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Seasonality and Capacity: an Application to Italy

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SEASONALITY AND CAPACITY: AN APPLICATION TO ITALY

by Guido de Blasio* and Federico Mini**

Abstract

Information on seasonal frequencies can provide valuable insights for understanding economic fluctuations. This is particularly true for Italy, where the variability of production in manufacturing is extremely high and almost entirely due to seasonal factors. This paper identifies the qualitative and quantitative features of seasonal fluctuations in Italy and compares them to those of France and Germany. Seasonality in Italy is twice as large as in France, six times larger as in Germany. Qualitatively, seasonal fluctuations are extremely homogeneous across technologically different manufacturing sectors, giving informal support to the contention that Italian seasonality may be due to endogenous factors (synergies across agents) as opposed to exogenous ones (seasonality resulting from changes in underlying technology and preferences). Next, we quantify the amount of seasonally-driven excess capacity in the Italian manufacturing sector, and show that it is around thirty percent higher than that in France or Germany.

JEL classification: E32, C49.
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Contents

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* Banca d'Italia and International Monetary Fund.

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1. Introduction[1]

Until recently, mainstream macroeconomic analysis, both theoretical and empirical, considered seasonal fluctuations as noise that needed to be removed before one could concentrate on the study of the underlying business cycle.

In recent times, however, this attitude has changed. Macroeconomists have become interested in seasonal fluctuations, and extensive research has examined seasonal fluctuations explicitly (Barsky and Miron, 1989; Beaulieu and Miron, 1991, 1992, and 1993; Braun and Evans, 1991, and 1994; Ghysels, 1991; Beaulieu, MacKie-Mason and Miron, 1992; Chatterjee and Ravikumar, 1992; Cecchetti, Kashyap and Wilcox, 1997; Carpenter and Levy, 1998). The main findings of this new strand of literature are as follows. First, the bulk of the variation in most monthly macroeconomic series is seasonal. Second, comovements of macroeconomic variables over the business cycle are mirrored by comovements over the seasonal cycle. The similarity in comovements suggests that similar mechanisms may drive both seasonal and business cycles. Accordingly, seasonal cycles provide useful information that can be employed to build and test macro models.

Following this new wave of theoretical and applied research on seasonal fluctuations, in this paper we take a closer look at seasonal fluctuations of manufacturing production in Italy in the last two decades, both at the aggregated and the branch level. To this end, we use a newly assembled data set on monthly industrial production, sales and orders, which reports disaggregated figures for the 44 branches in the Nace-Clio classification. To our knowledge, this paper is the first that focuses on Italian seasonality in manufacturing as an issue worth investigating.

Our results show that seasonal fluctuations in manufacturing output in Italy are extremely high when compared to those in France and Germany–Italy's two most important trade counterparts. The Italian seasonal pattern is characterized by a dramatic

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slowdown in August followed by a full recovery in September; a slowdown in November and December with an upturn in the first months of the year; an April decline followed by a May resurgence. This pattern is exceptionally similar across different manufacturing indicators (production, sales and orders) and across sectors.

Next, we estimate the amount of idle capacity associated with the strongly seasonal Italian production pattern, and compare it to France's and Germany's. We calculate that excess capacity in Italy is around 30 percent higher than it is in France and Germany. We use the term "excess" without attaching to it any judgement value. That is, the fact that Italy's unutilized capacity is larger than in France and Germany does not necessarily mean that the underlying seasonal pattern is endogenous, hence policy-actionable (as opposed to exogenous–explained by the given technology and preferences), and excessive from a welfare standpoint.

The plan of the paper is as follows. Section 2 reviews the most important theoretical contributions in the study of seasonality. Section 3 describes the data set. In section 4, we present the statistical methodology we use to measure seasonal movements. The empirical evidence on the qualitative and quantitative features of the seasonal Italian manufacturing cycle is discussed in section 5. Section 6 quantifies the magnitude of Italian excess capacity, and compares it to France's and Germany's. Conclusions are in section 7.

2. Theory

Are seasonal variations interesting? While the answer we propose in this paper is undoubtedly affirmative, the attitude of the economic theory on this issue has changed again only recently.

The original theoretical viewpoint was to consider seasonal fluctuations as a possible source of inefficiency. This stance is well represented by the work of Bursk (1931), Kuznets (1933), and Woytinsky (1939). For the purpose of this paper, it is important to note that the potential source of inefficiency pointed out by Kuznets was the waste associated with the seasonal excess capacity. The policy prescription that these authors called for was to dampen seasonal fluctuations.

Braun and Evans (1994) and Chatterjee and Ravikumar (1992) challenged this position by extending real business cycle theory to the seasonal cycle. As business cycles may represent the efficient response of the economy to changes in technology (see Kydland and Prescott, 1982, and Long and Plosser, 1983), these authors showed that, by allowing seasonal shifts in tastes and technology, a real business cycle model produces seasonal variations consistent in many respects with the fluctuations observed.

For instance, workers may prefer vacations in August. This shift in preferences raises the marginal cost of production, so firms optimally avoid production in August. Similarly, exogenous shifts in technology may induce reallocation of production away from low-productivity periods. Moreover, the seasonal pattern of some industries can be explained using a broader concept of technology (that is, not readily captured by standard differentiable cost functions). Two classical examples are the following. First, the automobile industry is characterized by its own seasonal pattern given the importance of yearly automobile shows. The point is clearly documented by Cooper and Haltiwanger (1993a) for the US case (note also that the seasonal pattern in the automobile industry drives seasonal movements for related industries–e.g., steel and rubber–with corresponding leads or lags due to production interrelations). Second, there is anecdotal evidence that certain sub-sectors within the textile industry are characterized by a double yearly cycle, in correspondence to the fall-winter and spring-summer fashion shows.

The “no welfare loss” implication of standard business-cycle models is thus extended to seasonal fluctuations as well, since policies that dampen seasonal fluctuations would reduce welfare by precluding the economy from optimally shifting production to seasons in which productivity is higher or leisure time is less valuable.

A fundamental attack to the “no welfare loss” view has been levied by the recent literature on endogenous seasonality. The main idea of this approach (Cooper and John, 1988; Hall, 1991; and Cooper and Haltiwanger, 1996) is that concentration of economic activities may be due to synergies across agents, rather than to shifts in tastes or technology. The key assumption is that there exist macroeconomic strategic complementarities, so that any given agent’s optimal level of activity varies with the aggregate level of economic activity. Synergies across firms and workers can induce seasonal patterns, since they can make it optimal to have all activities shut down at the same time.

These synergies can occur for a number of reasons. First, firms may find it convenient to close at the same time as their upstream or downstream partners do. For instance, instead of operating throughout the year at a lower than average level, they can decide to close for August (and operate at a higher rate for the rest of the year). Every firm could decide to close, because otherwise, given that all others have closed as well, it would be necessary to stockpile raw materials and inventory intermediate and final goods in order to operate during the slowdown period. These costs might outweigh the benefits of smoothing production (Beaulieu and Miron, 1992).

Second, firms may want to have all workers on vacation at the same time, so that the retooling or maintenance can take place more easily. Cooper and Haltiwanger (1993b) show that the automobile industry in the United States exhibits this feature, and periods of machine replacement and process innovation by independent producers in related (steel, rubber) industries are synchronized.

Finally, workers may find it desirable to take vacations in the same period with other members of the family, or when vacation resorts are livelier and more full of life, that is, when the rest of the population is on vacation as well.

The “endogenous seasonality” models typically display multiple equilibria that can be Pareto-ranked. In this class of models, however, the direction of the effect of seasonality on welfare is not clear-cut. On one hand, the concentration of activities in a particular season may be inefficient. For example, any individual firm can have an incentive to shut down in August and bunch production in September, given that all other firms do the same. No single firm can capture the positive external effect that could derive from a better coordination of economic activities, like decreasing the holding of excess capacity and reducing congestion effects. On the other hand, the economy can be stuck in sub-optimal equilibrium characterized by too little seasonality: further concentration in production would enable society to take full advantage of external economies.

From a policy standpoint, the crucial message of this class of models is a re-proposition of the original view: welfare implications of seasonal fluctuations cannot be ruled out. In this vein, appropriate policies affecting seasonal cycles could be efficiency enhancing.[2]

3. Data set

This paper uses data on Italian industrial production (IP), sales (S), and orders (O) between January 1981 and July 1997. The data are index numbers collected by the Italian National Statistical Agency (Istituto Nazionale di Statistica - ISTAT). Preliminary work was required to ensure continuity as well as comparability across the three sets of indicators. In particular, since several changes in the base year and in the classificatory system of economic activities took place over the years, a historical reconstruction has been performed. Moreover, since the indexes collected by ISTAT measure physical quantities for the industrial production and values for sales and orders, the last two indicators have been deflated. Such preliminary work, together with the detailed features of the data set used in this paper are discussed at length in de Blasio and Santi (1999). A summary description is presented in appendix.

The data set consists of 41 industrial series (15 for IP and S, only 11 for O) at the aggregation level of the Nace-Clio 44-sector classification. Note that four sectors (Food and Beverage; Tobacco; Rubber; and Other) do not report figures on orders, since in those industries suppliers do not normally take orders. We have constructed five aggregate series (IP15, S15, IP11, S11, and O11). The first two aggregate all 15 sector series, while the last three aggregate data only for those 11 sectors reporting figures on production, sales and orders (P11, S11, and O11 are thus directly comparable). Finally, all the 5 aggregate series have been constructed using the weights derived from the industrial production survey (see Appendix).

In order to compare Italian fluctuations in aggregate monthly production to France's and Germany's we use seasonally unadjusted time series on production index numbers provided by the International Monetary Fund.

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[2] The endogenous seasonality literature highlights that excessive seasonal cycles could also be due to unintended negative consequences of policies themselves.

4. Methodology

In this section we outline the statistical approach we adopt to quantify seasonality in the monthly time series of the Italian manufacturing sector.

By and large, there are three kinds of seasonality in time series that have been considered in the literature (Hylleberg, 1986; and Franses, 1996): stationary stochastic seasonality; non-stationary stochastic seasonality (unit roots), and deterministic seasonal dummies.

While there is wide agreement in the field that seasonal fluctuations account for a large portion of variation in time series, researchers are split about the most appropriate modeling strategy to describe seasonality.

Some argue that empirically observed seasonal fluctuations vary over time, so that in order to capture their changing nature, non-stationary stochastic or stationary stochastic models are the most appropriate. Among these, see for instance Canova and Hansen (1995), Hylleberg (1992, 1994) and Ghysels (1994).

Others, lead by Miron and his co-authors (see for instance, Barsky and Miron, 1989) claim that there is compelling evidence that suggests that the first two kinds of models of seasonality are likely to be poor approximations of reality. Most economic time series display huge differences in their means across seasons and these differences appear to be highly persistent. This fact can hardly be captured in models of the first two kinds. In fact, a stationary stochastic model implies a constant mean across seasons, while a non-stationary stochastic model cannot guarantee that differences in the seasonal means stay the same across sample periods.

Casual examination of the time series in our sample did not evidence any strongly changing seasonal pattern, which, as Franses (1996) remarks, "[…] can be easily visualized" (page 309). As a consequence, in what follows we model seasonality as a deterministic phenomenon. While we present statistical evidence in support of our choice of modeling approach (see *infra*), this should not be construed as an implicit endorsement of one school of thought over the other.

Deterministic seasonality appears to explain a very large amount of variation in our sample time series (see R^2 reported in Tables 6, 7a, 7b and 7c, *infra*) and provides an intuitive lens for the economic interpretation of empirical regularities. The intuitive appeal stems from the fact that, for economic time series, a number of factors driving seasonality tend to appear regularly in the same season year after year; that is, they are likely to generate seasonal dummy-type variations. Straightforward examples are holidays, calendar effects, and the weather. Obviously, the magnitude of the effects of these factors may change over time (e.g., while a Christmas-driven increase in shopping regularly repeats itself year after year, such an increase is clearly higher during booms than during recessions), and we recognize that for some time series in our sample a non-stationary stochastic model appears more appropriate (see Table 1). However, we believe that the approach followed here can be considered as a good first approximation.[3]

Therefore, following Barsky and Miron (1989), we model seasonality through deterministic seasonal dummies; that is, we assume:

(1)
$$x_t = \sum_{k=1}^{12} \xi_k d_t^k + \beta(B)\,\eta_t \, ,$$

where x_t is the log growth rate, d_t^k is a dummy for season k, β(B) is square summable and η_t is white noise . We estimate ξ_k in (1) by OLS, using the standard Newey and West (1987) procedure to correct standard errors since β(B) is not necessarily equal to one.

Other than by a priori arguments, the approach we chose here can indeed be justified by an empirical verification. To this aim, we first provide evidence on the absence of seasonal unit roots (no non-stationary stochastic seasonality). Then we examine whether the seasonal patterns differ across the Altissimo, Marchetti, and Oneto (2000) chronology of expansions and contractions in the Italian business cycle. As a further check of the fact that the deterministic seasonal dummies are constant over the sample time period, we applied the CUSUM test developed by Brown, Durbin and Evans (1975) to each sector and each aggregated time series (for Industrial Production, Sales, and Orders). Finally, we report the correlation between seasonal factors as identified

[3] Our approach to modeling seasonal effects is thus the same as in Sestito and Visco (1994), who use seasonal dummies to study the variability of industrial production and sales.

through the estimation of equation (1) above and through the application of the X-11 seasonal adjustment technique.

To test the presence of unit roots we use the technique developed by Hylleberg et al. (1990), and adapted to monthly data by Beaulieu and Miron (1993). This procedure, a generalization of the Dickey-Fuller approach, allows the testing of the null hypothesis that the series of interest exhibits some form of non-stationary stochastic seasonality[4] against the alternative that no seasonal unit root exists.[5] The results indicate that our data are not generally characterized by the presence of seasonal unit roots. At the 10 percent confidence level, H_0 is accepted only for 8 out of 46 series (41 original ones, plus 5 aggregate). At the 5 percent confidence level, H_0 is accepted in an additional 6 cases. (Table 1 summarizes test results; Table 2a, 2b and 2c report details on relevant test statistics for Industrial Production, Sales and Orders respectively.) Moreover, the critical test values we use are those derived by Beaulieu and Miron (1993) for samples of size 240 (20 years of monthly observations). Our sample, however, contains only 16½ years. This implies that applying the appropriate critical value would have made the rejection of the null hypothesis even easier.[6]

A more direct check on the appropriateness of the seasonal dummy approximation is to consider whether the seasonal patterns differ across booms and recessions. To this end, we split the time series on aggregated variables according the Altissimo, Marchetti, and Oneto (2000) chronology of the Italian business cycle. We then regress (by OLS) the log of growth rates on two sets of monthly dummies, one for expansion and the other for contraction periods. The results (Table 3) indicate that the two patterns are remarkably similar and not statistically different. Using a Wald test, we are not able to reject the

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[4] Hylleberg et al. (1990) show in fact that applying the Dickey-Fuller test directly to verify whether a=1 against the alternative a<1 in the model $x_t=ax_{t-s}+\varepsilon_t$ (s=12 in our case) unduly restricts the set of solutions of the autoregressive representation of x_t, $\varphi(B)x_t$ (where B is the backward shift) that can generate a seasonal unit root.

[5] We apply the test to log growth rate series to test for the presence of seasonal unit roots. The equation on which the test is based contains a deterministic component (monthly dummies) but no trend. The trend turned out to be insignificant for all sectors in preliminary estimation of the test regression.

[6] Applying the same test to France’s and Germany’s aggregated monthly production time series lead to the rejection of the null hypothesis at the 5 percent confidence level. Note that the test for the corresponding Italian aggregated series leads to rejection of the null hypothesis at the same level of confidence (5 percent).

composite null hypothesis that, for each month, the growth pattern does not differ between booms and recessions.[7]

Figures 1 to 4 show CUSUM tests for all time series in our sample based on recursive estimates of equation (1) (respectively, both at the single-industry and aggregated level for Industrial Production, Sales, and Orders). These results confirm that the deterministic seasonal component is quite constant along our sample period.

Finally, as an additional check, we computed the correlation coefficient between the seasonal deterministic (dummy) component of the unadjusted series and the seasonal factors as identified by applying the X-11 technique. As the X-11 technique removes both stationary stochastic seasonality *and* deterministic dummies, one would expect correlation coefficients between the alternatively computed seasonal factors to be close to 1 when stochastic seasonality plays a trivial role. As reported in table 4, with only one exception,[8] correlation coefficients were all above 90 percent, with 39 out of 46 being above 98 percent.

5. Significance and features of the seasonal cycle

Seasonal fluctuations in Italian manufacturing are quantitatively important. This section presents overwhelming evidence of this claim and then discusses some possible explanations.

We present three kinds of empirical evidence. First, we report the comparison among industrial production in France, Germany, and Italy (Table 5). Second, limited to Italy, we compare the evidence on production with that on sales and orders at the aggregate level (Table 6). Note that while sales represent a coincident variable, orders are a leading indicator for production (de Blasio and Santi, 1999). Finally, we report seasonal patterns at the single-industry level for the three indicators (Tables 7a, 7b and 7c).

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[7] These results are widely confirmed for the industry-level indicators of industrial production, sales and orders.

[8] The exception is the correlation coefficient for Orders in the Automobile sector.

Each of the tables presented contains summary statistics and seasonal dummy point estimates. The statistics are: i) The standard deviation of the fitted values of the regression (STDEV SEA); this is an estimate of the variability of the deterministic seasonal component of the dependent variable; ii) The standard error of the regression (STDEV NON SEA); this is an estimate of variability of the business cycle component of the dependent variable; iii) The R^2 of the regression, which measures the variation in the dependent variable due to seasonality as a percentage of total variation (seasonal and non-seasonal). The monthly entries are the OLS estimates of the coefficient of the seasonal dummies, in which the overall mean of the dependent variable has been subtracted from each dummy coefficient, so that the entries in the tables are the difference between the average growth of the variable in each month and the overall growth rate.[9]

As for the significance of the seasonal cycle, table 5 documents how, in Italy, the variability of the seasonal component in the log growth rate is more than 6 times the business-cycle one, or–equivalently–seasonal fluctuations account for a striking 97 percent of the observed total variation (seasonal and nonseasonal) in monthly production growth. For France, the ratio is 3:1, which implies that seasonals explain 93 percent of the total variation; in Germany, seasonals are even less of a factor (almost a 1:1 ratio to business-cycle variation, corresponding to a 62 percent of total variation explained by deterministic seasonal dummies).

The fact that in Italy business cycles represent a relatively small percentage of the overall fluctuations and the importance of the seasonal component are confirmed by the statistics for sales and orders. At the single-industry level, the significance of the seasonal cycle is also clearly established, with few exceptions (Tobacco sales; Automobile and Transportation orders) in which the seasonal and business cycles are of comparable magnitude.

Regarding the features, the seasonal industrial production cycle displays the following pattern: i) dramatic slowdown in August followed by a full recovery in September; ii) slowdown in November and December, followed by an upturn in the first

[9] The tables omit standard errors for clarity. The data however reject the null hypothesis of no seasonality at the one percent level for all variables.

three months of the year; iii) April decline followed by a May resurgence. This pattern is more or less mirrored by fluctuations in sales and orders. The only exception is that the fall/winter slowdown for sales and orders occurs in January.

The data at the industrial level, while confirming this general pattern, show a high degree of comovement across industries, for production, sales and orders alike. In particular, table 8 reports, for every industry, the average correlation between each industry's deterministic seasonal effects and those of all other industries. As for production, all average correlation coefficients are above 80 percent, with 10 out of 15 being 95 percent or more. Sales and orders exhibit the same high degree of comovement across sectors, although average correlation coefficients are marginally lower (in only two cases, Tobacco sales and Transportation orders, the average correlation with the other sectors is below 75 percent).

As for the aggregated series, the correlation coefficient between production deterministic seasonals and those for sales and orders respectively, is 97 percent in both cases; the correlation coefficient between sales and orders is an astounding 99 percent. In conclusion, all industries and all variables considered appear to be extremely synchronized over the seasonal cycle.

Determining whether the high seasonality in Italian manufacturing is due mostly to exogenous or endogenous factors is an interesting empirical question, which we do not address in this paper. However, the documented extremely high degree of co-movement across technologically diverse industries, and the much larger seasonal fluctuations in Italy as compared to France and Germany (which are likely to be quite similar as far as many exogenous factors are concerned), appears to support the contention that endogenous factors may play a role in Italy.

Regardless of the factors behind the observed high seasonality in Italian manufacturing, an interesting empirical question is to determine the amount of associated unutilized capacity in the Italian economy, and to compare it to its major European counterparts; the next section is devoted to this question.

6. Seasonally-driven excess capacity

In this section, we first test formally whether Italian production output figures are consistent with the idea that firms carry excess capacity across seasons rather than across business cycles. We then apply standard techniques to quantify the amount of unutilized capacity implied by the Italian seasonal cycle, and compare it to Germany's and France's.

As noted earlier, determining whether such unutilized capacity represents a welfare loss/gain for the Italian economy, or if it is simply due to exogenous factors, is beyond the scope of this paper. Part of the observed gap may measure some of Italy's efficiency losses due to a policy-actionable (endogenous) seasonal cycle that is too great. However, one cannot rule out that synergies in Italy are more pronounced than in France and Germany so that, in order to exploit them fully, excess capacity should be even greater.

In section 4 we showed that seasonality explains a great portion of production variability in Italy. Of course, this does not prove *per se* that capacity levels are predominately determined by factors classifiable as seasonal. In order to test directly such a proposition, following Beaulieu, McKie-Mason and Miron (1992),[10] we look at nonseasonal output residuals. In a scenario where capacity levels are determined so as to accommodate production in the high season, the fact that there is substantial excess capacity during the low season implies that nonseasonal shocks during such periods will produce more output variation than during the high season–where, instead, capacity constraints are effectively binding, thus "truncating" output variation by imposing a ceiling on it. The implication of the model is that there will be seasonal heteroskedasticity

[10] The primary objective of their formalization is to build a model that generates positive correlation between the magnitude of the seasonal cycle and the size of the business cycle, a phenomenon widely documented both across countries and across industries. The fact that industries with large business cycles also have large seasonal cycles is confirmed by the Italian data. For instance, using cross-section figures reported in table 7a for Italian manufacturing production, one finds that there is a statistically significant positive correlation across industries between the standard deviation of the seasonal component and the non seasonal component of production log growth rates. In the 15-observation OLS regression explaining non-seasonal standard deviation by a constant and the seasonal standard deviation, the coefficient on this latter variable (0.216) is significant at the 1 percent confidence level, while the R^2 is 55.6 percent. This result is confirmed (and somewhat stronger) when using standardized series (dividing by the total sum of squares): the coefficient on the standardized seasonal standard deviation is 0.384 and significant at the 1 percent confidence level, the R^2 is 79.14 percent.

in the nonseasonal output residuals, which will assume a particular form: variance in the low season is higher than in the high season.

In order to test whether this implication is confirmed by our data, two steps are needed. First, we need to test whether nonseasonal residuals are in fact heteroskedatic. Table 9 reports the results for White tests for any form of heteroskedasticity in the log growth rate series in each of the 15 industries and for the aggregated production log growth rate time series.[11] With the exception of Transportation, we are able to reject the null hypothesis of no seasonal heteroskedaticity at the 5 percent significance level–but only at the 10 percent level for the residual branch "Other."

Next, we need to check whether the data exhibit the expected heteroskedaticity pattern–negative correlation between the variance of the growth rate conditional on the month and the seasonal level production in that month. To calculate the seasonals in the level of production, we regress the log levels of industry production on 12 seasonal dummies and a linear time trend,[12] and use the 12 monthly dummies as estimates of the seasonals in the level of output. We then compute the Spearman rank correlation between the variance of the monthly production growth and the seasonal in the level of production.

Results reported in table 9 show that correlation is in fact negative in all cases, although statistically significant for only 5 branches: Petroleum and Coal, Agricultural and Industrial Machinery, Automobile, Transportation, and Food and Beverage. For these five branches, the null hypothesis of zero correlation is rejected in favor of the one-sided alternative of negative correlation at the 5 percent confidence level. These five branches accounted for 49.5 percent of Italy's total manufacturing production in the period 1990-97.

[11] Beaulieu, McKie-Mason and Miron (1992) recognize that testing the implication of the model is not straightforward because of unit roots in production time series. However, by simulating their model for a 20-year span on the basis of an integrated demand shock, they showed how the model produces heteroskedasticity in the log growth rate of output, with the growth rate variances declining as the seasonal level of output increases.

[12] Beaulieu, McKie-Mason and Miron (1992) use a quadratic trend in the regression used to estimate the seasonality in the level of production. When we tried such a specification, we got results that are equivalent to those reported–which are derived using a linear trend. In our sample, a linear trend consistently provided a better fit–in most cases an R2 above 90 percent–than a quadratic one.

In conclusion, for a relevant portion of Italy's manufacturing activities, there is reason to believe that the strong seasonality documented in section 4 explains capacity levels in several large industries. It would thus be interesting to quantify its extent.

Since time series on industrial capacity for Italy are not readily available, we use two different algorithms to calculate potential output time series in order to quantify the amount of excess capacity for Italy (both at the aggregated and branch level), and France and Germany (at only the aggregate level). The first is the recursive procedure proposed by De Long and Summers (1988), that is:

(2) $$y^*_{t+1} = y^*_t + \max\left[0, \max_{i=1tok}\left(\frac{y_{t+1} - y^*_t}{i}\right)\right].$$

This is to say, the potential output between period t and period t+1 lies along the slope of the steepest ascent that connects the current potential output and the actual output in any of the following k periods.

The second algorithm we consider is the Wharton method, which consists in choosing a number of "peaks" in the observed actual output series and defining potential output as the series obtained by linearly interpolating the values at periods in-between any two consecutive peaks (see Signorini, 1986, for an application to seasonally-adjusted Italian data). In order to be as judgment-free as possible in applying the Wharton method, we did not choose peaks individually; rather, we considered a peak any value y_t in the output time series that was greater than the previous and subsequent k periods (months in our case).[13]

We applied the two algorithms to time series in levels, obviously non-seasonally adjusted. While we experimented with different values for k, the results we report are for k=6 (increasing or decreasing k affected results only marginally). Aggregated results for France, Germany and Italy are presented in table 10, which reports the average unutilized

[13] The main difference between the two routines is that the first is always increasing, so that capacity cannot ever be scaled back, even in the face of prolonged recessions. The Wharton method, instead, allows for a 'tighter' fit of potential capacity around observed output, as potential capacity adjusts both upwards and downwards. Note, however, that the Wharton interpolation does not necessarily ensure that potential capacity is everywhere greater that actual output, while this is the case for the De Long-Summers routine.

excess capacity (in percentage points) in the sample period. The amount of capacity unutilized in Italy is higher than what is usually found when using seasonally adjusted data. The industrial output gap in Italy is approximately 30 percent higher than in Germany and in France, and this result is robust to the two alternative procedures used.

Table 10 reports the computed average excess capacity in the five major sectors that appear to be well described by the model above. With the exception of the excess capacity for the "Petroleum, Coal, etc." sector computed with the Wharton method, all other values are well above the overall average for manufacturing.

Estimated unutilized excess capacity in the Automobile sector is 1½ - 2 times the aggregated excess capacity. Considering both the weight of this sector in the Italian economy and its complementarity with other important sectors (steel, plastic), this is a fact policymakers can hardly ignore. In the Agricultural and Industrial Machinery sector, unutilized capacity is estimated to be between 14 percent to 55 percent higher than on average. Given the spillover effects in the rest of the economy, the welfare implications of such high seasonality–if endogenous–would probably be significant. The same applies to firms in the Food and Beverage sector, which has an estimated excess capacity 50 percent higher than in the aggregate manufacturing sector.

7. Conclusions

Information on seasonal frequencies can provide valuable insights for understanding economic fluctuations. In this paper, we presented empirical evidence on the extent of seasonal effects on Italian manufacturing production and quantified the consequences in terms of unutilized capacity.

The Italian seasonal pattern is fairly homogeneous both across industries and across growth time series for production, sales, and orders. Yet, it is extremely high compared to economies with similar fundamentals like France and Germany. While no conclusive answer about the source of seasonality is offered, the empirical evidence seems to be consistent with theoretical models where seasonality is endogenously determined.

As for the consequences on economic activity, we showed how the observed time series are consistent with the implications of models where seasonal factors explain capacity levels. High seasonality is indeed associated with high levels of unutilized capacity. When we quantify such excess capacity for France, Germany, and Italy, we find that excess capacity in the Italian manufacturing sector is, on average, around 30 percent higher than in France and Germany.

While these figures are simply suggestive, they are nonetheless quite interesting. The wide differences between the seasonal cycle in Italy on one hand and France and Germany on the other can hardly be overlooked. While the direction of the effects on welfare warrants further research, the possibility that seasonality is not welfare neutral opens up fascinating questions on the role of policy. It could well be the case that potential welfare gains can be captured through policies aimed at reducing capacity waste (although one cannot rule out that the pattern of the Italian seasonality is optimal given the degree of external economies).

Tables and Figures

Table 1

SEASONAL UNIT ROOTS

	Industrial Production	Sales	Orders
Petroleum, coal, metal and non metallic mineral	**		
Chemicals			
Agricultural and industrial machinery		*	
Computer and electronic			
Electric Machinery			
Automobile			*
Transportation (excluding automobile)	**		
Food & Beverage		**	n/a
Tobacco	**		n/a
Apparel			
Leather	**		**
Lumber			
Paper	*	*	*
Rubber	*	*	n/a
Other		*	n/a
Aggregate (15)			n/a
Aggregate (11)			

Note: The strategy to test for seasonal unit roots is as described in Beaulieu and Miron (1993). The null hypothesis, H_0, is that the series of interest has a unit root at a seasonal frequency. Test applied to log growth rates. Test specification: intercept, seasonal dummies, no trend. * H_0 accepted at 10 percent confidence level; ** H_0 accepted at 5 percent confidence level. Blank cells correspond to cases where H_0 is rejected at the 5 percent confidence level.

Table 2a

SEASONAL UNIT ROOTS TEST STATISTICS
(Industrial Production)

Sector	π_2	$F_{3,4}$	$F_{5,6}$	$F_{7,8}$	$F_{9,10}$	$F_{11,12}$
Petroleum, coal, metal and non metallic mineral	-5.25	10.39	12.80	15.46	8.98	17.22
Chemicals	-2.68	6.13	8.95	7.50	6.38	9.97
Agricultural and industrial machinery	-2.92	10.30	10.40	16.09	7.63	13.51
Computer and electronic	-4.52	11.58	6.78	8.67	9.32	24.01
Electric Machinery	-3.41	9.23	16.56	7.00	5.45	8.73
Automobile	-3.30	8.56	12.77	11.38	6.53	12.48
Transportation (excluding automobile)	-2.71	11.58	12.76	7.84	8.03	10.68
Food & Beverage	-3.51	5.20	13.85	5.93	8.22	5.30
Tobacco	-2.59	4.19	14.99	13.57	6.52	14.00
Apparel	-3.23	6.24	11.85	7.84	7.81	14.09
Leather	-2.62	6.14	15.71	11.12	6.04	6.08
Lumber	-3.37	8.14	11.80	13.03	6.54	10.49
Paper	-2.16	5.58	6.71	9.13	4.16	9.26
Rubber	-2.44	5.46	14.70	6.57	4.20	13.38
Other	-4.13	13.96	11.53	17.21	15.21	13.07
Aggregate (15)	-3.47	9.02	21.21	12.45	6.46	15.44
Aggregate (11)	-3.22	9.37	19.79	12.30	6.00	13.43

Note: Beaulieu and Miron (1993) illustrate that, in order to show that no unit root exists at any seasonal frequency, π_k (where π_k, k=1,2,...12 are the estimated coefficients in a specified, auxiliary regression) must not equal zero for k=2 and for at least one member of each of the sets {3,4}, {5,6}, {7,8}, {9,10}, {11,12}. The test on π_2 should be carried out as a one-sided test (the alternative being $\pi_2<0$). The tests on $\pi_{k-1}= \pi_k=0$ (for k even and greater than 2) are carried out with an F-statistic. While the test regression is estimated by ordinary least squares, the asymptotic and finite sample distributions change. Given our sample size, the critical values for the auxiliary test regression used in this paper (which includes an intercept, seasonal dummies, but no trend) are as follows. As for the test concerning the null $\pi_2=0$, the critical value is -2.76 at the 5 percent confidence level (-2.48 at the 10 percent). The critical values for the F-test are 6.26 and 5.27 at the 5 percent and 10 percent confidence level, respectively (see Beaulieu and Mirom, 1993).

Table 2b

SEASONAL UNIT ROOTS TEST STATISTICS
(Sales)

Sectors	π_2	$F_{3,4}$	$F_{5,6}$	$F_{7,8}$	$F_{9,10}$	$F_{11,12}$
Petroleum, coal, metal and non metallic mineral	-3.39	7.19	11.23	10.42	9.60	15.46
Chemicals	-3.91	9.86	10.35	12.43	8.11	14.10
Agricultural and industrial machinery	-2.39	9.34	12.76	14.10	8.45	16.60
Computer and electronic	-4.03	16.40	5.08	14.20	12.23	15.25
Electric Machinery	-2.84	7.35	12.23	7.10	6.31	8.54
Automobile	-3.33	5.92	8.32	7.15	5.43	18.12
Transportation (excluding automobile)	-4.32	10.55	15.08	8.76	14.25	9.28
Food & Beverage	-2.69	7.10	14.89	16.46	10.34	14.31
Tobacco	-3.58	15.22	13.09	15.46	13.66	17.20
Apparel	-3.77	8.28	10.40	2.64	6.96	9.77
Leather	-2.87	8.29	12.88	7.74	4.25	10.80
Lumber	-4.30	10.81	10.83	21.01	9.30	11.62
Paper	-1.57	6.72	6.82	7.14	7.91	15.79
Rubber	-2.15	6.48	17.25	6.28	5.52	10.05
Other	-2.17	15.47	8.90	17.32	8.67	9.03
Aggregate (15)	-3.32	8.24	20.42	11.83	6.64	15.82
Aggregate (11)	-3.44	8.92	19.86	11.56	6.93	15.71

Note: See Table 2a.

Table 2c

SEASONAL UNIT ROOTS TEST STATISTICS
(Orders)

Sectors	π_2	$F_{3,4}$	$F_{5,6}$	$F_{7,8}$	$F_{9,10}$	$F_{11,12}$
Petroleum, coal, metal and non metallic mineral	-4.86	11.71	9.84	15.55	15.84	18.61
Chemicals	-3.41	15.14	11.1	17.9	10	10.81
Agricultural and industrial machinery	-3.64	15.49	17.62	19.44	12.46	14.3
Computer and electronic	-3.45	7.63	8.56	11.7	10.12	6.24
Electric Machinery	-3.39	16.75	10.98	8.22	11.84	10.44
Automobile	-1.05	5.39	2.46	4.3	1.36	10.15
Transportation (excluding automobile)	-4.1	15.99	16.37	13.25	15.67	10.86
Food & Beverage						
Tobacco						
Apparel	-2.91	7.76	9.09	2.22	5.99	15.34
Leather	-2.63	8.27	8.79	1.29	8.04	21.37
Lumber	-4.14	7.65	10.18	14.75	9.01	13.63
Paper	-1.95	5.3	7.67	9.94	5.6	10.17
Rubber						
Other						
Aggregate (15)						
Aggregate (11)	-5.43	11.33	9.07	9.83	11.18	20.53

Note: See Table 2a.

Table 3

SEASONAL PATTERNS IN EXPANSIONS AND CONTRACTIONS

	Industrial Production All Sectors		Sales All Sectors		Orders All Sectors	
	Expansion	Contraction	Expansion	Contraction	Expansion	Contraction
January	6.11 (1.86)	8.97 (2.12)	-16.32 (1. 37)	-13.30 (2.58)	-9.21 (1.89)	-4.91 (1.96)
February	6.12 (1.28)	3.32 (1. 90)	10.28 (0.96)	8.05 (1.93)	5.94 (0.88)	2.79 (1.11)
March	9.50 (1.02)	9.63 (1.39)	11.45 (1. 43)	11.30 (1.83)	11.97 (1.60)	10.51 (2.17)
April	-10.69 (2.01)	-11.81 (1.48)	-11.18 (1.96)	-12.70 (1.26)	-14.94 (2.31)	-15.31 (1.54)
May	9.07 (2.29)	5.84 (2.43)	5.09 (2.25)	2.03 (2.40)	1.96 (2.27)	1.77 (2.29)
June	-0.17 (1.26)	-0.28. (1.77)	2.02 (1.25)	2.07 (1.59)	5.07 (1.60)	1.09 (1.29)
July	-0.08 (1.69)	1.52 (1.38)	4.72 (1.97)	5.29 (1.09)	-3.87 (2.26)	-0.64 (1.73)
August	-89.15 (3.35)	-92.55 (4.25)	-74.73 (2.96)	-76.11 (3.96)	-75.43 (5.27)	-79.23 (3.76)
September	90.14 (2.99)	87.99 (5.07)	74.23 (2.37)	72.42 (4.56)	80.46 (4.79)	80.34 (4.51)
October	0.76 (1.47)	3.25 (1.94)	0.47 (1.66)	1.15 (1.36)	0.34 (2.12)	1.39 (1.21)
November	-4.16 (1.81)	-4.77 (1.27)	-6.75 (2.10)	-6.89 (1.19)	-6.41 (2.95)	-10.51 (1.35)
December	-16.01 (1.18)	18.70 (1.05)	2.48 (0.40)	-0.35 (1.07)	7.58 (1.43)	3.70 (2.34)
STDEV SEA (1)	41.61	33.02	34.96	27.29	36.41	28.98
R^2	0.977		0.971		0.948	
Chi-12 (probability)	5.59 (0.935)		4.64 (0.969)		5.71 (0.930)	

Note: Test Applied to log growth rates, standard errors in parentheses. The regression was estimated using the Newey-West (1987) covariance matrix. (1) Sum of squared deviations from the mean of the fitted values from the estimated regression divided by (T-12).

Table 4

CORRELATION COEFFICIENTS BETWEEN DETERMINISTIC SEASONAL DUMMIES AND X-11 SEASONAL FACTORS

	Industrial Production	Sales	Orders
Sector 1	0.999	0.993	0.993
Sector 2	0.996	0.997	0.988
Sector 3	0.996	0.997	0.991
Sector 4	0.981	0.987	0.974
Sector 5	0.999	0.994	0.991
Sector 6	0.999	0.993	0.727
Sector 7	0.995	0.977	0.919
Sector 8	0.988	0.977	n/a
Sector 9	0.994	0.956	n/a
Sector 10	0.999	0.995	0.992
Sector 11	0.996	0.993	0.987
Sector 12	0.999	0.998	0.998
Sector 13	0.985	0.983	0.989
Sector 14	0.998	0.996	n/a
Sector 15	0.992	0.992	n/a
Aggregate (15)	0.996	0.992	n/a
Aggregate (11)	0.997	0.993	0.975

Table 5

SEASONAL PATTERNS: AGGREGATE PRODUCTION ITALY, FRANCE AND GERMANY

	France	Germany	Italy
STDEV SEAS	14.37	6.95	37.92
STDEV NONSEAS	4.05	5.45	6.09
R^2	0.927	0.620	0.975
January	2.05	-5.96	7.18
February	-3.86	1.99	5.34
March	5.91	11.33	9.19
April	-4.99	-4.74	-10.35
May	-4.51	-2.27	7.53
June	4.41	2.81	-0.15
July	-7.92	-5.06	0.80
August	-29.02	-5.30	-90.00
September	35.55	14.48	89.60
October	9.36	2.83	1.69
November	-1.42	-1.90	-4.43
December	-4.87	-8.45	-17.18

Note: The sample period is January 1981 to July 1997 for all three countries.

Table 6

SEASONAL PATTERNS: ITALY
AGGREGATE SERIES

	IP All Sectors	S All Sectors	IP 11 Sectors	S 11 Sectors	O 11 Sectors
STDEV SEAS	37.92	31.75	40.72	33.55	33.16
STDEV NONSEAS	6.09	5.65	6.37	5.71	8.11
R^2	0.97	0.97	0.98	0.97	0.94
January	7.18	-15.19	7.03	-15.55	-7.17
February	5.34	9.54	5.10	9.50	5.11
March	9.19	11.12	9.19	10.90	10.80
April	-10.35	-10.99	-9.98	-11.21	-14.21
May	7.53	3.63	7.23	3.13	1.52
June	-0.15	2.23	-0.21	2.31	3.65
July	0.80	5.10	0.91	5.78	-2.03
August	-90.00	-75.08	-98.57	-79.67	-76.38
September	89.60	73.78	95.24	78.02	80.43
October	1.69	0.14	2.02	-0.24	0.74
November	-4.43	-6.81	-3.33	-6.96	-8.20
December	-17.18	1.25	-15.40	2.72	5.88

Table 7a

SEASONAL PATTERNS: INDUSTRIAL PRODUCTION

	STDEV SEA	STDEV NONSEA	R2	Jen	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Petroleum, coal, metal and non metallic mineral	30.85	4.83	0.98	7.61	4.17	10.12	-8.22	7.28	-1.32	0.20	-72.78	71.79	2.65	-4.21	-18.05
Chemicals	29.45	4.75	0.97	5.76	3.38	8.31	-7.20	4.79	-1.27	1.08	-72.68	66.97	4.43	-2.23	-11.90
Agricultural and industrial machinery	49.28	9.08	0.97	-11.10	9.98	10.74	-7.71	6.75	0.14	4.87	-123.76	111.87	3.12	-0.41	-6.04
Computer and electronic	29.02	10.97	0.87	-34.24	17.35	9.36	-12.04	10.16	2.15	-15.85	-51.71	70.37	2.27	3.45	-1.97
Electric Machinery	57.28	11.04	0.96	15.14	5.75	9.49	-12.84	9.43	0.89	-2.76	-135.07	137.05	1.49	-4.02	-25.17
Automobile	79.47	22.97	0.92	19.74	4.10	9.31	-9.48	8.32	-3.84	2.74	-192.99	188.16	-0.03	-7.47	-19.26
Transportation (excluding automobile)	41.88	10.43	0.94	15.87	6.17	9.70	-9.61	9.87	-1.26	-1.46	-98.73	97.53	1.00	-5.75	-24.16
Food & Beverage	16.33	6.21	0.87	5.95	5.53	8.19	-14.45	9.74	0.49	-1.88	-16.18	40.59	-2.11	-12.12	-24.23
Tobacco	35.18	9.27	0.93	49.85	-0.87	9.28	-12.51	9.16	-8.21	-11.66	-59.34	72.68	6.18	-4.73	-48.91
Apparel	51.60	8.62	0.97	18.91	4.15	8.36	-13.73	6.44	-0.44	0.27	-124.39	120.98	-2.76	-1.48	-16.63
Leather	53.83	8.95	0.97	21.54	1.73	5.47	-18.30	6.07	4.55	8.88	-133.33	121.61	2.66	-7.36	-14.05
Lumber	56.86	9.51	0.97	-3.26	11.27	9.05	-8.17	8.15	0.26	5.09	-138.33	133.70	3.73	-5.05	-18.03
Paper	24.39	6.71	0.93	3.33	-1.69	8.23	-8.19	7.97	2.99	-1.61	-58.45	56.01	5.17	-3.36	-10.90
Rubber	54.90	10.22	0.97	21.45	4.86	7.96	-9.75	8.14	-0.48	1.00	-130.19	129.23	0.95	-6.17	-27.72
Other	53.85	18.32	0.90	-33.40	32.09	20.51	-11.94	13.10	4.78	11.29	-108.30	125.79	8.42	-13.24	-53.46

Table 7b

SEASONAL PATTERNS: SALES

	STDEV SEA	STDEV NONSEA	R2	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Petroleum, coal, metal and non metallic mineral	22.07	6.53	0.920	-8.60	4.39	7.32	-7.28	3.74	-0.64	1.97	-52.32	51.75	4.00	-5.15	0.23
Chemicals	30.03	5.90	0.963	-1.33	6.51	9.57	-8.79	3.69	-0.74	5.00	-75.61	67.05	3.15	-4.91	-4.54
Agricultural and industrial machinery	40.29	7.27	0.968	-41.30	13.47	13.93	-7.47	7.86	3.30	3.52	-97.72	82.53	5.31	-0.20	14.61
Computer and electronic	39.49	11.06	0.926	-82.73	21.08	21.24	-16.98	7.22	17.11	-15.31	-60.27	66.20	1.68	6.69	31.92
Electric Machinery	44.01	8.49	0.964	-55.40	13.82	15.67	-12.58	8.63	12.16	-7.43	-93.86	95.58	-2.14	1.44	22.20
Automobile	53.01	14.66	0.929	9.98	0.74	11.60	-4.49	0.87	-0.99	-0.46	-131.67	122.90	4.53	-5.65	-7.83
Transportation (excluding automobile)	44.57	24.55	0.764	-94.30	25.90	17.17	-2.05	6.33	3.92	0.02	-75.15	70.18	1.16	-2.15	45.77
Food & Beverage	13.38	6.05	0.830	-18.10	7.69	13.35	-9.56	6.45	2.23	-0.86	-23.91	27.05	2.19	-5.78	-1.97
Tobacco	25.56	28.20	0.444	-62.60	17.46	13.31	2.13	5.66	0.06	10.11	-20.49	8.30	-3.25	-18.25	44.51
Apparel	46.53	8.59	0.967	21.74	13.55	11.86	-23.17	-7.11	1.36	23.14	-98.42	111.78	-15.86	-22.85	-17.23
Leather	47.69	11.00	0.950	18.76	14.90	7.64	-25.73	-1.39	9.93	33.65	-113.64	100.37	-5.17	-21.03	-20.73
Lumber	51.99	7.31	0.981	-17.47	15.28	11.27	-8.99	8.64	-0.57	5.04	-128.41	118.65	6.43	-4.41	-7.36
Paper	23.45	7.82	0.900	-15.85	4.20	10.65	-8.60	4.88	1.95	-1.41	-51.98	56.38	2.92	-4.39	0.51
Rubber	49.49	8.92	0.969	11.50	10.28	9.48	-9.74	7.59	0.95	1.33	-119.87	114.84	0.97	-5.99	-22.59
Other	48.91	12.86	0.935	-40.07	24.28	16.95	-11.50	5.71	1.49	9.63	-105.89	114.86	10.30	-6.91	-21.75

Table 7c

SEASONAL PATTERNS: ORDERS

	STDEV SEA	STDEV NONSEA	R2	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Petroleum, coal, metal and non metallic mineral	32.10	15.52	0.81	-6.17	5.99	5.23	-8.59	7.23	2.22	-3.67	-76.52	76.59	3.32	-6.71	0.55
Chemicals	28.84	14.21	0.81	-6.22	-7.00	17.97	-13.52	-3.61	7.01	-5.42	-64.04	69.63	-0.15	-0.88	6.51
Agricultural and industrial machinery	32.20	13.75	0.85	-19.44	-0.22	14.03	-11.64	8.24	2.19	-4.11	-76.55	71.70	1.26	-2.07	16.07
Computer and electronic	35.46	20.35	0.75	-54.79	20.42	19.97	-15.69	2.73	18.36	-10.33	-72.10	64.69	7.81	-4.10	20.81
Electric Machinery	37.75	12.95	0.89	-29.65	-4.41	12.89	-13.72	1.21	15.59	-12.53	-82.14	85.46	-0.77	-0.81	28.94
Automobile	30.64	34.29	0.45	6.84	6.49	2.05	-1.22	-3.57	-0.84	-24.81	-62.54	78.66	7.86	-6.40	-1.15
Transportation (excluding automobile)	55.08	53.19	0.51	-111.96	11.87	30.43	-41.77	18.88	35.24	-40.93	-44.08	63.21	-16.34	-2.65	97.25
Food & Beverage	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Tobacco	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Apparel	44.01	10.61	0.95	34.94	20.91	7.10	-31.94	-12.98	-0.16	22.37	-86.35	101.82	-9.03	-25.62	-21.39
Leather	42.47	14.17	0.90	16.95	12.23	27.36	-4.63	-17.58	-18.03	18.83	-84.70	99.22	6.82	-25.81	-31.79
Lumber	42.89	8.80	0.96	4.34	6.83	8.93	-8.66	8.19	-1.70	-4.35	-100.62	103.71	3.82	-5.56	-15.50
Paper	39.23	10.55	0.93	18.84	-2.84	6.17	-12.26	6.09	-0.73	5.58	-95.10	89.63	3.28	-3.80	-14.99
Rubber	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Other	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a

AVERAGE CORRELATION COEFFICIENTS
ITALIAN MANUFACTURING SECTORS

	Industrial Production	Sales	Orders
Petroleum, coal, metal and non metallic mineral	0.96	0.89	0.89
Chemicals	0.96	0.87	0.89
Agricultural and industrial machinery	0.94	0.89	0.89
Computer and electronic	0.84	0.75	0.80
Electric Machinery	0.96	0.88	0.87
Automobile	0.95	0.84	0.85
Transportation (excluding automobile)	0.96	0.76	0.46
Food & Beverage	0.80	0.84	n/a
Tobacco	0.83	0.41	n/a
Apparel	0.95	0.80	0.78
Leather	0.95	0.80	0.78
Lumber	0.95	0.88	0.87
Paper	0.95	0.90	0.84
Rubber	0.96	0.83	n/a
Other	0.91	0.88	n/a

TESTS FOR HETEROSKEDASTICITY IN GROWTH RATES

	Heteroskedasticity		Spearman Rank Correlation	
	χ^2_{11}	Prob.	Value	Prob.
Petroleum, coal, metal and non metallic mineral	43.09	0.00	-0.503	0.047
Chemicals	67.87	0.00	-0.343	0.128
Agricultural and industrial machinery	48.48	0.00	-0.825	0.003
Computer and electronic	31.42	0.00	-0.231	0.222
Electric Machinery	78.09	0.00	-0.273	0.183
Automobile	94.64	0.00	-0.699	0.010
Transportation (excluding automobile)	16.31	0.13	-0.469	0.060
Food & Beverage	21.75	0.03	-0.622	0.019
Tobacco	25.38	0.01	-0.322	0.143
Apparel	53.57	0.00	-0.154	0.305
Leather	61.17	0.00	-0.350	0.123
Lumber	81.20	0.00	-0.217	0.236
Paper	77.56	0.00	-0.203	0.251
Rubber	78.00	0.00	-0.224	0.229
Other	18.58	0.07	-0.301	0.159
Aggregated	61.15	0.00	-0.154	0.305

Note: Given a random sample from a bivariate distribution, the Spearman rank correlation test is a non-parametric test that uses the ordinal ranks (rather than the actual, possibly cardinal, values) of the two sets of variables to determine whether there is a statistically significant correlation between them. In the case at hand, the sample size is 12, and the two random variables are the variance of the growth rate conditional on the month and the seasonal level production in that month. Under the alternative hypothesis of negative correlation, high rankings on one variable should be associated with low rankings on the other. The tabulated critical values for a one-tail test are -0.506 and -0.712 at the 5 percent and 10 percent confidence level, respectively.

Table 10

AGGREGATE EXCESS CAPACITY(PERCENTAGE)
FRANCE , GERMANY, ITALY
AND SELECTED ITALIAN MANUFACTURING SECTORS

	Algorithm	
	De Long-Summers	Wharton
France	10.3	9.7
Germany	10.2	9.1
Italy	13.4	12.5
Selected Italian Manufacturing Sectors		
Petroleum, coal, metal and non-metallic mineral	15.2	11.6
Agricultural and industrial machinery	20.8	15.3
Automobile	23.6	19.0
Transportation (excluding automobile)	22.0	16.8
Food and beverage	21.0	19.8
Italy aggregated (all sectors)	13.4	12.5

Note: De Long and Summers (1988) and the Wharton method are two techniques (described briefly in the text) that can be used to compute potential output time series based on information on actual output. For each of the alternative methods, we use the computed potential output series to derive time series on excess capacity.

Table 11

NACE-CLIO 44 SECTORS AND INDUSTRIAL PRODUCTION WEIGHTS

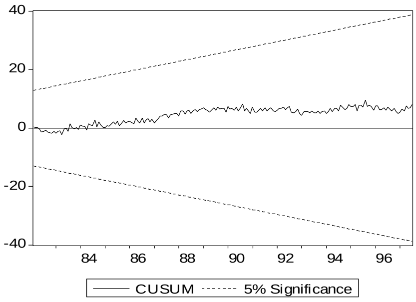
		Industrial Production Weights			
Sector	Nace-Clio Code	Jan 81 Dec 84	Jan 85 Dec 89	Jan 90 Jul 97	Orders
Petroleum, coal, metal and non metallic mineral	03+ 05+ 07+13+15+19	0.234	0.231	0.239	yes
Chemicals	17	0.071	0.081	0.087	yes
Agricultural and industrial machinery	21	0.082	0.095	0.094	yes
Computer and electronic	23	0.017	0.025	0.023	yes
Electric Machinery	25	0.068	0.088	0.069	yes
Automobile	27	0.045	0.044	0.048	yes
Transportation (excluding automobile)	29	0.024	0.026	0.030	yes
Food & Beverage	31+33+35+37	0.099	0.076	0.086	no
Tobacco	39	0.002	0.003	0.002	no
Apparel	41	0.138	0.131	0.122	yes
Leather	43	0.041	0.038	0.034	yes
Lumber	45	0.072	0.055	0.054	yes
Paper	47	0.055	0.056	0.062	yes
Rubber	49	0.040	0.037	0.040	no
Other	51	0.012	0.013	0.011	no

Source: de Blasio and Santi (1999).

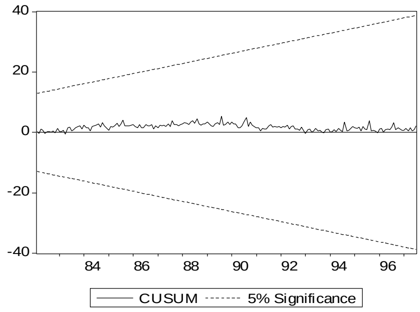
Figure 1

CUSUM TESTS, INDUSTRIAL PRODUCTION

Sector 1



Sector 2



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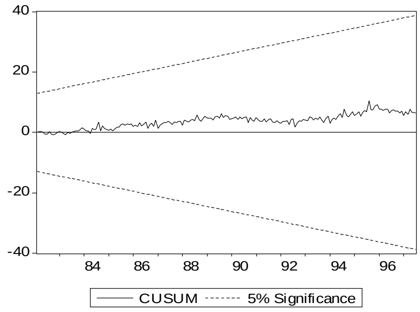

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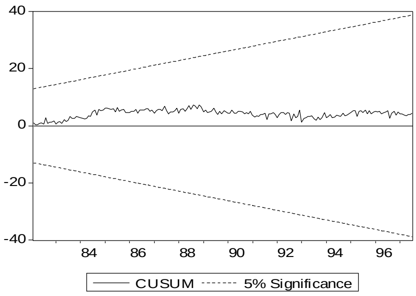

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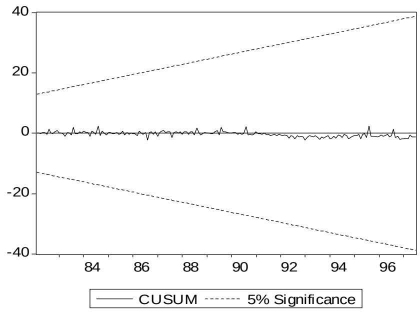

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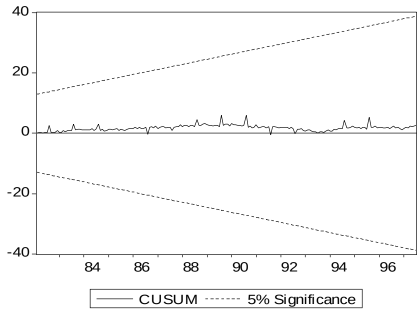

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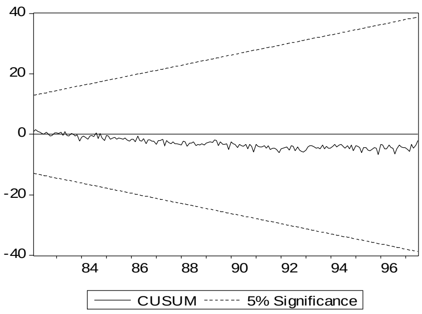

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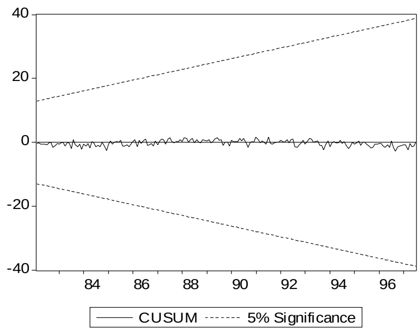

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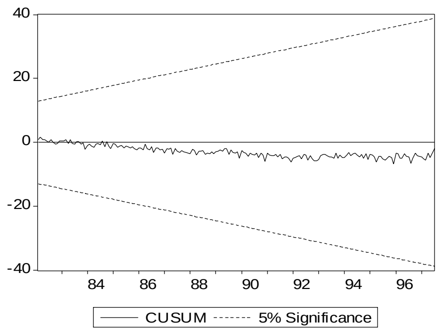
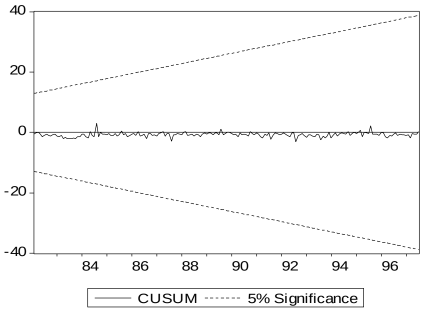


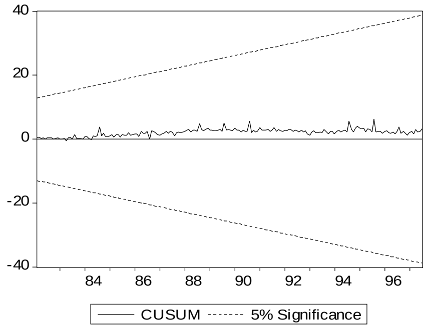
Figure 1

CUSUM TESTS, INDUSTRIAL PRODUCTION

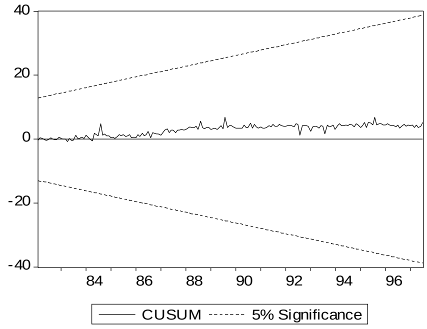
Sector 10



Sector 11



Sector 12



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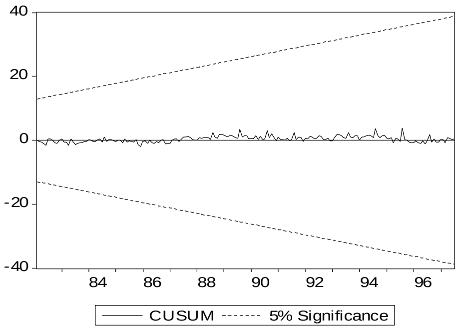

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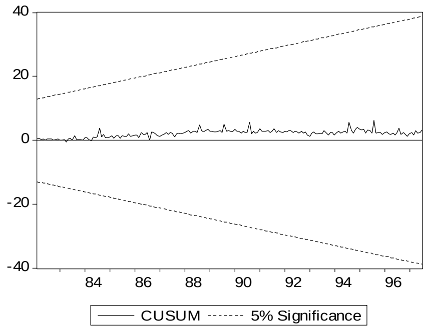

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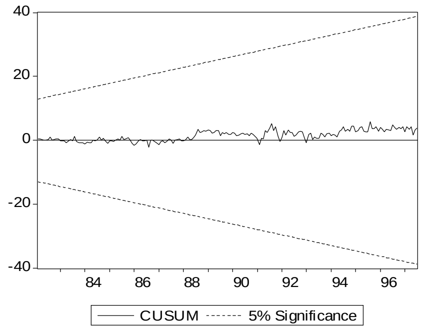


Figure 2

CUSUM TESTS, SALES

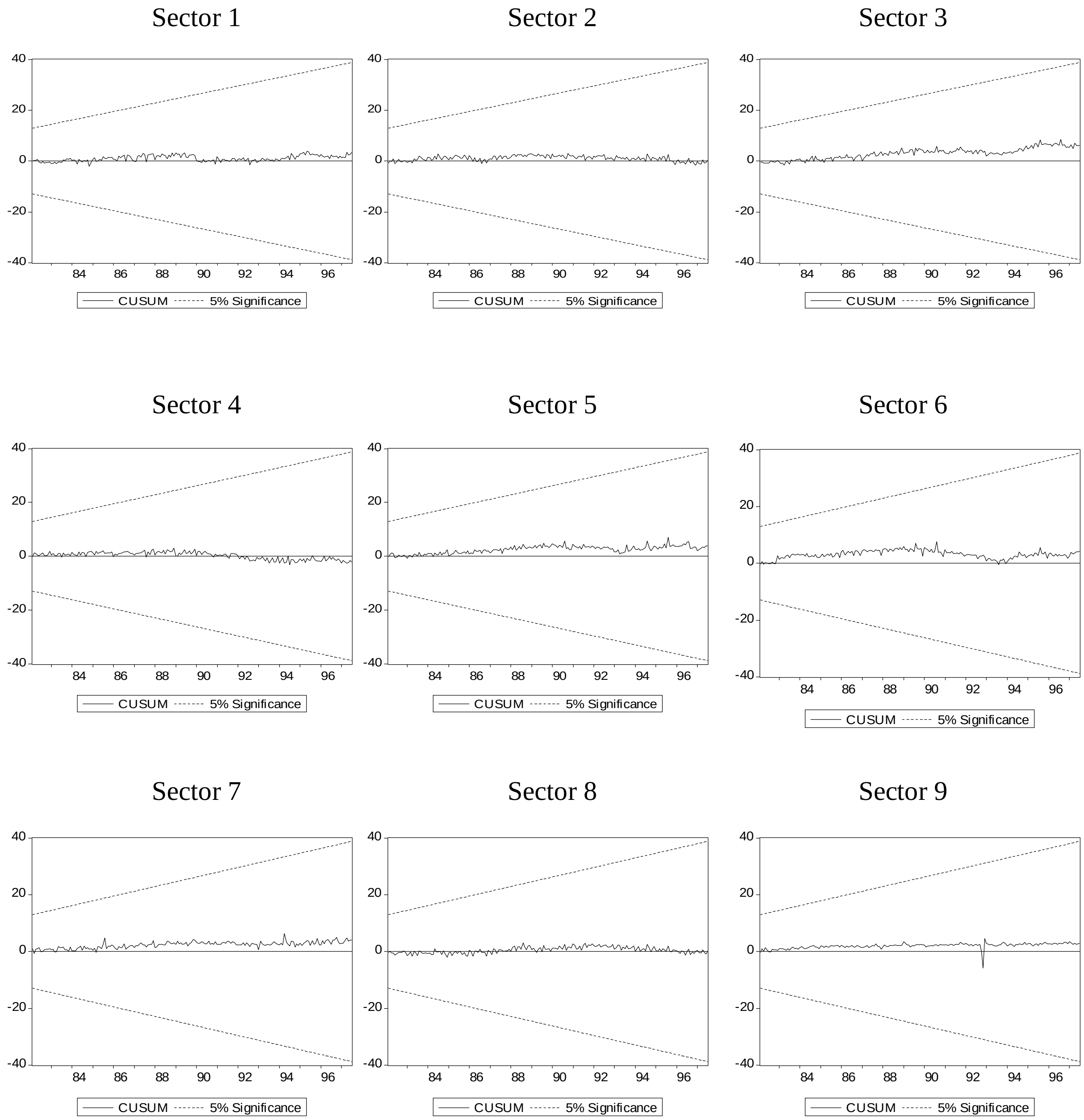
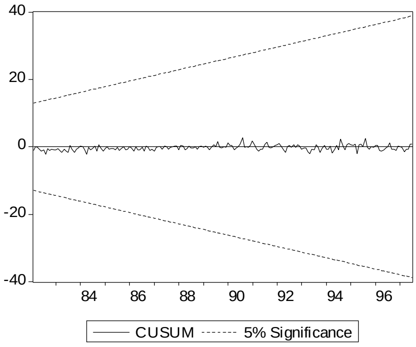


Figure 2

CUSUM TESTS, SALES

Sector 10



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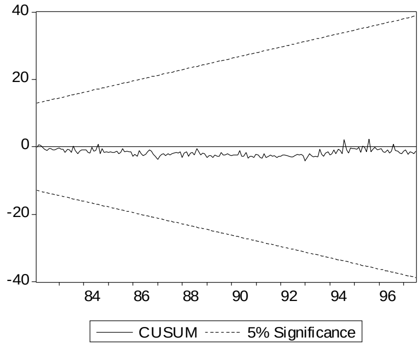

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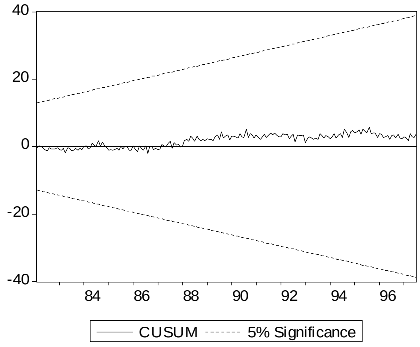
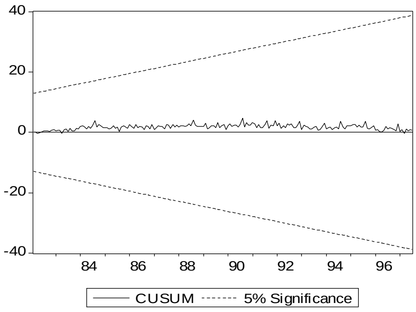
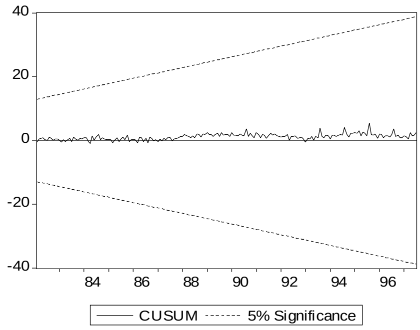


Sector 13



Sector 14



Sector 15

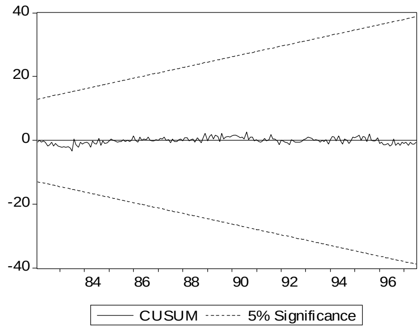
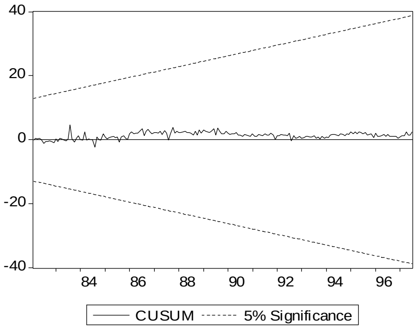


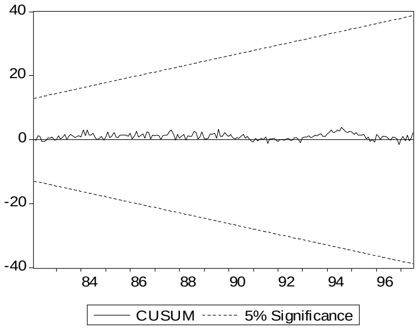
Figure 3

CUSUM TESTS, ORDERS

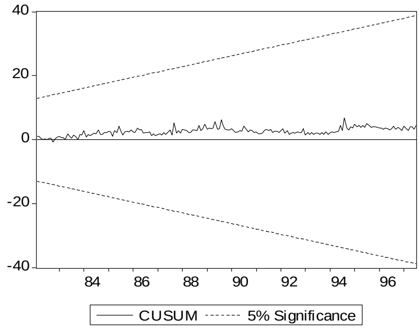
Sector 1



Sector 2



Sector 3



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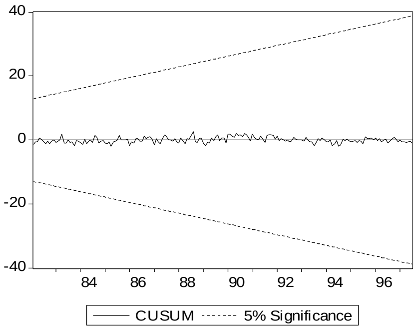
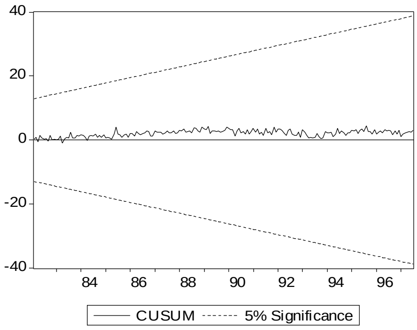


Sector 5



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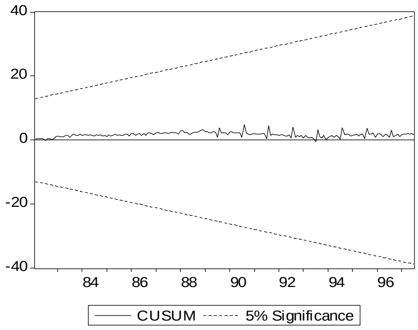

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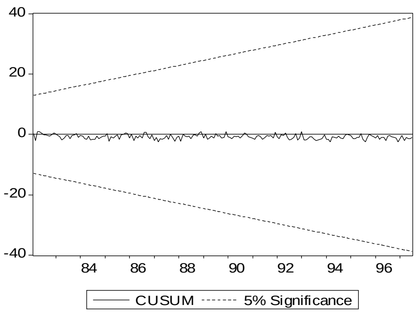
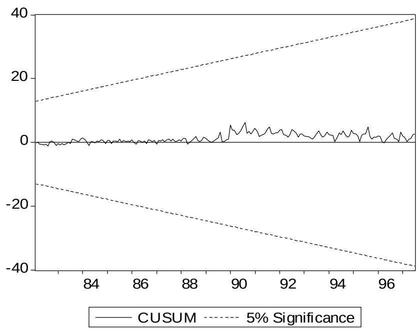


Sector 10



Sector 11

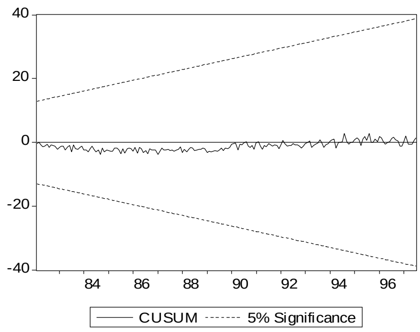
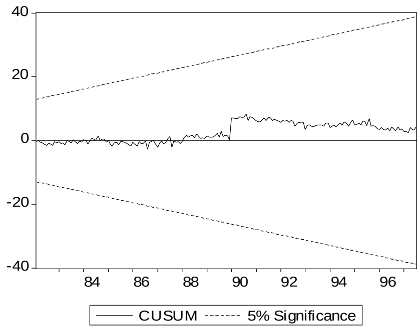


Figure 3

CUSUM TESTS, ORDERS

Sector 12



Sector 13

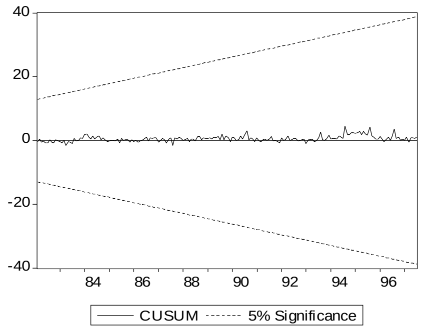
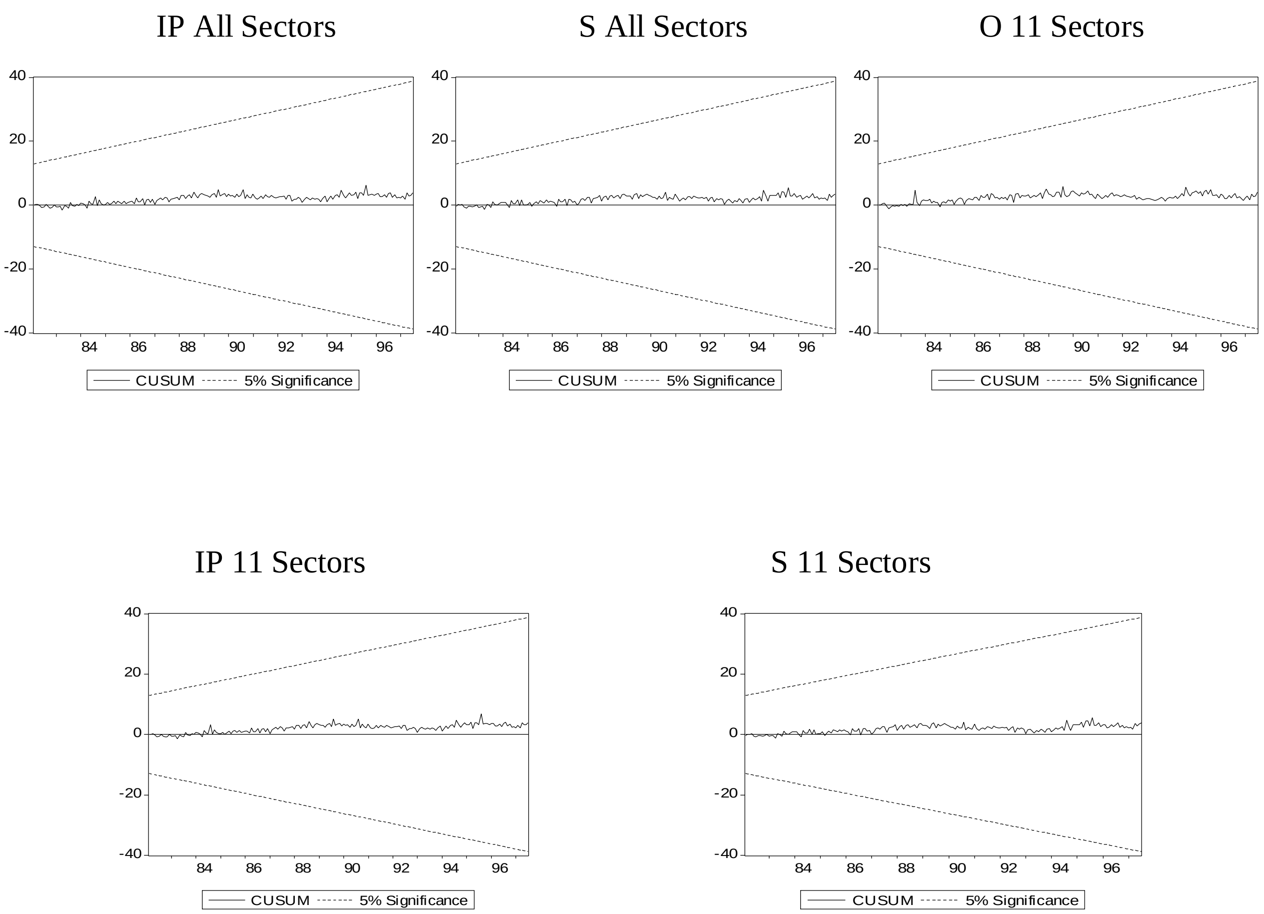


Figure 4

CUSUM TESTS, AGGREGATED SERIES



Appendix: Data Set Description

In this appendix the main features of the data-set are described. For an extensive discussion see de Blasio and Santi (1999).

The data set is comprised of Laspeyres indexes. Because of differences in the ISTAT surveys, mainly between industrial production on the one hand and sales and orders on the other, preliminary work has been carried out to ensure the comparability among indicators. First of all, since the indexes collected by ISTAT measure physical quantities for the industrial production and values for sales and orders, a deflation of the last two indicators has been carried out. As a deflator, the index for output prices has been used. Moreover, since sales and orders indexes are first collected separately for domestic and external sources and then aggregated, the deflator is constructed accordingly. Some work has been also required to ensure continuity. In particular, because of several changes in the base year and in the classificatory system of economic activities, an historical reconstruction has been performed.

Other differences are the following. (i) The scope of the surveys is dissimilar, since the industrial production survey also includes the branch Power, Gas and Water. (ii) The samples are unlike, since about 8,000 firms are included in the production survey, while 7,500 belong to the sales sample and 3,800 to the orders sample. Moreover, the sample selection process is different. (iii) The structure of the weights is different, since the weights for the production are derived from the ISTAT value added survey, while the weights for sales and orders are derived from the population by the "Sistema dei conti delle imprese" census survey. (iv) Sales and Orders, but not Production, might be affected by the degree of industrial vertical integration. To limit the impact of these divergences, the branch Power, Gas and Water has been excluded and all the aggregations have been performed using the weights derived from the industrial production survey for sales and orders as well. Moreover, sales and orders are corrected by the ratio of sales of goods produced over total sales. Table 11 describes the 15 Nace-Clio 44 Branches and their weights.

References

Altissimo, F., D. J. Marchetti and G. P. Oneto (2000), "The Italian Business Cycle: New Coincident and Leading Indicators and Some Stylized Facts", Banca D'Italia, Tema di Discussione, No. 377, Ottobre 2000.

Barsky, R. B. and J. A. Miron (1989), "The Seasonal Cycle and the Business Cycle", *Journal of Political Economy,* Vol. 97 (3), pp. 503-35.

Beaulieu, J.J., J. K. MacKie-Mason and J. A. Miron (1992), "Why Do Countries and Industries with Large Seasonal Cycles Also Have Large Business Cycles?", *Quarterly Journal of Economics*, Vol. 107 (2), pp. 621-56.

Beaulieu, J. J. and J. A. Miron (1991), "The Seasonal Cycle in U.S. Manufacturing", *Economic Letters*, Vol. 37 (2), pp. 115-18.

Beaulieu, J. J. and J. A. Miron (1992), "A Cross Country Comparison of Seasonal and Business Cycles", *Economic Journal*, Vol. 102 (413), pp. 772-88.

Beaulieu, J. J. and J. A. Miron (1993), "Seasonal Unit Roots and Deterministic Seasonals in Aggregate U.S. Data", *Journal of Econometrics*, Vol. 55, pp. 305-28.

Braun, R. A. and C. L. Evans (1991), "Seasonal Solow Residuals and Christmas: A Case for Labor Hoarding and Increasing Returns", Federal Reserve Bank of Chicago, Working Paper, No. 91-20.

Braun, R. A. and C. L. Evans (1994), "Seasonality and Equilibrium Business Cycle Theories", *Journal of Economic Dynamics and Control*, Vol. 19, pp. 503-31.

Brown, R., J. Durbin and J. Evans (1975), "Techniques for Testing the Constancy of Regression Relationships over Time", *Journal of the Royal Statistical Society*, Series B, Vol. 37, pp. 149-72.

Bursk, P. J. (1931), *Seasonal Variations in Employment in Manufacturing Industries,* Philadelphia, University of Pennsylvania Press.

Canova, F. and B. E. Hansen (1995), "Are Seasonal Patterns Constant over Time? A Test for Seasonal Stability", *Journal of Business and Economic Statistics*; Vol. 13, pp. 237-52.

Carpenter, R. E. and D. Levy (1998), "Seasonal Cycle, Business Cycles, and the Comovement of Inventory Investment and Output", *Journal of Money, Credit and Banking*, Vol. 30 (3), pp. 331-46.

Cecchetti, S. G., A. K. Kashyap and D. W. Wilcox (1997), "Interactions between the Seasonal and Business Cycles in Production and Inventories", *American Economic Review*, Vol. 87 (5), pp. 884-92.

Chatterjee, S. and B. Ravikumar (1992), "A Neoclassical Model of Seasonal Fluctuations", *Journal of Monetary Economics*, Vol. 29, pp. 59-86.

Cooper, R. and J. Haltiwanger (1993a), “Autos and the National Industry Recovery Act: Evidence on Industry Complementarities”, *Quarterly Journal of Economics*, Vol. 108, pp. 1043-71.

Cooper, R. and J. Haltiwanger (1993b), “The Macroeconomic Implications of Machine Replacement: Theory and Evidence”, *American Economic Review*, Vol. 83, pp. 360-82.

Cooper, R. and J. Haltiwanger (1996), “Evidence on Macroeconomic Complementarities”, *The Review of Economics and Statistics*, Vol. 78, pp. 78-93.

Cooper, R. and A. John (1988), “Coordinating Coordination Failure in Keynesian Models”, *Quarterly Journal of Economics*, Vol. 103, pp. 441-63.

de Blasio, G. and L. Santi (1999), “Ordinativi, produzione e fatturato nell’industria italiana”, Banca d’Italia, Supplementi al Bollettino Statistico della Banca d’Italia, No. IX (35).

De Long, B. J. and L. H. Summers (1988), “How Does Macroeconomic Policy Affect Output?”, *Brookings Papers on Economic Activity*, Vol. 2.

Franses, P. H. (1996), “Recent Advances in Modeling Seasonality”, *Journal of Economic Surveys*, Vol. 10 (3), pp. 299-345.

Ghysels, E. (1991), “On Seasonal Asymmetries and Their Implications for Stochastic and Deterministic Models of Seasonality”, University of Montreal, mimeo.

Ghysels, E. (1994), “On the Economics and Econometrics of Seasonality”, in C. A. Sims (ed.), *Advances in Econometrics, sixth World Congress of the Econometric Society*, Cambridge, UK, Cambridge University Press.

Hall, R. E. (1991), *Booms and Recessions in a Noisy Economy*, New Haven, Yale University Press.

Hylleberg, S. (1986), *Seasonality in Regression*, New York, Academic Press.

Hylleberg, S. (1992), *Modelling Seasonality*, Oxford University Press.

Hylleberg, S. (1994), “Modeling Seasonal Variation”, in C. P. Hargreaves (ed.), *Nonstationary time series analysis and cointegration*, Advanced Texts in Econometrics, Oxford, Oxford University Press.

Hylleberg, S., R. F. Engle, C. W. J. Granger and Y. S. Byung (1990), “Seasonal Integration and Co-Integration”, *Journal of Econometrics*, Vol. 44, pp. 215-38.

Kydland, F. E. and E. C. Prescott (1982), “Time to Build and Aggregate Fluctuations”, *Econometrica*, Vol. 50 (6), pp. 1345-70.

Kuznets, S. (1933), *Seasonal Variations in Industry and Trade*, New York, National Bureau of Economic Research.

Long, J. and C. Plosser (1983), “Real Business Cycle”, *Journal of Political Economy*, Vol. 91, pp. 36-69.

Newey, W. K. and K. D. West (1987), “A Simple, Positive Semi-definite, Heteroskedasticity and Autocorrelation Consistent Covariance Matrix”, *Econometrica*, Vol. 55(3), pp. 703-08.

Sestito, P. and I. Visco (1994), “Actual and 'Normal' Inventories of Finished Goods: Qualitative and Quantitative Evidence from the Italian Manufacturing Sector”, Banca d’Italia, Tema di Discussione, No. 218.

Signorini, L. F. (1986), “Nuove valutazioni della capacità utilizzata in Italia”, Banca d’Italia, Tema di Discussione, No. 60.

Woytinsky, W. S. (1939), *Seasonal variations in Employment in the United States*, Washington D.C., Social Science Research Council.

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