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Common factors, spatial dependence, and regional growth in the Italian manufacturing industry*

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Abstract

We review the methods currently available for the analysis of regional datasets characterised by possible non-stationarity over time and both strong and weak spatial dependence and present, as a representative case study, a comparative analysis of the regional development of the Italian manufacturing industries in the second halves of the 19th and 20th centuries. For highly heterogenous datasets we suggest a two-stages approach: (1) fit a dynamic factor model with endogenous determination of the number of factors; (2) estimate a spatial model for the de-factored data. Applying this strategy we find two similar non-stationary factors sufficient to explain long-run growth of the whole set of series examined in both centuries. Further, the results suggest that some conditional spatial error correction mechanisms seem to have been in action in both centuries.

Keywords: Cross-sectional dependence, approximate factor models, dynamic spatial panel models, Italy, manufacturing industries.

JEL codes: C38, C31, N13, N63, N93

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1 Introduction

Regional panel data of economic variables such as GDP or unemployment typically appear as sets of time series following closely related paths. In fact, often the links among the different series are so evident that it is natural to suspect all of them to depend upon some "common factor": a striking example are the Dutch provincial unemployment rates studied by Halleck Vega and Elhorst (2016). Interestingly, this seemingly obvious fact has for a long time been largely neglected by the spatial econometric literature, typically developed under the assumption that the value of a variable in each spatial unit is determined by a mixture of idiosyncratic shocks and spillovers from other units which, in accord with Tobler's (1970) "First law of geography", decay with distance. In other terms, the fundamental assumption of this literature is that the data are only weakly dependent over space. Spatial autoregressive (SAR), spatial error autocorrelation (SEM), and spatial Durbin (SDM) models, in static or panel form (see *e.g.,* Elhorst, 2010, 2014) have all been developed as modelling tools for spatially weakly dependent data, and are perfectly adequate in these circumstances. However, if the units included in the panel do depend upon some common factor their links will *not* decay with distance: in fact, two neighbouring units may be even less correlated than two units which are farther away from each other, but more strongly correlated with the common factor. Then spatial dependence is strong (or pervasive), and the SAR/SEM models are clearly not adequate any more. Which in these circumstances may be an adequate modelling strategy is however not so clear: Bailey, Holly and Pesaran (2016) suggested a two-stage approach, while on the other Halleck Vega and Elhorst (2016) (and later also Ciccarelli and Elhorst, 2016) a simultaneous one. In this paper we review the topic and present, as a case study, a comparative disaggregate analysis of the regional development of the Value Added in the Italian manufacturing industries in two periods about a century apart, 1861-1913 and 1970-2003[1]. This case study will highlight the need to consider for highly heterogenous panels a fully general method allowing endogenous determination of the number of factors. The paper is organized as follows: section 2 discusses the modelling set-up; section 3 provides a descriptive analysis of the data; section 4 presents the empirical estimates, while Section 5 concludes.

[1]In different ways, these are both important periods from the point of view of regional development in Italy. The first is indeed considered as a nodal point for all advanced capitalist countries (see *e.g.* Maddison 1995), while during the latter growth, strongly concentrated in the industrialised regions of North-West Italy in the 1950's and '60's, spread to the rest of the country as well (see *e.g.*, Terrasi, 1999; Bianchi, 2002).

2 Modelling Set-up

A panel of regional time series characterised by strong spatial dependence due to common factors and weak dependence due to spatial spillovers can be modelled following different approaches, with increasing degrees of generality. For the sake of simplicity we shall review them in turn assuming univariate spatial modelling, as the multivariate generalisation (Spatial Durbin models) is immediate.

Case A: Observed factor(s)

The simplest approach is assuming that the spatial units share one (or possibly more, the number clearly does not matter) observed common factor. From a univariate perspective a natural candidate is the national level of the variable of interest, as in the Brechling (1967) model of British regional unemployment. For a set of regions, other obvious examples of exogenous variables which may qualify as observable common factors include global variables, *e.g.*, oil prices, and national policy variables, *e.g.*, interest rates. Augmenting a spatial model with this observable common factor(s), so to model strong and weak spatial dependence simultaneously, is then a rather natural idea. For the sake of simplicity let us consider the case of a single, static factor, as the generalisation to dynamic factors is immediate.

Let Y be the variable of interest measured over $t = 1, \ldots, T$ periods in $r = 1, \ldots, R$ regions, and $\mathbf{Y}$ the $T \times R$ matrix collecting the time series for the R regions. Denoting by $\mathbf{W}$ the spatial weights matrix $\mathbf{W}$ of dimension $R \times R$, by $\mathbf{F}$ the $T \times 1$ vector of the observed common factor and by ε the matrix of idiosyncratic errors assumed to be spatially uncorrelated, a model including common factors and spatial lags can be essentially written as follows:

$$\mathbf{Y} = \mathbf{F\Lambda} + \mathbf{YW}\gamma_0 + \varepsilon \tag{1}$$

where $\mathbf{\Lambda}$, the $1 \times R$ vector of loadings mapping $\mathbf{F}$ onto $\mathbf{Y}$, and γ_0, the scalar spatial autoregressive coefficient, are estimated simultaneously. By analogy with Factor-Augmented VARs (FAVARs; Bernanke, Boivin, and Eliasz, 2005), model (1) can be labeled Factor-augmented Spatial Autoregressive model, FASAR. Rearranging and expanding the inverse of $(\mathbf{I} - \mathbf{W}\gamma)$ as a sum with geometrically decaying weights we obtain

$$\begin{aligned}
\mathbf{Y} &= (\mathbf{F\Lambda} + \varepsilon)(\mathbf{I} - \mathbf{W}\gamma_{\mathbf{0}})^{-1} \\
&= (\mathbf{F\Lambda} + \varepsilon)(\mathbf{I} + \mathbf{W}\gamma_{\mathbf{0}} + \mathbf{W}^2\gamma_0^2 + \ldots) \\
&= \mathbf{F\Lambda}(\mathbf{I} + \mathbf{W}\gamma_{\mathbf{0}} + \mathbf{W}^2\gamma_0^2 + \ldots) + \varepsilon(\mathbf{I} + \mathbf{W}\gamma_{\mathbf{0}} + \mathbf{W}^2\gamma_0^2 + \ldots) \\
&= \mathbf{F}\widetilde{\mathbf{\Lambda}} + \varepsilon(\mathbf{I} + \mathbf{W}\gamma_{\mathbf{0}} + \mathbf{W}^2\gamma_0^2 + \ldots)
\end{aligned} \tag{2}$$

where $\widetilde{\mathbf{\Lambda}} = \mathbf{\Lambda}(\mathbf{I} + \mathbf{W}\gamma_\mathbf{0} + \mathbf{W}^\mathbf{2}\gamma_\mathbf{0}^\mathbf{2} + \ldots)$ measures the impact of the common factor on each region taking into account both direct and indirect effects, and $(\mathbf{I} + \mathbf{W}\gamma_\mathbf{0} + \mathbf{W}^2\gamma_0^2 + \ldots)$ describes the spatial transmission of the shocks ε. As remarked above, this model has the clear advantage of allowing spatial spillovers to originate from both the idiosyncratic shocks, ε, and the common permanent components, $\mathbf{F\Lambda}$, and estimating their coefficients simultaneously. On the other hand, it hinges on the assumption that the common component is adequately captured by the observed factor F both in the time and space domain. The first part of the assumption is particularly important if Y is non-stationary. If this is the case and Y does not cointegrate with F we will have a unit root in the autoregressive part of the model, or, in case this is absent, in the model residuals. A formal test of cointegration between Y and F may be devised exploiting the rich literature on panel cointegration with dependent units (*e.g.*, Palm, Smeekens and Urbain, 2010, Di Iorio and Fachin, 2014). Further, the naive solution of thrusting the model as long as the point estimate of the AR coefficient is comfortably smaller than 1 will probably be adequate in most circumstances.

As far the space domain is concerned, the problem is that if the common factor does not capture all pervasive spatial dependence in Y the SAR part of the model, which assumes weak spatial dependence, is not legitimate. As discussed in Ciccarelli and Elhorst (2016), two diagnostics may help to test for the presence of unmodelled strong spatial dependence in the residuals: the CD cross-dependence test by Pesaran (2015) and the α measures of cross-sectional dependence by Bailey, Kapetanios and Pesaran (2015). The former, essentially the average cross-correlation coefficient rescaled for the time and cross-section sample sizes, is a test for the null hypothesis of weak dependence. To define more precisely what this means let us consider the behaviour of the average cross-correlation ($\overline{\rho}$) as the cross-section sample size N grows. To this end, let us write it as a function of the sample size as $\overline{\rho} = O(N^{2\alpha-2})$, so that α is the contraction rate of $\overline{\rho}$. Then, if $\alpha = 1$ average correlation tends to a non-zero value, as $O(N^{2\alpha-2}) = O(1)$. If instead $0 < \alpha < 1$, $\overline{\rho}$ will converge to zero as N grows. However, the speed of convergence will be fast enough to define the spatial dependence as weak only for $\alpha < 0.5$. When instead we have about $0.75 < \alpha < 1$ the convergence will be so slow that the dependence can be defined strong. Suppose now that these spatial diagnostics ($\overline{\rho}$, α) point to unmodelled strong spatial dependence in the residuals. The first hypothesis we might take into account is that the single factor assumption is correct, but the observed variable does not capture it adequately. We can then move to the next case.

Case B: A single unobservable factor

As anticipated above, this is the most obvious generalisation of the case of a single observable factor. Following Pesaran (2006), a simple consistent estimate of a single unobservable factor influencing a set of regional time series can be easily obtained taking their simple average. Obviously, in most circumstances this will not give a result appreciably different from using the national value, as done on *a priori* grounds in Case A above following the Brechling approach. Recalling that national values are weighted averages of the regional ones, Halleck Vega and Elhorst (2016) point out that the two solutions (simple averages and national values) are in fact also formally equivalent, as Pesaran (2006) remarks that any weighted average with weights $O(1/N)$ will satisfy the consistency requirement.

Once obtained the factor estimate we can then proceed exactly as in Case A, estimating the factor-augmented univariate or multivariate spatial model of interest. For instance, Ciccarelli and Elhorst (2016) estimate a Spatial Durbin model of the spatial diffusion of cigarette consumption in the 19th century Italian provinces including, along a set of explanatory variables, the simple average across provinces of the dependent variable (at time t and $t-1$, as in Halleck Vega and Elhorst, 2016) as an estimate of the common nation-wide trend. Carrion-i-Silvestre and Surdeanu (2016) use a similar approach to model a production function for the Spanish regions.

Now, suppose that the spatial diagnostics turn out to be still unsatisfactory: clearly, the necessary conclusion is that the assumption of a single factor is too restrictive. One solution might be to search for additional aggregate variables which may qualify as observable common factors, or, in case of plausible regional growth clubs, identify these groups on the basis of *a priori* information and compute the estimates of their respective common factors taking group averages. However, this is arguably a rather awkward process, with no guarantee to converge to a satisfactory model. Essentially, we need to allow for a more general structure, allowing from the outset for $N > 1$ unobservable factors. These may still be rather easily estimated, but at the cost of abandoning simultaneous modelling of strong and weak dependence and moving to the two-stages strategy advocated by Bailey *et al* (2016). Here we have two options, assuming the number N to be known or unknown. Let us see the former first.

Case C: A known number of unobservable factors

Since static factors are by definition orthogonal, if their number is known their estimation is easily carried out by iterated simple averages. More precisely, the estimate of the first latent factor will be the simple average of the $Y_i's$, and its loadings obtained by regression of the $Y_i's$ on the estimated factor. The second factor, orthogonal to the first, is simply the average of the regression residuals, and the loadings estimated in the same way; and so forth. Having estimated in this first stage the common components we may move in the second stage to model the de-factored data. These, provided the assumption on the number of common factors is correct and the cross-section sample size is large enough to yield good estimates of the latent factors, will be weakly dependent over space and time, and may be modelled using spatial econometric techniques, similarly to what prescribed by the spatial filtering approach by Getis and Griffith (2002). Formally, and using for the sake of exposition only, a static spatial model:

$$\mathbf{Y} = \mathbf{F}\boldsymbol{\Lambda} + \mathbf{Z} \tag{3a}$$

$$\mathbf{Z} = \mathbf{Z}\mathbf{W}\gamma + \mathbf{u} \tag{3b}$$

The assumption of cointegration between data and estimated factors may be tested, as suggested above, adapting some panel cointegration test. Since equation (3b) is a spatial model specified for the de-factored data, $\mathbf{Z}$, which are the residuals of the approximate factor model (3a), we can describe (3a)-(3b) as a Factor-augmented SEM, FASEM. Expanding the inverse the second equation may be written as:

$$\mathbf{Z} = \mathbf{u}(\mathbf{I} - \mathbf{W}\gamma)^{-1} \tag{4}$$

$$= \mathbf{u}(\mathbf{I} + \mathbf{W}\gamma + \mathbf{W}^2\gamma^2 + \ldots) \tag{5}$$

and the FASEM model in single-equation form as

$$\mathbf{Y} = \mathbf{F}\boldsymbol{\Lambda} + \mathbf{u}(\mathbf{I} + \mathbf{W}\gamma + \mathbf{W}^2\gamma^2 + \ldots)$$

which shows clearly how now the effects of the common factor on the various units are assumed to not produce any spillovers, while the shocks u are allowed to[2]. This assumption is thus added to the one that the number of common factors is known. Indirect indications on the validity of the latter assumption can be gained from the spatial properties of the residuals $\mathbf{u}$, which will be weakly dependent only if the number of factors included in (3b) is not smaller than the true number of latent factors. In other terms, the number of factors in (3a) can be simply fixed at a number large enough to ensure spatially uncorrelated residuals. Although this pragmatic approach may prove to be practically efficient, it could be argued

[2] Alternatively, substituting from (3a) into (3b) and rearranging, we can see that the spatial spillover coefficient of the factor is constrained to be equal to that of the spatially lagged dependent variable. This is the spatial analogue of what in the 1980's literature on dynamic modelling was defined the "common factor restriction" of the Cochrane-Orcutt transformation (Hoover, 1988). Clearly the term factor was used in a completely different sense.

that estimating the number of factors on the basis of a formalised procedure with known properties may be preferable to checking *ex-post* if the assumed number is adequate. The last, and most general, approach answers to this objection.

Case D: Unknown number of unobservable factors

This fully general set-up is at the basis of the approximate factor model literature. In this modelling tradition the most common solution is to estimate the latent factors using principal components (PC); Maximum Likelihood estimation is also possible, but definitely less popular (two examples are Watson and Engle, 1983, and Doz, Giannone and Reichlin, 2012). Approximate factor models, which allow for data-based consistent selection of the number of factors, enjoy growing popularity in macroeconometric and financial applications[3] where they are typically applied to datasets including a very large number of time series (in our case, the variable of interest over regions). For our purpose a fundamental difference with the average-based estimation method is that the PC procedure can only yield an estimate of the common components $\chi = \mathbf{F\Lambda}$; the common factor $\mathbf{F}$ as such is not identified. We will thus not be able to estimate FASARs including factors as regressors, and the two-stage approach leading to a FASEM specification (either static or dynamic) is the only feasible option even in the simplest case of a single factor.

In their more general form, approximate factor models allow for the possible existence of both non-stationary (trend) factors and stationary (cyclical) factors:

$$\mathbf{Y} = \mathbf{F\Lambda} + \mathbf{G\Phi} + \mathbf{Z} \tag{6}$$

where now $\mathbf{F}$ is a $T \times k_1$ matrix of non-stationary common factors, $\mathbf{\Lambda}$ the $k_1 \times N$ matrix of their loadings, $\mathbf{G}$ a $T \times k_0$ matrix of stationary common factors and $\mathbf{\Phi}$ the $k_0 \times N$ matrix of their loadings, $\mathbf{Z}$ the matrix of weakly dependent (over space and time) de-factored data. Since the stationary factors can be first differences of the non-stationary ones this more general model allows for dynamic factors. Although most of both the theoretical developments and applications of factor models are for stationary variables, results allowing consistent estimation of the number of factors (say, k) are discussed by Bai (2004) and, more recently, Barigozzi, Lippi and Luciani (2016). Estimation of factors and loadings is essentially based on PCs, as in the stationary case. An important advantage of PC estimation is that, since the estimated residuals converge asymptotically to the population unobserved values

[3] See, *e.g.*, Stock and Watson (2002a, 2002b), Forni, Hallin, Lippi and Reichlin (2005) Kapetanios and Pesaran (2007). Examples of applications to forecasting and construction of cyclical indicators are given by *e.g.*, Giannone, Reichlin and Small (2008) and Altissimo, Cristadoro, Forni, Lippi and Veronese (2010).

(Bai, 2004, lemma 1), their time series properties can be studied using standard (panel) unit root tests for observed data. An application along these lines using PC estimators of the common factors is included in Carrion-i-Silvestre and Surdeanu (2016), who use (along the cross-section averages mentioned above) the Cup-type estimators by Bai, Kao and Ng (2009).

Summing up, regional datasets showing signs of strong and weak spatial dependence may tackled following approaches with increasing degrees of generality, discussed above from Case A, known number of observable factor(s), to Case D, unknown number of unobservable factors. While some datasets may be successfully modelled using the simpler approaches, highly heterogenous ones are likely to require the the most complex one. In these circumstances the most general modelling strategy, which does not hinge upon any assumption on the number and observability of the factors, seems to be the following generalisation of the two-stage approach. First, fit the dynamic factor model (6) to the data, with the number of factors estimated using one of the information criteria proposed in the literature and factors and loadings estimated by PCs. Second, evaluate the hypotheses that the estimated residuals are weakly dependent over space (CD test, α exponent) and time (unit root tests, in standard and panel version). If neither is rejected, the factor model is adequate and a spatial model, possibly in panel form, for the de-factored data can be estimated.

We can now move to our case study, which will give the opportunity to discuss some important details.

3 Patterns of regional industrial growth

Understanding the processes driving regional development ideally requires annual time series of data disaggregated at both the spatial and industrial level. Historical data with this level of detail are generally not available, but Italy constitutes an exception. As a result of a long-term project sponsored by the Bank of Italy, Ciccarelli and Fenoaltea (2009, 2014) constructed annual time series of value added at 1911 prices for 12 manufacturing industries and 16 NUTS 2 areas (*regioni*, hereafter regions) for the period 1861, the year when the Kingdom of Italy was officially declared, to 1913, the eve of the First World War. Based on this recent dataset, we analyze consider 10 manufacturing industries (Foodstuffs, Textiles, Clothing, Leather, Wood, Metalmaking, Engineering, Non-metallic mineral products, Chemical and rubber, and Paper) in 16 regions, for a total of 159 industry/region combinations observed over 53 years.[4]

[4]The only exception is the Metalmaking sector, virtually absent in the southern region of Basilicata. We note that we omitted the data on the Tobacco and Sundry industries. The former was very small (on average accounting for less than 1% of total value added in manufacturing)

Paradoxically, historical data on industry are richer than those available for the more recent decades. In our case the longest and most detailed dataset available, assembled by the research centre CRENoS of the University of Cagliari and based on Istat data, covers value added at 1995 prices for six broad industry aggregates (Food, Beverages and Tobacco; Textiles, clothing, leather and footwear; Minerals and non-metallic mineral products; Metal products and machinery and transport equipment; Paper, and printing products; Wood, rubber and other industrial products) for 20 NUTS 2 regions. The time period cover the years from 1970 (the beginning of detailed Italian national accounts series) to 2003. We thus have 120 industry/region combinations observed over 34 years.[5]

The Italian manufacturing industry developed later than in more advanced European countries, so that our study covers the early phases of the country's industrialization. During 1861-1913 value added at 1911 prices of the aggregate of the 10 industries here considered grew at an average annual rate of about 2.3 percent. As a consequence, the 1913 figure was over three times that of 1861. Approximately a century later, average aggregate real growth turned out to be strikingly similar: about 2.5% from 1970 to 2003 for the entire Manufacturing industry.

Figure 1 shows that in both periods the contributions to growth varied significantly, with distributions of average growth rates over the industry/region pairs which at first sight also appear strikingly similar. The shapes are indeed almost identical, but examining their supports we can see that the 1970-2003 distribution is slightly more concentrated and shifted to the right with respect to that for 1861-1913 (1970-2003: minimum -0.4, maximum 9.3, range 9.7; 1861-1913: min -2.6, max 8.4, range 11.0). Consistently, the number of negative values identifying shrinking industry/region pairs was slightly higher in the 19th century (five against three). Even taking such a simplified view there clearly is a wide heterogeneity to be explained.

We can go into some detail by examining the marginal row and columns of Tables 1 and 2, which report simple averages[6] for each region and industry over the two periods. Let us discuss the 19th century first (Table 1). The traditional industries producing consumption goods (including Food and Textiles) generally grew more slowly (rates between 1.2 and 1.5 percent) than those essentially tied to the production of investment and intermediate goods (especially Metalmaking, Non metallic minerals, Chemicals and Paper, with growth rates between 3.5 and

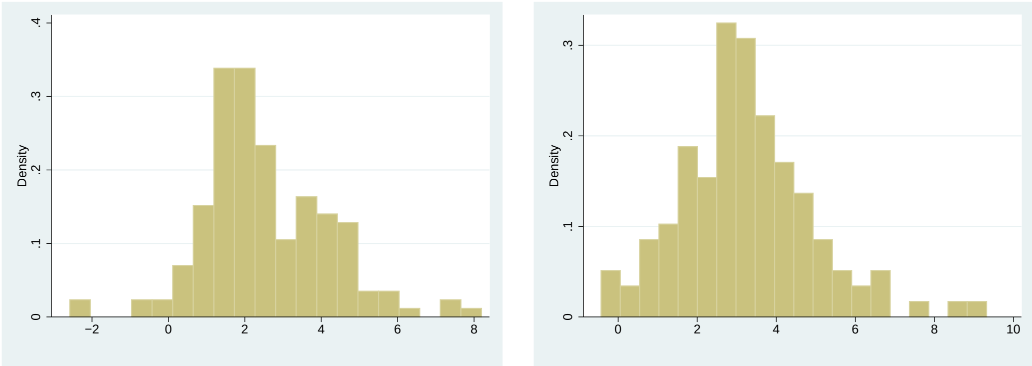
and run as a State monopoly, hence with peculiar localisation and growth patterns. Sundry industries had an even smaller share, on average about 0.5% of total value added, and is far too an heterogenous aggregate to be of any interest.

[5]Further details on both datasets are provided in the Appendix.

[6]Giving equal weight to all values, these reflect the underlying heterogeneity better than average growth rates of the regional and national industry aggregates.

Figure 1: Distribution over industries and regions of value added rates of growth.

A. 1861-1913 (16 regions, 10 industries) B.1970-2003 (20 regions, 6 industries)



Source: see text.

4.6 percent). The extremes of the ranking are on one side the stagnating Leather industry, with an average growth rate of just 0.3 percent, on the other the Metal-making industry, with a growth rate larger than 10 percent. Wide heterogeneity is also present among regions, with manufacturing valued added in Liguria (in the North-West; a map is reported in the Appendix) expanding three times as fast as Basilicata, in the South (respectively, 4.6 and 1.5 percent). Reading Table 1 row-wise is informative about regional growth of total manufacturing industry. In this metric, the leading role of the North-West (Piedmont, Liguria and Lombardy) is evident. A North-South divide is also clearly visible.[7] The North-West average, 3.4, is much higher than both that of the North-East (Emilia, Venetia) and of the Centre (from Tuscany to Latium), respectively 2.6 and 2.7 percent. These, in turn, are clearly higher than that of the South, 2.1 percent.

Table 2 refers to the more recent 1970-2003 period. Comparisons between historical and modern data are of course to be taken with caution, both for the broader definition of industry aggregates in modern data, and for the different internal composition of each industrial sector. With this important caveats in mind, we can see that in 1970-2003, as already in 1861-1913, the slowest growth of the aggregate take place in the core consumption goods industries, Food and Textiles (respectively, 2.9 and 1.7 p.c.). Metal and Non-metal, two industries producing essentially investment and intermediate goods, have instead two of the highest average rates of growth (both slightly above 3.5 p.c.).

The considerations made so far refer to long-run averages. Figures 2-3 illustrate

[7] Since the 1950's the area with a triangular shape with vertices in the main cities of these three regions Turin, Genoa, and Milan, has been commonly referring to as "the industrial triangle", to emphasise its leading role as the core of the Italian industrial system.

Table 1: Average growth rates of value added at 1911 prices ($\times$*100*) during 1861-1913, by sectors and regions

	(1) Food	(2) Text	(3) Cloth	(4) Leath	(5) Wood	(6) Metal	(7) Eng	(8) NMet	(9) Chem	(10) Paper	*Average*
PI	1.33	**3.19**	**2.55**	1.69	1.37	**4.97**	**3.50**	**3.80**	**4.47**	**4.94**	**3.18**
LI	**2.35**	**2.79**	**2.74**	**2.09**	**1.90**	**6.20**	**4.20**	4.92	**4.89**	3.75	**3.58**
LO	**1.51**	**3.48**	**2.35**	**1.95**	**1.92**	**4.80**	**3.89**	4.79	**4.97**	**5.12**	**3.48**
VE	1.20	**3.26**	1.41	1.58	1.56	**3.59**	1.97	**3.70**	**3.71**	3.92	**2.59**
EM	**2.03**	-0.28	**2.49**	1.84	**1.64**	**3.51**	**2.56**	**3.65**	**3.74**	4.47	2.57
TU	1.18	**2.43**	1.75	1.88	**1.62**	**5.94**	**2.58**	3.26	**4.56**	**4.65**	**2.99**
MA	0.96	0.32	1.61	1.80	1.33	2.86	1.51	**4.11**	**3.59**	**5.12**	*2.32*
UM	0.83	**2.62**	1.41	1.86	1.08	**8.36**	2.06	**4.39**	**7.34**	**4.85**	**3.48**
LA	1.14	-0.9	**2.68**	**1.96**	1.28	1.04	**2.74**	2.46	3.26	**5.78**	*2.14*
AB	0.78	1.35	1.33	1.86	1.48	**7.40**	0.66	2.44	3.42	**4.94**	*2.57*
CM	1.41	-0.61	1.60	**2.19**	1.44	**4.42**	**2.28**	1.81	2.67	3.97	*2.12*
AP	1.50	0.94	2.15	**2.26**	**2.20**	**2.89**	**2.24**	3.07	2.87	**5.88**	**2.60**
BA	0.34	-0.08	0.96	1.62	0.92	-	0.16	1.79	0.20	3.30	*1.02*
CL	1.12	0.59	1.48	**2.05**	**1.77**	-2.63	0.67	**5.18**	1.74	4.34	*1.63*
SI	**1.41**	-2.15	**2.17**	**2.19**	**1.69**	**2.46**	1.93	**4.16**	2.41	4.41	*2.07*
SA	**2.22**	**2.70**	**2.40**	**2.18**	**2.20**	**4.08**	1.73	3.09	1.53	4.17	**2.63**
Average	*1.33*	*1.23*	*1.94*	*1.92*	*1.59*	*3.99*	*2.17*	*3.54*	*3.46*	*4.60*	2.57

Column headers: Food: Foodstuffs; Text: Textiles; Cloth: Clothing; Leath: Leather; Metal: Metalmaking; Eng: Engineering; NMet: Non-metal mineral products; Chem: Chemicals and rubber. **Row headers:** PI: Piedmont; LI: Liguria; LO: Lombardy; VE: Venetia; EM = Emilia-Romagna; TU: Tuscany; MA: Marches; UM = Umbria; LA: Latium; AB = Abruzzi; CM = Campania; AP: Apulia; BA: Basilicata; CL: Calabria; SI: Sicily; SA; Sardinia. *In bold case*: values greater than the national column average (bottom row).
Source: Authors' elaborations on Ciccarelli and Fenoaltea (2009, 2014).

instead the annual evolution of value added in manufacturing, by regions and industries. Aggregate regional value added (Figure 2) tend to move together, even though the co-movement differ among the various regions. Cyclical peaks in the late 1880s and late 1970s occurred for instance in several regions.

Patterns of sectoral growth (Figure 3) are also of some interest. The upper part of the figure refers to the 1861-1913 period, and show that sectors tied to the production of consumption goods (Panel A.1) tends to evolve gradually, while cyclical variations are more pronounced for sectors related to the production of durables such as engineering, metalmaking, and wood (Panel A.2). The lower part of the figure refers to the more recent time period. The early 1980s registered a generalized slowdown in both the sector tied to the production of consumption goods and the production of durables.

The pictures, as expected, convey the general image of non-stationary, trending

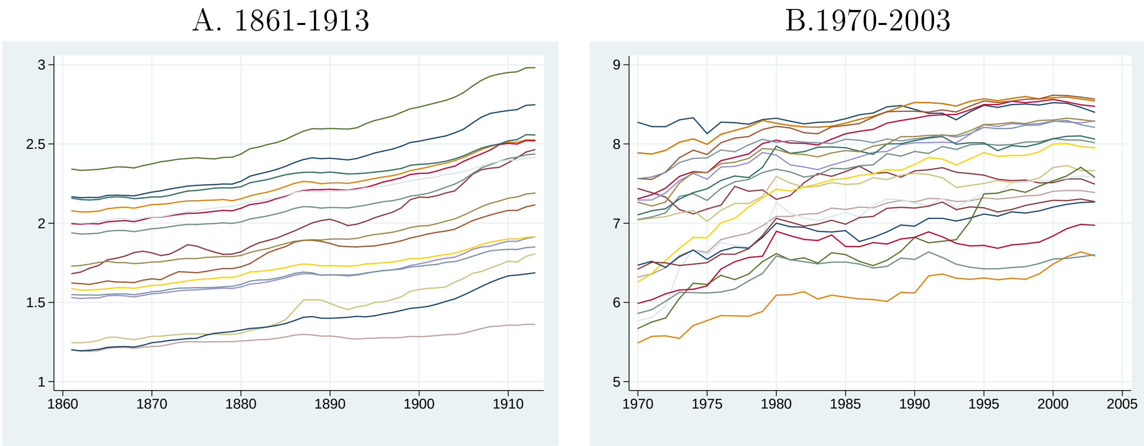
Table 2: Average growth rates of value added ($\times$*100*) during 1970-2003, by sectors and regions

	(1) Food	(2) Text	(3) Wood	(4) Metal	(5) NMet	(6) Paper	*Average*
PI	**3.04**	-0.16	1.35	-0.43	1.83	2.18	*1.30*
AV	1.39	0.34	1.09	-0.31	**5.44**	3.38	*1.89*
LO	2.65	1.74	2.43	2.12	2.90	3.68	*2.59*
LI	0.69	0.88	1.81	1.43	1.44	3.76	*1.67*
TA	2.42	**1.90**	3.36	3.36	**4.88**	**5.42**	**3.56**
VE	**3.10**	**2.80**	**4.25**	**4.53**	**3.81**	**6.14**	**4.11**
FV	**3.46**	0.81	3.29	2.93	**3.62**	**4.17**	*3.05*
EM	2.39	2.02	2.86	**3.93**	3.23	**4.64**	*3.18*
TU	1.71	0.64	2.73	3.29	2.81	**5.06**	*2.70*
UM	**3.15**	**2.64**	**4.50**	2.61	**4.57**	**4.45**	**3.65**
MA	**3.38**	**2.37**	**3.88**	**4.60**	2.93	2.17	*3.22*
LA	**3.25**	0.50	2.53	**4.60**	**3.62**	**5.14**	**3.27**
AB	**6.19**	**4.43**	**4.00**	**7.39**	**4.10**	**5.56**	**5.28**
MO	**6.72**	**3.00**	**6.51**	**8.65**	**3.72**	1.83	**5.07**
CM	2.57	1.59	2.82	3.34	2.54	4.04	*2.82*
AP	1.84	**2.76**	3.29	3.55	3.45	3.74	*3.11*
BA	**4.12**	1.61	**5.67**	**9.32**	**4.28**	2.45	**4.57**
CL	2.65	**1.99**	**3.48**	**5.04**	2.69	**6.67**	**3.75**
SI	0.89	1.17	3.29	3.08	**4.37**	3.80	*2.77*
SA	2.56	**1.96**	**4.41**	3.54	**5.00**	2.79	**3.38**
Average	*2.91*	*1.75*	*3.38*	*3.83*	*3.56*	*4.05*	*3.25*

Column headers: Food: Food, Beverages and Tobacco; Textiles; Textiles, Clothing, Leather and footwear; Wood: Wood, rubber and sundries products; Metal: Metal products, machinery and transport equipment; NMet: Non-metallic minerals and mineral products; Paper: Paper and printing. **Row headers:** PI: Piedmont; AV: Aosta Valley; LI: Liguria; TA: Trentino-Alto Adige; LO: Lombardy; VE: Venetia; EM = Emilia-Romagna; TU: Tuscany; MA: Marches; UM = Umbria; LA: Latium; AB = Abruzzi; MO: Molise; CM = Campania; AP: Apulia; BA: Basilicata; CL: Calabria; SI: Sicily; SA; Sardinia. ***In bold case***: values greater than the national column average (bottom row).
Source: Authors' elaborations on CRENoS data.

regional series. Following routine practice, we formally tested the hypothesis of non-stationarity using the ADF-GLS test by Elliot et al. (1996), allowing for a linear deterministic trend and selecting the lag length on the basis of the modified AIC criterion. The results, as detailed in section A2.1 of the Appendix, imply that the series as a panel are non-stationary.

Figure 2: Value added: regional aggregates, 1861-1913 and 1970-2003



Source: Panel A: Ciccarelli and Fenoaltea (2009, 2014). Panel B: CRENoS.

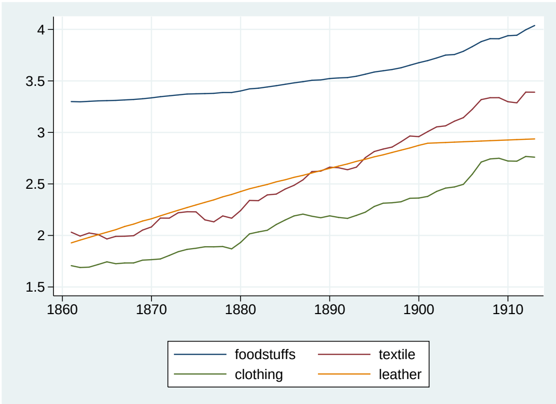
4 Modelling strong dependence

The descriptive analysis considered so far confirmed that our datasets, referring to 1861-1913 and 1970-2003, are non-stationary and considerably heterogenous. Of course, this is hardly surprising in view of the rather large cross-section sample sizes (respectively, 159 and 120 industry-region pairs), the large regional differentials, and, in the case of the 19th century data, the rather high level of detail of the disaggregation over industries, and long time span. The assumption of a single common factor is thus hardly defendable, and we shall follow the more general strategy outlined at the end of Section 2, estimating the factors and their loadings using PCs. Given the rather large combined industries$\times$regions cross-sectional dimension, the computationally convenient solution is to estimate the latent factors as the eigenvectors corresponding to the k largest eigenvalues of the $T \times T$ matrix $\mathbf{YY}'$ (*e.g.*, Bai, 2004). Given the factor estimates, the loadings are obtained as $\mathbf{\Lambda} = \mathbf{Y}'\mathbf{F}/T^2$. An often delicate point of principal components studies is dealing with the scale of the variables. Here we adopt total population as the scale element. While total population is available with annual frequency for 1970-2003, for the 19th century we have only data for selected benchmark years, when the population censuses were taken (1861, 1871, 1901, 1911).[8] In this case annual estimates have then been constructed by linear interpolation. We pass to illustrate the estimation of the factor models for the two datasets in turn.

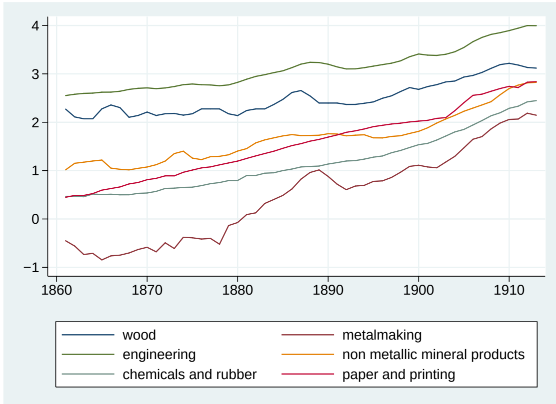
[8]Due to financial difficulties, the population census of 1891 was not taken.

Figure 3: Value added in the Italian industries.

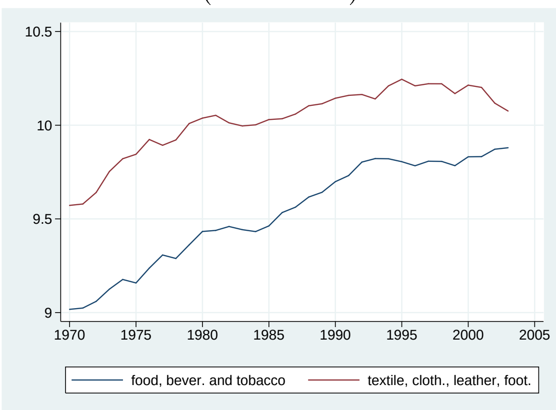
A1.Consumption goods
(1861-1913)



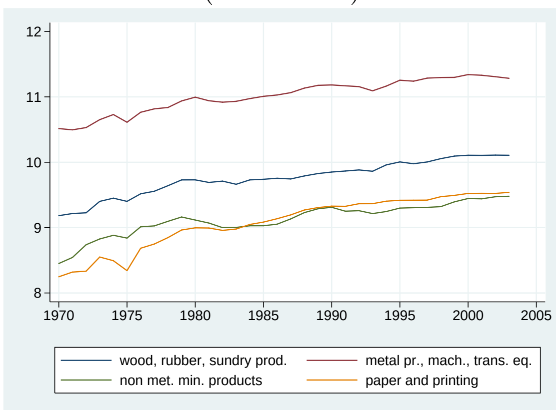
A2. Investments and intermediate goods
(1861-1913)



B1.Consumption goods
(1970-2003)



B2. Investments and intermediate goods
(1970-2003)



Source: see text.

4.1 Non-stationary common factors, 1861-1913

The first step of our analysis involves estimating the non-stationary factors through a static factor analysis, as in Bai (2004). Table 3 shows that by allowing for a maximum of four factors the three information criteria suggested by Bai give partially contrasting results.

The first information criterion, IPC_1, is minimised by three factors, but the difference with the value for two factors is marginal. The second, IPC_2, is equal at the second decimal point with two and three factors, and the third, IPC_3, favours one factor. With the maximum set at three factors IPC_1 and IPC_2 suggest instead two factors, while IPC_3 still one. Considering also that IPC_3 is consistent only when the cross-section dimension is not large relatively to the time dimension, the

Table 3: Static Factor Model Information Criteria, 1861-1913

	Max=4			*Max=3*		
Factors	IPC_1	IPC_2	IPC_3	IPC_1	IPC_2	IPC_3
1	3.20	3.24	**3.99**	3.41	3.47	**4.53**
2	2.55	**2.64**	4.13	**2.99**	**3.11**	5.19
3	**2.51**	**2.64**	4.85	3.17	3.35	6.45
4	2.82	2.99	5.91			

Figures in bold represent minimum value for each column (=best)

suggestions stemming from IPC_1 and IPC_2 may be considered overall as more reliable, and two factors seems a reasonable choice. This conclusion is further supported from the finding that the residuals are indeed stationary, implying that two $I(1)$ factors are sufficient to capture all non-stationarity of our dataset. Since the estimated residuals of factor models converge asymptotically to the population unobserved values (Bai, 2004, lemma 1) their time series properties can be studied using unit root tests designed for observed data. To this end we computed standard univariate ADF tests and the bootstrap panel unit root test by Chang (2004); all the results fully support stationarity.[9]

Figure 4, panel A illustrates the temporal evolution of the two non-stationary factors, that is the two orthogonal components that contribute to explain the growth of the manufacturing industries. The first factor is an essentially monotonous trend capturing long-term growth (hence, the “Trend” label). The second one is a long cycle, with peaks at the extremes of the sample and through in the 1890’s (when the trend also slowed down, with a few years of negative growth), a period long enough to make it non-stationary for the sample at hand. We shall refer to this second factor as “Cycle”.[10]

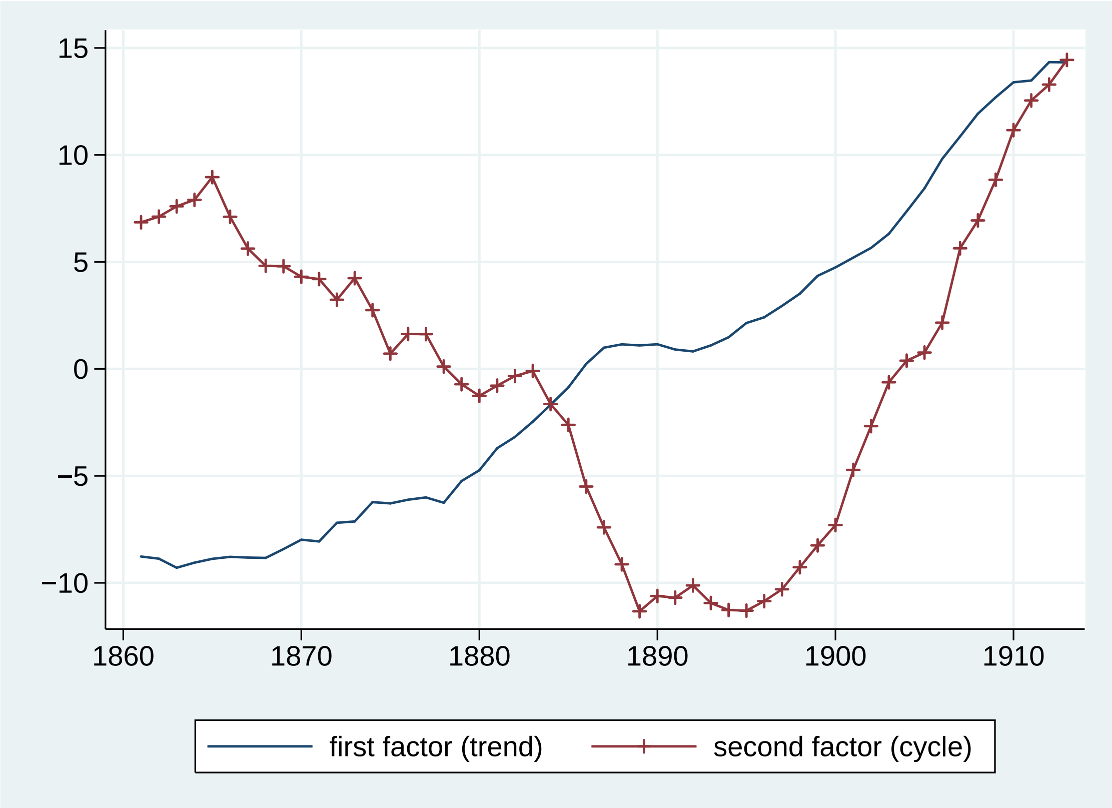
It is instructive to compare the paths followed by these two factors with the periodization proposed by Italy’s economic historians. The literature acknowledges that the years 1880-1887 ca. were of rapid industrial growth, the years 1887-1895 ca of economic crisis, and the years 1895-1913 ca of sustained growth again (Bachi, 1919; Luzzato, 1963, p. 263 referring to the 1889-1894 period as the “darkest years since unification”.

[9] Results are reported in section A2.2 of the Appendix.

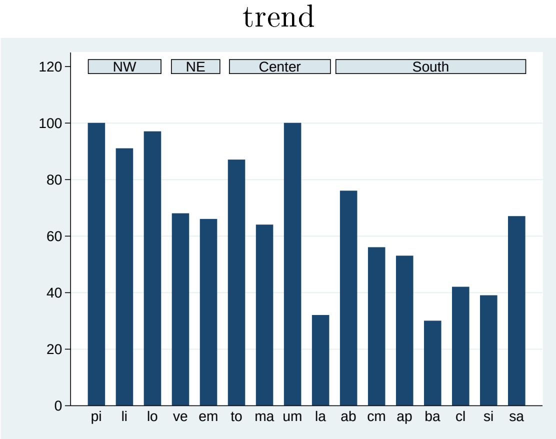
[10] But again this label should not be taken to imply that it is stationary, and a “Long Cycle” label might be admittedly more appropriate. Effectively this long cycle is remarkably close to the one identified by Kondratieff in his 1925 work (see, *e.g.*, Papageorgiou and Tsoulfidis, 2012).

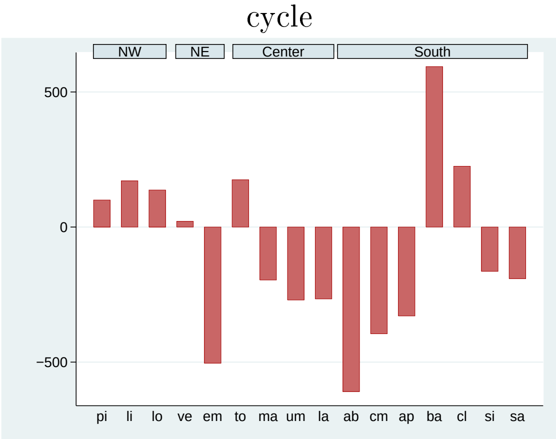
Figure 4: Estimates of non-stationary common factors and loadings, 1861-1913

A. Non-stationary common factors



B. Average loadings





NW=North-West (Piedmont, Liguria, Lombardy); NE = North-East (Venetia, Emilia); Center (Tuscany, Marches, Umbria, Latium); South (Abruzzi, Campania, Apulia, Basilicata, Calabria, Sicily, Sardinia).

Based on extremely detailed and documented statistical reconstructions Fenoaltea (2011) shows that the long swings of the Italian industry described above (the growth of the 1880s, the crisis of the 1890s, and the upswing of the new century) where not only an Italian phenomena. Rather, they represented a cofeature shared by the peripheral countries of the time, tied to the exogenous shift in the supply of foreign capital, and much involved the construction sector. The historical data show that during the 1890s new constructions in the railway sector, other public works and urban construction dropped considerably.[11] The historical data by Fenoaltea further confirm that the first decade of the 20th century was of rapid economic upsurge (on the point also see Ciccarelli and Fenoaltea, 2007). The above narrative is fully in line with the evidence of Figure 4, with mutually reinforcing rising Trend and Cycle since 1895 ca fueling the big spurt of the Italian economy during the *belle èpoque*.

The two non-stationary factors considered so far are not separately identified from the corresponding regional and sectoral loadings. The latter reveal essentially how national factors impact on regional and sectoral growth. Figure 4, panel B illustrate the averages over manufacturing sectors.[12] The 16 regions are ordered following the same North to South geographical order of Table 1. Even a quick glance at the loadings of the Trend, reveals immediately that the NW constitutes the leading area, the NE and Center the intermediate ones, and the the South the lagging behind. Setting the average over all industries for Piedmont=100, those of Liguria and Lombardy (the other two regions of the North-West) are respectively 91 and 97: the grand national average over industries and regions, 67, is almost one third lower. Both NE regions (Venetia and Emilia), have means close to the national average. The same holds for Centre (Tuscany, Marches, Umbria, Latium), where however the regional values vary widely between a minimum of 32 (Latium) and a maximum of 100 (Umbria), the latter tied to the rapid development of the State-protected Terni steel plant and ironworks since the mid-1880s. Finally, the average of the southern regions is 52, with values below the average registered in Basilicata, Calabria, and Sicily.

Figure 4, panel B also illustrates the average loading of the second non-stationary component, the Cycle (which, as panel A shows, has a minimum about in the mid-

[11] In 1887 the collapse of the real estate bubble caused a severe financial crisis. A number of major banks which had extended generous credit to the building sector ran into serious difficulties. The 1893 bankruptcy of the "Banca Romana" (one of the six national banks authorized at the time to issue paper money) and the arrest of its Governor Tanlongo marked an epoch. The Italian banking system was completely reshaped and the creation in the same year of the Bank of Italy, was one of the main institutional innovation of this period. It marked a decisive step towards the unification of note issuance and the control of money supply.

[12] All these remarks largely hold if we look at the medians, not reported here for reasons of space.

dle of the sample period, and approximately similar values at the extremes). We notice that the north-eastern and southern regions appear to be the most vulnerable to cyclical swings.[13] On the opposite, the north-western ones are the least affected by long-term cyclical fluctuations.

The joint analysis of Figure 4, panel A and B is particularly informative. The two factors have an opposite tendency up to the late 1880s (the Trend rises, the Cycle falls) but later, after the mid 1890s, tend to move together. It is interesting to note that the in North-West macro area, but to some extent also Tuscany, we find both high values of the average loadings of the Trend and positive values for those of the Cycle, so that it benefited particularly from the rapid acceleration of the manufacturing industry experienced by the Italian economy at about the turn of the century.[14]

Table 4: Averages across regions of the loadings of the non-stationary factors, 1861-1913

	Food	Text	Clothing	Leather	Wood
Trend	100	98.5	229.9	212.7	227.4
Cycle	-100	16.3	-16.3	190.4	-18.6

	Metal	Eng	NMet	Chem	Paper
Trend	586.6	236.4	343.7	440.1	609.4
Cycle	-19.3	-25.7	-205.0	-196.1	-145.7

Food: Foodstuffs; Text: Textiles; Cloth: Clothing; Leath: Leather; Metal: Metalmaking; Eng: Engineering; NMet: Non-metal mineral products; Chem: Chemicals and rubber.

Taking averages of the loadings in the other directions, over regions, is informative on the role played by the various manufacturing sectors. In Table 4 we report the averages over all regions taking (arbitrarily) Textiles as a reference sector, hence with its average normalised to 100 for the Trend and -100 for the Cycle, in order to preserve the signs. We can see that the highest loadings of the Trend are associated with industries producing investment and intermediate goods (Paper, Metalmaking, Chemicals). On the other hand, Non Mineral Metal products, Chemicals and Leather were amongst the sectors most sensitive to the Cycle.

[13] The case of Basilicata, the only region with positive and sizeable average loading of the Cycle is interesting and at the same time hard to interpret. It could be tied to its migration outflows. According to the population censuses of 1871, 1881, 1901 and 1911 Basilicata is the only Italian region registering a systematic reduction of its male labor force (men of age 15 years and above). Note that despite improving economic conditions during 1895-1913 ca, Italian emigration outflows were particularly sizeable.

[14] See Ciccarelli and Fachin (2016) for an empirical investigation of manufacturing productivity growth in Italian provinces during 1871-1911.

Overall, the evidence considered so far is consistent with the view that during 1861-1913 the Italian economy was characterized by the emergence and consolidation of the North-West as the main industrial area of the country. This development was in turn tied to the emergence and development of heavy manufacturing sectors, often subsidized by the State, such as metalmaking and engineering (Bianchi, 2002; Felice, 2015).

4.2 Stationary common factors, 1861-1913

We assess the existence of common stationary factors using two measures of cross-dependence, the CD test and the α exponent.

Table 5: Cross-section dependence statistics, 1861-1913

	Data	Residuals Step 1	Residuals Step 2
CD	530.55 [0.00]	15.32 [0.00]	-1.10 [0.86]
α	0.96	0.64	0.50

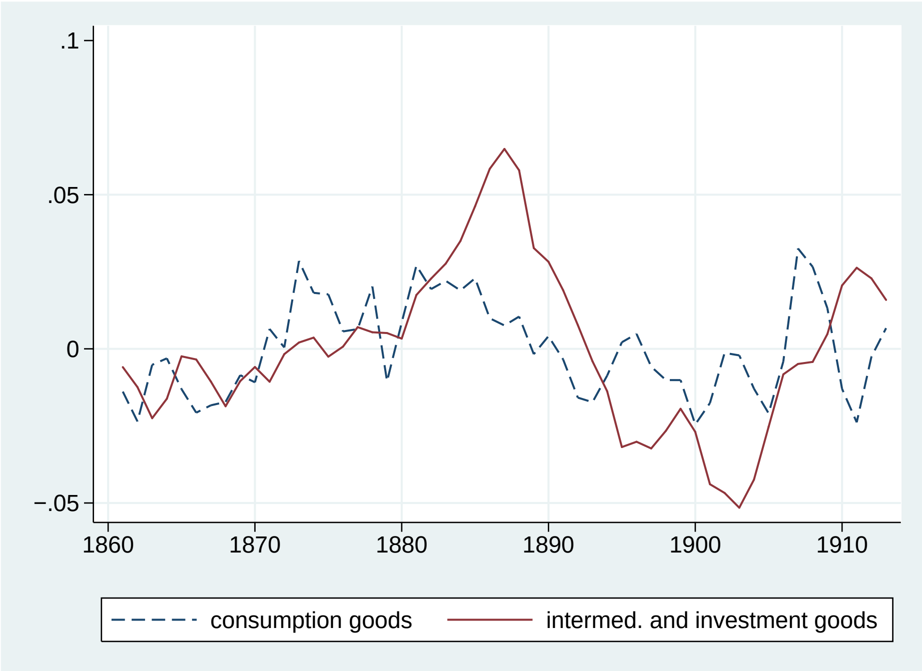
CD: H_0 : weak cross-section dependence, p-value in brackets. *Residuals Step 1*: residuals of Bai model with two non-stationary factors estimated by PC. *Residuals Step 2*: residuals of regression of *Residuals Step 1* on two cross-section averages.

Comparing the values obtained for the original data (Table 5, row 1, label "Data") and for the residuals of the Bai model allowing for two non-stationary factors (row 2, label "Residuals Step 1") we can see that accounting only for these leaves a considerable amount of unexplained pervasive dependence in the data. The α exponent[15], although much reduced (from 0.96 to 0.64) is still greater than 0.5 (the threshold value separating weak and strong dependence), and the hypothesis of weak dependence for and de-factored data is strongly rejected by the CD test in favour of that of strong dependence. Hence, there definitely seem to be some stationary common factors we need to estimate and remove before proceeding to the estimation of spatial models. Bai (2004) describes a generalized estimation procedure supposed to yield estimates of these factors and associated loadings. Unfortunately, implementation of this algorithm led to rather poor results, with all information criteria always suggesting the maximum number of factors, for any choice of this value. This is not entirely surprising, since Bailey, *et al.* (2016) and Maciejowska (2010) report exactly the same problem. Given the unreliability of Bai's algorithm we devised an hybrid approach, estimating the stationary factors à la Pesaran (2006) by cross-section averages of the residuals of the non-stationary

[15]Bailey *et al.* (2015) propose three different estimators of α, that here turned to be always identical.

factor model. Loadings can then obtained simply regressing the data to be de-factored on these estimates.

Figure 5: Estimates of stationary common factors, 1861-1913



The structure of our data leads naturally to hypothesise two factors, respectively common to the consumption goods industries (briefly, CG: Food, Textiles, Clothing, Leather) and the intermediate and investment goods ones (briefly, IIG: Wood, Metalmaking, Engineering, Non metallic mineral products, Chemicals, Paper). These averages are plotted in Figure 5.[16] The average of the residuals of the IIG industries shows much wider fluctuations than that over the CG ones. Our estimates of the $I(1)$ unobserved permanent components appear thus able to explain a much larger fraction of the fluctuations of value added for the CG industries than for the IIG ones. Further, in both cases the values around the downturn of the 1890s are positive (i.e., our estimates of the $I(1)$ unobserved permanent components are smaller than the actual data), while the opposite happens during the recovery that took place in the following decades. This pattern is particularly evident for the IIG industries. Transitory factors thus seem to have reduced both the adverse impact of the crisis and the speed of the recovery. Note further that from the third row of Table 5 (label "Residuals Step 2") we can see that by

[16] Interestingly, a similar pattern is illustrated in Fenoaltea (2011), p. 39 Figure 1.05, panel B, illustrating the temporal evolution of the annual changes in production during 1861-1913 separately for durable and non-durable industries.

subtracting from the residuals of the non-stationary Bai model the estimates of the common stationary components obtained in this way, no unexplained strong cross-section dependence is left in the data.

4.3 Common factors, 1970-2003

Let us now examine the static factor estimation for the 20th century data. Table 6 shows that the first two information criteria are minimised by the choice of two factors, while the third one by one factor only. However, recalling that IPC_3 is not reliable with the sample sizes at hand (large N/T ratio) we settle for two non-stationary factors.

Table 6: Static Factor Model Information Criteria, 1970-2003

	Max=4		
Factors	IPC_1	IPC_2	IPC_3
1	2.98	3.04	**4.06**
2	**2.91**	**3.02**	5.03
3	3.18	3.35	6.33
4	3.66	3.87	7.80

Bold face: min for each column (=best).

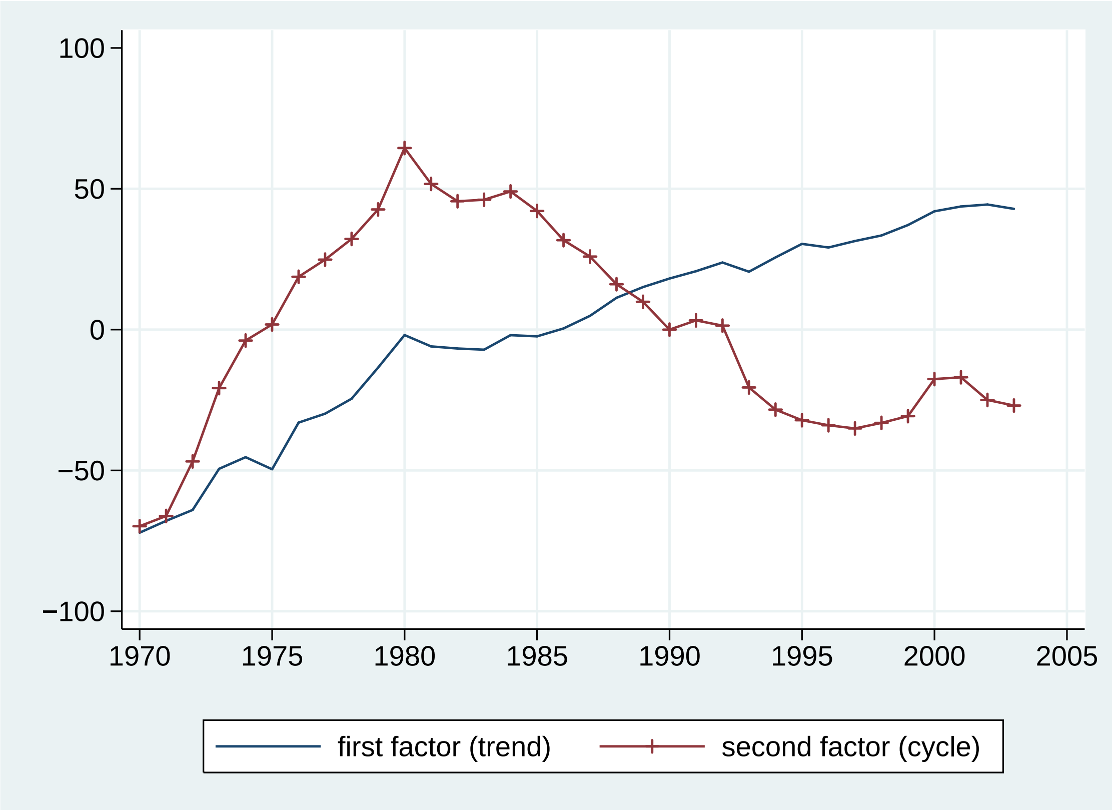
The two factors (Figure 6, panel A), are strikingly similar to those estimated for the 19th century: a trend, hereafter "Trend", and a very long cycle, hereafter "Cycle", with a single peak around 1980, when the Trend also slows down noticeably.[17] During the 1970s both factors grew, the Cycle at a more accelerate rate than the Trend, while since 1980 they essentially send opposite impulses, except a short swing upwards of the Cycle at the end of the sample. These patterns are fully in line with the widely accepted view of the Italian industrialization over the last 50 years (see, among others, Graziani, 2000; Bianchi, 2002.) After the end of the Bretton Woods era in 1971, currency devaluation was often used to gain price competitiveness against trade partners, especially so after the oil shocks of the 1970s. It was clear that CPI inflation rates above 20% were not sustainable. Italy joined the European Monetary System (EMS) in 1979 and the country was not allowed to devalue the currency as in the routine practice of the previous years.[18]

[17] As already noticed when considering the 19th century data, the "Cycle" label attached to the second factor should not be taken to imply that it is stationary, and a "Long Cycle" label might be in this respect considered more appropriate).

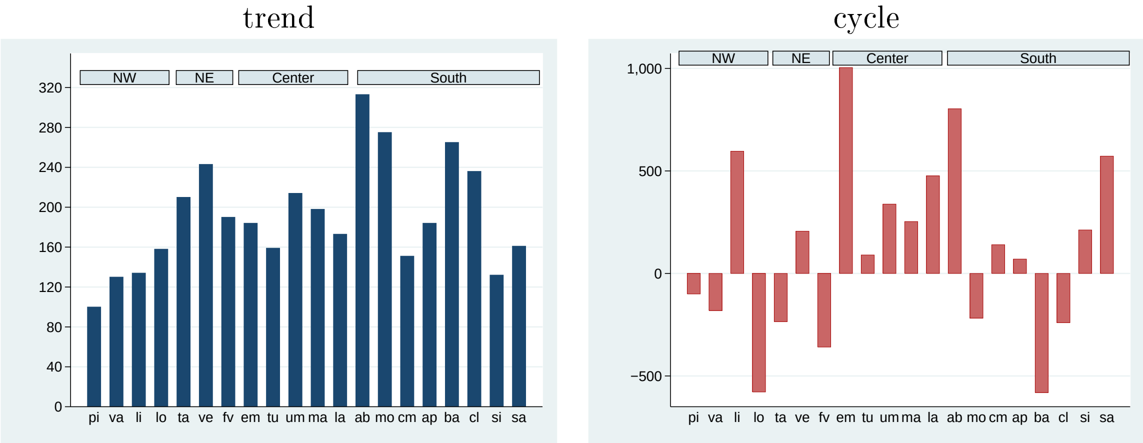
[18] Under the EMS member currencies agreed to keep their foreign exchange rates within a band of +/- 2.25%. An institutional arrangement resembling ultimately the market-based "gold points" mechanism of the Gold Standard international monetary regime operating in the 19th century.

Figure 6: Estimates of non-stationary common factors, 1970-2003

A. Non-stationary common factors



B. Average loadings



NW=North-West (Piedmont, Aosta Valley, Liguria, Lombardy); NE = North-East (Trentino-Alto Adige, Venetia, Friuli-Venezia Giulia); Center (Emilia, Tuscany, Marches, Umbria, Latium); South (Abruzzi, Molise, Campania, Apulia, Basilicata, Calabria, Sicily, Sardinia).

After the so called "divorce" of 1981, the Bank of Italy was freed from the obligation to purchase the unsold public debt at the Treasury auctions, and monetary policy become ultimately more restrictive (Toniolo, 2013). The changing macroeconomic scenario had a crucial impact on the structure and regional reallocation of Italian industry (Graziani 2000, Bianchi 2002, Bianco 2003). Employment in large firms, prevalently located in the North-West, reduced considerably in the 1980s (Toniolo, 2013, p. 471 reporting evidence on employees in plants with more than 500 hundred workers from 1927 to 2006). The reduction in employment went along with a general renewal of plants and machineries, and more flexible and innovative type of organization to increase productivity at levels at least compatible with the limits imposed by the EMS, and the related regime of restrictive monetary policy (Rossi, 2007).

Turning back to the empirical analysis, to check if our estimated factors are actually able to account for long-run growth of value added over regions and industries we first of all compute the ADF-GLS tests on the de-factored series. The plot of their $p-$values (see FigureA3 in the Appendix), shows that in most cases de-factoring appears to be effective and the residual series stationary. However, for a non-negligible number of series this is not the case. Of course, this is hardly surprising in view of the complex events rapidly summarised above. More precisely, we ind that out of 120 tests 13 are not significant at 5%, and 8 even at 10%. Consistently, Chang's panel $F-$test for the hypothesis that the de-factored data are $I(1)$, turns out to be equal to 61.34, not significant according to the bootstrap estimate of the p-value equal to 16.4 percent. Problems seem to be particularly common in the Textile industry, where the de-factored data for eight regions follow closely related paths with long swings away from the mean. We thus proceeded to further de-factor these series by simple OLS regressions from a factor defined as their average[19]. Formally we could say that the model has three factors, with the loadings of the third factor constrained to be zero for the all the other series. After this second-stage de-factoring the panel unit root test is 63.09, with a bootstrap p-value 12.1. This is somehow borderline, suggesting a non entirely negligible number of residuals still follow non-stationary patterns. Clearly, iterating the approach used for the Textile industry we could easily reduce to stationarity all the remaining non-stationary residuals. However, since these are scattered across different regions and industries with no obvious common links these other factors would be void of any meaning and only serve the purpose of mechanically capturing the residual long-run dependence. We thus decided to favour parsimony and settle for what we can label as a "two+one" specification of the non-stationary part of the factor model. The hypothesis that these three factors provide an ade-

[19]Details (residuals, tests and estimates) are not reported here for reasons of space, but are available on request.

quate representation is supported that the result of the cross-section dependence test, which does not reject the null hypothesis of weak dependence with a p-value close to 0.90 (see Table 7). We thus do not need to proceed to the estimation of stationary common factors, as it was instead necessary for the 19th century data. This conclusion however, does not exclude the existence of "cyclical clubs", *i.e.* groups of regions or industries following common idiosyncratic stationary cycles. Although clearly interesting to investigate for their own sake, in our modelling strategy such clubs are irrelevant, and the issue will thus not be pursued here.

Table 7: Cross-section dependence statistics, 1970-2003

	Data	Residuals Step 2
CD	346.91 [0.00]	−1.18 [0.88]
α	0.96	0.47

CD: H_0 : weak dependence, p-value in brackets. *Residuals Step 2*: residuals of Bai model with two non-stationary factors estimated by PC and one factor for the textile industry in eight regions.

Figure 6, panel B illustrates the regional averages of the loadings of both factors. The regions are ordered according to a geographical criterium with regions of the North-West followed by the regions of North-East, Center, and South. First of all, North-East and South have broadly comparable loadings of the Trend, in both cases much higher than those of the North-West, with the Centre falling somewhere in between. As far as the NE and the Centre are concerned this is consistent with the standard view that by the mid-'90's these two areas had caught up with the North-West. As noticed in Bianchi (2002) since the 1980s, production became less homogeneous and standardized, and more diverse and differentiated as organizations and economies of scale were replaced with organizations and economies of scope. Firms or relatively reduced size, often clustered in relatively small geographical areas and specialized in light sectors like foodstuffs, textile, leather, furniture flourished (on the so called "industrial districts" see e.g. Becattini et al., 2001). The phenomenon was particulary pronounced in the North-East and the Center of Italy, at the point that the traditional North-South partition of the country was more and more replaced in the literature with the three macro area North-West (NW), Center/North-East (NEC), and South (S), the so called "three Italies" (see Bagnasco 1977). The high values of the certain Southern regions (above all Abruzzi and Molise) are, on the contrary, somehow unexpected, as the catching-up process of South with the North is commonly considered to have stopped by the mid-'70s (*inter alia*, Terrasi, 1999, Di Liberto, 2008). However, one has to consider the possible counterbalancing role played by the loadings of the Cycle. Effectively, the joint analysis of Figure 6, panels A-B shows that the loadings of the Cycle, are positive in most Central regions, but also in certain Northern (see the case of Liguria) and Southern regions (see the cases of Abruzzo and Sardinia). Hence, in the expansionary phase (from 1980 until the mid-90's) the contributions to growth of the Cycle ($\lambda_{2j}\Delta F_{2t}$) are generally positive in most Northern regions (thus strengthening those coming from the Trend) and negative in the Central and Southern regions (thus weakening those from the Trend). Within the North-West, one notice the case of Liguria, once among leading industrial regions, with loadings not dissimilar by that of other Central and Southern regions (compare, for instance, with the loadings os Sardinia).

Table 8: Averages across regions of the loadings of the non-stationary factors, 1970-2003

	Food	Textiles	Non Met	Metal	Paper	Wood
Trend	100	61	102	124	141	110
Cycle	-100	64	33	168	22	69

Food: Food, Beverages and Tobacco; Textiles; Textiles, Clothing, Leather and footwear; Wood: Wood, rubber and sundries products; Metal: Metal products, machinery and transport equipment; Nmmp: Non-metallic minerals and mineral products; Paper: Paper and printing. *In bold case*: values greater than the national column average (bottom row). NB: the loadings of the trend are normalised on the Food industry (Food = 100 for the Trend and food =-100 for the Cycle.)

Comments for the structure across industries (Table 8) are unfortunately limited by the small number of cases. Two points stand out clearly: on one hand the decline of the Textile, Clothing and Leather industry, which has the smallest average loadings of the Trend and largest loadings of the Cycle (thus receiving large negative contributions to growth after 1980) and on the other the robust growth of the Paper and printing industry, which has opposite features (large Trend loadings and small Cycle loadings). The Food industry has an interesting loadings structure, with those of the Trend relatively small (hence, comparatively small contributions to growth) but those of the Cycle negative. Hence, the latter gave a negative contribution when the Cycle was in the expansionary phase (1970-1980), but a positive one in the contraction phase (1980-2003, most of the sample).

5 Modelling weak dependence

We have seen in the previous sections that using factor modelling we obtained for both temporal periods de-factored series that are stationary over time and only weakly dependent over the cross-section dimension. Ideally, the next step would be to estimate a full panel spatial autoregressive model including all regions and industries, so to model all their interactions. In principle, this is a straightforward task; the log-likelihood of model of this type is reported by *e.g.*, Elhorst (2014). In practice, this is not the case. First, we would need a spatial weight matrix with entries for all industry/region pairs. To construct such a matrix we would need information on disaggregated interregional trade flows which simply do not exist. Second, the likelihood would include a matrix of dimension $(T \cdot R \cdot N)^2$, in our case of an order so high (about 72×10^6) to be likely to cause serious computational problems. Clearly, in these circumstances we are forced to abandon the ambition of modelling all the interactions across industries and regions. Since for each industry we can construct a purely spatial weight matrix from geographic information, we may follow an option which is standard practice in the related literature on multi-regional input-output analysis (see, *e.g.*, Hewings, 1985), namely assuming that the global regions/industries spatial weight matrix is block-diagonal. In other terms, the weights are non-zero only for the spatial weights for the same industry in different regions. Formally, let $\mathbf{W}_{ij}$ be the $R \times R$ weights matrix measuring the proximity between industries i and j across the R regions. Then, under block-diagonality $\mathbf{W}_{ij} = \mathbf{0}_{R\times R}$ if $i \neq j$, and the overall spatial weight matrix is:

$$\mathbf{W}_{N\times R} = \begin{bmatrix} \mathbf{W}_{11} & \mathbf{0} & \dots & \mathbf{0} \\ \mathbf{0} & \mathbf{W}_{22} & \dots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \dots & \mathbf{W}_{NN} \end{bmatrix}$$

Under this contiguity structure the spatial models are estimated separately for each industry. Given the rather large dimension of the spatial units we adopted for all industries binary contiguity weights, with $w_{rs} = 1$ for regions r, s sharing a border and zero else. For the two main islands, Sicily and Sardinia, we proceeded as follows. Sicily has been considered a neighbour of Calabria, from which it is separated by the narrow (less than 5 km wide) strait of Messina. The regions closest to the other island, Sardinia, are Liguria, Tuscany and Latium. Since basic official statistics on Italian regional sea trade for the 20th century show that the three regions had good connections with Sardinia, they have been each included in Sardinia's neighbourhood. However, things were different in the previous century. Although Latium is close to Sardinia in bird fly distance, it had no important ports, present instead in Liguria and Tuscany.[20]

Denote by $\mathbf{Z} = \mathbf{Y} - \widehat{\mathbf{F}}\widehat{\mathbf{\Lambda}} - \widehat{\mathbf{G}}\widehat{\mathbf{\Phi}}$ the estimated de-factored data, where the hat

[20]For instance, we consulted historical sources on sea transport and found that in 1871 the total tonnage of ships registered in Liguria was above 600 thousands tonnes (of which 25 steam vessells), in Tuscany above 50 thousands, and in Latium only about 2 thousands. Thus, for this period we decided to include in the neighbourhood of Sardinia only Liguria and Tuscany.

indicates estimate[21]. Further, let $\mathbf{Z}^i$ be the $T \times R$ block of $\mathbf{Z}$ including the data for industry i in the R regions and $\mathbf{Z}_t^i$ its t-th row, which collects the observations for all regions at time t. These can be modelled using a Spatial Dynamic Panel:

$$\mathbf{Z}_t^i = \gamma_0 \mathbf{Z}_t^i \mathbf{W} + \gamma_1 \mathbf{Z}_{t-1}^i \mathbf{W} + \rho \mathbf{Z}_{t-1}^i + \mathbf{u}_t^i \tag{7}$$

The key parameter of (7) is the long-run, or static, spillover coefficient $(\gamma_0 + \gamma_1)/(1 - \rho)$. From the dynamic point of view the understanding of (7) may be considerably enhanced rewriting it in *Spatial Equilibrium Correction* (SEC) form, *i.e.* as

$$\Delta \mathbf{Z}_t^i = \gamma_0 \Delta \mathbf{Z}_t^i \mathbf{W} + (\gamma_0 + \gamma_1)(\mathbf{Z}_{t-1}^i \mathbf{W} - \mathbf{Z}_{t-1}^i) + (\rho + \gamma_0 + \gamma_1 - 1)\mathbf{Z}_{t-1}^i + \mathbf{u}_t^i \tag{8}$$

The global (time and spatial) stationarity condition of model (7) is $(\rho + \gamma_0 + \gamma_1) < 1$, which implies that the own starting level must have a negative effect, precisely the condition for regional convergence in the $\beta-$convergence literature.

According to equation (8), growth of value added of industry i in each region at time t around the path determined by the effect of the common factors depends upon three elements:

(i) contemporaneous growth of the same industry in the neighbouring regions, or dynamic spillover effect, $\gamma_0 \Delta \mathbf{Z}_t^i \mathbf{W}$;

(ii) a SEC, or convergence, term, active in presence of differentials between neighbouring regions[22], $(\gamma_0 + \gamma_1)(\mathbf{Z}_{t-1}^i \mathbf{W} - \mathbf{Z}_{t-1}^i)$;

(iii) finally, the own starting level, $(\rho + \gamma_0 + \gamma_1 - 1)\mathbf{Z}_{t-1}^i$.

Hence, conditionally on the common components, growth is expected to be higher in regions with lower own initial levels and with neighbours which have (i) high growth rates and (ii) higher initial levels.

The estimates for the preferred specifications, obtained using the ML estimator by Yu, de Jong and Lee (2008), are reported, respectively for the 19th century and 20th century datasets, in Tables 9 and 10. Let us examine them in turn.

[21] The data for the Leather industry in the 19th century appeared to be almost perfectly correlated with a common cycle, not captured by the filtering. We thus proceeded to further de-factor them fom their simple mean.

[22] Note that this univariate SEC (which has the effect of shrinking spatial differentials of a given variable) has nothing to do with the Error Correction Mechanism which may be defined for a set of variables cointegrated over space (which has the effect of making these to "move in harmony through space", Fingleton, 1999, p. 13).

Table 9: Dynamic Spatial Panel models of de-factored data - 1861-1913

	γ_0	$(\gamma_0+\gamma_1)$	$(\rho+\gamma_0+\gamma_1-1)$	R^2	$LR(\gamma_1=-\gamma_0)$	$\frac{(\gamma_0+\gamma_1)}{(1-\rho)}$
CG Industries						
Food	0.67 (0.02)	0.14 (0.03)	−0.10 (0.02)	0.49	22.94 [0.0]	0.58
Textiles	−0.15 (0.04)	–	−0.18 (0.02)	0.53	0.0001 [99.1]	–
Clothing	0.49 (0.03)	0.16 (0.03)	−0.14 (0.03)	0.50	23.49 [0.0]	0.53
Leather	0.25 (0.04)	0.05 (0.03)	−0.11 (0.03)	0.74	3.98 [4.6]	0.32
Wood	0.84 (0.007)	0.21 (0.02)	−0.06 (0.008)	0.38	71.3 [0.0]	0.79
IIG Industries						
Metal	0.25 (0.04)	–	−0.26 (0.02)	0.54	1.90 [16.8]	–
Eng	0.38 (0.04)	0.13 (0.03)	−0.17 (0.03)	0.53	15.66 [0.0]	0.45
Non Met	0.27 (0.04)	0.11 (0.03)	−0.15 (0.03)	0.59	10.54 [0.01]	0.43
Chemicals	0.27 (0.04)	0.08 (0.04)	−0.14 (0.04)	0.61	4.48 [3.4]	0.35
Paper	0.66 (0.02)	0.19 (0.03)	−0.10 (0.02)	0.57	46.16 [0.0]	0.67
mean	0.48^a	0.13^b	−0.12	0.55		0.51^b
median	0.44^a	0.14^b	−0.12	0.53		0.49^b

In brackets: s.e.'s of coefficient estimates, p-value $\times 100$ of LR test; R^2: squared correlation coefficient between observed and fitted values; ^{a}: of the positive values; ^{b}: excluding the missing values.

5.1 1861-1913

First of all, from the third column of Table 9 we notice that the term $(\rho+\gamma_0+\gamma_1-1)$ is always smaller enough than zero to conclude that the global stationarity condition is satisfied. Note that this implies a (*coeteris paribus*) negative link between initial level of the value added in a given region and its rate of growth. A second remark is that there seem to be considerable heterogeneity within both the consumption goods industries (Food, Textiles, Clothing, Leather) and the intermediate and investment goods ones (Wood, Metalmaking, Engineering, Non metallic mineral products, Chemicals, Paper), so that we shall comment from a general point of view. As a first step, let us examine the last column, which reports the long-run spillover coefficients $(\gamma_0+\gamma_1)/(1-\rho)$, the key parameter of the model in the form (7). There obviously is some heterogeneity, but mean and median are both close to 0.50, suggesting presence of rather strong spillover effects. Of course, we should keep in mind that these effects are conditional on those of the common factors, which vary considerably over regions. Moving to the coefficients of the

SEC reparametrisation (8), we can see from columns 1 and 2 that with two only exceptions both γ_0 and $(\gamma_0 + \gamma_1)$ have always the expected sign and are strongly significant. The two anomalies are the Textile and, partially, the Metal industry. In the former the restriction $(\gamma_0 + \gamma_1) = 0$ cannot be rejected, so that no convergence effects seem to have been in action, and the dynamic spillover coefficient γ_0 has a puzzling negative sign, while in the latter there is no convergence effect.

The dynamic spillover coefficient γ_0 is otherwise rather large, ranging from 0.25 to 0.84 with a median of 0.38. The equilibrium correction coefficients, $(\gamma_0 + \gamma_1)$, ranging from 0.05 to 0.21 with mean and median about 0.14, are somehow smaller but generally strongly significant. These values imply *coeteris paribus* adjustment periods ranging from 5 to 20 years with a typical length around 6 years, a rather short time (but again, conditionally on the effects of the common factors).

5.2 1970-2003

From Table 10 we first see that the global stationarity condition appears to be safely satisfied for the 1970-2003 models as well, confirming the (*coeteris paribus*) negative link between initial value and speed of growth. Second, there are again no obvious differences between the consumption goods industries (Foods, Textiles) on one side and the investment and intermediate goods industries on the other. Third, in the industries where the time-lagged spatial lag coefficient γ_1 is significant the hypothesis of no spatial equilibrium correction $(\gamma_1 = -\gamma_0)$ is always rejected, very strongly in two cases (Food and Non Metals, $p-$values practically zero) and rather strongly in the other two (Textiles and Metals, $p-$values 0.03 and 0.01). Conditional spatial equilibrium correction seems thus to have taken place in all industries. The long-run coefficients $(\gamma_0 + \gamma_1)$ are all but one in the 0.25-0.35 range. This implies adjustment periods between 3 and 4 years, shorter than those estimated for the 19th century. Finally, the long-run spillover coefficients $(\gamma_0 + \gamma_1)/(1 - \rho)$ range from 0.45 to 0.59, with median 0.47, smaller than that estimated for the 19th century data but nevertheless suggesting presence of non negligible spillover effects. Of course, we should always keep in mind that all these spatial correction effects are conditional on those of the common factors, which vary considerably over industries and regions.

6 Conclusions

Our purpose was twofold. First of all, to review the methods currently available for the analysis of regional datasets characterised by possible non-stationarity over time and both strong and weak spatial dependence. Second, to present a representative case study, a comparative analysis of the regional development of the Italian

Table 10: Dynamic Spatial Panel models of de-factored data - 1970-2003

	γ_0	$(\gamma_0+\gamma_1)$	$(\rho+\gamma_0+\gamma_1-1)$	R^2	$LR(\gamma_1=-\gamma_0)$	$\frac{(\gamma_0+\gamma_1)}{(1-\rho)}$
Food	0.50 (0.04)	0.32 (0.05)	−0.22 (0.05)	0.28	17.69 [0.0]	0.59
Textiles	0.18 (0.04)	0.09 (0.05)	−0.36 (0.06)	0.33	4.59 [0.03]	0.20
Metal	0.44 (0.04)	0.30 (0.06)	−0.32 (0.06)	0.16	6.04 [0.01]	0.49
Non Met	0.44 (0.04)	0.26 (0.06)	−0.32 (0.06)	0.18	12.4 [0.0]	0.45
Paper	0.30 (0.04)	0.30^a (0.04)	−0.36 (0.05)	0.13	$-^a$	0.45
Wood	0.34 (0.04)	0.34^a (0.04)	−0.31 (0.05)	0.14	$-^a$	0.53
mean	0.37	0.27	−0.32	0.20		0.45
median	0.39	0.30	−0.32	0.17		0.47

In brackets: s.e.'s of coefficient estimates, p-value $\times 100$ of LR test. ^{a} : $\gamma_1 = 0$. R^2: squared correlation coefficient between observed and fitted values.

manufacturing industry in the second halves of the 19th and 20the century.

With the respect to the first point, our conclusion is that the choice of the modelling strategies must be dictated by the characteristics of the dataset: how many common factors are likely to be present, and if they are observable or not. In the simple case when the common factor structure can be adequately specified *a priori*, the best option is arguably to follow Halleck Vega and Elhorst (2016), specifying factor-augmented spatial models capturing simultaneously weak and strong spatial dependence. In the more general (and probably common) case when the data depend upon an unknown number of unobservable common factors we suggest a two-step modelling strategy, similar to that advocated by Bailey *et al.* (2016). First, fit a dynamic factor model, with the number of factors estimated using one of the information criteria proposed in the literature and factors and loadings by PCs. As discussed below, in some circumstances an hybrid approach making joint use of PC and simple averages may be required. Second, test the hypotheses that the estimated residuals are (*i*) non-stationary over time, and, (*ii*) weakly dependent over space. If the former is rejected and the latter is not proceed to estimate a dynamic spatial panel model for the de-factored data.

Following this modelling strategy we have been able to explore thoroughly our datasets. The first step was to estimate the number of non-stationary factors. Exploiting the procedure by Bai (2004) we found just two non-stationary factors sufficient to explain long-run growth of the all the series examined both for the 19th and the 20th century. The factors are remarkably similar for the two datasets, an essentially monotonous trend and a very long cycle, non stationary over the period of study.

The second step, estimating the common stationary factors, turned out to be unnecessary for the 20th century data, as the weak dependence hypothesis cannot be rejected for the de-factored data. For the 19th century data the stationary factors could have been in principle be carried out also applying Bai's methods, but in practice this turned out to be unreliable. We thus opted for an hybrid approach, setting a priori the number of common stationary factors to two (the common cycles of consumption goods industries and intermediate and investment goods industries) and estimating them using cross-section averages as in Pesaran (2006). This choice, although entirely a priori, is supported by the finding that de-factored data are only weakly dependent over the cross-section dimension.

The final step of the study, namely the estimation of dynamic spatial panel models, revealed for both datasets a tendency to *conditional* convergence across neighbouring regions. In view of the large regional differentials typical of the Italian economy this may appear surprising. However, we should recall that these convergence effects are conditional on those of the common factors. The spatial structure of the loadings highlights a deep regional reallocation of the Italian manufacturing industry occurred over the last 150 years. In the 19th century factor loadings have a clear spatial pattern resulting in growth much faster in the North, especially the North-West, than in the South: we could thus have growing regional differentials in presence of significant *conditional* convergence effects. In the 20th century the spatial structure of the loadings changes, with the NW lagging behind, and the NE and some of the regions of the Centre and the South undergoing a phase of more accelerated growth, with positive contribution from both factors in the 1970's. Since about 1980, negative contributions from the second factor result in the convergence process of the South reaching an end, while this continued for the North-Eastern regions.

Appendix A

A1 Data

The data for 1861-1913 are taken from a comprehensive dataset of annual time series of value added at 1911 prices, disaggregated for 12 industries and 16 Italian regions at 1911 borders (Ciccarelli and Fenoaltea, 2009, 2014). The series are available at the Bank of Italy website `https://www.bancaditalia.it/pubblicazioni/altre-pubblicazioni-storiche/produzione-industriale-1861-1913/`, while others (including Food, Wood, Paper) are still preliminary, and are based on ongoing research. The data have been constructed on the basis of a wide set of primary historical sources, including industrial and population census. The estimation strategy varies with the industrial sector and the historical sources available, and thus cannot be described in full detail here. However, the first step has always been to obtain data for physical production of the single products at the regional level. For instance, in the case of the Chemical industry regional volume time series for about 100 products (various acids, fertilizers, rubber, etc.) have been constructed. Then, each volume series has been transformed into a value added series at 1911 prices using a unit value added coefficient evaluated for 1911. These coefficients have been estimated using historical data on wage and capital (for details see Ciccarelli and Fenoaltea, 2009, 2014 and references therein).

The data on value added at 1995 prices for 1970-2003 which cover six industries for 20 regions have been downloaded on October, 2, 2016 from the website of the CRENoS research centre of the University of Cagliari (`http://crenos.unica.it/crenos/databases/database-regio-it-1970-2004`).

Figure A1: Italian regions

The colors are broadly indicative of the macroareas (North-West, North-East,Center, Continental South and Islands) usually considered in the literature.

The four regions added to the 16 already existing in the 19th century are Aosta Valley, a small area of the Western Alps formerly included in Piedmont; Friuli-Venezia Giulia, formed by the north-eastern part of Venetia and the towns of

Trieste and Gorizia, part of the Austrian empire until 1918; Trentino-Alto Adige, north of Venetia, also annexed from Austria after the First World War; Molise, a small area formerly part of Abruzzi. Consequently, the modern regions Veneto and Abruzzi are respectively (and approximately) defined as 19th century Venetia minus Friuli-Venezia Giulia, and 19th century Abruzzi minus Molise. The borders of the 20 regions are mapped in Figure A1.

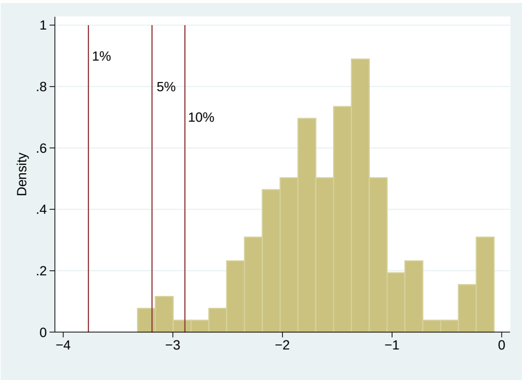
A2 Unit root tests

A2.1 Data

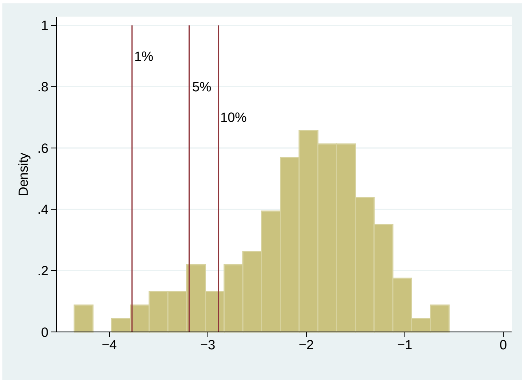
Following routine practice, we tested the hypothesis of non-stationarity of the data using the ADF-GLS test by Elliot et al. (1996), allowing for a linear deterministic trend and selecting the lag length on the basis of the modified AIC criterion. Results are summarised in Figure A2, panel A. As it is immediately seen, using customary significance values almost all statistics fall in the non-rejection region. More precisely, no statistic falls below the 1% critical value (the smallest statistic is -3.32, much higher than the 1% critical value, -3.77), and only two and five (out of 159, hence 1% and 3% of the total) respectively exceed the 5% and 10% critical values. In the light of this overwhelming evidence we did not consider necessary to run a proper panel unit root test to conclude the all the series of our dataset are non-stationary.

Figure A2: ADF-GLS unit root tests with constant and trend

A. 1861-1913



B. 1970-2003



The vertical lines represent the critical values of the test (10%=-2.89; 5%=-3.19;1%=-3.77)

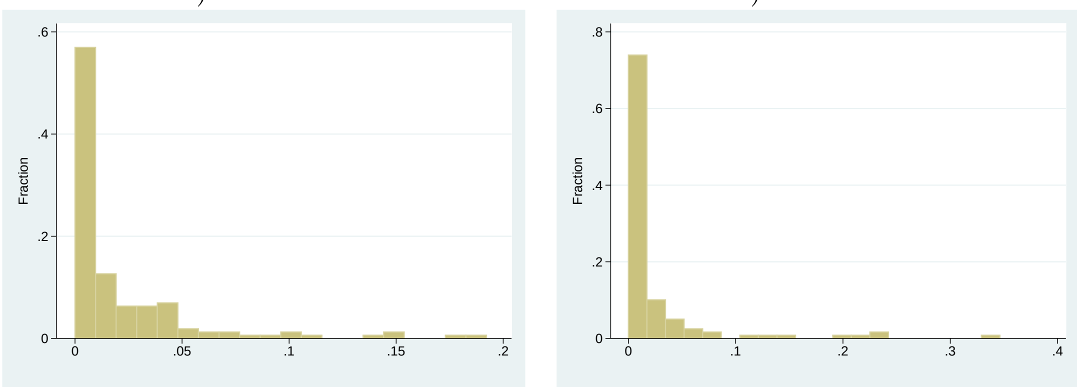
From Figure A2, panel B we can see that a century later behaviour appears somehow less non-stationary: for instance, at the 5% significance level one tenth of the tests suggest rejection. We thus run a formal panel unit root test, the bootstrap F-test by Chang (2004). The estimated F statistic for H_0 : "all series are $I(1)$" is 20.95, with a probability under H_0 estimated by the bootstrap (1000 redrawings) as 29.9 percent, comfortably higher than any customary value. We can then conclude that the series as a panel are non-stationary.

A2.2 Factor model residuals

Here we provide some more detail for the 19th century tests, as those for the modern period, also graphically illustrated in this Appendix, are discussed in the main text. Consistently with *a priori* expectations of stationarity, from Fig. A3 we can see that 90% of the p-values of the statistics for the individual residual series are smaller than 0.10. The impression of stationarity is fully confirmed by Chang's (2004) testing procedure. The F-statistic for H_0 : "all residuals are $I(1)$" is 165.26. Using 1000 redrawings the entire bootstrap estimate of the distribution of the statistics lies on the left of this value, so that the bootstrap estimate of its p-value is zero at all decimal digits.

Figure A3: P-values of the ADF unit root tests of non-stationarity of the residuals of the factor model with two non-stationary factors.

A) 1861-1913 B) 1970-2003



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