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Seasonality and Capacity: An Application to Italy

Guido de Blasio and Federico Mini

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Seasonality and Capacity: An Application to Italy

Prepared by Guido de Blasio and Federico Mini[1]

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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 discusses the option of exogenous seasonality resulting from changes in underlying technology and preferences, versus the possibility of endogenous seasonality arising because of synergies across agents. It then highlights the size of the seasonally-driven capacity slack and discusses its relevance from a welfare standpoint.

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Author's E-Mail Address: gdeblasio@imf.org; fmini@worldbank.org

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I. Introduction

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 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 which focuses on Italian seasonality in manufacturing as an issue worth investigating.

Our results show that manufacturing output seasonal fluctuations in Italy are extremely high in Italy when compared to France and Germany—Italy's two most important trade counterparts, and very influential partners in the newly established European Monetary Union. The Italian seasonal pattern is characterized by a dramatic slowdown in August followed by a full recovery in September; a late fall to winter slowdown 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 and across branches.

We try to interpret this empirical evidence with a view to shedding some light on possible explanations for the Italian manufacturing seasonal cycle, and its likely consequences.

As for the explanations, we consider exogenous seasonality, that is seasonality resulting from changes in underlying technology and preferences, versus the possibility of endogenous seasonality, that is changes in economic activities that arise because of synergies across agents that make it optimal to concentrate activity in a particular season. We provide suggestive evidence that this second explanation is likely to play a role in determining the Italian seasonal profile. In fact, significance and magnitude of the Italian seasonal cycle can be barely captured by standard real business cycle models.

As part of the observed seasonality in Italy is arguably endogenous—thus potentially actionable by policy—it is interesting to estimate the associated amount of excess capacity, and compare it to France's and Germany's. We calculate that excess capacity in Italy is around 30% 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 it is excessive from a welfare standpoint. Nevertheless, the results of this paper point out that seasonal variations can hardly be overlooked since they can easily affect welfare.

Some consequences could also stem from the fact that seasonal cycles are not of the same order of magnitude across partners in the newly established European Monetary Union. In fact, for a country that exhibits a higher seasonal pattern—and the associated capacity slack—the effects of a restrictive (unitary) monetary policy could typically occur too early with respect to the start of inflationary pressures as compared to the other partners.

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 presents the statistical methodology we use to measure seasonal movements. The empirical evidence on the significance and features of the Italian manufacturing seasonal cycle is discussed in Section 5. Section 6 quantifies the magnitude of Italian excess capacity, and compares it to France's and Germany's. Conclusion are in section 7.

II. 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 (re)changed 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 fluctuation.

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 shifts 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. 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 into high-productivity or low-utility seasons.

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 (Hall, 1991) 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. These 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 has 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 cycle could be efficiency-enhancing.[2]

III. DATA SET

This paper uses data of industrial production (IP), sales (S), and orders (O) for the Italian Manufacturing Sector over the period 1981:01 – 1997:07. 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.

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

The data set consists of 41 industrial series (15 for IP and S and 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.[3]

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 IMF.

IV. Methodology

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

In principle, there are three kinds of seasonality in time series which have been considered in the literature (Hylleberg, 1986, and Franses, 1996): stationary stochastic seasonality; non-stationary stochastic seasonality (unit roots), and deterministic seasonal dummies. There is however (Barsky and Miron, 1989) compelling evidence that suggests that the first two kinds of models of seasonality are likely to be a 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 be hardly 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 can not guarantee that differences in the seasonal means stay the same across sample periods.

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. While it is clear that 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 increase is clearly higher during booms than during recessions), nevertheless the approach followed here can be considered as a good first approximation. Moreover, from a quantitative point of view, several empirical studies show that the effects typically associated with the variation over time of the seasonal dummy coefficients can be easily considered of a second order. Therefore, following Barsky and Miron (1989), we model seasonality through deterministic seasonal dummies, while allowing for stationary stochastic seasonality, that is we assume:

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[3] See appendix.

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

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 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 presence of seasonal unit roots and then we examine whether the seasonal patterns differ across the Altissimo, Marchetti, and Oneto (1999) chronology of expansions and contractions in the Italian business cycle.

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 to test the null hypothesis that the series of interest exhibits some form 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, H0 is accepted only 8 out of 41 series (Table 1). Moreover, the test critical 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 of 16 and a half years. This implies that applying the appropriate critical value would have made the rejection of the null hypotheses 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,

[4] Hylleberg et al. (1990) show in fact that applying the Dickey-Fuller test directly to test 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) which 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 on the time series on France's and Germanys aggregated monthly production time series lead to the rejection of the null hypothesis at the 5% confidence level.

and Oneto (1999) chronology of the Italian business cycle. We then regress (by OLS) the log of growth rates on two set of monthly dummies, one for expansion and the other for contraction periods. The results (Table 2) indicate that the two patterns are remarkably similar and not statistically different. Using a Wald test, we are not able to reject the composite null hypothesis that, for each month, the growth pattern does not differ between booms and recessions.[7]

V. 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 3). Second, limited to Italy, we compare the evidence on production with that on sales and orders at the aggregate level (Table 4). Note that, while sales represent a coincident variable, orders are a leading indicator for production (de Blasio and Santi, 1999). Finally, we compare the three indicators is presented at single-industry level (Table 5 to Table 7).

Each of the tables presented contains summary statistics and seasonal dummy point estimates. The statistics are: 1-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; 2-The standard error of the regression (STDEV NON SEA); this is an estimate of variability of the business cycle component of the dependent variable. 3-The R2 of the regression, which measures the percentage of the variation in the dependent variable due to seasonality. 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.[8]

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

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

[8] The tables omit standard errors for clarity. The data however reject the null hypothesis of no seasonality at the 1 percent level for all variables.

The fact that in Italy business cycles represent a relatively small percentage of the overall fluctuations, and the importance of the seasonal component is 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: 1-A dramatic slowdown in August followed by a full recovery in September. 2-A late fall to winter slowdown (November and December), subsequently an upturn in the first three months of the year; 3-An April decline followed by a May resurgence. This pattern is more or less mirrored by fluctuations in sales and orders. The only exception is the late fall to winter slowdown, in which a January decline substitutes the December's one.

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 correlations are above 80%, with 10 out of 15 being 95% or more. Sales and orders exhibit the same high degree of comovement across sectors, although average correlations are marginally lower (in only two cases, Tobacco sales and Transportation Excluding Automobile orders, the average correlation with the other sectors is below 75%).

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

The results reported might shed some light on the likely explanations of the Italian high seasonality. Our results show that, even though the real business cycle-type can account for the timing of seasonal slowdowns, they nevertheless appear to offer, at best, an incomplete explanation for the observed seasonal changes.

Consider first the real business cycle explanation for seasonality that relies on shifts in preferences or technology. The traditional explanation for exogenous changes in preference and productivity is the weather. Table 9 reports monthly average temperature as well as average precipitation across the northern regions of the country where the Italian manufacturing sector is heavily concentrated. It is clear that there is no dramatic change in the weather and precipitation between July and August that can explain the huge downturn in the industrial sector. Moreover, weather data are clearly useless for the late fall to winter slowdown as well as for the April decline. It goes without saying that our results rule out also the technology shifts explanation, since it would require a degree of non-linearity in production that is clearly implausible.

A different possible explanation, close to the real business cycle one, calls for a broader concept of technology (that is, not readily captured by standard differentiable cost functions). Some industries could have a specific seasonal profile. 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, in such study, the seasonal pattern in the automobile industry drives seasonal movements for related (steel, rubber) industries, with corresponding lead 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 of the fall-winter and spring-summer fashion shows.

Accordingly, the high aggregate seasonal cycle could be due to a high weight of heavily seasonal branches in the manufacturing. However, this could not explain the observed extremely high degree of comovements across IP, S and O as well across branches. In fact, if seasonality due to idiosyncratic, industry-specific arrangements, is important, different industries would display heterogeneous seasonal profiles. This is not clearly the case in Italy. In other words, following the examples above, while seasonality in textile and automobile sectors can heavily weight in determining aggregate seasonality in Italy, there is no direct economic reason why they should be so synchronized.

Our results call for an alternative explanation for the observed high degree of seasonality in Italy that, while not dismissing a role for the weather or technology in determining the timing of the slowdowns, could nevertheless provide elements critical to account for the magnitude of the seasonal variations. We argue that the recent class of models of strategic complementarities can likely provide such an explanation. These models are based on the intuition (Cooper and John, 1988, Cooper and Haltiwanger, 1996) that the optimal action of one agent is an increasing function of the action of others.

Synergies across firms and workers can induce the seasonal pattern observed, 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 (see Hall, 1991). First, firms may find it convenient to close at the same time their upstream or downstream partners do. Instead of operating throughout the year at a lower average level, they can decide to close for August (and operating at an higher rate for the rest of the year). Each firm could decide to close because otherwise, given that all others have closed, it would have to stockpile raw materials and inventory intermediate and final goods in order to operate during the slowdown period, and these cost may 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 U.S. automobile industry 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.

From a policy standpoint, the message of this class of models can hardly be overemphasized. To the extent that seasonality is (at least in part) explained by synergies or strategic interactions, its effects are not irrelevant for welfare. Typically, strategic interaction models display multiple Pareto-ranked equilibria, and policy can indeed have a role in enhancing welfare if it can "unlock" the economy from an inferior equilibrium.

Having said this, the documented high Italian seasonal cycle need not be "excessive" from a welfare standpoint: such conclusion (and the associated policy prescriptions) can only be based on further empirical analysis. Indeed, the observed seasonality could be either too much or too little as compared to the socially optimal. In the first case, the negative effect would be due to the extra capacity that firms carry across seasons. In the second case, there would be still untapped efficiency gains from synchronizing production.

Regardless of its welfare implications, an interesting empirical question is to determine the amount of unutilized capacity in the Italian economy, and compare it to its major European counterparts; next section is devoted to providing an answer to such question.

VI. Excess Capacity Seasonally-Driven

In the previous section we contended that the Italian high degree of seasonality cannot be wholly attributed to exogenous factors. Instead, some non negligible portion of it is arguably the result of endogenous forces that can be affected by policy.

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 to Germany's and France's.

As noted earlier, the observed gap may measure some of Italy's efficiency losses from a policy-actionable too big seasonal cycle. However, one cannot rule out that synergies in Italy are more pronounced than in France and Germany, and that in order to fully exploit them, the excess capacity should be even greater.

In Section IV 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 proposition, following Beaulieu, Jeffrey and Miron (1992)[9], we look at nonseasonal

[9] The primary objective of their formalization is to build a model that generates positive correlation between the magnitude of the seasonal and the business cycle, a phenomenon (continued...)

output residuals. In a scenario where capacity level are determined 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 thus that there will be seasonal heteroskedasticity 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, Table 10 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.[10] With the exception of Transportation (Excluding Automobile), we are able to reject the null hypothesis of no seasonal heteroskedaticity at the 5% significance level—but only at the 10% for the residual branch "Other".

Next, we check whether the data exhibit the expected heteroskedaticity pattern—negative correlation between monthly growth rates and level production in that month. In order to do so, we compute the Spearman rank correlation between the variance of the monthly production growth and the seasonal in the level of production (calculated regressing the log levels of industry production on 12 seasonal dummies and a quadratic trend).

Results reported in Table 10 show that correlation is in fact negative in all cases, although statistically significant for only 5 branches: Petroleum, Coal, etc.; Agricultural and Industrial Machinery; Automobile, Transportation (Excluding Automobile); and Food and Beverage. These 5 branches accounted for 49.5% of Italy's total manufacturing production in the period 1990-1997.

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widely documented both across countries and across industries. The fact that industries with large business cycles have also large seasonal cycles is confirmed by the Italian data. For instance, using cross-section figures reported in Table 4 for the 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 ant the seasonal standard deviation, the coefficient on this latter variable—0.216— is significant at the 1% confidence level, while the R^2 is 55.6%.

[10] Beaulieu et. Al. (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 a 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.

In conclusion, for a relevant portion of Italy's manufacturing activities, there is reason to believe that the strong seasonality documented in Section IV explains capacity levels in several large industries. It would be 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), France and Germany (aggregate level only for these latter). The first is the recursive procedure proposed by De Long and Summers (1988), that is:

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

In words, the potential output between period t and period t+1 lies along the slope of 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 define 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 picks individually; rather, we considered a peak any value yt in the output time series that was greater than the previous and subsequent k periods (months in our case).[11]

We applied the two algorithms to time series in level, 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 11, which reports the average unutilized excess capacity (in percentage points) in the sample period. The amount of capacity unutilized in Italy is higher, contrary to what is usually found when using seasonally adjusted data. The industrial output gap in Italy is approximately 30% higher than in Germany and in France, and this result is robust to the two alternative procedure used.

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[11] 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 assures that potential capacity is everywhere greater that actual output, while this is the case for the De Long-Summers routine.

Table 12 reports the computed average excess capacity 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 between one and a half times to close to double aggregated unutilized excess capacity. Considering both the weight of this sector in the Italian economy, and the complementarities with other important sectors (steel, plastic), this is a fact policy makers can hardly ignore. In the Agricultural and Industry machinery sector, unutilized excess capacity is estimated to be between 14% to 55% higher than on average; given the spill-over effects in the rest of the economy, the welfare effects of high seasonality in this sector are probably not negligible. Finally, although some of the seasonal variation in Food and Beverage is arguably due to exogenous factors, these cannot probably explain by themselves the circumstance that firms in these sector have estimated excess capacity 50% higher than in the aggregate manufacturing sector. As a greater fraction of firms in this sector produce for final markets, policy affecting socially undesirable seasonal effects would translate more directly into relatively better prices for the public.

Although only suggestive, these results are quite engaging. As highlighted by Kuznets (1933), a potential waste could be associated with seasonal excess capacity and this may well affect country's competitiveness. A possible counter-argument is that an excess of capacity, no matter how established, could however represent a source of flexibility. For example, high-seasonal countries or industries could more easily accommodate an unexpected increase in demand, given their excess capacity. While this argument has some merits, it is nevertheless clear that, as far as Italy is concerned, its effectiveness is limited by the existence of a single monetary policy. In a monetary union a higher-than-area-wide, seasonally-driven excess capacity is unlikely to provide exploitable extra flexibility. The point is that inflationary pressure might occur first in low seasonal countries, and this will call for a restrictive change in monetary policy. Stated differently, for a country that exhibits an higher seasonal pattern, a restrictive change in monetary policy stance will typically occur too early with respect to the start of inflationary pressures.

In conclusion, the analysis above raises some interesting questions: can it really be the case that the gains from concentrating production in Italy are so big to warrant at least 30% more excess capacity than France's and Germany's? Can a country that exhibits a higher seasonal pattern find itself unduly penalized in a monetary union?

VII. Conclusions

Information at 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 highlighted possible explanations and likely consequences.

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 a 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 unused excess capacity in the Italian manufacturing sector is, on average, around 30% higher.

While these figures are simply suggestive, they are nonetheless quite interesting. The wide differences between the (endogenous) seasonal cycle in Italy on one hand and in 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 can well be the case that potential welfare gains can be captured through policies aimed at reducing capacity waste. It can also be the case that the pattern of the Italian seasonality is optimal given the degree of external economies. Moreover, the working of the European Monetary Union poses new challenges. According to our findings, the Italian manufacturing sector might still have room for expansion when the economies of its other European partners are starting to overheat. A single monetary policy tailored on the needs of countries with homogeneous, and less pronounced seasonality in production—as France and Germany—could thus be unduly restrictive for a "more seasonal" country as Italy.

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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 one hand, and sales and orders, on the other hand, a preliminary work has been carried on 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, since 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 includes also 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 13 describes the 15 Nace-Clio 44 Branches and their weights.

Table 1. Seasonal Unit Roots

	Sec 1	Sec 2	Sec 3	Sec 4	Sec 5	Sec 6	Sec 7	Sec 8	Sec 9	Sec 10	Sec 11	Sec 12	Sec 13	Sec 14	Sec 15	Aggregate (15)	Aggregate (11)
Industrial Production	no	no	no	no	No	no	no	no	no	no	no	no	yes	yes	no	no	no
Sales	no	no	yes	no	No	no	no	no	no	no	no	no	yes	yes	yes	no	no
Orders	no	no	no	no	No	yes	no	n/a	n/a	no	no	no	yes	n/a	n/a	no	no

Test applied to log growth rates. Test specification: Intercept, seasonal dummies, no trend. 10% confidence level. Names of the sectors are reported in Table A1.1

Table 2. Seasonal Patterns in Expansions and Contractions

	jan	feb	mar	apr	may	jun	jul	aug	sep	oct	nov	dec	R2	chi-12	STDEV SEA
IP all sectors															
Expansion	6.11	6.12	9.50	-10.69	9.07	-0.17	-0.08	-89.15	90.14	0.76	-4.16	-16.01	0.977	5.59	41.61
Contraction	8.97	3.32	9.63	-11.81	5.84	-0.28	1.52	-92.55	87.99	3.25	-4.77	-18.70		(0.935)	33.02
S all sectors															
Expansion	-16.32	10.28	11.45	-11.18	5.09	2.02	4.72	-74.73	74.23	-0.47	-6.75	2.48	0.971	4.64	34.96
contraction	-13.30	8.05	11.30	-12.70	2.03	2.07	5.29	-76.11	72.42	1.15	-6.89	-0.35		(0.969)	27.29
O all (11) sectors															
expansion	-9.21	5.94	11.97	-14.94	1.96	5.07	-3.87	-75.43	80.46	0.34	-6.41	7.58	0.948	5.71	36.41
contraction	-4.91	2.79	10.51	-15.31	1.77	1.09	-0.64	-79.23	80.34	1.39	-10.51	3.70		(0.930)	28.98

Test applied to log growth rates. Stdev sea is the sum of squared deviations from the mean of the fitted values of the estimated regression divided by T-12. Regression was estimated using Newey-West (1987) covariance matrix

Table 3. Seasonal Patterns: Aggregate Production, France, Germany and Italy

	STDEV SEA	STDEV NONSEA	R2	jan	feb	mar	apr	may	jun	jul	aug	sep	oct	nov	dec
France	14.37	4.05	0.927	2.05	-3.86	5.91	-4.99	-4.51	4.41	-7.92	-29.02	35.55	9.36	-1.42	-4.87
Germany	6.95	5.45	0.620	-5.96	1.99	11.33	-4.74	-2.27	2.81	-5.06	-5.30	14.48	2.83	-1.90	-8.45
Italy	37.92	6.09	0.975	7.18	5.34	9.19	-10.35	7.53	-0.15	0.80	-90.00	89.60	1.69	-4.43	-17.18

Table 4. Seasonal Patterns: Italy—Aggregate Series

	STDEV SEA	STDEV NONSEA	R2	jan	feb	mar	apr	may	jun	jul	aug	sep	oct	nov	dec
IP all sectors	37.92	6.09	0.97	7.18	5.34	9.19	-10.35	7.53	-0.15	0.80	-90.00	89.60	1.69	-4.43	-17.18
S all sectors	31.75	5.65	0.97	-15.19	9.54	11.12	-10.99	3.63	2.23	5.10	-75.08	73.78	0.14	-6.81	1.25
IP 11 sectors	40.72	6.37	0.98	7.03	5.10	9.19	-9.98	7.23	-0.21	0.91	-98.57	95.24	2.02	-3.33	-15.40
S 11 sectors	33.55	5.71	0.97	-15.55	9.50	10.90	-11.21	3.13	2.31	5.78	-79.67	78.02	-0.24	-6.96	2.72
O 11 sectors	33.16	8.11	0.94	-7.17	5.11	10.80	-14.21	1.52	3.65	-2.03	-76.38	80.43	0.74	-8.20	5.88

Table 5. Seasonal Patterns: Industrial Production

	STDEV SEA	STDEV NONSEA	R2	jan	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 6. 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 7. 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

Table 8. Average Correlations, Italian Manufacturing Industries

	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

Table 9. Temperature and Rainfall in Northern Italy

	Jan	feb	mar	apr	may	jun	jul	aug	sep	oct	nov	dec
Temperature (centigrade)	1.1	3.5	7.6	12.1	16.7	20.7	23.3	22.5	18.9	13.4	7.0	2.5
Rainfall (cm)	49.2	51.4	68.08	90	95.55	80.3	57.65	68.98	69.28	85.58	88.18	55.63

Source: World Climate. (1) Average of Turin, Milan, Venice, and Bologna.

Table 10. 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	-0.350	0.123
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	-0.315	0.148
Automobile	94.64	0.00	-0.727	0.008
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	-0.315	0.148
Apparel	53.57	0.00	-0.217	0.236
Leather	61.17	0.00	-0.350	0.123
Lumber	81.20	0.00	-0.259	0.195
Paper	77.56	0.00	-0.154	0.305
Rubber	78.00	0.00	-0.294	0.165
Other	18.58	0.07	-0.301	0.159
Aggregated	61.15	0.00	-0.154	0.305

Table 11. Aggregated Excess Capacity (Percentage) France, Germany and Italy

	Algorithm	
	De Long-Summers	Wharton
France	10.3	9.7
Germany	10.2	9.1
Italy	13.4	12.5

Table 12. Excess Capacity (Percentage) Selected Manufacturing Branches, Italy

	Algorithm	
	De Long-Summers	Wharton
Petroleum, coal, metal and non metallic mineral	15.8	11.6
Agricultural and industrial machinery	20.8	15.3
Automobile	23.6	19.0
Transportation (excluding automobile)	22.0	16.8
Food & Beverage	21.0	19.8
Italy aggregated	13.4	12.5

Table 13. Nace-Clio 44 Branches and Industrial Production weights

Sec	Branch	Code Nace-Clio	Industrial Production Weights			Orders
			81:01-84:12	85:01-89:12	90:01-97:07	
1	Petroleum, coal, metal and non metallic mineral	03+ 05+ 07+13+15+19	0.234	0.231	0.239	yes
2	Chemicals	17	0.071	0.081	0.087	yes
3	Agricultural and industrial machinery	21	0.082	0.095	0.094	yes
4	Computer and electronic	23	0.017	0.025	0.023	yes
5	Electric machinery	25	0.068	0.088	0.069	yes
6	Automobile	27	0.045	0.044	0.048	yes
7	Transportation (excluding automobile)	29	0.024	0.026	0.030	yes
8	Food and beverage	31+33+35+37	0.099	0.076	0.086	no
9	Tobacco	39	0.002	0.003	0.002	no
10	Apparel	41	0.138	0.131	0.122	yes
11	Leather	43	0.041	0.038	0.034	yes
12	Lumber	45	0.072	0.055	0.054	yes
13	Paper	47	0.055	0.056	0.062	yes
14	Rubber	49	0.040	0.037	0.040	no
15	Other	51	0.012	0.013	0.011	no

Source: de Blasio and Santi (1999)