The Italian Business Cycle from the Unification until Today: A Disaggregate Approach*

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Abstract

Growth and fluctuations in the Italian economy since the 19th century have long eluded research. Existing Historical National Account estimates of the Italian economy are only partly compatible with each other and in cases at odds with international evidence. In this paper, we study disaggregate evidence on the Italian business cycle from just after the country's unification in 1861 until the financial crisis of 2008. We employ dynamic factor analysis to substitute for the often scant value added information. Our results indicate that aggregation bias matters: models with time-invariant coefficients replicate much of the earlier research on the Italian economy, in particular for the 19th century. Allowing instead for even a small degree of time variation in the factor loadings, our results lend support to recent reassessments of Italy's economic performance. We find evidence of high volatility during the unification period, followed by well-behaved cyclical patterns until 1913. Supporting recent research, we find no evidence of an economic boom during World War I. Our results also identify strong volatility during post World War II supergrowth, as well as subsequent moderation.

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1 Introduction

Growth and fluctuations in the Italian economy since the unification of 1861 have long eluded scholarly research. Scattered time series evidence, scarcity of business census data and a markedly uneven development across principal sectors and regions of the Italian economy made the study of macroeconomic dynamics a rather daunting task[1]. As a consequence, Historical National Account (HNA) reconstructions of the Italian economy have produced a variety of estimates that were only partly compatible with each other and in cases at odds with international evidence. Research has tended to concentrate on short sub-periods of the history of united Italy, with some periods remaining largely unexplored. A good number of studies has focused on the period going from the country's unification in 1861 until the start of World War I in 1913. Thanks to the work of many scholars, spearheaded by Stefano Fenoaltea, our understanding of economic conditions in Italy during this period has improved substantially in recent years. Another period that has received a good deal of attention is the latter part of the 20th century. This time-span featured the 1970s oil shocks - which officially ended Italy's honeymoon with sustained economic growth - and the Great Moderation which affected Italy together with most advanced economies worldwide. Studies which look at the Italian business cycle over the long run have been rare; in fact we are aware of only one (DelliGatti, Gallegati, and Gallegati (2005)), but this is based on data that is now regarded as seriously flawed, especially for the pre-World War II era. This paper aims to fill this gap in the literature by investigating the Italian business cycle for a period of almost 150 years and by employing an advanced econometric technique which can account for the both the paucity of reliable aggregate time series and the deep structural change the Italian economy underwent since the country's unification. Figures 1a and 1b demonstrate these far reaching transformations by presenting the changing shares of labor and value added in the three principal sectors of the Italian economy.

[1] See Fenoaltea (2010) for a recap of Italian HNA reconstructions.

(Figure 1 about here)

More precisely, we study the Italian business cycle from just after the country's unification which took place in 1861 until the onset of the financial crisis in 2008. Our investigation focuses on the whole span of the period as well as several significant sub-periods. In particular, we zoom in on the years between the Unification and World War I, the inter-war period, the post-World War II era and the most critical years within these time periods. Our methodology of choice is Dynamic Factor Analysis (DFA), which relies on the use of large datasets of disaggregated time series. By exploiting the co-movement of these series, the model isolates common latent components which drive the economy and which we interpret as indexes of economic activity. In line with pioneers of business cycle analysis such as Burns and Mitchell (1946), and more recent theoretical and empirical contributions by authors such as Lucas (1977) and Stock and Watson (1989), we do not consider the business cycle as simply the oscillations of GDP around a trend, but as the co-movement of a large array of economic indicators. Our approach is similar to Ritschl, Sarferaz, and Uebele (2008) and Sarferaz and Uebele (2009). We believe it constitutes an important complement to the reconstruction of GDP series derived from Historical National Accounts (HNA). For many countries, including Italy, long stretches of economic history are covered only by scant and rudimental statistics. DFA can help overcome some of the pitfalls of this data, especially with regard to aggregation. This is the case, for example, because DFA does not require data on the structure of the economy, contrary to classic national accounts reconstructions which inevitably feature sectoral weights. This is a considerable advantage, considering that it is extremely difficult to empirically identify appropriate weights (Hoppit, 1990). Moreover, the dynamic nature of our model helps to account for structural changes in the economy and variations in volatility. Indeed, our results indicate that aggregation bias matters: models with time-invariant coefficients replicate much of the earlier research on the Italian economy, in particular for the 19th century. Allowing instead for even a small degree of time variation in the factor loadings, our results lend support to recent reassessments of Italy's economic performance.

Regarding the 1861-1913 period, the initial reference point consisted in the series reconstructed by the Instituto Nazionale di Satistica (ISTAT, 1958), which guided early researchers. These, however, have come to be regarded as largely inconsistent, especially with regard to aggregate measures. The new evidence points to a slow but persistent growth in economic activity during the years before WWI, rather than the sudden take-off envisaged by authors such as Gerschenkron (1955) and Maddison (1991). The Italian economy did accelerate its rate of growth after the turn of the century, but this change is no longer considered a structural break, but rather a cyclical upswing due to the international investment cycle (Fenoaltea, 2005). While this view of trend growth is now consensual, cyclical fluctuations still elude a similar unanimity. Quite the opposite, both the volatility of the Italian business cycle from the Unification until WWI and its turning points have not been firmly established. Our results confirm the recent findings by Ciccarelli and Fenoaltea (2007) of high volatility during the unification period, followed by well-behaved cyclical patterns until 1913.

For the inter-war period, the principal source of doubt is represented by the growth of the Italian economy during World War I. Early researchers (Maddison, 1991; Rossi, Sorgato, and Toniolo, 1993) established that the Italian economy grew strongly, at least during the first years of the conflict. The phenomenon was attributed to an increase in public expenditure, which supposedly more than compensated for the decrease in private spending (Mattesini and Quintieri, 1997). However, scholars have long been sceptical. As highlighted by Broadberry (2005), if Italy did indeed grow strongly during WWI it would be the only European country to have done so. In fact, all other nations significantly involved in the conflict experienced more or less severe slowdowns. On a purely intuitive level, it is hard to square the dispatch of hundreds of thousands of men to the front with growing production in an economy that was still largely agrarian and relied heavily on manual labor. New quantitative evidence is indeed placing a question mark behind the story of an Italian boom during World War I. Baffigi (2011) recently re-estimated the Italian GDP from 1861 to 2011 and found substantially slower growth during the war years than that envisaged by earlier estimates. Carreras and Felice (2012) have argued that Italian industrial production decreased during the years of the conflict, contrary to the claims of earlier accounts. The results of this paper support these

reassessments by nding no evidence of an economic boom during the First World War.

In the post-WWII period, uncertainty over growth and business cycle facts is signi cantly lower. Better data collection and more advanced statistical methods paved the way for a sound and reliable monitoring of economic activity. Nonetheless, the immediate post war decades pose a puzzle. In fact, based on the available GDP series the fteen years after the end World War II appear to have been characterized by the absence of a signi cant business cycle. It is well known that during the post-war reconstruction and \economic miracle", Italy was growing strongly and steadily. However, the absence of uctuations is peculiar if compared to the rest of the history of united Italy, which is characterized by a pronounced and relatively regular cyclicality. This period also poses an interesting test for di erent hypotheses regarding the origeg obusinngcsycle.ev that theele pole wele periot

the data is quite fragmented and the series which are complete for the whole length of the period are relatively few. For this reason, each time span studied features a di erent number and combination of series. In selecting the series, two elements were taken into consideration. First of all, the dataset needs to be representative of the Italian economy. Using only industrial or agricultural series would lead to an inadequate representation of the variability of economic activity, a point recently emphasized by Broadberry, Giordano, and Zollino (2011). The available series were therefore combined into balanced datasets featuring a wide array of economic indicators. Secondly, the crucial feature of the series is their cyclical component. Given that the trend component is ltered out prior to the application of DFA, series which feature awed trend growth can still provide useful information about volatility. In our case, this consideration applies mainly to the agricultural ISTAT series between 1861 and 1913. Federico (2003) has reconstructed agricultural production estimates - summarized by an aggregate value added series - which correct the distortion of the ISTAT estimate. However, Federico's series are widely believed to under-represent volatility (Marchionatti and Sella, 2012; Ciccarelli and Fenoaltea, 2007). The original disaggregated ISTAT series, instead, carry valuable cyclical information. As Ciccareli and Fenoaltea put it: \[...] the new series is a mirror-image of the agricultural statistics generated at the time: these apparently got the longer-term movements wildly wrong - and transmitted their errors even to their distant progeny [...] - but they clearly incorporated the perceived short-term variations in the harvest." On top of this, the Federico series, while reliable at the aggregate level, cannot be directly used in a study employing disaggregate series, since its various components have not been published. For these reasons, we use the ISTAT physical production series for agriculture. The other ISTAT series we use in our analysis cover imports and exports of various goods, population, industrial production and transportation services. For the period 1861-1913, a detailed account of industrial production is provided by new estimates by Ciccarelli and Fenoaltea (2009, 2012). These are clearly superior to earlier estimates, notwithstanding the fact that they too feature data interpolations. Thanks to these series, the 1861-1913 dataset covers a very substantial chunk of the Italian economy and is large even by the standard of papers using similar methodologies. For the inter-war period, the ISTAT series are integrated with the industrial production series of Carreras and Felice

(2012), while for the period from the end of World War II to 2008, we rely on a wide range of series from ISTAT. In all cases, we were able to produce a representative picture of the cyclical variability of economic activity in Italy. See Appendix B for a description of the data used in each sub-period.

As highlighted by Canova (1998, 1999), business cycle dynamics can be sensitive to the de-trending method used in the analysis. Different filtering techniques tend to yield different business cycle facts. Specifically for the case of pre-World War I Italy, Marchionatti and Sella (2012) show how traditional filtering techniques can mask relevant cyclical features and that spectral methods are needed to uncover cycles in seemingly smooth series. In this paper we address the filtering issue by using a variety of de-trending methods to ensure the robustness of the results. Comin and Gertler (2006) have argued that the focus of business cycle research on short term volatility in economic activity can mask interesting features of the data such as longer cycles with a duration of up to 200 quarters, which they refer to as medium-term cycles. These get filtered out with traditional de-trending techniques. The observation is certainly valuable, but we leave its application to Italy to future research.

3 A Structural Dynamic Factor Model

The methodology used in this paper can be traced back to the contributions of Sargent and Sims (1977), Geweke (1977) and Stock and Watson (1989) who postulated that a panel dataset can be summarized by an unobserved latent common component that captures the co-movements of the cross section, and a variable-specific idiosyncratic component. Identifying dynamic factors within the dataset can thus uncover the latent forces that drive an economy. Identifying dynamic factors within the dataset can thus uncover the latent forces that drive an economy. Bayesian dynamic factor models were developed by Otrok and Whiteman (1998) and Kim and Nelson (1999), amongst others. DelNegro and Otrok (2003) generalize the estimation procedure to dynamic factor models with time-varying parameters. The model employed here was applied to similar studies of the business cycle over the very long run and for periods with scant and unreliable data sources by Ritschl, Sarferaz, and Uebele (2008) and Sarferaz and Uebele (2009). The first paper deals with the United States between 1867 and 1995, while the second covers Germany in the period 1820-1913. Both

papers have demonstrated that the methodology is ideal for the study of business cycles in historical context and that it represents an important complement to HNAs. Turning points are generally estimated precisely, while variability of economic activity is reassessed in a way that eschews potential dampening or exacerbating effects of aggregation due to deflators and sectoral weights. Moreover, information that would normally be discarded as inadequate to enter national accounts can be used for the cyclical information it carries.

Let a data panel Y_t, spanning a cross section of N series and an observation period of length T, be by a one-factor model with time-varying factor loadings. The observation equation then is:

$$Y_t = \Lambda_t f_t + U_t \tag{1}$$

where f_t represents a 1×1 latent factor, while Λ_t is a $N \times 1$ coefficient vector linking the common factor to the i-th variable at time t, and U_t is an $N \times 1$ vector of variable-specific idiosyncratic components. The latent factor captures the common dynamics of the dataset and is our primary object of interest.[2]. We assume that the factor evolves according to an AR(q) process:

$$f_t = \varphi_1 f_{t-1} + \ldots + \varphi_q f_{t-q} + \nu_t \tag{2}$$

with $\nu_t \sim \mathcal{N}(0, \sigma_\nu^2)$. The idiosyncratic components U_t are assumed to follow an AR(p) process:

$$U_t = \Phi_1 U_{t-1} + \ldots + \Phi_p U_{t-p} + \chi_t \tag{3}$$

where $\Phi_1, \ldots, \Phi_p$ are $N \times N$ diagonal matrices and $\chi_t \sim \mathcal{N}(0_{N \times 1}, \Sigma_\chi)$ with

$$\Sigma_\chi = \begin{bmatrix} \sigma_{1,\chi}^2 & 0 & \cdots & 0 \\ 0 & \sigma_{2,\chi}^2 & \vdots & \vdots \\ \vdots & \cdots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{N,\chi}^2 \end{bmatrix}$$

[2]Generalization to several factors is straightforward.

The factor loadings or coefficients on the factor in equation (1), λ_t, are assumed to either be constant or (in the time-varying model) follow a driftless random walk, as in DelNegro and Otrok (2003), DelNegro and Otrok (2008)[3]:

$$\lambda_t = \mathcal{I}_N \lambda_{t-1} + \epsilon_t \tag{4}$$

where $\mathcal{I}_N$ is a $N \times N$ identity matrix and $\epsilon_t \sim \mathcal{N}(0_{N \times 1}, \Sigma_\epsilon)$ with

$$\Sigma_\epsilon = \begin{bmatrix} \sigma^2_{1,\epsilon} & 0 & \cdots & 0 \\ 0 & \sigma^2_{2,\epsilon} & \vdots & \vdots \\ \vdots & \cdots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma^2_{N,\epsilon} \end{bmatrix}$$

and where the disturbances χ_t and ϵ_t are independent of each other.

The above setup specifies an exact factor model in the sense that it assigns all comovement between the series to the factor. This identifying assumption arises quite naturally in our context, where we use comovement to obtain a measure of aggregate activity and its volatility. The setup also restricts the innovations to the transition equations for the factor, the factor loadings, and the idiosyncratic component to be i.i.d. Generalizations to stochastic volatility have been introduced in a VAR context by Cogley and Sargent (2005) and Primiceri (2005), and in a dynamic factor model by DelNegro and Otrok (2008). Not allowing for stochastic volatility in our setup is again an identifying assumption. It has the effect of assigning all volatility to either the factor or the factor loadings, with priors chosen such as to control Σ_ϵ, the variance term in the law of motion for the factor loadings in eq. (4) above.

The dynamic factor in this model is identified up to a scaling constant and a sign restriction. We deal with scale indeterminacy by normalizing the standard deviation of the factor innovations to $\sigma_\nu = 1$. The sign indeterminacy of the factor loadings λ_t and the factor f_t is resolved by a sign convention, i.e. by restricting one of the factor loadings to be positive (see Geweke and Zhou (1996)). Neither operation involves loss in generality.

[3] An alternative approach to capturing time variation is to specify multi-factor models with constant factor loadings, where higher-order factors are interpreted as correction factors that pick up the time variation.

3.1 Priors

Before proceeding to the estimation of the system, we specify prior assumptions. For the most part, these priors are chosen as convenient initial conditions for burn-in of the Markov chains, without affecting their steady states. Other priors are informative and have a substantive interpretation in terms of our research question, the time variation taken up by the factor loadings rather than the factor itself. To tackle this, we obtain results for different degrees of tightness of these priors, varying from diffuse to rather tight. We adopt priors for four groups of parameters of the above system. These are, in turn, the parameters in the factor equation (2), the parameters in equation (3) governing the law of motion of the idiosyncratic component, the parameters in the law of motion of the factor loadings (4), and the parameters in the observation equation (1).

For the AR parameters $\varphi_1, \varphi_2, \ldots, \varphi_q$ of the factor equation, we specify the following prior:

$$\varphi^{prior} \sim \mathcal{N}(\underline{\varphi}, \underline{V}_{\varphi})$$

where $\underline{\varphi} = 0_{q \times 1}$ and

$$\underline{V}_{\varphi} = \tau_1 \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & \frac{1}{2} & \vdots & \vdots \\ \vdots & \cdots & \ddots & 0 \\ 0 & \cdots & 0 & \frac{1}{q} \end{bmatrix}$$

Analogously, for the AR parameters $\theta_1, \theta_2, \ldots, \theta_p$ of the law of motion of the idiosyncratic components, we specify the following prior:

$$\theta^{prior} \sim \mathcal{N}(\underline{\theta}, \underline{V}_{\theta})$$

where $\underline{\theta} = 0_{p \times 1}$ and

$$\underline{V}_{\theta} = \tau_2 \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & \frac{1}{2} & \vdots & \vdots \\ \vdots & \cdots & \ddots & 0 \\ 0 & \cdots & 0 & \frac{1}{p} \end{bmatrix}$$

We choose $\tau_1 = 0.2$ and $\tau_2 = 1$. Both priors are shrinkage priors that punish more distant lags on the autoregressive terms, in the spirit of Doan, Litterman, and Sims (1984). This is implemented by progressively decreasing the uncertainty about the mean prior belief that the parameters are zero as lag length increases. Related priors are employed in Kose, Otrok and Whiteman (2003) and del Negro and Otrok (2008).

For the variances of the disturbances in χ_t, we specified the following prior:

$$\sigma_{\chi}^{2\ prior} \sim \mathcal{IG}\left(\frac{\alpha_{\chi}}{2}, \frac{\delta_{\chi}}{2}\right)$$

We choose $\alpha_{\chi} = 6$ and $\delta_{\chi} = 0.001$, which implies a fairly loose prior. $\mathcal{IG}$ denotes the inverted gamma distribution.

For the factor loadings, we distinguish two cases. With constant factor loadings (disregarding structural change), the relevant prior for each individual factor loading is:

$$\lambda^{prior} \sim \mathcal{N}(\underline{\lambda}, \underline{V}_{\lambda})$$

where $\underline{\lambda} = 0$ and $\underline{V}_{\lambda} = 100$.

With time-varying factor loadings, for each of the variances of the disturbances in ϵ_t the prior is:

$$\sigma_{\epsilon}^{2\ prior} \sim \mathcal{IG}\left(\frac{\alpha_{\epsilon}}{2}, \frac{\delta_{\epsilon}}{2}\right)$$

In the sequel, the differences between constant and time-varying factor loadings will play a role. For the latter, we will assume the prior values for α_{ϵ} and δ_{ϵ} suggested by DelNegro and Otrok (2008).[4]

[4] We experimented with a grid of prior values, finding the qualitative results to be unchanged.

3.2 Estimation

We estimate the model by Gibbs sampling. In our case, the estimation procedure is subdivided into three blocks: First, the parameters of the model c, φ, θ_r for s = $1, \ldots, q$ and r = $1, \ldots, p$ are calculated. Second, conditional on the estimated values of the first block, the factor f_t is computed. Finally, conditional on the results of the previous blocks we estimate the factor loadings. After the estimation of the third block, we start the next iteration step again at the first block by conditioning on the last iteration step. [5].

We obtained estimatesfor lag lengths p = $1, q$ = 8, taking 30,000 draws and discarding the first 9,000 as burn-in. Specifications with constant and time-varying factor loadings are reported alongside each other. Convergence of the Gibbs sampler was checked by varying the starting values and comparing the results within and across chains. All series were detrended using the Hodrick-Prescott (6.25) filter suggested by Ravn and Uhlig (2002) for business cycle frequencies, and were subsequently standardized.[6]

4 Estimation Results

This section presents results from estimating the factor model with time-varying factor loadings. For the observation period from 1861-2008 as a whole, only a comparatively narrow database is available. It is dominated mostly by agricultural series, which vary in quality over time. Deeper insights can be gained from analyzing relevant subperiods. This section surveys the evidence by subperiods, with the World Wars as the major watersheds. Historical national account estimates of Italian GDP present conflicting views of economic activity between the unification and World War I. Figures 2a and 2b show HNA estimates by Maddison (1991) and Baffigi (2011), respectively. Both are detrended with HP (6.25) as suggested by Ravn and Uhlig (2002).

(Figures 2 about here)

[5] See the appendix for a more detailed description of the estimation procedure.

[6] We also experimented with λ = 100, as well as Baxter/King and Christiano/Fitzgerald filters, and found the qualitative results to be robust.

4.1 From the Unification to World War I

Various GDP estimates for the period 1863 to 1913 give rather different accounts of Italy's macroeconomic performance. Data from older research, represented by Maddison (1991) and Maddison (2003), paint a picture of uneven growth with high and increasing volatility. On the contrary, data revisions by Fenoaltea (2005), Ciccarelli and Fenoaltea (2007) and Baffigi (2011) suggest high initial levels of volatility, with a marked transition to a more regular cyclical pattern around 1890. Figure 2 contrasts the two GDP series, each filtered with HP(6.25). Ciccarelli and Fenoaltea (2007) point out that, unsurprisingly, the cycle was dominated by agriculture with industry playing a limited role and services playing almost no role. The fall in volatility, according to this version of the story, should therefore be attributed to a drastic fall in the volatility of agricultural production. Marchionatti and Sella (2012) re-examine the period using spectral methods. They come to the conclusion that the fall in volatility found by Ciccarelli and Fenoaltea is spurious and to be attributed to the excessively mild cyclicality of the aggregate agricultural series constructed by Federico (2003) and incorporated in the GDP series used by Ciccarelli and Fenoaltea (and Baffigi as well). The authors find a remarkable overlap between their results and the account produced in the early 20th century by the *Turin School of Economics* led by the distinguished Italian economist Luigi Einaudi. In fact, there is also a substantial overlap between the business cycle dynamics described by Einaudi and Ciccarelli and Fenoaltea, with the main difference being precisely the volatility of growth after 1890, high according to Einaudi, low according to Ciccarelli and Fenoaltea. Another defining feature of this sub-period is the increase in the growth rate which Italy experienced after the turn of the century. Early accounts by Gerschenkron (1955, 1968) and Romeo (1959) interpreted this as a structural break due to Italy entering a new stage of long-term growth after having fulfilled the prerequisites to become a modern economy. Doubts were successively raised on the "take off" or "big-push" interpretation (Bonelli (1978); Cafagna (1983a), Cafagna (1983b); Toniolo (2003)), but recent GDP estimates by Fenoaltea (2005) and (Baffigi (2011) still feature a growth acceleration starting from 1900. Fenoaltea (2005) does not see this as a structural break, but

rather as a cyclical upswing caused by the international investment cycle with the Kondratieff cycle in agriculture also playing a role. This presumed cycle is a low frequency component and will not be treated in this paper. According to Ciccarelli and Fenoaltea (2007), the availability of foreign capital also played a role in the 1870s and 1880s upswings.

Our findings contribute to this debate. We confirm the cyclical upswings of the 1870s and 1880s. We also find a significant increase in economic activity from 1863 until 1865 as well as the severe crisis of 1887-1890 caused, according to Rossi and Toniolo (1992), by a depression of investment demand and manufacturing output which led to bank failures and a political crisis that threatened to cause to a coup d'etat.

(Figure 3 about here)

More importantly we show evidence of a reduction in volatility starting from 1890 as previously envisaged by Fenoaltea and Ciccarelli but dismissed by Marchionatti and Sella. We also find that, indeed, the reduction in volatility was caused by a fall in volatility of the agricultural sector. Crucially, we can dismiss the idea that the decrease in volatility is due to the very mild cyclical pattern in the agricultural series of Federico (2003), since we use the original ISTAT series instead. The question of why such a drastic decrease in volatility took place is unresolved. A hypothesis is that its origin lies in the Unification process and the creation of a single Italian market.

One way of looking into this is to estimate a model of economic activity with constant factor loadings. This shuts down structural change as captured by the time-variant model, and helps to identify sectors that contributed to volatility during particular periods.

(Figure 4 about here)

In our dataset, a pattern of high initial volatility is still preserved. However, the 1870s now come out as the most volatile period, whereas the 1860s seem markedly less volatile. We are also able to reproduce the traditional evidence of increasing volatility in the 19th century. Figure 5 presents a factor model with constant loadings from the series underlying

earlier estimates like Maddison (1991).

(Figure 5 about here)

As can be seen from Figure 5, volatility increases over the course of the 19th century, a property that is also visible in the detrended version of the Maddison estimate in figure 2a above. For the same estimate, we found the pattern of decreasing volatility to reestablish itself if allowing for changing factor loadings. Clearly, the Maddison series appears to suffer from index number problems.

In passing, we note that similar issues of changing volatility exist with the nominal series. Figure 6 shows bouts of volatility in the unification period and again right before World War I.

(Figure 6 about here)

Given this evidence, attempts to calculate HNA estimates of GDP from deflating nominal series would be quite likely to be prone to bias. This is one reason why we took care to identify physical volume series and base our own estimates on these whenever possible.

4.2 From World War I until World War II

In Italy, in contrast to countries like Germany or the US, the period comprising the two World Wars has not received as much attention as could be expected. A comparison with the enormous amount of work that went into the years between the Unification and WWI is emblematic of this. While economic analyses of the Fascist era certainly abound, these concentrate mainly on the policies of the Fascist government and their effect on the war effort and long term growth. Earlier years in the period received even less attention, so much so that estimates by Maddison (1991), depicting an unprecedented but implausible boom during WWI were accepted for years with the explanation that public expenditure more than compensated for the fall in private expenditure (Fua (1981), Mattesini and Quintieri (1997)). It is clear that, until very recently, a reliable quantitative reconstruction of the

Italian economy for this period was lacking. A recent major step in this direction was represented by Baffigi's reconstruction of the Italian GDP over the whole length of its united history, which features a much more muted growth rate during WWI. Another is (Carreras and Felice (2012)) re-estimation of industrial production for the period 1911-1951. Contrary to previous accounts, the authors find that industrial production fell during the conflict, a result that contributes to demolishing the myth of a boom in those years. In fact, such a boom would be in sharp contrasts with the experience of all other countries significantly involved in the conflict (Broadberry, 2005).

We find that the Italian economy grew mildly in the first years of the war and experienced a severe crisis in the final phase of the war. After the end of the conflict, production bounced back strongly, but the 1920s were, overall, a period of stagnation. The 1930s were a period of crisis. This was presumably milder than that in the US or Germany, but nonetheless aggregate production fell 1930 and 1934 and then again in 1936-37, in line with the dynamics of the world economy. The preparations for the war effort led to a temporary and sharp growth in economic activity, followed by a dramatic collapse already in 1940.

(Figure 7 about here)

Indeed, a similar pattern obtains from the non-agricultural evidence for the same period, shown in Figure 8.

(Figure 8 about here)

Overall, we see the interwar evidence from our activity indices as confirming the recent downward revisions of Italian growth rates during World War I. We reestimated our results with many different datasets and found this evidence to be robust.

Again, strong volatility in the nominal series offers a potential explanation of the apparent bias plaguing earlier research.

(Figure 9 about here)

Figure 9 suggests a sequence of strong nominal shocks during and immediately after World War I, with an even more extreme pattern of such shocks in World War II. While the shocks around World War I are quite significant, the discontinuities in Italy's performance around world War II are massive, to the effect of almost precluding analysis of economic performance across the war even with our approach.

4.3 From the End of World War II until Today

After the end of the Second World War, Italy embarked on a somewhat unexpected period of super-growth. Like Germany and Japan, and in sharp contrast with the first post-war years, Italy grew at unprecedented rates, which led to commentators using the term \economic miracle". At the same time, improved data collection and more advanced statistical methods gradually refined the monitoring of the economy. This had already received a boost with the founding of the Istituto Nazionale di Statistica (ISTAT) in 1926. Key figures in the political and economic life of the country were interested in a closer monitoring of new-born Republic. Luigi Einaudi, in particular, was deeply aware of the importance of quantitative data for economic analysis and policy making (Marchionatti and Sella, 2012). Given this backdrop, uncertainty over business cycle facts in the post-WWII era is significantly lower than for preceding periods. Nonetheless, an analysis of this period with our methodology is relevant for two reasons. First of all, based on existing GDP reconstructions the fifteen years following the end of World War II were remarkably devoid of cyclical fluctuations. This is in significant contrast with all other periods of Italian economic history which were characterized by pronounced and fairly regular business cycle dynamics. While it is firmly established that the Italian economy grew strongly during those years, the absence of a cycle is highly suspicious and could be an artifact of the data. Secondly, our investigation can help qualify the Great Moderation. This consists in a reduction in the volatility of both output and inflation which characterized most industrial economies from around 1979 until 2006. Several authors (for example Stock and Watson (2004), DelNegro and Otrok (2008) identified this secular change in Italy as well, mainly by looking at changes in the volatility of GDP series. Our methodology offers an alternative approach to verifying the existence

and extent of this moderation. Figure 10 has the evidence.

(Figure 10 about here)

Contrary to what is found in GDP series, we find strong volatility in economic activity in the post war years. We find troughs in 1949, 1956 and 1961 and peaks in 1948, 1951, 1959 and 1963. During the first half of the sixties the cycle becomes much milder and the rest of the century exhibits well known dynamics. We can see the first and second oil shocks (1973 and 1979), and the subsequent moderation. However, we find that the moderation is not long lived, with high volatility resuming in the latter half of the 90s.

(Figure 11 about here)

This picture changes if we exclude agriculture as in Figure 11: a much more stable volatility pattern emerges. Again, however, the Great Moderation since the mid-1980s is conspicuous by its absence. There is no visible change in the pattern, and indeed, no significant variation over previous cyclical patterns either.

Thus, to the extent a moderation in Italian GDP existed and was not merely an artifact, it must be due to a composition effect that our dataset does not fully capture, the emergence of modern service sectors that did not yet exist in postwar Italy.

5 Conclusion

This paper has taken a disaggregate approach to measuring the Italian business cycle from the unification to today. We employed factor analysis to estimate indices of economic activity in the relevant subperiods divided by the World Wars. To tackle structural change, our approach allows factor loadings to vary over time. Our results confirm recent skepticism about the traditional evidence on Italian GDP growth. In particular, we find no evidence of increasing business cycle volatility prior to World War I. On the contrary, we argue that high volatility during the unification period was followed by a stable cyclical pattern that persisted until 1913. Our findings also cast further doubt on Maddison's (1991) claim of a wartime

boom during World War I. We nd no such boom but instead a markedly volatile pattern of wartime economic activity. We also remain skep;tical about postwar moderation in Italian growth. Any such moderation would have to be rooted in agriculture, as the non-agricultural series we examine exhibit no pattern of declining volatility in the postwar period. We remain agnostic about the Great Moderation since the 1980s, which our dataset may have failed to detect. On the other hand, we can rmly conclude that any such moderation would have had to originate in new industries, probably in the service sector, that our dataset failed to capture. Whether this was indeed the case is beyond the scope of the present paper, and must be left for future research.

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A Appendix

A.1 Estimation

A.1.1 Estimating the Parameters

In this section we condition on the factor f_t and the factor loadings $\ _t$, in order to estimate the parameters of the model.[7] Because equation (1) is a set of N independent regressions with autoregressive error terms, it is possible to estimate $\ _1, \ _2, \ldots, \ _p, \ _\chi$ and $\ _\epsilon$ equation by equation. We rewrite equation (3) as:

$$u_i = X_{i,u}\theta_i + \chi_i \tag{5}$$

where $u_i = [u_{i,p+1}\ u_{i,p+2}\ \ldots\ u_{i,T}]^0$ is $T-p \times 1$, $\theta_i = [\theta_{i,1}\ \theta_{i,2}\ \ldots\ \theta_{i,p}]^0$, is $p \times 1$ and $\chi_i = [\chi_{i,p+1}\ \chi_{i,p+2}\ \ldots\ \chi_{i,T}]^0$ is $T-p \times 1$ and

$$X_{i,u} = \begin{bmatrix} u_{i,p} & u_{i,p\ 1} & \cdots & u_{i,1} \\ u_{i,p+1} & u_{i,p} & \cdots & u_{i,2} \\ \vdots & \vdots & \vdots & \vdots \\ u_{i,T\ 1} & u_{i,T\ 2} & \cdots & u_{i,T\ p} \end{bmatrix}$$

which is a $T-p \times p$ for $i = 1, 2, \ldots, N$.

Combining the priors described in section 3.1 with the likelihood function conditional on the initial observations we obtain the following posterior distributions.

The posterior of the AR-parameters of the idiosyncratic components is:

$$\theta_i \sim N(\overline{\theta_i}, \overline{V}_{i,\theta})I_S \tag{6}$$

where

$$\overline{\theta_i} = \left(\underline{V}_\theta^{\ 1} + (\sigma^2_{i,\chi})^{\ 1} X^0_{i,u}X_{i,u}\right)^{\ 1}\left(\underline{V}_\theta^{\ 1}\underline{\theta} + (\sigma^2_{i,\chi})^{\ 1}X^0_{i,u}u_i\right)$$

and

$$\overline{V}_{i,\theta} = \left(\underline{V}_\theta^{\ 1} + (\sigma^2_{i,\chi})^{\ 1}X^0_{i,u}X_{i,u}\right)^{\ 1}.$$

where I_S is an indicator function enforcing stationarity.

The posterior of the variance of the idiosyncratic component $\sigma_{i,\chi}$ is:

$$\sigma^2_{i,\chi} \sim \mathcal{IG}\left(\frac{(T+\alpha_\chi)}{2}, \frac{((u_i - X_i\theta_i)^0(u_i - X_i\theta_i) + \delta_\chi)}{2}\right) \tag{7}$$

The posterior of the variance of the factor loadings $\sigma_{i,\epsilon}$ is:

$$\sigma^2_{i,\epsilon} \sim \mathcal{IG}\left(\frac{(T+\alpha_\epsilon)}{2}, \frac{((\ \ \lambda_i)^0(\ \ \lambda_i) + \delta_\epsilon)}{2}\right) \tag{8}$$

[7] See also Chib (1993).

where $\lambda_i = [\lambda_{i,1}\ \lambda_{i,2}\ \ldots\ \lambda_{i,T}]'$ and is the first difference operator for this vector. To estimate the AR -parameters of the factor $\varphi_1, \varphi_2, \ldots, \varphi_q$ we find it useful to rewrite equation (2) as:

$$f = X_f \varphi + \nu \tag{9}$$

where $f = [f_{q+1}\ f_{q+2}\ \ldots\ f_T]'$ is $T - q \times 1$, $\varphi = [\varphi_1\ \varphi_2\ \ldots\ \varphi_q]'$ is $q \times 1$, $\nu = [\nu_{q+1}\ \nu_{q+2}\ \ldots\ \nu_T]'$ is $T - q \times 1$ and

$$X_f = \begin{bmatrix} f_q & f_{q-1} & \cdots & f_1 \\ f_{q+1} & f_q & \cdots & f_2 \\ \vdots & \vdots & \vdots & \vdots \\ f_{T-1} & f_{T-2} & \cdots & f_{T-q} \end{bmatrix}$$

which is $T - q \times q$. Thus, the posterior of the AR-parameters of the factor is:

$$\varphi \sim N(\overline{\varphi}, \overline{V}_\varphi) I_{S'} \tag{10}$$

where

$$\overline{\varphi} = \left(\underline{V}_\varphi^{-1} + (X_f' X_f)\right)^{-1} \left(\underline{V}_\varphi^{-1} \underline{\varphi} + (X_f' f)\right)$$

and

$$\overline{V}_f = \left(\underline{V}_\varphi^{-1} + X_f' X_f\right)^{-1}.$$

where $I_{S'}$ is an indicator function enforcing stationarity.

To estimate the factor loadings, when they are assumed to be constant, we rewrite equation (1) as:

$$y_i = \lambda_i f + \chi \tag{11}$$

where $y_i = [(1 - \theta(L)_i) y_{i,p+1}\ (1 - \theta(L)_i) y_{i,p+2} \ldots\ (1 - \theta(L)_i) y_{i,T}]'$ which is $T - p \times 1$ and $f = [(1 - \theta(L)_i) f_{p+1}\ (1 - \theta(L)_i) f_{p+2}\ \ldots\ (1 - \theta(L)_i) f_T]'$, which is $T - p \times 1$ with $\theta(L)_i = (\theta_{i,1} + \theta_{i,2} + \cdots + \theta_{i,p})$ for $i = 1, 2, \ldots, N$. Thus, the posterior for the constant factor loadings is:

$$\lambda_i \sim N(\overline{\lambda_i}, \overline{V}_{i,\lambda}) \tag{12}$$

where

$$\overline{\lambda_i} = \left(\underline{V}_\lambda^{-1} + (\sigma_{i,\chi}^2)^{-1} f' f\right)^{-1} \left(\underline{V}_\lambda^{-1} \underline{\lambda} + (\sigma_{i,\chi}^2)^{-1} f' y_i\right)$$

and

$$\overline{V}_{i,\lambda} = \left(\underline{V}_\lambda^{-1} + (\sigma_{i,\chi}^2)^{-1} f' f\right)^{-1}.$$

A.1.2 Estimating the Latent Factor

To estimate the common latent factor we condition on the parameters of the model $\equiv (\varphi_1, \varphi_2, \ldots, \varphi_q, \ _1, \ _2, \ldots, \ _p)$ and the factor loadings $\ _t$. We begin by quasi-di erencing equation (1) and use it as our observation equation in the following state-space system:

$$Y_t = H_t F_t + \chi_t \tag{13}$$

where

$$Y_t = (\mathcal{I}_N - \ (L)) Y_t$$

$$H_t = [\ _t - \ _1 \ _{t\ 1} - \ _2 \ _{t\ 2} \cdots \ _p \ _{t\ p} \ 0_{N\ q\ p\ 1}]$$

with

$$(L) = (\ _1 + \ _2 + \cdots + \ _p)$$

Our state equation is:

$$F_t = \ F_{t\ 1} + \widetilde{\nu}_t \tag{14}$$

where $F_t = [f_t, f_{t\ 1}, \ldots, f_{t\ q+1}]^0$ is $q \times 1$, which is denoted as the state vector, $\widetilde{\nu}_t = [\nu_t \ 0 \ \ldots \ 0]^0$ is $q \times 1$ and

$$= \begin{bmatrix} \varphi_1 & \varphi_2 & \cdots & \varphi_q \\ & \mathcal{I}_{q\ 1} & & 0_{q\ 1\ 1} \end{bmatrix}$$

which is $q \times q$. For all empirical results shown below we use $q > p$.

To calculate the common factor we use the algorithm suggested by Carter and Kohn (1994) and Fruhwirth-Schnatter (1994). This procedure draws the vector $F = [F_1 \ F_2 \ \ldots \ F_T]$ from its joint distribution given by:

$$p(F| \ , Y, \ ) = p(F_T| \ _T, y_T, \ ) \prod_{t=1}^{T\ 1} p(F_t|F_{t+1}, \ _t, \ , Y^t) \tag{15}$$

where $= [\ _1 \ _2 \ \ldots \ _T]$ and $Y^t = [Y_1 \ Y_2 \ \ldots \ Y_t]$. Because the error terms in equations (13) and (14) are Gaussian equation (15)can be rewritten as:

$$p(F| \ , Y, \ ) = N(F_{TjT}, P_{TjT}) \prod_{t=1}^{T\ 1} N(F_{tjt,F_{t+1}}, P_{tjt,F_{t+1}}) \tag{16}$$

with

$$
\begin{aligned}
F_{T|T} &= E(F_T|\ \ ,\ \ ,Y) && (17)\\
P_{T|T} &= Cov(F_T|\ \ ,\ \ ,Y) && (18)
\end{aligned}
$$

and

$$
\begin{aligned}
F_{t|t,F_{t+1}} &= E(F_t|F_{t+1},\ \ ,\ \ ,Y) && (19)\\
P_{t|t,F_{t+1}} &= Cov(F_t|F_{t+1},\ \ ,\ \ ,Y) && (20)
\end{aligned}
$$

We obtain $F_{T|T}$ and $P_{T|T}$ from the last step of the Kalman filter iteration and use them as the conditional mean and covariance matrix for the multivariate normal distribution $N(F_{T|T}, P_{T|T})$ to draw F_T. To illustrate the Kalman Filter we work with the state-space system equations (13) and (14). We begin with the prediction steps:

$$
\begin{aligned}
F_{t|t-1} &= \quad F_{t-1|t-1} && (21)\\
P_{t|t-1} &= \quad P_{t-1|t-1} \quad + Q && (22)
\end{aligned}
$$

where

$$
Q = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 \end{bmatrix}
$$

which is $q \times q$. To update these predictions we first have to derive the forecast error:

$$
\kappa_t = Y_t - H_t F_{t|t-1} \tag{23}
$$

its variance:

$$
\ \ = H_t P_{t|t-1} H_t' + \ \ _{\chi} \tag{24}
$$

and the Kalman gain:

$$
K_t = P_{t|t-1} H_t' \ \ ^{-1}. \tag{25}
$$

Thus, the updating equations are:

$$
\begin{aligned}
F_{t|t} &= F_{t|t-1} + K_t \kappa_t, && (26)\\
P_{t|t} &= P_{t|t-1} + K_t H_t P_{t|t-1}, && (27)
\end{aligned}
$$

To obtain draws for $F_1, F_2, \ldots, F_{T-1}$ we sample from $N(F_{t|t,F_{t+1}}, P_{t|t,F_{t+1}})$, using a backwards moving updating scheme, incorporating at time t information about F_t contained in

period $t + 1$. More precisely, we move backwards and generate F_t for $t = T - 1, \ldots, p + 1$ at each step while using information from the Kalman filter and F_{t+1} from the previous step. We do this until $p + 1$ and calculate $f_1, f_2, \ldots, f_p$ in an one-step procedure.

The updating equations are:

$$F_{t|t,F_{t+1}} = F_{t|t} + P_{t|t}\,{}'P^{-1}_{t+1|t}(F_{t+1} - F_{t+1|t}) \tag{28}$$

and

$$P_{t|t,F_{t+1}} = P_{t|t} - P_{t|t}\,{}'P^{-1}_{t+1|t}\,P_{t|t} \tag{29}$$

A.1.3 Estimating the Time-Varying Factor Loadings

To estimate the time-varying factor loadings we condition on the parameters and the factor f_t. Because equation (1) and equation (4) are N independent linear regressions, the factor loadings can be estimated equation by equation. Hence, we use the following state-space system and begin with the observation equation:

$$y_{i,t} = z_{i,t}\widetilde{\lambda}_{i,t} + \chi_{i,t} \tag{30}$$

where $y_{i,t} = (1 - \theta(L)_i)y_{i,t}$, $z_{i,t} = [f_t \ - \theta_{i,1}f_{t-1} \ \ldots \theta_{i,p}f_{t-p}]$, which is $1 \times p + 1$, $\widetilde{\lambda}_{i,t} = [\lambda_{i,t} \ \lambda_{i,t-1} \ \ldots \ \lambda_{i,t-p}]'$, which is $p + 1 \times 1$ and with $\theta(L)_i = (\theta_{i,1} + \theta_{i,2} + \cdots + \theta_{i,p})$ for $i = 1, 2, \ldots, N$.

The state equation is:

$$\widetilde{\lambda}_{i,t} = A\widetilde{\lambda}_{i,t-1} \tag{31}$$

where

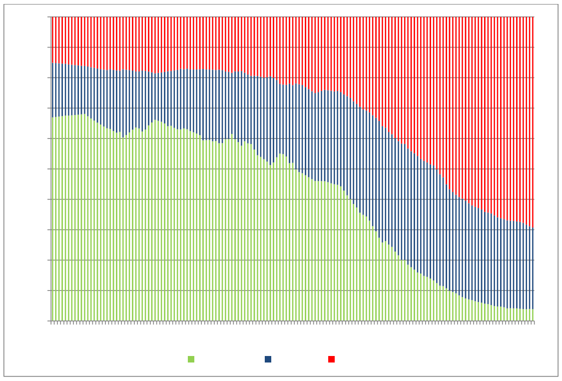
$$A = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ & \mathcal{I}_p & & 0_{p \times 1} \end{bmatrix}$$

which is $p + 1 \times p + 1$. After we have defined the state-space system, calculating the time-varying factor loadings is straightforward as we just have to apply the Carter and Kohn (1994) and Fruhwirth-Schnatter (1994) algorithm described above (see also DelNegro and Otrok, 2003).

A.2 Figures

Figure 1: Sectoral Change in the Italian Economy, 1861-2008.

(a) Workforce by sector



(b) Value added by sector

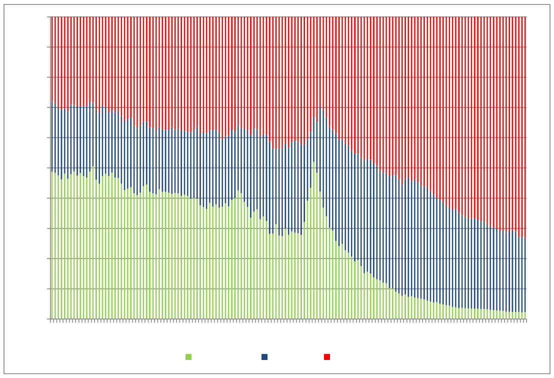


Figure 2: GDP estimates, 1861-2008.

(a) Maddison (1991)

(b) Ba gi (2011)

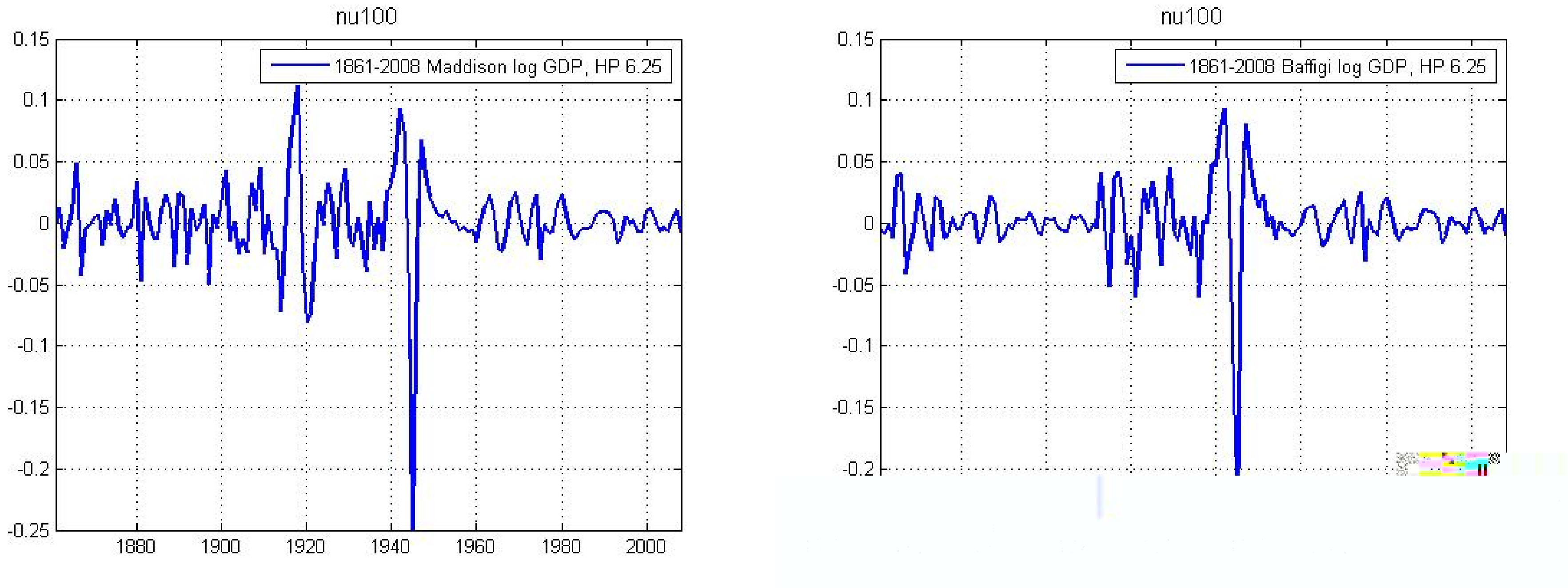


Figure 3: The Italian Business Cycle, 1861-1913. TVAR Factor from 116 series

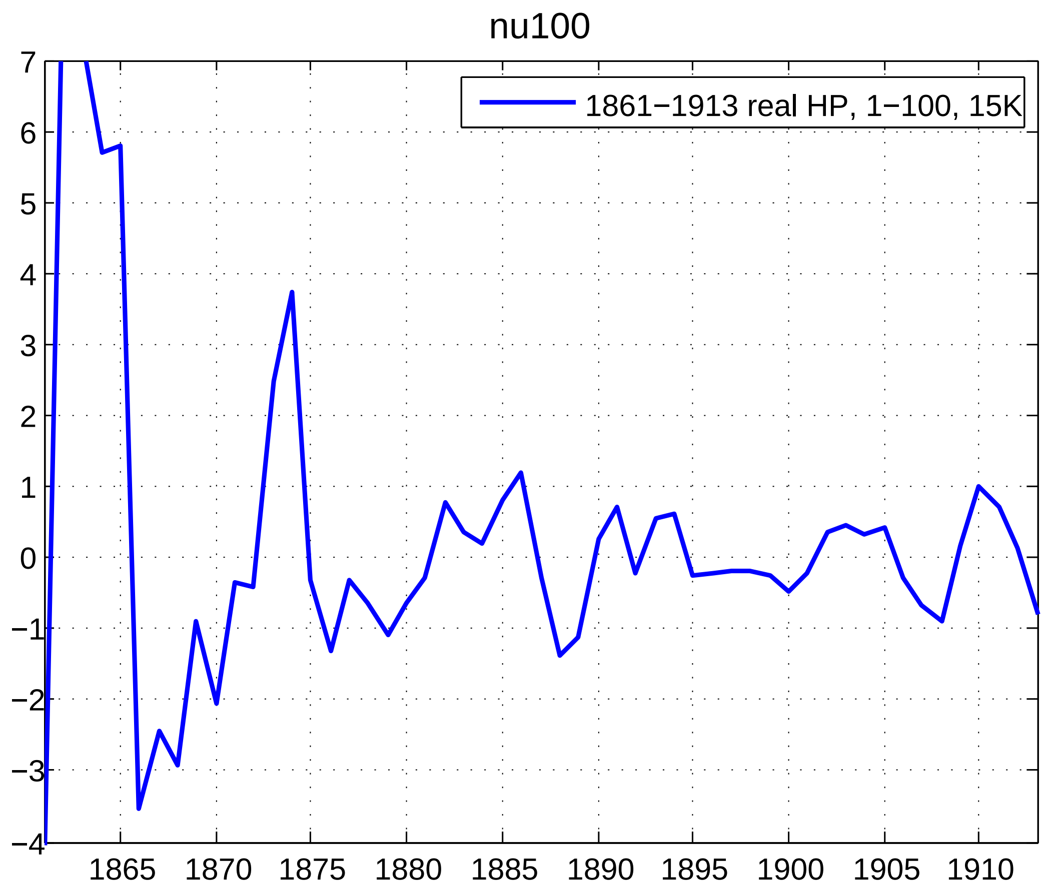


Figure 4: The Italian Business Cycle, 1861-1913. Non-Agricultural Real Series, Constant FL

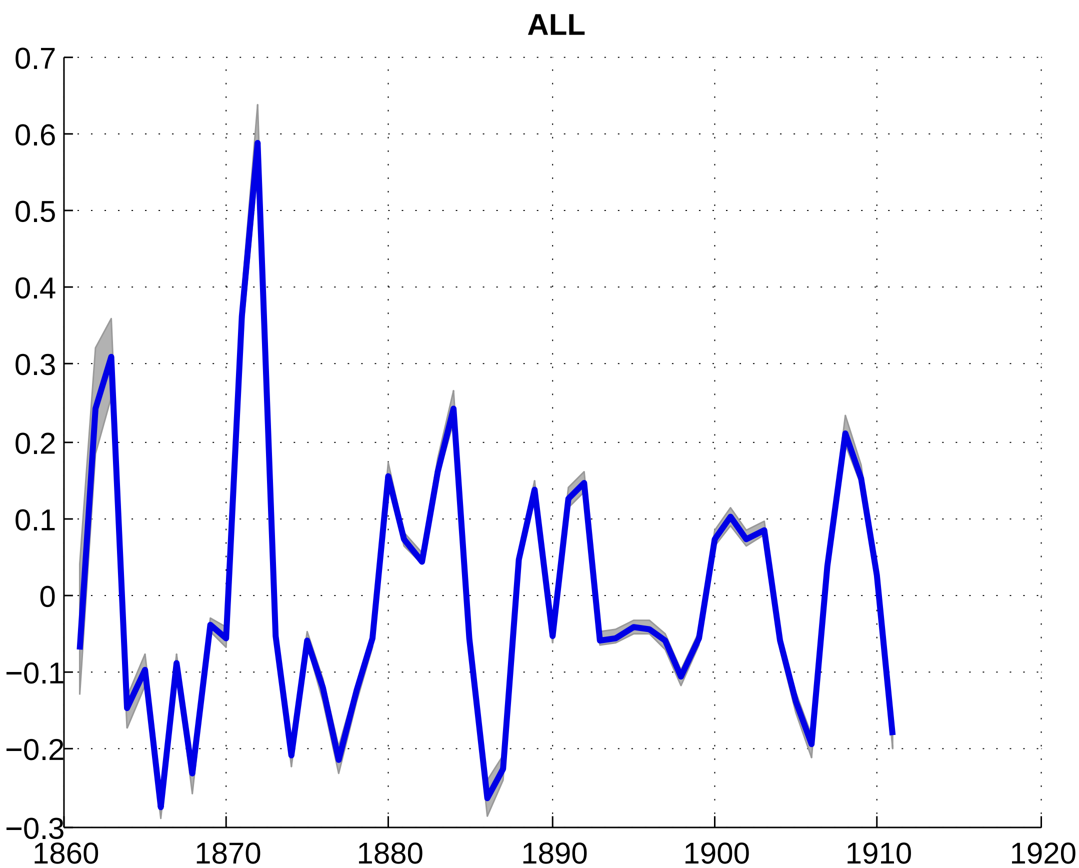


Figure 5: The Italian Business Cycle, 1861-1913. Increasing Volatility in the Maddison Data, Constant FL

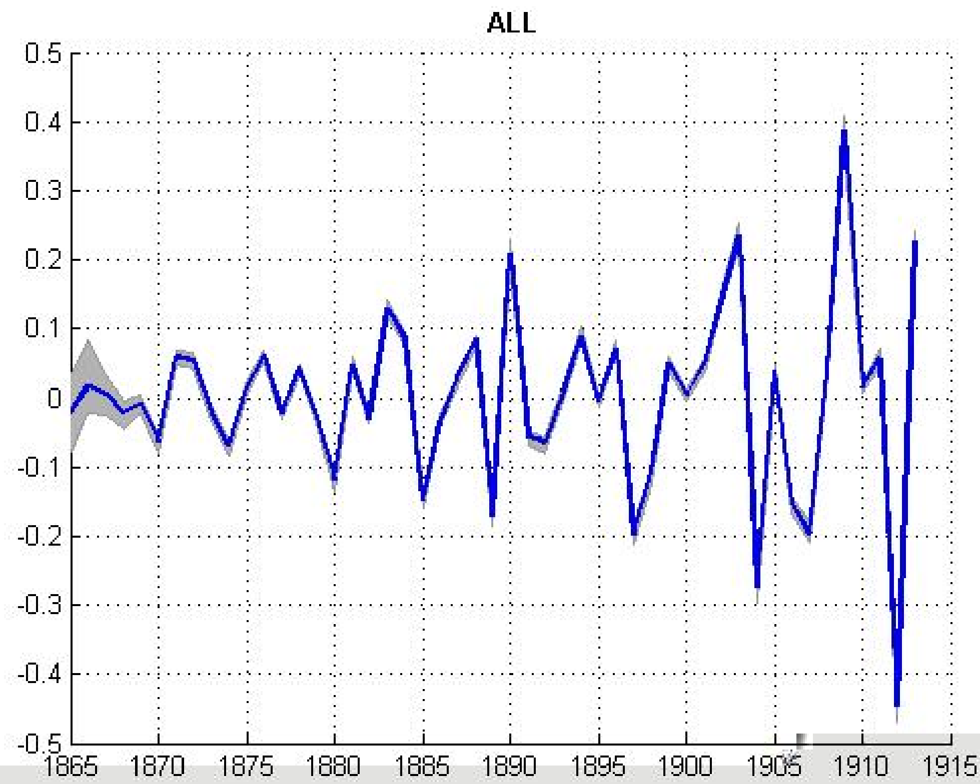


Figure 6: The Italian Business Cycle, 1861-1913. Nominal Series

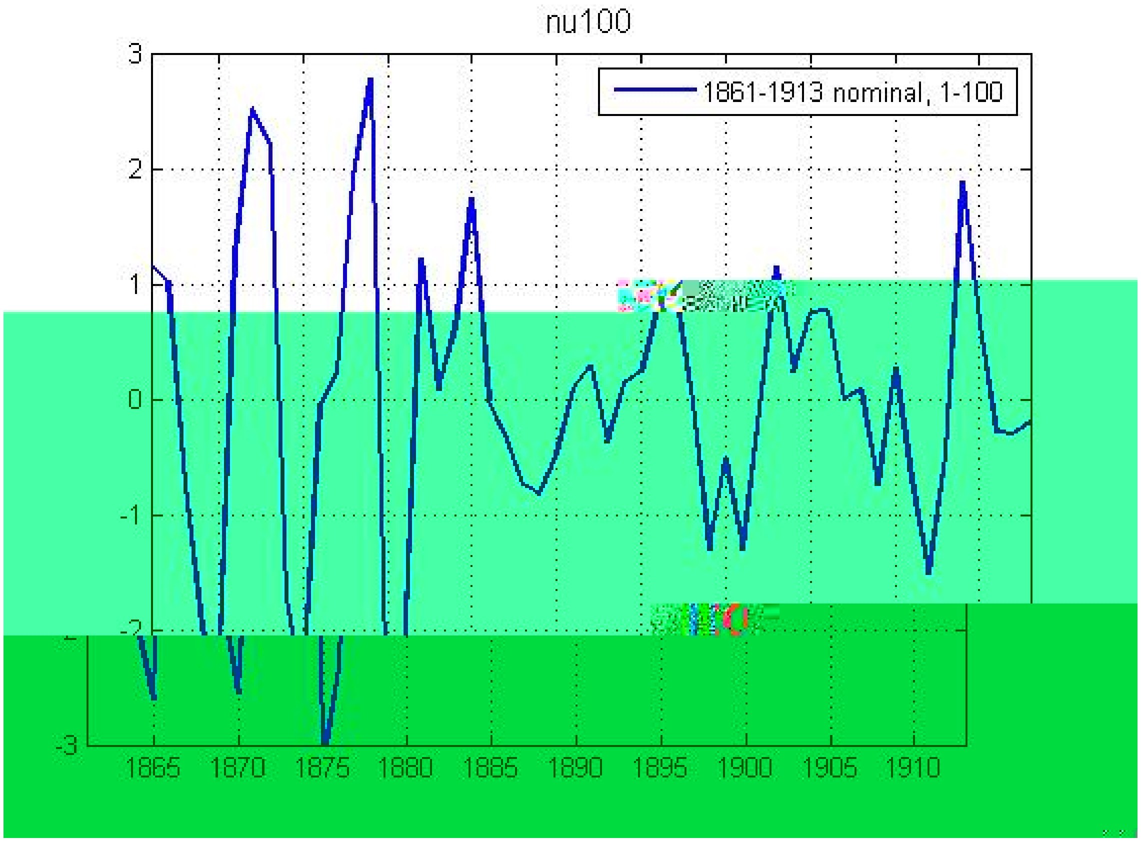


Figure 7: The Italian Business Cycle, 1914-1942. TVAR Factor from 103 series

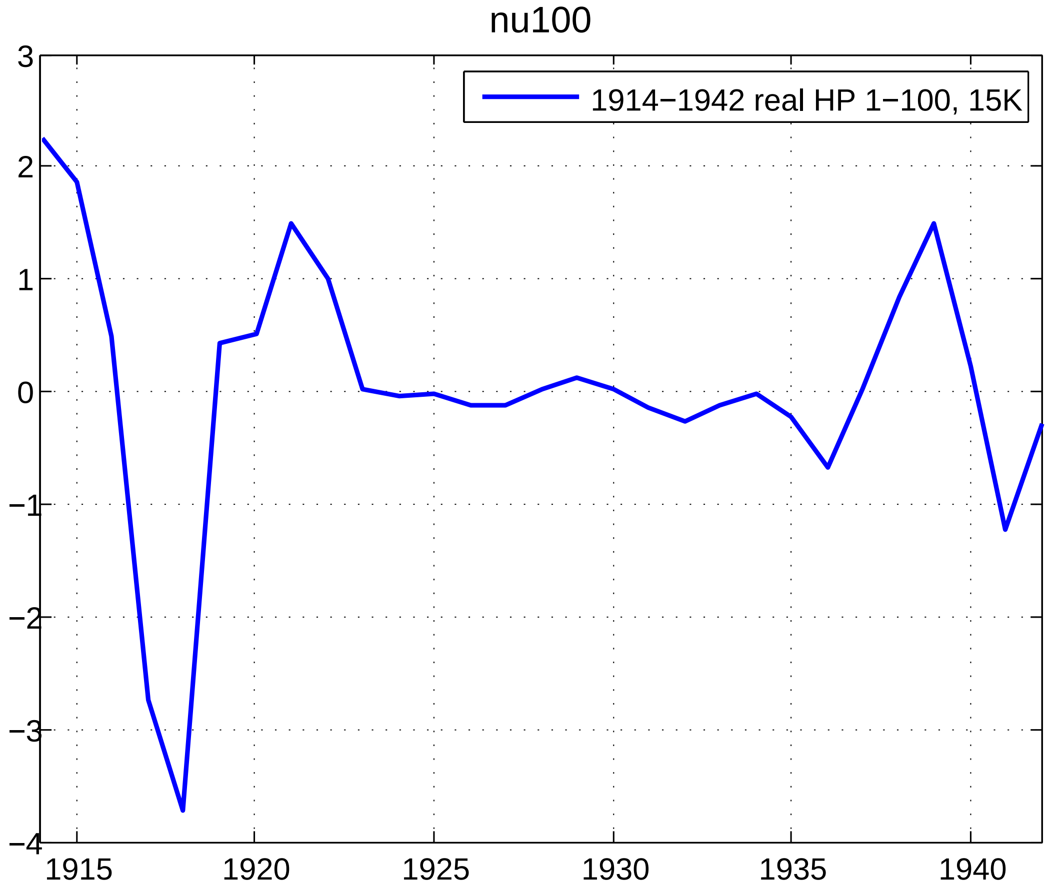


Figure 8: The Italian Business Cycle, 1914-1942. Non-agricultural real series

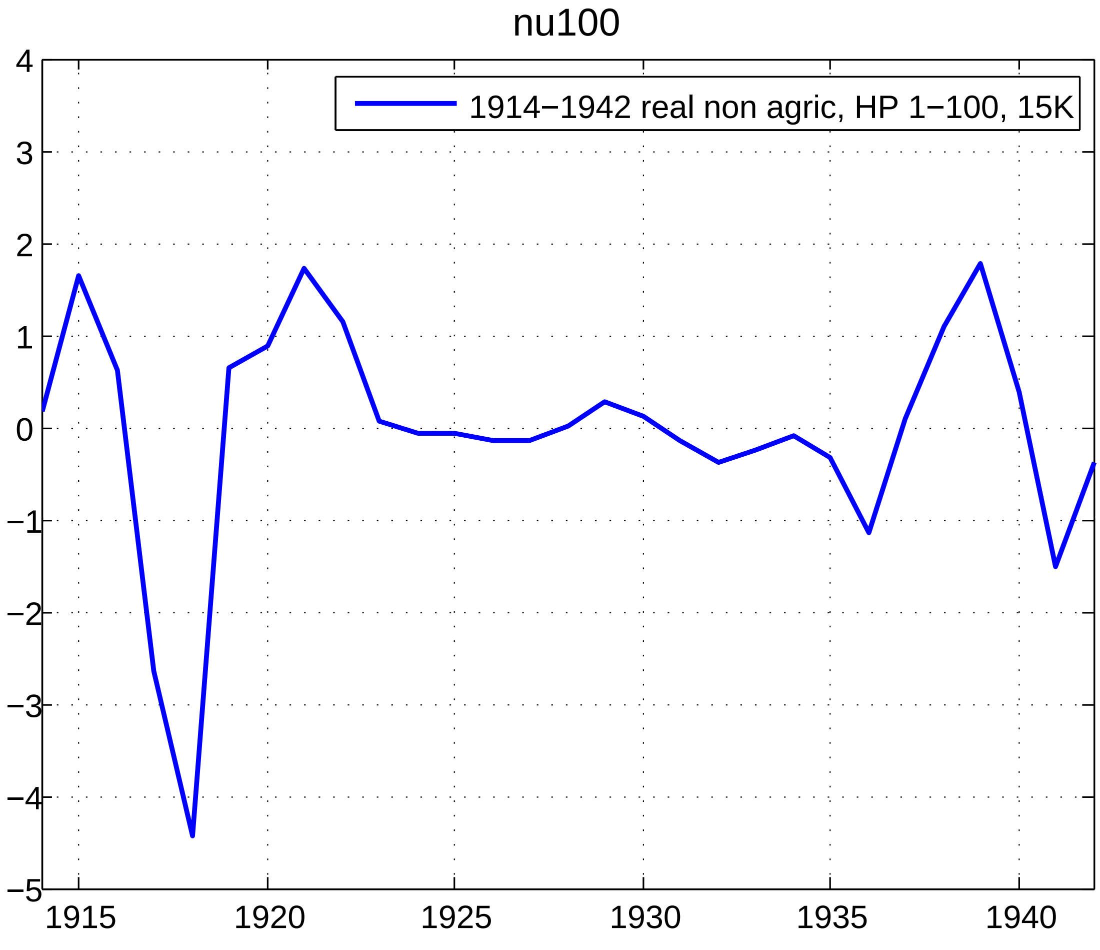


Figure 9: In ation in the long term, 1890-1985. Nominal series

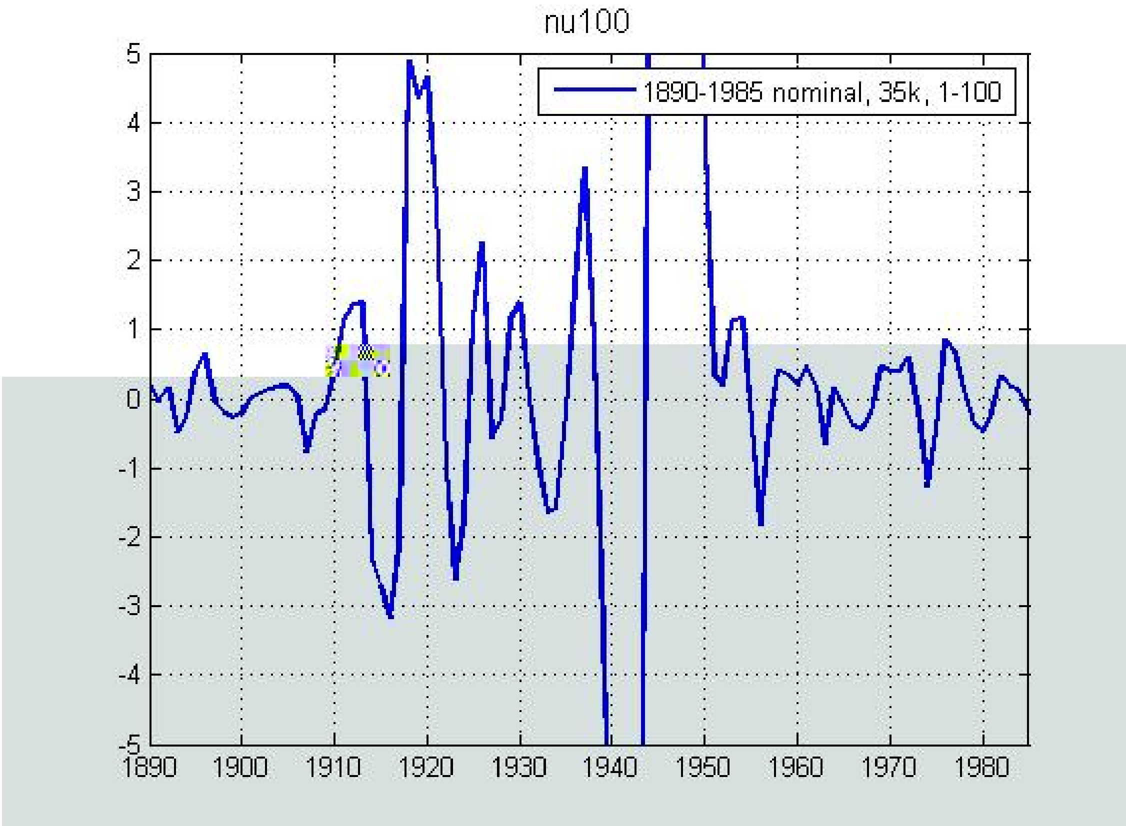


Figure 10: The Italian Business Cycle, 1947-2008. TVAR Factor, real series

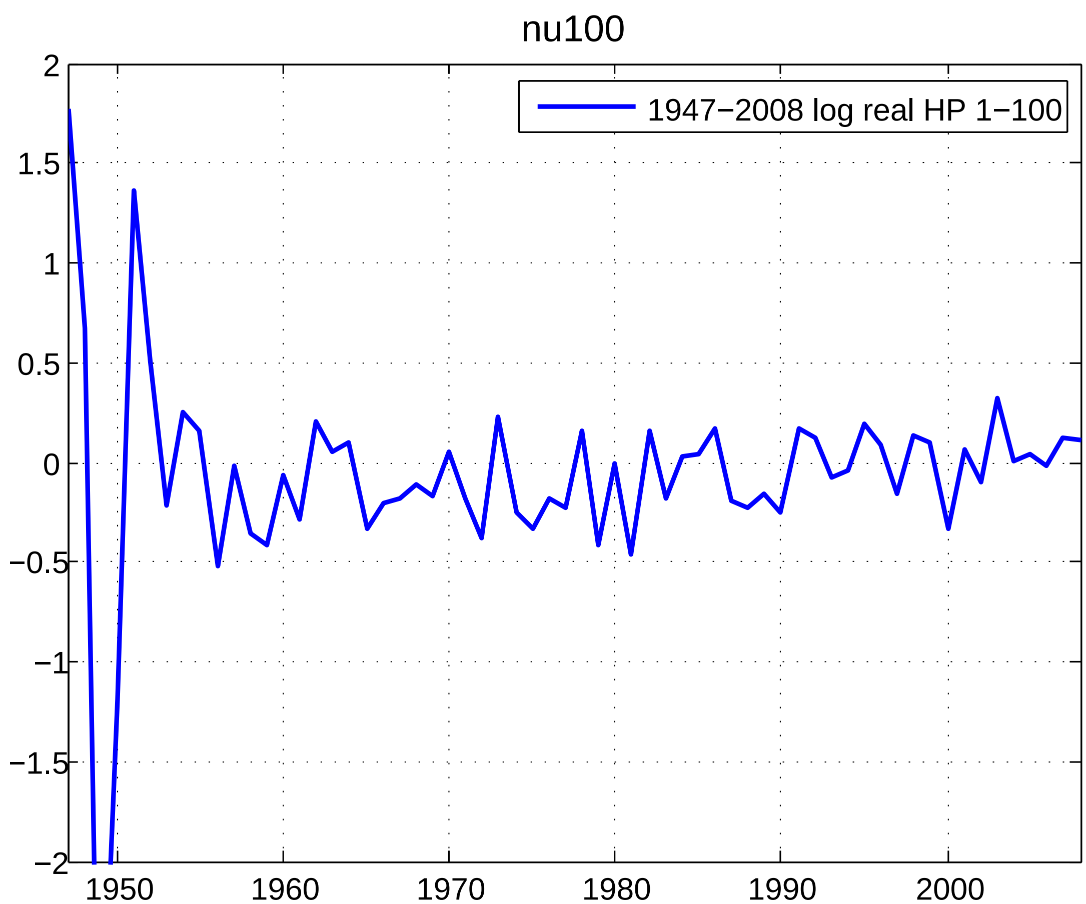
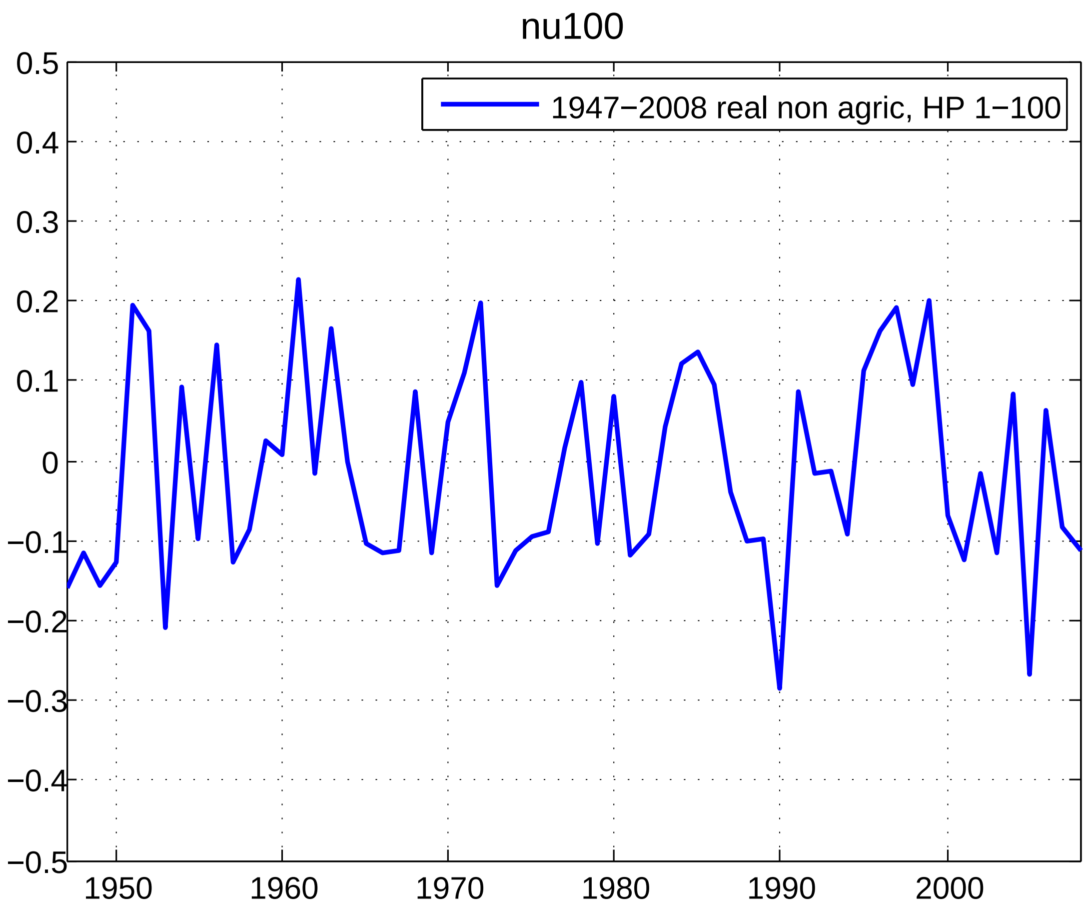


Figure 11: The Italian Business Cycle, 1947-2008. TVAR Factor



Appendix B: Tables

Table B-1: Data and Sources

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	Series	1863-1913	1914-1942	1947-2008
1	Wheat Production	x	x	x
2	Rye Production	x	x	
3	Barley Production	x	x	x
4	Hay Production	x	x	x
5	Rice Production	x	x	x
6	Corn Production	x	x	x
7	Broad-beans Production	x		x
8	Beans Production	x	x	x
9	Potatoes Production	x	x	x
10	Wine Grape Production	x	x	x
11	Wine Production	x	x	x
12	Olives Production	x	x	x
13	Olive Oil Production	x	x	x
14	Oranges Production	x	x	x
15	Mandarins Production	x	x	x
16	Lemons Production	x	x	x
17	Other Critic Fruits Production	x	x	x
18	Almonds Production	x	x	x
19	Hazelnuts Production	x	x	x
20	Peas Production		x	x
21	Chickpeas Production	x	x	x
22	Lentils Production		x	x
23	Sugar-beets Production		x	x
24	Tobacco Production		x	x
25	Hemp Production		x	
26	Flax Production		x	
27	Forage Production		x	x
28	Fresh Broad-Beans Production		x	x
29	Fresh Beans Production		x	x
30	Fresh Peas Production		x	
31	Garlic and Onions Production		x	x
32	Asparagus Production		x	x
33	Artichokes Production		x	x
34	Fennel Production		x	x
35	Cabbage Production		x	x
36	Cauli ower Production		x	x
37	Tomatoes Production		x	x
38	Watermelon Production		x	x
39	Apricots Production		x	x
40	Cherries production		x	x
41	Peaches production		x	x
42	Plums production		x	x
43	Apples Production		x	x
44	Pears production		x	x
45	Figs production		x	
46	Walnuts Production		x	
47	Sun owers Production			x
48	Soy Production			x
49	Cork Production			x
50	Chestnut Production			x
51	Pine Nuts Production			x
52	Mushrooms Production			x
53	Acorns Production			x
54	Cows	x	x	x
55	Sheep	x	x	x
56	Pigs	x	x	x
57	Horses	x	x	x

Overview cont'd

	Series	1863-1913	1914-1942	1947-2008
58	Eggs	x	x	x
59	Butter	x	x	x
60	Cheese	x	x	x
61	Fish	x	x	x
62	Cocoons	x	x	
63	Wool	x	x	
64	Milk	x	x	
65	Silk	x	x	
66	Energy production		x	x
67	Energy consumption			x
68	Energy consumption (industry)			x
69	Corn imports	x	x	x
70	Cotton imports	x	x	x
71	Iron imports	x	x	x
72	Iron and Steel imports	x	x	x
73	Machinery imports	x	x	x
74	Coal imports	x	x	x
75	Oil imports	x	x	x
76	Cheese exports	x	x	x
77	Citric fruits exports	x	x	x
78	Wine exports	x	x	x
79	Cotton exports	x	x	x
80	Railway system length	x	x	x
81	Carbon Fossils production	x		
82	Peat production	x		
83	Mineral oil production	x		
84	Iron ore production	x		
85	Copper ore production	x		
86	Lead ore production	x		
87	Zinc ore production	x		
88	Gold ore production	x		
89	Manganese ore production	x		
90	Mercury ore production	x		
91	Pyrite production	x		
92	Sulphur production	x		
93	Molten sulphur production	x		
94	Salt Mineral production	x		
95	Other salt production	x		
96	Asphalt mineral production	x		
97	Boric acid production	x		
98	Graphite production	x		
99	Allumite production	x		
100	Sea salt production	x		
101	Mineral water production	x		
102	Marble production	x		
103	Chalk production	x		
104	Cement production	x		
105	Lime production	x		
106	Clay production	x		
107	Glass material production	x		
108	Other cave production	x		
109	New rails (value added)	x		
110	New buildings (value added)	x		
111	Buildings upkeep (value added)	x		
112	Gas production	x		
113	Cast iron production	x		
114	Iron/steel production	x		
115	Cast iron 2 production	x		
116	Copper production	x		
117	Gold production	x		
118	Silver production	x		

Overview cont'd

	Series	1863-1913	1914-1942	1947-2008
119	Lead production	x		
120	Mercury production	x		
121	New military ship tonnage	x	x	
122	New net ship tonnage	x	x	
123	Tramway material production (value added)	x		
124	Rail upkeep (value added)	x		
125	Blacksmith upkeep(value added)	x		
126	Other ironmongery upkeep (value added)	x		
127	New ironmongery (value added)	x		
128	Cement production	x		
129	Chalk production	x		
130	Lime production	x		
131	Bricks for constructions production	x		
132	Bricks production	x		
133	Glass production	x		
134	Other furnace production	x		
135	Common materials production	x		
136	Cut stones production	x		
137	Matches production (value added)	x		
138	Wax soap production (value added)	x		
139	Ammunition production (value added)	x		
140	Dye production (value added)	x		
141	Pharmaceuticals production (value added)	x		
142	Other non-organic production	x		
143	Other organic production	x		
144	Re nery production	x		
145	Oil and carbon derivatives production	x		
146	Sugar production		x	
147	Glucose production		x	
148	Alcohol 1 production		x	
149	Alcohol 2 production		x	
150	Beer production		x	
150	Cotton production		x	
151	Silk production		x	
152	Engines production		x	
153	Postal carriages production		x	
154	Cotton 2 exports		x	x
155	Arti cial bers exports		x	x
156	Motor vehicles production		x	x
157	Mining industry		x	
158	Foodstu s industry		x	
159	Tobacco industry		x	
160	Textiles industry		x	
161	Clothing industry		x	
162	Leather industry		x	
163	Wood industry		x	
164	Metal making industry		x	
165	Engineering industry		x	
166	Non metal minerals industry		x	
167	Chemical industry		x	
168	Paper industry		x	
169	Sundry industry		x	
170	Construction industry		x	
171	Utilities industry		x	
172	Number of workers	x	x	x
173	Tonnage of ship arrivals	x	x	
174	Ship passengers		x	
175	Number of new ships	x	x	
176	Tonnage of new ships		x	
177	Population		x	x
178	Motor-way system length			x

Overview cont'd

	Series	1863-1913	1914-1942	1947-2008
179	Rail cargo			x
180	Rail passengers			x
181	Air cargo			x
182	Number of Entertainment tickets			x