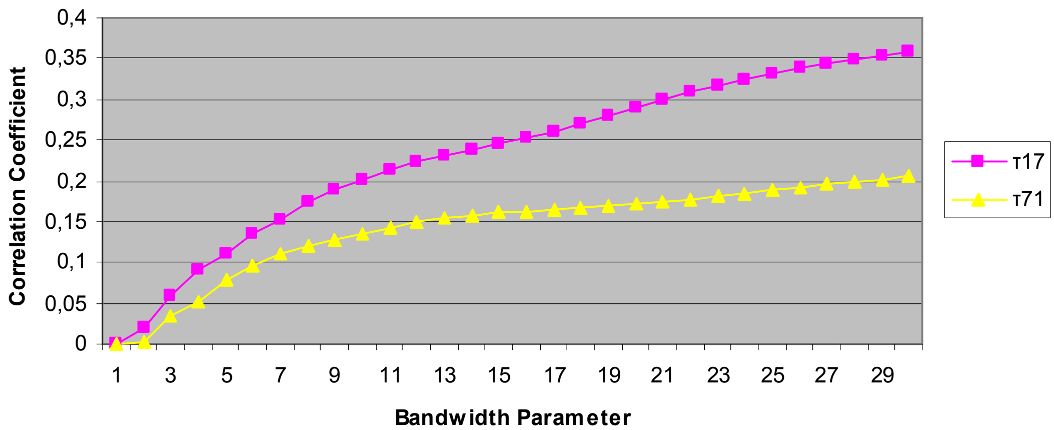

Figure 8: Estimated correlation coefficients: France output growth and France 3–month interest rate

The results from the Granger causality test for the France industrial production and the 3-month interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
3M $\nrightarrow$ IP	0.473019 [0.7894]	2
IP $\rightarrow$ 3M	32.65262 [0.0000]	2

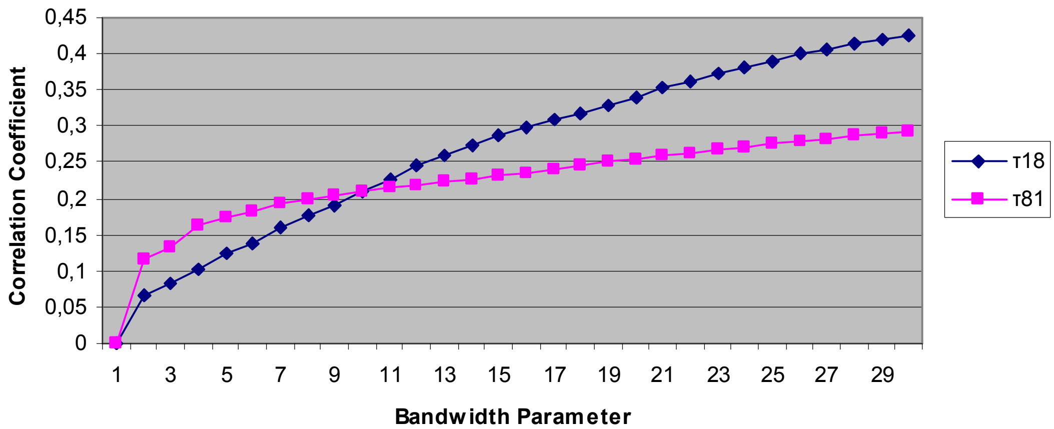

Figure 9: Estimated correlation coefficients: France output growth and France 1–year interest rate

The results from the Granger causality test for the France industrial production and the 1-year interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
1Y $\nrightarrow$ IP	3.15E-05 [0.9955]	1
IP $\nrightarrow$ 1Y	0.355378 [0.5511]	1

4. A.7. Italian financial variables and output growth

Table A7 presents the estimated temporal correlation for all the financial variables that were examined for this country. Among the various groups of the Italian financial variables examined, the Milan Comit general share price index, the Italian yield (IT10Y-IT3M), and real M1 (RM1) were found to exhibit the strongest temporal correlations (t_{21}) with respect to Italy output growth.
Our estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to the value of the current financial variable at hand ($u_{1,t-i} \rightarrow u_{2,t}$), and the temporal correlation coefficient t_{21}, which describes feedbacks from past values of the financial variable at hand to current output growth (i.e., in the opposite direction ($u_{2,t-i} \rightarrow u_{1,t}$), for alternative values of the bandwidth parameter S_T are reported in figures 1-9

for the Bartlett kernel. The bandwidth parameter takes values in the interval [1, 30] by steps of one.

Figure 1 shows, for the Italy stock price index and the Italy output growth, that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{21}, that describes feedbacks from past real stock returns to current output growth ($u_{2,t-i} \rightarrow u_{1,t}$), increase as well. Similarly the estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to current real stock returns ($u_{1,t-i} \rightarrow u_{2,t}$), are positive and increase as the bandwidth parameter increases too.

The rate of growth of the estimates of t_{21} does not remain constant over the whole range of values of the bandwidth parameter S_T. When $S_T \in$ [1, 13], $\hat{t}_{21}$ increases at an increasing rate and for S_T=13, the estimate of t_{21} is equal to 0.37 for the Bartlett kernel.

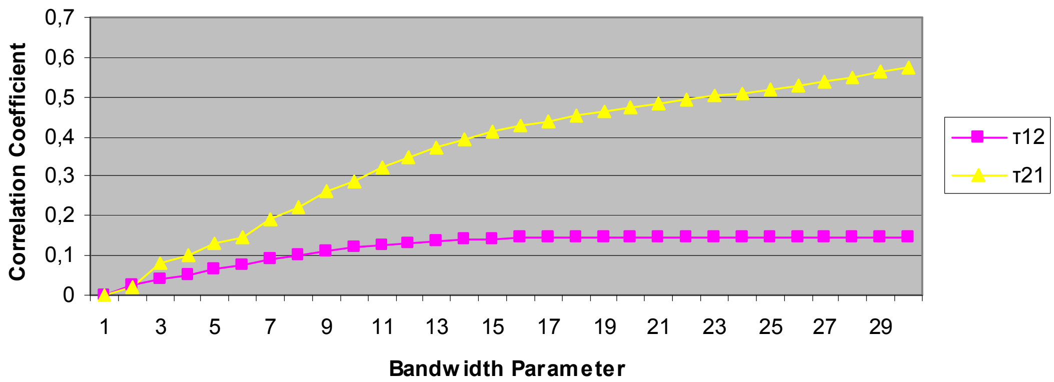

Figure 1: Estimated correlation coefficients: Italy output growth and returns from the Italy Stock price index

Beyond this point, $\hat{t}_{21}$ increases at a decreasing rate thus reaching its maximum value of 0.57 for S_T=30. What the evidence here suggests is that the major feedbacks, from past stock price changes to output growth, occur within the first 13 months, with a maximum feedback of around 30 months. The relationship between past Italy output growth and stock price changes is found to be significantly different from zero. The estimate of t_{12} follows a decreasing rate when $S_T \in$ [1, 7] with $\hat{t}_{12}$ =0.09 when S_T=7 and reaches its maximum value of 0.1458 for S_T=18.

What our results show is that there is a strong positive relationship (temporal correlation) between past stock price changes and current Italy output growth, as expected. Basically, this implies that, and for the Italy, stock prices are useful predictors of output for a horizon of up to 30 months.

The results from the Granger causality test for the Italy industrial production and the stock index are:

GRANGER CAUSALITY	CHI-SQ	DF
IND $\longrightarrow$ IP	8.465021 [0.0373]	3
IP $\not\longrightarrow$ IND	0.627304 [0.8902]	3

Figure 2 shows the results for the Italy yield spread (IT10Y-IT3M) and the Italy output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{31} increase as well. The estimates of the temporal correlation coefficient t_{13} are again positive and they also increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{31} does not remain constant over the whole range of values of the bandwidth parameter S_T.

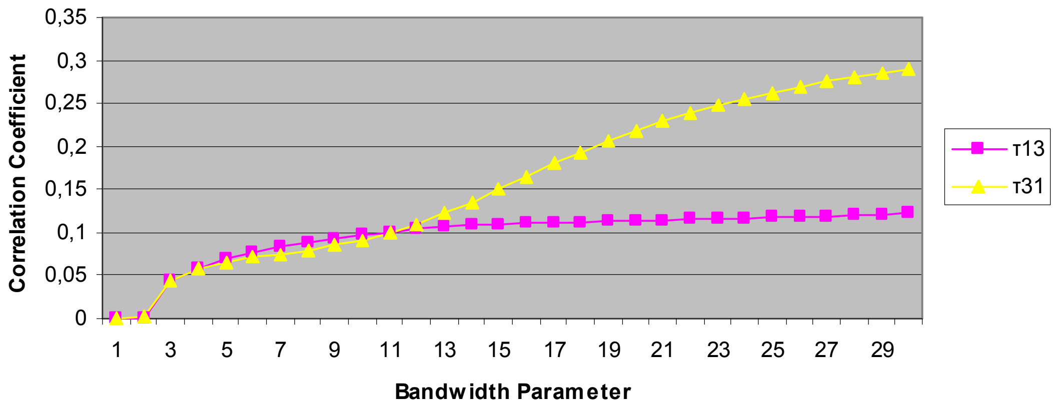

Figure 2: Estimated correlation coefficients: Italy output growth and Italy Yield (IT10Y-IT3M)

For S_T=3, the estimate of t_{31} is equal to 0.04, for the Bartlett kernel. Beyond this point, $\hat{t}_{31}$ increases at a decreasing rate, with a value of $\hat{t}_{31}$ =0.10 for S_T=11 and reaching its maximum value of 0.28 for S_T=30. What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 11 months, although weaker feedbacks may last up to 30 months. These results show, with regards to the Italy yield spread (IT10Y-IT3M) and the future Italy output growth that their relationship is positive, as expected. Our evidence suggests that the major effect on the future Italy output growth is within the first 11 months, although weaker effects may also last up to three years. This basically implies that the yield spread is a useful predictor of Italian output up to a three-year horizon. The relationship between the Italian output growth and the future yield spread is found to be significantly different from zero. The estimate of t_{13} follows an increasing rate when $S_T \in [1, 5]$ with $\hat{t}_{13}$ =0.070 when S_T=5 and reaches its maximum value of 0.12 for S_T=30. So, our evidence here suggests a positive

relationship, with major effects reaching the first five months, but weaker effects may last for up to 30 months as well.
The results from the Granger causality test for the Italy industrial production and the yield spread (IT10Y-IT3M) are:

GRANGER CAUSALITY	CHI-SQ	DF
S3 $\longrightarrow$ IP	43.05798 [0.0098]	24
IP $\longrightarrow$ S3	51.45675 [0.0009]	24

Real M1 (RM1) has an estimated temporal correlation coefficient t_{91} that is mainly positive and remains close to zero for all values of the bandwidth parameter as we can see from figure 3.
The relationship between the Italy output growth and the future real M1 is found to be significantly different from zero. The estimate of t_{19} follows an increasing rate when $S_T \in$ [1, 12] with $\hat{t}_{19}$ =0.073 when S_T =12 and reaches its maximum value of 0.34 for S_T =30.

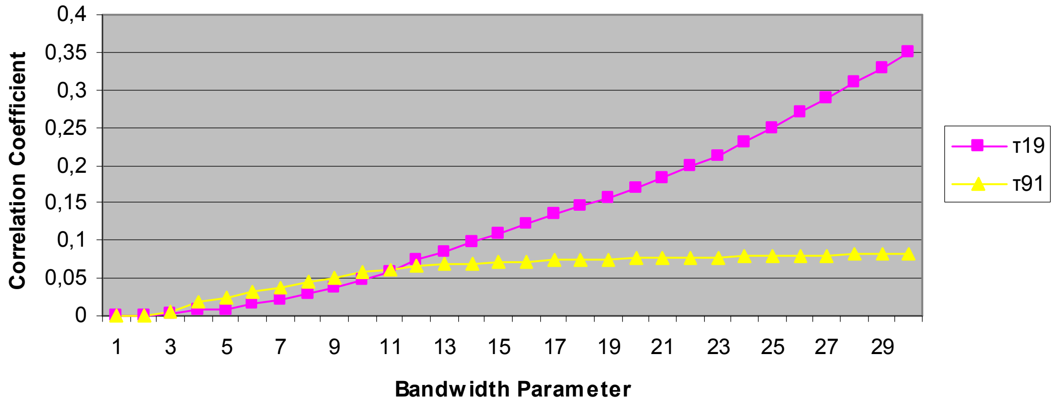

Figure 3: Estimated correlation coefficients: Italy output growth and Italy real money (M1)

So, our evidence here suggests a strong positive relationship between the Italy output growth and the future real M1, with major effects reaching the first twelve months, but weaker effects may last for up to 30 months as well.
The results from the Granger causality test for the Italy industrial production and the real M1 (RM1) are:

GRANGER CAUSALITY	CHI-SQ	DF
RM1 $\not\longrightarrow$ IP	7.286394 [0.8381]	12
IP $\longrightarrow$ RM1 (10%)	19.63689 [0.0743]	12

In the case of the spread (IT10Y-IT1M) the results do not differentiate at all and show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{41} increase as well. The estimates of the temporal correlation coefficient t_{14} are mainly positive and remain close to zero for all values of the bandwidth parameter. The rate of growth of the

estimates of t_{41} again does not remain constant over the whole range of values of the bandwidth parameter S_T.
Figure 4 shows the results for the Italy yield spread (IT10Y-IT1M) and the Italy output growth.

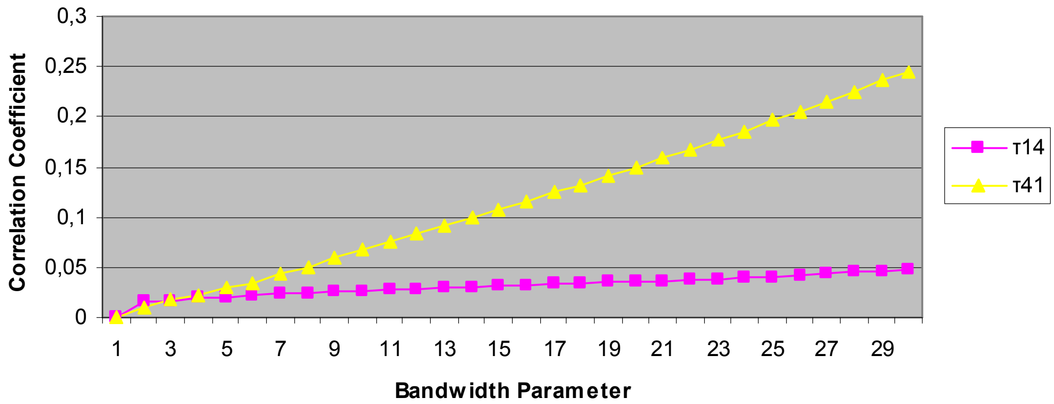

Figure 4: Estimated correlation coefficients: Italy output growth and Italy Yield (IT10Y-IT1M)

For S_T=2, the estimate of t_{41} is equal to 0.009, for the Bartlett kernel. Beyond this point, $\hat{t}_{41}$ increases at a decreasing rate, with a value of $\hat{t}_{41}$=0.075 for S_T=11 and reaching its maximum value of 0.24 for S_T=30. What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 11 months, although weaker feedbacks may last up to 30 months. What these results show, with regards to the Italy yield spread (IT10Y-IT1M) and the future Italy output growth is that their relationship is positive, as expected. The relationship between the Italy output growth and the future yield spread is found to be not significantly different from zero.
The results from the Granger causality test for the Italy industrial production and the yield spread (IT10Y-IT1M) are:

GRANGER CAUSALITY	CHI-SQ	DF
S1 $\longrightarrow$ IP	57.73358 [0.0001]	24
IP $\longrightarrow$ S1	38.35329 [0.0319]	24

Real M2 (RM2) show similar pattern with RM1 and the relationship is stronger than is RM1. This is confirmed by our results, shown in figure 5, which show that real M2 (RM2) has an estimated temporal correlation coefficient t_{101} that increases at a decreasing rate.

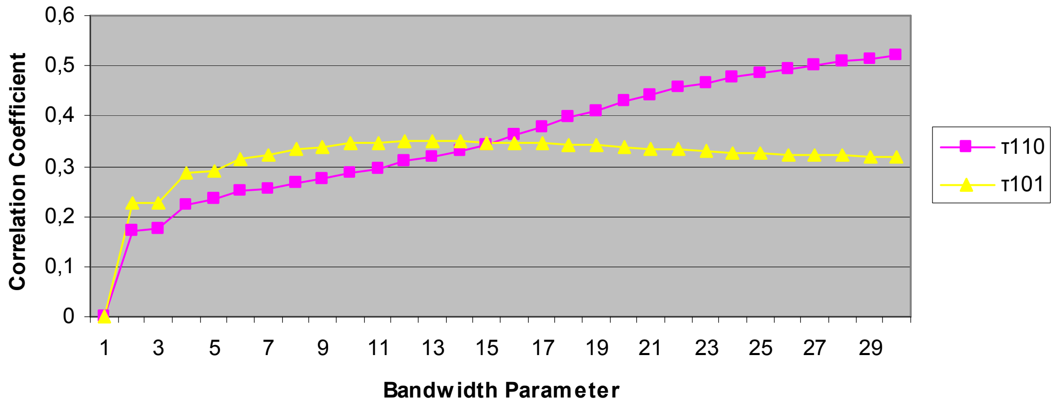

Figure 5: Estimated correlation coefficients: Italy output growth and Italy real money (M2)

For S_T=4, the estimate of t_{101} is equal to 0.28 for the Bartlett kernel. Beyond this point $\hat{t}_{101}$ increases at a decreasing rate and reaching its maximum value of 0.35 for S_T=12. What the evidence here suggests is that the major feedbacks from real M2 to output growth occur within the first four months with a maximum feedback of around 12 months. The relationship between the Italy output growth and the future real M2 is found to be significantly different from zero. The estimate of t_{110} follows an increasing rate when $S_T \in$ [1, 4] with $\hat{t}_{110}$ =0.22 when S_T=4 and reaches its maximum value of 0.52 for S_T=30. So, our evidence here suggests a strong positive relationship between the Italy output growth and the future real M2, with major effects reaching the first 4 months, but weaker effects may last for up to 30 months as well.

The results from the Granger causality test for the Italy industrial production and the real M2 (RM2) are:

GRANGER CAUSALITY	CHI-SQ	DF
RM2 $\not\longrightarrow$ IP	6.523424 [0.8874]	12
IP $\longrightarrow$ RM2	28.43596 [0.0048]	12

The various interest rates (10–year government bond, 1-month, 3-month and 1-year interest rates) which we examined have results that are similar with that of the other variables.

Figure 6 shows the results for the Italy 10–year government bond and the Italian output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{51} increase as well. The estimates of the temporal correlation coefficient t_{15} are mainly positive and remain close to zero for all values of the bandwidth parameter. The rate of growth of the estimates of t_{51} does not remain constant over the whole range of values of the bandwidth parameter S_T.

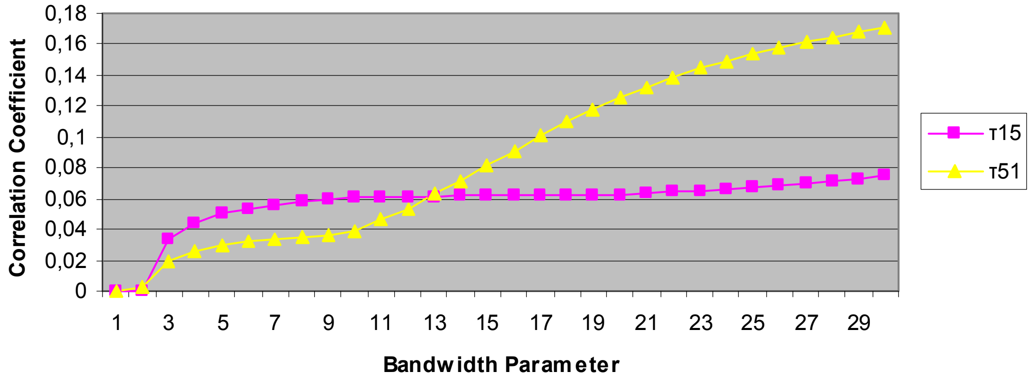

Figure 6: Estimated correlation coefficients: Italy output growth and Italy 10–year government bond

For S_T=4, the estimate of t_{51} is equal to 0.026, for the Bartlett kernel. Beyond this point, $\hat{t}_{51}$ increases at a decreasing rate, and reaching its maximum value of 0.17 for S_T=30. What the evidence here suggests is that the major feedbacks from the 10–year government bond to output growth occur approximately within the first 4 months, although weaker feedbacks may last up to 30 months. What the results showed, for the Italy 10–year government bond and the future Italy output growth is that their relationship is strong.
Our evidence suggests that the major effect on the future Italy output growth is within the first four months, although weaker effects may also last up to three years. The relationship between the Italy output growth and the future 10–year government bond is found to be not significantly different from zero. The results from the Granger causality test for the Italy industrial production and the 10-year government bond are:

GRANGER CAUSALITY	CHI-SQ	DF
$10Y \longrightarrow IP$ (10%)	7.388148 [0.0605]	3
$IP \not\longrightarrow 10Y$	2.711799 [0.4382]	3

Familiar results are exported and for the other interest rates. Figures 7, 8, and 9 also show the correlation coefficients for the 3-month, 1-month and 1-year Italian interest rates with respect with the Italy output growth.

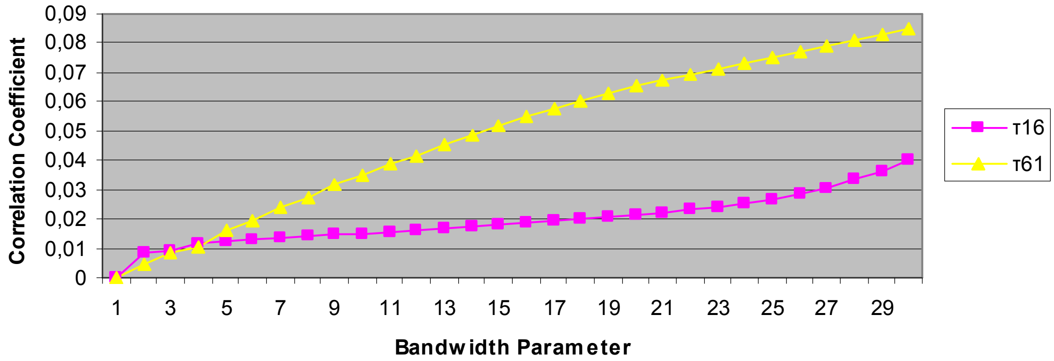

Figure 7: Estimated correlation coefficients: Italy output growth and Italy 1–month interest rate

The results from the Granger causality test for the Italy industrial production and the 1-month interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
$1M \nrightarrow IP$	1.291985 [0.5241]	2
$IP \nrightarrow 1M$	1.747509 [0.4174]	2

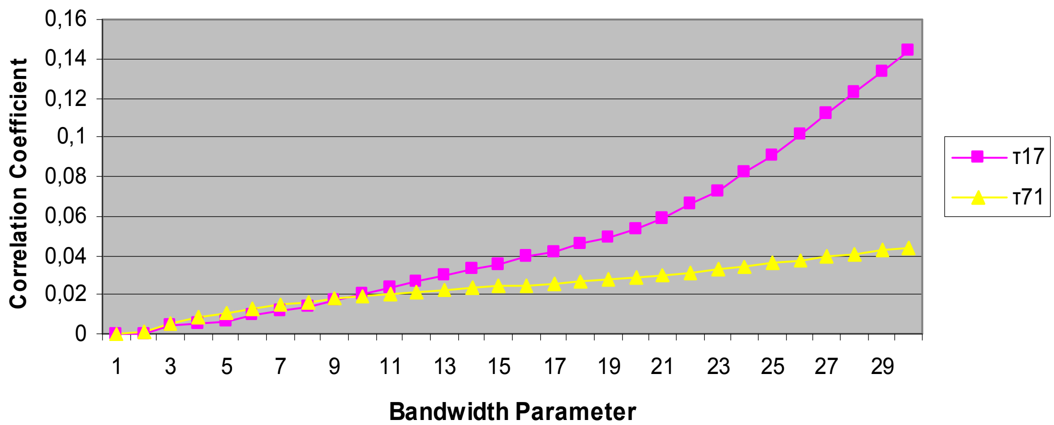

Figure 8: Estimated correlation coefficients: Italy output growth and Italy 3–month interest rate

The results from the Granger causality test for the Italy industrial production and the 3-month interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
$3M \nrightarrow IP$	1.372434 [0.5035]	2
$IP \nrightarrow 3M$	1.465698 [0.4805]	2

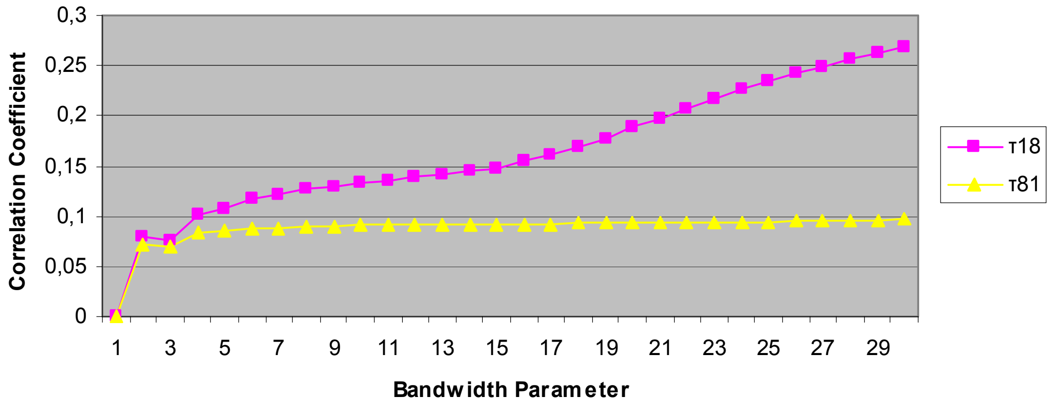

Figure 9: Estimated correlation coefficients: Italy output growth and Italy 1–year interest rate

The results from the Granger causality test for the Italy industrial production and the 1-year interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
$1Y \not\longrightarrow IP$	3.782413 [0.1509]	2
$IP \longrightarrow 1Y$	7.567702 [0.0227]	2

4. B.1. South Africa financial variables and output growth

Table B1 presents the estimated temporal correlation for all the financial variables that were examined in this paper. Among the various groups of the South Africa financial variables examined, the DataStream total market stock price index, the South Africa yield (SA10Y-SA3M), and real M1 (RM1) were found to exhibit the strongest temporal correlations (t_{21}) with respect to South Africa output growth.

Our estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to the value of the current financial variable at hand ($u_{1,t-i} \rightarrow u_{2,t}$), and the temporal correlation coefficient t_{21}, which describes feedbacks from past values of the financial variable at hand to current output growth (i.e., in the opposite direction ($u_{2,t-i} \rightarrow u_{1,t}$), for alternative values of the bandwidth parameter S_T are reported in figures 1-9 for the Bartlett kernel. The bandwidth parameter takes values in the interval [1, 36] by steps of one.

Figure 1 shows, for the South Africa stock price index and the South Africa output growth, that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{21}, that describes feedbacks from past real stock returns to current output growth ($u_{2,t-i} \rightarrow u_{1,t}$), increase as well. Similarly the estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to current real stock returns ($u_{1,t-i} \rightarrow u_{2,t}$), are positive and increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{21} does not remain constant over the whole range of values of the bandwidth parameter S_T.

When $S_T \in$ [1, 11], $\hat{t}_{21}$ increases at an increasing rate and for S_T=11, the estimate of t_{21} is equal to 0.30 for the Bartlett kernel. Beyond this point, $\hat{t}_{21}$ increases at a decreasing rate thus reaching its maximum value of 0.41 for S_T=36.

What the evidence here suggests is that the major feedbacks, from past stock price changes to output growth, occur within the first 11 months, with a maximum feedback of around 36 months.

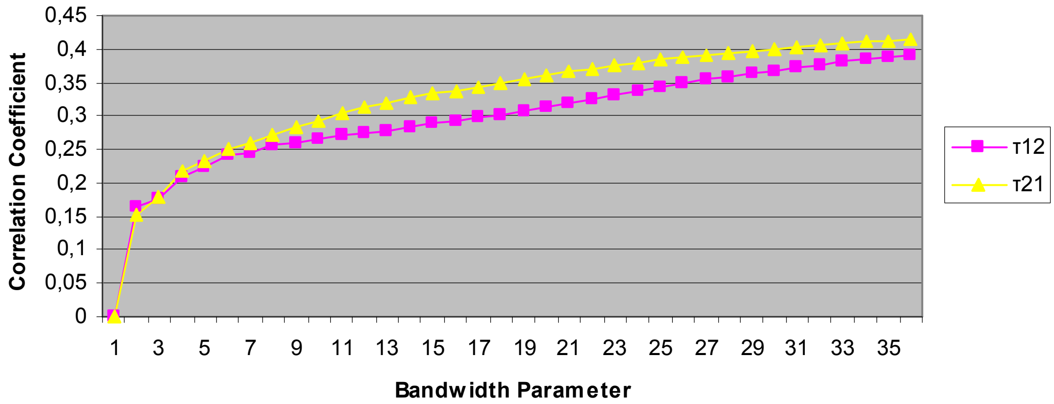

Figure 1: Estimated correlation coefficients: South Africa output growth and returns from the South Africa Stock price index

The relationship between past South Africa output growth and stock price changes is found to be significantly different from zero. The estimate of t_{12} follows a increasing rate when $S_T \in$ [1, 6] with $\hat{t}_{12}$ =0.24 when S_T=6 and reaches its maximum value of 0.39 for S_T=36.

What our results show is that there is a strong positive relationship (temporal correlation) between past stock price changes and current South Africa output growth, as expected. Basically, this implies that, and for the South Africa, stock prices are useful predictors of output for a horizon of up to 36 months. The results from the Granger causality test for the South Africa industrial production and the stock index are:

GRANGER CAUSALITY	CHI-SQ	DF
IND $\not\rightarrow$ IP	1.233785 [0.8725]	4
IP $\not\rightarrow$ IND	2.478038 [0.6486]	4

Figure 2 shows the results for the South Africa yield spread (SA10Y-SA3M) and the South Africa output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{31} increase as well. The estimates of the temporal correlation coefficient t_{13} are again positive and they also increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{31} does not remain constant over the whole range of values of the bandwidth parameter S_T. For S_T=3, the estimate of t_{31} is equal to 0.11, for the Bartlett kernel. Beyond this point, $\hat{t}_{31}$ increases at a decreasing rate, with a value of $\hat{t}_{31}$ =0.29 for S_T=11 and reaching its maximum value of 0.40 for S_T=36.

What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 11 months, although weaker feedbacks may last up to 36 months.

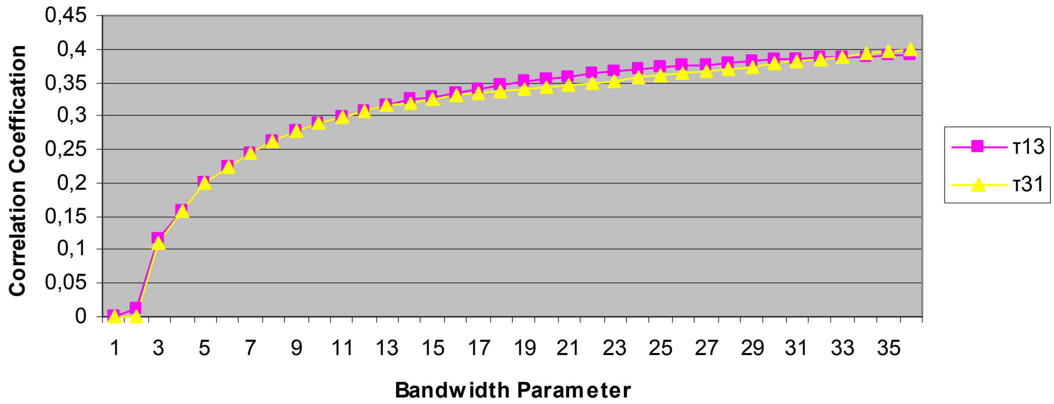

Figure 2: Estimated correlation coefficients: South Africa output growth and South Africa Yield (SA10Y-SA3M)

These results show, with regards to the South Africa yield spread (SA10Y-SA3M) and the future South Africa output growth that their relationship is positive, as expected. Our evidence suggests that the major effect on the future South Africa output growth is within the first 11 months, although weaker effects may also last up to three years. This basically implies that the yield spread is a useful predictor of South Africa output up to a three-year horizon. The relationship between the South Africa output growth and the future yield spread is found to be significantly different from zero. The estimate of t_{13} follows an increasing rate when $S_T \in$ [1, 11] with $\hat{t}_{13}$ =0.29 when S_T=11 and reaches its maximum value of 0.39 for S_T=36. So, our evidence here suggests a positive relationship, with major effects reaching the first eleven months, but weaker effects may last for up to 36 months as well. The results from the Granger causality test for the South Africa industrial production and the yield spread (SA10Y-SA3M) are:

GRANGER CAUSALITY	CHI-SQ	DF
S3 $\longrightarrow$ IP	29.48706 [0.0117]	4
IP $\longrightarrow$ S3 (10%)	14.81811 [0.0995]	4

Real M1 (RM1) has an estimated temporal correlation coefficient t_{91} that increases at a decreasing rate as we can see from figure 3. For S_T=11, the estimate of t_{91} is equal to 0.22 for the Bartlett kernel. Beyond this point $\hat{t}_{91}$ increases at a decreasing rate and reaching its maximum value of 0.35 for S_T=36. What the evidence here suggests is that the major feedbacks from real M1 to output growth occur within the first eleven months with a maximum feedback of around 36 months.

The relationship between the South Africa output growth and the future real M1 is found to be significantly different from zero. The estimate of t_{19} follows an increasing rate when $S_T \in$ [1, 11] with $\hat{t}_{19}$ =0.24 when S_T=11 and reaches its maximum value of 0.42 for S_T=36.

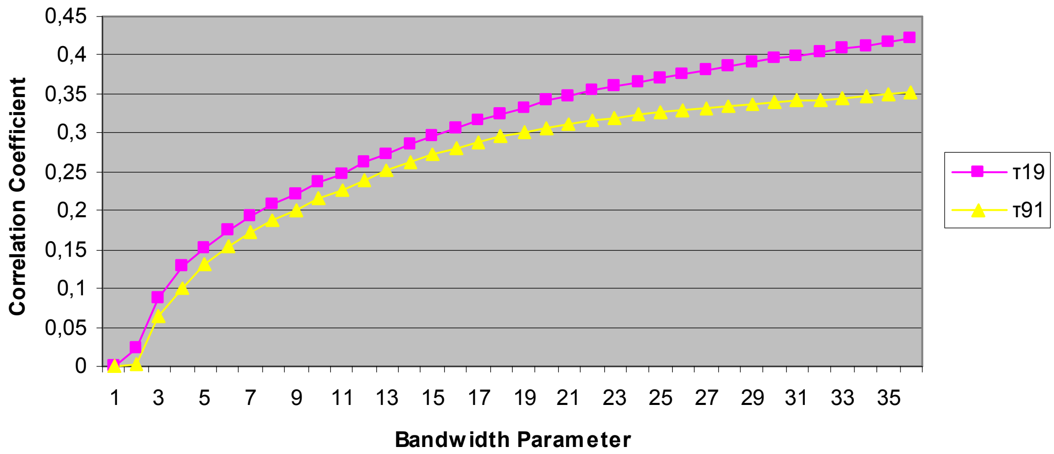

Figure 3: Estimated correlation coefficients: South Africa output growth and South Africa real money (M1)

So, our evidence here suggests a strong positive relationship and between the South Africa output growth and the future real M1, with major effects reaching the first eleven months, but weaker effects may last for up to 36 months as well.

The results from the Granger causality test for the South Africa industrial production and the real M1 (RM1) are:

GRANGER CAUSALITY	CHI-SQ	DF
RM1 $\nrightarrow$ IP	2.900625 [0.4072]	3
IP $\nrightarrow$ RM1	0.896394 [0.8263]	3

In the case of the spread (SA10Y-SA1M) the results do not differentiate at all and show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{41} increase as well. The estimates of the temporal correlation coefficient t_{14} are again positive and they also increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{41} again does not remain constant over the whole range of values of the bandwidth parameter S_T.

Figure 4 shows the results for the South Africa yield spread (SA10Y-SA1M) and the South Africa output growth.

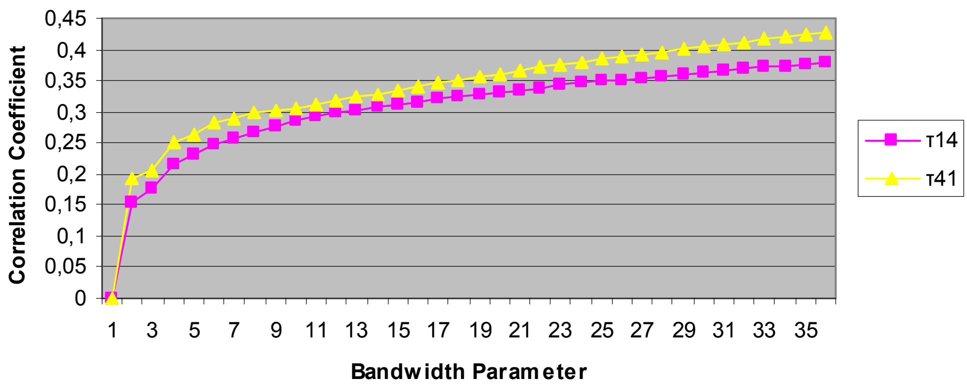

Figure 4: Estimated correlation coefficients: South Africa output growth and South Africa Yield (SA10Y-SA1M)

For S_T=2, the estimate of t_{41} is equal to 0.19, for the Bartlett kernel. Beyond this point, $\hat{t}_{41}$ increases at a decreasing rate, with a value of $\hat{t}_{41}$ =0.28 for S_T=6 and reaching its maximum value of 0.42 for S_T=36. What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 6 months, although weaker feedbacks may last up to 36 months. What these results show, with regards to the South Africa yield spread (SA10Y-SA1M) and the future South Africa output growth is that their relationship is positive, as expected. The relationship between the South Africa output growth and the future yield spread is found to be significantly different from zero. The estimate of t_{14} follows an increasing rate when $S_T \in$ [1, 7] with $\hat{t}_{14}$ =0.25 when S_T=7 and reaches its maximum value of 0.37 for S_T=36. So, our evidence here suggests a strong positive relationship, with major effects reaching the first 7 months, but weaker effects may last for up to 36 months as well.
The results from the Granger causality test for the South Africa industrial production and the yield spread (SA10Y-SA1M) are:

GRANGER CAUSALITY	CHI-SQ	DF
S1 $\longrightarrow$ IP	21.85447 [0.0174]	7
IP $\longrightarrow$ S1 (10%)	17.61590 [0.0538]	7

Real M2 (RM2) show similar pattern with RM1 and the relationship is as strong as RM1. This is confirmed by our results, shown in figure 5, which show that real M2 (RM2) has an estimated temporal correlation coefficient t_{101} that increases at a decreasing rate.

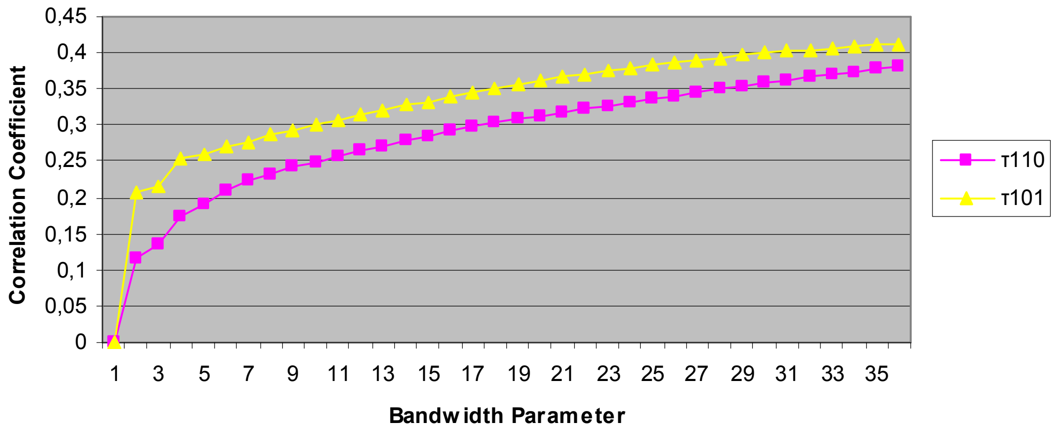

Figure 5: Estimated correlation coefficients: South Africa output growth and South Africa real money (M2)

For S_T=4, the estimate of t_{101} is equal to 0.25 for the Bartlett kernel. Beyond this point $\hat{t}_{101}$ increases at a decreasing rate and reaching its maximum value of 0.41 for S_T=36. What the evidence here suggests is that the major feedbacks from South Africa real M2 to output growth occur within the first four months with a maximum feedback of around 36 months. The relationship between the South Africa output growth and the future real M2 is found to be significantly different from zero. The estimate of t_{110} follows an increasing rate when $S_T \in$ [1, 6] with $\hat{t}_{110}$ =0.21 when S_T=6 and reaches its maximum value of 0.38 for S_T=36. So, our evidence here suggests a strong positive relationship between the South Africa output growth and the future real M2, with major effects reaching the first 6 months, but weaker effects may last for up to 36 months as well.

The results from the Granger causality test for the South Africa industrial production and the real M2 (RM2) are:

GRANGER CAUSALITY	CHI-SQ	DF
RM2 $\not\longrightarrow$ IP	14.21691 [0.6517]	17
IP $\longrightarrow$ RM2	30.94086 [0.0203]	17

The various interest rates (10–year government bond, 1-month, 3-month and 1-year interest rates) which we examined have results that are similar with that of the other variables.

Figure 6 shows the results for the South Africa 10–year government bond and the South Africa output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{51} increase as well. The estimates of the temporal correlation coefficient t_{15} are again positive and they also increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{51} does not remain constant over the whole range of values of the bandwidth parameter S_T.

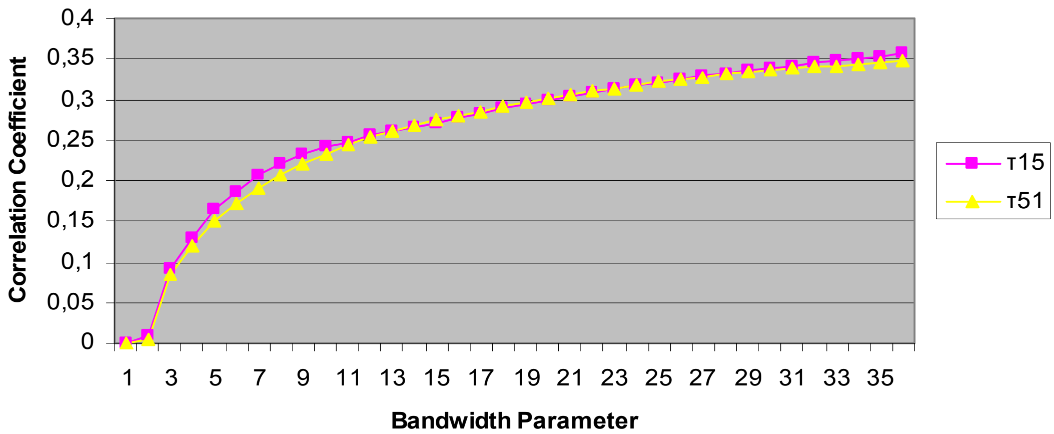

Figure 6: Estimated correlation coefficients: South Africa output growth and South Africa 10–year government bond

For S_T=7, the estimate of t_{51} is equal to 0.19, for the Bartlett kernel. Beyond this point, $\hat{t}_{51}$ increases at a decreasing rate, and reaching its maximum value of 0.34 for S_T=36. What the evidence here suggests is that the major feedbacks from the 10–year government bond to output growth occur

approximately within the first 7 months, although weaker feedbacks may last up to 36 months. What the results showed, for the South Africa 10–year government bond and the future South Africa output growth is that their relationship is strong.
Our evidence suggests that the major effect on the future South Africa output growth is within the first seven months, although weaker effects may also last up to three years. The relationship between the South Africa output growth and the future 10–year government bond is found to be significantly different from zero and as strong as that of the opposite direction. The estimate of t_{15} follows an increasing rate when $S_T \in [1, 8]$ with $\hat{t}_{15}$ =0.22 when S_T =8 and reaches its maximum value of 0.35 for S_T =36. So, our evidence here suggests a strong positive relationship between the South Africa output growth and the future 10–year government bond, with major effects reaching the first 8 months, but weaker effects may last for up to 36 months as well.
The results from the Granger causality test for the South Africa industrial production and the 10-year government bond are:

GRANGER CAUSALITY	CHI-SQ	DF
$10Y \longrightarrow IP$ (10%)	4.921306 [0.0854]	2
$IP \longrightarrow 10Y$ (10%)	5.497404 [0.0640]	2

Familiar results are exported and for the other interest rates. Figures 7, 8, and 9 also show the correlation coefficients for the 3-month, 1-month and 1-year South Africa interest rates with respect with the South Africa output growth.

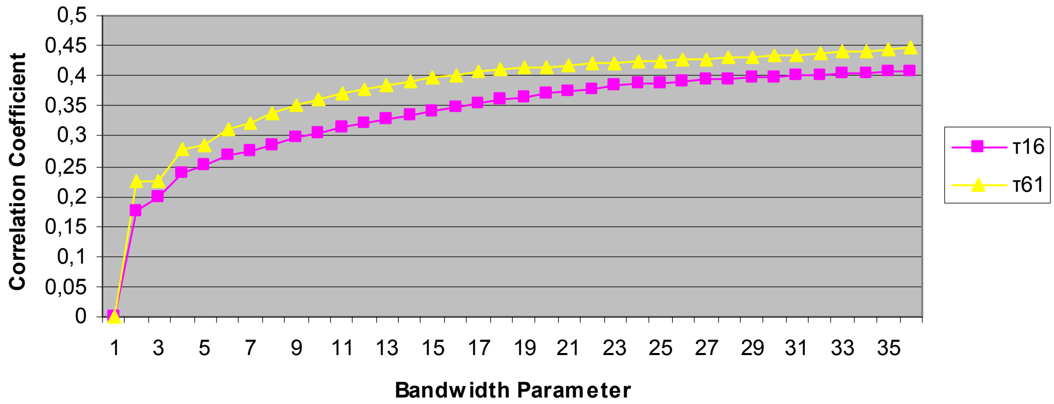

Figure 7: Estimated correlation coefficients: South Africa output growth and South Africa 1–month interest rate

The results from the Granger causality test for the South Africa industrial production and the 1-month interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
$1M \not\longrightarrow IP$	0.198191 [0.9779]	3
$IP \not\longrightarrow 1M$	4.802951 [0.1868]	3

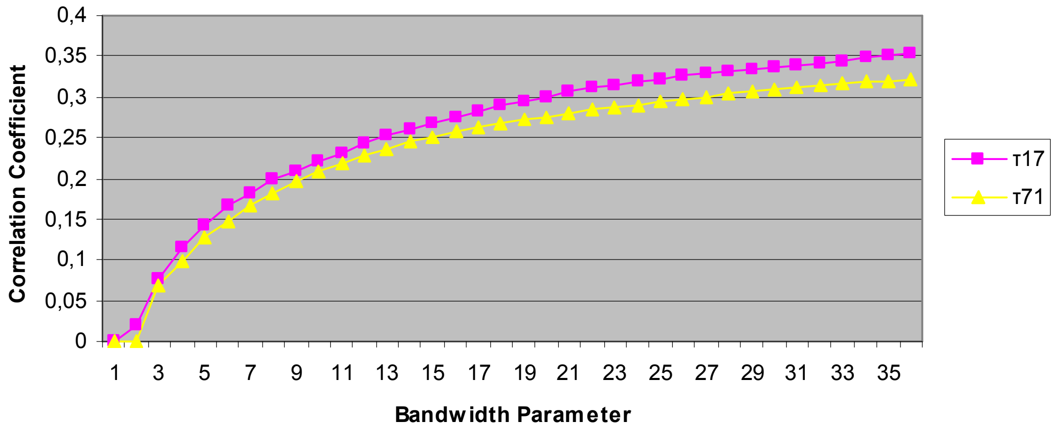

Figure 8: Estimated correlation coefficients: South Africa output growth and South Africa 3–month interest rate

The results from the Granger causality test for the South Africa industrial production and the 3-month interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
3M $\not\longrightarrow$ IP	0.943633 [0.8149]	3
IP $\longrightarrow$ 3M (10%)	7.226302 [0.0650]	3

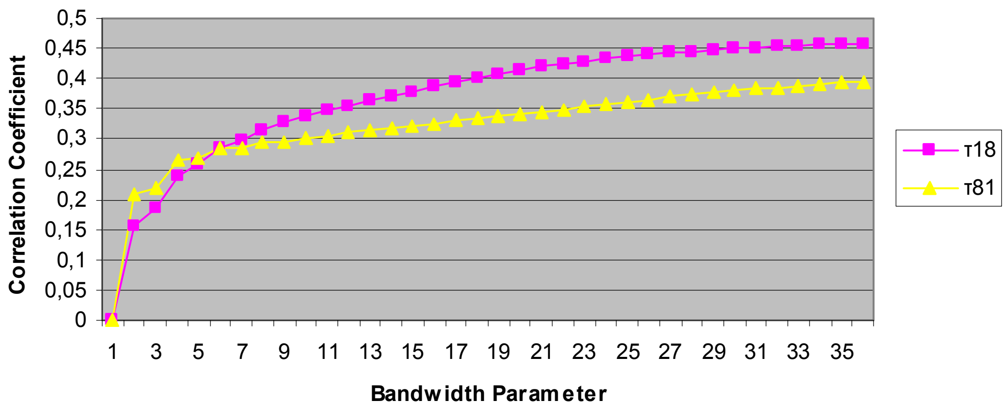

Figure 9: Estimated correlation coefficients: South Africa output growth and South Africa 1–year interest rate

The results from the Granger causality test for the South Africa industrial production and the 1-year interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
1Y $\not\longrightarrow$ IP	1.075734 [0.7829]	3
IP $\not\longrightarrow$ 1Y	3.014298 [0.3894]	3

4. B.2. India financial variables and output growth

Table B2 presents the estimated temporal correlation for all the financial variables that were examined in this paper. Among the various groups of the India financial variables examined, the Bombay stock exchange-national 100 share price index, the India yield (IN10Y-IN3M), and real M1 (RM1) were found to exhibit the strongest temporal correlations (t_{21}) with respect to India output growth.

Our estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to the value of the current financial variable at hand ($u_{1,t-i} \rightarrow u_{2,t}$), and the temporal correlation coefficient t_{21}, which describes feedbacks from past values of the financial variable at hand to current output growth (i.e., in the opposite direction ($u_{2,t-i} \rightarrow u_{1,t}$), for alternative values of the bandwidth parameter S_T are reported in figures 1-9 for the Bartlett kernel. The bandwidth parameter takes values in the interval [1, 30] by steps of one.

Figure 1 shows, for the India stock price index and the India output growth, that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{21}, that describes feedbacks from past real stock returns to current output growth ($u_{2,t-i} \rightarrow u_{1,t}$), increase as well. Similarly the estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to current real stock returns ($u_{1,t-i} \rightarrow u_{2,t}$), are positive and increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{21} does not remain constant over the whole range of values of the bandwidth parameter S_T. When $S_T \in$ [1, 9], $\hat{t}_{21}$ increases at an increasing rate and for S_T=9, the estimate of t_{21} is equal to 0.39 for the Bartlett kernel.

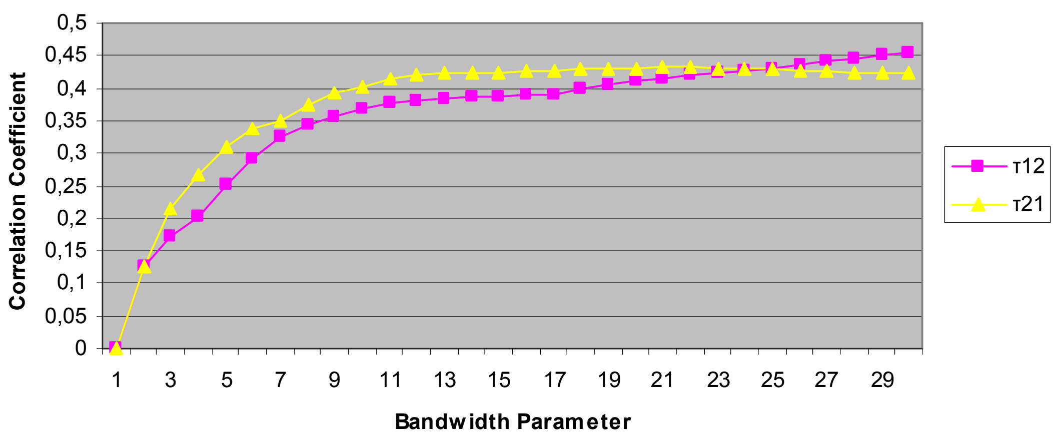

Figure 1: Estimated correlation coefficients: India output growth and returns from the India Stock price index

Beyond this point, $\hat{t}_{21}$ increases at a decreasing rate thus reaching its maximum value of 0.43 for S_T=22. What the evidence here suggests is that the major feedbacks, from past stock price changes to output growth, occur within the first 9 months, with a maximum feedback of around 22 months. The relationship between past India output growth and stock price changes is found to be significantly different from zero. The estimate of t_{12} follows a increasing rate when $S_T \in [1, 8]$ with $\hat{t}_{12}$ =0.34 when S_T=8 and reaches its maximum value of 0.45 for S_T=30.

What our results show is that there is a strong positive relationship (temporal correlation) between past stock price changes and current India output growth, as expected. Basically, this implies that, and for the India, stock prices are useful predictors of output for a horizon of up to 22 months.

The results from the Granger causality test for the India industrial production and the stock index are:

GRANGER CAUSALITY	CHI-SQ	DF
IND $\nrightarrow$ IP	0.266672 [0.6056]	1
IP $\nrightarrow$ IND	0.025689 [0.8727]	1

Figure 2 shows the results for the India yield spread (IN10Y-IN3M) and the India output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{31} increase as well. The estimates of the temporal correlation coefficient t_{13} are again positive and they also increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{31} does not remain constant over the whole range of values of the bandwidth parameter S_T.

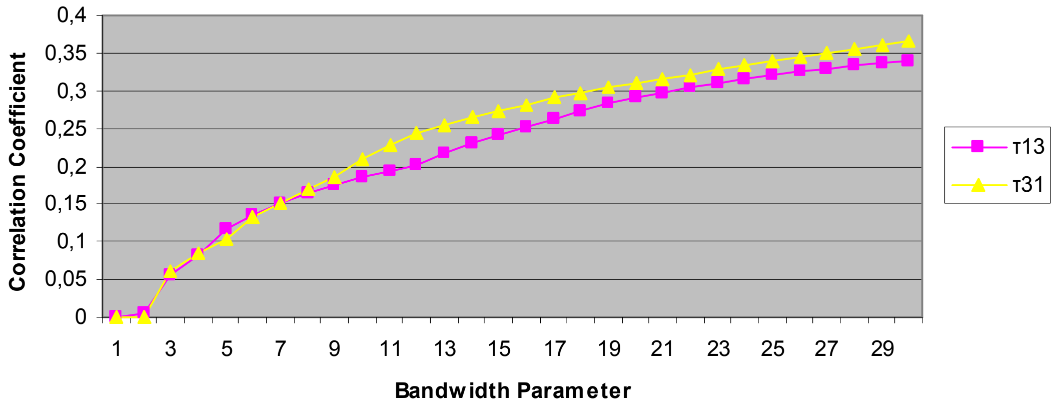

Figure 2: Estimated correlation coefficients: India output growth and India Yield (IN10Y-IN3M)

For S_T=3, the estimate of t_{31} is equal to 0.06, for the Bartlett kernel. Beyond this point, $\hat{t}_{31}$ increases at a decreasing rate, with a value of $\hat{t}_{31}$ =0.22 for S_T=11 and reaching its maximum value of 0.36 for S_T=30. What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 11 months, although weaker feedbacks may last up to 30 months. These results show, with regards to the India yield spread (IN10Y-IN3M) and the future India output growth that their relationship is positive, as expected. Our evidence suggests that the major effect on the future India output growth is within the first 11 months, although weaker effects may also last up to three years. This basically implies that the yield spread is a useful predictor of India output up to a three-year horizon. The relationship between the India output growth and the future yield spread is found to be significantly different from zero. The estimate of t_{13} follows an increasing rate when $S_T \in$ [1, 9] with $\hat{t}_{13}$ =0.17 when S_T =9 and reaches its maximum value of 0.34 for S_T =30. So, our evidence here suggests a positive relationship, with major effects reaching the first nine months, but weaker effects may last for up to 30 months as well.

The results from the Granger causality test for the India industrial production and the yield spread (IN10Y-IN3M) are:

GRANGER CAUSALITY	CHI-SQ	DF
$S3 \nrightarrow IP$	0.431596 [0.5112]	1
$IP \nrightarrow S3$	0.133703 [0.7146]	1

Real M1 (RM1) has an estimated temporal correlation coefficient t_{91} that increases at a decreasing rate as we can see from figure 3. For S_T =12, the estimate of t_{91} is equal to 0.27 for the Bartlett kernel. Beyond this point $\hat{t}_{91}$ increases at a decreasing rate and reaching its maximum value of 0.38 for S_T =30. What the evidence here suggests is that the major feedbacks from India real M1 to output growth occur within the first twelve months with a maximum feedback of around 30 months.

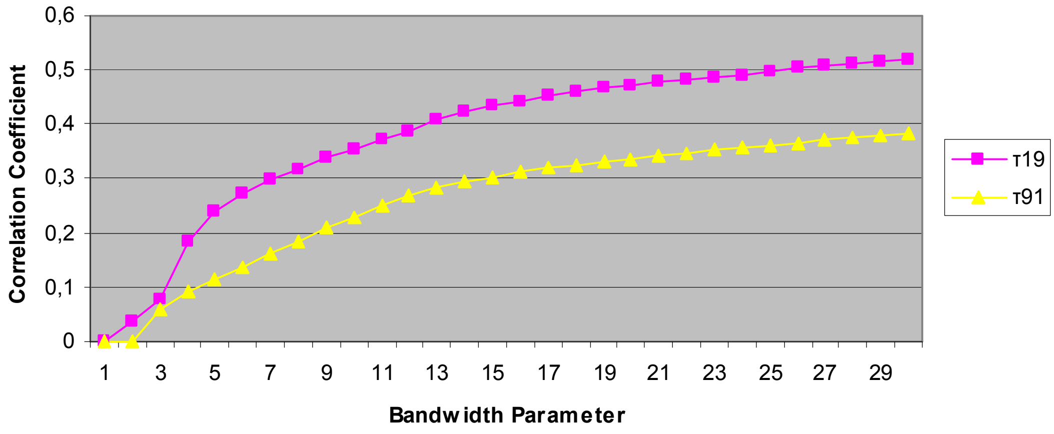

Figure 3: Estimated correlation coefficients: India output growth and India real money (M1)

The relationship between the India output growth and the future real M1 is found to be significantly different from zero. The estimate of t_{19} follows an increasing rate when $S_T \in$ [1, 9] with $\hat{t}_{19}$ =0.34 when S_T =9 and reaches its maximum value of 0.51 for S_T =30. So, our evidence here suggests a strong positive relationship and between the India output growth and the future real

M1, with major effects reaching the first nine months, but weaker effects may last for up to 30 months as well.

The results from the Granger causality test for the India industrial production and the real M1 (RM1) are:

GRANGER CAUSALITY	CHI-SQ	DF
RM1 $\longrightarrow$ IP	23.49853 [0.0090]	10
IP $\not\longrightarrow$ RM1	10.78001 [0.3749]	10

In the case of the spread (IN10Y-IN1M) the results do not differentiate at all and show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{41} increase as well. The estimates of the temporal correlation coefficient t_{14} are again positive and they also increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{41} again does not remain constant over the whole range of values of the bandwidth parameter S_T.

Figure 4 shows the results for the India yield spread (IN10Y-IN1M) and the India output growth.

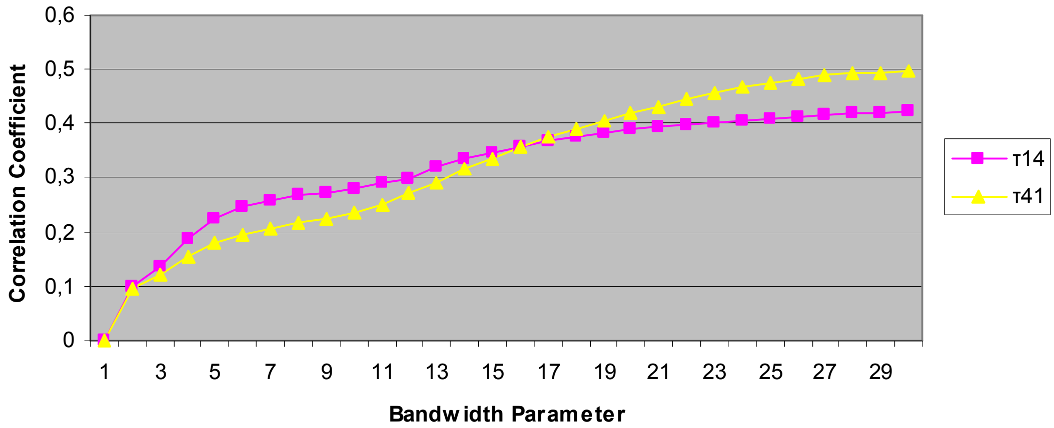

Figure 4: Estimated correlation coefficients: India output growth and India Yield (IN10Y-IN1M)

For S_T=3, the estimate of t_{41} is equal to 0.12, for the Bartlett kernel. Beyond this point, $\hat{t}_{41}$ increases at a decreasing rate, with a value of $\hat{t}_{41}$ =0.19 for S_T=6 and reaching its maximum value of 0.49 for S_T=30. What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 6 months, although weaker feedbacks may last up to 30 months. What these results show, with regards to the India yield spread (IN10Y-IN1M) and the future India output growth is that their relationship is positive, as expected. The relationship between the India output growth and the future yield spread is found to be significantly different from zero. The estimate of t_{14} follows an increasing rate when $S_T \in$ [1, 6] with $\hat{t}_{14}$ =0.24 when S_T=6 and reaches its maximum value of 0.42 for S_T=30. So, our evidence here suggests a strong positive relationship, with major effects

reaching the first 6 months, but weaker effects may last for up to 30 months as well.
The results from the Granger causality test for the India industrial production and the yield spread (IN10Y-IN1M) are:

GRANGER CAUSALITY	CHI-SQ	DF
S1 $\not\longrightarrow$ IP	3.801014 [0.1495]	2
IP $\not\longrightarrow$ S1	2.643972 [0.2666]	2

Real M2 (RM2) show similar pattern with RM1 and the relationship is as strong as RM1. This is confirmed by our results, shown in figure 5, which show that real M2 (RM2) has an estimated temporal correlation coefficient t_{101} that increases at a decreasing rate.

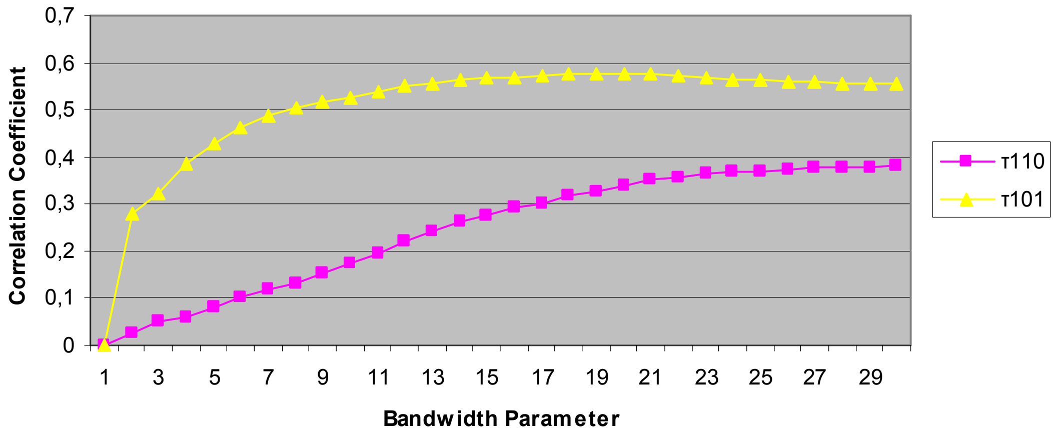

Figure 5: Estimated correlation coefficients: India output growth and India real money (M2)

For S_T=6, the estimate of t_{101} is equal to 0.46 for the Bartlett kernel. Beyond this point $\hat{t}_{101}$ increases at a decreasing rate and reaching its maximum value of 0.57 for S_T=20. What the evidence here suggests is that the major feedbacks from India real M2 to output growth occur within the first six months with a maximum feedback of around 20 months. The relationship between the India output growth and the future real M2 is found to be significantly different from zero. The estimate of t_{110} follows an increasing rate when $S_T \in$ [1, 7] with $\hat{t}_{110}$ =0.11 when S_T=7 and reaches its maximum value of 0.38 for S_T=30. So, our evidence here suggests a strong positive relationship between the India output growth and the future real M2, with major effects reaching the first 7 months, but weaker effects may last for up to 30 months as well.
The results from the Granger causality test for the India industrial production and the real M2 (RM2) are:

GRANGER CAUSALITY	CHI-SQ	DF
RM2 $\longrightarrow$ IP	23.93812 [0.0062]	9
IP $\not\longrightarrow$ RM2	9.867952 [0.2441]	9

The various interest rates (10–year government bond, 1-month, 3-month and 1-year interest rates) which we examined have results that are similar with that of the other variables.
Figure 6 shows the results for the India 10–year government bond and the India output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{51} increase as well. The estimates of the temporal correlation coefficient t_{15} are again positive and they also increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{51} does not remain constant over the whole range of values of the bandwidth parameter S_T.

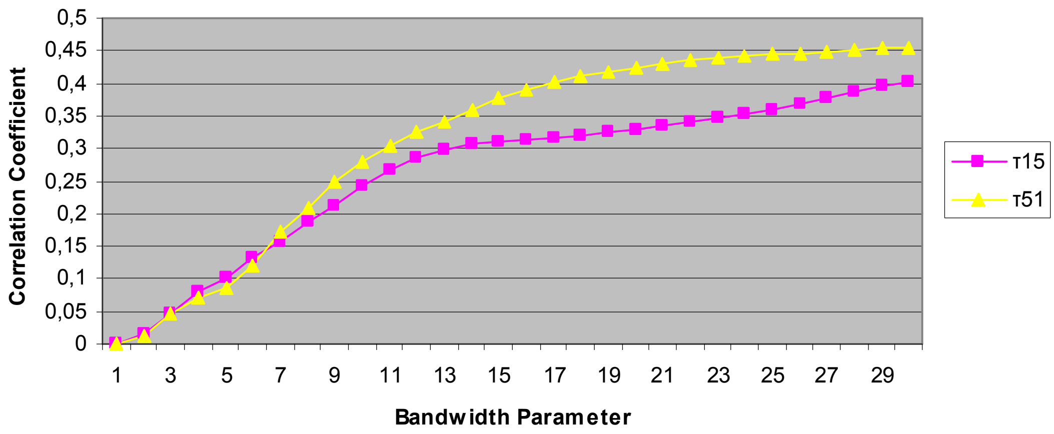

Figure 6: Estimated correlation coefficients: India output growth and India 10–year government bond

For S_T=11, the estimate of t_{51} is equal to 0.30, for the Bartlett kernel. Beyond this point, $\hat{t}_{51}$ increases at a decreasing rate, and reaching its maximum value of 0.45 for S_T=30. What the evidence here suggests is that the major feedbacks from the 10–year government bond to output growth occur approximately within the first 11 months, although weaker feedbacks may last up to 30 months. What the results showed, for the India 10–year government bond and the future India output growth is that their relationship is strong.
Our evidence suggests that the major effect on the future India output growth is within the first eleven months, although weaker effects may also last up to three years. The relationship between the India output growth and the future 10–year government bond is found to be significantly different from zero and as strong as that of the opposite direction. The estimate of t_{15} follows an increasing rate when $S_T \in$ [1, 11] with $\hat{t}_{15}$ =0.26 when S_T=11 and reaches its maximum value of 0.40 for S_T=30. So, our evidence here suggests a strong positive relationship between the India output growth and the future 10–year government bond, with major effects reaching the first 11 months, but weaker effects may last for up to 30 months as well.

The results from the Granger causality test for the India industrial production and the 10-year government bond are:

GRANGER CAUSALITY	CHI-SQ	DF
10Y $\nrightarrow$ IP	1.410109 [0.2350]	1
IP $\longrightarrow$ 10Y	6.492393 [0.0108]	1

Familiar results are exported and for the other interest rates. Figures 7, 8, and 9 also show the correlation coefficients for the 3-month, 1-month and 1-year India interest rates with respect with the India output growth.

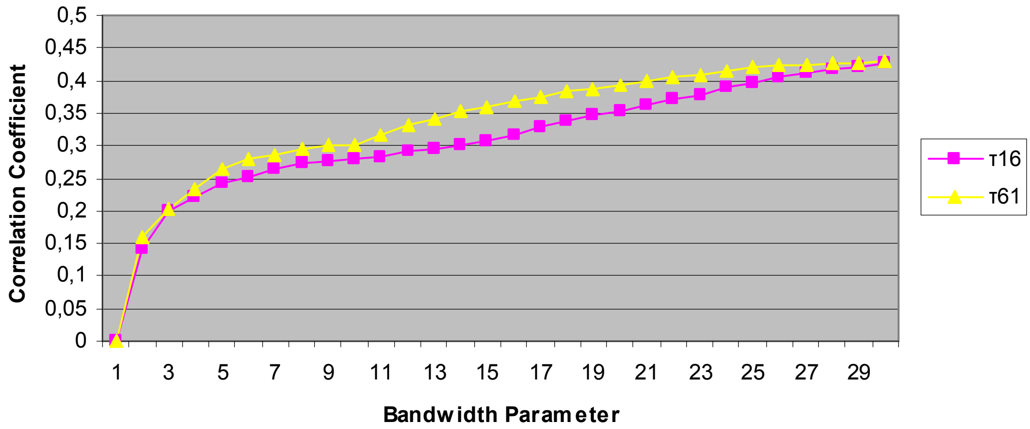

Figure 7: Estimated correlation coefficients: India output growth and India 1–month interest rate

The results from the Granger causality test for the India industrial production and the 1-month interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
1M $\longrightarrow$ IP	22.18808 [0.0104]	8
IP $\nrightarrow$ 1M	21.10000 [0.9361]	8

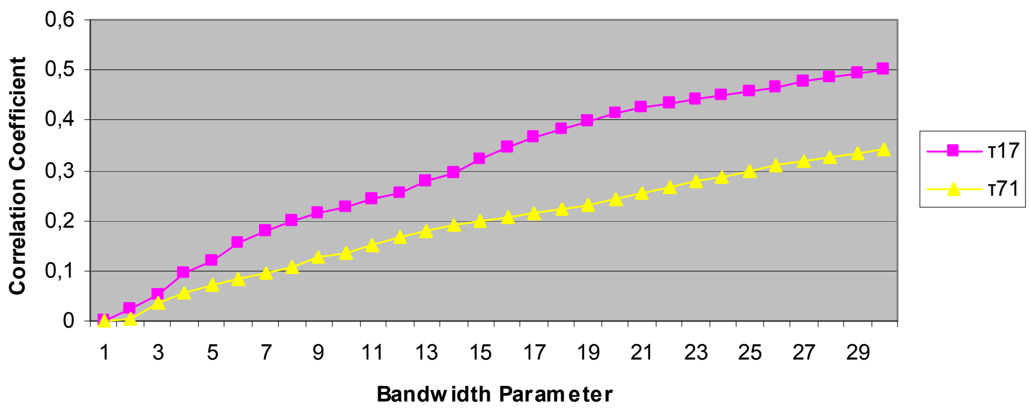

Figure 8: Estimated correlation coefficients: India output growth and India 3–month interest rate

The results from the Granger causality test for the India industrial production and the 3-month interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
$3M \longrightarrow IP$	4.086957 [0.0432]	1
$IP \nrightarrow 3M$	2.103360 [0.1470]	1

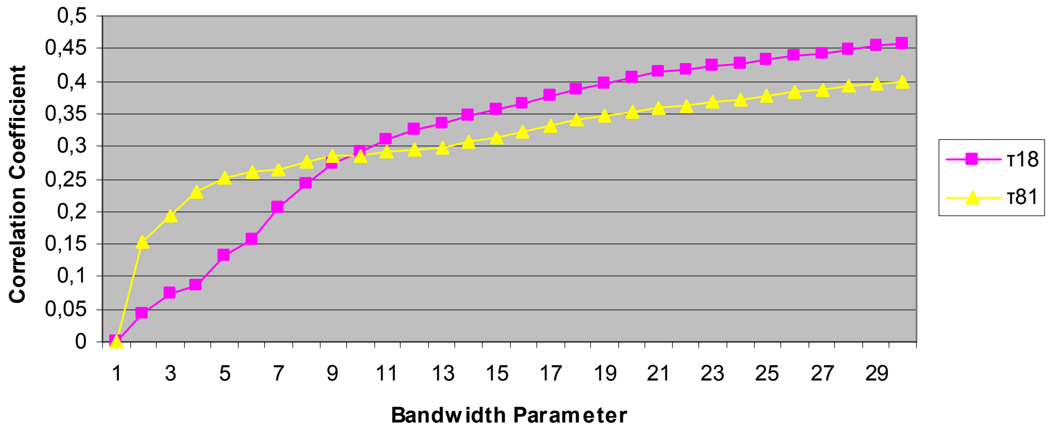

Figure 9: Estimated correlation coefficients: India output growth and India 1–year interest rate

The results from the Granger causality test for the India industrial production and the 1-year interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
$1Y \nrightarrow IP$	1.223118 [0.2687]	1
$IP \longrightarrow 1Y$ (10%)	3.621319 [0.0570]	1

4. B.3. Malaysian financial variables and output growth

Table B3 presents the estimated temporal correlation for all the financial variables that were examined in this paper. Among the various groups of the Malaysia financial variables examined, the Kuala Lumpur se composite index, the Malaysia yield (MY10Y-MY3M), and real M1 (RM1) were found to exhibit the strongest temporal correlations (t_{21}) with respect to Malaysia output growth.
Our estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to the value of the current financial variable at hand ($u_{1,t-i} \rightarrow u_{2,t}$), and the temporal correlation coefficient t_{21}, which describes feedbacks from past values of the financial variable at hand to current output growth (i.e., in the opposite direction ($u_{2,t-i} \rightarrow u_{1,t}$), for alternative values of the bandwidth parameter S_T are reported in figures 1-9

for the Bartlett kernel. The bandwidth parameter takes values in the interval [1, 36] by steps of one.

Figure 1 shows, for the Malaysia stock price index and the Malaysia output growth, that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{21}, that describes feedbacks from past real stock returns to current output growth ($u_{2,t-i} \rightarrow u_{1,t}$), increase as well. Similarly the estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to current real stock returns ($u_{1,t-i} \rightarrow u_{2,t}$), are positive and increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{21} does not remain constant over the whole range of values of the bandwidth parameter S_T. When $S_T \in$ [1, 10], $\hat{t}_{21}$ increases at an increasing rate and for S_T=10, the estimate of t_{21} is equal to 0.34 for the Bartlett kernel.

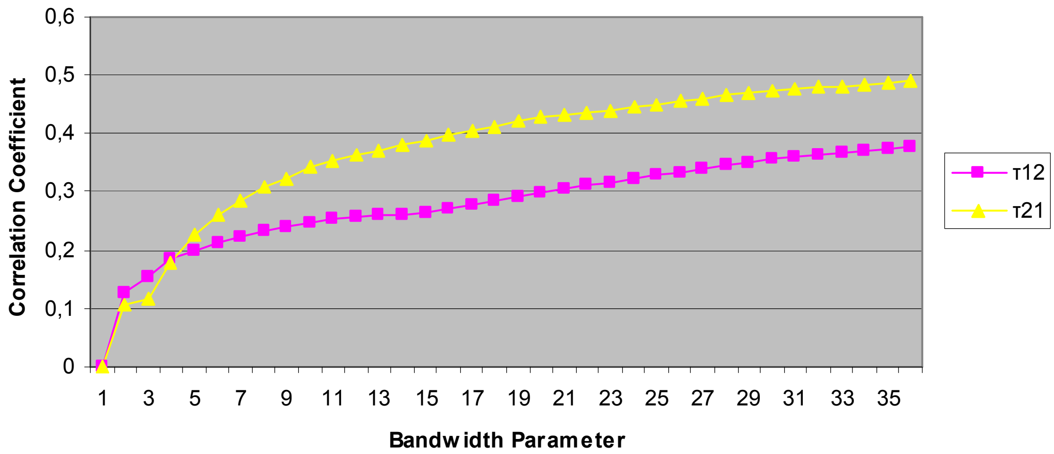

Figure 1: Estimated correlation coefficients: Malaysia output growth and returns from the Malaysia Stock price index

Beyond this point, $\hat{t}_{21}$ increases at a decreasing rate thus reaching its maximum value of 0.48 for S_T=36. What the evidence here suggests is that the major feedbacks, from past stock price changes to output growth, occur within the first 10 months, with a maximum feedback of around 36 months. The relationship between past Malaysia output growth and stock price changes is found to be significantly different from zero. The estimate of t_{12} follows a increasing rate when $S_T \in$ [1, 6] with $\hat{t}_{12}$ =0.21 when S_T=6 and reaches its maximum value of 0.38 for S_T=36.

What our results show is that there is a strong positive relationship (temporal correlation) between past stock price changes and current Malaysia output growth, as expected. Basically, this implies that, and for the Malaysia, stock prices are useful predictors of output for a horizon of up to 36 months.

The results from the Granger causality test for the Malaysia industrial production and the stock index are:

GRANGER CAUSALITY	CHI-SQ	DF
IND $\longrightarrow$ IP	86.57763 [0.0311]	24
IP $\nrightarrow$ IND	20.43439 [0.2237]	24

Figure 2 shows the results for the Malaysia yield spread (MY10Y-MY3M) and the Malaysia output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{31} increase as well. The estimates of the temporal correlation coefficient t_{13} are again positive and they also increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{31} does not remain constant over the whole range of values of the bandwidth parameter S_T.

For S_T=3, the estimate of t_{31} is equal to 0.09, for the Bartlett kernel. Beyond this point, $\hat{t}_{31}$ increases at a decreasing rate, with a value of $\hat{t}_{31}$=0.25 for S_T=9 and reaching its maximum value of 0.42 for S_T=36. What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 9 months, although weaker feedbacks may last up to 36 months.

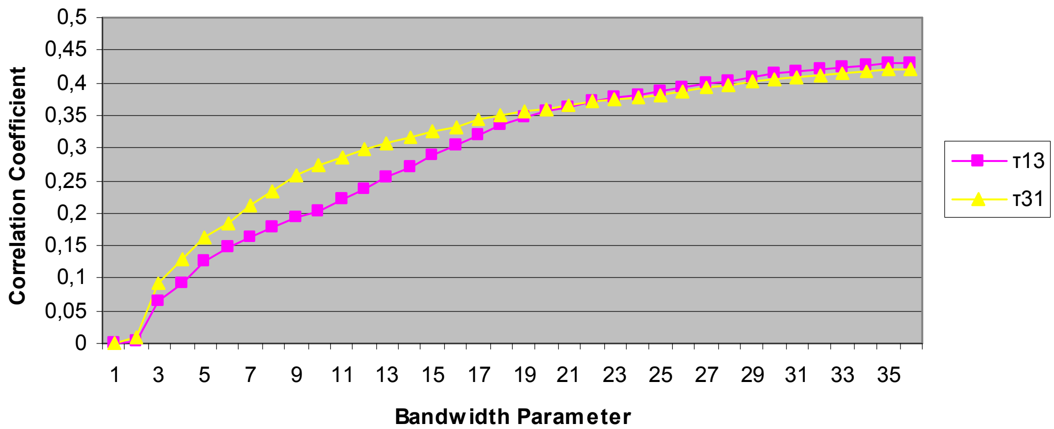

Figure 2: Estimated correlation coefficients: Malaysia output growth and Malaysia Yield (MY10Y-MY3M)

These results show, with regards to the Malaysia yield spread (MY10Y-MY3M) and the future Malaysia output growth that their relationship is positive, as expected. Our evidence suggests that the major effect on the future Malaysia output growth is within the first 9 months, although weaker effects may also last up to three years. This basically implies that the yield spread is a useful predictor of Malaysia output up to a three-year horizon. The relationship between the Malaysia output growth and the future yield spread is found to be significantly different from zero. The estimate of t_{13} follows an increasing rate when $S_T \in$ [1, 6] with $\hat{t}_{13}$=0.15 when S_T=6 and reaches its

maximum value of 0.43 for S_T=36. So, our evidence here suggests a positive relationship, with major effects reaching the first six months, but weaker effects may last for up to 36 months as well.
The results from the Granger causality test for the Malaysia industrial production and the yield spread (MY10Y-MY3M) are:

GRANGER CAUSALITY	CHI-SQ	DF
S3 $\longrightarrow$ IP (10%)	58.27572 [0.1000]	23
IP $\not\longrightarrow$ S3	28.11112 [0.8375]	23

Real M1 (RM1) has an estimated temporal correlation coefficient t_{91} that increases at a decreasing rate as we can see from figure 3. For S_T=9, the estimate of t_{91} is equal to 0.28 for the Bartlett kernel. Beyond this point $\hat{t}_{91}$ increases at a decreasing rate and reaching its maximum value of 0.44 for S_T=36.

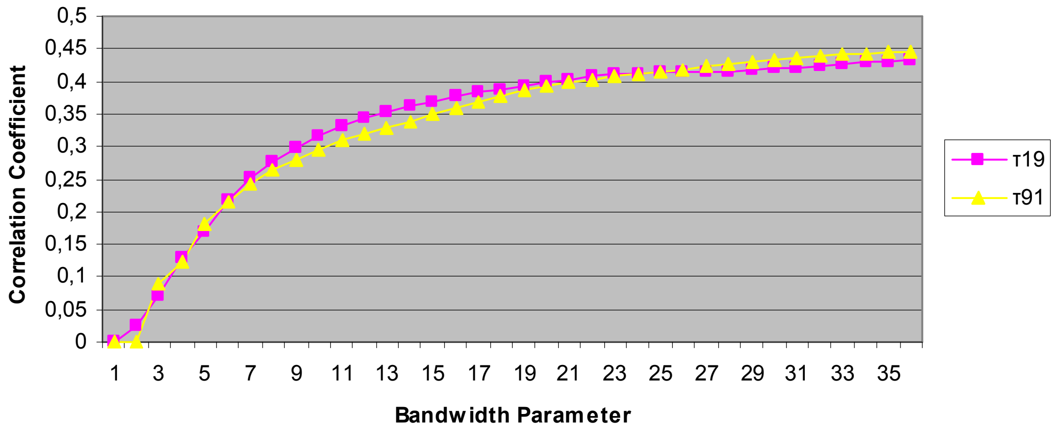

Figure 3: Estimated correlation coefficients: Malaysia output growth and Malaysia real money (M1)

What the evidence here suggests is that the major feedbacks from Malaysia real M1 to output growth occur within the first nine months with a maximum feedback of around 36 months.
The relationship between the Malaysia output growth and the future real M1 is found to be significantly different from zero. The estimate of t_{19} follows an increasing rate when $S_T \in$ [1, 9] with $\hat{t}_{19}$=0.29 when S_T=9 and reaches its maximum value of 0.43 for S_T=36. So, our evidence here suggests a strong positive relationship and between the Malaysia output growth and the future real M1, with major effects reaching the first nine months, but weaker effects may last for up to 36 months as well.
The results from the Granger causality test for the Malaysia industrial production and the real M1 (RM1) are:

GRANGER CAUSALITY	CHI-SQ	DF
RM1 $\longrightarrow$ IP	25.38743 [0.0027]	13
IP $\longrightarrow$ RM1	56.22685 [0.0003]	13

In the case of the spread (MY10Y-MY1M) the results do not differentiate at all and show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{41} increase as well. The estimates of the temporal correlation coefficient t_{14} are again positive and they also increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{41} again does not remain constant over the whole range of values of the bandwidth parameter S_T.

Figure 4 shows the results for the Malaysia yield spread (MY10Y-MY1M) and the Malaysia output growth.

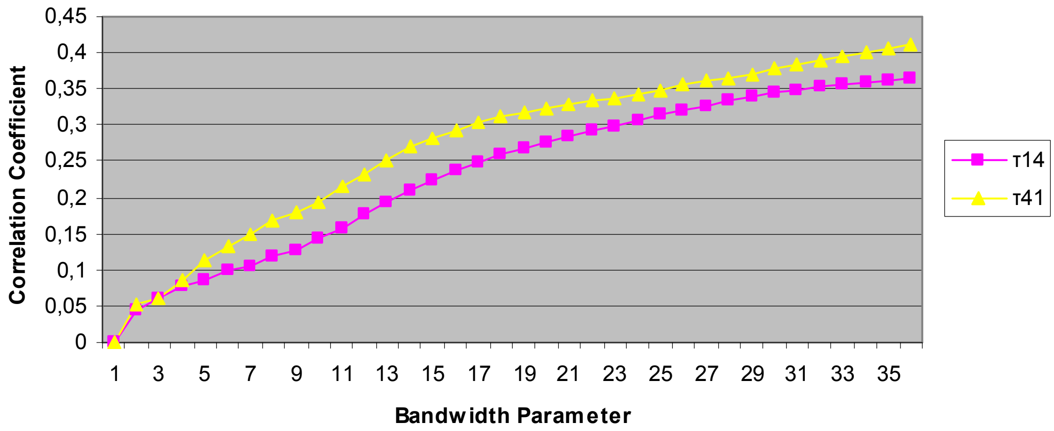

Figure 4: Estimated correlation coefficients: Malaysia output growth and Malaysia Yield (MY10Y-MY1M)

For S_T=2, the estimate of t_{41} is equal to 0.05, for the Bartlett kernel. Beyond this point, $\hat{t}_{41}$ increases at a decreasing rate, with a value of $\hat{t}_{41}$=0.18 for S_T=9 and reaching its maximum value of 0.41 for S_T=36. What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 9 months, although weaker feedbacks may last up to 36 months. What these results show, with regards to the Malaysia yield spread (MY10Y-MY1M) and the future Malaysia output growth is that their relationship is positive, as expected. The relationship between the Malaysia output growth and the future yield spread is found to be significantly different from zero. The estimate of t_{14} follows an increasing rate when $S_T \in$ [1, 11] with $\hat{t}_{14}$=0.16 when S_T=11 and reaches its maximum value of 0.36 for S_T=36. So, our evidence here suggests a strong positive relationship, with major effects reaching the first 11 months, but weaker effects may last for up to 36 months as well.

The results from the Granger causality test for the Malaysia industrial production and the yield spread (MY10Y-MY1M) are:

GRANGER CAUSALITY	CHI-SQ	DF
$S1 \nrightarrow IP$	113.2650 [0.4899]	16
$IP \nrightarrow S1$	42.20245 [0.1335]	16

Real M2 (RM2) show similar pattern with RM1 and the relationship is as strong as RM1. This is confirmed by our results, shown in figure 5, which show that real M2 (RM2) has an estimated temporal correlation coefficient t_{101} that increases at a decreasing rate.

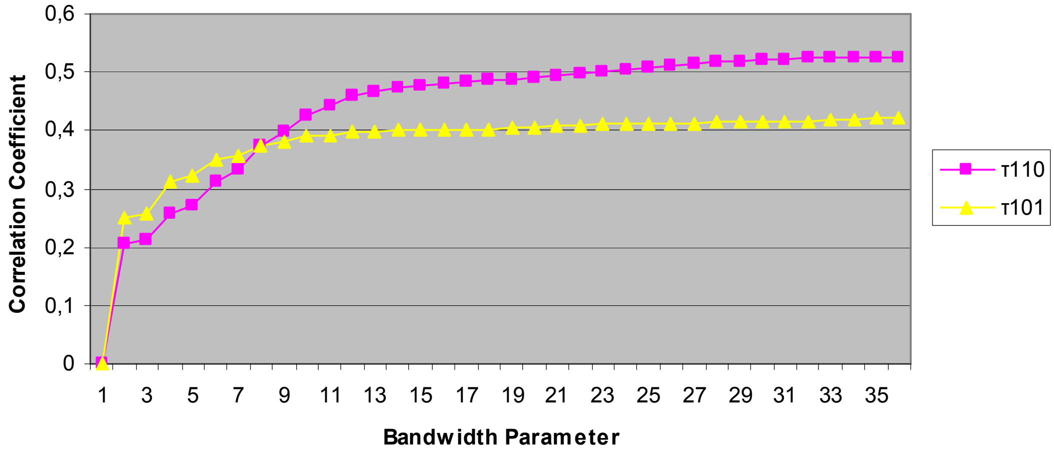

Figure 5: Estimated correlation coefficients: Malaysia output growth and Malaysia real money (M2)

For S_T=6, the estimate of t_{101} is equal to 0.35 for the Bartlett kernel. Beyond this point $\hat{t}_{101}$ increases at a decreasing rate and reaching its maximum value of 0.42 for S_T=36. What the evidence here suggests is that the major feedbacks from Malaysia real M2 to output growth occur within the first six months with a maximum feedback of around 36 months. The relationship between the Malaysia output growth and the future real M2 is found to be significantly different from zero. The estimate of t_{110} follows an increasing rate when $S_T \in$ [1, 11] with $\hat{t}_{110}$ =0.44 when S_T=11 and reaches its maximum value of 0.52 for S_T=35. So, our evidence here suggests a strong positive relationship between the Malaysia output growth and the future real M2, with major effects reaching the first 11 months, but weaker effects may last for up to 35 months as well.
The results from the Granger causality test for the Malaysia industrial production and the real M2 (RM2) are:

GRANGER CAUSALITY	CHI-SQ	DF
RM2 $\longrightarrow$ IP	42.35895 [0.0318]	13
IP $\longrightarrow$ RM2 (10%)	23.22702 [0.0504]	13

The various interest rates (10–year government bond, 1-month, 3-month and 1-year interest rates) which we examined have results that are similar with that of the other variables.
Figure 6 shows the results for the Malaysia 10–year government bond and the Malaysia output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{51} increase as well. The estimates of the temporal correlation coefficient t_{15} are again positive and they also increase as the bandwidth parameter increases too.

The rate of growth of the estimates of t_{51} does not remain constant over the whole range of values of the bandwidth parameter S_T.

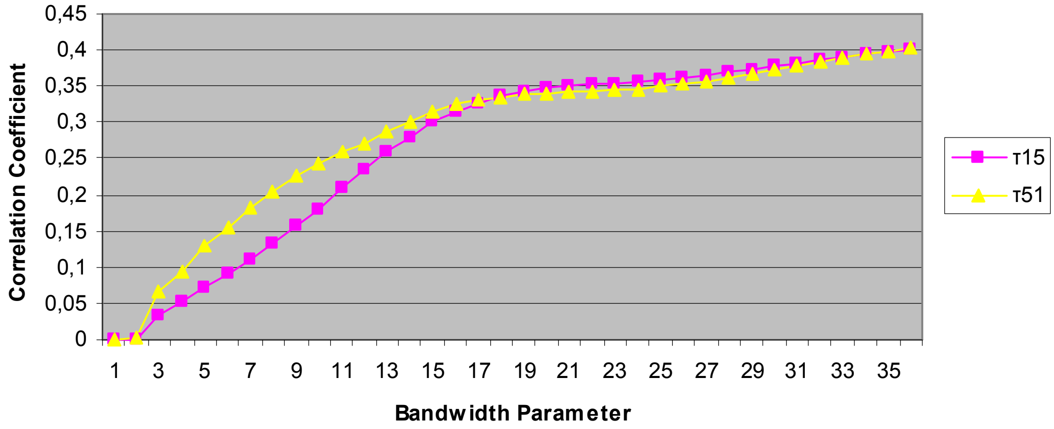

Figure 6: Estimated correlation coefficients: Malaysia output growth and Malaysia 10–year government bond

For S_T=8, the estimate of t_{51} is equal to 0.20, for the Bartlett kernel. Beyond this point, $\hat{t}_{51}$ increases at a decreasing rate, and reaching its maximum value of 0.40 for S_T=36. What the evidence here suggests is that the major feedbacks from the 10–year government bond to output growth occur approximately within the first 8 months, although weaker feedbacks may last up to 36 months. What the results showed, for the Malaysia 10–year government bond and the future Malaysia output growth is that their relationship is strong.

Our evidence suggests that the major effect on the future Malaysia output growth is within the first eight months, although weaker effects may also last up to three years. The relationship between the Malaysia output growth and the future 10–year government bond is found to be significantly different from zero and as strong as that of the opposite direction. The estimate of t_{15} follows an increasing rate when $S_T \in$ [1, 13] with $\hat{t}_{15}$ =0.26 when S_T=13 and reaches its maximum value of 0.40 for S_T=36. So, our evidence here suggests a strong positive relationship between the Malaysia output growth and the future 10–year government bond, with major effects reaching the first 13 months, but weaker effects may last for up to 36 months as well.

The results from the Granger causality test for the Malaysia industrial production and the 10-year government bond are:

GRANGER CAUSALITY	CHI-SQ	DF
$10Y \nrightarrow IP$	6.723278 [0.8493]	12
$IP \nrightarrow 10Y$	19.08178 [0.2338]	12

Familiar results are exported and for the other interest rates. Figures 7, 8, and 9 also show the correlation coefficients for the 3-month, 1-month and 1-year Malaysia interest rates with respect with the Malaysia output growth.

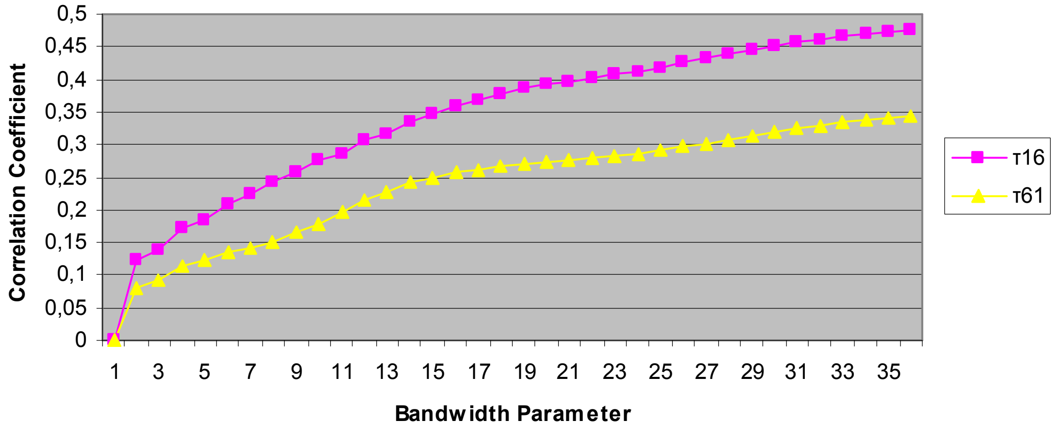

Figure 7: Estimated correlation coefficients: Malaysia output growth and Malaysia 1–month interest rate

The results from the Granger causality test for the Malaysia industrial production and the 1-month interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
1M $\nrightarrow$ IP	18.85375 [0.4563]	15
IP $\longrightarrow$ 1M (10%)	39.94719 [0.0839]	15

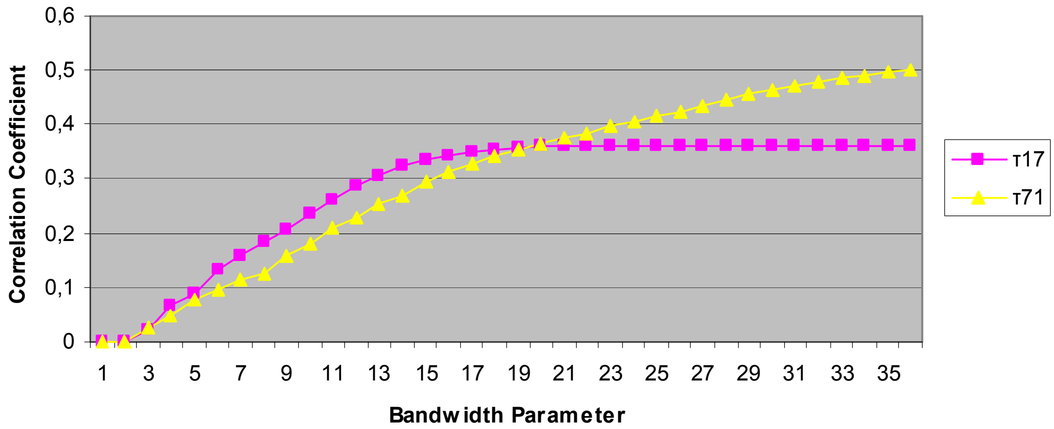

Figure 8: Estimated correlation coefficients: Malaysia output growth and Malaysia 3–month interest rate

The results from the Granger causality test for the Malaysia industrial production and the 3-month interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
3M $\longrightarrow$ IP	50.20797 [0.0072]	17
IP $\nrightarrow$ 3M	20.21212 [0.4005]	17

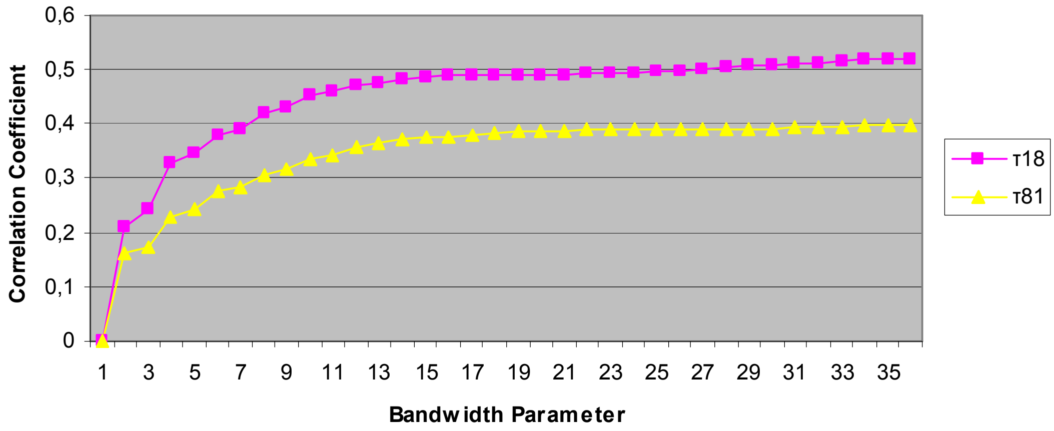

Figure 9: Estimated correlation coefficients: Malaysia output growth and Malaysia 1–year interest rate

The results from the Granger causality test for the Malaysia industrial production and the 1-year interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
1Y $\nrightarrow$ IP	17.30163 [0.4039]	16
IP $\longrightarrow$ 1Y (10%)	102.7893 [0.0531]	16

4. B.4. Taiwan financial variables and output growth

Table B4 presents the estimated temporal correlation for all the financial variables that were examined in this paper. Among the various groups of the Taiwan financial variables examined, the Taiwan stock exchange, the Taiwan yield (TW10Y-TW3M), and real M1 (RM1) were found to exhibit the strongest temporal correlations (t_{21}) with respect to Taiwan output growth.

Our estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to the value of the current financial variable at hand ($u_{1,t-i} \rightarrow u_{2,t}$), and the temporal correlation coefficient t_{21}, which describes feedbacks from past values of the financial variable at hand to current output growth (i.e., in the opposite direction ($u_{2,t-i} \rightarrow u_{1,t}$), for alternative values of the bandwidth parameter S_T are reported in figures 1-7 for the Bartlett kernel. The bandwidth parameter takes values in the interval [1, 36] by steps of one.

Figure 1 shows, for the Taiwan stock price index and the Taiwan output growth, that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{21}, that describes feedbacks from past real stock returns to current output growth ($u_{2,t-i} \rightarrow u_{1,t}$), increase as well. Similarly the estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to current real stock returns

($u_{1,t-i} \rightarrow u_{2,t}$), are positive and increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{21} does not remain constant over the whole range of values of the bandwidth parameter S_T. When $S_T \in$ [1, 8], $\hat{t}_{21}$ increases at an increasing rate and for S_T=8, the estimate of t_{21} is equal to 0.38 for the Bartlett kernel.

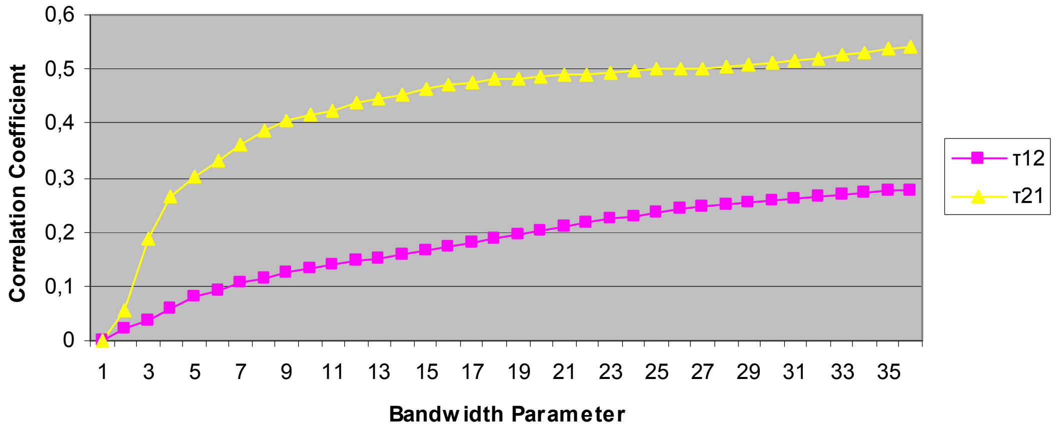

Figure 1: Estimated correlation coefficients: Taiwan output growth and returns from the Taiwan Stock price index

Beyond this point, $\hat{t}_{21}$ increases at a decreasing rate thus reaching its maximum value of 0.54 for S_T=36. What the evidence here suggests is that the major feedbacks, from past stock price changes to output growth, occur within the first 8 months, with a maximum feedback of around 36 months. The relationship between past Taiwan output growth and stock price changes is found to be significantly different from zero. The estimate of t_{12} follows a increasing rate when $S_T \in$ [1, 7] with $\hat{t}_{12}$ =0.10 when S_T=7 and reaches its maximum value of 0.27 for S_T=36.

What our results show is that there is a strong positive relationship (temporal correlation) between past stock price changes and current Taiwan output growth, as expected. Basically, this implies that, and for the Taiwan, stock prices are useful predictors of output for a horizon of up to 36 months.

The results from the Granger causality test for the Taiwan industrial production and the stock index are:

GRANGER CAUSALITY	CHI-SQ	DF
IND $\longrightarrow$ IP	76.30967 [0.0106]	13
IP $\not\longrightarrow$ IND	30.63972 [0.2641]	13

Figure 2 shows the results for the Taiwan yield spread (TW10Y-TW3M) and the Taiwan output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{31} increase as well. The estimates of the temporal correlation coefficient t_{13} are again positive and they also increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{31} does not remain constant over the whole range of values of the bandwidth parameter S_T.

For S_T=3, the estimate of t_{31} is equal to 0.044, for the Bartlett kernel. Beyond this point, $\hat{t}_{31}$ increases at a decreasing rate, with a value of $\hat{t}_{31}$=0.19 for S_T=9 and reaching its maximum value of 0.34 for S_T=36. What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 9 months, although weaker feedbacks may last up to 36 months.

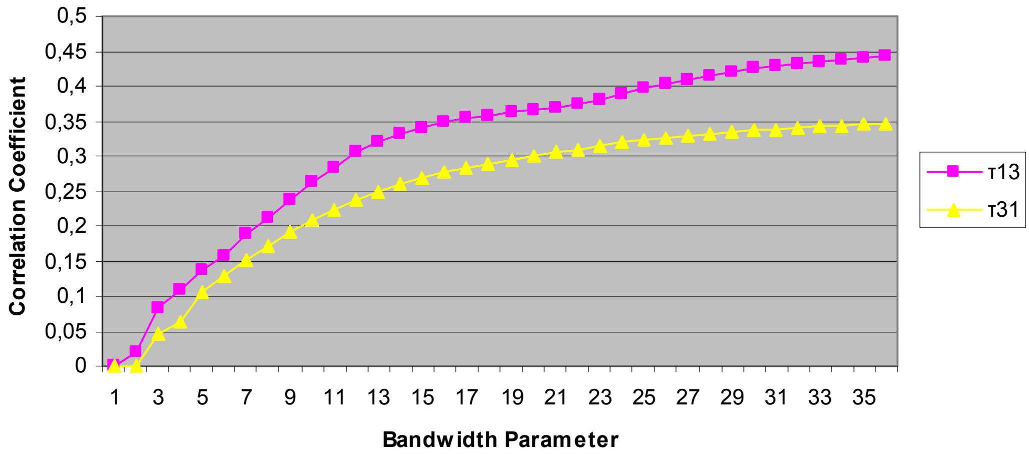

Figure 2: Estimated correlation coefficients: Taiwan output growth and Taiwan Yield (TW10Y-TW3M)

These results show, with regards to the Taiwan yield spread (TW10Y-TW3M) and the future Taiwan output growth that their relationship is positive, as expected. Our evidence suggests that the major effect on the future Taiwan output growth is within the first 9 months, although weaker effects may also last up to three years. This basically implies that the yield spread is a useful predictor of Taiwan output up to a three-year horizon. The relationship between the Taiwan output growth and the future yield spread is found to be significantly different from zero. The estimate of t_{13} follows an increasing rate when $S_T \in$ [1, 11] with $\hat{t}_{13}$=0.28 when S_T=11 and reaches its maximum value of 0.44 for S_T=36. So, our evidence here suggests a strong positive relation-ship, with major effects reaching the first eleven months, but weaker effects may last for up to 36 months as well.

The results from the Granger causality test for the Taiwan industrial production and the yield spread (TW10Y-TW3M) are:

GRANGER CAUSALITY	CHI-SQ	DF
S3 $\longrightarrow$ IP (10%)	31.47392 [0.0617]	15
IP $\not\longrightarrow$ S3	36.08423 [0.6100]	15

Real M1 (RM1) has an estimated temporal correlation coefficient t_{81} that increases at a decreasing rate as we can see from figure 3. For S_T=8, the estimate of t_{81} is equal to 0.10 for the Bartlett kernel. Beyond this point $\hat{t}_{81}$ increases at a decreasing rate and reaching its maximum value of 0.18 for S_T=36.

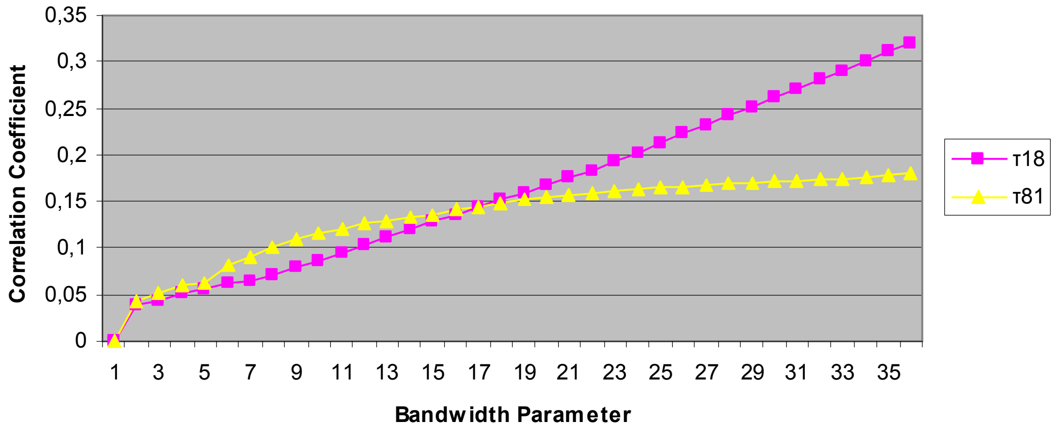

Figure 3: Estimated correlation coefficients: Taiwan output growth and Taiwan real money (M1)

What the evidence here suggests is that the major feedbacks from Taiwan real M1 to output growth occur within the first eight months with a maximum feedback of around 36 months.

The relationship between the Taiwan output growth and the future real M1 is found to be significantly different from zero. The estimate of t_{18} follows an increasing rate when $S_T \in$ [1, 4] with $\hat{t}_{18}$=0.05 when S_T=4 and reaches its maximum value of 0.32 for S_T=36. So, our evidence here suggests a strong positive relationship and between the Taiwan output growth and the future real M1, with major effects reaching the first four months, but weaker effects may last for up to 36 months as well.

The results from the Granger causality test for the Taiwan industrial production and the real M1 (RM1) are:

GRANGER CAUSALITY	CHI-SQ	DF
RM1 $\longrightarrow$ IP	43.34082 [0.0000]	11
IP $\longrightarrow$ RM1	64.52347 [0.0000]	11

In the case of the spread (TW10Y-TW1M) the results do not differentiate at all and show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{41} increase as well. The estimates of the temporal correlation coefficient t_{14} are again positive and they also increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{41} again does not remain constant over the whole range of values of the bandwidth parameter S_T.

Figure 4 shows the results for the Taiwan yield spread (TW10Y-TW1M) and the Taiwan output growth.

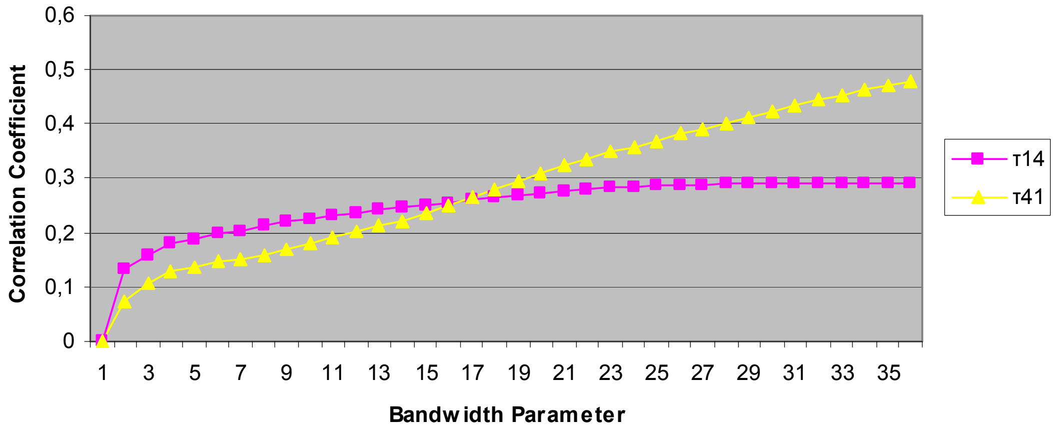

Figure 4: Estimated correlation coefficients: Taiwan output growth and Taiwan Yield (TW10Y-TW1M)

For S_T=2, the estimate of t_{41} is equal to 0.07, for the Bartlett kernel. Beyond this point, $\hat{t}_{41}$ increases at a decreasing rate, with a value of $\hat{t}_{41}$ =0.14 for S_T=6 and reaching its maximum value of 0.47 for S_T=36. What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 6 months, although weaker feedbacks may last up to 36 months. What these results show, with regards to the Taiwan yield spread (TW10Y-TW1M) and the future Taiwan output growth is that their relationship is positive, as expected. The relationship between the Taiwan output growth and the future yield spread is found to be significantly different from zero. The estimate of t_{14} follows an increasing rate when $S_T \in$ [1, 4] with $\hat{t}_{14}$ =0.18 when S_T=4 and reaches its maximum value of 0.29 for S_T=36. So, our evidence here suggests a strong positive relationship, with major effects reaching the first 4 months, but weaker effects may last for up to 36 months as well.

The results from the Granger causality test for the Taiwan industrial production and the yield spread (TW10Y-TW1M) are:

GRANGER CAUSALITY	CHI-SQ	DF
$S1 \not\longrightarrow IP$	32.51009 [0.7209]	38
$IP \longrightarrow S1$	101.1331 [0.0000]	38

The various interest rates (10–year government bond, 1-month and 3-month interest rates) which we examined have results that are similar with that of the other variables.

Figure 5 shows the results for the Taiwan 10–year government bond and the Taiwan output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{51} increase as well. The estimates of the temporal correlation coefficient t_{15} are again positive and they also increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{51} does not remain constant over the whole range of values of the bandwidth parameter S_T.

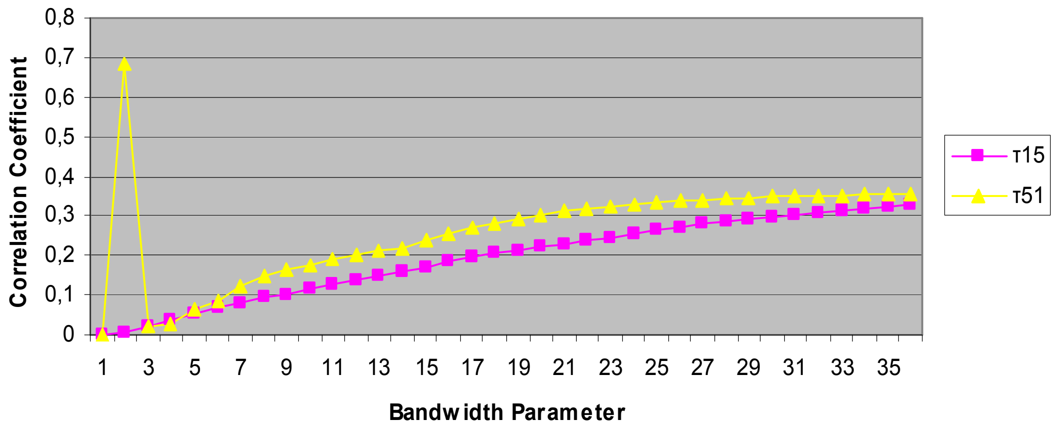

Figure 5: Estimated correlation coefficients: Taiwan output growth and Taiwan 10–year government bond

For S_T=8, the estimate of t_{51} is equal to 0.14, for the Bartlett kernel. Beyond this point, $\hat{t}_{51}$ increases at a decreasing rate, and reaching its maximum value of 0.35 for S_T=36.

What the evidence here suggests is that the major feedbacks from the 10–year government bond to output growth occur approximately within the first 8 months, although weaker feedbacks may last up to 36 months. What the results showed, for the Taiwan 10–year government bond and the future Taiwan output growth is that their relationship is strong.

Our evidence suggests that the major effect on the future Taiwan output growth is within the first eight months, although weaker effects may also last up to three years. The relationship between the Taiwan output growth and the future 10–year government bond is found to be significantly different from zero and as strong as that of the opposite direction. The estimate of t_{15} follows an increasing rate when $S_T \in$ [1, 9] with $\hat{t}_{15}$ =0.10 when S_T=9 and reaches its maximum value of 0.32 for S_T=36. So, our evidence here suggests a strong positive relationship between the Taiwan output growth and the future 10–year government bond, with major effects reaching the first 9 months, but weaker effects may last for up to 36 months as well.

The results from the Granger causality test for the Taiwan industrial production and the 10-year government bond are:

GRANGER CAUSALITY	CHI-SQ	DF
$10Y \not\rightarrow IP$	118.8425 [0.3660]	13
$IP \not\rightarrow 10Y$	26.87791 [0.9959]	13

Familiar results are exported and for the other interest rates. Figures 6 and 7 also show the correlation coefficients for the 3-month and 1-month Taiwan interest rates with respect with the Taiwan output growth.

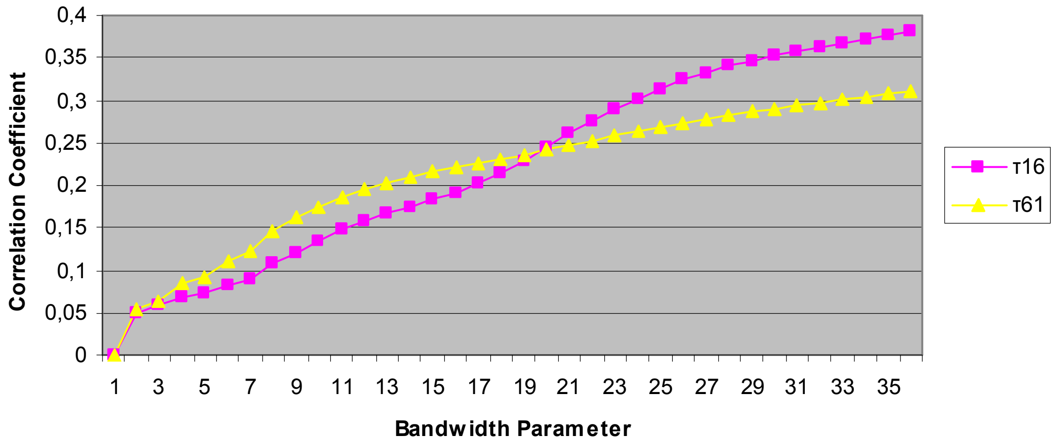

Figure 6: Estimated correlation coefficients: Taiwan output growth and Taiwan 1–month interest rate

The results from the Granger causality test for the Taiwan industrial production and the 1-month interest rate are

GRANGER CAUSALITY	CHI-SQ	DF
1M $\longrightarrow$ IP	77.08211 [0.0003]	39
IP $\longrightarrow$ 1M	165.6704 [0.0000]	39

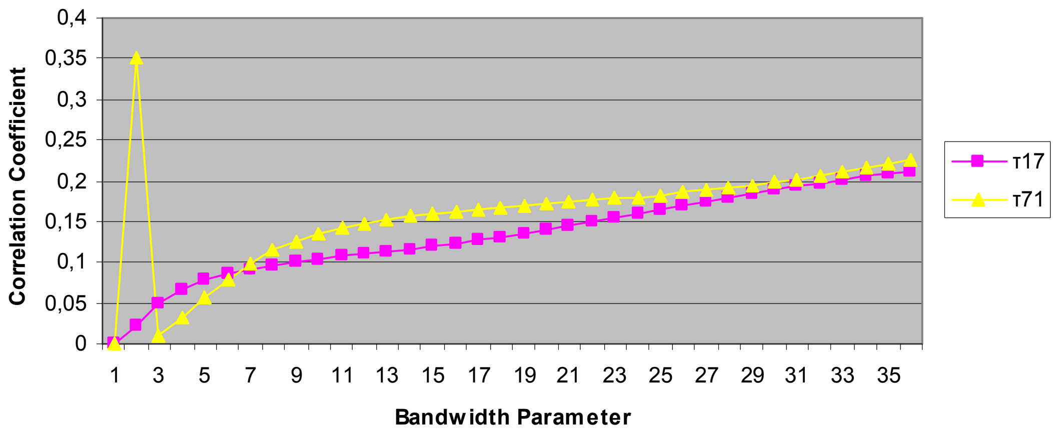

Figure 7: Estimated correlation coefficients: Taiwan output growth and Taiwan 3–month interest rate

The results from the Granger causality test for the Taiwan industrial production and the 3-month interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
3M $\not\longrightarrow$ IP	1071.020 [0.3641]	14
IP $\not\longrightarrow$ 3M	13.00932 [0.5577]	14

4. B.5. Portuguese financial variables and output growth

Table B5 presents the estimated temporal correlation for all the financial variables that were examined in this paper. Among the various groups of the Portugal financial variables examined, the PSI General Stock Price Index, the Portugal yield (PT10Y-PT3M), and real M1 (RM1) were found to exhibit the strongest temporal correlations (t_{21}) with respect to Portugal output growth.
Our estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to the value of the current financial variable at hand ($u_{1,t-i} \rightarrow u_{2,t}$), and the temporal correlation coefficient t_{21}, which describes feedbacks from past values of the financial variable at hand to current output growth (i.e., in the opposite direction ($u_{2,t-i} \rightarrow u_{1,t}$), for alternative values of the bandwidth parameter S_T are reported in figures 1-8 for the Bartlett kernel. The bandwidth parameter takes values in the interval [1, 36] by steps of one.
Figure 1 shows, for the Portugal stock price index and the Portugal output growth, that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{21}, that describes feedbacks from past real stock returns to current output growth ($u_{2,t-i} \rightarrow u_{1,t}$), increase as well. The estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to current real stock returns ($u_{1,t-i} \rightarrow u_{2,t}$), are mainly positive and remain close to zero for all values of the bandwidth parameter. The rate of growth of the estimates of t_{21} does not remain constant over the whole range of values of the bandwidth parameter S_T. When $S_T \in$ [1, 9], $\hat{t}_{21}$ increases at an increasing rate and for S_T=9, the estimate of t_{21} is equal to 0.034 for the Bartlett kernel.

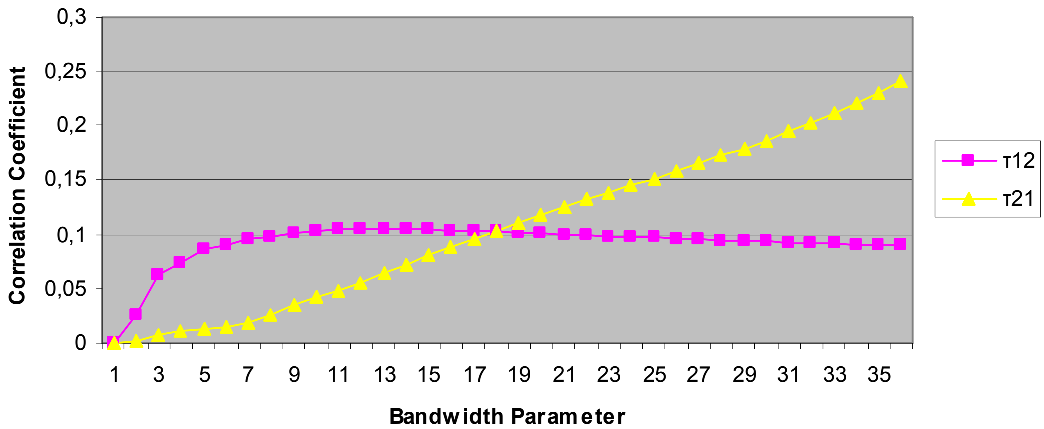

Figure 1: Estimated correlation coefficients: Portugal output growth and returns from the Portugal Stock price index

Beyond this point, $\hat{t}_{21}$ increases at a decreasing rate thus reaching its maximum value of 0.24 for S_T=36. What the evidence here suggests is that the major feedbacks, from past stock price changes to output growth, occur

within the first 9 months, with a maximum feedback of around 36 months. The relationship between past Portugal output growth and stock price changes is found to be not significantly different from zero.
What our results show is that there is a strong positive relationship (temporal correlation) between past stock price changes and current Portugal output growth, as expected. Basically, this implies that, and for the Portugal, stock prices are useful predictors of output for a horizon of up to 36 months.
The results from the Granger causality test for the Portugal industrial production and the stock index are:

GRANGER CAUSALITY	CHI-SQ	DF
$IND \nrightarrow IP$	2.865282 [0.2387]	2
$IP \nrightarrow IND$	1.939540 [0.3792]	2

Figure 2 shows the results for the Portugal yield spread (PT10Y-PT3M) and the Portugal output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{31} increase as well. The estimates of the temporal correlation coefficient t_{13} are positive and they also increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{31} does not remain constant over the whole range of values of the bandwidth parameter S_T.

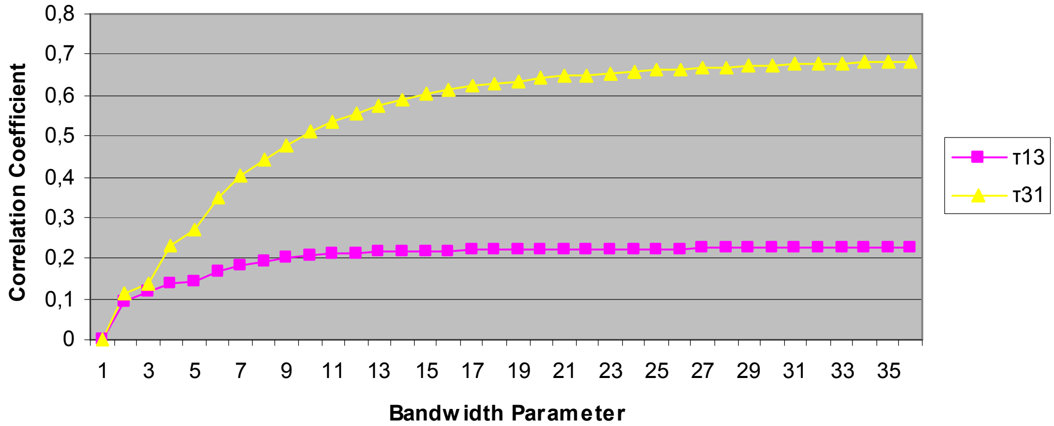

Figure 2: Estimated correlation coefficients: Portugal output growth and Portugal Yield (PT10Y-PT3M)

For S_T=2, the estimate of t_{31} is equal to 0.11, for the Bartlett kernel. Beyond this point, $\hat{t}_{31}$ increases at a decreasing rate, with a value of $\hat{t}_{31}$=0.47 for S_T=9 and reaching its maximum value of 0.68 for S_T=36. What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 9 months, although weaker feedbacks may last up to 36 months.
These results show, with regards to the Portugal yield spread (PT10Y-PT3M) and the future Portugal output growth that their relationship is positive, as expected. Our evidence suggests that the major effect on the future Portugal output growth is within the first 9 months, although weaker effects may also

last up to three years. This basically implies that the yield spread is a useful predictor of Portugal output up to a three-year horizon. The relationship between the Portugal output growth and the future yield spread is found to be significantly different from zero. The estimate of t_{13} follows an increasing rate when $S_T \in [1, 7]$ with $\hat{t}_{13}$ =0.18 when S_T =7 and reaches its maximum value of 0.22 for S_T =36. So, our evidence here suggests a strong positive relationship, with major effects reaching the first seven months, but weaker effects may last for up to 36 months as well.

The results from the Granger causality test for the Portugal industrial production and the yield spread (PT10Y-PT3M) are:

GRANGER CAUSALITY	CHI-SQ	DF
$S3 \nrightarrow IP$	1.055949 [0.5898]	2
$IP \nrightarrow S3$	0.154248 [0.9258]	2

Real M1 (RM1) has an estimated temporal correlation coefficient t_{91} that increases at a decreasing rate as we can see from figure 3. For S_T =8, the estimate of t_{91} is equal to 0.33 for the Bartlett kernel. Beyond this point $\hat{t}_{91}$ increases at a decreasing rate and reaching its maximum value of 0.41 for S_T =36.

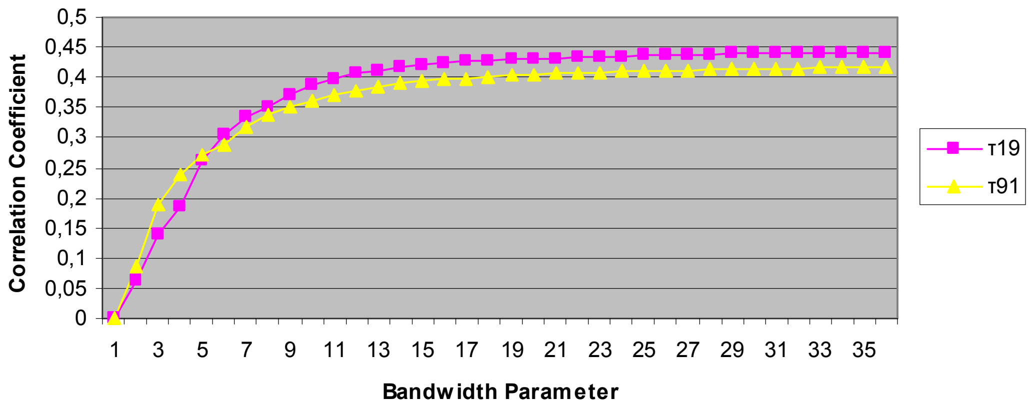

Figure 3: Estimated correlation coefficients: Portugal output growth and Portugal real money (M1)

What the evidence here suggests is that the major feedbacks from Portugal real M1 to output growth occur within the first eight months with a maximum feedback of around 36 months.

The relationship between the Portugal output growth and the future real M1 is found to be significantly different from zero. The estimate of t_{19} follows an increasing rate when $S_T \in [1, 9]$ with $\hat{t}_{19}$ =0.37 when S_T =9 and reaches its maximum value of 0.44 for S_T =36. So, our evidence here suggests a strong positive relationship and between the Portugal output growth and the future real M1, with major effects reaching the first nine months, but weaker effects may last for up to 36 months as well.

The results from the Granger causality test for the Portugal industrial production and the real M1 (RM1) are:

GRANGER CAUSALITY	CHI-SQ	DF
RM1 $\nrightarrow$ IP	2.949186 [0.2289]	2
IP $\nrightarrow$ RM1	0.435664 [0.8043]	2

In the case of the spread (PT10Y-PT1M) the results do not differentiate at all and show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{41} increase as well. The estimates of the temporal correlation coefficient t_{14} are mainly positive and remain close to zero for all values of the bandwidth parameter. The rate of growth of the estimates of t_{41} again does not remain constant over the whole range of values of the bandwidth parameter S_T.

Figure 4 shows the results for the Portugal yield spread (PT10Y-PT1M) and the Portugal output growth.

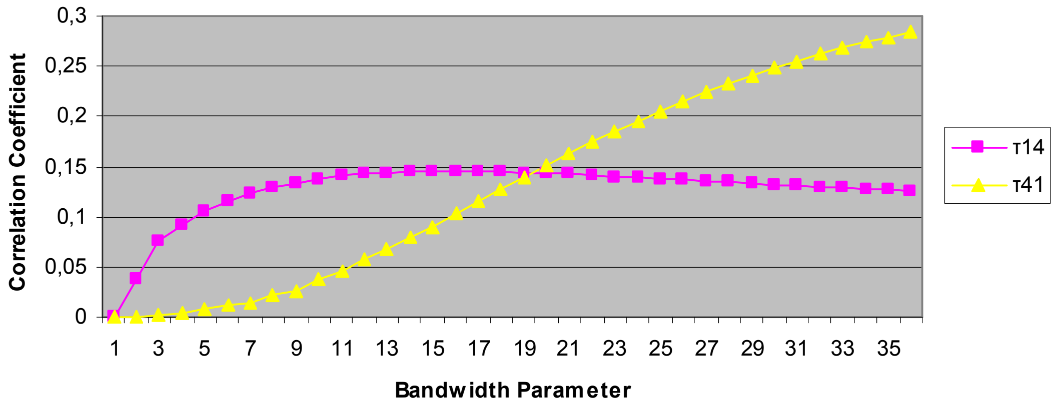

Figure 4: Estimated correlation coefficients: Portugal output growth and Portugal Yield (PT10Y-PT1M)

For S_T=3, the estimate of t_{41} is equal to 0.002, for the Bartlett kernel. Beyond this point, $\hat{t}_{41}$ increases at a decreasing rate, with a value of $\hat{t}_{41}$ =0.046 for S_T=11 and reaching its maximum value of 0.28 for S_T=36. What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 11 months, although weaker feedbacks may last up to 36 months. What these results show, with regards to the Portugal yield spread (PT10Y-PT1M) and the future Portugal output growth is that their relationship is positive, as expected. The relationship between the Portugal output growth and the future yield spread is found to be not significantly different from zero.

The results from the Granger causality test for the Portugal industrial production and the yield spread (PT10Y-PT1M) are:

GRANGER CAUSALITY	CHI-SQ	DF
S1 $\nrightarrow$ IP	2.213113 [0.3307]	2
IP $\nrightarrow$ S1	3.203414 [0.2016]	2

The various interest rates (10–year government bond, 1-month, 3-month and 1-year interest rates) which we examined have results that are similar with that of the other variables.
Figure 5 shows the results for the Portugal 10–year government bond and the Portugal output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{51} increase as well. The estimates of the temporal correlation coefficient t_{15} are again positive and they also increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{51} does not remain constant over the whole range of values of the bandwidth parameter S_T.

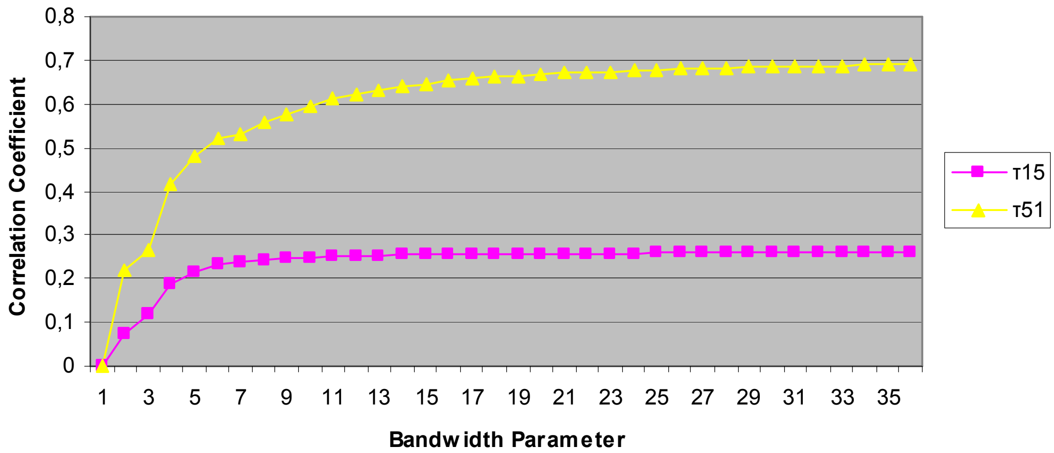

Figure 5: Estimated correlation coefficients: Portugal output growth and Portugal 10–year government bond

For S_T=6, the estimate of t_{51} is equal to 0.52, for the Bartlett kernel. Beyond this point, $\hat{t}_{51}$ increases at a decreasing rate, and reaching its maximum value of 0.69 for S_T=36. What the evidence here suggests is that the major feedbacks from the 10–year government bond to output growth occur approximately within the first 6 months, although weaker feedbacks may last up to 36 months. What the results showed, for the Portugal 10–year government bond and the future Portugal output growth is that their relationship is strong.
Our evidence suggests that the major effect on the future Portugal output growth is within the first six months, although weaker effects may also last up to three years. The relationship between the Portugal output growth and the future 10–year government bond is found to be significantly different from zero but not as strong as that of the opposite direction. The estimate of t_{15} follows an increasing rate when $S_T \in$ [1, 4] with $\hat{t}_{15}$ =0.18 when S_T=4 and reaches its maximum value of 0.26 for S_T=36. So, our evidence here suggests a strong positive relationship between the Portugal output growth and the future 10–year government bond, with major effects reaching the first 4 months, but weaker effects may last for up to 36 months as well.

The results from the Granger causality test for the Portugal industrial production and the 10-year government bond are:

GRANGER CAUSALITY	CHI-SQ	DF
10Y $\nrightarrow$ IP	0.113931 [0.9446]	2
IP $\nrightarrow$ 10Y	1.999556 [0.3680]	2

Familiar results are exported and for the other interest rates. Figures 6, 7 and 8 also show the correlation coefficients for the 3-month, 1-month and 1-year Portugal interest rates with respect with the Portugal output growth.

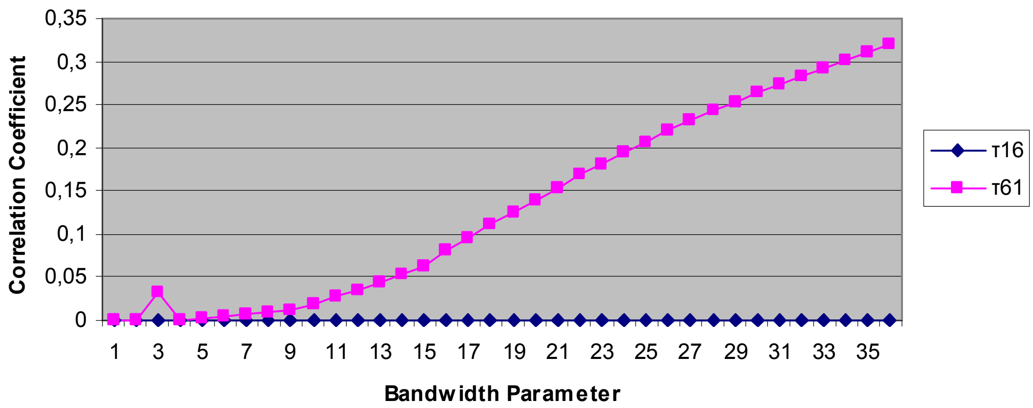

Figure 6: Estimated correlation coefficients: Portugal output growth and Portugal 1–month interest rate

The results from the Granger causality test for the Portugal industrial production and the 1-month interest rate are

GRANGER CAUSALITY	CHI-SQ	DF
1M $\nrightarrow$ IP	1.563390 [0.4576]	2
IP $\longrightarrow$ 1M (10%)	5.640267 [0.0596]	2

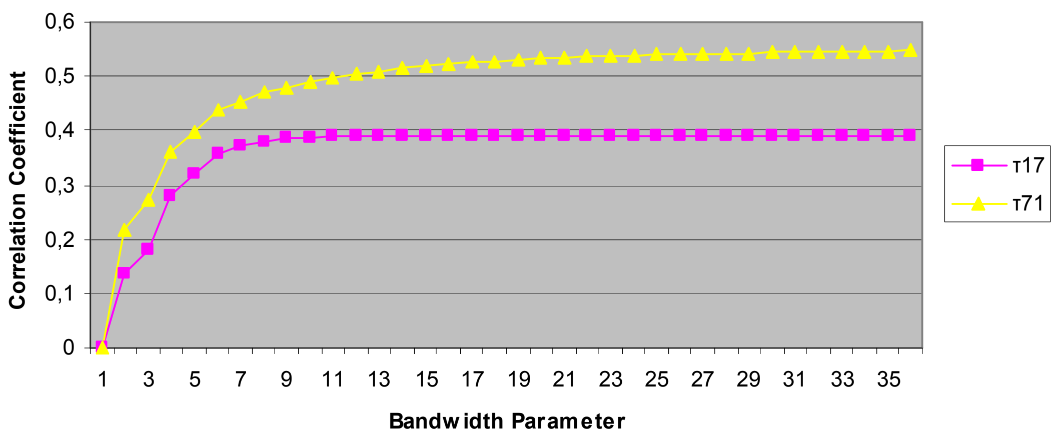

Figure 7: Estimated correlation coefficients: Portugal output growth and Portugal 3–month interest rate

The results from the Granger causality test for the Portugal industrial production and the 3-month interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
$3M \longrightarrow IP$	3.111547 [0.0179]	16
$IP \longrightarrow 3M$ (10%)	0.658647 [0.0677]	16

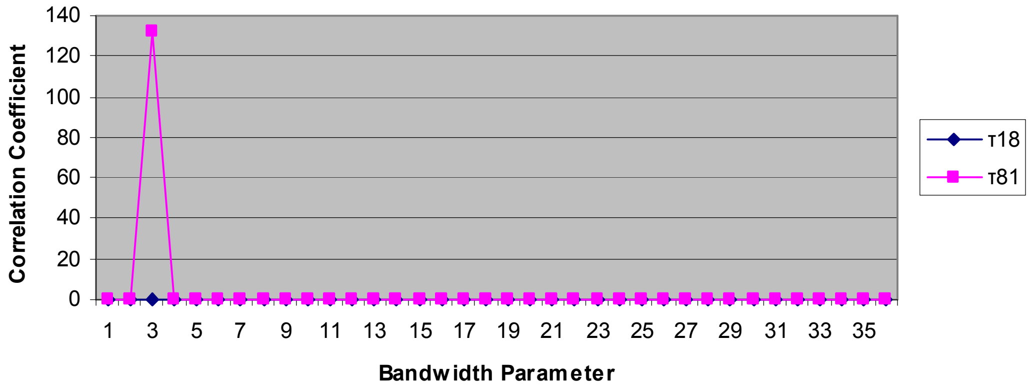

Figure 8: Estimated correlation coefficients: Portugal output growth and Portugal 1–year interest rate

The results from the Granger causality test for the Portugal industrial production and the 1-year interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
$1Y \nrightarrow IP$	4.409566 [0.3701]	2
$IP \nrightarrow 1Y$	3.290752 [0.8856]	2

4. B.6. Greek financial variables and output growth

Table B6 presents the estimated temporal correlation for all the financial variables that were examined in this paper. Among the various groups of the Greek financial variables examined, the Athens Stock Exchange General Share Price Index and the Greek yield (GR10Y-GR3M) were found to exhibit the strongest temporal correlations (t_{21}) with respect to Greek output growth. Our estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to the value of the current financial variable at hand ($u_{1,t-i} \rightarrow u_{2,t}$), and the temporal correlation coefficient t_{21}, which describes feedbacks from past values of the financial variable at hand to current output growth (i.e., in the opposite direction ($u_{2,t-i} \rightarrow u_{1,t}$), for alternative values of the bandwidth parameter S_T are reported in figures 1-6 for the Bartlett kernel. The bandwidth parameter takes values in the interval [1, 30] by steps of one.

Figure 1 shows, for the Greek stock price index and the Greek output growth, that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{21}, that describes feedbacks from past real stock returns to current output growth ($u_{2,t-i} \to u_{1,t}$), increase as well. Similarly the estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to current real stock returns ($u_{1,t-i} \to u_{2,t}$), are positive and increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{21} does not remain constant over the whole range of values of the bandwidth parameter S_T. When $S_T \in$ [1, 6], $\hat{t}_{21}$ increases at an increasing rate and for S_T=6, the estimate of t_{21} is equal to 0.12 for the Bartlett kernel.

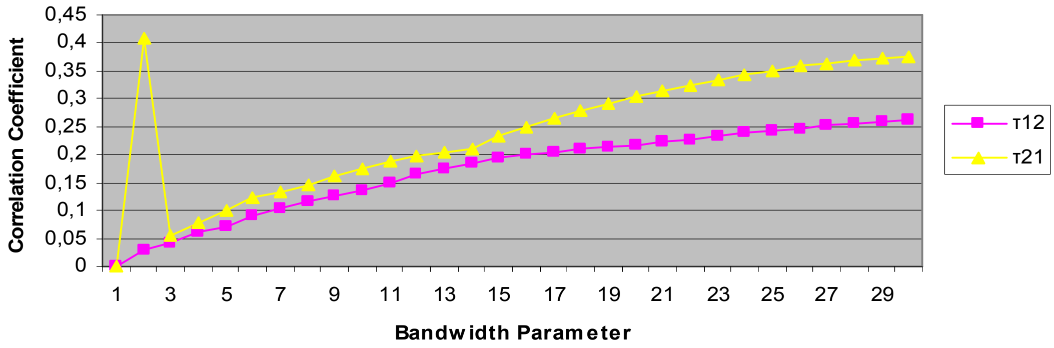

Figure 1: Estimated correlation coefficients: Greek output growth and returns from the Greek Stock price index

Beyond this point, $\hat{t}_{21}$ increases at a decreasing rate thus reaching its maximum value of 0.37 for S_T=30. What the evidence here suggests is that the major feedbacks, from past stock price changes to output growth, occur within the first 6 months, with a maximum feedback of around 30 months. The relationship between past Greek output growth and stock price changes is found to be significantly different from zero. The estimate of t_{12} follows a increasing rate when $S_T \in$ [1, 7] with $\hat{t}_{12}$ =0.10 when S_T=7 and reaches its maximum value of 0.26 for S_T=30.

What our results show is that there is a strong positive relationship (temporal correlation) between past stock price changes and current Greek output growth, as expected. Basically, this implies that, and for the Greece, stock prices are useful predictors of output for a horizon of up to 30 months.

The results from the Granger causality test for the Greek industrial production and the stock index are:

GRANGER CAUSALITY	CHI-SQ	DF
IND $\longrightarrow$ IP	95.20215 [0.0000]	42
IP $\longrightarrow$ IND	77.46966 [0.0007]	42

Figure 2 shows the results for the Greek yield spread (GR10Y-GR3M) and the Greek output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{31} increase as well. The estimates of the temporal correlation coefficient t_{13} are again positive and they also increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{31} does not remain constant over the whole range of values of the bandwidth parameter S_T.

For S_T=2, the estimate of t_{31} is equal to 0.07, for the Bartlett kernel. Beyond this point, $\hat{t}_{31}$ increases at a decreasing rate, with a value of $\hat{t}_{31}$=0.15 for S_T=6 and reaching its maximum value of 0.27 for S_T=30. What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 6 months, although weaker feedbacks may last up to 30 months.

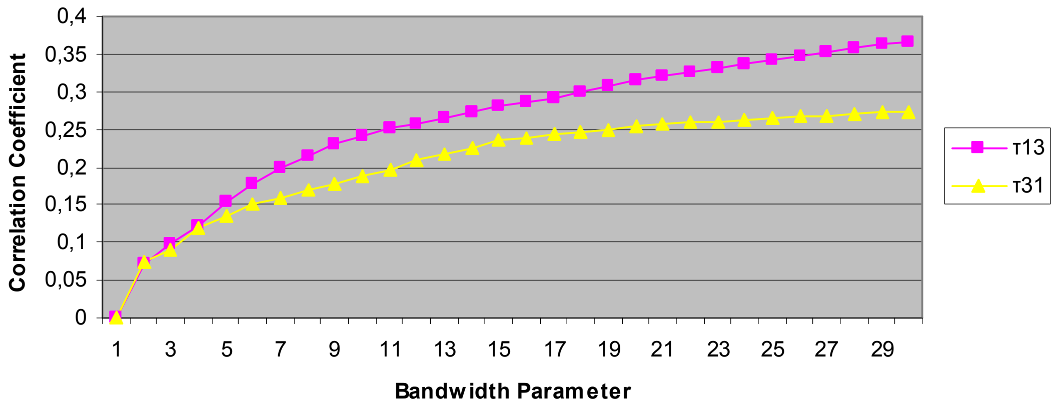

Figure 2: Estimated correlation coefficients: Greek output growth and Greek Yield (GR10Y-GR3M)

These results show, with regards to the Greek yield spread (GR10Y-GR3M) and the future Greek output growth that their relationship is positive, as expected. Our evidence suggests that the major effect on the future Greek output growth is within the first 6 months, although weaker effects may also last up to three years. This basically implies that the yield spread is a useful predictor of Greek output up to a three-year horizon. The relationship between the Greek output growth and the future yield spread is found to be significantly different from zero. The estimate of t_{13} follows an increasing rate when $S_T \in$ [1, 9] with $\hat{t}_{13}$ =0.23 when S_T=9 and reaches its maximum value of 0.36 for S_T=30. So, our evidence here suggests a positive relationship, with major effects reaching the first nine months, but weaker effects may last for up to 30 months as well.

The results from the Granger causality test for the Greek industrial production and the yield spread (GR10Y-GR3M) are:

GRANGER CAUSALITY	CHI-SQ	DF
S3 $\not\rightarrow$ IP	52.66020 [0.3823]	12
IP $\not\rightarrow$ S3	22.42329 [0.1133]	12

In the case of the spread (GR10Y-GR1M) the results do not differentiate at all and show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{41} increase as well. The estimates of the temporal correlation coefficient t_{14} are again positive and they also increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{41} again does not remain constant over the whole range of values of the bandwidth parameter S_T.
Figure 3 shows the results for the Greek yield spread (GR10Y-GR1M) and the Greek output growth.

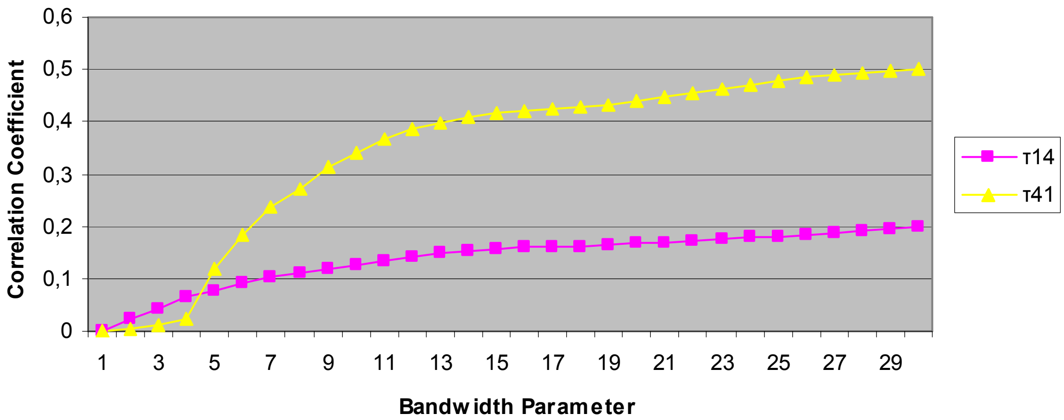

Figure 3: Estimated correlation coefficients: Greek output growth and Greek Yield (GR10Y-GR1M)

For S_T=5, the estimate of t_{41} is equal to 0.12, for the Bartlett kernel. Beyond this point, $\hat{t}_{41}$ increases at a decreasing rate, with a value of $\hat{t}_{41}$ =0.31 for S_T=9 and reaching its maximum value of 0.50 for S_T=30. What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 9 months, although weaker feedbacks may last up to 30 months. What these results show, with regards to the Greek yield spread (GR10Y-GR1M) and the future Greek output growth is that their relationship is positive, as expected. The relationship between the Greek output growth and the future yield spread is found to be significantly different from zero. The estimate of t_{14} follows an increasing rate when $S_T \in$ [1, 7] with $\hat{t}_{14}$ =0.10 when S_T=7 and reaches its maximum value of 0.20 for S_T=30. So, our evidence here suggests a strong positive relationship, with major effects reaching the first 7 months, but weaker effects may last for up to 30 months as well.
The results from the Granger causality test for the Greek industrial production and the yield spread (GR10Y-GR1M) are:

GRANGER CAUSALITY	CHI-SQ	DF
$S1 \not\longrightarrow IP$	34.42367 [0.7906]	42
$IP \longrightarrow S1$	77.81999 [0.0006]	42

The various interest rates (10–year government bond, 1-month and 3-month interest rates) which we examined have results that are similar with that of the other variables.

Figure 4 shows the results for the Greek 10–year government bond and the Greek output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{51} increase as well. The estimates of the temporal correlation coefficient t_{15} are again positive and they also increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{51} does not remain constant over the whole range of values of the bandwidth parameter S_T.

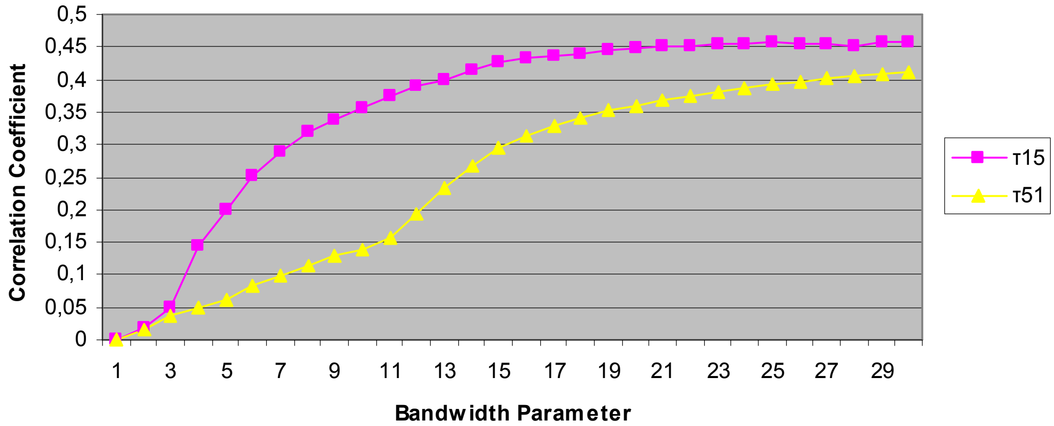

Figure 4: Estimated correlation coefficients: Greek output growth and Greek 10–year government bond

For S_T=15, the estimate of t_{51} is equal to 0.29, for the Bartlett kernel. Beyond this point, $\hat{t}_{51}$ increases at a decreasing rate, and reaching its maximum value of 0.41 for S_T=30. What the evidence here suggests is that the major feedbacks from the 10–year government bond to output growth occur approximately within the first 15 months, although weaker feedbacks may last up to 30 months. What the results showed, for the Greek 10–year government bond and the future Greek output growth is that their relationship is strong.

Our evidence suggests that the major effect on the future Greek output growth is within the first 15 months, although weaker effects may also last up to three years. The relationship between the Greek output growth and the future 10–year government bond is found to be significantly different from zero and as strong as that of the opposite direction. The estimate of t_{15} follows an increasing rate when $S_T \in [1, 9]$ with $\hat{t}_{15}$=0.33 when S_T=9 and reaches its maximum value of 0.45 for S_T=30. So, our evidence here suggests a strong positive relationship between the Greek output growth and the future 10–year government bond, with major effects reaching the first 9 months, but weaker effects may last for up to 30 months as well.

The results from the Granger causality test for the Greek industrial production and the 10-year government bond are:

GRANGER CAUSALITY	CHI-SQ	DF
10Y $\longrightarrow$ IP (10%)	42.82890 [0.0773]	23
IP $\not\longrightarrow$ 10Y	27.20026 [0.4296]	23

Familiar results are exported and for the other interest rates. Figures 5 and 6 also show the correlation coefficients for the 3-month and 1-month Greek interest rates with respect with the Greek output growth.

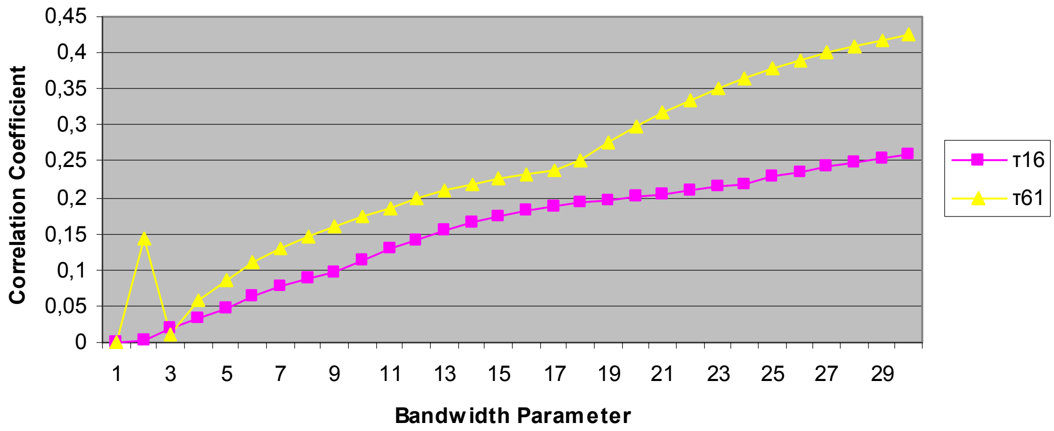

Figure 5: Estimated correlation coefficients: Greek output growth and Greek 1–month interest rate

The results from the Granger causality test for the Greek industrial production and the 1-month interest rate are

GRANGER CAUSALITY	CHI-SQ	DF
1M $\not\longrightarrow$ IP	38.44367 [0.6279]	42
IP $\longrightarrow$ 1M	136.6953 [0.0000]	42

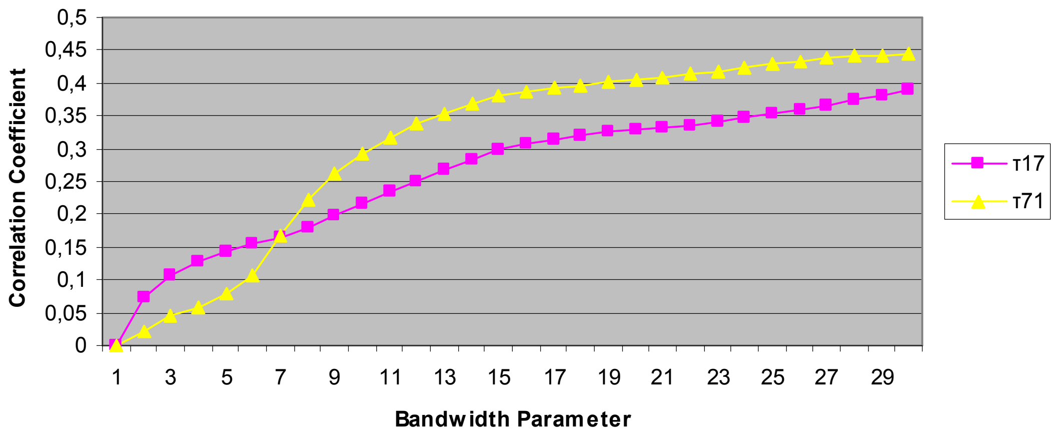

Figure 6: Estimated correlation coefficients: Greek output growth and Greek 3–month interest rate

The results from the Granger causality test for the Greek industrial production and the 3-month interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
$3M \nrightarrow IP$	12.48461 [0.1919]	12
$IP \nrightarrow 3M$	67.95277 [0.2493]	12

4. B.7. Korean financial variables and output growth

Table B7 presents the estimated temporal correlation for all the financial variables that were examined in this paper. Among the various groups of the Korean financial variables examined, the KOSPI Stock Price Index, the Korean yield (KO10Y-KO3M), and real M1 (RM1) were found to exhibit the strongest temporal correlations (t_{21}) with respect to Korean output growth.

Our estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to the value of the current financial variable at hand ($u_{1,t-i} \to u_{2,t}$), and the temporal correlation coefficient t_{21}, which describes feedbacks from past values of the financial variable at hand to current output growth (i.e., in the opposite direction ($u_{2,t-i} \to u_{1,t}$), for alternative values of the bandwidth parameter S_T are reported in figures 1-6 for the Bartlett kernel. The bandwidth parameter takes values in the interval [1, 36] by steps of one.

Figure 1 shows, for the Korean stock price index and the Korean output growth, that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{21}, that describes feedbacks from past real stock returns to current output growth ($u_{2,t-i} \to u_{1,t}$), increase as well. Similarly the estimates of the temporal correlation coefficient t_{12}, which in our case describes feedbacks from past output growth to current real stock returns ($u_{1,t-i} \to u_{2,t}$), are positive and increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{21} does not remain constant over the whole range of values of the bandwidth parameter S_T. When $S_T \in$ [1, 11], $\hat{t}_{21}$ increases at an increasing rate and for S_T=11, the estimate of t_{21} is equal to 0.29 for the Bartlett kernel. Beyond this point, $\hat{t}_{21}$ increases at a decreasing rate thus reaching its maximum value of 0.49 for S_T=36. What the evidence here suggests is that the major feedbacks, from past stock price changes to output growth, occur within the first 11 months, with a maximum feedback of around 36 months. The relationship between past Korean output growth and stock price changes is found to be significantly different from zero. The estimate of t_{12} follows a increasing rate when $S_T \in$ [1, 6] with $\hat{t}_{12}$=0.10 when S_T=6 and reaches its maximum value of 0.33 for S_T=36.

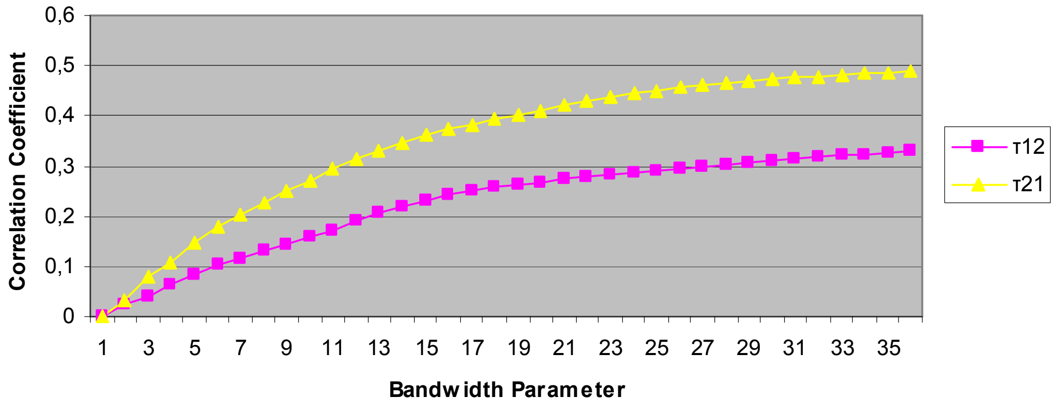

Figure 1: Estimated correlation coefficients: Korean output growth and returns from the Korean Stock price index

What our results show is that there is a strong positive relationship (temporal correlation) between past stock price changes and current Korean output growth, as expected. Basically, this implies that, and for the Korean, stock prices are useful predictors of output for a horizon of up to 36 months.

The results from the Granger causality test for the Korean industrial production and the stock index are:

GRANGER CAUSALITY	CHI-SQ	DF
IND $\longrightarrow$ IP	7.537991 [0.0060]	1
IP $\longrightarrow$ IND (10%)	2.970208 [0.0848]	1

Figure 2 shows the results for the Korean yield spread (KO10Y-KO3M) and the Korean output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{31} increase as well. The estimates of the temporal correlation coefficient t_{13} are again positive and they also increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{31} does not remain constant over the whole range of values of the bandwidth parameter S_T.

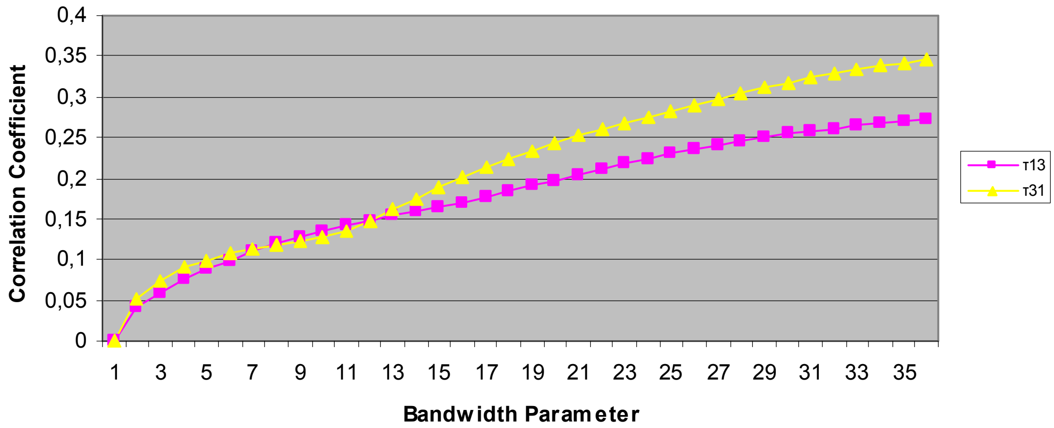

Figure 2: Estimated correlation coefficients: Korean output growth and Korean Yield (KO10Y-KO3M)

For S_T=2, the estimate of t_{31} is equal to 0.05, for the Bartlett kernel. Beyond this point, $\hat{t}_{31}$ increases at a decreasing rate, with a value of $\hat{t}_{31}$=0.16 for S_T=13 and reaching its maximum value of 0.34 for S_T=36. What the evidence here suggests is that the major feedbacks from the yield spread to output growth occur approximately within the first 13 months, although weaker feedbacks may last up to 36 months.

These results show, with regards to the Korean yield spread (KO10Y-KO3M) and the future Korean output growth that their relationship is positive, as expected. Our evidence suggests that the major effect on the future Korean output growth is within the first 13 months, although weaker effects may also last up to three years. This basically implies that the yield spread is a useful predictor of Korean output up to a three-year horizon. The relationship between the Korean output growth and the future yield spread is found to be significantly different from zero. The estimate of t_{13} follows an increasing rate when $S_T \in$ [1, 11] with $\hat{t}_{13}$=0.14 when S_T=11 and reaches its maximum value of 0.27 for S_T=36. So, our evidence here suggests a positive relationship, with major effects reaching the first eleven months, but weaker effects may last for up to 36 months as well.

The results from the Granger causality test for the Korean industrial production and the yield spread (KO10Y-KO3M) are:

GRANGER CAUSALITY	CHI-SQ	DF
$S3 \longrightarrow IP$ (10%)	7.340711 [0.0618]	3
$IP \not\longrightarrow S3$	5.771540 [0.1233]	3

Real M1 (RM1) has an estimated temporal correlation coefficient t_{61} that increases at a decreasing rate as we can see from figure 3. For S_T=12, the estimate of t_{61} is equal to 0.10 for the Bartlett kernel. Beyond this point $\hat{t}_{61}$ increases at a decreasing rate and reaching its maximum value of 0.23 for S_T=36.

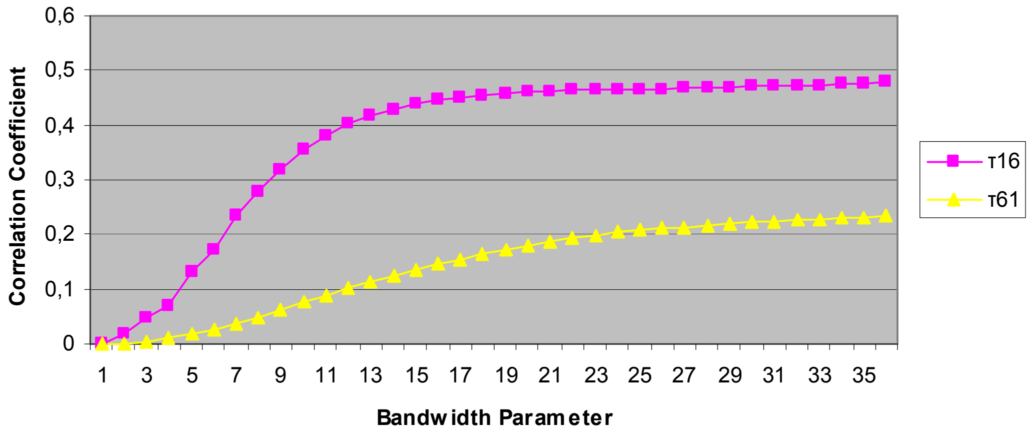

Figure 3: Estimated correlation coefficients: Korean output growth and Korean real money (M1)

What the evidence here suggests is that the major feedbacks from Korean real M1 to output growth occur within the first twelve months with a maximum feedback of around 36 months. The relationship between the Korean output growth and the future real M1 is found to be significantly different from zero.

The estimate of t_{16} follows an increasing rate when $S_T \in$ [1, 9] with $\hat{t}_{16}$ =0.32 when S_T =9 and reaches its maximum value of 0.47 for S_T =36. So, our evidence here suggests a strong positive relationship and between the Korean output growth and the future real M1, with major effects reaching the first nine months, but weaker effects may last for up to 36 months as well.
The results from the Granger causality test for the Korean industrial production and the real M1 (RM1) are:

GRANGER CAUSALITY	CHI-SQ	DF
RM1 $\longrightarrow$ IP (10%)	10.02399 [0.0746]	5
IP $\not\longrightarrow$ RM1	7.008080 [0.2200]	5

Real M2 (RM2) show similar pattern with RM1 but the relationship is stronger than RM1. This is confirmed by our results, shown in figure 4, which show that real M2 (RM2) has an estimated temporal correlation coefficient t_{71} that increases at a decreasing rate.

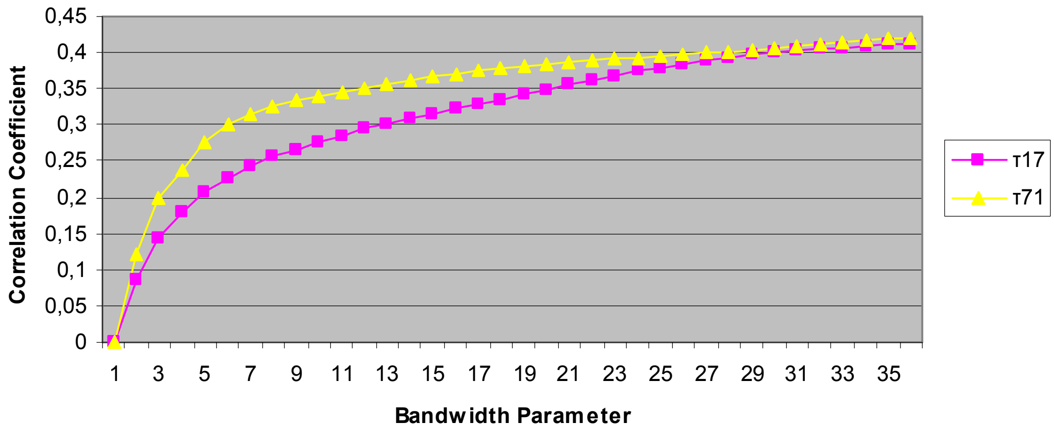

Figure 4: Estimated correlation coefficients: Korean output growth and Korean real money (M2)

For S_T =6, the estimate of t_{71} is equal to 0.30 for the Bartlett kernel. Beyond this point $\hat{t}_{71}$ increases at a decreasing rate and reaching its maximum value of 0.42 for S_T =36. What the evidence here suggests is that the major feedbacks from Korean real M2 to output growth occur within the first six months with a maximum feedback of around 36 months. The relationship between the Korean output growth and the future real M2 is found to be significantly different from zero. The estimate of t_{17} follows an increasing rate when $S_T \in$ [1, 6] with $\hat{t}_{17}$ =0.22 when S_T =6 and reaches its maximum value of 0.41 for S_T =36. So, our evidence here suggests a strong positive relationship between the Korean output growth and the future real M2, with major effects reaching the first 6 months, but weaker effects may last for up to 36 months as well.

The results from the Granger causality test for the Korean industrial production and the real M2 (RM2) are:

GRANGER CAUSALITY	CHI-SQ	DF
RM2 $\nrightarrow$ IP	1.762131 [0.6232]	3
IP $\longrightarrow$ RM2 (10%)	7.414675 [0.0598]	3

The various interest rates (10–year government bond and 3-month interest rate) which we examined have results that are similar with that of the other variables.

Figure 5 shows the results for the Korean 10–year government bond and the Korean output growth. The results show that when the bandwidth parameter increases, our estimates of the temporal correlation coefficient t_{41} increase as well. The estimates of the temporal correlation coefficient t_{14} are again positive and they also increase as the bandwidth parameter increases too. The rate of growth of the estimates of t_{41} does not remain constant over the whole range of values of the bandwidth parameter S_T.

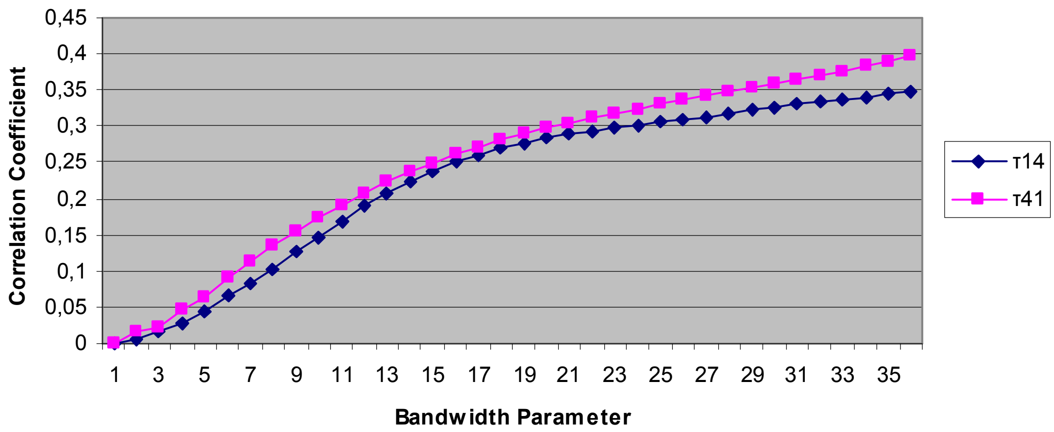

Figure 5: Estimated correlation coefficients: Korean output growth and Korean 10–year government bond

For S_T=9, the estimate of t_{41} is equal to 0.15, for the Bartlett kernel. Beyond this point, $\hat{t}_{41}$ increases at a decreasing rate, and reaching its maximum value of 0.39 for S_T=36. What the evidence here suggests is that the major feedbacks from the 10–year government bond to output growth occur approximately within the first 9 months, although weaker feedbacks may last up to 36 months. What the results showed, for the Korean 10–year government bond and the future Korean output growth is that their relationship is strong.

Our evidence suggests that the major effect on the future Korean output growth is within the first nine months, although weaker effects may also last up to three years. The relationship between the Korean output growth and the future 10–year government bond is found to be significantly different from zero and as strong as that of the opposite direction. The estimate of t_{14} follows an increasing rate when $S_T \in$ [1, 13] with $\hat{t}_{14}$ =0.20 when S_T =13 and reaches its maximum value of 0.34 for S_T =36. So, our evidence here suggests a strong positive relationship between the Korean output growth and the future 10–year government bond, with major effects reaching the first 13 months, but weaker effects may last for up to 36 months as well.

The results from the Granger causality test for the Korean industrial production and the 10-year government bond are:

GRANGER CAUSALITY	CHI-SQ	DF
10Y $\nrightarrow$ IP	1.815587 [0.6115]	3
IP $\nrightarrow$ 10Y	5.253527 [0.1541]	3

Familiar results are exported and for the other interest rate. Figure 6 also show the correlation coefficients for the 3-month Korean interest rate with respect with the Korean output growth.

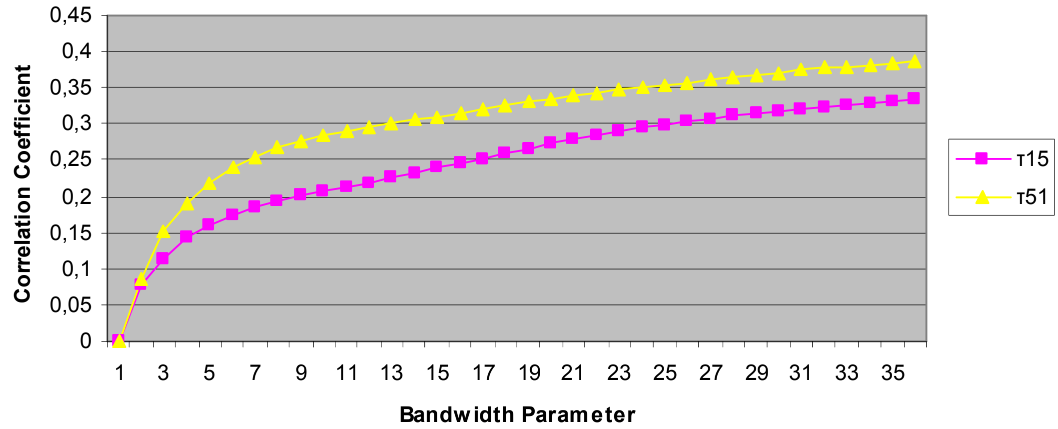

Figure 6: Estimated correlation coefficients: Korean output growth and Korean 3–month interest rate

The results from the Granger causality test for the Korean industrial production and the 3-month interest rate are:

GRANGER CAUSALITY	CHI-SQ	DF
3M $\longrightarrow$ IP (10%)	8.128330 [0.0870]	4
IP $\longrightarrow$ 3M (10%)	7.990415 [0.0919]	4

5. Conclusion

Much of the empirical evidence from parametric models has shown that financial variables are very useful in helping to forecast future output growth. However, it is well known that statistical inference, within a specific parametric model, can be affected by weather, or that not all the underlying assumptions are appropriate for the dataset at hand. Given that in the context of financial data the presence of long-range dependence may call for a dynamic model with an unusually long lag structure, the usual practice of the researchers of using more parsimonious models may prove extremely costly in terms of the desirable properties of estimators and related test-statistics.

In this paper, as a complement to parametric studies, we re-examined the bivariate relationship between selected financial variables and output growth in two groups of countries, the G7 countries and 7 emerging countries, by employing an appropriate non-parametric technique. This allowed us to explore the links between these variables and assess the robustness obtained with parametric techniques. In particular, we used the methodology proposed by Andrews (1991) to obtain non-parametric estimates of the long-run covariance matrix between financial variables and output growth.

Our findings broadly confirm the theoretical explanations and evidence provided by earlier parametric studies on the relationship between these financial variables and output growth. We have also tested the same bivariate relationships with the full parametric model of Granger causality and the results are presented along with these of the non-parametric method so as to see the differences between the two methods. The results from the two models are familiar and are comparable mainly for the United States and for Canada among the G7 countries and for Korea and Malaysia among the emerging countries. Finally the variables which show the same results and for the two models are the stock returns, the yield spread (10Y-3M) and the monetary aggregate RM1.

The methodology employed here can be extended to the investigation of the links between other selected economic variables in order to assess the robustness of results obtained with parametric techniques. It can also be applied to other cases where the parametric approach leaves empirical questions open, as an alternative to typical Granger- causality testing. For example, a promising route for further research may be the non-parametric estimation of the long-run covariance matrix between output, or alternative measures of economic activity, and various sectoral stock market indices.

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6. Appendix A

UNITED STATES UNIT ROOT TESTS

	AUGMENTED DICKEY- FULLER	PHILLIPS PERRON
INDUSTRIAL PRODUCTION	-10.75948 [0.0000]	-15.29443 [0.0000]
STOCK INDEX	-16.49524 [0.0000]	-16.49885 [0.0000]
10-YEAR GOVERNMENT BOND	-16.37670 [0.0000]	-16.36809 [0.0000]
SPREAD (10Y-3M)	-2.088196 [0.0355]	-2.013103 [0.0424]
3-MONTH INTEREST RATE	-1.743772 [0.0771]	-2.585555 [0.0097]
1-YEAR INTEREST RATE	-14.34497 [0.0000]	-14.46920 [0.0000]
1-MONTH INTEREST RATE	-2.772735 [0.0056]	-2.811955 [0.0050]
SPREAD (10Y-1M)	-2.232745 [0.0249]	-2.254474 [0.0236]
REAL M1	-5.635117 [0.0000]	-13.01845 [0.0000]
REAL M2	-7.426122 [0.0000]	-7.465594 [0.0000]
REAL M3	-1.929072 [0.0515]	-7.498667 [0.0000]

UNITED KINGDOM UNIT ROOT TESTS

	AUGMENTED DICKEY- FULLER	**PHILLIPS PERRON**
INDUSTRIAL PRODUCTION	-28.44717 [0.0000]	-28.53014 [0.0000]
STOCK INDEX	-19.23719 [0.0000]	-19.12834 [0.0000]
10-YEAR GOVERNMENT BOND	-22.12521 [0.0000]	-22.07705 [0.0000]
SPREAD (10Y-3M)	-3.433435 [0.0006]	-3.787155 [0.0002]
3-MONTH INTEREST RATE	-16.87474 [0.0000]	-16.92873 [0.0000]
1-YEAR INTEREST RATE	-16.97962 [0.0000]	-16.98454 [0.0000]
1-MONTH INTEREST RATE	-16.49589 [0.0000]	-16.50383 [0.0000]
SPREAD (10Y-1M)	-3.315080 [0.0010]	-3.627557 [0.0003]
REAL M2	-3.919748 [0.0001]	-13.78949 [0.0000]
REAL M3	-15.89891 [0.0000]	-15.85310 [0.0000]

JAPAN UNIT ROOT TESTS

	AUGMENTED DICKEY- FULLER	PHILLIPS PERRON
INDUSTRIAL PRODUCTION	-6.243706 [0.0000]	-29.70580 [0.0000]
STOCK INDEX	-9.445183 [0.0000]	-9.480928 [0.0000]
10-YEAR GOVERNMENT BOND	-6.628133 [0.0000]	-11.31554 [0.0000]
SPREAD (10Y-3M)	-8.100790 [0.0000]	-7.865914 [0.0000]
3-MONTH INTEREST RATE	-8.625920 [0.0000]	-8.490183 [0.0000]
1-YEAR INTEREST RATE	-9.532563 [0.0000]	-9.611241 [0.0000]
1-MONTH INTEREST RATE	-1.702927 [0.0016]	-3.189812 [0.0016]
SPREAD (10Y-1M)	-6.620596 [0.0000]	-10.64398 [0.0000]
REAL M1	-2.471493 [0.0132]	-9.744333 [0.0000]
REAL M2	-2.881950 [0.0039]	-9.064494 [0.0000]

ITALY UNIT ROOT TESTS

	AUGMENTED DICKEY- FULLER	**PHILLIPS PERRON**
INDUSTRIAL PRODUCTION	-33.08396	-33.53485
	[0.0000]	[0.0000]
STOCK INDEX	-12.17175	-12.17310
	[0.0000]	[0.0000]
10-YEAR GOVERNMENT BOND	-11.86418	-11.86418
	[0.0000]	[0.0000]
SPREAD (10Y-3M)	-10.88149	-10.89515
	[0.0000]	[0.0000]
3-MONTH INTEREST RATE	-2.048854	-2.212685
	[0.0392]	[0.0264]
1-YEAR INTEREST RATE	-2.100587	-1.823120
	[0.0137]	[0.0347]
1-MONTH INTEREST RATE	-2.160994	-2.242663
	[0.0300]	[0.0245]
SPREAD (10Y-1M)	-11.52369	-11.52071
	[0.0000]	[0.0000]
REAL M1	-2.212591	-19.10877
	[0.0262]	[0.0000]
REAL M2	-3.536340	-18.73951
	[0.0004]	[0.0000]
REAL M3	-2.513148	-15.79845
	[0.0118]	[0.0000]

CANADA UNIT ROOT TESTS

	AUGMENTED DICKEY- FULLER	PHILLIPS PERRON
INDUSTRIAL PRODUCTION	-7.247946	-28.31619
	[0.0000]	[0.0000]
STOCK INDEX	-15.83546	-15.85636
	[0.0000]	[0.0000]
10-YEAR GOVERNMENT BOND	-17.52841	-17.56500
	[0.0000]	[0.0000]
SPREAD (10Y-3M)	-2.136936	-2.231115
	[0.0316]	[0.0250]
3-MONTH INTEREST RATE	-9.363142	-14.98001
	[0.0000]	[0.0000]
1-YEAR INTEREST RATE	-10.22098	-16.19003
	[0.0000]	[0.0000]
1-MONTH INTEREST RATE	-9.471686	-14.98620
	[0.0000]	[0.0000]
SPREAD (10Y-1M)	-2.298046	-2.234713
	[0.0211]	[0.0248]
REAL M1	-17.79357	-18.49556
	[0.0000]	[0.0000]
REAL M2	-6.144385	-15.60027
	[0.0000]	[0.0000]
REAL M3	-6.631965	-15.83698
	[0.0000]	[0.0000]

GERMANY UNIT ROOT TESTS

	AUGMENTED DICKEY- FULLER	PHILLIPS PERRON
INDUSTRIAL PRODUCTION	-3.757358	-31.81481
	[0.0002]	[0.0000]
STOCK INDEX	-13.02738	-13.03130
	[0.0000]	[0.0000]
10-YEAR GOVERNMENT BOND	-5.570681	-9.565709
	[0.0000]	[0.0000]
SPREAD (10Y-3M)	-10.01012	-10.61511
	[0.0000]	[0.0000]
3-MONTH INTEREST RATE	-8.679247	-9.236267
	[0.0000]	[0.0000]
1-YEAR INTEREST RATE	-2.600980	-2.388345
	[0.0094]	[0.0168]
1-MONTH INTEREST RATE	-2.145005	-2.428423
	[0.0311]	[0.0151]
SPREAD (10Y-1M)	-12.24359	-12.24377
	[0.0000]	[0.0000]
REAL M1	-3.134721	-14.06200
	[0.0018]	[0.0000]
REAL M2	-13.48288	-13.48288
	[0.0000]	[0.0000]
REAL M3	-11.07805	-11.16940
	[0.0000]	[0.0000]

FRANCE UNIT ROOT TESTS

	AUGMENTED DICKEY- FULLER	PHILLIPS PERRON
INDUSTRIAL PRODUCTION	-26.42463	-25.91538
	[0.0000]	[0.0000]
STOCK INDEX	-11.95892	-12.05136
	[0.0000]	[0.0000]
10-YEAR GOVERNMENT BOND	-13.85304	-14.90828
	[0.0000]	[0.0000]
SPREAD (10Y-3M)	-2.054769	-2.035069
	[0.0386]	[0.0404]
3-MONTH INTEREST RATE	-14.57414	-14.57507
	[0.0000]	[0.0000]
1-YEAR INTEREST RATE	-11.98654	-12.12847
	[0.0000]	[0.0000]
1-MONTH INTEREST RATE	-15.14217	-15.12230
	[0.0000]	[0.0000]
SPREAD (10Y-1M)	-2.221087	-2.158823
	[0.0257]	[0.0300]
REAL M1	-2.387012	-19.18999
	[0.0168]	[0.0000]
REAL M2	-2.411085	-17.93539
	[0.0156]	[0.0000]
REAL M3	-1.963274	-16.80482
	[0.0477]	[0.0000]

GREECE UNIT ROOT TESTS

	AUGMENTED DICKEY- FULLER	**PHILLIPS PERRON**
INDUSTRIAL	-2.249989	-28.59838
PRODUCTION	[0.0240]	[0.0000]
STOCK INDEX	-10.20601	-10.25725
	[0.0000]	[0.0000]
10-YEAR	-3.320856	-3.641241
GOVERNMENT BOND	[0.0010]	[0.0003]
SPREAD (10Y-3M)	-2.075128	-2.021128
	[0.0369]	[0.0419]
3-MONTH INTEREST	-11.03390	-11.08361
RATE	[0.0000]	[0.0000]
1-YEAR INTEREST	-3.339017	-3.124705
RATE	[0.0010]	[0.0020]
1-MONTH INTEREST	-2.546996	-3.054632
RATE	[0.0110]	[0.0025]
SPREAD (10Y-1M)	-10.89332	-10.90930
	[0.0000]	[0.0000]

INDIA UNIT ROOT TESTS

	AUGMENTED DICKEY- FULLER	PHILLIPS PERRON
INDUSTRIAL PRODUCTION	-4.305695 [0.0000]	-13.92456 [0.0000]
STOCK INDEX	-8.771953 [0.0000]	-8.770428 [0.0000]
10-YEAR GOVERNMENT BOND	-9.073258 [0.0000]	-9.064078 [0.0000]
SPREAD (10Y-3M)	-2.255606 [0.0240]	-2.937892 [0.0037]
3-MONTH INTEREST RATE	-10.87486 [0.0000]	-10.87736 [0.0000]
1-YEAR INTEREST RATE	-9.708663 [0.0000]	-9.799434 [0.0000]
1-MONTH INTEREST RATE	-4.214873 [0.0000]	-11.47622 [0.0000]
SPREAD (10Y-1M)	-3.567712 [0.0005]	-8.292917 [0.0000]
REAL M1	-0.958100 [0.3000]	-8.235665 [0.0000]
REAL M2	-0.954354 [0.3015]	-8.138090 [0.0000]
REAL M3	-6.252136 [0.0000]	-6.210249 [0.0000]

MALAYSIA UNIT ROOT TESTS

	AUGMENTED DICKEY- FULLER	PHILLIPS PERRON
INDUSTRIAL PRODUCTION	-3.327077 [0.0009]	-31.09027 [0.0000]
STOCK INDEX	-8.727028 [0.0000]	-8.665243 [0.0000]
10-YEAR GOVERNMENT BOND	-6.680626 [0.0000]	-6.724683 [0.0000]
SPREAD (10Y-3M)	-10.57198 [0.0000]	-10.60391 [0.0000]
3-MONTH INTEREST RATE	-8.270759 [0.0000]	-8.123295 [0.0000]
1-YEAR INTEREST RATE	-10.30266 [0.0000]	-10.43380 [0.0000]
1-MONTH INTEREST RATE	-8.158621 [0.0000]	-8.145470 [0.0000]
SPREAD (10Y-1M)	-10.57161 [0.0000]	-10.55854 [0.0000]
REAL M1	-8.975972 [0.0000]	-8.953104 [0.0000]
REAL M2	-6.293072 [0.0000]	-10.61886 [0.0000]
REAL M3	-5.194918 [0.0000]	-10.74849 [0.0000]

PORTUGAL UNIT ROOT TESTS

	AUGMENTED DICKEY- FULLER	PHILLIPS PERRON
INDUSTRIAL PRODUCTION	-13.07277 [0.0000]	-22.79479 [0.0000]
STOCK INDEX	-7.120499 [0.0000]	-7.168323 [0.0000]
10-YEAR GOVERNMENT BOND	-3.073198 [0.0024]	-3.525191 [0.0005]
SPREAD (10Y-3M)	-4.212831 [0.0001]	-8.535198 [0.0000]
3-MONTH INTEREST RATE	-3.754857 [0.0002]	-3.759791 [0.0002]
1-YEAR INTEREST RATE	-3.886303 [0.0001]	-4.097193 [0.0001]
1-MONTH INTEREST RATE	-6.333939 [0.0000]	-6.412719 [0.0000]
SPREAD (10Y-1M)	-7.623477 [0.0000]	-7.809798 [0.0000]
REAL M1	-7.771634 [0.0000]	-11.03948 [0.0000]
REAL M2	-7.275694 [0.0000]	-9.791459 [0.0000]

SOUTH AFRICA UNIT ROOT TESTS

	AUGMENTED DICKEY- FULLER	PHILLIPS PERRON
INDUSTRIAL PRODUCTION	-11.94840 [0.0000]	-30.79486 [0.0000]
STOCK INDEX	-14.88773 [0.0000]	-14.48137 [0.0000]
10-YEAR GOVERNMENT BOND	-13.76537 [0.0000]	-13.61984 [0.0000]
SPREAD (10Y-3M)	-2.798598 [0.0052]	-3.024033 [0.0026]
3-MONTH INTEREST RATE	-7.130722 [0.0000]	-11.65915 [0.0000]
1-YEAR INTEREST RATE	-13.43288 [0.0000]	-13.61368 [0.0000]
1-MONTH INTEREST RATE	-13.06303 [0.0000]	-13.47775 [0.0000]
SPREAD (10Y-1M)	-2.300876 [0.0209]	-2.774362 [0.0056]
REAL M1	-9.870781 [0.0000]	-24.82069 [0.0000]
REAL M2	-3.398754 [0.0007]	-22.25110 [0.0000]
REAL M3	-5.286293 [0.0000]	-22.06497 [0.0000]

TAIWAN UNIT ROOT TESTS

	AUGMENTED DICKEY- FULLER	PHILLIPS PERRON
INDUSTRIAL PRODUCTION	-2.288168	-29.11034
	[0.0216]	[0.0000]
STOCK INDEX	-10.07746	-10.09433
	[0.0000]	[0.0000]
10-YEAR GOVERNMENT BOND	-7.608076	-7.551635
	[0.0000]	[0.0000]
SPREAD (10Y-3M)	-2.235309	-2.223773
	[0.0251]	[0.0258]
3-MONTH INTEREST RATE	-12.54101	-12.44056
	[0.0000]	[0.0000]
1-MONTH INTEREST RATE	-1.950445	-2.253201
	[0.0490]	[0.0236]
SPREAD (10Y-1M)	-2.293962	-3.521726
	[0.0216]	[0.0005]
REAL M1	-1.885539	-12.90614
	[0.0568]	[0.0000]
REAL M2	-1.450955	-9.469495
	[0.1369]	[0.0000]

KOREA UNIT ROOT TESTS

	AUGMENTED DICKEY- FULLER	**PHILLIPS PERRON**
INDUSTRIAL PRODUCTION	-9.259475 [0.0000]	-27.74124 [0.0000]
STOCK INDEX	-11.19209 [0.0000]	-11.12101 [0.0000]
10-YEAR GOVERNMENT BOND	-9.037395 [0.0000]	-9.256667 [0.0000]
SPREAD (10Y-3M)	-3.077548 [0.0022]	-2.633423 [0.0086]
3-MONTH INTEREST RATE	-8.163140 [0.0000]	-8.163140 [0.0000]
REAL M1	-11.73376 [0.0000]	-46.04688 [0.0001]
REAL M2	-3.017751 [0.0027]	-10.60000 [0.0000]
REAL M3	-1.833655 [0.0637]	-8.681729 [0.0000]

Appendix B

TABLE A1 (Bartlett kernel-Parzen kernel)

Estimated temporal correlations for all the Canadian financial variables used

Variables		S_T =3	S_T =6	S_T =9	S_T =12	S_T =18	S_T =24	S_T =36	S_T =45
Stock Index	t_{12}	0,1007	0,1728	0,2126	0,234	0,2509	0,2665	0,2864	0,2997
	t_{21}	0,1019	0,1608	0,1781	0,1934	0,2182	0,2411	0,298	0,3403
Can(10Y-3M)	t_{13}	0,0853	0,1797	0,2367	0,2696	0,3162	0,3396	0,3583	0,3703
	t_{31}	0,0938	0,1787	0,2378	0,2702	0,322	0,3647	0,4209	0,4529
Can(10Y-1M)	t_{14}	0,1166	0,2102	0,2327	0,2565	0,283	0,2988	0,32	0,3315
	t_{41}	0,1346	0,2521	0,2674	0,2817	0,2954	0,3102	0,3526	0,385
10-year bond	t_{15}	0,0873	0,1736	0,2243	0,2598	0,3085	0,3303	0,3406	0,3499
	t_{51}	0,0641	0,1484	0,209	0,244	0,2953	0,3301	0,3692	0,3928
1-month rate	t_{16}	0,1229	0,1798	0,1992	0,2161	0,2331	0,2415	0,255	0,2682
	t_{61}	0,1278	0,1773	0,1949	0,2096	0,2344	0,263	0,2947	0,3094
3-month rate	t_{17}	0,0538	0,1211	0,1586	0,1877	0,2334	0,2631	0,2939	0,3136
	t_{71}	0,0609	0,1383	0,1807	0,2063	0,2393	0,2591	0,2942	0,3146
1-year rate	t_{18}	0,1393	0,2134	0,2303	0,2433	0,2578	0,2655	0,2849	0,3062
	t_{81}	0,1358	0,1847	0,1926	0,2038	0,2234	0,2464	0,2728	0,2859
RM1	t_{19}	0,0619	0,1395	0,1958	0,2408	0,2931	0,3183	0,3577	0,3838
	t_{91}	0,0778	0,164	0,2093	0,2344	0,2574	0,2694	0,2909	0,3037
RM2	t_{110}	0,2842	0,3943	0,4162	0,4417	0,4735	0,4906	0,5141	0,5275
	t_{101}	0,2752	0,3577	0,3708	0,3815	0,3853	0,3925	0,391	0,3881
Stock Index	t_{12}	0,0991	0,1404	0,1811	0,2105	0,2405	0,2544	0,2718	0,282
	t_{21}	0,1018	0,1416	0,1669	0,1811	0,2002	0,2166	0,2496	0,2771
Can(10Y-3M)	t_{13}	0,0257	0,1362	0,1953	0,2337	0,2817	0,3129	0,3466	0,3585
	t_{31}	0,0329	0,141	0,1959	0,2338	0,283	0,3186	0,3748	0,4062
Can(10Y-1M)	t_{14}	0,1141	0,1726	0,2164	0,2387	0,2644	0,2819	0,3043	0,3157
	t_{41}	0,1345	0,2139	0,2602	0,2767	0,2897	0,298	0,3177	0,3373
10-year bond	t_{15}	0,0249	0,1346	0,1882	0,2231	0,2713	0,304	0,3361	0,3445
	t_{51}	0,0177	0,1075	0,1639	0,204	0,2564	0,2917	0,3388	0,3617
1-month rate	t_{16}	0,1176	0,1643	0,1869	0,2014	0,2209	0,2328	0,2458	0,2526
	t_{61}	0,1325	0,1655	0,1832	0,1964	0,2147	0,2318	0,2666	0,2856
3-month rate	t_{17}	0,0155	0,0864	0,1297	0,158	0,1976	0,2284	0,2696	0,2882
	t_{71}	0,0168	0,1001	0,1488	0,1796	0,2156	0,2381	0,2677	0,2853
1-year rate	t_{18}	0,144	0,1927	0,2203	0,2341	0,2489	0,258	0,27	0,2794
	t_{81}	0,1418	0,1773	0,1906	0,1971	0,2083	0,2214	0,2493	0,2651
RM1	t_{19}	0,0203	0,1039	0,1519	0,1902	0,2501	0,2881	0,329	0,3496
	t_{91}	0,0219	0,1239	0,177	0,2088	0,243	0,2595	0,2763	0,2863
RM2	t_{110}	0,2914	0,373	0,4068	0,4248	0,4507	0,4709	0,4966	0,5092
	t_{101}	0,2859	0,3502	0,369	0,3783	0,3861	0,3887	0,3933	0,3937

TABLE A2 (Bartlett kernel-Parzen kernel)

Estimated temporal correlations for all the United States financial variables used

Variables		S_T =3	S_T =6	S_T =9	S_T =12	S_T =18	S_T =24	S_T =36	S_T =45
Stock Index	t_{12}	0,0277	0,0371	0,0491	0,061	0,0899	0,1203	0,1859	0,2425
	t_{21}	0,0966	0,1573	0,2154	0,2639	0,3441	0,4063	0,4924	0,5248
US(10Y-3M)	t_{13}	0,0201	0,0427	0,0514	0,0603	0,083	0,1059	0,155	0,2015
	t_{31}	0,0313	0,0746	0,1137	0,1598	0,2703	0,3817	0,5257	0,581
US(10Y-1M)	t_{14}	0,0213	0,0363	0,0628	0,0897	0,1468	0,2128	0,3398	0,393
	t_{41}	0,0563	0,0738	0,0832	0,0906	0,1251	0,1826	0,2952	0,3676
10-year bond	t_{15}	0,0435	0,1157	0,1724	0,2238	0,3075	0,3774	0,4711	0,4995
	t_{51}	0,0076	0,0296	0,0442	0,0583	0,0844	0,1105	0,1684	0,222
1-month rate	t_{16}	0,2615	0,3968	0,4564	0,4921	0,5434	0,5616	0,5685	0,5651
	t_{61}	0,3019	0,3744	0,3794	0,3758	0,3716	0,3766	0,3895	0,4011
3-month rate	t_{17}	0,0413	0,084	0,1055	0,114	0,1249	0,1412	0,1747	0,225
	t_{71}	0,0558	0,1353	0,1817	0,2146	0,2598	0,2846	0,3149	0,3341
1-year rate	t_{18}	0,0194	0,033	0,0457	0,0595	0,1047	0,1427	0,223	0,2913
	t_{81}	0,057	0,1104	0,1645	0,2101	0,3052	0,3812	0,4809	0,5288
RM1	t_{19}	0,0326	0,0665	0,0994	0,1265	0,1745	0,2257	0,3129	0,3544
	t_{91}	0,0226	0,0684	0,0853	0,1015	0,1669	0,2595	0,3988	0,4621
RM2	t_{110}	0,0459	0,0871	0,1378	0,1876	0,2743	0,3647	0,4986	0,5499
	t_{101}	0,0297	0,044	0,0536	0,0605	0,0771	0,0994	0,1511	0,1999
Stock Index	t_{12}	0,0258	0,0344	0,0403	0,0476	0,0644	0,0839	0,1265	0,1614
	t_{21}	0,0655	0,1316	0,172	0,2096	0,2757	0,3318	0,4197	0,469
US(10Y-3M)	t_{13}	0,0086	0,0331	0,0453	0,0522	0,0642	0,0785	0,1101	0,1364
	t_{31}	0,0143	0,0545	0,0823	0,1091	0,1731	0,2472	0,3931	0,479
US(10Y-1M)	t_{14}	0,0205	0,03	0,0402	0,0568	0,0956	0,1362	0,2265	0,2938
	t_{41}	0,0518	0,0701	0,0779	0,0838	0,0961	0,1189	0,191	0,2516
10-year bond	t_{15}	0,0376	0,0797	0,1245	0,1651	0,2348	0,2943	0,3921	0,4459
	t_{51}	0,0029	0,0184	0,032	0,0428	0,0621	0,0802	0,1172	0,1475
1-month rate	t_{16}	0,2478	0,3609	0,4184	0,4562	0,5085	0,5421	0,5728	0,5787
	t_{61}	0,3044	0,3783	0,3895	0,3896	0,3832	0,3779	0,379	0,3846
3-month rate	t_{17}	0,0149	0,065	0,0908	0,1052	0,1189	0,127	0,1455	0,1635
	t_{71}	0,031	0,0971	0,1447	0,1784	0,2245	0,2558	0,2928	0,3104
1-year rate	t_{18}	0,0154	0,0273	0,0356	0,0441	0,0653	0,0935	0,1501	0,1938
	t_{81}	0,0407	0,0848	0,1207	0,1565	0,2237	0,2874	0,3949	0,4554
RM1	t_{19}	0,0133	0,0504	0,0745	0,0957	0,1332	0,1678	0,2372	0,285
	t_{91}	0,0065	0,0471	0,0726	0,086	0,112	0,1544	0,2696	0,3499
RM2	t_{110}	0,024	0,0677	0,0968	0,1299	0,1973	0,2606	0,3805	0,4554
	t_{101}	0,0243	0,0392	0,0471	0,0533	0,0636	0,0751	0,1051	0,1318

TABLE A3 (Bartlett kernel-Parzen kernel)

Estimated temporal correlations for all the Japanese financial variables used

Variables		S_T =3	S_T =6	S_T =9	S_T =12	S_T =18	S_T =24	S_T =30
Stock Index	t_{12}	0,0613	0,1124	0,1385	0,145	0,1548	0,1687	0,1825
	t_{21}	0,0201	0,0628	0,1198	0,1567	0,192	0,2346	0,2748
JP(10Y-3M)	t_{13}	0,0369	0,0529	0,0572	0,0588	0,0594	0,0657	0,0801
	t_{31}	0,0574	0,0808	0,0944	0,107	0,1234	0,1356	0,1467
JP(10Y-1M)	t_{14}	0,0301	0,0642	0,0778	0,0911	0,1333	0,1823	0,2269
	t_{41}	0,0027	0,0115	0,0215	0,0383	0,0751	0,1292	0,1948
10-year bond	t_{15}	0,0966	0,1697	0,2209	0,2395	0,2699	0,3042	0,3356
	t_{51}	0,1412	0,2249	0,2552	0,2741	0,3031	0,3145	0,3196
1-month rate	t_{16}	0,0234	0,0339	0,044	0,0642	0,1151	0,1765	0,2399
	t_{61}	0,0004	0,0023	0,0075	0,016	0,0448	0,0853	0,1336
3-month rate	t_{17}	0,1687	0,3063	0,3752	0,3991	0,4383	0,4724	0,5001
	t_{71}	0,2493	0,3459	0,3623	0,3725	0,3821	0,3773	0,3693
1-year rate	t_{18}	0,0331	0,0415	0,0477	0,0704	0,126	0,1929	0,2653
	t_{81}	0,0001	0,0039	0,0081	0,0136	0,0282	0,0499	0,0773
RM1	t_{19}	0,1996	0,3097	0,3534	0,3868	0,4202	0,4566	0,4837
	t_{91}	0,2553	0,3372	0,3521	0,3561	0,3604	0,3558	0,3463
Stock Index	t_{12}	0,0414	0,0901	0,1199	0,1385	0,1531	0,1596	0,167
	t_{21}	0,00894	0,0406	0,0726	0,1089	0,1636	0,196	0,2238
JP(10Y-3M)	t_{13}	0,03543	0,0475	0,0542	0,0579	0,06	0,0606	0,0634
	t_{31}	0,05444	0,0728	0,0843	0,0941	0,1096	0,1212	0,1305
JP(10Y-1M)	t_{14}	0,01931	0,0439	0,0653	0,0777	0,0988	0,1261	0,1572
	t_{41}	0,00235	0,0068	0,0126	0,0203	0,0412	0,0675	0,101
10-year bond	t_{15}	0,07608	0,1317	0,1798	0,2146	0,2475	0,2687	0,2903
	t_{51}	0,09736	0,189	0,2342	0,2578	0,2836	0,3009	0,3119
1-month rate	t_{16}	0,01921	0,0295	0,0358	0,044	0,0693	0,1036	0,1433
	t_{61}	0,00025	0,0012	0,003	0,0065	0,0191	0,0383	0,0634
3-month rate	t_{17}	0,13414	0,2403	0,3197	0,3701	0,4132	0,438	0,4607
	t_{71}	0,21078	0,319	0,3584	0,3714	0,3811	0,3845	0,3832
1-year rate	t_{18}	0,03178	0,0406	0,0436	0,0493	0,0753	0,113	0,1569
	t_{81}	3,29E+02	0,002	0,0043	0,0073	0,015	0,0253	0,0386
RM1	t_{19}	0,1882	0,2717	0,321	0,3542	0,395	0,4204	0,443
	t_{91}	0,24256	0,3226	0,3486	0,3587	0,3631	0,3631	0,3606

TABLE A4 (Bartlett kernel-Parzen kernel)

Estimated temporal correlations for all the United Kingdom financial variables used

Variables		S_T =3	S_T =6	S_T =9	S_T =12	S_T =18	S_T =24	S_T =36	S_T =45
Stock Index	t_{12}	0,005	0,0117	0,02	0,0273	0,0409	0,0551	0,0885	0,1117
	t_{21}	0,0074	0,0281	0,0515	0,0796	0,1414	0,2071	0,3234	0,3821
UK(10Y-3M)	t_{13}	0,085	0,1433	0,1665	0,1789	0,1894	0,1984	0,2255	0,2594
	t_{31}	0,1197	0,1895	0,2398	0,273	0,3102	0,3348	0,3575	0,3646
UK(10Y-1M)	t_{14}	0,0244	0,0329	0,0424	0,0518	0,0795	0,1211	0,2168	0,2775
	t_{41}	0,0062	0,0215	0,0434	0,0748	0,1369	0,2001	0,2949	0,3342
10-year bond	t_{15}	0,0627	0,0951	0,1088	0,1266	0,1626	0,1941	0,2428	0,2804
	t_{51}	0,0879	0,1129	0,1166	0,1175	0,1193	0,1248	0,1375	0,1617
1-month rate	t_{16}	0,0071	0,0259	0,0492	0,0717	0,1215	0,1916	0,3105	0,3681
	t_{61}	0,0027	0,0129	0,0208	0,0315	0,0525	0,0748	0,1265	0,1573
3-month rate	t_{17}	0,13	0,1863	0,2156	0,2391	0,2701	0,2861	0,3187	0,3475
	t_{71}	0,1761	0,254	0,2791	0,2874	0,2968	0,3017	0,3042	0,3138
1-year rate	t_{18}	0,0097	0,0277	0,0452	0,0614	0,1066	0,1848	0,3425	0,4263
	t_{81}	0,0073	0,0213	0,0369	0,0541	0,0875	0,1179	0,1671	0,1969
RM1	t_{19}	0,1185	0,1949	0,2286	0,2532	0,2902	0,3135	0,3414	0,36
	t_{91}	0,155	0,2151	0,2555	0,2881	0,3386	0,3841	0,4197	0,4329
Stock Index	t_{12}	0,0032	0,0077	0,0129	0,0184	0,0288	0,0384	0,0584	0,0749
	t_{21}	0,0037	0,0155	0,0305	0,047	0,0856	0,1281	0,2165	0,2784
UK(10Y-3M)	t_{13}	0,0623	0,1198	0,1497	0,1664	0,1833	0,1912	0,204	0,217
	t_{31}	0,0999	0,1588	0,1997	0,2335	0,2799	0,3081	0,3417	0,356
UK(10Y-1M)	t_{14}	0,0219	0,0299	0,035	0,0409	0,055	0,0744	0,129	0,1769
	t_{41}	0,002	0,0122	0,0238	0,0397	0,0809	0,1248	0,2085	0,2608
10-year bond	t_{15}	0,0536	0,0849	0,0992	0,1092	0,1318	0,1558	0,1991	0,2265
	t_{51}	0,0794	0,1089	0,1167	0,1191	0,1196	0,1202	0,126	0,1329
1-month rate	t_{16}	0,0047	0,013	0,0282	0,0448	0,0768	0,1132	0,201	0,2648
	t_{61}	0,0023	0,0073	0,0137	0,0198	0,0337	0,0484	0,0803	0,1062
3-month rate	t_{17}	0,1008	0,1667	0,1953	0,2147	0,2451	0,2663	0,2928	0,3093
	t_{71}	0,1328	0,2252	0,2627	0,2807	0,294	0,2992	0,3042	0,306
1-year rate	t_{18}	0,0064	0,0176	0,0301	0,0425	0,0663	0,099	0,1957	0,2763
	t_{81}	0,0027	0,0135	0,0233	0,0341	0,0576	0,0808	0,1225	0,1497
RM1	t_{19}	0,0847	0,167	0,2061	0,2295	0,2624	0,2868	0,3195	0,3358
	t_{91}	0,133	0,1972	0,2281	0,2538	0,2968	0,3324	0,3879	0,4128

TABLE A5 (Bartlett kernel-Parzen kernel)

Estimated temporal correlations for all the German financial variables used

Variables		S_T =3	S_T =6	S_T =9	S_T =12	S_T =18	S_T =24	S_T =30
Stock Index	t_{12}	0,0163	0,0262	0,0318	0,0354	0,0393	0,046	0,0525
	t_{21}	0,0707	0,1485	0,2055	0,2622	0,3948	0,4642	0,5283
BD(10Y-3M)	t_{13}	0,1933	0,3507	0,417	0,4364	0,4446	0,4327	0,4226
	t_{31}	0,0877	0,1443	0,1757	0,2074	0,2525	0,2937	0,3185
BD(10Y-1M)	t_{14}	0,0165	0,027	0,0326	0,0365	0,0435	0,054	0,0689
	t_{41}	0,1142	0,2656	0,3809	0,4363	0,5289	0,5859	0,6335
10-year bond	t_{15}	0,0289	0,0551	0,0761	0,0894	0,1082	0,1223	0,1354
	t_{51}	0,0315	0,0574	0,0693	0,0809	0,0994	0,1118	0,1201
1-month rate	t_{16}	0,0305	0,0491	0,0592	0,0688	0,0884	0,118	0,1553
	t_{61}	0,0324	0,0593	0,076	0,086	0,1132	0,1412	0,1696
3-month rate	t_{17}	0,0094	0,0201	0,0263	0,0322	0,0463	0,0677	0,0929
	t_{71}	0,01	0,0256	0,0355	0,0441	0,0546	0,0607	0,0681
1-year rate	t_{18}	0,0199	0,0345	0,0444	0,0541	0,075	0,0986	0,1273
	t_{81}	0,0135	0,0209	0,0254	0,0303	0,0386	0,0469	0,0565
RM1	t_{19}	0,0456	0,0969	0,1263	0,1381	0,1554	0,1776	0,2021
	t_{91}	0,0283	0,0604	0,0793	0,0917	0,107	0,1211	0,1291
RM2	t_{110}	0,1411	0,224	0,2747	0,2976	0,3362	0,37	0,403
	t_{101}	0,1308	0,1804	0,2273	0,2572	0,3064	0,3398	0,3668

Estimated temporal correlations for all the German financial variables used (Parzen)

Stock Index	t_{12}	0,0156	0,0223	0,0275	0,0316	0,0366	0,0398	0,0436
	t_{21}	0,0282	0,1088	0,1617	0,2023	0,2872	0,3701	0,4359
BD(10Y-3M)	t_{13}	0,0554	0,2847	0,3762	0,4221	0,4557	0,4596	0,4531
	t_{31}	0,0272	0,1265	0,1569	0,1772	0,2153	0,2487	0,2778
BD(10Y-1M)	t_{14}	0,0165	0,027	0,0326	0,0365	0,0435	0,054	0,0689
	t_{41}	0,1142	0,2656	0,3809	0,4363	0,5289	0,5859	0,6335
10-year bond	t_{15}	0,0134	0,0417	0,0595	0,0737	0,0933	0,1069	0,1178
	t_{51}	0,0105	0,0462	0,061	0,07	0,0847	0,0972	0,1071
1-month rate	t_{16}	0,0197	0,0424	0,0526	0,0595	0,0722	0,0862	0,1043
	t_{61}	0,0227	0,0475	0,0636	0,0749	0,0916	0,1095	0,1287
3-month rate	t_{17}	0,0081	0,0156	0,0213	0,026	0,034	0,0443	0,0581
	t_{71}	0,0028	0,0174	0,0272	0,0349	0,0462	0,0539	0,0594
1-year rate	t_{18}	0,0149	0,0285	0,0374	0,0446	0,0581	0,0725	0,0886
	t_{81}	0,0129	0,0189	0,0226	0,0256	0,0318	0,0379	0,0439
RM1	t_{19}	0,0199	0,072	0,104	0,1247	0,1447	0,1574	0,1713
	t_{91}	0,0078	0,0448	0,0646	0,0784	0,0956	0,1072	0,1169
RM2	t_{110}	0,1327	0,1943	0,237	0,2703	0,3087	0,3347	0,3586
	t_{101}	0,1317	0,1678	0,1935	0,221	0,2656	0,3003	0,3277

TABLE A6 (Bartlett kernel-Parzen kernel)

Estimated temporal correlations for all the France financial variables used

Variables		S_T =3	S_T =6	S_T =9	S_T =12	S_T =18	S_T =24	S_T =30
Stock Index	t_{12}	0,0676	0,1326	0,1894	0,2538	0,338	0,4025	0,4614
	t_{21}	0,0971	0,1586	0,2035	0,2297	0,2557	0,2851	0,3131
FR(10Y-3M)	t_{13}	0,0312	0,0703	0,0888	0,1031	0,1413	0,1774	0,2037
	t_{31}	0,0317	0,0763	0,1068	0,1352	0,1891	0,2356	0,2804
FR(10Y-1M)	t_{14}	0,1438	0,1995	0,2472	0,2874	0,3474	0,3987	0,4338
	t_{41}	0,0914	0,1405	0,2056	0,2435	0,3085	0,3583	0,3829
10-year bond	t_{15}	0,0347	0,0855	0,1098	0,1301	0,1794	0,2345	0,2803
	t_{51}	0,0154	0,0793	0,1239	0,1627	0,218	0,2603	0,3105
1-month rate	t_{16}	0,0939	0,1682	0,236	0,2799	0,329	0,3637	0,3863
	t_{61}	0,0875	0,1309	0,1983	0,2316	0,2757	0,3281	0,3681
3-month rate	t_{17}	0,0584	0,1355	0,189	0,223	0,2706	0,324	0,3582
	t_{71}	0,0353	0,0969	0,1268	0,1497	0,1672	0,1847	0,2054
1-year rate	t_{18}	0,0841	0,1393	0,1912	0,2454	0,3175	0,3821	0,4262
	t_{81}	0,1326	0,1832	0,2048	0,2192	0,2453	0,2714	0,2924
RM1	t_{19}	0,0654	0,1778	0,2429	0,2913	0,3524	0,4134	0,4534
	t_{91}	0,032	0,1173	0,1597	0,189	0,2319	0,2728	0,3072
RM2	t_{110}	0,1519	0,1984	0,2229	0,2497	0,2858	0,3164	0,3394
	t_{101}	0,2278	0,3224	0,3736	0,3917	0,4135	0,4302	0,4397
Stock Index	t_{12}	0,0607	0,1036	0,1426	0,1833	0,2654	0,3285	0,3789
	t_{21}	0,0783	0,1366	0,1736	0,2027	0,2395	0,2602	0,278
FR(10Y-3M)	t_{13}	0,0082	0,0524	0,077	0,0915	0,1133	0,1377	0,1625
	t_{31}	0,0099	0,0546	0,0845	0,1074	0,147	0,1841	0,2186
FR(10Y-1M)	t_{14}	0,1248	0,1879	0,2172	0,2463	0,2986	0,3423	0,3794
	t_{41}	0,0825	0,1265	0,1606	0,1981	0,2591	0,3051	0,3412
10-year bond	t_{15}	0,0125	0,0618	0,0924	0,1116	0,1413	0,1742	0,2102
	t_{51}	0,007	0,0365	0,0831	0,1208	0,1749	0,2145	0,2477
1-month rate	t_{16}	0,0833	0,1344	0,1851	0,23	0,2931	0,3303	0,3562
	t_{61}	0,082	0,1178	0,15	0,1884	0,243	0,2778	0,31
3-month rate	t_{17}	0,0302	0,0986	0,1465	0,1845	0,2354	0,2716	0,3051
	t_{71}	0,0109	0,0627	0,1026	0,1281	0,1572	0,1717	0,1828
1-year rate	t_{18}	0,0728	0,1169	0,1539	0,1895	0,257	0,3122	0,3583
	t_{81}	0,1238	0,1759	0,1969	0,2097	0,2279	0,2449	0,262
RM1	t_{19}	0,0345	0,1249	0,1919	0,2407	0,3067	0,3527	0,3927
	t_{91}	0,0095	0,0754	0,1269	0,1597	0,2019	0,2319	0,2591
RM2	t_{110}	0,1435	0,1938	0,2133	0,2285	0,2588	0,2848	0,3067
	t_{101}	0,2202	0,3051	0,3488	0,378	0,4062	0,4201	0,4305

TABLE A7 (Bartlett kernel-Parzen kernel)

Estimated temporal correlations for all the Italian financial variables used

Variables		S_T =3	S_T =6	S_T =9	S_T =12	S_T =18	S_T =24	S_T =30
Stock Index	t_{12}	0,0379	0,0747	0,1114	0,133	0,1458	0,144	0,1445
	t_{21}	0,0781	0,1441	0,26	0,3454	0,4527	0,51	0,5733
IT(10Y-3M)	t_{13}	0,0446	0,0764	0,0928	0,1033	0,1121	0,1166	0,122
	t_{31}	0,0436	0,0716	0,0846	0,1087	0,1934	0,2555	0,2899
IT(10Y-1M)	t_{14}	0,0151	0,0218	0,0254	0,0286	0,034	0,0396	0,0485
	t_{41}	0,0175	0,034	0,0588	0,084	0,1317	0,1857	0,2451
10-year bond	t_{15}	0,0332	0,0537	0,0592	0,0613	0,0621	0,0663	0,0745
	t_{51}	0,0197	0,0319	0,0367	0,0536	0,1101	0,1494	0,1709
1-month rate	t_{16}	0,009	0,0132	0,0147	0,0162	0,02	0,0255	0,0403
	t_{61}	0,0086	0,0191	0,0314	0,0417	0,0603	0,0733	0,085
3-month rate	t_{17}	0,0039	0,0097	0,0168	0,0268	0,0456	0,0819	0,144
	t_{71}	0,0058	0,0126	0,0177	0,0211	0,027	0,0345	0,0437
1-year rate	t_{18}	0,076	0,1178	0,13	0,1388	0,1698	0,2258	0,269
	t_{81}	0,0695	0,0882	0,0904	0,0918	0,0924	0,0936	0,0965
RM1	t_{19}	0,0034	0,0159	0,036	0,0734	0,1465	0,2316	0,3485
	t_{91}	0,0057	0,032	0,0508	0,0652	0,0743	0,0785	0,083
RM2	t_{110}	0,175	0,2498	0,2744	0,3086	0,3967	0,4765	0,5211
	t_{101}	0,2271	0,3133	0,3379	0,3506	0,3427	0,3272	0,3181
Stock Index	t_{12}	0,0303	0,0573	0,0825	0,1052	0,1356	0,1475	0,15
	t_{21}	0,0378	0,114	0,1712	0,2379	0,3582	0,4392	0,4935
IT(10Y-3M)	t_{13}	0,0131	0,0644	0,0826	0,093	0,1064	0,1133	0,1173
	t_{31}	0,0142	0,0625	0,0764	0,0858	0,1205	0,1723	0,2214
IT(10Y-1M)	t_{14}	0,0158	0,0202	0,023	0,0252	0,0294	0,0333	0,0372
	t_{41}	0,012	0,0254	0,0385	0,0541	0,0882	0,1232	0,16
10-year bond	t_{15}	0,0099	0,0471	0,0572	0,0609	0,0632	0,0638	0,0655
	t_{51}	0,0071	0,028	0,034	0,038	0,0602	0,095	0,1273
1-month rate	t_{16}	0,0089	0,0123	0,0138	0,0148	0,0168	0,0194	0,0231
	t_{61}	0,0061	0,0132	0,0212	0,0292	0,0441	0,0571	0,0677
3-month rate	t_{17}	0,0014	0,0063	0,0105	0,0157	0,0283	0,0427	0,0644
	t_{71}	0,0023	0,0095	0,0137	0,017	0,0221	0,0264	0,0312
1-year rate	t_{18}	0,0804	0,1063	0,1224	0,1315	0,1441	0,1652	0,1962
	t_{81}	0,0737	0,0876	0,0915	0,0927	0,0933	0,0935	0,0939
RM1	t_{19}	0,0018	0,0073	0,0175	0,0332	0,0789	0,131	0,1895
	t_{91}	0,002	0,0181	0,034	0,0478	0,0668	0,0754	0,0795
RM2	t_{110}	0,1769	0,2361	0,2624	0,2799	0,3215	0,379	0,436
	t_{101}	0,2353	0,299	0,3274	0,3438	0,3557	0,3513	0,3413

TABLE B1 (Bartlett kernel-Parzen kernel)

Estimated temporal correlations for all the South African financial variables used

Variables		S_T=3	S_T=6	S_T=9	S_T=12	S_T=18	S_T=24	S_T=36
Stock Index	t_{12}	0,177	0,2402	0,2605	0,2738	0,302	0,337	0,3916
	t_{21}	0,1786	0,2504	0,2826	0,3121	0,349	0,3793	0,4139
SA(10Y-3M)	t_{13}	0,1152	0,2231	0,2763	0,3083	0,3458	0,3693	0,3908
	t_{31}	0,1104	0,2242	0,276	0,3074	0,337	0,3564	0,399
SA(10Y-1M)	t_{14}	0,1776	0,2469	0,2778	0,2976	0,3237	0,3456	0,3788
	t_{41}	0,2062	0,2813	0,3028	0,3172	0,3506	0,3805	0,4276
10-year bond	t_{15}	0,0913	0,1867	0,232	0,2556	0,2887	0,3173	0,3567
	t_{51}	0,0849	0,1719	0,2208	0,2537	0,2911	0,318	0,348
1-month rate	t_{16}	0,2002	0,2674	0,2964	0,3205	0,3593	0,3859	0,408
	t_{61}	0,2242	0,3118	0,3509	0,3773	0,4097	0,4227	0,4456
3-month rate	t_{17}	0,0772	0,1664	0,2088	0,2429	0,289	0,3188	0,3531
	t_{71}	0,0686	0,1483	0,196	0,2284	0,2674	0,2904	0,3221
1-year rate	t_{18}	0,1839	0,2862	0,3267	0,3557	0,4004	0,4322	0,4582
	t_{81}	0,2181	0,2847	0,2962	0,3108	0,3339	0,3571	0,3946
RM1	t_{19}	0,0866	0,1761	0,2202	0,2614	0,3249	0,3649	0,4207
	t_{91}	0,065	0,1546	0,2004	0,24	0,2949	0,3236	0,3516
RM2	t_{110}	0,1349	0,211	0,2424	0,2643	0,3036	0,3312	0,3804
	t_{101}	0,2149	0,2704	0,2931	0,3148	0,3509	0,3796	0,4126
Stock Index	t_{12}	0,1719	0,2262	0,2494	0,2634	0,2819	0,3004	0,3433
	t_{21}	0,1648	0,233	0,2629	0,2843	0,3197	0,3463	0,3852
SA(10Y-3M)	t_{13}	0,0406	0,1774	0,2401	0,2767	0,3198	0,3457	0,3764
	t_{31}	0,0306	0,1763	0,2409	0,277	0,318	0,3395	0,367
SA(10Y-1M)	t_{14}	0,1657	0,2312	0,2599	0,2791	0,3051	0,323	0,3513
	t_{41}	0,2031	0,2678	0,294	0,3075	0,3271	0,3474	0,3861
10-year bond	t_{15}	0,0332	0,1448	0,2003	0,2318	0,2656	0,2879	0,3241
	t_{51}	0,0269	0,1333	0,1852	0,2191	0,2627	0,2897	0,3248
1-month rate	t_{16}	0,1891	0,2566	0,2807	0,2982	0,3289	0,3549	0,3898
	t_{61}	0,2321	0,2936	0,3255	0,3505	0,3861	0,408	0,4299
3-month rate	t_{17}	0,0356	0,1267	0,1773	0,2091	0,2533	0,2853	0,3265
	t_{71}	0,0192	0,1113	0,1609	0,1938	0,2379	0,2658	0,2994
1-year rate	t_{18}	0,1695	0,2539	0,2992	0,3281	0,3668	0,3964	0,4376
	t_{81}	0,2193	0,2794	0,296	0,3036	0,3175	0,3322	0,3629
RM1	t_{19}	0,0417	0,1381	0,1877	0,2207	0,2735	0,3163	0,3749
	t_{91}	0,0191	0,1124	0,1658	0,2003	0,2511	0,2883	0,3305
RM2	t_{110}	0,1256	0,1864	0,2211	0,2428	0,2736	0,2987	0,3395
	t_{101}	0,2157	0,2702	0,2849	0,2967	0,3219	0,3459	0,3841

TABLE B2 (Bartlett kernel-Parzen kernel)

Estimated temporal correlations for all the India financial variables used

Variables		S_T=3	S_T=6	S_T=9	S_T=12	S_T=18	S_T=24	S_T=30
Stock Index	t_{12}	0,1728	0,2921	0,3562	0,3815	0,3983	0,427	0,4553
	t_{21}	0,2158	0,3361	0,3929	0,4199	0,4281	0,43	0,4225
IN(10Y-3M)	t_{13}	0,0559	0,1356	0,175	0,2004	0,2731	0,3149	0,3393
	t_{31}	0,0616	0,1327	0,1867	0,2434	0,297	0,3335	0,3657
IN(10Y-1M)	t_{14}	0,1347	0,2454	0,274	0,2978	0,3741	0,4041	0,4237
	t_{41}	0,1222	0,1946	0,2263	0,2735	0,391	0,4665	0,4971
10-year bond	t_{15}	0,0458	0,1305	0,212	0,2854	0,3202	0,3528	0,4025
	t_{51}	0,0468	0,121	0,2478	0,3258	0,4111	0,4408	0,455
1-month rate	t_{16}	0,2001	0,2501	0,2768	0,2905	0,336	0,3882	0,426
	t_{61}	0,2009	0,2783	0,2995	0,3318	0,3821	0,4145	0,4289
3-month rate	t_{17}	0,0535	0,1552	0,2134	0,2531	0,3821	0,4498	0,4991
	t_{71}	0,0375	0,0831	0,1253	0,167	0,224	0,2874	0,3399
1-year rate	t_{18}	0,0749	0,1568	0,274	0,3255	0,3862	0,4275	0,458
	t_{81}	0,1933	0,2609	0,2845	0,2947	0,34	0,3726	0,4
RM1	t_{19}	0,0789	0,2708	0,3385	0,3882	0,4594	0,491	0,5175
	t_{91}	0,0578	0,135	0,2097	0,2705	0,3249	0,3562	0,3827
RM2	t_{110}	0,05	0,1021	0,1546	0,2222	0,3165	0,3674	0,3809
	t_{101}	0,3233	0,4633	0,5183	0,5512	0,5768	0,5658	0,5544
Stock Index	t_{12}	0,1424	0,2379	0,3128	0,361	0,3974	0,4103	0,4235
	t_{21}	0,1526	0,3006	0,3632	0,3991	0,4332	0,4407	0,4398
IN(10Y-3M)	t_{13}	0,0171	0,0977	0,1479	0,1781	0,2231	0,2658	0,3009
	t_{31}	0,016	0,0969	0,1457	0,1874	0,2547	0,2977	0,3272
IN(10Y-1M)	t_{14}	0,1125	0,2074	0,2624	0,2865	0,3259	0,3678	0,3987
	t_{41}	0,107	0,1719	0,209	0,2331	0,2951	0,3702	0,4336
10-year bond	t_{15}	0,0223	0,0874	0,1462	0,205	0,2944	0,3329	0,3551
	t_{51}	0,0212	0,0774	0,1441	0,2253	0,346	0,4112	0,4441
1-month rate	t_{16}	0,1595	0,2482	0,272	0,2851	0,3038	0,3312	0,3643
	t_{61}	0,1745	0,2633	0,2966	0,3115	0,3445	0,3776	0,4033
3-month rate	t_{17}	0,0329	0,1041	0,1653	0,2101	0,2835	0,3601	0,4224
	t_{71}	0,014	0,0625	0,0925	0,1205	0,1755	0,2204	0,2625
1-year rate	t_{18}	0,052	0,1101	0,1821	0,2544	0,3432	0,3902	0,4216
	t_{81}	0,1685	0,2549	0,28	0,292	0,3099	0,3347	0,3595
RM1	t_{19}	0,0492	0,1925	0,2945	0,347	0,4164	0,4611	0,4894
	t_{91}	0,0142	0,1004	0,1545	0,2031	0,2818	0,3263	0,3527
RM2	t_{110}	0,0327	0,072	0,1093	0,1484	0,2344	0,3054	0,3523
	t_{101}	0,3006	0,4278	0,4925	0,5302	0,5697	0,5855	0,5847

TABLE B3 (Bartlett kernel-Parzen kernel)

Estimated temporal correlations for all the Malaysian financial variables used

Variables		S_T =3	S_T =6	S_T =9	S_T =12	S_T =18	S_T =24	S_T =36
Stock Index	t_{12}	0,1557	0,2138	0,2401	0,2585	0,2848	0,3232	0,3787
	t_{21}	0,1153	0,2605	0,3221	0,3647	0,4131	0,4463	0,4886
MY(10Y-3M)	t_{13}	0,0638	0,1484	0,192	0,2347	0,3338	0,3802	0,4305
	t_{31}	0,0934	0,1843	0,2565	0,2976	0,3495	0,3781	0,4218
MY(10Y-1M)	t_{14}	0,0617	0,0982	0,1281	0,178	0,2596	0,3069	0,3643
	t_{41}	0,0616	0,1326	0,1806	0,2317	0,3106	0,3434	0,4102
10-year bond	t_{15}	0,0339	0,0905	0,1568	0,234	0,3354	0,356	0,3998
	t_{51}	0,0669	0,1535	0,2264	0,2712	0,3352	0,3464	0,4019
1-month rate	t_{16}	0,1377	0,2072	0,2573	0,3061	0,3784	0,4124	0,4745
	t_{61}	0,0907	0,1345	0,1644	0,215	0,266	0,2867	0,3432
3-month rate	t_{17}	0,0222	0,1334	0,2069	0,2865	0,355	0,3607	0,362
	t_{71}	0,0247	0,0961	0,1565	0,229	0,3419	0,4049	0,5018
1-year rate	t_{18}	0,2432	0,3805	0,4325	0,4718	0,4899	0,4947	0,52
	t_{81}	0,1748	0,2746	0,3173	0,3567	0,3822	0,3904	0,3984
RM1	t_{19}	0,072	0,2188	0,2973	0,3449	0,3879	0,4119	0,4321
	t_{91}	0,0879	0,2134	0,2798	0,3184	0,3769	0,4109	0,4454
RM2	t_{110}	0,2124	0,3118	0,399	0,4592	0,4854	0,504	0,5247
	t_{101}	0,2555	0,3491	0,3797	0,3987	0,4028	0,4105	0,4222
Stock Index	t_{12}	0,1387	0,2016	0,2262	0,2428	0,264	0,2838	0,33
	t_{21}	0,1132	0,197	0,2747	0,3228	0,3782	0,4131	0,4586
MY(10Y-3M)	t_{13}	0,0192	0,1063	0,1578	0,192	0,2552	0,3175	0,395
	t_{31}	0,0324	0,1435	0,2037	0,25	0,3121	0,3493	0,3933
MY(10Y-1M)	t_{14}	0,0498	0,0843	0,1052	0,1279	0,1874	0,244	0,32
	t_{41}	0,0559	0,0979	0,1421	0,1779	0,2465	0,3004	0,3618
10-year bond	t_{15}	0,0096	0,0599	0,1015	0,1475	0,2484	0,322	0,3782
	t_{51}	0,0207	0,1096	0,1707	0,2194	0,2909	0,3335	0,3683
1-month rate	t_{16}	0,1309	0,1849	0,2212	0,2551	0,3186	0,3685	0,4295
	t_{61}	0,0864	0,1229	0,1428	0,1641	0,2203	0,2602	0,3026
3-month rate	t_{17}	0,0067	0,0697	0,1399	0,1993	0,296	0,3509	0,3774
	t_{71}	0,008	0,058	0,104	0,1477	0,2421	0,3225	0,4284
1-year rate	t_{18}	0,2259	0,3434	0,3999	0,4364	0,4812	0,4972	0,5073
	t_{81}	0,1715	0,242	0,2861	0,3186	0,364	0,3856	0,3974
RM1	t_{19}	0,0372	0,1424	0,2317	0,2923	0,36	0,393	0,4211
	t_{91}	0,0236	0,1475	0,2294	0,2796	0,3372	0,3757	0,4227
RM2	t_{110}	0,2139	0,2768	0,3289	0,387	0,4662	0,4961	0,5182
	t_{101}	0,2604	0,331	0,3645	0,3859	0,4058	0,411	0,4157

TABLE B4 (Bartlett kernel-Parzen kernel)

Estimated temporal correlations for all the Taiwan financial variables used

Variables		S_T =3	S_T =6	S_T =9	S_T =12	S_T =18	S_T =24	S_T =36
Stock Index	t_{12}	0,0382	0,0933	0,1263	0,1463	0,1894	0,2298	0,2775
	t_{21}	0,1876	0,3314	0,4062	0,4363	0,4806	0,4971	0,5402
TW(10Y-3M)	t_{13}	0,0817	0,1566	0,238	0,305	0,3576	0,3883	0,4421
	t_{31}	0,045	0,1272	0,191	0,2362	0,2886	0,3187	0,3465
TW(10Y-1M)	t_{14}	0,1575	0,1989	0,2207	0,2367	0,2647	0,2844	0,2914
	t_{41}	0,1061	0,1458	0,1681	0,2028	0,278	0,3581	0,478
10-year bond	t_{15}	0,0201	0,0698	0,1033	0,1404	0,2042	0,2545	0,3286
	t_{51}	0,0196	0,0847	0,1664	0,199	0,2816	0,329	0,356
1-month rate	t_{16}	0,059	0,0819	0,1207	0,1588	0,215	0,3022	0,3809
	t_{61}	0,0639	0,1112	0,1621	0,1953	0,2306	0,2631	0,3108
3-month rate	t_{17}	0,0645	0,0913	0,1098	0,1197	0,168	0,2079	0,2435
	t_{71}	0,0363	0,1182	0,1445	0,1582	0,1746	0,2098	0,3394
RM1	t_{18}	0,0431	0,0619	0,079	0,1021	0,1518	0,2025	0,32
	t_{81}	0,0505	0,0809	0,1088	0,126	0,1486	0,1629	0,1808
Stock Index	t_{12}	0,0274	0,0676	0,1011	0,1249	0,1577	0,1864	0,2385
	t_{21}	0,0903	0,2854	0,3675	0,4131	0,4624	0,4885	0,5144
TW(10Y-3M)	t_{13}	0,0377	0,1244	0,1788	0,2302	0,3151	0,3604	0,4087
	t_{31}	0,0118	0,0808	0,1399	0,1857	0,2499	0,2888	0,3305
TW(10Y-1M)	t_{14}	0,1429	0,1982	0,2129	0,2243	0,2453	0,2635	0,2874
	t_{41}	0,0855	0,1395	0,1567	0,172	0,2132	0,2657	0,3723
10-year bond	t_{15}	0,0093	0,0435	0,0753	0,102	0,15	0,1935	0,267
	t_{51}	0,005	0,0428	0,1016	0,1538	0,2183	0,2698	0,3384
1-month rate	t_{16}	0,0541	0,0753	0,0902	0,1143	0,1637	0,2104	0,3076
	t_{61}	0,0592	0,0915	0,1205	0,153	0,2025	0,2318	0,2737
3-month rate	t_{17}	0,049	0,0852	0,0995	0,1105	0,1312	0,1599	0,2122
	t_{71}	0,0091	0,0797	0,1261	0,1484	0,1678	0,1803	0,2257
RM1	t_{18}	0,0413	0,0561	0,0658	0,0775	0,1087	0,1428	0,2163
	t_{81}	0,0465	0,0657	0,0852	0,1053	0,1309	0,147	0,1671

TABLE B5 (Bartlett kernel-Parzen kernel)

Estimated temporal correlations for all the Portuguese financial variables used

Variables		S_T =3	S_T =6	S_T =9	S_T =12	S_T =18	S_T =24	S_T =36
Stock Index	t_{12}	6,19E-02	9,07E-02	1,02E-01	1,05E-01	1,02E-01	9,75E-02	8,96E-02
	t_{21}	0,00674	0,01519	0,034409	0,05573	0,10368	0,14503	0,240308
PT(10Y-3M)	t_{13}	0,11905	0,16646	0,201411	0,21266	0,21973	0,22262	0,225173
	t_{31}	0,13967	0,35073	0,475281	0,55658	0,62844	0,65775	0,683672
PT(10Y-1M)	t_{14}	7,47E-02	1,15E-01	1,34E-01	1,43E-01	1,45E-01	1,39E-01	1,26E-01
	t_{41}	0,00189	0,01131	0,025616	0,05795	0,12775	0,19495	0,284505
10-year bond	t_{15}	0,11749	0,23383	0,245268	0,2517	0,25625	0,25822	0,260003
	t_{51}	0,2658	0,52147	0,57649	0,62362	0,66059	0,67623	0,690352
1-month rate	t_{16}	0	0	0	0	0	0	0
	t_{61}	3,23E-02	0,00479	0,012104	0,03581	0,11123	0,19493	0,318931
3-month rate	t_{17}	0,18085	0,35744	0,385053	0,39037	0,39121	0,39152	0,391836
	t_{71}	0,27276	0,43649	0,478469	0,50324	0,52813	0,53822	0,547081
1-year rate	t_{18}	3,57E-02	5,04E-02	5,42E-02	5,49E-02	5,13E-02	4,79E-02	4,31E-02
	t_{81}	1,32E+02	0,01194	0,025822	0,05976	0,11588	0,18299	0,324502
RM1	t_{19}	0,13946	0,30368	0,372136	0,40674	0,4276	0,43527	0,441986
	t_{91}	0,18891	0,28771	0,350689	0,37691	0,40076	0,40939	0,416929
Stock Index	t_{12}	3,57E-02	8,01E-02	9,52E-02	1,02E-01	1,07E-01	1,05E-01	9,86E-02
	t_{21}	0,00336	0,0113	0,01808	0,0298	0,0602	0,09243	0,15367
PT(10Y-3M)	t_{13}	0,10409	0,14748	0,174518	0,19832	0,22	0,22579	0,22843
	t_{31}	0,12486	0,24262	0,367216	0,46405	0,58078	0,63777	0,68481
PT(10Y-1M)	t_{14}	4,87E-02	9,97E-02	1,21E-01	1,34E-01	1,46E-01	1,48E-01	1,41E-01
	t_{41}	0,00113	0,00538	0,012988	0,0247	0,06256	0,11	0,20214
10-year bond	t_{15}	0,08613	0,19488	0,244622	0,25774	0,26256	0,26327	0,26334
	t_{51}	0,23997	0,43633	0,546845	0,59382	0,64549	0,67241	0,69462
1-month rate	t_{16}	0	0	0	0	0	0	0
	t_{61}	8,76E-03	0,00163	0,0057	0,01244	0,04161	0,09043	0,20155
3-month rate	t_{17}	0,15231	0,2896	0,367018	0,39361	0,40249	0,40076	0,39712
	t_{71}	0,23935	0,37982	0,451452	0,48488	0,51635	0,53244	0,54724
1-year rate	t_{18}	3,32E-02	4,67E-02	5,21E-02	5,46E-02	5,53E-02	5,32E-02	4,82E-02
	t_{81}	3,62E+01	0,00438	0,013161	0,02565	0,06282	0,1037	0,19675
RM1	t_{19}	0,08449	0,22032	0,318058	0,37147	0,4193	0,43648	0,44675
	t_{91}	0,11696	0,25999	0,315038	0,34956	0,38802	0,40516	0,41845

TABLE B6 (Bartlett kernel-Parzen kernel)

Estimated temporal correlations for all the Greek financial variables used

Variables		S_T =3	S_T =6	S_T =9	S_T =12	S_T =18	S_T =24	S_T =30
Stock Index	t_{12}	0,0422	0,0898	0,1267	0,1638	0,2098	0,238	0,2609
	t_{21}	0,0561	0,1217	0,161	0,197	0,2778	0,3427	0,3769
GR(10Y-3M)	t_{13}	0,0979	0,1778	0,2308	0,2581	0,3005	0,3373	0,3667
	t_{31}	0,0908	0,1497	0,1771	0,2086	0,2461	0,2627	0,2737
GR(10Y-1M)	t_{14}	0,0406	0,0899	0,1179	0,1416	0,1622	0,1778	0,1982
	t_{41}	0,0104	0,1835	0,313	0,3864	0,4287	0,4689	0,5014
10-year bond	t_{15}	0,0482	0,2529	0,338	0,388	0,4391	0,4546	0,4578
	t_{51}	0,0379	0,0821	0,1274	0,1924	0,3409	0,388	0,4105
1-month rate	t_{16}	0,0196	0,0645	0,0977	0,1405	0,192	0,2195	0,2587
	t_{61}	0,0112	0,1103	0,1601	0,1978	0,2501	0,3643	0,4241
3-month rate	t_{17}	0,1058	0,1551	0,1974	0,2487	0,3198	0,3479	0,3888
	t_{71}	0,0447	0,1058	0,2628	0,3374	0,3978	0,4243	0,4453
Stock Index	t_{12}	0,0323	0,0676	0,0988	0,1263	0,1749	0,2094	0,233
	t_{21}	0,013	0,0909	0,134	0,1645	0,2142	0,26801	0,3167
PT(10Y-3M)	t_{13}	0,0808	0,1427	0,1932	0,2305	0,2742	0,3031	0,3278
	t_{31}	0,0808	0,1317	0,1623	0,1828	0,2196	0,24618	0,262
PT(10Y-1M)	t_{14}	0,0267	0,0686	0,099	0,1208	0,1518	0,16814	0,1789
	t_{41}	0,0054	0,0583	0,1912	0,2996	0,4159	0,45721	0,4792
10-year bond	t_{15}	0,0272	0,1507	0,273	0,346	0,4224	0,45702	0,4704
	t_{51}	0,022	0,0574	0,0906	0,1242	0,2221	0,31885	0,3788
1-month rate	t_{16}	0,0065	0,0381	0,0705	0,0992	0,1528	0,19175	0,2186
	t_{61}	0,0026	0,0594	0,1207	0,1617	0,2161	0,26454	0,3227
3-month rate	t_{17}	0,0845	0,1442	0,1711	0,199	0,2656	0,31508	0,3456
	t_{71}	0,0275	0,0698	0,1388	0,2313	0,3576	0,41063	0,4346

TABLE B7 (Bartlett kernel-Parzen kernel)

Estimated temporal correlations for all the Korean financial variables used

Variables		S_T =3	S_T =6	S_T =9	S_T =12	S_T =18	S_T =24	S_T =36
Stock Index	t_{12}	0,0412	0,1032	0,1435	0,1897	0,256484	0,2875803	0,3283765
	t_{21}	0,079	0,1777	0,2496	0,3123	0,3921434	0,4446343	0,4897081
KO(10Y-3M)	t_{13}	0,0582	0,0991	0,1277	0,1483	0,1832503	0,22383	0,2727381
	t_{31}	0,0727	0,1073	0,1229	0,1467	0,2231411	0,2755995	0,3462194
10-year bond	t_{14}	0,0155	0,0651	0,1261	0,1895	0,2695204	0,3016929	0,3473025
	t_{41}	0,0211	0,0917	0,1534	0,208	0,2811109	0,3238456	0,3974312
3-month rate	t_{15}	0,1145	0,1736	0,201	0,2184	0,2592401	0,294438	0,332796
	t_{51}	0,1529	0,2403	0,2756	0,2965	0,3260043	0,3509762	0,3853409
RM1	t_{16}	0,0487	0,1735	0,3197	0,4014	0,4554149	0,4640605	0,4778818
	t_{61}	0,0043	0,0265	0,0623	0,1022	0,1646853	0,2033154	0,2334449
RM2	t_{17}	0,1422	0,2268	0,2658	0,2943	0,3350369	0,3741954	0,4125346
	t_{71}	0,1995	0,3003	0,3342	0,3508	0,3785302	0,3930214	0,420191
Stock Index	t_{12}	0,03	0,0711	0,1091	0,1405	0,2005	0,2477	0,301
	t_{21}	0,0454	0,1252	0,1903	0,2431	0,3276	0,3876	0,4594
KO(10Y-3M)	t_{13}	0,047	0,0831	0,1075	0,1274	0,1576	0,1834	0,234
	t_{31}	0,0591	0,0977	0,1153	0,1267	0,1617	0,2095	0,2902
10-year bond	t_{14}	0,0075	0,0342	0,0712	0,1133	0,1968	0,2579	0,3197
	t_{41}	0,0174	0,0502	0,0975	0,1425	0,2175	0,2725	0,3423
3-month rate	t_{15}	0,09	0,1535	0,1836	0,2022	0,229	0,2552	0,301
	t_{51}	0,1055	0,2064	0,2525	0,2787	0,3075	0,3273	0,3594
RM1	t_{16}	0,0284	0,093	0,1932	0,2906	0,416	0,4684	0,4907
	t_{61}	0,0025	0,0122	0,0305	0,0546	0,1078	0,1543	0,2124
RM2	t_{17}	0,1027	0,1929	0,2385	0,2669	0,3049	0,3343	0,3823
	t_{71}	0,1449	0,2595	0,3125	0,3391	0,3643	0,3803	0,402