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Why Italy and not Spain? Comparing two industrialization processes from a dissagregate time-series perspective

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Abstract

This study presents new evidence concerning the uneven processes of industrialization in nineteenth century Spain and Italy based on a disaggregate analysis of the productive sectors from which the behaviour of the aggregate indices is comprised. The use of multivariate time-series analysis techniques can aid our understanding and characterization of these two processes of industrialization. The identification of those sectors with key roles in leading industrial growth provides new evidence concerning the factors that governed the behaviour of the aggregates in the two economies. In addition, the analysis of the existence of interindustry linkages reveals the scale of the industrialization process, and where significant differences exist, accounts for many of the divergences recorded in the historiography for the period 1850-1913.

Why Italy and not Spain?
A comparison of two processes of industrialization from a disaggregate time-series perspective

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Introduction

In 1996 and 1997 *Economic History Review* published two appraisals of recent contributions on the contemporary economic development of Spain and Italy prior to the Second World War. In his study of Spain, James Simpson described the situation as one of slow growth.[1] By contrast, Giovanni Federico entitled his study "Italy, 1860-1940: a little known success story".[2] The assessments of these two authors were based on the growing quantitative evidence of the healthy growth experienced in the Italian economy during the *giolittiano* period, in contrast to the relative stagnation of the Spanish economy during the second half of the nineteenth century, especially during the Restoration of the Bourbon monarchy.

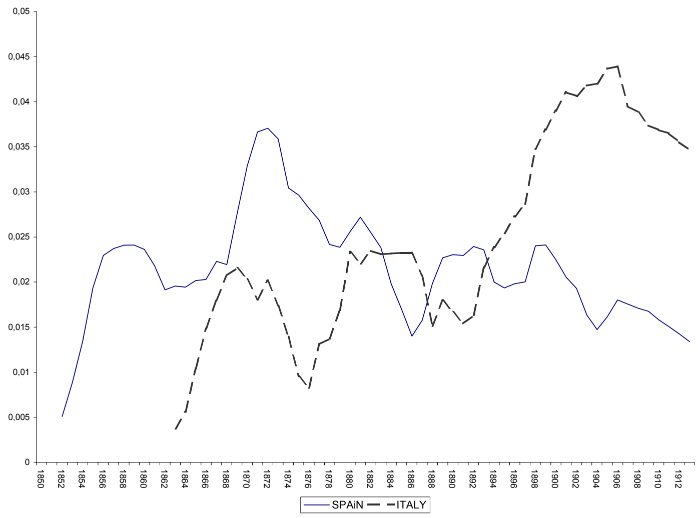
A comparison of the evolution in industrial output shows that this situation is the result of marked differences in the rate of industrial development. The indices of industrial output that are available support the opinions presented in seminal historiographical studies of the development of nineteenth century Spain and Italy. In 1975, Nadal[3] considered that industrialization in Spain had failed to take a strong foothold; after a promising early start, the sector lost momentum as the last thirty years of the nineteenth century wore on. In contrast, the pioneer works of Gerschenkron stated that only during the final decade of the nineteenth century did a break occur in the behaviour of Italian industry, which was to represent the beginning of the process of industrialization.[4]

[1] Simpson (1997).
[2] Federico (1996). A similar interpretation is provided by Rossi and Toniolo (1992) and (1993).
[3] Nadal (1975).
[4] Gerschenkron (1966).

Graph 1

Trend growth in industrial output

(Kalman Filter Estimation)



Using more recent evidence, Graph 1 quantifies the behaviour of the two aggregates.[5] It shows the estimated growth of industrial output in Italy and Spain once the cyclical and trend components are separated via the Kalman filter.[6] It can be seen that the rate of growth of Spanish industry began to slow down at the start of the 1870s. In contrast, in Italy, industrial production continued to grow, particularly from the last decade of the nineteenth century onwards.

The object of this study is to characterize the processes of industrial growth described using multivariate time-series techniques, in the hope that our comparison will help us to define the causes of the apparent divergence between the paths of development taken by Italy and Spain in the second half of the nineteenth century.

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[5] The Indices of Industrial Output used for Spain and Italy in this study are those presented by Carreras (1983).

[6] For more on the method used in making the estimation see Harvey and Jaeger (1993).

To do so, in the first section we outline the methodology of the study, stressing its links with other recent studies that have provided a macroeconomic characterization of the process of industrialization in Britain. We then present and discuss the data used. The third section analyses the situation in Spain, and studies the existence of stochastic trends in the industrial output by sector groupings and analyses the existence of common trends in and between different groupings of industry. Section 4 does the same for the Italian economy. Finally, section 5 presents the study's main conclusions from the perspective of an understanding of the uneven behaviour of Spanish and Italian industries on the basis of a comparison of the results from the two previous sections.

Macroeconomic characterization of the processes of industrialization: methodological considerations

The studies carried out in the 1980s that reworked basic macroeconomic series, including domestic product and industrial output (Harley, 1982, Crafts, 1985, and Crafts and Harley, 1992), led economic historians to revise the traditional theories according to which the Industrial Revolution was held to be a process that caused a sudden transformation of British society and its economy.[7]

This new quantitative evidence has helped to refine these interpretations from a range of perspectives. On the one hand, a more gradual vision of British economic development during the eighteenth and nineteenth centuries has come to be accepted. On the other, stress has been laid on the importance of agrarian change and the foreign sector in accounting for the growth in per capita GDP. Finally, historians have emphasised the localization of major changes in techniques and forms of production in a small range of sectors, such as cotton, iron and steel, and transport. It was this group that contributed, almost exclusively, to the total factor productivity (TFP) growth in industrial output during the key period of what was known as the British Industrial Revolution.

[7] This was the view presented in the contemporary accounts, and that which was described in the classic studies of Economic History such as Deane and Cole (1969), Landes (1969).

Thus, having abandoned the idea that the process of industrialisation was a central element in accounting for economic development, new evidence has been presented that requires a more careful interpretation. British industry recorded very high growth rates between 1776 and 1834, but after this period such rates were not recorded again. Indeed, after this episode, the rate of industrial growth would never be the same.

With this the evidence for analysis, the problem has come to be seen in terms that are of greater interest, and of more relevance, to theoretical and applied economists. It is these scholars who can help in the development of theoretical frameworks that might provide hypotheses to explain this type of behaviour, and empirical methods that can be applied in their testing.

This approach is precisely that which has been adopted by Nick Crafts (1995) in an influential study. In this paper, Crafts tackles the quantitative and qualitative evidence describing the process of industrialization in Britain with various proposals emanating from economic growth theory. With new data, he argues that the neoclassical models, even if we consider the extensions made to them in the 1990s (Mankiw, Romer and Weil, 1992), fail to provide a full explanation of the data available on the British Industrial Revolution. In other words, he rules out any interpretation based on these models because it means that the total factor productivity growth that appears in the growth accounting exercises applied to the period to be considered in a totally exogenous way.

He argues that the new economic growth theory offers various ways of explaining this growth endogenously. Thus, he distinguishes between those models in which it is capital accumulation, albeit defined in its widest sense (Rebelo, 1991), that is the source of growth and those which attach greater importance to technical progress and its further development via learning processes (Grosman and Helpman, 1991 and Young, 1993).

After comparing the interpretations of these models with the quantitative and qualitative evidence available for Great Britain, he concludes that the first group of models does not offer a good explanation of British industrialisation. In particular, he points out that although the consideration in its entirety of the externalities generated by the accumulation of certain forms of capital might account for the totality of growth without the need to consider technical progress, it could hardly explain other evidence available for the period. After 1899 the rate of TFP growth fell and even became negative, without there being any evidence to suggest the existence of a reduction in the rate of investment in machinery, infrastructure, human capital, and other forms of capital suggested by models of this type.

In contrast, he argues that the second group of models offers explanations that are in closer agreement with available evidence. On the one hand, the microeconomic bases highlighted in these models coincide more closely with the qualitative accounts offered by economic historians. On the other hand, they can provide a good explanation of the quantitative evidence available in as much as, in the case of models such as those described by Young (1993), the existence of processes of bounded learning shed light on the existence of long periods of time with strong TFP growth as well as a down turn in this growth in the long run.

From an empirical perspective, attempts have been made to settle the debate using techniques of time-series analysis. In other words, by seeking to characterize the aggregate series of industrial output in a way that we can identify the type of components that generate this persistence in their stochastic or deterministic growth rates.

This line of analysis is the one taken by Greasley and Oxley (1994) for the British Industrial Revolution. The authors provide evidence to support the existence of stochastic trends in the industrial output series and claim that the industrial revolution constitutes a distinct macroeconomic epoch. Mills and Crafts (1992) and (1994) on the other hand, argue that the statistical behaviour of the domestic product and industrial output series can be better characterized as that of stationary series with break points. In particular, they point out that the industrial production series behaves like a stationary series with break points and a deterministic tendency in the years, 1776, 1834 and 1874.

Seen in these terms, the studies of this type tackle a debate that cannot easily be settled. In as much as the theoretical models suggest different ways to interpret the existence of persistence phenomena in the time series, the testing of alternative hypotheses via their statistical properties is hindered by the time period analysed, when not sufficiently long, and by the quality of the aggregate series being studied.

Finally, in the last few years a method has been proposed that takes the analysis and characterization of the processes of industrial growth a step further. Recently, Greasley and Oxley (2000) have used the disaggregated information that forms the basis of the industrial ouptut index to further our understanding and characterisation of British industrialisation using techniques of multivariate time-series.[8] The authors argue that the use of information grouped by sector allows them to overcome some of the typical problems in preparing historical indices of aggregate industrial production. In particular, reference is made to the criticisms these receive in relation to the weightings assigned to the data from different sectors.

In addition, some studies have undertaken a generic criticism of the implications of the statistical characterization of aggregate series. Norrbin (1995) points out the difficulty in drawing conclusions from aggregate series, that is, series that are the weighted sum of many individual behaviours. In these conditions, the characterization of an aggregate series based on a single stochastic behaviour hides the statistical wealth contained in the whole series. He proposes studying directly the statistical properties of the disaggregate series.

We believe that proposals of this type are particularly appropriate for the characterization of the processes of industrialization. First, if what we seek to understand is the genesis of persistence phenomena in the behaviour of the aggregate series and we accept that such behaviour might be due to the existence of macroinventions and learning processes, then the existence of persistence phenomena can be related to the number of sectors that share this dynamic, as well as to the existence of technological connections between different sectors, which share major technological developments or which allow the survival of learning processes.

[8] Greasley and Oxley (2000).

This is the approach adopted in this study, as we believe the use of disaggregate information to be particularly appropriate for an analysis of the Italian and Spanish processes of industrial growth. In both cases, the indices of aggregate industrial output are the object of continuous criticism and revision.[9] In addition, the application of techniques of time-series analysis in a comparative allows us to extract more information than that which could be derived from a national study. First, by identifying which are the key sectors in the industrial growth in each case provides evidence as to which factors determined the comparative behaviour of the aggregates. In addition, the analysis of the existence of interindustry linkages reveals the scale of the industrialization process, and where significant differences exist, accounts for many of the divergences recorded by the historiography.

Sector data

The data needed to undertake an exercise of this kind are indices of industrial output for each sector in constant or physical terms. The number of series considered should offer a wide coverage of total industrial output and a disaggregation that allows the existence of specific *shocks* to be identified for individual activities. Finally, given that the aim of this study is an international comparison, it is essential that the base series be homogenous.

Given these requirements, from among the industrial output indices available, we chose to work with those compiled by Albert Carreras, both in the case of Spain and Italy, taking advantage of the rich data source used in his PhD thesis entitled: "Spanish and Italian industrial output from the middle of the XIX century to the present day".[10] In fact, none of the alternatives met all the requirements of the study we proposed undertaking.

[9] In the case of Spain see the critical review undertaken by Prados de la Escosura of the index drawn up by Carreras. Prados de la Escosura (1988), pp. 139-167. Prados de la Escosura has offered a number of reworkings of this index, the most recent being Prados de la Escosura (1995). In the case of Italy a number of estimations are available for the period 1861-1913, Gerschenkron (1966), Ercolani (1969), Fenoaltea (1982) and Carreras (1983). Critical commentaries on these estimations can be found in Carreras (1983), pp. 737-743, and in Federico and Toniolo (1991).

[10] Carreras (1983).

In the case of Spain, a possible alternative might have been to have used the basic series forming the aggregate index drawn up by Prados de la Escosura. However, he offers an insufficient number of sector series and, furthermore, the different aggregations on which it is based would make comparison with the Italian series difficult.[11] In the case of Italy, perhaps the most appropriate alternative would have been the sector indices used by Fenoaltea in drawing up his industrial output index.[12] However, the use of Fenoaltea's data would have given rise to problems in conducting the comparison with Spain. First, Fenoaltea excludes mining and the silk industry, both of which are included in the Spanish estimations. Second, he always, where available, makes use of output data. This hinders any comparison with the Spanish series, which was not drawn up from direct indicators of output. As is well known, in Spain, the lack of sources has meant that the industrial output series has had to be prepared using an estimate based on the apparent consumption of raw materials. Thus, the advantage of the Italian industrial output series prepared by Carreras is that it renounces the use of direct information on output and draws up sectoral series using similar criteria to those used for Spain. This procedure discards information that might be relevant, but ensures that the two series are homogenous.

We aimed at studying the greatest number of years in the period before the First World War. To do this, we decided to maximize the number of years analysed, imposing as the sole restriction the existence of data for a sufficient number of sectors. Thus, while Carreras' index of industrial output for Spain begins in 1842, the number of series available for this data was insufficient. The number of disaggregate series only becomes large enough in 1850 for us to be able to carry out our study. In the case of Italy, the minimum number of series is reached in the first year, that is 1861, for which data for unified Italy become available.

[11] In the most recent version, the author presents output series for ten groups of industry together with a mining output series, beginning in 1850, Prados de la Escosura (1995).
[12] We refer only to those that are currently available, as the new industrial output series currently being prepared by Fenoaltea have not yet been published. Fenoaltea (forthcoming).

Finally, the data base in the case of Spain comprises 30 sectoral series and the aggregate industrial output index, for the period 1850-1913.[13] In the case of Italy, it comprises 35 sectoral series and the aggregate industrial output index, while the period considered is 1861-1913.[14] The disaggregate series are grouped, in both cases, in five groups: Energy, Minerals, Transformation of metals, Food, Textiles and Other Industries.

Spain: stochastic trends and common movements in the disaggregate industrial output data

The disaggregate time series analysis gives rise to a set of highly interesting perspectives for the historical study of industrialization. First, if the aggregate indices contain stochastic trends, only those sectors in which this type of behaviour is recorded can contribute to explaining the growth trend in the aggregate.[15] Thus, those industries that make it up, whose production evolves by following a stationary trend, cannot mould their trend behaviour, as this has a stochastic character that is absent in this series set. Therefore, the delimitation of individual industries with stochastic trend behaviour allows us to identify the sectors that characterize the long-term behaviour of the aggregate indices.

In addition, the existence of stochastic trends in aggregate and disaggregate series of industrial output has been associated with the appearance of productivity shocks that have persistent effects.[16] At the sector level, this evidence could respond to the introduction of technical innovations with permanent effects on output.

Thus, the first step in our study is to identify the existence of stochastic trends in the aggregate indices of industrial production. In this case, the task was undertaken not only

[13] Actually Carreras provides 33 sectoral series for the whole of the period considered. In our case we have aggregated four of them in one (TME5) which is the sum of the series corresponding to the transformation of mercury, silver, lead and zinc.
[14] In the case of Italy 45 sectoral series are actually available, though we have made the following aggregations. The series MIN1 is the sum of antimony, manganese, mercury, lead and zinc. TME3 aggregates the first transformation of mercury, silver and lead. TME6, the manufacture of tin, lead and zinc. VAR5, materials for the railways, groups together the series for the production of locomotives, carriages and wagons.
[15] In Greasley and Oxley (2000), p.100, it is argued that the persistence in the aggregate indices can only be explained by the existence of disaggregate series that show nonstationary behaviour.
[16] King, Plosser and Stock (1991) and Norrbin (1995).

with Carreras' index (1983), but also with that prepared by Prados de la Escosura (1995). The results are shown in Table 1. It can be seen that the null hypothesis of stationarity is rejected in the aggregate series while the existence of a stochastic trend is not rejected by the Augmented Dickey-Fuller test (ADF).[17]

Table 1

Identification tests in aggregate series

Industrial Output Series	ADF	c,t (a)	k (b)	Reject I(1) (c)
Carreras	-2,8559	c,t	3	---
Prados	-2,1115	c	3	---

Notes.- The critical values are from MacKinnon (1991).
(a) Deterministic elements included: (c) constant, (t) trend
(b) Number of lags considered
(c) Level of significance at which the null hypothesis is rejected. A maximum level of significance of 10% was considered. (---) denotes the non rejection of this hypothesis.

Based on this evidence, the next step is to identify which disaggregate series contain stochastic trends and, therefore, might help account for the trend behaviour of the aggregate indices. The results of this exercise are shown in table 1 of Appendix 1. Below, in Table 2, the sectors in which the existence of stochastic trends are identified and those that show a stationary behaviour are listed.

All the industrial groups include one or more sectors that have stochastic trends and which, therefore, collaborate in the genesis of the growth of the aggregate series. In particular, and in relation to the most widely expressed opinions in the historiography concerning which sectors provide the key to explaining Spain's industrial progress, it can be seen that the sectors that are most characteristic of Spanish industrialisation - namely the coal, iron, mercury and copper mining industries, the production of iron, steel and copper and, of course, cotton yarns and pieces - contain stochastic trends in their output time series.

[17] For the procedure taken see Banerjee et al. (1992) and Harris (1995).

Table 2

Summary of the results of the identification tests in the disaggregate series

Series with stochastic trends		**Stationary series**	
ENERGY			
Series	**Code**	**Series**	**Code**
Coal	M2	Gas	M1
MINERALS			
Iron	M3	Manganese	M4
Mercury	M5	Sea salt	M6
Pyrites	M7	Lead	M8
PRODUCTION and TRANSFORMATION OF METALS			
Pig Iron	TME1	Transformation of Copper	TME4
Iron and steel	TME2	Mercury-Silver-Lead-Zinc	TME5
Copper	TME3	Transformation of Iron	TME6
Tin	TME7		
FOOD			
Cocoa	ALI1	Preserves	ALI3
Coffee	ALI2		
Tobacco	ALI4		
TEXTILES			
Cotton Yarn	TEX1	Wool	TEX3
Cotton Pieces	TEX2	Silk	TEX4
Hemp and Linen Yarn	TEX5	Hemp and Linen Goods	TEX6
		Jute	TEX7
OTHERS			
Shipbuilding	VAR4	Leather and Furs	VAR1
		Cork	VAR2
		Paper	VAR3

Note.- See table 1 in Appendix 1.

It is interesting to highlight how light industrial sectors such as tobacco, coffee and the production of chocolate present this behaviour, as does an industry in the heavy industrial sector, namely shipbuilding. In contrast, important sectors of Spain's industrial output, including paper, cork, leather, preserves and wool, reject the presence of stochastic trends. A final point of note is the absence of stochastic trends in the transformation of metals (with the exception of tin),when they are to be found in their production phases.

These results widen the list of sectors involved in the nineteenth century industrialisation of Spain - in comparison to the basic three in Britain (cotton, iron and steel and coal) - to include the mining of certain metals, which indeed were the focus of early studies of Spanish industrialisation in the 1970s.[18] A number of sectors are also identified which,

[18] Nadal (1975), Tortella (1973).

while not of the same weight, present a growth rate that shows the existence of behaviours that were typical of those activities that incorporated technological innovations which had a persistent effect on their growth rates. Thus, the high rate of modernization experienced by the tobacco industry since the last decades of the nineteenth century,[19] the incorporation of steam driven machines in the production of chocolate, the shift occurring in the shipbuilding industry towards the production of boats with steel hulls, all well documented by the historiography, appear to have been sufficiently far-reaching to have endowed their output series with this behaviour.[20]

However, at the same time the absence of sectors with a high specific weight in Spain's traditional industry is confirmed. This result should come as no surprise. In the case of wool, a number of studies have described the slow, incomplete process of mechanisation in the sector. In fact, by 1900, almost 50% of the wool mills in Spain were still operated manually.[21] With some exceptions, the leather and tanning industries continued to use the technology of the XVIII century throughout the period under review. Only the introduction of electric energy and the extraordinary circumstances surrounding the First World War began to change these parameters.[22] The mechanization of paper production, associated with the introduction of uninterrupted production, was perhaps initiated in the second third of the nineteenth century, but its diffusion did not lead to the abandoning of manual production in many areas. Furthermore the use of wood pulp as a basic fibre was unheard of until well into the XX century.[23] The modernization of the preserves sector was insignificant until well into the XX century. Fish processing and, above all, the introduction of uninterrupted production techniques was not complete until the 1960s.[24] The cork industry was also slow to incorporate technical innovations, which, since the end of the

[19] Alonso (1994) identifies three main periods in this process of modernization: 1887-1903, 1905-1913 and 1921-29. The changes saw the introduction of steam as the main energy source, as well as the mechanization of the processes of preparation and elaboration of loose tobacco, and the introduction of mechanization in operations involving the rolling of cigarettes. Alonso (1994), pp. 181-187.
[20] For a general overview of the technological changes in these sectors, see Nadal (1988).
[21] Nadal (1988), p. 38. For a summary of the changes and restrictions present in the mechanization of woollen textiles see Benaul (1994).
[22] The technological backwardness of the processes used in most of Spain's tanneries until well into the XX century is well documented in Torras i Ribe (1994).
[23] In 1890, only two factories used wood pulp as their basic input. Gutierrez (1994), p. 356-359.
[24] See Carmona (1994), pp. 140-144.

nineteenth century, had allowed the German, British and US manufacturers to mechanize production and to offer new products such as the agglomerates.[25]

In short, seen in this light, the industrialization of Spain was characterized by the coexistence of many different individual experiences. Overall, however, the absence of any significant changes in a wide range of sectors, with considerable importance in any estimation of the industrial output of Spain, characterised the industrialisation of Spain. By contrast, our study also reveals the number of sectors involved in the delimitation of the dynamic trend of the aggregate. This is in fact more numerous than the much smaller group composed of those that have been called the sector leaders of the nineteenth century process of industrialisation.

However, attempting to characterize the evolution of the aggregate by considering such a wide set of individual experiences is hardly recommendable. Indeed, the techniques of time series analysis allow us to explore a hypothesis whereby we can undertake a simpler characterisation of the dynamics of the aggregate and of the series of which it is comprised. We can try to identify the existence, within each sector, of a trend or a small group of trends that serve to characterize the evolution of the set. In other words, we can try to identify the existence of stochastic common trends within the different industrial aggregates.

The existence of these behaviour types has a direct historical interpretation. First, the proclivity with which technological waves appear in productive sectors with common features is a fact that has frequently been described in the historiography. Furthermore, in some sectors, it is the modernization of certain lines of production which stimulate the adoption of similar innovations in other production lines.

This is the test that we ran on all those groups in which more than one series with a stochastic trend had previously been detected, namely minerals, transformed metals, textiles and others. To do this, the procedure followed was that proposed in Johansen (1988) and developed further in Johansen (1991) and (1995). It involved determining the

[25] Zapata (1996), pp. 44-46.

number of cointegrating vectors among the nonstationary series identified in each group, and then using this information to determine the number of different stochastic trends. Thus, it should be borne in mind that the number of lags in the vector autoregressive (VAR) model estimated in each case was determined using the criteria of maximizing the corresponding probability function.[26] In Table 3 the results obtained are summarised for the industrial groups. A detailed view is to be found in tables 2 to 5 of Appendix 1.

Table 3

Summary of VAR model estimates by sector

Sectors	Series with stochastic trends	Cointegrating vectors	Stochastic trends
Energy	1	---	1
Minerals	3	2	1
Transformation of metals	4	2	2
Food	3	2	1
Textiles	3	2	1
Others	1	---	1

Note.- See tables 2 to 5 of Appendix 1.

We can conclude that in three of the four groups, one sole trend defines the behaviour of all the nonstationary series in the group. Only in the group of transformed metals does the existence of two cointegrating vectors present in four series with a stochastic trend point to the persistence of two distinctive stochastic trends. This can be interpreted as an indication of the existence of intraindustry linkages that permit the appearance of common trends in the behaviour of each group of industries.

Thus, in the case of the textile industry, Jordi Nadal argues that the process of modernization of the hemp-linen and woollen industries was the result of the imitation of the cotton model. The food industries followed similar technological processes (adoption of rolling systems in all processes involving milling), albeit marked by the specific requirements of each line of production. As for the mining industries, they introduced the same types of technical progress, including the use of steam power in all extraction

[26] Hamilton (1994).

processes.[27] It is therefore of little surprise that its behaviour is marked by the persistence of the same type of shocks.

To obtain a simpler characterization of the evolution of the aggregate, and to compare the existence of stochastic common trends between sectors belonging to different industrial aggregates, we studied the existence of cointegrating vectors in which industries from different sectors participated. Evidence of this type allows us to identify the existence of permanent interindustry linkages. Specifically, of the possible combinations we present those that link the behaviour of the textile sector with the rest of the groups. The reason for this is that the historiography identifies this as being the pioneer sector and the leader of the Spanish industrialization process. Furthermore, the existence of important connections between this industry and a large number of productive sectors have been described. Links have been highlighted with the development of the merchant marine, with the leather industry and with coal production, necessary for the transmission of energy.[28]

A summary of the results obtained is shown in Table 4. Here again, detailed results can be found in tables 6 to 10 of Appendix 1.

Table 4
Summary of VAR model estimates between sectors

Sectors	Series with stochastic trends	Cointegrating vectors	Stochastic trends
Textiles/Energy	4	2	2
Textiles/Minerals	6	4	2
Textiles/Trans-formation of Metals	7	3	4
Textiles/Food	6	4	2
Textiles/Others	4	2	2

Note.- See tables 6 to 10 of Appendix 1.

In none of the combinations analysed is the number of cointegrating vectors higher than that detected when the industrial sectors are considered separately. In other words, no

[27] Nadal (1988) provides a general overview of the technological changes introduced in the different sectors during this period.
[28] Nadal (1988), p. 37.

stochastic common trends were found between the different industrial groups, which would have accounted for the absence of any intersectoral links that had permanent effects. This evidence, therefore, highlights the little importance attached to interindustry links in the industrialization of nineteenth century Spain. The process, therefore, did not enjoy the breadth nor the intersectoral linkages that most probably characterized other contemporary national experiences. Below, we seek to examine this hypothesis in greater detail.

The Italian experience: a comparison

Having characterized the behaviour of Spanish industry, the same type of analysis was then conducted for the Italian series of industrial output. A comparison of these results should shed light on the characteristic elements of the uneven trends in the behaviour of the Spanish and Italian aggregates of industrial output.

As with Spain, the first step is to determine the existence of stochastic trends in the aggregate series of industrial production. In this case, the analysis was conducted on three aggregate estimations: one that can be deduced from the individual series from which we built this analysis (Carreras, 1983), one devised by Ercolani following a revision of the ISTAT series (Ercolani, 1969) and one provided by Fenoaltea (1967, 1982). Table 5 shows how, regardless of the industrial aggregate under consideration, the series behave in a nonstationary way. However, the result obtained in Ercolani's series should be treated with caution as it seems to present a break point during this period.[29] Were this to be the case, the tests to which the series are subjected when seeking to identify them might be biased towards the rejection of the hypothesis of stationarity when, in fact, the series is stationary around a mean or a broken deterministic trend.

[29] In particular the appearance of a break point is associated with the existence of a structural change in the model estimated for the data generating process. This might be related to a significant change in the parameter associated with the mean, the trend or both. In this case, this possibility was pointed out earlier by Federico and Toniolo (1991).

Table 5

Identification tests in aggregate series

Industrial Output Series	ADF	c,t	K	Rejection I(1)
Carreras	-1,6511	c,t	0	---
Fenoaltea	-2,2110	c, t	1	---
Ercolani	-1,0345	c, t	0	---

Note.- See Table 1.

Given these circumstances, it becomes necessary to identify the disaggregate series that present stochastic trends. This evidence is also summarised in Table 6, while detailed information can be found in table 1 of Appendix 2. Note that the number of series containing stochastic trends is greater in the Italian than in the Spanish case. The comparison between the two countries reveals the existence, in the case of Italy, of nonstationary behaviour in a number of metal transformation industries, in food sectors with a high specific weight, such as flour and preserves and in most of the sectors of textile production.

These results endorse the findings reported in the historiography of the development of Italian industry. Although opinion is not unanimous, a number of studies have highlighted the large number of sectors involved in the industrial *boom* of the *giolittiano* period.[30] Thus, in addition to the leading roles attributed to the cotton industry, iron and steel and mining, sectors that were not leaders, such as the silk and wool industries in the textiles sector,[31] flour and oil in the food sector, and the production of gas in the energy sector,[32] also presented strong rates of growth. Finally, a further constant in accounting for the dynamic state of Italian industry was the role played by sectors linked to mechanical engineering.[33] These findings seem to be supported by the evidence presented in Table 6 which allows us to characterize the Italian industrialisation process as one which included, in contrast with the Spanish case, a wide spectrum of sectors.

[30] Toniolo (1988) and Zamagni (1993).
[31] See Federico (1997) for the case of the silk industry and Fenoaltea (2000) for that of the woollen industry.
[32] Zamagni (1993), p. 94.
[33] Zamagni (1993), pp. 95-96

Table 6

Summary of the results of the identification tests in the disaggregate series

Series with stochastic trends		**Stationary series**	
ENERGY			
Series	**Code**	**Series**	**Code**
Coal	M3	Petroleum drilling	M4
Gas	M2	Petroleum refining	M1
MINERALS			
Iron	MIN3	Antimony-Manganese-Mercury-Lead-Zinc	MIN1
Copper	MIN2	Sea salt	MIN5
Pyrites	MIN4		
Sulfur	MIN6		
PRODUCTION and TRANSFORMATION OF METALS			
Pig Iron	TME1	Production Mercury-Silver-Lead	TME3
Soft Iron	TME2	Transformation of copper	TME5
Transformation of iron and steel	TME4		
Transformation Tin-Lead-Zinc	TME6		
FOOD			
Oleaginous oil	ALI2	Olive oil	ALI1
Preserves	ALI3	Coffee	ALI6
Flour	ALI4		
Chocolate	ALI5		
Tobacco	ALI7		
TEXTILES			
Cotton Yarns	TEX1	Jute	TEX7
Cotton Pieces	TEX2		
Hemp and Linen Yarns	TEX5		
Hemp and Linen Cloths	TEX6		
Wool	TEX3		
Silk	TEX4		
OTHERS			
Shipbuilding	VAR4	Paper and Cardboard	VAR1
Cork	VAR2	Marble	VAR3
Locomotives-Carriages –Wagons	VAR5		

Note – See table 1 in Appendix 2.

However, we can improve our understanding of the process of industrialization in Italy by studying the presence of stochastic common trends within the industrial aggregates. As mentioned above, the aim was to evaluate the frequency with which technological waves appeared in productive sectors with common characteristics. To do this, the same steps were taken as in the Spanish case. In other words, the existence of cointegrating vectors was tested between the series that make up the basic sector aggregates. The results of the exercise are summarized in Table 7 and provided in detail in tables 2 to7 of Appendix 2.

Table 7

Summary of VAR model estimates by sector

Sectors Considered	Series with stochastic trends	Cointegrating Vectors	Stochastic trends
Energy	2	1	1
Minerals	4	1	3
Transformation of metals	4	1	3
Food	5	1	4
Textiles	6	3	3
Others	3	---	3

Note.- See tables 2 to 7 of Appendix 2.

The results provide evidence of the presence of cointegrating vectors, stochastic common trends, within all the industrial groups, except that which has the most mixed composition, that of Others. The technological *shocks* received within each sector have common effects. However, unlike in Spain and with the exception of the energy sector, the presence of these linkages does not allow the behaviour of the series of each group to be characterized as having been moulded by a single stochastic trend. In this respect, therefore, the Italian process of industrialization has a much more complex characterization.

In this case, it is even more necessary to carry out the second analysis, that is to test for the existence of stochastic common trends between industrial sectors belonging to different productive aggregates. This test, as well as providing a simpler characterization of the Italian industrialization process, should also help illustrate the existence of intersector linkages which, as we have seen, did not develop in the case of Spain. For the sake of symmetry, the sector chosen for establishing the combinations is the textile sector. The results are summarised in Table 8 and presented in detail in tables 8 to 12 of Appendix 2.

Table 8
Summary of VAR model estimates between sectors

Sectors Considered	Series with stochastic trends	Cointegrating Vectors	Stochastic trends
Textiles/Energy	**8**	**5**	**3**
Textiles/Minerals	**10**	**8**	**2**
Textiles/Trans-formation of Metals	**10**	**8**	**2**
Textiles/Food	**11**	**8**	**3**
Textiles/Others	**9**	**4**	**5**

Note.- See tables 8 to12 in Appendix 2.

In all cases, the joint analysis of the sectors that make up the two industrial aggregates allows us to reduce the number of stochastic trends with respect to the sum of those identified when each of the aggregates was analysed separately. This can be seen as evidence supporting the existence of technological *shocks* with permanent effects that were shared by sectors belonging to different branches of industrial production. In Italy, therefore, the existence of connections between industries belonging to different productive aggregates is found. This type of evidence might be related to the presence of phenomena of technological convergence between different industrial sectors.

In short, the Italian process of industrialization had effects that were much more far reaching than those produced by Spanish industrialization. Thus, the technological *shocks* received by certain sectors were able to mould the behaviour of other branches of industrial production in Italy.

Conclusions

The analysis undertaken here seeks to fulfil two aims. On the one hand, the debate centred around Britain's Industrial Revolution has resulted in a conventional interpretation of the industrialization process which requires a plausible theoretical explanation - the persistence of the effects of technological shocks on the industrial output series. Second, historians of industrialization in Spain and Italy have often tried to identify the causes of the uneven behaviour of the economies of the two countries in the second half of the nineteenth century, when the success of Italian industry stood out in stark contrast to the sluggish rhythm of industrial growth in Spain.

By analysing disaggregate series of industrial output, we have been able to highlight the distinctive features of industrial growth in Spain and Italy. This aids our overall understanding of the uneven evolution of the two aggregates within the framework of the conventional interpretation of nineteenth century processes of industrialization.

First, the identification of stochastic trends in the series of aggregate series of industrial output allows us to define the number of sectors that take a leading role in the industrialization process. In Italy, this process was moulded by the behaviour of a larger number of sectors than it was in Spain. In addition, the presence of stochastic trends was not limited to the more emblematic sectors of the process of industrialization, but extended over a wider range of industries, indicating that industrialization had a wider base in Italy than in Spain.

We also found that when focusing the analysis on the comparative behaviour of the sectors that make up an industrial aggregate, the situation in Italy presented greater complexity than that in Spain. In Spain, the dynamic of each group was determined by a single stochastic trend, whereas in Italy, although stochastic common trends were present in all groups, the interpretation of the behaviour of each group could not be reduced to the presence of a single stochastic trend.

The study of the existence of stochastic common trends among industries belonging to different sector aggregates reveals another very important finding. In Spain, this type of connection is conspicuous by its absence. In Italy, however, these connections are found in all the combinations analysed. The difference is plain to see and highlights a key point in the understanding of the differences found in the behaviour of the two processes of industrialization. In the case of Spain, the technological *shocks* experienced by one sector were not transmitted to other groups. But in the Italian case this was standard. This point, considered from the point of view of the existence or absence of processes of technological convergence between sectors, has been identified by Spanish historiography as one of the key factors in the limited industrial development in nineteenth century Spain. The evidence presented here supports this hypothesis.

To conclude, the range and the number of the sectors involved and the intersector linkages established characterize the process of industrialization in Italy. These features were, however, noticeably lacking in Spain, where fewer industries were involved and where barely any intersector connections were established. The consideration of these constants is an important element in understanding the underlying causes of the differences in the evolution of the two economies.

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Appendix 1. SPAIN

Table 1

Identification tests in the disaggregate series

ENERGY		ADF	c,t	k	Rejection I(1)
M1	Gas	-3,9715	c	0	1%
M2	Coal	-2,9151	c,t	1	---
MINERALS		**ADF**	**c,t**	**k**	**Rejection I(1)**
M3	Iron	-1,2523	c	0	---
M4	Manganese	-2,7417	c	1	10%
M5	Mercury	-0,2961	---	4	---
M6	Sea salt	-5,3241	c,t	0	1%
M7	Pyrites	-2,2157	c	2	---
M8	Lead	-3,1509	c	2	5%
TRANSFORMATION OF METALS		**ADF**	**c,t**	**k**	**Rejection I(1)**
TME1	Pig Iron	-2,7009	c,t	0	---
TME2	Iron and Steel	-3,1585	c,t	1	---
TME3	Copper	-1,4101	c,t	1	---
TME4	Transformation of Copper	-4,1981	c,t	2	1%
TME5	Mercury-Silver-Lead-Zinc	-2,7456	---	3	1%
TME6	Transf. of Iron	-3,3127	c,t	1	10%
TME7	Tin	-2,6527	c,t	4	---
FOOD		**ADF**	**c,t**	**k**	**Rejection I(1)**
ALI1	Cocoa	-2,5928	c,t	4	---
ALI2	Coffee	-2,3402	c	3	---
ALI3	Preserves	-7,9738	c,t	0	1%
ALI4	Tobacco	-2,6843	c,t	1	---
TEXTILES		**ADF**	**c,t**	**k**	**Rejection I(1)**
TEX1	Cotton Yarn	-2,4291	c,t	4	---
TEX2	Cotton Pieces	-2,4741	c,t	1	---
TEX3	Wool	-3,2910	c	4	5%
TEX4	Silk	-3,7699	c	1	1%
TEX5	Hemp and Linen Yarn	-1,6132	c	3	---
TEX6	Hemp and Linen Goods	-3,7720	c	0	1%
TEX7	Jute	-3,5732	c	1	1%
OTHERS		**ADF**	**c,t**	**k**	**Rejection I(1)**
VAR1	Leather and Furs	-5,0857	c,t	0	1%
VAR2	Cork	-8,3176	c,t	0	1%
VAR3	Paper	-3,4272	c,t	2	10%
VAR4	Shipbuilding	-0,3836	---	2	---

Note.- See Table 1 in text.

Table 2. MINERALS

H(0)	H(1)	*Maximal eigenvalue*	*Trace statisitc*
r=0	r=1	22.86[b]	45.93[a]
r≤1	r=2	15.82[b]	23.07[b]
r≤2	r=3	7.25	7.25

Series: M3, M5, M7
[a] ([b]) Rejection of the null hypothesis at a significance level of 1% (5%)
The critical values are from Osterwald-Lenum (1992)

Table 3. TRANSFORMATION OF METALS

H(0)	H(1)	*Maximal eigenvalue*	*Trace Statistic*
r=0	r=1	30.14[b]	67.43[a]
r≤1	r=2	22.62[b]	37.29[b]
r≤2	r=3	8.80	14.67
r≤3	r=4	5.87	5.87

Series: TME1, TME2, TME3, TME7
[a] ([b]) Rejection of the null hypothesis at a significance level of 1% (5%)
The critical values are from Osterwald-Lenum (1992)

Table 4. FOOD

H(0)	H(1)	*Maximal eigenvalue*	*Trace Statistic*
r=0	r=1	25.01[b]	52.84[a]
r≤1	r=2	20.09[b]	27.83[a]
r≤2	r=3	7.74	7.74

Series: ALI1, ALI2, ALI4
[a] ([b]) Rejection of the null hypothesis at a significance level of 1% (5%)
The critical values are from Osterwald-Lenum (1992)

Table 5. TEXTILES

H(0)	H(1)	*Maximal eigenvalue*	*Trace Statistic*
r=0	r=1	22.78[b]	43.41[a]
r≤1	r=2	11.69	20.63[b]
r≤2	r=3	8.94	8.94

Series: TEX1, TEX2, TEX5
[a] ([b]) Rejection of the null hypothesis at a significance level of 1% (5%)
The critical values are from Osterwald-Lenum (1992)

Table 6. TEXTILES / ENERGY

H(0)	H(1)	*Maximal eigenvalue*	*Trace Statistic*
r=0	r=1	28.82[b]	69.04[a]
r≤1	r=2	23.94[b]	40.22[b]
r≤2	r=3	11.07	16.28
r≤3	r=4	5.21	5.21

Series: TEX1, TEX2, TEX5, M2
[a] ([b]) Rejection of the null hypothesis at a significance level of 1% (5%)
The critical values are from Osterwald-Lenum (1992)

Table 7. TEXTILES / MINERALS

H(0)	H(1)	*Maximal eigenvalue*	*Trace Statistic*
r=0	r=1	56.59[a]	172.10[a]
r≤1	r=2	46.33[a]	115.51[a]
r≤2	r=3	33.96[a]	69.18[a]
r≤3	r=4	16.73	35.22[b]
r≤4	r=5	12.04	18.49
r≤5	r=6	6.45	6.45

Series: TEX1, TEX2, TEX5, M3, M5, M7
[a] ([b]) Rejection of the null hypothesis at a significance level of 1% (5%)
The critical values are from Osterwald-Lenum (1992)

Table 8. TEXTILES / TRANSFORMATION OF METALS

H(0)	H(1)	*Maximal eigenvalue*	*Trace Statistic*
r=0	r=1	48.97[b]	171.95[a]
r≤1	r=2	43.85[b]	122.98[a]
r≤2	r=3	34.79[b]	79.13[b]
r≤3	r=4	14.99	44.34
r≤4	r=5	12.00	29.35
r≤5	r=6	9.97	17.35
r≤6	r=7	7.38	7.38

Series: TEX1, TEX2, TEX5, TME1, TME2, TME3, TME7
[a] ([b]) Rejection of the null hypothesis at a significance level of 1% (5%)
The critical values are from Osterwald-Lenum (1992)

Table 9. TEXTILES / FOOD

H(0)	H(1)	*Maximal eigenvalue*	*Trace Statistic*
r=0	r=1	40.97[b]	140.94[a]
r≤1	r=2	34.41[b]	99.98[a]
r≤2	r=3	29.45[b]	65.57[a]
r≤3	r=4	23.54[b]	36.11[b]
r≤4	r=5	8.40	12.57
r≤5	r=6	4.18	4.18

Series: TEX1, TEX2, TEX5, ALI1, ALI2, ALI4
[a] ([b]) Rejection of the null hypothesis at a significance level of 1% (5%)
The critical values are from Osterwald-Lenum (1992)

Table 10. TEXTILES / SHIPBUILDING

H(0)	H(1)	*Maximal eigenvalue*	*Trace Statistic*
r=0	r=1	36.70[a]	71.87[a]
r≤1	r=2	25.03[b]	35.17[b]
r≤2	r=3	6.75	10.14
r≤3	r=4	3.39	3.39

Series: TEX1, TEX2, TEX5, VAR4
[a] ([b]) Rejection of the null hypothesis at a significance level of 1% (5%)
The critical values are from Osterwald-Lenum (1992)

Appendix 2. ITALY

Table 1
Identification tests in the disaggregate series

ENERGY		ADF	c,t	k	Rejection I(1)
M1	Petroleum refining	-3,7736	c,t	4	5%
M2	Gas	-2,2825	c	4	---
M3	Coal	-2,4959	c,t	0	---
M4	Petroleum drilling	-4,8194	c,t	2	1%
MINERALES		**ADF**	**c,t**	**k**	**Rejection I(1)**
MIN1	Others-1	-2,6964	c	0	10%
MIN2	Copper	-0,9458	---	0	---
MIN3	Iron	-2,0831	c,t	2	---
MIN4	Pyrites	-2,5616	c,t	3	---
MIN5	Sea salt	-3,3163	c,t	0	10%
MIN6	Sulfur	-2,2767	c	0	---
TRANSFORMATION OF METALS		**ADF**	**c,t**	**k**	**Rejection I(1)**
TME1	Pig iron	-0,4365	c,t	0	---
TME2	Soft iron	-2,6868	c,t	1	---
TME3	Others-2	-3,0876	c	2	5%
TME4	Transformation of iron and steel	-2,7518	c,t	2	---
TME5	Transformation of copper	-4,0812	c,t	2	5%
TME6	Others-3	-1,8847	c,t	2	---
FOOD		**ADF**	**c,t**	**k**	**Rejection I(1)**
ALI1	Olive oil	-3,5817	c,t	1	5%
ALI2	Oleaginous oil	-1,5007	c	0	---
ALI3	Preserves	-1,9324	c,t	4	---
ALI4	Flour	-1,2711	c,t	2	---
ALI5	Chocolate	-0,9081	c	2	---
ALI6	Coffee	-2,0998	---	2	5%
ALI7	Tobacco	-2,3247	c	3	---
TEXTILES		**ADF**	**c,t**	**k**	**Rejection I(1)**
TEX1	Cotton Yarns	-2,0974	c,t	4	---
TEX2	Cotton Pieces	-3,1289	c,t	4	---
TEX3	Wool	-2,9875	c,t	1	---
TEX4	Silk	-3,0165	c,t	3	---
TEX5	Hemp and linen yarns	-2,6570	c,t	3	---
TEX6	Hemp and linen cloths	-2,5911	c,t	3	---
TEX7	Jute	-3,6026	c,t	2	5%
OTHERS		**ADF**	**c,t**	**k**	**Rejection I(1)**
VAR1	Paper and Cardboard	-3,4352	---	4	1%
VAR2	Cork	-2,0314	c,t	0	---
VAR3	Marble	-3,5929	c,t	1	5%
VAR4	Shipbuilding	-1,6078	c	3	---
VAR5	Locomotives-Carriages-Wagons	-2,1811	c,t	4	---

Note.- See Table 1 in text.

Table 2. ENERGY

H(0)	H(1)	*Maximal eigenvalue*	*Trace Statistc*
r=0	r=1	23.04[a]	29.33[a]
r≤1	r=2	6.29	6.29

Series: M2, M3
[a] ([b]) Rejection of the null hypothesis at a significance level of 1% (5%)
The critical values are from Osterwald-Lenum (1992)

Table 3. MINERALS

H(0)	H(1)	*Maximal eigenvalue*	*Trace Statistic*
r=0	r=1	30.84[b]	58.00[b]
r≤1	r=2	16.08	27.16
r≤2	r=3	6.94	11.08
r≤3	r=4	4.14	4.14

Series: MIN2, MIN3, MIN4, MIN6
[a] ([b]) Rejection of the null hypothesis at a significance level of 1% (5%)
The critical values are from Osterwald-Lenum (1992)

Table 4. TRANSFORMATION OF METALS

H(0)	H(1)	*Maximal eigenvalue*	*Trace Statistic*
r=0	r=1	28.32[b]	55.34[b]
r≤1	r=2	12.57	27.02
r≤2	r=3	9.67	14.45
r≤3	r=4	4.78	4.78

Series: TME1, TME2, TME4, TME6
[a] ([b]) Rejection of the null hypothesis at a significance level of 1% (5%)
The critical values are from Osterwald-Lenum (1992)

Table 5. FOOD

H(0)	H(1)	*Maximal eigenvalue*	*Trace Statistic*
r=0	r=1	43.14[a]	78.44[b]
r≤1	r=2	16.99	35.30
r≤2	r=3	8.656	18.31
r≤3	r=4	5.27	9.44
r≤4	r=5	4.17	4.17

Series: ALI2, ALI3, ALI4, ALI5, ALI7
[a] ([b]) Rejection of the null hypothesis at a significance level of 1% (5%)
The critical values are from Osterwald-Lenum (1992)

Table 6. TEXTILES

H(0)	H(1)	*Maximal eigenvalue*	*Trace Statistic*
r=0	r=1	49.95[a]	142.99[a]
r≤1	r=2	37.25[b]	93.04[a]
r≤2	r=3	31.05[b]	55.79[b]
r≤3	r=4	11.01	24.74
r≤4	r=5	8.60	13.73
r≤5	r=6	5.13	5.13

Series: TEX1, TEX2, TEX3, TEX4, TEX5, TEX6
[a] ([b]) Rejection of the null hypothesis at a significance level of 1% (5%)
The critical values are from Osterwald-Lenum (1992)

Table 7. OTHERS

H(0)	H(1)	*Maximal eigenvalue*	*Trace Statistic*
r=0	r=1	10.40	21.70
r≤1	r=2	7.23	11.30
r≤2	r=3	4.07	4.07

Series: VAR2, VAR4, VAR5
[a] ([b]) Rejection of the null hypothesis at a significance level of 1% (5%)
The critical values are from Osterwald-Lenum (1992)

Table 8. TEXTILES / ENERGY

H(0)	H(1)	*Maximal eigenvalue*	*Trace Statistic*
r=0	r=1	112.50[a]	326.80[a]
r≤1	r=2	68.13[a]	214.30[a]
r≤2	r=3	51.67[a]	146.17[a]
r≤3	r=4	39.79[a]	94.50[a]
r≤4	r=5	24.17	54.71[b]
r≤5	r=6	12.89	30.54
r≤6	r=7	10.33	17.65
r≤7	r=8	7.32	7.32

Series: TEX1, TEX2, TEX3, TEX4, TEX5, TEX6, M2, M3
[a] ([b]) Rejection of the null hypothesis at a significance level of 1% (5%)
The critical values are from Osterwald-Lenum (1992)

Table 9. TEXTILES / MINERALS

H(0)	H(1)	*Maximal eigenvalue*	*Trace Statistic*
r=0	r=1	139.15[a]	510.38[a]
r≤1	r=2	88.47[a]	371.23[a]
r≤2	r=3	75.91[a]	282.76[a]
r≤3	r=4	56.70[a]	206.85[a]
r≤4	r=5	50.09[a]	150.15[a]
r≤5	r=6	34.45[b]	100.06[a]
r≤6	r=7	28.78[b]	65.61[a]
r≤7	r=8	17.03	36.83[b]
r≤8	r=9	12.72	19.80
r≤9	r=10	7.08	7.08

Series: TEX1, TEX2, TEX3, TEX4, TEX5, TEX6, MIN2, MIN3, MIN4, MIN6
[a] ([b]) Rejection of the null hypothesis at a significance level of 1% (5%)
The critical values are from Osterwald-Lenum (1992)

Table 10. TEXTILES / TRANSFORMATION OF METALS

H(0)	H(1)	*Maximal eigenvalue*	*Trace Statistic*
r=0	r=1	126.91[a]	521.63[a]
r≤1	r=2	98.72[a]	394.72[a]
r≤2	r=3	76.28[a]	296.00[a]
r≤3	r=4	72.73[a]	219.72[a]
r≤4	r=5	48.49[a]	146.99[a]
r≤5	r=6	34.95[b]	98.50[a]
r≤6	r=7	28.37[b]	63.55[a]
r≤7	r=8	15.90	35.18[b]
r≤8	r=9	11.18	19.28
r≤9	r=10	8.10	8.10

Series: TEX1, TEX2, TEX3, TEX4, TEX5, TEX6, TME1, TME2, TME4, TME6
[a] ([b]) Rejection of the null hypothesis at a significance level of 1% (5%)
The critical values are from Osterwald-Lenum (1992)

Table 11. TEXTILES / FOOD

H(0)	H(1)	*Maximal eigenvalue*	*Trace Statistic*
r=0	r=1	162.11[a]	638.95[a]
r≤1	r=2	112.06[a]	476.84[a]
r≤2	r=3	97.19[a]	364.78[a]
r≤3	r=4	63.01[a]	267.59[a]
r≤4	r=5	61.29[a]	204.58[a]
r≤5	r=6	46.85[a]	143.29[a]
r≤6	r=7	34.81[b]	96.64[a]
r≤7	r=8	28.42[b]	61.83[a]
r≤8	r=9	17.76	33.41
r≤9	r=10	9.41	15.65
r≤10	r=11	6.24	6.24

Series: TEX1, TEX2, TEX3, TEX4, TEX5, TEX6, ALI2, ALI3, ALI4, ALI5, ALI7
[a] ([b]) Rejection of the null hypothesis at a significance level of 1% (5%)
The critical values are from Osterwald-Lenum (1992)

Table 12. TEXTILES / OTHERS

H(0)	H(1)	*Maximal eigenvalue*	*Trace Statistic*
r=0	r=1	79.84[a]	330.34[a]
r≤1	r=2	73.81[a]	250.50[a]
r≤2	r=3	64.37[a]	176.69[a]
r≤3	r=4	40.58[b]	112.32[a]
r≤4	r=5	26.22	71.74
r≤5	r=6	19.44	45.52
r≤6	r=7	11.05	26.08
r≤7	r=8	9.19	15.03
r≤8	r=9	5.84	5.84

Series: TEX1, TEX2, TEX3, TEX4, TEX5, TEX6, VAR2, VAR4, VAR5
[a] ([b]) Rejection of the null hypothesis at a significance level of 1% (5%)
The critical values are from Osterwald-Lenum (1992)