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CHANGES IN SEASONAL PATTERNS : ARE THEY CYCLICAL

by

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RÉSUMÉ

Cet article explore l'hypothèse de variation cyclique dans la structure saisonnière. Des techniques graphiques ainsi que des tests généralisés de prédiction d'un changement structurel sont utilisés afin d'identifier et de tester la structure d'une composante saisonnière changeante. Les résultats indiquent que la composante saisonnière est instable. Dans plusieurs cas, les changements dans la composante saisonnière sont liés aux différents niveaux du cycle économique. Dans d'autres cas, la structure des changements est plutôt énigmatique. Un cas particulièrement intéressant est celui de la masse monétaire M1 qui manifeste une tendance ascendante dans le taux de croissance au deuxième trimestre durant la période après la Seconde Guerre mondiale.

Mots clés : stabilité structurelle, saisonnalité, variation cyclique.

ABSTRACT

This paper explores the hypothesis of cyclical variation in seasonal patterns. Graphical techniques and generalized predictive tests for structural changes are used to identify and test patterns of changing seasonality. The results indicate that seasonals are unstable. In many cases, changes in the seasonals are linked to the stages of the business cycle. In others, the pattern of changes is rather puzzling. Particularly interesting is the case of M1 which displays an upward trend in the second quarter growth rate throughout the post-WWII era.

Key words : structural stability, seasonality, cyclical variation.

1 Introduction

The observation that seasonal patterns in many macroeconomic variables appear to change through time was noted by a number of researchers (see e.g., Bell and Hillmer (1984)). Since then several statistical tests have been suggested to formally examine the stability of seasonal patterns, notably by Franzini and Harvey (1983), Ghysels (1990), Canova and Hansen (1991), Sutradhar, MacNeill and Dagum (1991), among others. It has been argued that since seasonals drift through time a simple deterministic seasonal dummy model should be rejected in favor of a linear stochastic time series model with seasonal differencing. A standard justification for using a model with seasonal unit roots is that changes in seasonal patterns are long run phenomena apparently linked to modifications of institutional factors of the economy. [1] While the latter may certainly be a contributing element to the changes we observe, other shorter run factors may also play a significant role. For example, Ghysels (1990) reports empirical evidence suggesting that changes in seasonal patterns of several post WWII aggregate quarterly U.S. time series appear to be linked to the stages of the business cycle and suggests extending the notion of asymmetries in time series (see e.g. Neftci (1984)) to that of seasonal patterns. Given this evidence models which represents seasonal factors with deterministic dummies (no-change model) as well as models which employs seasonal unit roots (long run changes) are inappropriate. In addition, variation through time in seasonal means affects standard tests for unit roots at seasonal frequencies [2].

The idea of conditioning the seasonal mean shift on the business cycle was motivated by the fact that most conventional dynamic structural models of macro time series suggest nontrivial interactions between the seasonal component and the other types of fluctuations. Ghysels (1990) implemented this idea using a model where seasonal

[1] Most of these arguments pre-date the development of formal tests for seasonal unit roots as for instance in Dickey, Hasza and Fuller (1984), Osborn at al. (1988), Hylleberg, Engle, Granger and Yoo (1990), Ghysels, Lee and Noh (1991).

[2] The arguments are similar to those made about overall mean shifts and tests for unit roots at the zero frequency, see e.g. Perron (1990) and Perron and Vogelsang (1991).

dummies were allowed to differ in expansions and recessions, hence yielding a stochastic seasonal process which was a rough first moment approximation to the complex and nontrivial interactions existing among the components of economic time series. The empirical evidence contained in that paper, while indicative of the possible interactions existing i9n many series, was not conclusive as it was based on a relatively simple time series model with the N.B.E.R. business cycle chronology as the basis for the switching regime indicator function.

In this paper we document the existence of medium run changes in seasonal patterns quite thoroughly for a large class of U.S. time series, including historical series (before WWII and even last century) and many of the most commonly used quarterly and monthly aggregated and disaggregated data. We employ both an informal graphical method recently advocated by Franses (1991) as well as recently developed formal statistical tests which exploit some recent advances in the theory of structural stability tests for dynamic single and multiple equation systems. The hypothesis of interest here is one where we allow for the presence of possibly multiple breaks at unknown dates. Generalized Predictive tests for structural stability, as proposed by Dufour, Ghysels and Hall (1991), are used to identify and test patterns of changing seasonality. Such statistics prove to be particularly well suited to examine the presence of cyclical variation in seasonal patterns as they are exploratory and can detect single or multiple shifts that are either temporary or permanent in nature.

We find that the majority of US aggregate time series we examined possess seasonals which drift over time and that, in some cases, these changes are linked to the stages of the business cycle. The evidence for disaggregated data is statistically less significant but economically more compelling because structural changes tend to emerge primarily during recessions. We also attempt to quantify the forecasting improvements one can obtain by allowing seasonals to evolve over time. We demonstrate that in many instances both a model which conditions the seasonal switches on business cycle phases and a flexible Bayesian model which allows the coefficients of the dummies to

drift over time improve the forecasting performance of a model where seasonals are represented by dummies. In particular, for the Bayesian model and for almost all post WWII series, the average forecasting gain at each step is about 10%.

The rest of the paper is organized as follows. Section 2 is devoted to documenting seasonal patterns and their variation through time. In section 3 we briefly review the statistical tests which are applied in section 4. Section 5 discusses the forecasting costs of treating seasonal patterns as constant. Section 6 concludes the paper discussing the implications of our findings for some issues of interest in the current macroeconomic literature.

2 Seasonal patterns and their instability

In this section we employ a simple and elegant graphical representation developed by Frances (1991), also used in Hylleberg, Jorgensen and Sorensen (1991), which we adopt and extend to examine seasonal instability and to highlight a possible relationship between the pattern of seasonal instabilities and phases of the business cycle. We limit our attention to quarterly time series since graphical methods are cumbersome to read and interpret with monthly data. Also, although Frances' representation requires no formal assumption of stationarity, we do transform most series to consider the first differences of the logs of the raw data because we would like the graphs to display those series which we formally examine in the next section. Let $\{y_{in}\}$ represent all observations pertaining to quarter $i = 1,..,4$ where n is a yearly sampling index. One then plots the four annual series $\{y_{1n}, ..., y_{4n}\}$, where each series represents a particular quarter of the year onto one graph. To highlight a possible relationship between the pattern of seasonal instabilities and phases of the business cycle, we shade recession years according to the N.B.E.R. business cycle chronology.

The plots can be used as specification diagnostics for the process generating seasonal patterns. The graphs should display stationary plots if the data generating process is one of deterministic mean shifts for each quarter around a stationary first differenced process. Parallel plots indicate a completely deterministic process. On the other hand if the data was generated by a process that requires seasonal differencing to yield stationarity, i.e. the application of the $(1 - \ell^4)$ operator, then the plots of the four annual observations of quarters should drift apart as the quarterly processes would not be stationary around a particular (seasonal) mean. Two special cases of drifts should be mentioned: when the plots of certain seasons cross, i.e. summer becomes winter, there may be evidence of a seasonal unit root. On the other hand, if the plots drift together toward a common mean, then seasonal cointegration may be present

Evidence on the pattern of seasonal changes and their relationship with the US business cycle is presented in figure 1 where we plot the four quarters for six US aggregated time series (GNP, Fix Investments (IFIX), Consumption of Durables (CDUR), M1, Employment (EMPL) and Final Sales (FINSALE)). All series but FINSALE are in log first difference.

In all six graphs there is visual evidence that seasonals tend to be sensitive to the various stages of the business cycle. Naturally, these graphs are only suggestive. While the lines representing quarters often cross, it appears that the crossing tends to occur most often in recession periods. We should note though that these patterns may be due in part to the construction of the shaded areas representing recessions. Since the NBER business cycle chronology is monthly, some convention is required to translate a monthly series into shadings on the graphs containing annual plots of quarterly data. The approach we use is similar to that of Ghysels (1990b). The monthly NBER chronology is converted to a quarter chronology by adopting a "majority rule", i.e. if at least two months of the quarter are in an expansion (contraction), the quarter is classified as an expansion (contraction) and an area on the graph is shaded if at least one quarter of the year is in a recession. One drawback of this approach is that because growth rates slow down during recessions, we should expect a convergence of the seasonal growth rates toward zero during these episodes.

Concentrating on the evidence emerging from 1970 on, the plot of IFIX indicates a

tendency of the four quarterly time series to converge in recessions and to diverge in expansions suggesting that for this variable seasonal and cyclical components interact multiplicatively. CDUR also provides an example of the tendency of seasonals to follow business cycle phases. In this case, however, there appears to be parallel movements of the four quarters over the cycle: in expansions all quarters shifts up and in recessions all quarters tend to shift down, suggesting the presence of a cyclical level effect. This pattern also emerges to a lesser extent also in GNP and FINSALE where the first quarter (the lowest time series in each plot) seems to move in the opposite direction of the other three quarters over the cycle. In EMPL the pattern of changes is even more complicated. In particular, while in the early period the behavior of the four time series roughly matches the behavior of the four quarters of GNP, in the last 10 years a seasonal inversion tends to appear.

The most striking pattern however, emerges with the M1 series which displays a clear upward trend in the second quarter (the solid line in the plot) [3]. Right after WWII there was approximately a 3% decline in M1 in the second quarter. Gradually this has changed to a 3% increase. It should be noted that the gradual upward trend shows a sharp dip in the second quarter of 1980, during the era of monetary policy changes in the US. Figure 2 highlights these features by plotting the time series for each quarter separately around its mean.

The presence of an upward trend in the first difference of M1 it rather puzzling from an economic point of view. However, it may shed some light on a number of statistical results that have been found in the literature. It is typically believed that the first difference of the *seasonally adjusted* M1 series is nonstationary. Sims (1972) in his seminal paper on money, income and causality suggested using the $(1 - .75\ell)^2$ filter to make the M1 series stationary. Eichenbaum and Singleton (1986) and others have used a twice differenced M1 series in their VARs. Stock and Watson (1989) performing a set of formal unit root tests found no evidence in favour of a second difference filter

[3] To a much lesser extent such a pattern is also visible in the first quarter of FINSALE.

but fitted a significant linear trend to the first differenced data. Our plots indicate that the linear trend specification seems most appropriate but it appears that the trending growth of M1 is entirely due to its second quarter.

A final point concerns studies involving *seasonally unadjusted* M1. Recently Lee and Siklos (1991) report test results suggesting that, besides a unit root at the zero frequency, unadjusted M1 has a unit root at the biannual frequency. They use this evidence to question findings and arguments contained in Barsky and Miron (1989) which are based on a seasonal dummy specification for univariate seasonally unadjusted series. Figure 2 seems to indicate that the biannual unit root may be spurious and a consequence of the fact that the second quarter is trending.

Although for reasons of space we are constrained to present only the plots of six macro time series, we found the patterns we present to be very typical of all the US quarterly aggregate time series we examined [4].

Based on these results, we conclude that there is compelling evidence of seasonal instability. Unfortunately, various complicated patterns make it difficult to provide a unified explanation for the phenomena. We noted examples of quarterly time series converging, crossing, approaching zero and then moving away from it and in one case slightly diverging. However, and more importantly for this paper, there is evidence that stages of the business cycle have something to do with this instability. Roughly speaking we find that quarters tend either to move together or in the opposite direction in expansions and recessions. A striking exception is M1, where the second quarter shows a clear upward trend.

Next we attempt to formally quantify these visual exercises using Generalized Predictive Tests (GPT) for structural stability (see Dufour, Ghysels and Hall (1991)). The task is to examine whether there is an overall tendency for structural instability to appear at particular points of the business cycle.

[4] Plots with other 19 quarterly time series are available on request.

3 Regression Models and Tests

Consider the following linear regression equation:

$$x_t = \sum_{s=1}^{S} \phi_s d_t^s + \sum_{j=1}^{p} a_j x_{t-j} + \eta_t \quad t \in T \tag{3.1}$$

where T is a subset of the integers $\mathcal{Z}$. It is assumed that the random disturbances $\{\eta_t, \ t \in T\}$ are independent or represent a martingale difference sequence. The d_t^s process is a standard seasonal dummy process and ϕ_s, $s = 1, ..., S$ are the seasonal mean shifts, assumed to be invariant through time. The tests will be performed on single equations, like (3.1), on a vector of seasons within a particular year and on vectors containing innovations of a particular season over a number of years (matching the quarterly graphs which appeared in the previous section). For convenience define the residual process as:

$$\eta_t \equiv f(x_t, \beta) \equiv x_t - \sum_{s=1}^{S} \phi_s d_t^s - \sum_{j=1}^{p} a_j x_{t-j} \tag{3.2}$$

where $\beta = (\phi_1, \ldots, \phi_s, a_1, \ldots a_p)'$.

The problem of whether seasonal patterns are time varying is closely related to the question of structural stability. Testing the structural invariance of a model has been considered in many research papers and has a long history. Most of the existing results are derived for the case of a linear regression equation where the null of structural invariance is tested against the alternative that there is a single breakpoint with known or unknown location. Such tests are either (1) Wald, likelihood ratio or Lagrange multiplier tests (see e.g. Andrews and Fair (1988)), (2) predictive out-of-sample tests (see Ghysels and Hall (1990a,b) or Huffman and Pagan (1989)) or (3) recursive CUSUM-type tests (see Brown, Durbin and Evans (1975) and Ploberger et. al. (1989)). The requirement that there is only one structural break under the alternative however is not suited for the context we are dealing with. Another possibility often encountered in the analysis of structural stability is that the parameters of the model drift under the alternative (for instance, they behave like a random walk). In many of the suggested formal statistical tests for the stability of seasonal patterns, like Franzini and Harvey (1983), Canova and Hansen (1991) and Sutradhar, MacNeill and Dagum (1991), the null of stability is tested against the alternative of drifting seasonals. It is clear that such an alternative is not very well suited either when one wants to analyze changes in seasonal patterns which are recurrent and of quasi-periodic nature.

The question of testing for cyclicality of seasonal patterns is more complicated than in standard problems because, if seasonals truly change with the stages of the business cycle, there is not a once and overall mean shift but instead we are faced with recurrent shifts at unknown dates

To address this question we adopt the approach recently developed by Dufour, Ghysels and Hall (1991), referred to as Generalized Predictive Tests (GPT). The procedure is analogous to Chow's predictive test (see Chow (1960)) yet it is applicable in the linear regression without the requirement of i.i.d. Gaussian errors and in general multi-equation nonlinear dynamic models. It can be viewed as an extension of the exploratory technique studied in Dufour (1980, 1982) for the case of linear regressions and of the predictive structural stability tests for general nonlinear models, derived in Ghysels and Hall (1990a). Generalized predictive tests in their standard form are not directly applicable to testing changes in seasonal patterns without some reinterpretation and modifications. Yet, the testing strategy comes the closest to taking a formal statistical look at the problem without a priori imposing the NBER business cycle chronology, as done in Ghysels (1990), a general random walk alternative for parameter variation, as in Canova and Hansen (1991), or a Markovian (periodic) stochastic regime switching structure, as in Ghysels (1991b). Generalized predictive tests are useful in our context, because they are not designed against a two-regime alternative nor a random walk alternative, but instead allow for an exploratory analysis of patterns of structural changes that might occur, in the same spirit as the informal graphical method we used in the previous section. We summarize the basic features of the procedure in section 3.1. In section 3.2 we discuss the potential problems and discuss the

modifications needed for our analysis.

3.1 Generalized Predictive Tests - A Brief Review

Generalized predictive tests are applicable when the parameters of the model are stable during a given (relatively large) estimation subperiod and the form and timing of possible structural change(s) during the second (prediction) subperiod are left unspecified. The procedure has several attractive features:

- the tests are based on out-of-sample predicted residuals.
- the prediction subsample considered can be arbitrarily small (e.g., one observation).
- one needs to estimate the coefficient vector β from one sample only (the estimation period).
- For the test to apply is only necessary that the first subperiod parameter estimate $\hat{\beta}$ is consistent. It need not be asymptotically normal, it may, in principle, converge at any rate to the true β vector and its asymptotic covariance matrix is not necessary to perform the tests.
- Very general forms of temporal dependence between model disturbances are allowed.

Suppose that $T = \{-t_1+1,\ldots,0,1,\ldots,t_2\}$ and the sample period T is split into two parts : $T_1 = \{-t_1+1,\ldots,0\}$ and $T_2 = \{1,\ldots,t_2\}$. The first sample is assumed to be large to allow the estimation of the model with asymptotic distribution theory being a reasonable approximation for the sampling distribution. However, the second sample need not be large. Further, we suppose that the model is stable over the first period T_1, while it is not necessarily stable over the second period T_2. Our task is to detect the presence of structural changes during this second period. In particular, we would like to analyze the timing and form of possible shifts over the latter period.

The null hypothesis is defined as

$$H_0 : E(f[x_t, \beta_0]) = 0 \; \forall \; t \; \varepsilon \; T \tag{3.3}$$

while the alternatives considered are subsets of the general alternative

$$H_1 : E(f[x_t, \beta_0]) = 0 \; \forall \; t \; \varepsilon \; T_1 \text{ and } E(f[x_t, \beta_0]) \neq 0 \text{ for some } t \; \varepsilon \; T_2 \tag{3.4}$$

A natural way of testing structural constancy consists of estimating the model from the first sample and then checking whether the estimated disturbances from the second sample, i.e. the "predicted residuals", are "large". More precisely, if $\tilde{\beta}_{T_1}$ is an estimator of β obtained from sample T_1, we check whether the predicted residuals

$$\tilde{\eta}_t(T_1) \equiv f[x_t, \tilde{\beta}_{T_1}] \, , \; t \; \varepsilon \; T_2 \tag{3.5}$$

are statistically "large". Under general regularity conditions discussed in Dufour, Ghysels and Hall (1991, section 3), $\tilde{\eta}_t(T_1)$ and η_t have the same asymptotic distribution as $T_1 \to \infty$ provided $plim_{T_1 \to \infty} \tilde{\beta}_{T_1} = \beta_0$.

Two types of predictive tests have been suggested. One examines individual values of $\tilde{\eta}_t(T_1)$, $t \; \varepsilon \; T_2$, for evidence of structural instability: these tests are called individual or sequential predictive tests (SPT). The other examines several or all the values of $\tilde{\eta}_t(T_1)$, $t \; \varepsilon \; T_2$, stacked into vectors for evidence of instability: these tests are referred to as joint predictive tests (JPT). By looking at individual elements of $\tilde{\eta}_t(T_1)$, we can assess which time periods exhibit discrepancies, while by stacking quarters or months into a vector we can construct a joint test for structural stability over an entire year. Finally, by taking a particular month or quarter over several years we will be able to study its evolutionary pattern over time. Individual predictive test statistics are:

$$\tilde{\nu}_t(T_1) = \frac{\tilde{\eta}_t(T_1)}{\tilde{\sigma}(T_1)} \quad t \; \varepsilon \; T_2 \tag{3.6}$$

where $\tilde{\sigma}(T_1)$ is the estimated variance of the residuals using the first sample. Under appropriate regularity conditions, the asymptotic distribution (as $T_1 \to \infty$) of $\tilde{\nu}_t(T_1)$ is identical to the distribution of $\nu_t = \frac{\eta_t}{\sigma}$ where σ is the standard error of the η_t process.

The joint predictive test statistics we consider are:

$$\tilde{U}^y_\tau(T_1) = \tilde{u}^y_\tau(T_1)'[\tilde{\Delta}_y(T_1)]^{-1}\tilde{u}^y_\tau(T_1) \quad \tau = 1, \ldots, m^2_y \tag{3.7a}$$

$$\tilde{U}^s_\tau(T_1) = \tilde{u}^s_\tau(T_1)'[\tilde{\Delta}_s(T_1)]^{-1}\tilde{u}^s_\tau(T_1) \quad \tau = 1, \ldots, m^2_s \tag{3.7b}$$

where $\tilde{u}^y_\tau(T_1)$ is a vector of predicted residuals collecting all quarterly (or monthly) residuals from a particular year in the second subsample T_2 and m^2_y is the number of years in the second subsample. Likewise $\tilde{u}^s_\tau(T_1)$ is a vector collecting all predicted residuals from a particular season over the entire subsample T_2 so that m^2_s equals either 4 or 12. The covariance matrices $\tilde{\Delta}_y(T_1) \equiv \text{diag}(\tilde{\sigma}(T_1))$ and $\tilde{\Delta}_s(T_1) \equiv \text{diag}(\tilde{\sigma}(T_1))$, with the number of elements equal to m^2_y and m^2_s are consistent estimators of the covariance matrices of the u_y and u_s obtained in the first subsample, i.e. as $T_1 \to \infty$, $\tilde{\Delta}_y(T_1) \to \sigma * I$ and $\tilde{\Delta}_s(T_1) \to \sigma * I$ [5].

Deciding whether $\tilde{\eta}_t(T_1)$ is "large" requires being able to determine the (unconditional) distribution of η_t. In deriving these test statistics, Dufour, Ghysels and Hall observe that distributional assumptions about model disturbances η_t play a vital role even asymptotically.

A testing strategy which only requires very weak distributional assumptions consists of using Markov inequalities. Simplicity and generality are the major advantages of this approach. Under suitable regularity conditions we can construct an upper bound on the p-values of $\tilde{\eta}_t(T_1)$ as:

$$\hat{p}_t(\tilde{\beta}, \tilde{\eta}, r) \equiv \frac{t_1^{-1} \sum_{j=-t_1+1}^{0} |\tilde{\eta}_j(T_1)|^r}{|\tilde{\eta}_t(T_1)|^r} \quad t \; \varepsilon \; T_2, \; r = 1, \ldots, m \tag{3.11}$$

Hence, sample T_1 is used to estimate the r^{th} moment required to calculate the upper bounds on the p-values in the second sample T_2. Although the choice of r is arbitrary, we will focus on second moments, i.e. $r = 2$. The principle of constructing upper bounds on the p-values for realizations of $\{\eta_t, \; t \; \varepsilon \; T_2\}$ can be extended to $\tilde{U}^j$, $j = s, y$

[5]The implicit restriction in this formulation is that $\tilde{\eta}_t(T_1)$ is homoskedastic. When the process is a martingale difference this assumption can be easily relaxed (see Dufour, Ghysels and Hall (1991)) and GPT still be applied

as discussed in detail in Dufour, Ghysels and Hall (1991). The upper bound for the p-values in these cases is given by:

$$\hat{p}_t(\tilde{\beta}, j, r) \equiv \frac{(m_j^1)^{-1} \sum_{\tau=1}^{m_j^1} |\tilde{U}_\tau^j(T_1)|^r}{|\tilde{U}_\tau^j(T_1)|^r} \quad t \in T_2,\ r = 1, \ldots, m \tag{3.12}$$

where $j = s, y$, m_y^1 is the number of years in T_1 and m_s^1 is the number of seasons [6].

3.2 Unit roots at seasonal frequencies, stochastic switching and GPT

In this paper GPT will be applied to a context which slightly deviates from the setup for which they were originally developed. Consequently, one needs to be aware of two potential problems that arise in our framework and may invalidate inference: the possibility that the data generating process (DGP) has unit roots at frequencies other than the zero one (in particular, at seasonal frequencies) and the possibility that stochastic switching in the DGP appears within the estimation sample.

As most of the data we use is first differenced, we may rule out the presence of unit roots at the zero frequency but, as part of the univariate characterization of seasonality, one might expect the possibility that unit roots appear at some or all seasonal frequencies. Evidence on this issue is overall mixed when one uses the formal statistical apparatus of Hylleberg, Engle, Granger and Yoo (1990) (HEGY), which, according to the simulation results reported in Ghysels, Lee and Noh (1991), compares most favorably in terms of finite sample size and power among a set of alternative procedures. Indeed, the empirical evidence concerning GNP for several countries (reported in Hylleberg, Jorgensen and Sorensen (1991)) and other quarterly data (presented in Beaulieu and Miron (1992) and Ghysels, Lee and Siklos (1992)) indicate that for some series unit root tests do not reject the null hypothesis at some seasonal frequencies.

[6] It is also possible to perform tests under the assumption the η's are jointly normally distributed and Dufour, Ghysels and Hall describe in detail this type of tests. While the assumption of normality may be appropriate, we prefer to present robust results based on Markov inequalities, since they require very weak assumptions. Obviously, if the normality assumption is correct, tests conducted under the normal distribution will be more appropriate as they will be more powerful and the size properties would not be conservative under the null.

The latter two papers are particularly relevant here as they examine some of the same data used in this paper.

The presence of unit roots at some or all of the seasonal frequencies does not create particular problems here. To apply Generalized Predictive Tests we only need to estimate the vector β, which includes the seasonal dummies and the polynomial lagged coefficients, consistently. No mention is made of the rate of convergence of the estimator may be slower or faster than the usual root-T. Moreover, the asymptotic distribution of $\hat{\beta}$ does not necessarily have to be known since only consistency of first sample estimators is required to apply the test. If unit roots are thought to be present at some of the seasonal frequencies the polynomial $a(\ell)$ must include, at least, enough lags to encompass all of the HEGY-type transformations which would remove such roots. This means that in the quarterly (monthly) case at least three (eleven) lags should be included. The $a(\ell)$ polynomial is included in (3.1) to prewhiten the residuals and to ensure that they behave like an uncorrelated sequence. If prewhitening does not take place (as in Ghysels (1990)) the error process need not be any longer an uncorrelated process (or a martingale difference). In that case one has to assume that unit roots at seasonal frequencies are not present to guarantee standard asymptotic results (see e.g. Gallant and White (1988)).

In addition to the issue of unit roots at seasonal frequencies, there is a second potential source of misleading inference regarding instability. The tests described in the previous section are readily applicable if seasonals were stable over the sample T_1 and then, due to institutional changes or other factors not necessarily known to the econometrician, would show patterns of permanent or transitory changes. The complication, however, may arise when seasonals are unstable throughout the sample not just on T_2. This is certainly the case when seasonal instability is linked to business cycle fluctuations. Hence the parameters obtained from T_1 are essentially drawn from an unstable sample. While this is a matter of concern, it is not necessarily fatal and does not prevent us from applying and properly interpreting the test results. An example may clarify this point. Let us assume that the true model is one where seasonal patterns are subject to cyclical changes. For simplicity we focus on one of the four seasonal mean shifts. To describe business cycle variations, we assume there are two states, one being a recession and the other an expansion (as in Hamilton (1989)). Furthermore, let the steady state probability of recession be λ and the mean of the quarter during this regime be x_1. Expansions have steady state probability of $1-\lambda$ and the mean of the quarter in this state is $x_2 > x_1$. In such a situation, for T_1 sufficiently large, the estimate of the mean of the quarter is $x_3 = \lambda x_1 + (1-\lambda)x_2$ which, by construction, is bounded below by x_1 and above by x_2. When it comes to testing the hypothesis of stability with data from the second sample and we are in an expansion (recession), we draw observations from a sample with mean x_2 (x_1) and compare them with observations from a sample whose estimated mean is x_3. It is fairly clear that, under these conditions, we should expect to reject the hypothesis of stability as the observations from the second sample will have low p-values when compared with the estimated distribution from the first sample.

In what follows, we will not use generalized predictive tests in their most general form. In particular, we choose the estimation sample T_1, to be equal to 75% of the entire data set, while the prediction sample T_2 represents the remaining 25%. Although this choice is arbitrary, it avoids possible data mining connected with the choice of the ending date of the estimation period. Evidence of stability of first sample estimates will be examined in detail for each of the data sets we examine.

4 Empirical Results

4.1 The Data

We apply GPT to three data sets. The first one was originally examined by Barsky and Miron (1989) in their study of the relationship between seasonal and cyclical fluctuations. The data set includes 25 variables which cover practically all the major nonseasonally adjusted US macroeconomic variables (total fixed investment, fixed res-

idential investments, fix nonresidential investments, fixed non residential structures, fixed non residential producer durables, total consumption, consumption of durables, consumption of nondurables, consumption of services, federal government expenditure, import and exports, final business sales, changes in business inventories, CPI, 1 month T-bill rates, M1, Unemployment, labor force, employment, monetary base, money multiplier, hours and wage rates). The original sources are described in the appendix of the Barsky and Miron paper. The sample covers data from 1946,1 to 1985,4 except for M1 (starting date 1947,1), for unemployment and labor force (starting date 1948,1), employment (starting date 1951,1), the monetary base and the money multiplier (starting date 1959,1) and hours and wage (starting date 1964,1). For all series but hours and wage T_1 ends in 1974,1. For hours and wage T_1 ends in 1977,1.

The second data set includes six monthly historical time series. They are: an index of aggregate industrial production for the period 1884,1-1939,12 (IP), an index of pigiron production (PIGIRON) , two financial time series: the call money rate (CALLMONY) and a stock market index (STOPRICE), an index of wholesale prices (WPI) and a high powered money (MONEY) series. These last five series cover the years 1890,1-1936,12. The first series was reconstructed by Miron and Romer (1990), the next three series are obtained from Macaulay (1938), the WPI index from the Bureau of Labor statistics and the M1 series was reconstructed by Canova (1991) using Treasury Bulletins and other publications.

The call money rate is the renewal rate at the desk of the New York Stock Exchange and refers to loans made for indefinite period of time but callable with 24 hours notice and requiring a collateral to the bank issuing the loan. The stock market index refers to the index number of the price of railroad stocks weighted by the number of shares outstanding at the beginning of the period. The high powered money series includes gold coins and certificates, silver dollars and certificates, Treasury and US notes, subsidiary silver outside the Treasury and, after 1914, Federal Reserve Notes. For all series in this data set T_1 ends in 1926,1.

The third data set is the same one used by Beaulieu and Miron (1991) and contains monthly data for two digit manufacturing industries. It includes data on outputs (Y4), shipments (SH), wholesale price indices (PR), weekly hours of production workers (HOURS) and total employment of production workers (EMPL). Y4 is composed of shipments plus the change in inventories which include both finished goods and work in progress. The data on shipments is collected by the Bureau of Economic Analysis of the Department of Commerce (BEA) and data on work in progress is collected by the Bureau of Labor Statistics (BLS). The hours and employment series are from the BLS Establishement's Survey. Finally, the wholesale price index is from BLS. One should note that the commodity classification of BLS differs from the commodity classification of BEA so that there is no particular matching between price and Y4 categories [7]. Data on Y4 shipments and prices are from 1967,1 to 1987,12. Data for employment and hours the 1947,1-1987,12 sample. Since presenting the results for the entire data is cumbersome and tedious (there are more than 220 series in this disaggregated data set), we concentrate on the attributes of three industries which appear to be particularly sensitive to business cycle conditions. Of these three industries two of them are from the nondurable category: textile and petroleum (BEA code numbers 22 and 29) and one from the durable category : machinery (BEA code number 35). For all series in this data set T_1 ends in 1980,1 except for HOURS and EMPL where T_1 ends in 1977,1.

Before discussing the results obtained with each data set we provide some evidence on the appropriateness of the assumption that the model (3.1) is stable on T_1. For this purpose we computed recursive residuals for each series in each data set and performed sequential Chow tests for the stability of the estimates in the first sample. The results, not reported for reason of space but available on request, suggest that for

[7]The BEA classification is as follows: 20=food, 21=tobacco, 22=textile, 23=apparel, 24=lumber, 25=furniture, 26=Paper, 27=printing, 28=chemicals, 29=petroleum, 30=Rubber, 31=leather, 32=stone,clay,glass, 33=primary metal, 34=fabricated metal, 35=machinery, 36=electric machinery, 37= transportation equipment, 38= Instrument, 39=others. The BEA classification code also provides a series for aggregated 2-digit durable industries, one for aggregated 2-digit nondurable industries and a series for total aggregated 2-digit industries.

the first data set the sample 47,1-74,1 is approximately stable and no evidence of strong departures from the basic assumptions appear. The evidence for the second data set is less compelling. Money, WPI and Pigiron production all display significant outliers around WWI years and the IP series displays an evident heteroskedastic behavior after 1916. However, with a dummy accounting for WWI years much of these instabilities disappear. Finally, call money rate residuals have significant outliers at times when financial crises occurred and these effects are not easily accounted for with standard intervention techniques. The third data set is again more supportive of the assumption of stable first sample. For many series we found no evidence of structural change of any kind. The exceptions are the production and shipments series in the textile industry whose residuals display increased volatility after 1978 and hours and employment in the petroleum industry which show outliers in 1953 and 1969, respectively.

4.2 Post WWII US Quarterly Macro Variables

For many series in this data set there is a tendency for the p-values of the Markov inequalities for SPT to go below the 5% mark during recessions. This tendency however is not generalized. For example, all three labor series (Unemployment, Employment and Labor Force) and the money multiplier series do not display any statistically significant evidence of instabilities, even though the unemployment series display economically important spikes in the p-values during recessions (see figure 3). On the other hand, series like Consumption of services, Imports and M1 tend to pass the 5% mark in expansions as well as recessions. In addition, the effects of recessions on the seasonal patterns of the series are not all alike. While during the 74-75 recession structural changes appear to be minor (the only exceptions here are the three consumption series), a clear pattern of instabilities appear in the last two recessions (79-81) and (81-83), with a strong concentration of structural changes during the 81-83 contraction. The exception in this case is the FINSALE series which seems to display instabilities only during the 79-81 recession [8].

The joint annual tests (see table I) confirm the results of the STP and suggest (a) the emergence of structural instabilities in the last two recession of the sample and (b) a tendency toward long run drifts. Finally, the joint test for each season over the entire sample strongly supports the idea that all the series but the T-bill rate, which does not display any significant seasonal, and the unemployment rate in the fall are unstable.

4.3 Historical Monthly Time Series

When we consider a plot of SPT (see figure 4) all of the series of this data set behave similarly but the evidence of instabilities is mixed. The IP and Pigiron series display instabilities in 1927 and 1930, the CALLMONY rate in 1926-27 and 1934, while WPI in 1928-1929 and 1933-34. All of these statistically significant changes appear to be connected with the two recessions in the prediction sample. The results obtained with STOPRICE and MONEY, which show instabilities in all the years between 1926 and 1933, confirm the intuition that the great crash had a long lasting structural effect on these two variables. However, all of series in this data set also display structural changes which appear to be unrelated to either the great depression or the recessions in the prediction sample.

The JPT are less supportive of the idea that any seasonal changes occurred in the predictive sample (see table II). The only joint yearly test which is significant is the one for the stock price index while a marginal significance level obtains for IP. One interpretation of this result is that although changes may have occurred within the sample, they tended to average out throughout the year. This impression is confirmed by the monthly tests which suggest that time variations in the seasonal patterns are concentrated, for most series, in the late spring and in the early summer months.

[8] These features also emerge when we use normal probabilities and the effects are more pronounced. In general the 5% mark is passed in both of the last two recessions for almost all series (the exception here is the T-bill rate). Also to be noted are the behavior of the labor series, which never reach the 5% limit, and of the wage series, which seems to be unstable throughout the sample.

4.4 Disaggregated Macro Data

The evidence emerging from the third data set is supportive of the idea that business cycle fluctuations play a nontrivial effect on the pattern of seasonality of existing disaggregated time series (see figure.5 and table III). Except for the price level in the petroleum industry and shipments in the machinery industry, we see that there is a tendency for the p-values of the Markov inequalities of SPT for many series to pass the 5% bound exactly in recessions. It is also worth emphasizing that, because of the relatively small sample size available for production, shipment and prices (20 years), the 5% mark for Markov inequalities is probably too demanding and one should look for tendencies more than for direct violations of this bound.

Although insignificant from the statistical point of view, the evidence provided by the employment series in all three industries is economically important. Figure 5 indicates that time when seasonals appear to be varying is during recessions. One can think of many explanations for this tendency. Given the existing rigidities in adjusting employment levels, the most obvious one is that in recessions firms are willing to provide longer vacation time for workers thereby altering the existing pattern of seasonality in employment. Interestingly enough, this asymmetric pattern is not evident in productive hours. It is still true that seasonals tend to vary over the cycle but seasonal changes are more symmetric over the business cycle. Finally, one should note that seasonal changes in output and shipments display almost identical behavior, with seasonal changes in shipments being only slightly more cyclical.

The joint tests confirm these results. All series but employment in the petroleum industry display both changes in their joint yearly pattern as well as changes in the pattern over months in the sample. The employment series in the petroleum industry do display instabilities when individual months are considered but these changes appear to average out over the year.

5 The Costs of Treating Seasonality as Constant

The last section provided evidence suggesting that seasonals are unstable in the medium run and perhaps related to business cycle fluctuations. To determine the costs a researcher incurs by assuming a model in which seasonals are represented by time invariant seasonal dummies, when the actual data generating process for the seasonals varies with the stages of the business cycle, we conduct a simple forecasting exercise. Ghysels, Lee and Siklos (1992) examine the costs of incorrectly specifying the seasonal component of a series from the point of view of the autocorrelation function of the data.

To determine the forecasting costs of a wrong model specification we construct a statistic similar to the Theil-U. The denominator of the statistic is the Mean Square Error (MSE) of a model whose seasonals are treated as constant over time (seasonal dummy model). The numerator is either the MSE of a model where seasonal dummies are allowed to change with the stages of the business cycle (as in Ghysels (1990)) or the MSE of a model where the coefficients of the dummies are allowed to drift over time according to a Litterman-type prior (as in Canova (1992)). This statistic provides a useful measure of the forecasting performance of alternative models, allows a rough calculation of the gains obtained by taking into account the evidence we uncovered in previous sections and has a very simple interpretation. If a value less than 1 obtains, the model with changing seasonals dominates a model with constant deterministic dummies and viceversa if a value greater than 1 obtains. The three model specifications we employ are given by (3.1), by :

$$x_t = \sum_s (\phi_s + \chi\delta_s) d_t^s + \sum_{j=1}^{p} a_j x_{t-j} + \eta_t \qquad (5.1)$$

and by:

$$x_t = \sum_s \phi_{st} d_t^s + \sum_{j=1}^{p} a_{jt} x_{t-j} + \eta_t \qquad (5.2)$$

$$\beta_t = G\beta_{t-1} + u_t \qquad (5.3)$$

where χ is a dummy variable which is equal to 1 if the economy is in an expansion according to NBER chronology and 0 otherwise, δ's are seasonal dummies, $\beta_t' = [\phi_{1t}, ...\phi_{st}, a_{1t}, ...a_{jt}]$, $G = \text{blockdiag}[G_1, G_2]$, $G_1 = \theta_1 * I$, $G_2 = I$, $u_t' = [u_{1t}, 0], u_{1t} = \text{diag}[\sigma_u^2] * \theta_2$. θ_1 and θ_2 are hyperparameters which will be selected with a rough specification search a-la Litterman. In all three specifications, p lags of x_t are included to prewhiten the residuals. In (5.1) and (5.2)-(5.3) only the coefficients of the dummies are allowed to vary over time while the AR coefficients are taken to be time invariant. This allows us to focus the attention on changes over time in seasonality since the three models differ only in the treatment of the seasonal component of the series. The basic constant seasonal dummy model (3.1) is nested in the two above specifications by simply setting $\chi = 0$, $\forall t$ in (5.1) and $\theta_1 = 1$ and $\theta_2 = 0$ in (5.2)-(5.3). In addition, by setting $\theta_1 = 1$ and θ_2 to a dummy variable which takes a value different than one at business cycle turning point we can approximately nest model (5.1) into model (5.2)-(5.3). Therefore (5.2)-(5.3) is the most general seasonal specification we use.

To conduct forecasts in real time with model (5.1), we move business cycle turning points in the forecasting sample 2 quarters forward. That is, if a recession started, say, in the first quarter of 1980, agents using (5.1) as their forecasting model would not have been able to use this information until the third quarter of 1980. To make the comparison across models reasonable we therefore maintain this informational delay in our forecasting exercise. For the model (5.2)-(5.3) and for all series we examined, we selected $\theta_2 = 0.01$ while, depending on the series, θ_1 ranges from 0.80 to 1.03. Finally, p is set to 4 for quarterly data and 12 with monthly data.

The results of the forecasting exercise for selected series are presented in table 4. We report results for a total of 18 series only (7 from the first data set, all of the second data set and 5 from the third data set). It should be clear however, that the results we present are very much representative of the patterns we obtained with the 251 series included in all the three data sets [9]. The estimation samples for the three

[9] For the interested reader results for the remaining series are available on request.

data sets are 1951,1-1976,4 for aggregated quarterly series, 1880,1-1925,12 for historical monthly series and 1947,1-1976,12 (or 1967,1-1979,12) for disaggregated monthly series. The forecasting samples are 1977,1-1985,1; 1926,1-1936,12 and 1977,1 (1980,1)-1987,12, respectively. We present results for 1, 4 and 9 steps ahead for quarterly data and 1, 4 and 13 steps ahead for monthly data.

Table 4 indicates that there are some gains from modelling cyclical changes in seasonality. The gains are not overwhelming with model (5.1). Although this may be due to its extreme simplicity, it is comforting to see that, independent of the forecasting horizon, the model outperforms on average a model with unchanged seasonals in more than half of the cases examined. When we model changes in the seasonal patterns flexibly with a Bayesian prior the evidence is much more supportive. The generic time varying coefficients (TVC) model outperforms the basic dummy model for 6 of the 7 aggregated quarterly macro data and for all disaggregated macro data. Although formal statements are not possible because there is no analytical closed form expression for the asymptotic standard error of the statistics we use, it is interesting to note that the TVC model outperforms the dummy model for these two data sets on average over variables and steps by about 10%. For historical data the TVC model and the dummy model appear to be substantially equivalent with the only significant difference emerging for the call money rate. This evidence seems to support the idea that changes in the seasonal patterns of interest rates occurred throughout the 1880-1936 sample.

In conclusion, we find that there are gains to be made by modelling cyclical fluctuations in seasonal patterns. Although more evidence should be collected before conclusions can be generalized, the results suggest that the costs of taking a short cut approach to account for seasonal fluctuations may be substantial.

6 Conclusions

This paper documents the existence of medium run changes in seasonal patterns quite thoroughly for a large class of U.S. time series, including aggregated historical series

as well as many of the most commonly used quarterly and monthly aggregated and disaggregated data. In documenting these changes we rely both on the simple graphical method recently advocated by Franses (1991) and on recent advances in the theory of structural stability tests for dynamic single and multiple equation systems as proposed by Dufour, Ghysels and Hall (1991).

We find that for the majority of the aggregate US time series examined seasonals vary over time and, in some cases, these variations are linked to the stages of the business cycle. The evidence for disaggregated data is less statistically significant but more compelling from an economic point of view since changes appear to occur primarily in recession. We demonstrated with a simple forecasting exercise that there are gains to be made by more carefully modelling the seasonal components of the series. In particular, by allowing a flexible pattern of time variations in the seasonal dummies we find that the forecasting performance of a model with constant seasonals can be improved (in MSE terms) by 10% on average.

Our results have important implications for current applied macroeconomic practice. Most of the existing literature has neglected to take into account seasonal fluctuations, by using either seasonally adjusted data in the analysis of macro issues or models which implicitly abstract from seasonal components. The few studies who explicitely examine the information contained in seasonal fluctuations assume that, for all purposes, they can be captured with deterministic dummies (see e.g. Miron (1986) or Singleton (1988)).

Modelling seasonal fluctuations with dummies has gained widespread acceptance in macroeconomics for four reasons. First, it is a simple procedure which can be mechanically applied to any time series and easily reproduced, reducing judmental decisions on the possible forms seasonality take. Second, for most series, seasonal dummies capture a substantial portion of the existing seasonal fluctuations. Third, the procedure implements a traditional statistical view that the business and seasonal cycle are phenomena to be studied separately. Finally, the application of dummies to seasonally unadjusted series generates seasonal facts which correspond to economists' prior notion of seasonal fluctuations.

Despite its widespread use, this approach neglects two important facts. First, the traditional separation of seasonal and business cycles is not an attribute of modern business cycle theory which, in general, embody extensive cross frequency restrictions. Second, some economic models (see Hansen and Sargent (1992)) do contain explicit information about the interaction of seasonal and business cycles.

If one takes the point of view that it is desirable to characterize cyclical and seasonal fluctuations in macro aggregates and wish to examine the validity of models using the restrictions they imply on the interaction between the various components of the series, our results suggest a number of conclusions.

First, cataloging business cycle facts with seasonally adjusted data is improper unless the seasonal adjustement takes into account the particular form of interaction existing among the components of the series (and this is seldom the case). Second, aggregate macroeconomic models should explicitly examine not only seasonal fluctuations but also the seasonal and cyclical interaction in order to provide a guideline to organize the facts we have described in this paper. Third, the asymmetric behavior of seasonals over the business cycle makes it clear that linear-quadratic models or models which are linear-quadratic approximated around the steady state are incapable of capturing important features of the data. Theoretical models with some form of threshold may be more useful in characterizing the cyclical/seasonal properteies of the data. Finally, the observation that the sectorial monthly employment series display the most interesting economic variations in seasonals while aggregate quarterly emplyment series do not, speaks against the use of representative agent general equilibrium models. It also suggests that rigidities in sectorial labor markets may have something to do with the presence of nonlinear effects in existing macroeconomic time series.

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Table I: Aggregate Macro Data
P-values for Joint Markov Inqualities
Sample 1974,1-1985,4

Variable	1974	1975	1976	1977	1978	1979	1980	1981	1982	1983	1984	1985	Spring	Summer	Fall	Winter	Overall
IFIX	0.08	0.17	0.08	0.07	0.02	0.02	0.08	0.01	0.00	0.06	0.00	0.00	0.00	0.00	0.00	0.00	0.00
IFIXR	0.11	0.34	0.17	0.06	0.02	0.04	0.06	0.02	0.01	0.02	0.01	0.01	0.00	0.00	0.00	0.00	0.00
IFIXNR	0.15	0.13	0.10	0.07	0.03	0.02	0.07	0.03	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
IFIXNRS	0.05	0.05	0.05	0.20	0.04	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
IFIXNRPD	0.27	0.70	0.07	0.03	0.02	0.02	0.05	0.02	0.02	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CNS	0.10	0.05	0.07	0.05	0.05	0.05	0.02	0.01	0.02	0.00	0.03	0.01	0.00	0.00	0.00	0.00	0.00
CND	0.10	0.45	0.10	0.02	0.03	0.02	0.01	0.01	0.00	0.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00
CDUR	0.13	0.08	0.09	0.25	0.05	0.06	0.05	0.01	0.04	0.03	0.02	0.01	0.00	0.00	0.00	0.00	0.00
CSER	0.27	0.12	0.09	0.03	0.03	0.04	0.02	0.04	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00
GNP	0.14	0.27	0.27	1.00	0.09	0.11	0.21	0.20	0.03	0.27	0.02	0.02	0.00	0.00	0.00	0.00	0.00
GOVFED	0.07	0.25	0.46	0.17	0.09	0.04	0.01	0.02	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
IMPORT	0.36	0.82	0.02	0.17	0.58	0.17	0.03	0.01	0.02	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.00
EXPORT	0.24	0.05	0.06	0.15	0.08	0.02	0.08	0.01	0.03	0.01	0.01	0.03	0.00	0.00	0.00	0.00	0.00
BUSINV	0.07	0.06	0.09	0.60	0.21	0.70	0.07	0.05	0.01	0.01	0.00	0.01	0.00	0.00	0.00	0.00	0.00
FINSALE	0.07	0.14	0.07	0.14	0.02	0.02	0.02	0.01	0.06	0.00	0.01	0.02	0.00	0.00	0.00	0.00	0.00
CPI	0.06	0.07	0.13	0.15	0.09	0.03	0.01	0.02	0.03	0.01	0.03	0.16	0.00	0.00	0.00	0.00	0.00
T-BILL	0.17	0.29	0.53	1.00	1.00	0.27	0.14	0.01	0.06	0.03	1.00	0.48	0.08	0.07	0.12	0.15	0.09
M1	0.53	0.07	0.02	0.03	0.04	0.01	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00
UNEMP	1.00	0.08	1.00	0.44	0.35	0.72	1.00	0.21	0.43	0.28	0.30	1.00	0.00	0.03	0.07	0.00	0.00
LABFOR	0.05	0.04	0.05	0.06	0.06	0.05	0.02	0.10	0.13	0.04	0.02	0.03	0.00	0.00	0.00	0.00	0.00
EMPL	0.15	0.03	0.10	0.18	0.11	0.12	0.22	0.23	0.01	0.02	0.02	0.02	0.00	0.00	0.00	0.00	0.00
MONBASE	0.21	0.08	1.00	0.10	0.23	0.06	0.04	0.01	0.04	0.07	0.04	0.13	0.00	0.00	0.00	0.00	0.00
MONMULT	0.09	0.10	0.05	0.12	0.05	0.02	0.01	0.01	0.02	0.05	0.03	0.06	0.00	0.00	0.00	0.00	0.00
WAGE				0.79	1.00	0.18	0.13	0.08	0.20	0.14	0.13	0.26	0.00	0.00	0.00	0.02	0.00
HOURS				0.05	0.00	0.00	0.01	0.00	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00	0.00

Notes: The year entry refers to the test for the joint behaviour of that year. The season entry refers to the joint behavior of that season over all the years of the sample. Overall refer to a test for all the years in the sample.

Table II: Historical Data
P-values for Joint Markov Inqualities
Sample 1926,1-1939,12

	Call Rate	Money	WPI	Stock Index	Pigiron	IP
1926	1.00	1.00	0.43	0.15	1.00	0.51
1927	1.00	0.88	1.00	0.12	0.10	0.20
1928	1.00	0.64	1.00	0.13	1.00	0.13
1929	1.00	0.62	1.00	0.04	1.00	0.13
1930	0.53	0.66	1.00	0.00	1.00	0.15
1931	1.00	0.49	0.94	0.02	0.77	0.22
1932	0.52	0.46	1.00	0.01	1.00	0.11
1933	1.00	0.72	1.00	0.03	1.00	0.19
1934	1.00	0.06	0.49	0.02	0.67	0.07
1935	1.00	1.00	0.73	0.08	0.72	0.07
1936	1.00	1.00	1.00	0.13	1.00	0.06
1937						0.17
1938						0.09
1939						0.24
January	0.12	0.00	1.00	0.00	0.02	0.00
February	0.05	0.01	0.51	0.09	0.02	0.01
March	1.00	0.00	0.31	0.00	1.00	0.01
April	0.39	0.00	0.07	0.00	1.00	0.03
May	0.07	0.03	0.08	0.02	0.32	0.01
June	0.03	1.00	0.13	0.03	0.03	0.02
July	0.11	0.01	0.11	0.19	0.80	0.01
August	0.81	0.05	1.00	0.00	0.00	0.01
September	1.00	0.00	0.65	0.00	0.03	0.19
October	0.13	0.02	0.36	0.00	1.00	0.00
November	1.00	0.05	1.00	0.00	0.09	0.00
December	1.00	0.07	0.16	0.00	0.11	0.00
Overall	0.05	0.00	0.02	0.00	0.01	0.00

Notes: The year entry refers to the test for the joint behaviour of that year. The month entry refers to the joint behavior of that month over all the years of the sample. Overall referes to the joint test for all the years in the sample.

Table III: Disaggregated Data
P-values for Joint Markov Inqualities
Sample 1977,1-1987,12

	Y422	Y429	Y435	SP22	SP29	SP35	PR22	PR29	PR35	EMP22	EMP29	EMP35	PDHR22	PDHR29	PDHR35
1977										1.00	1.00	0.02	0.02	0.41	0.02
1978										1.00	1.00	0.14	0.09	0.22	0.03
1979										1.00	1.00	0.08	0.06	0.12	0.03
1980										1.00	1.00	0.01	0.02	0.00	0.01
1981										0.23	0.02	0.02	0.05	0.03	0.06
1982	0.01	0.01	0.01	0.02	0.00	0.02	0.03	0.05	0.04	0.43	1.00	0.04	0.00	0.16	0.01
1983	0.01	0.00	0.01	0.02	0.00	0.03	0.02	0.01	0.08	0.16	1.00	0.02	0.00	0.09	0.03
1984	0.00	0.00	0.01	0.01	0.00	0.01	0.05	0.04	0.06	1.00	1.00	0.05	0.02	0.17	0.06
1985	0.00	0.00	0.00	0.02	0.00	0.00	0.02	0.04	0.16	0.61	1.00	0.15	0.04	0.24	0.08
1986	0.00	0.00	0.00	0.03	0.02	0.00	0.06	0.01	0.08	0.49	1.00	0.27	0.02	0.06	0.04
1987	0.00	0.00	0.00	0.02	0.00	0.00	0.10	0.00	0.10	0.94	1.00	0.37	0.03	0.17	0.10
January	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.00	0.01	0.03	0.00	0.00	0.01	0.01	0.00
February	0.00	0.01	0.00	0.02	0.00	0.00	0.03	0.05	0.01	1.00	0.02	0.01	0.00	0.00	0.00
March	0.32	0.00	0.00	1.00	0.00	0.00	0.00	0.00	0.01	0.05	0.03	0.00	0.00	0.01	0.01
April	0.00	0.00	0.00	0.04	0.01	0.00	0.09	0.00	0.14	0.03	0.20	0.00	0.01	1.00	0.02
May	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.00	0.02	0.00	0.01	0.00	0.05	0.02	0.00
June	0.00	0.04	0.00	0.02	0.06	0.00	0.09	0.00	0.00	0.12	0.00	0.01	0.00	0.01	0.01
July	0.19	0.01	0.00	0.00	0.01	0.00	0.00	0.00	0.03	0.28	0.08	0.03	0.02	0.00	0.01
August	0.00	0.01	0.00	0.04	0.00	0.00	0.02	0.00	0.02	0.11	0.00	0.00	0.01	0.02	0.01
September	0.02	0.02	0.00	0.04	0.00	0.00	0.74	0.00	0.00	0.05	0.02	0.06	0.09	0.00	0.00
October	0.00	0.01	0.26	0.00	0.00	0.03	0.00	0.00	0.06	0.05	0.01	0.05	0.01	0.00	0.00
November	0.00	0.00	0.01	0.02	0.00	0.00	0.00	0.00	0.01	0.03	0.00	0.01	0.04	0.00	0.01
December	0.00	0.01	0.00	0.00	0.00	0.00	0.02	0.00	0.97	0.06	1.00	0.00	0.00	0.00	0.00
Overall	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: The year entry refers to the test for the joint behaviour of that year. The month entry refers to the joint behavior of that month over all the years of the second sample. Overall refers to a tests for the joint behavior over the entire sample. Y4 are output series, SH are shipment series, PR are price series, EMP employment series and PDHR are production hours. Industry 22 is textile, industry 29 is petroleum and industry 35 is machinery.

Table IV: Forecasting Statistics
Modified U-statistic

	Interactive Model				Time Varying Model			
Variable/Step	1	4	9	13	1	4	9	13
	Aggregate Quarterly Macro Data Sample 77,1-85,4							
GNP	1.01	1.01	1.00		0.88	0.88	0.92	
IFIX	0.98	0.98	0.99		0.90	0.90	0.94	
CDUR	1.01	1.01	1.01		0.86	0.86	0.93	
M1	1.01	1.00	1.00		0.91	0.91	0.97	
EMPL	0.92	0.95	1.16		1.02	0.86	1.01	
FINSALE	1.01	1.01	1.01		0.84	0.85	0.92	
MONMULT	0.96	0.95	0.94		0.97	0.98	1.00	
	Historical Macro Data Sample: 1926,1-1936,12							
IP	1.01	1.01		1.01	0.99	0.99		0.99
CALL RATE	1.03	1.02		1.00	0.87	0.87		0.86
MONEY	1.07	1.07		1.05	0.99	1.00		0.98
WPI	1.20	1.18		1.10	0.99	0.99		0.99
STOCK INDEX	0.98	0.98		0.99	1.00	1.00		1.00
PIGIRON	1.71	1.74		1.58	0.99	0.99		0.99
	Disaggregated Macro Data Sample: 1977,1(1980,1)-1987,12							
Y435	0.98	0.98		0.98	0.79	0.79		0.90
SH35	0.99	0.99		1.00	0.70	0.70		0.83
PR35	0.95	0.91		0.73	0.90	0.91		0.92
EMP35	1.01	1.01		1.01	0.99	0.99		0.99
HOURS35	0.97	0.97		0.96	0.99	1.00		0.98

Notes: In the aggregate macro data GNP is gross national product, IFIX is fixed investments, CDUR is consumption of durables, M1 is money, EMPL is employment, FINSALE is final sales, MONMULT is the money multiplier. In the historical macro data IP is the Miron-Romer (1990) Index of Industrial Production, CALL RATE is the call money rate, MONEY is a measure of money, WPI is the wholesale price index, STOCK INDEX is a stock price index and PIGIRON is pigiron production. The disaggregate macro data refer to industry 35 (Machinery) and Y4 is a measure of output, SH is a measure of shipments, PR is the price of output, EMP is a measure of employment and HOURS is a measure of production hours. "Interactive model" refers to a model where seasonal dummies are interacted with a cyclical dummy. "Time Varying Model" refers to a model where time variation in the dummies is modelled with a Bayesian prior.

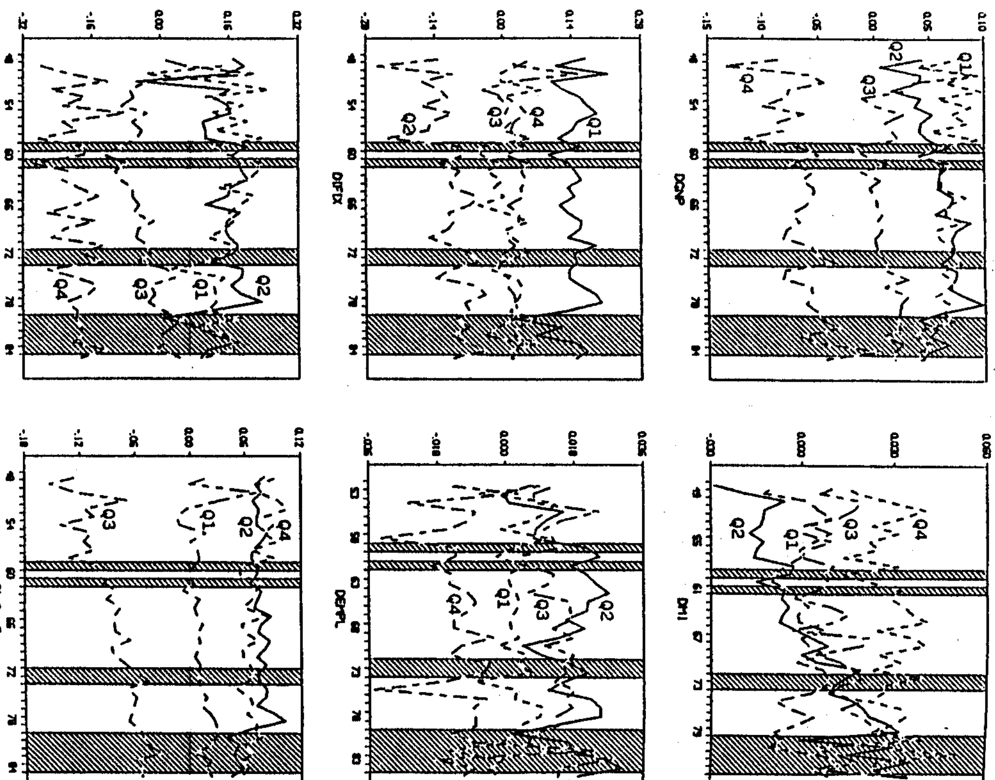

FIGURE 1: ANNUAL PLOTS OF QUARTERLY DATA

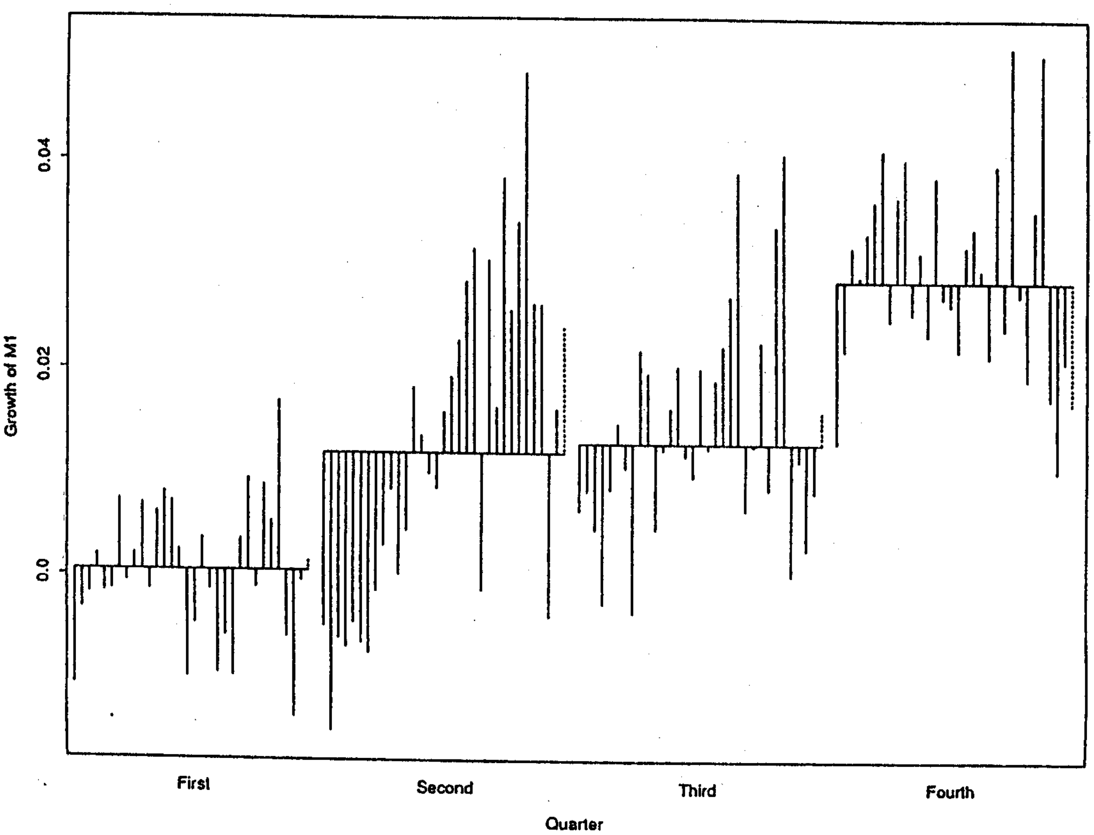

FIGURE 2: QUARTERLY GROWTH OF M1: 1959:1 TO 1991:3 (NSA)

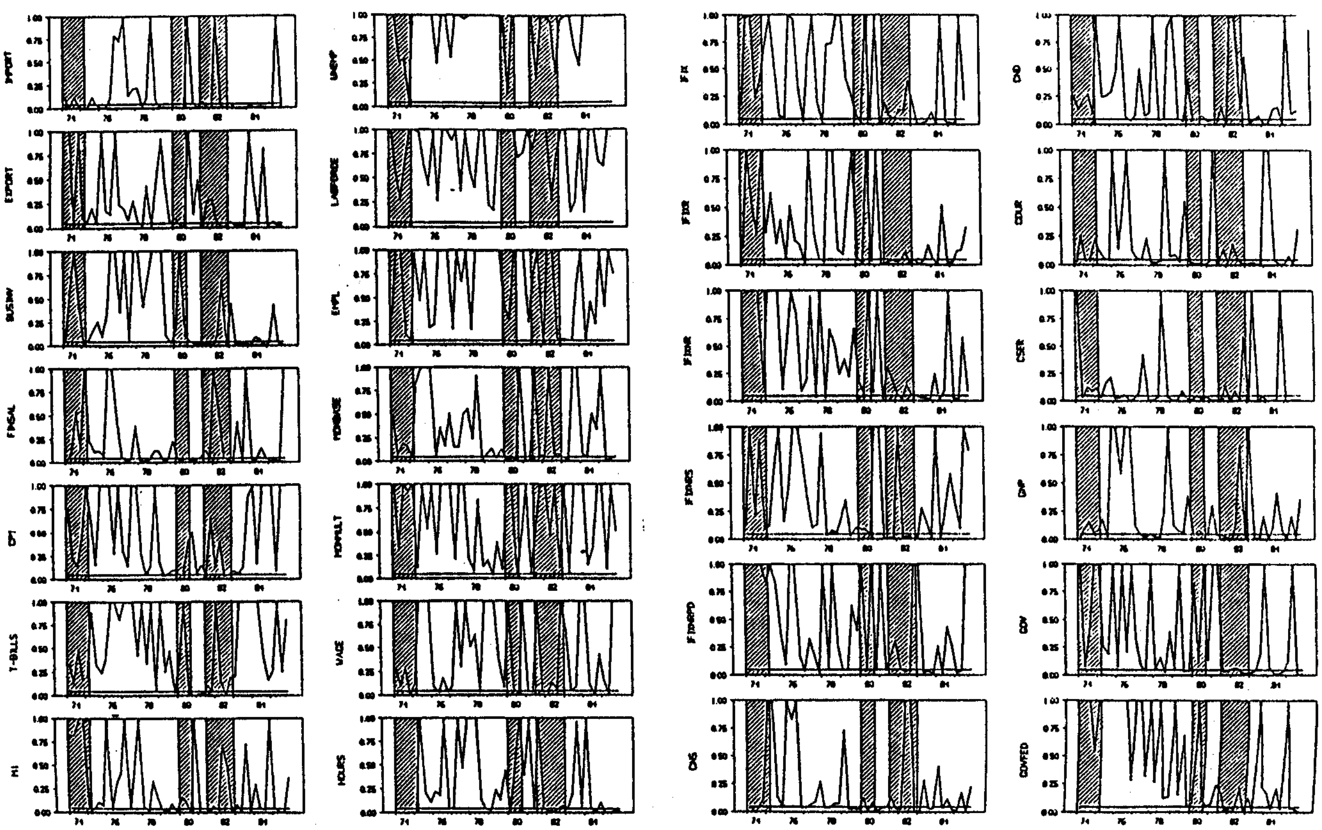

FIGURE 3: AGGREGATED QUARTERLY MACRO SERIES? P-VALUES FOR MARKOV INEQUALITIES

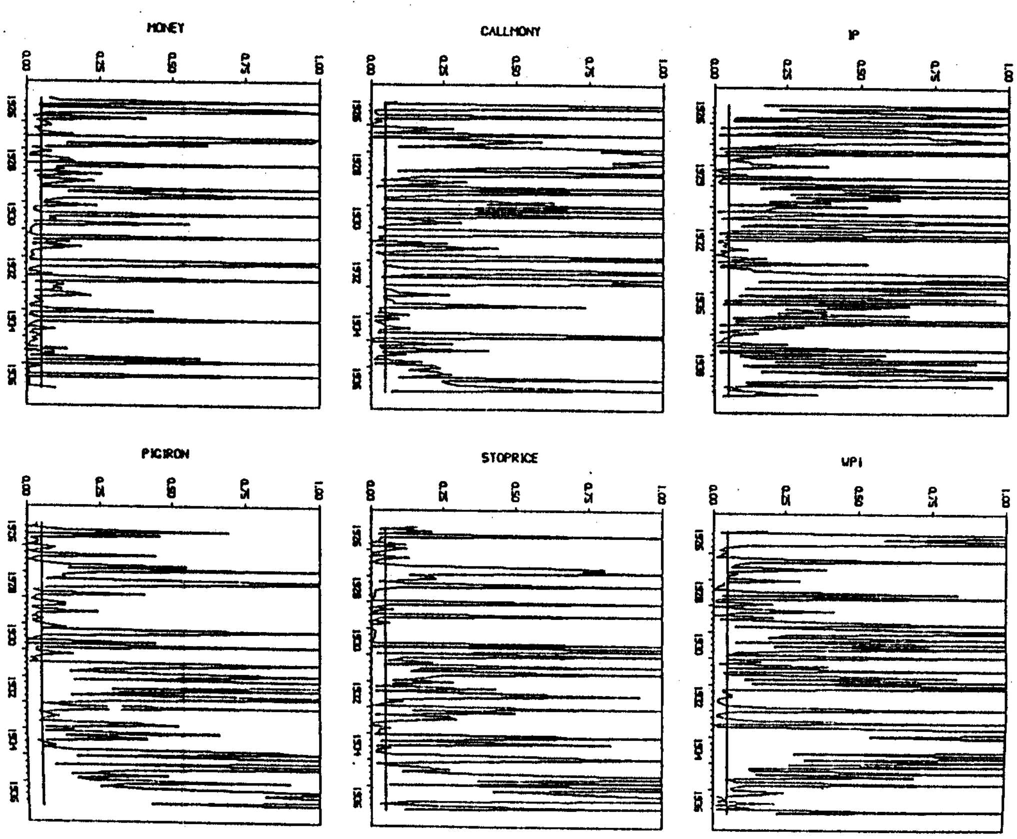

FIGURE 4: AGGREGATED HISTORICAL MACRO SERIES, P-VALUES FOR MARKOV INEQUALITIES

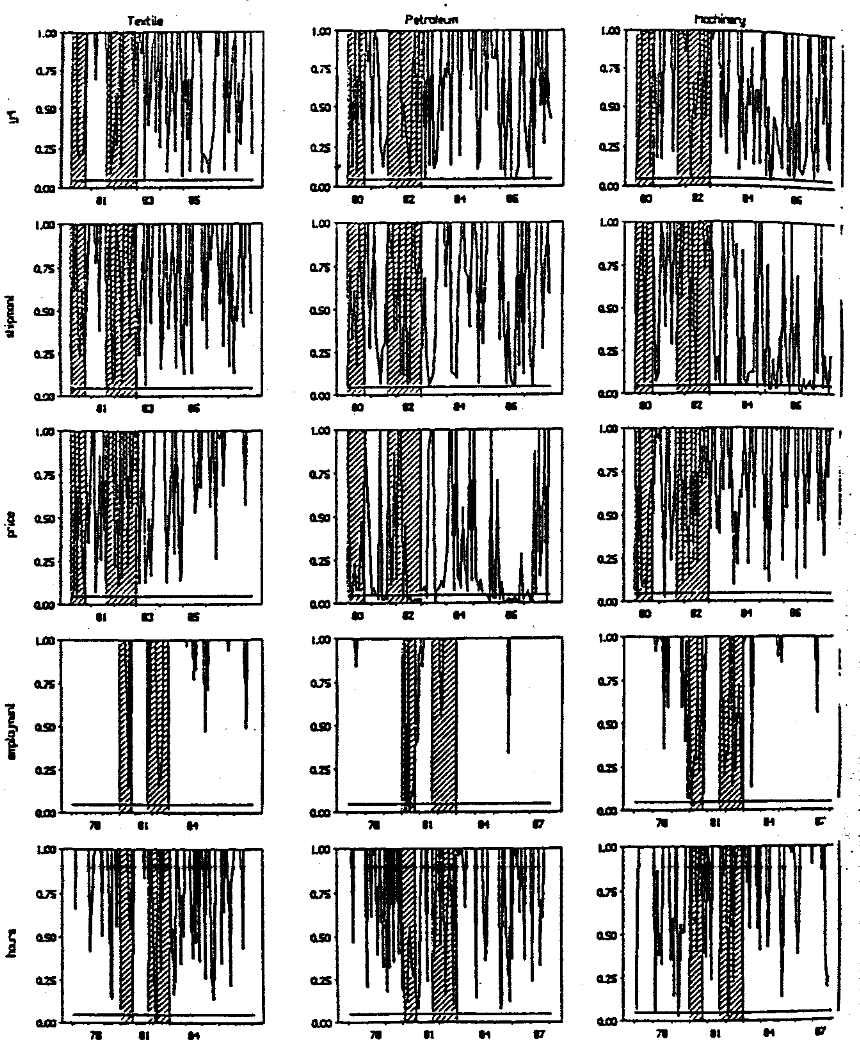

FIGURE 5: DISAGGREGATED MACRO DATA, P-VALUES FOR MARKOV INEQUALITIES

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