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Competitiveness of the Euro Zone Manufacturing: A Panel Data Analysis

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Abstract The purpose of this paper is to assess the main aspects involved in the competitiveness of manufacturing industries in the Euro zone area (EZ-12). To this end, we apply the generalized method of moments to a panel data error correction model. Our sample spans the period from 1970 to 2007, and our findings provide insight into the impact of manufacturing on the international competitiveness of European firms and industries. From the estimated magnitude of the relevant coefficients, we conclude that in the long run, a change in labor and capital compensation is not fully passed on to manufacturing growth, while an increase in the market power of the manufacturing sector will negatively affect its competitiveness.

Keywords Competitiveness · Euro zone manufacturing · Panel data · Generalized method of moments

JEL E00 · L6 · L16 · C33

Introduction

Despite the changing face of the business economy, manufacturing still plays a key role in Europe's prosperity (European Commission 2011a). The manufacturing industry in Europe has been going through a process of structural changes for decades (European Commission 2009). The current and sudden economic crisis that has affected the Euro zone area in recent years has pointed to the importance of adjustment and structural change more than ever (European Commission 2011b). Indeed,

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there is a compelling need for better understanding and more insight into the adjustment pressure that individual economic sectors experience, the adjustment performance of sectors and countries, and the institutional framework that directly impacts the need and the capabilities of change. The ability of the manufacturing industry to adapt to change and proactively stimulate structural change is pivotal for achieving the European Union's (EU) overall growth and job objectives (Ibid). The EU's ability to adapt to changing market realities and technological developments seems to lag behind those of its key competitors, notably the U.S., but probably even more behind new global players such as Russia, India, or China (Stehrer et al. 2011).

Competitiveness has become a cornerstone in an increasingly open and integrated world economy (European Commission 2010). Despite its widespread importance, the concept of competitiveness is often controversial and misunderstood. There is neither general consensus among the economists and government officials regarding the definition of competitiveness nor a universally accepted theory to explain it. According to the eminent Harvard professor M. Porter (2005), competitiveness is the fundamental determinant of the level of prosperity a country can sustain. To firms, competitiveness means the ability to compete in world markets with a global strategy (Porter 1998a, b). Economic success has been closely associated with the level of competitiveness, i.e., the ability to compete. However, there has been controversy in defining the relevant factors involved and the corresponding concept of competitiveness. In particular, while competitiveness is readily defined at the firm level, the concept becomes rather vague when applied at the industry and national levels. The EU has often tried to redefine the term by providing sectoral competitiveness indicators and shares. According to the latest definition, exemplified in the 2011 European Competitiveness Report (European Commission 2011b, p. 33), the key factor for competitiveness in the long run is the impact of overall economic activity on productivity attained through industrial R&D activity and innovation.

The purpose of this paper is to assess the main drivers involved in the competitiveness of manufacturing industries in the Euro zone area (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, and Spain). The econometric estimation is based on pooled time-series cross-section data for 13 industries covering the period 1970–2007. Based on a disaggregated data set, our findings provide useful insight into the impact of manufacturing on the international competitiveness of the European firms and industries.

The remainder of this paper is structured as follows. The next section provides a detailed overview of the manufacturing industry in the Euro zone area (12 countries involved) in terms of its performance and structure based on disaggregated data for its subsectors. The section following that gives a detailed description of the empirical model and the methodology employed, while the final section interprets the main results of the econometric analysis. Finally, we provide suggestions for further research in our conclusive remarks.

Manufacturing in the Euro Zone Area

Manufacturing includes the highest number of larger (>100 employees) companies in the Euro zone area across various sectors (i.e., construction, energy, services, etc.). It also includes numerous large-scale modern internationally competitive companies with significant exporting activity (European Commission 2011c).

Performance of the Sector

Over the period 1990–2010, the manufacturing production index has shown an upward trend equal to 1 % per annum on average (Fig. 1). However, during the last four years (2007–2010), the relevant index fell by 11.3 %. This evolution is attributed to the current and sudden financial crisis that hit Europe, especially the Euro zone countries (notably Greece, Portugal, and Spain), putting the stability and the future of the European Monetary Union (EMU) in great jeopardy. Among the Euro zone countries forming the EMU (EZ-17), industrial production rose 8 % and fell to 9 % (Eurostat 2010). The highest increases were registered in Ireland (+12.2 %), Slovakia (+7.8 %), Poland (+7.1 %), and Sweden (+6.0 %); the largest decreases were in Greece (−12.4 %), Luxembourg (−11.3 %), Finland (−6.0 %), and Italy (−4.2 %) (Ibid).

In other words, there are significant disparities among the Euro zone countries. In particular, Germany and France are outpacing the rest of the Euro zone, but some of the region's weaker economies even appear to be slipping back into recession (e.g., Greece, Portugal, Spain, and Italy). Finally, it is worth mentioning that the slowdown within the European Union affects a reduced pace of activity worldwide.

Industry Structure

It is well known that the most significant sector in the Euro zone manufacturing industry is transport equipment (Nace codes 34 and 35), covering nearly 15 % of the total gross output in 2007 compared to 8 % in 1970. This is followed by the basic metal industry (Nace codes 27–28) with 14 % (European Commission 2009). In contrast, the textile sector (Nace codes 17–19), which incorporates a wide range of activities such as production of clothes, leather, and footwear, etc., has shown a

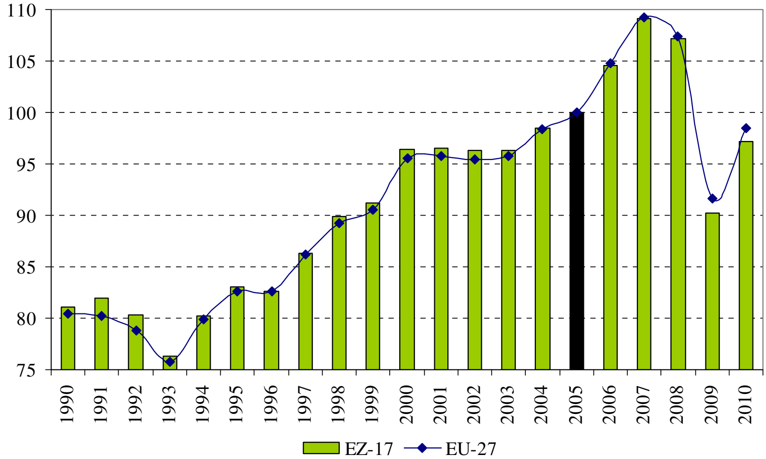

Fig. 1 Manufacturing Production Index in EU-27 and EZ-17 (2005=100).*(Working day adjusted).* **Source:** Eurostat, New Cronos Database—Structural Business Statistics (SBS)

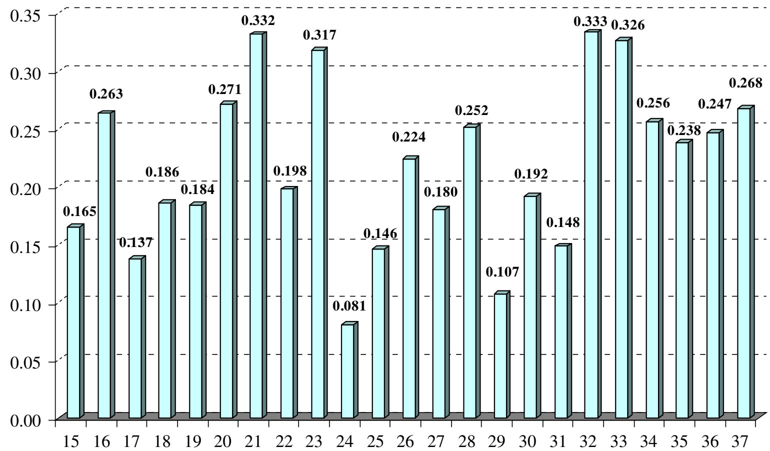

Fig. 2 Adjusted HHI in the manufacturing sub-sectors within the EZ-12.*(2007)*. **Source**: Authors' projections based on EU-KLEMS database

tremendous decrease within the examined period, reaching nearly 5 % in 2007 compared to 12 % in 1970. Similarly, the competitiveness of the food and tobacco industry (Nace codes 15–16) has shown a downward trend (from 16 % in 1970 to almost 12 % in 2007). This evolution is strongly related with the deindustrialisation of the European economy, which becomes particularly evident in the 1980s. Further, it is associated with the structural reformulation of European manufacturing, which is moving away from more labor intensive sectors such as the food and clothing industries and towards more capital intensive ones (i.e., basic and fabricated metal, electrical equipment, machinery, etc.).

In contrast to the previous trend, other subsectors of EZ-12 manufacturing (i.e., wood and cork, pulp, printing, and publishing, chemicals, rubber, and plastics)[1] did not show significant variations, since their shares have remained quite stable over the investigated periods (2007 against 1970). According to the latest data (Fig. 2), sectors such as radio, television, and communication equipment (Nace 32), pulp and paper (Nace 21), and, further, medical precision and optical instruments (Nace 33) are the most concentrated industries in the Euro zone area (HHI[2] index equals to 0.333, 0.332, and 0.326 respectively). On the contrary, chemicals and chemical products (Nace 24), machinery (Nace 29), and textiles (Nace 17) are among the most competitive sectors in the EZ-12, since their HHI indices do not exceed 0.15 in absolute terms.

The seven largest of the 13 manufacturing activities at NACE sub-section level together accounted for over 79 % of EZ-12 manufacturing value-added in 2007 (Table 2). The single-largest activity in value-added terms was basic metals and fabricated metal products (14.7 %), followed by electrical and optical equipment (12.9 %). In terms of employment, the seven largest subsectors together accounted for over 75.7 %% of EZ-12 employment (2007). The single-largest activity in

[1] Nace codes 20, 21–22, 24 and 25 respectively (See Appendix Table 6).

[2] HHI is given by $H = \sum_i (S_i)^2$ where S is the share of firm i in industry sales. The adjusted HHI is defined as $H = (H - 1/N)/(1 - 1/N)$, where N is the number of companies in the industry. The closer this is to 1, the more concentrated the industry.

employment terms was again the basic metals and fabricated metal products (16.0 %), followed by the food industry (13.3 %). The difference in shares of the Euro zone value-added and employment indicates differences in labor productivity (value-added per person employed) across the activities. In particular, EZ-12 labor productivity in manufacturing was 62,400 euro in 2007 (Table 1), thus, approximately 10–15 % more than the nonfinancial business economy average. Among the various subsectors, coke, refined petroleum products, and nuclear fuel displayed a level of 153,000 euro, which is almost three times as much as the manufacturing average (62,000 euro). The subsector chemicals and chemical products showed labor productivity equal to 124,000 euro (almost two times above the manufacturing average).

Empirical Methodology

In this section, we present the econometric methodology we have followed. We used a panel data set in order to investigate for possible cointegrating vectors instead of time series analysis because residual based cointegration tests are known to have low power and are subject to normalization problems. Since economic time series are typically short, it is desirable to exploit panel data in order to draw sharper inferences (Christopoulos and Tsionas 2003).

In order to perform an in depth investigation of industry competitiveness in the Euro zone area (EZ-12), we used a dataset of 494 observations (n=13 and T=38) for 13 manufacturing subsectors covering the period 1970–2007. All variables are in their natural logarithms and, except for the Producer Price Index (deflator),[3] are taken from the EU-KLEMS[4] database. The interpretation of the variables comes as follows: GO is the gross output divided by Producer Price Index (2005=100), GVA is the gross value-added measured in real terms, INT is the intermediate inputs at real purchasers' prices, HHI is the adjusted Hirschman-Herfindahl index, LAB (or labor compensation) stands for the ratio of highly skilled (white-collar workers) employees' salaries to unskilled ones (blue-collar workers) divided by the producer price index, and CAP is the capital compensation in real terms. Finally, R&D is the research and development stock expressed in real terms. All variables, with the exception of HHI, are expressed in million of euros.

Consider the dynamic model with invariant individual term, α_i (Arellano and Bond 1991),

$$y_{i,t} = \beta y_{i,t-1} + \alpha_i + \varepsilon_{i,t}. \tag{1}$$

[3] The producer price index for the EU-15 is taken from the European Central Bank.

[4] The EU-KLEMS project, which was funded by the European Commission (Research Directorate General), aims to create a database on measures of economic growth, productivity, employment creation, capital formation, and technological change at the industry level for all EU member states from 1970 onwards (from 1990 for the recently acceded Member States). The database uses a 63-industry breakdown for the major of the EU's 25 Member States as well as for the US, Japan, and Canada. For more information visit the website http://www.euklems.net.

Table 1 Main indicators of manufacturing by subsector, EZ-12, 2007

Sectors	Gross value added		Employment		Labor compensation		Capital compensation		(current prices) Labor productivity (Gross value added / Employment)
	Million Euro	%	Thousand	%	Million Euro	%	Million Euro	%	Thousand Euro
Total industries	7,686,865	100.0	142,671	100.0	4,810,717	100.0	2,876,148	100.0	53.9
Manufacturing	1,453,762	18.9	23,302	16.3	960,122	20.0	493,639	17.2	62.4
Food, beverages, and tobacco	140,695	9.7	3,101	13.3	92,380	9.6	48,314	9.8	45.4
Textiles, leather, and footwear	70,574	4.9	1,797	7.7	52,233	5.4	18,342	3.7	39.3
Wood, wood products, and cork	30,211	2.1	758	3.3	22,227	2.3	7,984	1.6	39.9
Pulp, paper, printing, and publishing	106,843	7.3	1,741	7.5	64,375	6.7	42,468	8.6	61.4
Coke, refined petroleum, and nuclear fuel	16,652	1.1	109	0.5	5,144	0.5	11,507	2.3	152.8
Chemicals and chemical products	154,900	10.7	1,252	5.4	78,758	8.2	76,142	15.4	123.7
Rubber and plastics	66,773	4.6	1,090	4.7	45,836	4.8	20,937	4.2	61.3
Other non metallic mineral	64,567	4.4	1,100	4.7	41,104	4.3	23,462	4.8	58.7
Basic metals and fabricated metal	213,422	14.7	3,724	16.0	140,497	14.6	72,925	14.8	57.3
Machinery, n.e.c[a]	177,025	12.2	2,713	11.6	125,755	13.1	51,270	10.4	65.3
Electrical and optical equipment	187,776	12.9	2,444	10.5	127,090	13.2	60,686	12.3	76.8
Transport equipment	167,751	11.5	2,118	9.1	121,337	12.6	46,414	9.4	79.2
Manufacturing, recycling, n.e.c[a]	56,574	3.9	1,356	5.8	43,386	4.5	13,187	2.7	41.7

EU-KLEMS database

[a] Not elsewhere classified

First, differences eliminate the invariant individual term α_i and the model becomes

$$y_{i,t} - y_{i,t-1} = \beta(y_{i,t-1} - y_{i,t-2}) + \varepsilon_{i,t} - \varepsilon_{i,t-1}. \tag{2}$$

Since an OLS estimator is biased under the presence of autocorrelation (Wooldridge 2002), a GMM estimator with instruments Π, which are not correlated with the error term and satisfy specific orthogonality conditions,[5] is

$$\arg\min_{\mu} \phi' W \phi = \underset{GMM}{\widehat{\mu}} = \frac{dy'_{-1} \Pi V_N^{-1} \Pi' dy}{dy'_{-1} \Pi V_N^{-1} \Pi' dy_{-1}} \tag{3}$$

where W is the inverse of the covariance matrix, V_N^{-1} of the ϕ_i, and $\Pi = (\Pi'_1 ......\Pi'_N)$ a $N(T-2)xm$ matrix.[6]

If we extend the dynamic model with additional independent variables (Hansen 1982), we get

$$y_{i,t} = \beta y_{i,t-1} + \gamma x'_{i,t} + \alpha_i + \varepsilon_{i,t} \tag{4}$$

and the GMM estimator becomes

$$\widehat{v}_{GMM} = \left[(D\overline{X})' \Pi V_N^{-1} \Pi' (D\overline{X})\right]^{-1} (D\overline{X})' \Pi V_N^{-1} \Pi' dy \tag{5}$$

where $D\overline{X}$ is a matrix composed of $(T-2)NxK$ elements of $d\overline{x}_{i,t}$. In this case, the instrumental matrix Π is equal to $\Pi_i = diag\left(dy_{i,1}....dy_{i,s}, dx'_{i,1}.....dx'_{i,s+1}\right)$, $i = 1.....N$, $s = 1....T-2$.

In order to investigate the main drivers of EZ-12 manufacturing competitiveness, we followed the error correction mechanism attributed to Engle and Granger (1987). The main reason for using this approach instead of using a VAR/VECM model is that the latter is more sensitive to the number of lags that can be used (Kremers et al. 1992). This is a two-stage procedure in which the first step corresponds to two multiequational models (output and value specification respectively) applying GMM and the second stage corresponds to the estimation of uniequational error-correction models including the long-run relations estimated in the previous step. The basic statistical assumption underlying this approach is that the variables are stationary with the first two moments of the underlying data generation process not depending on time. In fact, many time series are not well characterized as being stationary processes, so the first step is to examine the stationarity of the variables. In other words, we have to check for the presence of unit roots. If variables are non-stationary I(1) processes, then there may be a linear combination which is a stationary I(0) processes. If this is the case then the variables are cointegrated. Using an error

[5] $E\begin{bmatrix} d_{u,3}.......d_{y,i} & & \\ . & . & . \\ d_{u,i,T} & & d_{y,i,T-2} \end{bmatrix}_{mx1} = E(Z'u_i) = E(\phi_i) = 0,\ u_i = \alpha_i + \varepsilon_{i,t}$

$Z_i = diag\left[d_{y,i,1}......d_{y,s}\right]_{T-2xm}$, $s = 1....T-2$

$du_{i,t} = \left[du_{i,3}......du_{i,T}\right]'$ and T the periods of cross section observations.

[6] Estimation of $\underset{GMM}{\mu}$ is based on the empirical moments $\phi = E(\phi_i) = \left(\frac{1}{N}\right)\sum_{i=1}^{N} \Pi'_i du_i = \frac{1}{N}\Pi' du.$

N is the number of cross sectional observations.

correction model (ECM), short and long-run effects can be captured by estimating the short and long-run elasticities, respectively (Banerjee et al. 1993). Therefore, the long-run equation relationships are the following:

$$GO_t = \beta_0 + \beta_1 LAB_t + \beta_2 CAP_t + \beta_3 INT_t + \beta_4 HHI_t + \beta_5 R\&D_t + \varepsilon_t \tag{6}$$

and

$$GVA_t = \beta_0 + \beta_1 LAB_t + \beta_2 CAP_t + \beta_3 INT_t + \beta_4 HHI_t + \beta_5 R\&D_t + \varepsilon_t \tag{7}$$

where ε_t is the disturbance term.

There are two main reasons for using two dependent variables (GO and GVA) in the error correction mechanism is twofold. We want to use the two alternative measurements of competitiveness (output and value added approach), while we also want to check or the robustness of the empirical results.

Next we estimate the subsequent ECMs (short-run responses), which are given by the following equations:

$$\Delta(GO_t) = \alpha_0 + \sum_{i=1}^{p} a_i \Delta GO_{\mathrm{t-i}} + \sum_{i=0}^{k} b_i \Delta LAB_{\mathrm{t-i}} + \sum_{i=0}^{l} c_i \Delta CAP_{\mathrm{t-i}} + \sum_{i=0}^{m} d_i \Delta INT_{\mathrm{t-i}} + \sum_{i=0}^{n} e_i \Delta HII_{\mathrm{t-i}} \sum_{i=0}^{o} f_i \Delta R\,\&\,D_{\mathrm{t-i}} + \lambda u_{t-1} + \varepsilon_t \tag{8}$$

and

$$\Delta(GVA_t) = a_0 + \sum_{i=1}^{p} a_i \Delta GVA_{\mathrm{t-i}} + \sum_{i=0}^{k} b_i \Delta LAB_{\mathrm{t-i}} + \sum_{i=0}^{l} c_i \Delta CAP_{\mathrm{t-i}} + \sum_{i=0}^{m} d_i \Delta INT_{\mathrm{t-i}} + \sum_{i=0}^{n} e_i \Delta HII_{\mathrm{t-i}} \sum_{i=0}^{o} f_i \Delta R\,\&\,D_{\mathrm{t-i}} + \lambda u_{t-1} + \varepsilon_t \tag{9}$$

where Δ is the first difference operator and u_{t-1} is the lagged disturbance term of the long-run equations (Eqs. 6 and 7). The coefficient of the error correction term λ measures the speed of adjustment towards the long-run equilibrium and is expected to have a minus sign. Finally, the orders *p,k,l,m,n,and o*, represent the number of lagged terms for decreases and increases in the explanatory variables respectively, and are chosen by using the Akaike information criterion so as to make ε_t white noise.

Stationarity and Cointegration

To avoid generating spurious results due to the presence of unit roots, all the variables of the model were first examined for stationarity and transformed by differencing if needed. Given the relatively short span of the cross section element (n=13), all the commonly used unit root tests (Augmented Dickey –Fuller, Phillips-Perron, and KPSS tests) may have low power separately, (Christopoulos and Tsionas 2003). Thus, our results for the stationarity properties of the data could be seriously misguided. An increase in the power of individual unit root tests can be achieved by pooling individual time series and performing panel unit root tests (Banerjee 1999).

Table 2 Panel unit root test results[a]

Variable	Levin, Lin and Chu-t test	Im, Pesaran and Shin W-test	ADF–Fisher Chi-square	PP–Fisher Chi-square	Hadri z-statistic
Levels					
Dependent variables					
GO	0.591 I(1)	1.214 I(1)	18.918 I(1)	26.458 I(1)	11.703* I(1)
GVA	0.648 I(1)	−1.840 I(1)	−36.543 I(1)	−31.523 I(1)	1.745** I(1)
Control variables					
CAP	−0.806 I(1)	−1.145 I(1)	27.965 I(1)	31.606 I(1)	9.411* I(1)
INT	0.246 I(1)	−2.433* I(0)	42.186 I(1)	35.766 I(1)	4.056* I(1)
LAB	−0.021 I(1)	−1.782** I(0)	36.101 I(1)	30.179 I(1)	2.328* I(1)
R&D	0.194 I(1)	−0.180 I(1)	27.526 I(1)	15.483 I(1)	6.517* I(1)
HHI	0.474 I(1)	0.633 I(1)	27.594 I(1)	28.132 I(1)	8.197* I(1)
First differences					
Dependent variables					
Δ(GO)	−11.307* I(0)	−14.776* I(0)	229.612* I(0)	232.893* I(0)	−1.062 I(0)
Δ(GVA)	−3.262* I(0)	−6.954* I(0)	93.468* I(0)	191.425* I(0)	0.799 I(0)
Control variables					
Δ(CAP)	−7.897* I(0)	−10.554* I(0)	157.459* I(0)	284.079* I(0)	−1.518 I(0)
Δ(INT)	−2.339* I(0)	–	104.599* I(0)	199.118* I(0)	0.970 I(0)
Δ(LAB)	−4.829* I(0)	–	89.456* I(0)	340.001* I(0)	1.696** I(1)
Δ(R&D)	−7.740* I(0)	−13.125* I(0)	201.934* I(0)	202.965* I(0)	1.583 I(0)
Δ(HHI)	13.942* I(0)	−14.250 * I(0)	169.555* I(0)	189.247* I(0)	0.486 I(0)

[a] Under the null hypothesis Hadri test assumes the absence of a unit root whereas the other unit root tests assume a unit root (Hadri 2000). The lag lengths were selected by using Schwarz criterion with an individual intercept as an exogenous regressor. The number in parenthesis shows the order of integration. Significant at *1 % and **5 % respectively

To test for the existence of a unit root in a panel data setting, we have used various econometric tests (Im, Pesaran, and Shin W-test, Fisher type tests, Levin, Lin, and Chu-t test, and Hadri test).[7] Applying the relevant tests (Table 2), we observe that the null-hypothesis of a unit root cannot be rejected at 5 % critical value for all of the relevant variables. In other words they are integrated of order one I(1), including a deterministic component (intercept).

Table 3 presents the panel cointegration tests. It is clear that the null hypothesis of no cointegration is rejected at the 1 % level according to the employed cointegration tests. In particular, by employing the Fisher test (Johansen 1992; Maddala and Wu 1999), it is evident that there is one cointegrating vector at the 5 % level.

[7] We have used Eviews 6 in order to perform the econometric analysis. The data are available from the authors upon request.

Table 3 Panel cointegration tests[a]

Dependent variable	Fisher (combined Johansen)	Kao (Engle-Granger based)	Pedroni (Engle-Granger based)
GO	Trace statistic	−2.465*	−3.633* (PP-Statistic)
	230.0* [r=0] 29.0 [r>=1]		4.115* (ADF-Statistic)
	Maximum eigenvalues		
	137.5* [r=0] 29.1 [r>=1]		
GVA	Trace statistic	−2.879*	−4.036* (PP-Statistic)
	225.9* [r=0] 27.6 [r>=1]		−4.344* (ADF-Statistic)
	Maximum eigenvalues		
	162.4* [r=0] 36.9 [r>=1]		

[a] Null hypothesis implies absence of cointegration, while r denotes the number of cointegrating equations with no deterministic trend (Pedroni 1999). Significant at *1 % and **5 % respectively

Empirical Results

In this section, we present our empirical findings from the estimation of the two asymmetric ECMs, starting from the long-run (cointegrated) equations (see next subsection) followed by the short-run estimations. The econometric estimation was based on pooled time-series cross-section data for 13 industries covering the period 1970–2007. The models were estimated by incorporating corrections for auto-correlated errors within cross-sectional units. In order to correct for cross-section fixed effects, we used differenced data in the estimation procedure (Arellano and Bond 1991).

Long-run Estimations

In this subsection, we estimate long run coefficients, given established cointegration. That is, given that Eqs. 6 and 7 represent structural and not spurious long-run relations, we proceed to estimate the parameters. To implement GMM, we have used as instruments the first differences (Δ) of all the variables of the models lagged L=2 periods. The econometric results with different dependent variables as proxies for competitiveness are in Table 4.

In the first specification (Eq. 6), the estimated coefficient of LAB is significantly different from zero at the 5 % significance level. The magnitude of the relevant coefficient means that a 1 % increase in employees' salaries (compensation of labor) will lead to an increase of gross output in the manufacturing sector by almost 0.13 %. The positive sign of the coefficient can be interpreted as follows. On the one hand, better salaries to skilled employees tend to increase labor productivity, which in turn affects manufacturing output. On the other hand, such an increase will negatively affect labor cost and lead to a possible input substitution (i.e., labor from capital). Therefore, in the long run, a change in labor substitution is not fully passed to manufacturing growth. Variations in capital growth (CAP) do play a significant role in certain formations. In particular, the relevant coefficient is positively related to industry growth (0.09). In other words, an increase in the cost of capital by using

Table 4 Long-run estimations[a]

Control variables / Dependent variable	LAB	CAP	INT	HHI	R&D	J-statistic	Instrument rank
GO	0.13* (3.40)	0.09* (5.53)	0.75* (18.17)	−0.02*** (−1.82)	0.02 (0.68)	22.95	12
GVA	0.36** (2.38)	0.49* (5.59)	0.82* (19.18)	−0.05*** (−1.85)	0.06 (0.30)	15.02	12

[a] The number in parentheses represents the reported t-statistic. Significant at *1 % **5 % and ***10 % respectively

more advanced technology or better machinery equipment will tend to increase the gross output, whereas the reverse holds in case of a decrease.

The level of intermediate inputs is positively statistically related with manufacturing growth (0.75). This means that a 10 % increase in the cost of intermediate inputs will lead to an increase of gross output in the manufacturing sector by almost 7.5 %. Market structure (HHI) plays a crucial role in the manufacturing competitiveness. In particular, there is a small negative but statistically significant relationship between the concentration level and manufacturing competitiveness (−0.02). In other words, an increase in the Hirschman-Herfindahl index, revealing a more oligopolistic market structure in the long-run, will decrease industry performance, while the reverse holds in case of a decrease of market power. This finding shows that market structure affects the level of manufacturing competitiveness and, thus, the overall performance of the sector. Moreover, research and development (R&D) does not affect manufacturing competitiveness, since the estimated coefficient (0.02) is not statistically significant. Finally, the instrument rank is greater than the number of estimated coefficients ($p=12$), while the reported J-statistic[8] is 2.95 (p-value=0.88), implying that the instrument list satisfies the orthogonality conditions.

The second specification (Eq. 7), which measures manufacturing competitiveness in terms of value (gross value-added), gave similar results, confirming the robustness of the empirical analysis. In particular, all the relevant variables except for R&D are statistically significant and in alignment with other empirical studies (Sun et al. 2010). Labor and capital compensation are positively related with the gross value-added, and the relevant coefficients are estimated to 0.36 and 0.49 respectively. The level of intermediate inputs affects the sector's performance since the relevant coefficient is positive and equal to 0.82, while market structure is negatively related with the manufacturing competitiveness (−0.05). Finally, the relevant long-run equation passes a series of diagnostic tests. In particular, the instrument rank is greater than the number of estimated coefficients ($p=12$), while the reported J-statistic is 5.02

[8] The J statistic is the most common diagnostic utilized in GMM estimation to evaluate the suitability of the model (Hansen 1982). A rejection of the null hypothesis implies that the instruments are not satisfying the required orthogonality conditions. This may be either because they are not truly exogenous, or because they are being incorrectly excluded from the regression. The J-statistic is distributed as χ^2 (p-k), where k is the number of estimated coefficients and p is the instrument rank.

(p-value=0.65), implying that the instrument list satisfies the orthogonality conditions.

Short-run Estimations

To implement GMM we have used as instruments the exogenous variables of the models lagged L and lead LD periods. In the output specification (Eq. 8) the model gave acceptable results as reported below by setting L=LD=2. In the other specification (Eq. 9) we set L=2. From the empirical results (Table 5), we conclude that in the first ECM (Eq. 8), covering the period 1970–2007 (first column), all the estimated coefficients except market structure (ΔHHI) are statistically significant and have the anticipated signs. In particular, the short-run elasticity of labor (ΔLAB) is estimated to be 0.18, indicating that a 10 % increase in labor cost will lead to an increase of gross output in the manufacturing sector by almost 1.8 %. Capital growth (ΔCAP) affects the level of the manufacturing competitiveness. The relevant coefficient is positively related to industry growth and estimated to 0.07, which is smaller than its long-run counterpart (0.09). This means that an increase in the cost of capital (e.g., better technology, or the introduction of a capital intensive technological process) will tend to increase gross output and, thus, the sector's performance. The short-run response of the level of intermediate inputs (ΔINTERM) affects manufacturing growth with an estimated coefficient equal to 0.724 (slightly lower than the long-run coefficient). This means that a 10 % increase in the cost of intermediate inputs will lead to an increase of gross output in the manufacturing sector by almost 7.2 %.

Market structure (ΔHHI) does not affect the level of competitiveness in the short-run since the estimated coefficient, although negative, is not statistically significant, despite the opposite finding in the long-run. On the contrary, research and development stock (ΔR&D) is positively significantly related with the manufacturing competitiveness (0.04) revealing that in the short-run, an increase in the R&D expenditures, which is a rather common business strategy in the value-added industries (i.e., pharmaceuticals, transport equipment, electrical and optical equipment, etc), will tend to increase manufacturing gross output.

Further, the error-correction term is negative and statistically significant (−0.28), representing a low speed of adjustment in the long-run equilibrium. Finally, the instrument rank is greater than the number of estimated coefficients (p=24), while the reported J-statistic is 1.84 (P-value=0.99), implying that the instrument list satisfies the orthogonality conditions. It is worth mentioning that the aforementioned results do not vary significantly if we estimate the relevant ECM for the two distinct sub-periods (1970–1986 and 1987–2007).[9]

Regarding the second specification of our empirical model (Eq. 9), all the estimated coefficients of the independent variables except the ΔHHI and the ΔR&D are statistically significant and have the anticipated signs. In particular, the short-run elasticity of labor (ΔLAB), which is higher than its long-run counterpart, is estimated

[9] Due to space limitation, the long-run estimation results for the two separated cointegrated equations (see eq.8 and 9) regarding the two sub-periods (1970–1986 and 1987–2007) are omitted, but they are available from the authors upon request.

Table 5 Short-run estimations of the ECMs[a]

	Δ(GO)[1]	Δ(GO)[2]	Δ(GO)[3]	Δ(GVA) [1]	Δ(GVA) [2]	Δ(GVA) [3]
Variables						
ΔGO_{t-1}	−0.035* (−4.55)	0.005 (0.82)	−0.028* (−3.43)	−0.341* (−3.82)	−0.036 (−0.92)	0.042 (0.18)
ΔGO_{t-2}	−0.027** (−3.34)	0.008*** (1.74)	−0.065* (−5.19)	−0.302** (−3.66)	−0.015 (−0.47)	0.135 (0.63)
ΔGO_{t-3}	−0.070* (−5.83)	–	–	–	−0.089*** (−1.68)	0.728* (3.61)
ΔHHI_t	−0.007 (−1.28)	0.001 (0.20)	−0.008 (−1.53)	−0.005 (−0.16)	0.021 (0.62)	−0.049 (−0.45)
ΔCAP_t	0.073* (17.60)	0.084* (11.99)	0.070* (18.36)	0.262* (6.12)	0.315* (6.59)	0.353* (4.28)
ΔLAB_t	0.181* (13.35)	0.158* (7.52)	0.193* (13.02)	0.683* (8.32)	0.945* (7.40)	0.930* (5.20)
$\Delta R\&D_t$	0.045** (2.12)	−0.006 (−0.33)	0.050** (1.97)	0.029 (0.157)	−0.322*** (−1.93)	0.420 (1.49)
$\Delta INTERM_t$	0.724* (63.58)	0.755* (36.44)	0.746* (53.83)	0.284** (2.26)	−0.082 (−0.75)	0.162 (0.62)
ECM_{t-1}	−0.280* (−8.14)	−0.346* (−6.77)	−0.204* (−3.86)	−0.267* (−3.573)	−0.295* (−2.606)	−0.170*** (−1.71)
Diagnostics						
Standard error of regression	0.010	0.007	0.009	0.051	0.026	0.093
J-statistic	1.84 [0.99]	6.80 [0.97]	2.42 [0.99]	4.29 [0.36]	3.45 [0.32]	2.33 [0.50]
Instrument rank	24.00	24.00	24.00	12.00	12.00	12.00

[a] [1] Sample period 1970–2007 (whole period) [2] Sample period 1970–1986 (period) [3] Sample period 1987–2007. The numbers in parentheses and in the square brackets are *t* and *p* values respectively. Significant at *1 % **5 % and ***10 % respectively

to 0.68, implying that a 10 % increase in labor cost will lead to an increase of the dependent variable by almost 6.8 %. Capital growth (ΔCAP) positively affects the level of the manufacturing competitiveness with the estimated coefficient being equal to 0.26. The level of the intermediate inputs variations (ΔINTERM) is strongly related to the manufacturing growth, since the estimated coefficient is 0.28 which is higher than the long-run coefficient. This means that a 10 % increase in the cost of intermediate inputs (e.g., raw materials) will lead to an increase of gross output in the manufacturing sector by almost 2.8 %.

However, in the short-run perspective, the level of market concentration (ΔHHI) does not play a significant role in the overall sector performance, since the estimated coefficient is not statistically significant (−0.005). Further, the estimated coefficient of the research and development stock variable (ΔR&D) is not statistically significant, revealing that R&D expenditures do not increase the gross value added of the manufacturing sector and thus, its competitiveness. The error-correction term is negative and statistically significant (−0.26). Finally, the instrument rank is greater than the number of estimated coefficients (p=12) while the reported J-statistic and the p-value is 4.29 and 0.36 respectively, which in turn cannot reject the null hypothesis (validity of the instrument list). The empirical results do not change dramatically if we split the estimated period into two sub-periods covering the years from 1970 to 1986 and 1987 to 2007 (see columns 5 and 6 on Table 5).[10]

Concluding Remarks and Suggestions for Further Research

The Euro zone's manufacturing sector is of great importance to the EU's competitiveness and sustainability. Its high performance levels can lead to increases in the EU's GDP and, thus, to employment growth. However, the last recession has dramatically affected the EU's industrial activity. This calls for additional research efforts in order to facilitate manufacturing out of its current decline. The present paper contributes to such endeavours by highlighting the importance of incorporating alternative approximations into an analysis of industry competitiveness. The literature is rather unclear about this concept, with the result that different proxies may lead to different conclusions. In order to deal with this issue, we have used two specific indicators, i.e., output growth and value-added growth, to proxy manufacturing competitiveness in the Euro zone area.

[10] The main reason for splitting the sample period was not to search for possible structural breaks in the long-run estimated relations, but to investigate the main determinants of the competitiveness of the manufacturing industries in the EZ-12 before and after the enlargement of the European Union (EU-12) with the accession of Portugal and Spain respectively (1986).

To attain our objective, in the present empirical research we applied the generalized method of moments (GMM) estimation to various error correction models in order to measure the competitiveness of the manufacturing sector within the Euro zone. We relied on a data set comprising of 494 annual observations (1970–2007) for twelve Euro zone countries. Further, we used panel data analysis and sophisticated econometric techniques (GMM) in order to estimate asymmetric ECMs.

Our econometric results indicated that one of the main drivers of the industry competitiveness is related to the market structure of the sector. However, that finding was valid only in the long-run. In particular, an increase in the market power of the manufacturing sector proved to negatively affect its competitiveness. This finding links the market structure of a sector/industry with its overall performance, and seems to confirm the structure-conduct-performance paradigm (S-C-P). Besides market structure, manufacturing inputs (labor, capital, and intermediate inputs) positively affected the industry competitiveness in the long and the short run. From the estimated magnitude of the relevant coefficients, we concluded that in the long run, a change in labor and capital substitution is not fully passed to the manufacturing growth. Furthermore, research and development stock did not affect the manufacturing competitiveness since the estimated coefficients in the alternative specifications were not statistically significant in the long run. However, in the short-run (taking gross output as a proxy for manufacturing competitiveness), there was a positively and statistically significant relationship revealing that an increase in the R&D expenditure, in particular in the value-added industries (i.e., pharmaceuticals, transport equipment, electrical and optical equipment, etc.), will tend to increase manufacturing gross output.

Given the above contribution, the analysis could be further expanded in order to tackle a number of constraints which may be addressed in future work. In particular, an analysis using more disaggregated data (i.e., three-digit NACE codes) may reach different conclusions. Such a consideration would better capture the industrial competitive dynamism in the Euro zone area, and lead relevant research to further outcomes concerning industrial policy. Further, a possible split of the sample into two distinct subsamples including on the one hand the Mediterranean countries (Greece, Portugal, Spain, Italy, etc.) and on the other hand the northwest Euro zone countries (Germany, France, Belgium, Austria, etc.) could provide useful insights into the impact of manufacturing competitiveness.

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Appendix

Table 6 Two-digit codes in the Nace classification system for manufacturing (C)

Sector	Nace code
Food and beverages	15
Tobacco	16
Textiles	17
Wearing apparel, dressing, and dying of fur	18
Leather, leather, and footwear	19
Wood and cork	20
Pulp and paper products	21
Printing, publishing, and reproduction	22
Coke, refined petroleum, and nuclear fuel	23
Chemicals and chemical products	24
Rubber and plastics	25
Other non-metallic mineral	26
Basic metals	27
Fabricated metal	28
Machinery, n.e.c[a]	29
Office, accounting, and computing machinery	30
Electrical machinery and apparatus, n.e.c[a]	31
Radio, television, and communication equipment	32
Medical, precision, and optical instruments	33
Motor vehicles, trailers, and semi-trailers	34
Other transport equipment	35
Manufacturing, n.e.c[a]	36
Recycling	37

[a] Not elsewhere classified

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