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Manufacturing as an engine of growth: Which is the best fuel?

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Manufacturing as an engine of growth: Which is the best fuel?

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Abstract

Recent contributions of the development economics literature question the role of the manufacturing sector as an engine of growth. The experience of countries like India, which is investing in the services sector, and failures of industrialization in Africa and Latin America have led to scepticism about the effectiveness of manufacturing to foster development. The contribution of this paper is twofold. First, with the use of GMM techniques to treat the endogeneity bias and a sample of 80 countries for the period 1980 – 2010, the paper provides new evidence supporting the role of the manufacturing sector as an engine of growth. Second, the paper investigates which fuel is best for the engine. By applying a LMDI (Log Mean Divisia Index) technique, we decompose the manufacturing sector's growth rate into components of intensive and extensive industrialization. Whereas intensive industrialization refers to an increase of manufacturing value added based on drivers that strengthen manufacturing industries (in terms of productivity and structural change), extensive industrialization is an increase of manufacturing value added based on a driver (total employment) that does not promote a transition in which the manufacturing sector assumes a leading role. We find that intensive rather than extensive industrialization enhances economic growth and that not every dollar for additional industrialization matters for development.

1. Introduction

The development economics literature is still inconclusive on how to best promote growth and prosperity in emerging and low income countries. On the one hand, the competitive advantage theory maintains that countries ought to specialize in those industries in which they are able to produce at lower costs than competitors. Another strand of research related to post-Keynesian and evolutionary economics asserts that countries ought to focus on strategic sectors that can stimulate productivity and innovation in the entire economy. A wide range of literature emphasizes the role of manufacturing as an engine of growth. The creation of backward and forward linkages, the spread of technology knowledge and "training on the job" effects are all mechanisms that can stimulate growth through the development of the manufacturing sector. Even when initially not endowed with a comparative advantage, a country's manufacturing sector can grow on account of economies of scale, internal market demand opportunities and productivity improvements and consequently generate positive effects on the entire economy given that appropriate infant industry strategies are in place.

Kaldor (1960) conceptually introduced the benefits of manufacturing: "As the industrial sector expands, it absorbs a growing amount of goods and services produced outside the industrial sector: these may be the products of agriculture or mining (food and industrial materials), or manufactures which it does not provide itself, or not in sufficient quantities, and which have to be imported… Further industrial growth generates demand for many kinds of services – banking, insurance and professional services of various kinds – and is thus partly responsible for a fast expansion of the "tertiary sector" (Kaldor, 1960, p. 33). Kaldor was the first to hypothesize about stylized facts and empirical regularities regarding the benefits of the manufacturing sector for the entire economy. These regularities are summarized in the following *laws*:

1) The manufacturing sector is the engine of GDP growth.

2) The manufacturing sector's productivity is positively related to the growth of the manufacturing sector (this is also known as Verdoorn's Law). Increasing returns to scale in terms of lower average costs and positive effects on capital accumulation and technical progress are drivers of this mechanism.

3) The productivity of the non-manufacturing sector is positively related to the growth of the manufacturing sector.

This paper focuses on the first of these laws applying new methodologies to determine whether the manufacturing value added growth rate affects the GDP growth rate. Kaldor was the first to postulate and empirically test the "engine of growth hypothesis" with a simple cross-country estimate over 1953-1954/1963-1964 in 12 OECD countries. Fifty years after the first Kaldor tests, the hypothesis is still relevant because literature is increasingly focusing on the role of services as an engine of growth (Park and Shin, 2012). These contributions tend to reduce the emphasis on the manufacturing sector's role for development.

The literature on econometrics has made some methodological advances since the first Kaldor experiment. Panel analyses and the availability of datasets have made more precise estimates possible. All these studies generally confirm the validity of the first Kaldor Law. Using a sample of 92 countries in the period 1960 – 2010, Lavopa and Szirmai's study (2012) supports the engine of growth hypothesis for manufacturing. Pacheco and Thirlwall (2013) used a sample of 89 countries in the period 1990 – 2011 and found that trade is the most important transmission channel from manufacturing growth to economic growth. Acevedo et al. (2009) tested the first Kaldor Law for 18 Latin American countries. Their results support the first Kaldor Law, but do not confirm that manufacturing is the most important engine of growth when compared with services. Similar results were found for 7 Latin American countries in Labanio and Moro (2013). Felipe et al. (2007), albeit confirming Kaldor's Law, concluded that agriculture and services had a higher elasticity than manufacturing in South East Asian countries. Conversely, Wells and Thirlwall (2003) determined that manufacturing is more relevant than agriculture and services in African countries.

However, one of the weak points of the current literature on the first Kaldor Law is the problem of the endogeneity bias. Economic growth and manufacturing value added growth could be reciprocally correlated, but Ordinary Least Squares (OLS) estimates of this relationship imply that causality points toward one direction: from manufacturing growth to total GDP growth. The OLS technique produces biased estimates (simultaneity bias). A simultaneity bias occurs when regressors are not truly exogenous, that is, when there is reverse causation and the dependant variable (in Kaldor's equation, GDP growth rate) causes the regressor (in Kaldor's equation, manufacturing value added growth rate). A simultaneity bias is usually reflected in correlation between the regressor and the error term[1]. Measurement errors, defined as the difference

[1] To show that OLS hypotheses are rejected with an endogeneity bias, let us assume the model $y = \alpha + \beta X + \varepsilon$. OLS implies exogeneity of X, meaning that it is not true that y affects X (simultaneity bias). The exogeneity hypothesis is reflected in the assumption that COV(X, ε) = 0. If there is an endogeneity bias and it is simultaneously true that $X = \alpha + \beta Y + \varepsilon$, we can write $y = \alpha + \beta(y + \beta x + \varepsilon) + \varepsilon$, but in this case, COV(X, ε)=COV(ε , ε) $\neq 0$.

between the actual value of a variable and the value obtained by a measurement and model misspecification due to the omission of relevant explanatory variables may also play a role in generating an endogeneity bias.

To overcome this limitation, this paper applies the Generalized Method of Moments (GMM), a modern econometric tool, to deal with this bias.

Two research questions are thereby addressed:

1) Is the manufacturing sector still an engine of economic growth?

2) If manufacturing is still an engine of growth, which is the best fuel?

To the best of our knowledge, no studies have been carried out to date that focus on the significance of single drivers of manufacturing value added growth for economic growth. To fill this gap, we apply a decomposition analysis to calculate the contribution of different drivers to manufacturing value added growth. We decompose manufacturing value added growth into three components based on variations in a) the manufacturing sector's productivity, b) the share of employment in or from the manufacturing sector and c) increases in total employment. In this paper, we associate the first two components with "intensive industrialization" as they represent components that strengthen the manufacturing sector. The third component, in contrast, is associated with "extensive industrialization" as it represents the variation of value added based on total employment, which does not specifically refer to the manufacturing sector and does not foster a leading role for the manufacturing sector in the economy. This distinction enables us to identify different "fuels" in the process of industrialization and extend empirical testing of the first Kaldor Law to capture a wide range of different "types" of industrialization.

In section 2, we explain our methodology in depth to answer our research questions and provide further details on the Kaldor equation, the decomposition technique as well as the GMM technique. We present the data in section 3. In section 4, we discuss the results and draw conclusions in the final section.

2. Methodology

2.1 The equations

The first Kaldor Law describes the relation between the GDP growth rate and the manufacturing growth rate as follows:

$$1) GDPGR_{it} = \alpha + \beta MANGR_{it} + z_t + \varepsilon$$

Where GDPGR is GDP growth rate and MANGR is manufacturing growth rate, z represents time effects, i.e., time-specific effects that can influence the GDP/manufacturing value added relationship over time. The most important coefficient in this equation is β, which represents the variation of GDP growth rate when the manufacturing growth rate varies. If the manufacturing growth rate varies by 1 percent, β signifies the variation of GDP that derives from the respective percentage increase in manufacturing.

This equation can be tested using different econometric techniques.

Pooled OLS. The Pooled OLS technique estimates equation (1) with the implicit assumption of homogeneity across countries. This means that fixed effects (*f*) or country-specific effects are not included in the equation. To account for heterogeneity across countries, we introduce dummy variables (*IC)* expressing the income category of countries[2]. In the pooled OLS regression equation, (1) is transformed into:

$$2) GDPGR_{it} = \alpha + \beta MANGR_{it} + z_t + IC_i + \varepsilon_{i,t}$$

Fixed effects model and random effects model. The fixed effects model allows the introduction of heterogeneity across countries. Two different methodologies are very common in the econometric literature. The main assumption of the fixed effects model is that the error term ε is divided into two different components as follows:

$$3) \varepsilon_{i,t} = \mu_{i,t} + f_i$$

Where $\mu_{i,t}$ is the traditional idyosincratic random error and *f* represents country-specific effects. In the fixed effects model, *f* depends on the regressors, whereas in the random effects model, *f* is not correlated to the regressors, hence, *f* is a random variable. As the fixed effects model does not allow the estimation of time invariant variables, Kaldor's equation is estimated without income category dummies *IC* as follows:

$$4) GDPGR_{it} = \alpha + \beta MANGR_{it} + z_t + f_i + \mu_{i,t}$$

In the random effects model, *f* is a random variable which is not correlated to the error term.

$$5) f_i \approx N(0, \sigma^2)$$

[2] Countries are categorized in accordance with the World Bank classification.

As in Holland et al. (2012), to account for some persistency in GDPGR, i.e., to capture possible autocorrelation effects, we also estimate equation (1) with a lagged dependant variable as follows:

$$6) GDPGR_{it} = \alpha + \delta GDPGR_{it-1} + \beta MANGR_{it} + z_t + f_i + \mu_{i,t}$$

The engine of growth hypothesis is tested on the basis of the Fagerberg-Verspagen (1999) technique. We test whether the coefficient of manufacturing growth β is positive and whether it is larger than the share of manufacturing in GDP. If the coefficient is larger than the share of manufacturing in GDP and if this difference is significant, it is interpreted as (not definitive) support for the engine of growth hypothesis[3].

2.2 Generalized method of moments: A methodology to improve estimates of OLS, fixed effects and random effects techniques

As pointed out by Bond et al. (2001), it is well known that when we have a dynamic model specification as described in equation (6), OLS gives an estimate of δ which is biased upwards in case of individual-specific effects and biased downwards with fixed effects (Nickell, 1981). Therefore, a GMM technique is useful in case of a lagged dependant variable to correct this bias.

Yet even in equations (1), (2) and (4) where the lagged version is not used as a regressor, the GMM technique is useful to treat the endogeneity bias. As stated earlier, endogeneity occurs when there is reciprocal causality between the dependant variable and the regressors. This simultaneity bias is reflected in the presence of a correlation between the regressor and the error term. Even in the random effects model (equations (4) and (5)), which by construction are not characterized by a correlation between the regressors and the country-specific error term *f*, endogeneity may emerge, as regressors could be correlated with the error component $\mu_{i,t}$.

Blundell et al. (1992) assert that “However, if we are unwilling to assume that Qir [independent variable in the equation] is strictly exogenous…or wish to entertain the possibility of more general dynamic models including the lagged dependent variable, then both the within groups estimator and the GLS estimator are inconsistent” (Blundell et al., p. 242). In other words, the presence of the lagged dependant variable as a regressor or even in the absence of a lagged variable, the correlation between the regressor and the error term creates a bias in the estimates.

[3] The Fagerberg-Verspagen test does not represent definitive evidence of the engine of growth hypothesis. First, even if the manufacturing sector coefficient is higher than the manufacturing value added share, other sectors may be characterized by higher impacts. Secondly, it does not tell us anything about the causality of impacts of manufacturing growth/economic growth. See Lavopa and Szirmai (2012) for a detailed discussion on this issue.

In the literature on the first Kaldor Law, scholars adopted the 2SLS IV technique to treat endogeneity (see Lavopa and Szirmai, 2012; Pacheco, López and Thirlwall, 2013). In case of endogeneity, the 2SLS technique can correct the bias via a two-stage procedure. Take, for example, a simple model of the form Y= f(X) in which the regressor is endogenous. In that case, the two stages can be summarized as follows: 1) as a first step, we need to identify those exogenous instruments *Z* that affect the endogenous variable but are not affected by the dependant variable *Y*[4]. We then regress the endogenous variable *X* on the selected instruments *Z*, *X=f(Z)*. 2) In a second step, the fitted values of the first stage regression *X* are then used to estimate *Y=f(X)*. The problem with this technique is that it is quite difficult in many cases to identify suitable external instruments. The Generalized Method of Moments has been proven to be more efficient[5] than the 2SLS technique in cases of overidentification[6]. The basic idea behind the GMM strategy is to use past values of the endogenous variables as internal instruments. Different alternatives exist for GMM estimates.

The difference GMM estimator requires first differencing the equation. In the case of equation (4), first differencing eliminates country-specific fixed effects that represent a source of endogeneity[7]. With the difference GMM technique, the dependant variable in difference is instrumented with the past values of the regressor in levels (Arellano and Bond, 1991).

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[4] An often mentioned example of a correct application of the instruments variable technique is represented by the estimate of the price of agricultural goods (P) as a function of agricultural production (AP). The simultaneity bias for such a model is evident, as it is reasonable to assume a biunivocal relationship between the two variables. The application of an IV technique requires the following two steps: 1) Selection of appropriate external instruments Z that affect the AP but are not affected by P, and the estimation of AP = f(Z). Climate conditions are a good candidate for Z, as they affect agricultural production AP but are not affected by the price of agricultural products (P). In the second step, the fitted values of X are applied in the equation X = f(Z) to estimate Y = f(X).

[5] An estimator is said to be efficient within a class if it has lower variance than all other estimators in that class.

[6] OLS is said to be exactly identified. In a simple equation $Y = \alpha + \beta X + \varepsilon$, the coefficients α and β are estimated by using the two moment conditions $\frac{1}{n}\sum_i \hat{e} = \frac{1}{n}\sum_i (Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_i) = 0$ and $\frac{1}{n}\sum_i e_i X_i = \frac{1}{n}\sum_i (Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_i) = 0$. OLS is exactly identified, as two parameters are estimated through two moment conditions. With the GMM technique, there are more moment conditions than unknown parameters. Rather than satisfying one moment condition and violating another, the generalized method of moments (GMM) strategy chooses an estimator that balances each population moment condition against the others, seeking residuals that trade off violations of one moment restriction against violations of the other moment restrictions. A GMM estimator may satisfy no one moment condition, but it may come close to satisfying them all.

[7] First differencing and means deviations are two techniques used to treat unobserved heterogeneity and potential endogeneity. For example, in a fixed effects (within estimator) equation with country-specific and time effects $y_{it} = x_{it}\beta + \mu + \alpha_i + \gamma_t + \varepsilon_{it}$ least squares estimates of the slope in this model are obtained by regression of $y^*_{it} = y_{it} - \overset{\approx}{y}_i - \overset{\approx}{y}_t + \overset{\approx}{y}$ on $x^*_{it} = x_{it} - \overset{\approx}{x}_i - \overset{\approx}{x}_t + \overset{\approx}{x}$. The sign $\approx$ represents an average across time. A model specification where variables are deviations from the average allows to estimate slopes by eliminating the influence of country-specific fixed effects and the endogeneity bias. In a second step, country-specific fixed effects can then be estimated as $\hat{\alpha}_i = (\overset{\approx}{y}_i - \overset{\approx}{y}) - (\overset{\approx}{x}_i - \overset{\approx}{x})` b$ (Green 2001)

One problem with the original Arellano-Bond estimator is that lagged levels may be poor instruments for first differences (Roodman, 2006). Arellano and Bover (1995) proposed the *system GMM* estimator and assert that additional instruments "can dramatically increase efficiency", if the original equation in levels is added to the system (Roodman, 2006)[9]. Using system GMM, additional variables in levels are instrumented with suitable lags of their own first differences. The assumption is that these differences are uncorrelated with the unobserved country effects.

The Arellano-Bond and Blundell-Bond estimators have one- and two-step variants. Although the two-step estimator is asymptotically more efficient, the reported two-step standard errors tend to be severely downward biased (Arellano and Bond, 1991). A finite-sample correction can increase the efficiency of two-step robust estimations over one-step robust estimations, especially for system GMM (Windmejier, 2005).

One problem with GMM estimates is that they may not be reliable if the time dimension of the panel dataset and the number of past values is too high, because the strength of robustness tests decreases and secondly, because large instrument collection can overfit endogenous variables. Something similar happens with OLS when additional regressors automatically increase the R-square[8] indicator regardless of the relevance and significance of the additional variables.

There are two techniques to reduce the number of internal instrumental variables in GMM estimation: 1) *lags truncation* which only uses certain lags instead of all available lags for instruments. Separate instruments are generated for each period, but the number per period is capped; 2) The *collapse* technique (Roodman 2006) which creates one instrument for each variable and lag distance instead of one for each time period, variable and lag distance. There is no clear guideline on the "optimal number" of instruments to use and which one of the two techniques (lags truncation and collapse) is more suitable to avoid overfitting in GMM estimates.

The robustness and goodness of fit of a GMM estimate can be checked against some findings in the literature[9]. A simple rule of thumb is that the number of instruments must be lower than the

[8] R^2 represents the "goodness of fit" indicator of OLS estimates. It lies in the range [0, 1], with 0 indicating the lowest goodness of fit level and 1 the maximum value.

[9] For example, we know that the estimated value of the coefficient associated with the lagged dependant variable cannot be a unit root (equal to 1). In this particular case, the system GMM estimate would be biased (Roodman 2006). Moreover, Bond et al. (2001) highlight that OLS levels will give an estimate of the lagged dependant variable coefficient that is biased upwards in the presence of individual-specific effects, and that within groups [fixed effects] will give an estimate of the lagged dependent variable that is severely biased downwards in short panels. Hence, when we use a GMM technique for an equation including a lagged dependant variable, we can look at the lagged regressor coefficient to check whether it lies outside the fixed effects/OLS range. If this were the case, it would be a sign of a bias in the GMM estimates.

number of countries (Roodman, 2006). Other tests are also useful to test the robustness of GMM estimates. Specifically, we apply the autocorrelation tests, the over identification Hansen/Sargan test to all variables and to endogenous variables only, and the difference - in – Sargan/Hansen test of exogeneity for the GMM instruments of endogenous variables and for the exogenous regressors (time and income dummy variables *z* and *IC).* These tests support an accurate specification of the model estimated with GMM techniques. The results of these tests are presented in the results section. Technical details are included in Annex I.

Table 1 Synthesis of econometric methodologies adopted in this paper

Pooled OLS	Fixed effects	Random effects	Difference GMM	System GMM
An Ordinary Least Squares methodology applied to a panel sample	Fixed effects improves pooled OLS when there is heterogeneity across countries and it is reasonable to assume that country-specific effects are correlated to the regressors	Random effects improves fixed effects when unobservable heterogeneity is not correlated to regressors	**Difference GMM** treats endogeneity in pooled OLS, fixed effects and random effects models. Equations in differences are instrumented with lagged internal values in levels. The estimation procedure applies the **Windmejer robust standard errors** correction. The **two-step** GMM improves the **one step** GMM in case of heteroschedasticity. **Lags truncation** or **collapse** are used to control for instruments proliferation	**System GMM** improves difference GMM by adding instruments in differences for equations in levels. It improves GMM if in difference GMM instruments are poor. **Windmejer correction**, **one/two-step** estimators and techniques to reduce **instruments proliferation** may be applied

2.3 Which is the best fuel for the engine of growth?

The literature still does not provide unambiguous answers on how to best enhance growth by promoting the manufacturing sector. The manufacturing sector can have a positive impact on the general economy through different channels:

1) Compared with other sectors, manufacturing provides greater opportunities to accumulate capital, exploit static and dynamic economies of scale, acquire new technologies and foster embodied and disembodied technological change (Szirmai et al., 2013, Weiss, 2005);

2) Manufacturing activities increase knowledge and productivity through “training on the job” mechanisms (Araujo et al., 2009);

3) Structural change towards medium-/high-tech manufacturing sectors helps diffuse knowledge and the promotion of technological change (Industrial Development Report, 2013).

All these mechanisms, albeit very different, have a common characteristic: to be operational, they require drivers that specifically promote a leading role for the manufacturing sector. These may refer to drivers that facilitate the penetration of industries or factors that strengthen the manufacturing sector’s capacity to improve the technological intensity of economic activities.

On the other hand, it is very unlikely that industries that are unable to propagate innovation and to absorb/propagate value added and labour can significantly contribute to economic growth. McMillan and Rodrik (2011) and the Industrial Development Report (2013) discuss cases in which the industrialization process was unsuccessful. Africa and South America are world regions where industrialization did not promote a sustained growth process, whereas in China and South East Asia, manufacturing growth was key in boosting development. Research is crucial if we want to understand which drivers of industrialization are more effective in maximizing GDP growth.

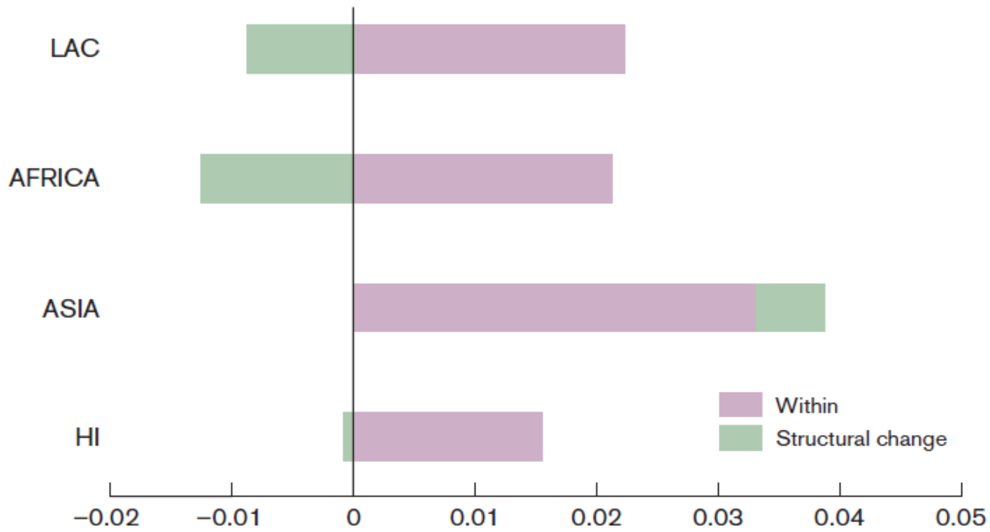
The literature on decomposition analysis offers some background which may help fill the research gap. Accounting techniques exist to calculate the contribution of different components to variations of value added on the basis of well-known identities. The World Bank (2005) explains techniques to analyse the contribution of different components to variations of value added in detail. The simplest equation used by the World Bank is the following:

$$7)\frac{Y}{E}=\sum_{s}\frac{Y_i}{E_i}\frac{E_i}{E}$$

where Y is GDP, E is employment, s is sector. From equation (7), changes in labour productivity $\frac{Y}{E}$ can be decomposed into the productivity effect $\frac{Y_i}{E_i}$ of each sector and labour force share of sector s. From an operational point of view, this equation helps answer the following question: given an economy where labour productivity (GDP/total employment) increases by X percent, what is the contribution of variations in productivity and in labour force shares in each of these sectors?

This equation is very simple, but central in the industrial economics literature as it describes to what extent "within" and "between" sector effects influence growth. In their seminal paper, McMillan and Rodrik (2011) show that improvements within each sector may not suffice to stimulate growth. In Latin America, industry restructuring initiated by the trade liberalization of the 1990s improved the competitiveness of the local industry, but released labour that was absorbed by less productive sectors or even caused unemployment. As Figure 2 indicates, whereas the "within" effect of productivity within each sector was positive in Latin America, the "between" group effect representing the movements of labour across sectors was negative. In other words, there was a negative contribution of structural change to growth.

Figure 1Decomposition of productivity growth by region, 1990–2005 (percentage points)



Source: McMillan and Rodrik 2011.

Structural change is another crucial concept in industrial economics literature. It refers to long-term and persistent shifts in the sectoral composition of economic systems (Chenery et al., 1986). As emphasized by UNIDO, structural change is key for generating a sustained growth process. Ocampo (2005) points out that growth enhancing structural change is primarily fed by two mechanisms: 1) a shift toward high-productivity industries, and 2) the creation of new inter-sectoral linkages leading to a more intensely integrated production structure. According to UNIDO (2012), upgrading and diversification from low labour intensive/low skills industries to technology intensive, high skills industries promotes the allocation of resources towards the most productive industries and the transition to sustained growth. McMillan and Rodrik's work underscores that structural change may also have a negative effect on growth if variations in labour shares are absorbed by unproductive industries.

The first Kaldor Law and the concept of structural change do not coincide but overlap to some extent. Pasinetti (1993) asserts that a transition from an economy based on agriculture to one based on industry is an inevitable step for achieving sustained growth: “The pure and simple observation of any series of empirical data regarding the dynamics of various sectors in industrial economic systems, suggests, without any shadow of doubt, that in all countries a continuous process is in motion, leading to an irreversible tendency, concerning the relative change of the three broad sectors, as per capita income increases. In the less developed countries, the agricultural sector (though increasing in absolute value) decreases relative to the other two sectors, as the economic system develops” (Pasinetti, 1993, p. 4). A transition from agriculture to manufacturing would certainly be reflected in an increase of the manufacturing value added growth rate and of the GDP growth rate representing the pillars of the first Kaldor Law equation (equation 1).

The two concepts do not coincide because the underlying assumption of the Kaldor Law is that a percentage increase in the manufacturing value added growth rate has a positive impact on the GDP growth rate, even if the share of manufacturing value added and/or the labour share decline[10].

For this paper, we adapt equation (7) to specifically examine the manufacturing sector’s growth rate as follows:

$$8) MVA = \frac{MVA}{ME}\frac{ME}{E}E$$

Where MVA is manufacturing value added, ME is manufacturing employment and E is total employment. If we compare equations (7) and (8), we find three main differences:

1) The variable on the left hand side of equation (8) is manufacturing value added (MVA) rather than GDP. This is also reflected in the absence of subscript s representing other sectors beyond manufacturing (other industries, agriculture and services). The first Kaldor Law focuses on manufacturing value added growth as an engine of growth and we are therefore not interested in drivers of growth in other sectors beyond manufacturing.

[10] In the structuralist and post-Keynesian literature, there are examples of scholars analysing structural change both in terms of value added shares (see DESA, 2006) and labour share (e.g. McMillan and Rodrik). There is no unanimous consensus on this issue.

2) As the first Kaldor Law focuses on the manufacturing value added growth rate, we are interested in determining contributors to manufacturing value added variations rather than manufacturing productivity.

3) Equation (8) is an identity with three components on the right hand side, whereas the identity of (7) has only two components. This choice is made to obtain a more complete (even if not exhaustive) description of manufacturing value added growth drivers.

According to equation (8), variations of manufacturing value added can be analysed on the basis of three components:

Manufacturing productivity. This component is important in the context of the overall economy of a country considering that positive spillovers proliferate more easily to other economic sectors in terms of learning and knowledge diffusion when the manufacturing sector is more productive. An increase in the manufacturing sector's productivity may not initiate a structural change process, because an increase in the manufacturing sector's productivity may: 1) generate a reduction in terms of labour force share. This is what happened in Latin America due to trade liberalization in the 1990s. 2) generate a reduction in value added share if the manufacturing sector's increase in productivity is lower than in other sectors.

Manufacturing labour force share. This component complements the definition of structural change. An increase in labour force share indirectly implies a reduction in the labour force share of other sectors. A change in the structural composition of an economy represents the essence of the structural change concept which is considered key for sustained growth and development (UNIDO, 2012).

Total employment. An increase in the availability of labour inputs does not change the structural composition of the economy towards the manufacturing sector or the capacity of the manufacturing sector to generate knowledge and know-how through productivity spillovers. It only increases manufacturing value added through an increase of total employment, which does not represent a driver that strengthens the manufacturing sector specifically. We refer to the variation of manufacturing value added that derives from this component as "extensive industrialization". It represents an increase in manufacturing value added based on the mere increase of inputs deployment (keeping the manufacturing value added share constant) as opposed to intensive industrialization, which represents an increase in manufacturing value added based on manufacturing productivity and structural change [11].

Using the decomposition analysis, we can study the contribution of each of the three components on variations of manufacturing value added as follows:

9) $$\Delta MVA_{it} = \Delta productivity_{it} + \Delta manlabshare_{it} + \Delta totempl_{it}$$

where ΔMVA is the variation of manufacturing value added productivity, $\Delta manlabshare$ the variation of manufacturing value added depending on manufacturing employment share variations and $\Delta totempl$ is the variation of manufacturing value added depending on total employment variations. Decomposition is applied through a Log Mean Divisia Index (LMDI) technique which allows decomposing a multiplicative identity into three additive components as in equation (8)[12]. The LMDI technique assumes that the contribution of each component is calculated by keeping the other components constant over time.

If we consider that *t* refers to the time period during which we observe the manufacturing value added variation *t* and if we assume that the initial level of manufacturing value added is observed at time *t-s*, we can divide both sides of equation (9) by the initial value of manufacturing value added at time *t-s*

10) $$\frac{\Delta MVA_{it}}{MVA_{it-s}} = \frac{\Delta productivity_{it}}{MVA_{it-s}} + \frac{\Delta manlabshare_{it}}{MVA_{it-s}} + \frac{\Delta totempl_{it}}{MVA_{it-s}}$$

This identity states that the growth rate of manufacturing value added can be expressed as the sum of the growth rate of manufacturing value added based on productivity, manufacturing employment share and total employment variations as follows:

11) $$MANGR_{it} = MANGRPROD_{it} + MANGRMANEMPL_{it} + MANGRTOTEMPL_{it}$$

Where MANGR represents the growth rate of manufacturing value added, MANGRPROD is the growth rate of manufacturing value added based on manufacturing productivity variations, MANGRMANEMPL is the growth rate of manufacturing value added based on manufacturing

[11] The concepts we adopt on extensive and intensive industrialization recall the well-known concepts of intensive and extensive agriculture, where intensive agriculture represents an increase in agricultural value added based on productivity, and extensive agriculture represents an increase in agricultural value added based on inputs and in particular on land availability. In our formulation, an additional component representing structural change (manufacturing labour force) which is not related to inputs availability (in our case labour) is included as an intensive industrialization component.

[12] Annex II contains more information on the LMDI technique.

employment share variations and MANGRTOTEMPL is the growth rate of manufacturing value added based on total employment variations. If we replace MANGR in equation (6) with equation (10), the modified first Kaldor Law equation becomes:

$$12) GDPGR_{it} = \alpha + \delta GDPGR_{it-1} + \beta_1 MANGRPROD_{it} + \beta_2 MANGRMANEM_{it} + \beta_3 MANGRTOTEM_{it} + z_t + f_i + \mu_{i,t}$$

From our estimates we expect a positive sign for intensive industrialization components β_1 and β_2 (which in the literature is represented as a positive impact of manufacturing productivity and structural change on GDP growth rate) and an ambiguous sign of β_3, the total employment component.

There are overwhelming theoretical arguments supporting the idea that an increase in total employment increases both manufacturing value added and GDP. In the simplest form of the Cobb Douglas function, the total output Y = f(K L) where Y is output, K is capital and L is labour. The total output depends on total employment L. If there is an increase of total employment in the manufacturing sector—even excluding indirect effects through forward and backward linkages on the rest of the economy—the increase in value added of the manufacturing sector will be reflected in an increase in GDP.

An increase in manufacturing value added fuelled exclusively by total employment cannot be considered a driver of economic growth. In the absence of manufacturing productivity improvements or structural change, manufacturing growth may go hand in hand with stagnation of other economic sectors.

The ambiguity about the possible impact on the rest of the economy of the manufacturing value added growth rate based on total employment is reflected in uncertainty on the expected sign of the coefficient β_3.

We introduce the decomposition analysis and in particular the LMDI technique into the analytical framework of the first Kaldor Law. The decomposition analysis is an already consolidated methodology in the literature. Attempts have been made in the field of industrial economics to apply decomposition techniques to analyse industries in different countries. Tregenna (2011) recently analysed changes in employment shares and levels and found that in most countries the decline in manufacturing employment is associated with rising labour productivity. Timmer et al. (2007) applied a modified version of the shift and share analysis to data on growth in Asian and Latin American countries and found that manufacturing is more important in periods of normal growth whereas services take a leading role in periods of growth accelerations.

Table 2 Synthesis description of the manufacturing value added growth rate decomposition factors

	Meaning	**Relation to the concept of structural change**	**Expected sign of the coefficient**
MANGRPROD	Share of the manufacturing value added growth rate based on productivity variations	Ambiguous relation. An increase of productivity in the manufacturing sector may or may not increase the share of manufacturing value added and/or employment	We expect an increase of productivity in the manufacturing sector to have a positive impact on the overall economy through spillover effects
MANGRMANEM	Share of the manufacturing value added growth rate based on manufacturing employment share variations	Close relation. An increase in the manufacturing sector’s labour share implies a change of the structural composition of the economy, and in particular a strengthening of the industrialization process	We expect an increase in the manufacturing employment share to have a positive impact on GDP growth rate. In the initial stages of development, the transition from agriculture to industry boosts growth. In higher income countries, a shift of labour towards more productive sectors generates growth enhancing structural change
MANGRTOTEM	Share of the manufacturing value added growth rate based on total employment variations	No relation. An increase in total employment signifies “extensive” industrialization where the manufacturing sector grows in the absence of structural change and productivity improvements	We do not expect a sign for this variable. An increase in labour availability has a positive impact on manufacturing value added and GDP, but the impact of this increase on the rest of the economy is unclear

2.4 Some descriptive evidence on the manufacturing value added decomposition

To provide intuitive evidence of the impact of intensive and extensive industrialization on growth in different countries, we slightly modify equation (9) as follows:

$$9')\ \frac{\Delta MVA_{it}}{MVA_{it-s}} = \frac{\Delta productivity_{it} + \Delta manlabshare_{it}}{MVA_{it-s}} + \frac{\Delta totempl_{it}}{MVA_{it-s}}$$

where the term $\frac{\Delta productivity_{it} + \Delta manlabshare_{it}}{MVA_{it-s}}$ entails intensive industrialization and the term $\frac{\Delta totempl_{it}}{MVA_{it-s}}$ extensive industrialization.

We plot annual compounded growth rates of extensive and intensive industrialization for 52 countries over the period 1990 – 2005. Countries and time periods are selected only on the basis of availability criteria.

Figure 2 provides some preliminary evidence on the differential role played by intensive and extensive industrialization in cross-country data. When looking at extensive industrialization, we do not see a clear difference between well-known examples of successful growth-enhancing industrialization, such as in China, Thailand, Malaysia and Republic of Korea, and countries characterized by slow industrialization and growth (e.g. Malawi, Venezuela, Zambia and South Africa). What seems to make an actual difference is the intensive industrialization growth rate which is positive for rapidly industrializing countries and negative for slowly industrializing countries (Table 3). The country that experienced the highest growth rate, China, was also the country with the most intensive industrialization growth rate. It follows that extensive industrialization does not seem to be key in explaining rapid industrialization of countries.

Intensive industrialization growth rates have more power in explaining economic growth rates than extensive industrialization growth rates. The correlation between intensive industrialization and GDP growth rate is twice (Figure 4, 0.48) the correlation between an extensive growth rate and economic growth (Figure 5, 0.24). Moreover, if we consider the set of countries with positive intensive industrialization, their GDP growth rates are on average 1.3 percent higher than those of countries with negative intensive industrialization growth rates, but 0.1 percent lower extensive industrialization growth rates. In other words, negative intensive industrialization growth rates restrict GDP growth, but we do not have strong evidence that low extensive industrialization restricts GDP growth.

Such descriptive statistics only offer partial evidence that intensive industrialization components play a more important role in moulding the GDP growth rate's path than extensive industrialization components[13]. We now present some more elaborate econometric evidence which investigates this issue further.

Table 3 Compounded annual growth rate of China, Thailand, Malaysia, Republic of Korea, Malawi, Venezuela, Zambia and South Africa

	Compounded annual GDP growth rate 1990 - 2005	Variation of manufactur-ing value added (millions of local currency unit) 1990 - 2005	Variation of manufacturing value added based on manufacturing productivity (millions of local currency unit) 1990 - 2005	Variation of manufacturing value added based on manufacturing employment share (millions of local currency unit) 1990 - 2005	Variation of manufacturing value added based on total employment (millions of local currency unit) 1990 - 2005	Compounded annual intensive industrialization growth rate 1990 – 2005 (millions of local currency unit) 1990 - 2005	Compounded extensive industrialization growth rate (millions of local currency unit) 1990 – 2005
China	9.9%	4,933,862	4,570,620	-124,772	488,014	11.5%	2.5%
Malaysia	6.7%	48,939	7,737	19,286	56,334	6.1%	3.8%
Korea	5.4%	140,617,500	161,459,306	-48,744,626	27,902,820	6.4%	2.2%
Thailand	4.5%	885,565	391,415	341,499	152,651	5.9%	1.7%
Venezuela	2.8%	15,486	24,943	-48,614	39,157	-1.7%	2.2%
South Africa	2.5%	63,384	-80,839	18,902	125,320	-2.5%	3.4%
Zambia	2.5%	-4,725	-479	-10,868	6,621	-4.9%	1.8%
Malawi	2.4%	56,334	29,311	7,737	19,286	-5.0%	1.7%

[13] Countries ranked according to GDP growth rates, intensive industrialization growth rates and extensive industrialization growth rates are included in Annex V.

Figure 2Extensive vs intensive industrialization

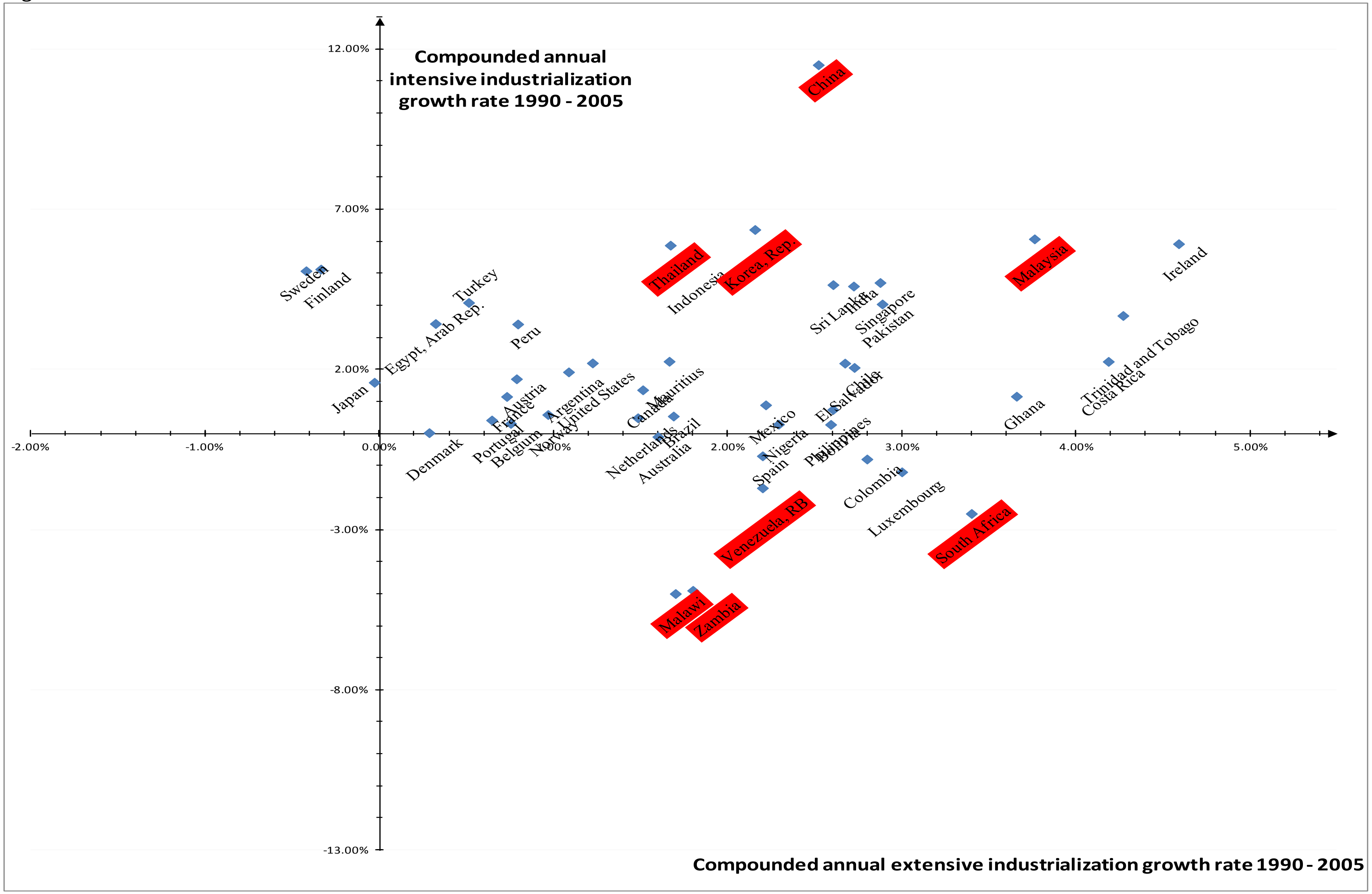


Figure 3Correlation between compounded annual intensive industrialization growth rate and compounded annual GDP growth rate over the period 1990 – 2005

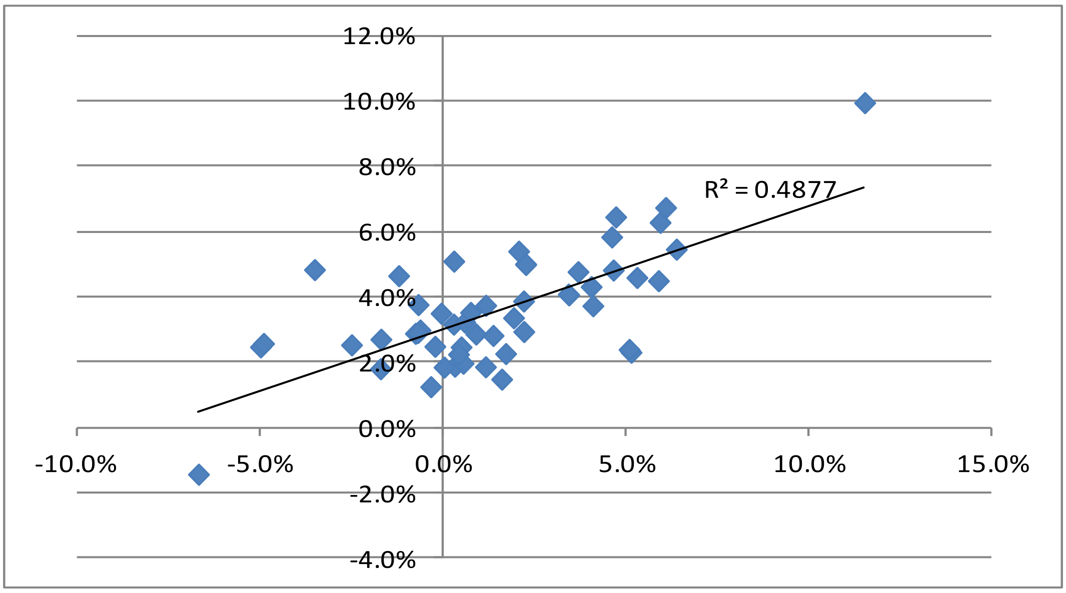


Figure 4Correlation between compounded annual extensive industrialization growth rate and compounded annual GDP growth rate over the period 1990 – 2005

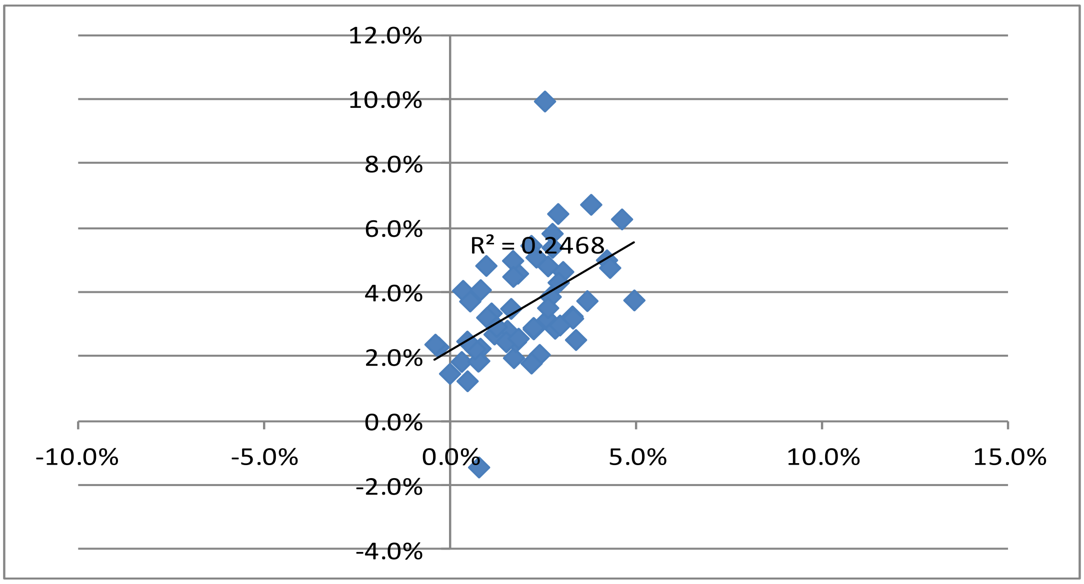


Table 4 Average compounded annual GDP growth rate, average compounded annual intensive and extensive industrialization growth rates for the group of countries with a positive average compounded annual growth rate and for the group of countries with a negative average compounded annual intensive industrialization growth rate over the period 1990 – 2005

	Average compounded annual GDP growth rate 1990 – 2005	Average compounded annual extensive industrialization growth rate 1990 – 2005
Group of countries with a positive compounded annual intensive industrialization growth rate 1990 – 2005	3.9	1.8
Group of countries with a negative compounded annual intensive industrialization growth rate 1990 – 2005	2.6	1.9

3. Data

We calculate 5-year compounded annual GDP and manufacturing value added growth rates as in Lavopa and Szirmai (2012). We believe that the impact of the manufacturing value added growth rate is not perceptible in a given single year, and we therefore capture the 5-year medium-term effects. Another advantage of the 5-year growth rate technique is that we do not have to model an overly sophisticated lags structure for the first Kaldor Law.

The dataset encompasses 130 countries for the period 1960 – 2011. The coverage of each country depends on data availability (see Annex III). This dataset has been built on five major sources:

- McMillan and Rodrik's (2011) database on sectoral employment and value added (M&R, 2011);
- EU-KLEMS Database (EUKLEMS);
- World Bank, World Development Indicators Database (WDI);
- International Labour Organization, Key Indicators of the Labor Market Database, version 7.0 (KILM7);
- Penn World Tables 8.0 (PWT8).

Our preferred data source was the database published in M&R (2011), which contains comparable data on employment and valued added by major sectors of the economy over a long period (35 years on average) for 37 countries[14]. The majority of countries included in our sample, however, are not captured in this dataset and we therefore used the best available data from other sources to build comparable estimates on the relevant variables.

For the European and OECD countries not covered in M&R (2011), we used the EUKLEMS Database, which contains data on employment and valued added of 34 industries for the period 1970 – 2011[15].

For the remaining countries[16], the data was derived from WDI. Since this data source only contains data on the share of industry[17] in total employment, the share of manufacturing employment was calculated using additional data from the KILM 7 database[18]. We calculated the share of manufacturing in industrial employment for each country based on this data and applied this share to the corresponding share of industrial employment published by WDI. WDI data cover the years from 1980 to 2013.

To retain maximum comparability between the countries of our sample, the value for total employment was controlled using the same data source for all countries. Consequently, the value for total employment of each country was taken from PWT8. This data source contains information for 167 countries between 1950 and 2011[19]. The absolute number of employees in manufacturing was calculated multiplying the shares obtained from the sources mentioned above by the estimates of total employment provided by PWT8.

Eighty countries in the period 1980 – 2010 were used for the analysis to ensure full data coverage of all variables needed to apply the GMM technique to the first Kaldor Law[20]. A first rule of thumb to avoid overfitting is that the number of countries should be higher than the number of time periods. Our sample fits this case because the number of countries is several times larger than the six periods studied.

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[14] This database, in turn, is an extension of the Groningen 10-Sector database (Timmer et al., 2007). The 10 sectors included are agriculture, hunting, forestry and fishing; mining and quarrying; manufacturing; electricity, gas and water supply; construction; wholesale and retail trade, hotels and restaurants; transport, storage, and communication; finance, insurance, real estate and business services; government services; and community, social and personal services.

[15] For the details, see: http://euklems.net/

[16] This group actually represents the major part of our dataset, encompassing 75 of the 130 countries.

[17] That is, manufacturing plus mining, public utilities and construction.

[18] For the details, see www.ilo.org/kilm

[19] For the details, see: http://www.rug.nl/research/ggdc/data/penn-world-table

[20] Details about the sample and the countries used to run the econometric estimate is included in Annex III and Annex IV.

4. Results and discussion

The results of the regression are presented in Table 5 and 6. Table 5 presents the results of the estimates for equations (1) – (6) capturing values related to different econometric techniques. In Table 5, two variables are significant and have a positive value: the constant and the manufacturing value added growth rate.

Using the pooled OLS/fixed effect/random effects techniques, the constant term varies in the range 1.8 percent – 2.1 percent. This means that when the manufacturing value added growth range does not change, the economic growth rate grows, on average, within the range captured by the constant term. It is interesting to note that when we apply GMM techniques, the value of the constant term decreases.

When we consider the pooled OLS/fixed effect/random effects, the coefficient MANGR lies in the range 0.47 percent – 0.48 percent, whereas when we apply the GMM technique, the coefficient lies within the range 0.53 percent – 0.87 percent. This means that when the manufacturing value added growth rate increases by 1 percent, the GDP growth rate increases within that range.

The higher value of the manufacturing value added coefficient when we apply the GMM technique implies that traditional techniques which do not treat endogeneity appropriately (see Section 2), bias the MANGR coefficient estimate downwards. This finding confirms the results of Avacedo et al. (2009) who show that GMM estimates are higher than pooled OLS/fixed effects/random effects estimates using a GMM first difference approach.

Our estimates also confirm the engine of growth hypothesis. We find that the lowest estimate of the MANGR variable (0.472 percent in the pooled OLS regression) is higher than the maximum share of manufacturing value added that we observe in all periods considered in all countries (0.400 equivalent to 40 percent). These results provide robust even if not definitive support for the first Kaldor Law and the engine of growth hypothesis of manufacturing.

It is interesting to note that nearly all time period dummies are not significant, which implies that the impact of the manufacturing sector on GDP growth is quite stable over time. When GMM techniques are applied, regional dummies based on the differentiation of income levels become significant. In particular, low income countries show higher growth rates than high income countries (1.4 percent on average).

Table 6 shows in more detail how the different manufacturing value added components impact GDP growth rate. Again we find that the constant term tends to decrease when applying the GMM techniques in comparison with in particular the fixed effects and random effects models.

Time periods are again insignificant in all econometric techniques, even with this specification, whereas the regional dummy is significant only when using the GMM techniques. Again we find that low income countries show a higher growth rate on average than high income countries (between 2.8 percent and 4.3 percent on average).

Two main findings emerge on the manufacturing value added growth components:

1) With the pooled OLS/fixed effects/random effects, the variable that has the highest significant coefficient is MANGRTOTEM representing the extensive industrialization growth rate. The productivity MANGRPROD and manufacturing employment coefficients MANGRMANEM are also significant with a positive sign, but show a lower coefficient.

2) The MANGRTOTEM coefficient is no longer significant when applying the GMM techniques. The productivity coefficient MANGRPROD is the one with the highest value. The implication is that traditional econometric techniques tend to overestimate the extensive industrialization growth rate in the extended Kaldor equation. Only intensive industrialization matters for growth in the GMM techniques.

The GMM result is also robust to lags truncation which reduces the number of instruments needed to decrease the risk of overfitting. All robustness tests show that the GMM specification is robust in terms of the selection of exogenous variables, the absence of autocorrelation and the choice of instruments.

5. Conclusion and policy implications

The results of our study contribute to the debate on a different approach to development and industrial policy. Kaldor’s Law has represented the theoretical foundation of a development paradigm based on industrial growth. Accordingly, upgrading towards higher levels of GDP per capita should necessarily undergo an increase in the weight of industry in the overall economy. The neoclassical paradigm rejects this approach based on the idea that countries should focus on those sectors in which they have a comparative advantage and better production cost conditions. Kaldor’s approach is based on the idea of strengthening those modern sectors with the highest potential to spread positive externalities to the rest of the economy, in particular the manufacturing sector. In line with this approach, it is important to help the manufacturing sector grow, even if manufacturing is not competitive in the initial stages of development. Economies of scale will help the manufacturing sector in low income countries become more competitive over time and spread positive externalities to other important complementary sectors such as agriculture and services.

In retrospect, we know that industrialization as an engine of growth worked for some regions, but not for others. This implies that the discussion should now focus on the modalities by which industrialization is implemented and in particular on the drivers of industrialization. This paper, which analyses intensive vs extensive industrialization, contributes to this discussion.

Whereas intensive industrialization enhances the growth of the manufacturing sector through increases in manufacturing productivity and in manufacturing employment share (structural change), extensive industrialization is the growth of manufacturing value added deriving from additional deployment of labour under the assumption that manufacturing labour shares and manufacturing productivity remain constant.

We conclude that the Kaldor Law is valid, as manufacturing remains an engine of growth, though not every dollar of additional manufacturing value added contributes to growth. Intensive rather than extensive industrialization is found to be closely linked to the GDP economic growth rate variable.

A comparison between China and South Africa, two emerging countries, is useful to better understand our research results. In South Africa, productivity of the manufacturing sector dropped 50 percent over the period 1990 – 2005, but total employment doubled (extensive industrialization). With a predominantly extensive industrialization component, South Africa only registered a 2.5 percent annual increase in GDP growth compared to an annual 12 percent GDP growth rate in China, where manufacturing labour productivity increased by more than 500 percent and the overall intensive industrialization component was four times larger than the extensive component of manufacturing growth. In China, the boom of intensive industrialization could explain the country's exceptional GDP growth performance.

Industrial policies and strategies fully designed to promote productivity and technological change could trigger those virtuous spillover mechanisms that benefit other economic sectors. Moreover, new isolated industrial activities with poor backward and forward linkages that do not increase the manufacturing employment share are unlikely to generate the engine of growth process that Kaldor described so well in his pioneering work. In other words, structural change towards the manufacturing sector and manufacturing productivity are the key policy variables to be prioritized by policymakers.

Table 5 Estimation results of the first Kaldor Law

	Pooled OLS	Fixed effects	Random effects	One step difference GMM estimator (robust standard errors)	Two-step difference GMM estimator (robust standard errors)	Two-step system GMM (robust standard errors)	Two-step system GMM (robust standard errors) “parsimonious” (only second lag and third lag)	Two-step system GMM (robust standard errors) “parsimonious” (only second lag)	Two-step system GMM estimation (robust standard errors) + lagged dependant variable	Two-step system GMM estimation (robust standard errors) + lagged dependant variable (only second and third lag)	Two-step system GMM estimation (robust standard errors) + lagged dependant variable (only second lag)
Observations	300	300	300	216	216	300	300	300	216	216	216
Constant	.01848***	.02007***	.02124***			.00982***	0.00992***	0.00759**	0.01298***	0.01341***	0.01306***
L.GDPGR									0.20136***	0.21202**	0.21861**
MANGR	.46200***	.48123***	.47499***	.53896***	.64960***	.79350***	0.80460***	0.87087***	0.55185***	0.53820***	0.55547***
1985 - 1990	-.00184	-.00052	-.00102	-.00087	-.00122	-.00036	0.00006	0.00121	-0.00490**	-0.00462*	-0.00459*
1990 - 1995	.00262	.00148	.00149	-.00187	-.00166	.00062	-0.00114	-0.00038	-0.00259	-0.00205	-0.00307
1995 - 2000	.00438	.00291	.00303	-.00176	.00018	0.00128	0.00156	0.00219	-0.00190	-0.00199	-0.00238
Low income	-.00259					.00806	0.00778	0.00833	0.01560***	0.01467***	0.01489***
Low medium income	.00177					-.00104	-0.00229	-0.00278	0.00095	0.00093	0.00028
Upper middle income	.00524					.00049	0.00018	-0.00185	0.00003	-0.00024	0.00010

R2	0.54	0.53	0.53								
Hansen/Sargan test of overidentifying restrictions				0.568	0.568	0.658	0.576	0.882	0.632	0.403	0.466
AR test				AR(1): 0.004 AR(2): 0.596	AR(1): 0.008 AR(2): 0.416	AR(1): 0.010 AR(2): 0.298	AR(1): 0.011 AR(2): 0.318	AR(1): 0.013 AR(2): 0.315	AR(1): 0.002 AR(2): 0.454	AR(1): 0.010 AR(2): 0.484	AR(1): 0.010 AR(2): 0.497
Hansen/Sargan test applied only to instruments of endogenous variables	0			0.543	0.543	0.612	0.574	0.329	0.688	0.444	0.348
Difference in Sargan/Hansen test for exogenous variables				0.447	0.447	0.539	0.465	0.912	0.369	0.336	0.563
Difference in Sargan/Hansen test for GMM instruments for levels						0.606	0.527	0.894	0.335	0.293	0.609
Number of instruments				13	13	21	18	15	33	29	23

*** significant 1% significance level
** significant 5% significance level
*significant 10% significance level

Table 6 Estimation results of the modified first Kaldor Law

0	Pooled OLS	Fixed effects	Random effects	One-step difference GMM estimator (robust standard errors)	Two-step difference GMM estimator (robust standard errors)	Two-step system GMM (robust standard errors)	Two-step system GMM (robust standard errors) “parsimonious” (only second lag and third lag)	Two-step system GMM (robust standard errors) “parsimonious” (only second lag)	Two-step system GMM estimation (robust standard errors) + lagged dependant variable	Two-step system GMM estimation (robust standard errors) + lagged dependant variable (only second and third lag)	Two-step system GMM estimation (robust standard errors) + lagged dependant variable (only second lag)
Observations	300	300	300	216	216	300	300	300	216	216	216
Constant	.01527***	.01922***	.02030***			.016531***	0.01702***	0.01508**	0.01858***	0.01667***	0.01770**
L.gdpgr									0.17826	0.22320*	0.23422
MANGRTOTEM	.61069***	.59013***	.60086***	. .36554*	.36750*	.36397	0.35655	.31364	0.28286	0.34275	0.25412
MANGRMANEM	.30711***	.36634***	.34965***	.53638***	.53955***	.63937***	0.65192***	.57622***	0.39831***	0.37556***	0.35707***
MANGRPROD	.43175***	.43464***	.42585***	.58123***	.63300***	.70191***	0.69677***	.67548***	0.50672***	0.47373***	0.46536***
1985 - 1990	-.00100	.00037	.00006	-.00292	-.00382	-.00143	-0.00164	-.00258	-0.00728	-0.00794	-0.00745
1990 - 1995	.00356	.00292	.00308	.00155	.00015	.00277	0.00264	.00313	-0.00421	-0.00478	-0.00317
1995 - 1990	.00596*	.00405	.00466	.00140	-.00003	.00191	0.00141	.00396	-0.00482	-0.00491	-0.00367
Low income	.00911					.02829**	0.02820**	.03153***	0.04310***	0.04082***	0.03917***

Low medium income	.00345					.00714	0.00721	.01155*	0.00780*	0.00781	0.00718
Upper middle income	.00482					.00513	0.00502	.0067518	0.00677*	0.00662	0.00468
R2	0.52	0.50	0.51								
Hansen/Sargan test				0.424	0.424	0.794	0.738	0.686	0.541	0.411	0.494
AR test				AR(1): 0.003 AR(2): 0.632	AR(1): 0.004 AR(2): 0.499	AR(1): 0.005 AR(2): 0.497	AR(1): 0.004 AR(2): 0.483	AR(1): 0.004 AR(2): 0.654	AR(1): 0.025 AR(2): 0.698	AR(1): 0.030 AR(2): 0.515	AR(1): 0.069 AR(2): 0.602
Hansen/Sargan test applied only to instruments of endogenous variables				0.516	0.516	0.822	0.742	0.883	0.641	0.482	0.335
Difference in Sargan/Hansen test for exogenous variables				0.211	0.211	0.423	0.477	0.203	0.232	0.263	0.781
Difference in Sargan/Hansen test for GMM instruments for levels						0.827	0.852	0.943	0.607	0.605	0.975
				28	28	44	40	31	55	51	39

*** significant 1% significance level
** significant 5% significance level
*significant 10% significance level

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Annex I Robustness tests for GMM estimates

Autocorrelation test

One first important GMM specification test is the autocorrelation AR(1) test in first difference. Given the model

$$A1)\ y_{it} = \alpha y_{it-1} + \beta x_{it} + \varepsilon_{it}$$

taking the first difference of this model in difference GMM, we obtain:

$$A2)\ y_{it} - y_{it-1} = \alpha(y_{it-1} - y_{t-2}) + \beta(x_{it} - x_{it-1}) + (\varepsilon_{it} - \varepsilon_{t-1})$$

that is:

$$A3)\ \Delta y_{it} = \alpha + \beta \Delta x_{it} + \Delta \varepsilon_{it}$$

As $\Delta\varepsilon_{it} = (\varepsilon_{it} - \varepsilon_{t-1})$ by construction equation (1) is autocorrelated of order 1 (AR(1)) as $\Delta\varepsilon_{it-1} = (\varepsilon_{it-1} - \varepsilon_{t-2})$ shares with $\Delta\varepsilon_{it}$ the variable ε_{t-1}. By construction we therefore expect the existence of AR(1) in the first difference, but not AR(2) when we estimate a difference GMM.

Hansen/Sargan test for overidentification

The Sargan test is used to verify whether the instruments, as a group, appear exogenous. The Sargan statistics are not robust to heteroskedasticity or autocorrelation. With robust standard errors the Sargan statistics' asymptotic distribution is not known and we therefore prefer the Sargan/Hansen test. The Sargan/Hansen test is robust to autocorrelation and heteroschedasticity, but may still be weak in terms of instruments' proliferation. The Sargan/Hansen statistics can also be used to test the validity of subsets of instruments by applying a difference "in-Sargan/Hansen" test, also known as a C statistic. The C statistic is based on an estimation with and without a subset of suspect instruments under the null of exogeneity of the full instrument set. We apply the difference in Sargan/ Hansen test to the GMM instruments for levels and to the assumed exogenous variables (*IC* and *z* in our model).

Annex II. The Log Mean Divisia Index (LMDI) technique

Decomposition is a technique which has recently been used extensively in the field of environmental and energy economics. The IDR 2011 uses the LMDI technique to analyse different determinants of energy intensity shifts in terms of technological effect and structural change, whereas the IDR 2013 uses the LMDI technique to analyse determinants of emissions variations on the basis of GDP, energy emissions intensity and energy intensity variations. However, LMDI is an interdisciplinary technique which can be used whenever the contribution of different components expressed in a multiplicative form needs to be calculated into additive variations. Given an initial multiplicative equation, this is as follows:

$$A1) Z = A * B * C$$

It is possible to express equation (1) in the form

$$A2) Z = \Delta A + \Delta B + \Delta C$$

being

$$A3) \Delta A = w_i \ln(\frac{A_t}{A_0})$$

$$A4) \Delta B = w_i \ln(\frac{B_t}{B_0})$$

$$A5) \Delta C = w_i \ln(\frac{C_t}{C_0})$$

$$A6) w_i = \frac{E_i^T - E_i^0}{\ln E_i^t - \ln E_i^0}$$

Ang (2005)[21] proves that Z is perfectly decomposable with this technique, as Z can be decomposed into three components referring to equation (1) without any residual that can hardly be interpreted. Outside the environmental and energy strand of research, the LMDI technique is slowly spreading to studies on other topics. Wan et al. (2011), for example, apply the LMDI technique to investigate the impact of R&D input on economic growth.

Annex III. The full sample

Country	Time coverage			Source
	From	Until		
Albania	1,996	2,004		WDI and ILO KILM7
Algeria	2,001	2,004		WDI and ILO KILM7
Argentina	1,960	2,005		M&R (2011)
Armenia	2,002	2,008		WDI and ILO KILM7
Australia	1,970	2,007		EUKLEMS
Austria	1,970	2,007		EUKLEMS
Azerbaijan	1,992	2,010		WDI and ILO KILM7
Bahrain	1,981	1,985		WDI and ILO KILM7
Bangladesh	1,984	2,005		WDI and ILO KILM7
Belarus	1,990	1,994		WDI and ILO KILM7
Belgium	1,970	2,007		EUKLEMS
Benin	2,003	2,003		WDI and ILO KILM7
Bolivia	1,960	2,005		M&R (2011)
Botswana	1,985	2,006		WDI and ILO KILM7
Brazil	1,960	2,005		M&R (2011)
Bulgaria	1,997	2,010		WDI and ILO KILM7
Burkina Faso	1,994	2,005		WDI and ILO KILM7
Burundi	2,005	1,998		WDI and ILO KILM7

[21] http://www.ise.nus.edu.sg/staff/angbw/pdf/A_Simple_Guide_to_LMDI.pdf

Cambodia	1,998	2,011		WDI and ILO KILM7
Cameroon	1,986	2,001		WDI and ILO KILM7
Canada	1,981	2,008		WDI and ILO KILM7
Chad	2,009	1,993		WDI and ILO KILM7
Chile	1,960	2,005		M&R (2011)
Country	Time coverage			Source
	From	Until		
China	1,990	2,007		M&R (2011)
Colombia	1,960	2,005		M&R (2011)
Congo, Rep.	2,005	2,005		WDI and ILO KILM7
Costa Rica	1,960	2,005		M&R (2011)
Croatia	1,996	2,011		WDI and ILO KILM7
Cuba	1,991	2,010		WDI and ILO KILM7
Cyprus	1,970	2,007		EUKLEMS
Czech Republic	1,970	2,007		EUKLEMS
Denmark	1,960	2,005		M&R (2011)
Dominican Republic	1,991	2,010		WDI and ILO KILM7
Ecuador	1,988	2,010		WDI and ILO KILM7
Egypt, Arab Rep.	1,987	2,010		WDI and ILO KILM7
El Salvador	1,980	2,010		WDI and ILO KILM7
Estonia	1,970	2,007		EUKLEMS
Ethiopia	1,990	2,005		M&R (2011)
Finland	1,970	2,007		EUKLEMS
France	1,960	2,005		M&R (2011)
Gabon	1,993	2,005		WDI and ILO KILM7
Gambia, The	1,993	1,993		WDI and ILO KILM7
Georgia	1,998	2,007		WDI and ILO KILM7
Germany	1,991	2,010		WDI and ILO

				KILM7
Ghana	1,990	2,005		M&R (2011)
Greece	1,970	2,007		EUKLEMS
Guatemala	1,981	2,006		WDI and ILO KILM7
Guinea	1,994	1,994		WDI and ILO KILM7
Haiti	1,997	1,999		WDI and ILO KILM7
Country	Time coverage			Source
	From	Until		
Honduras	1,980	2,010		WDI and ILO KILM7
Hong Kong SAR China	1,974	2,005		M&R (2011)
Hungary	1,970	2,007		EUKLEMS
India	1,960	2,005		M&R (2011)
Indonesia	1,961	2,005		M&R (2011)
Iran, Islamic Rep.	1,996	2,007		WDI and ILO KILM7
Iraq	2,004	2,003		WDI and ILO KILM7
Ireland	1,970	2,007		EUKLEMS
Italy	1,960	2,005		M&R (2011)
Jamaica	1,992	2,011		WDI and ILO KILM7
Japan	1,960	2,005		M&R (2011)
Jordan	1,983	2,011		WDI and ILO KILM7
Kazakhstan	2,000	2,011		WDI and ILO KILM7
Kenya	1,990	2,006		M&R (2011)
Korea, Rep.	1,963	2,005		M&R (2011)
Kuwait	1,995	2,003		WDI and ILO KILM7
Kyrgyz Republic	1,990	2,008		WDI and ILO KILM7
Lao PDR	1,995	1,995		WDI and ILO KILM7
Latvia	1,970	2,007		EUKLEMS
Lesotho	1,997	1,999		WDI and ILO KILM7
Liberia	2,007	2,007		WDI and ILO

				KILM7
Lithuania	1,970	2,007		EUKLEMS
Luxembourg	1,970	2,007		EUKLEMS
Macedonia, FYR	2,002	2,008		WDI and ILO KILM7
Madagascar	2,003	2,005		WDI and ILO KILM7
Malawi	1,990	2,005		M&R (2011)
Country	Time coverage			Source
	From	Until		
Malaysia	1,975	2,005		M&R (2011)
Mali	2,004	2,004		WDI and ILO KILM7
Malta	1,970	2,007		EUKLEMS
Mauritius	1,990	2,008		M&R (2011)
Mexico	1,960	2,005		M&R (2011)
Moldova	1,995	2,011		WDI and ILO KILM7
Mongolia	1,995	2,009		WDI and ILO KILM7
Morocco	2,002	2,011		WDI and ILO KILM7
Mozambique	2,003	2,003		WDI and ILO KILM7
Myanmar	1,980	1,998		WDI and ILO KILM7
Namibia	2,000	2,008		WDI and ILO KILM7
Nepal	1,991	2,001		WDI and ILO KILM7
Netherlands	1,960	2,005		M&R (2011)
Nicaragua	1,994	2,010		WDI and ILO KILM7
Nigeria	1,983	2,007		M&R (2011)
Norway	1,980	2,010		WDI and ILO KILM7
Oman	1,993	2,000		WDI and ILO KILM7
Pakistan	1,980	2,008		WDI and ILO KILM7
Panama	1,982	2,011		WDI and ILO KILM7

Papua New Guinea	2,000	2,000		WDI and ILO KILM7
Paraguay	1,991	2,011		WDI and ILO KILM7
Peru	1,960	2,005		M&R (2011)
Philippines	1,971	2,005		M&R (2011)
Poland	1,970	2,006		EUKLEMS
Portugal	1,970	2,006		EUKLEMS
Country	Time coverage			Source
	From	Until		
Puerto Rico	1,980	1,991		WDI and ILO KILM7
Romania	2,004	2,010		WDI and ILO KILM7
Rwanda	1,989	2,005		WDI and ILO KILM7
Saudi Arabia	1,999	2,009		WDI and ILO KILM7
Senegal	1,990	2,005		M&R (2011)
Sierra Leone	2,003	2,004		WDI and ILO KILM7
Singapore	1,970	2,005		M&R (2011)
Slovak Republic	1,970	2,007		EUKLEMS
Slovenia	1,970	2,006		EUKLEMS
South Africa	1,990	2,009		M&R (2011)
Spain	1,960	2,005		M&R (2011)
Sri Lanka	1,981	2,010		WDI and ILO KILM7
Sweden	1,960	2,005		M&R (2011)
Syrian Arab Republic	2,000	2,002		WDI and ILO KILM7
Tajikistan	2,004	2,004		WDI and ILO KILM7
Tanzania	1,991	2,006		WDI and ILO KILM7
Thailand	1,960	2,005		M&R (2011)
Togo	2,006	2,006		WDI and ILO KILM7
Trinidad and Tobago	1,984	2,008		WDI and ILO KILM7
Tunisia	1,980	1,989		WDI and ILO KILM7

Turkey	1,988	2,009		M&R (2011)
Uganda	2,002	2,009		WDI and ILO KILM7
United Arab Emirates	2,001	2,008		WDI and ILO KILM7
United Kingdom	1,960	2,005		M&R (2011)
United States	1,960	2,005		M&R (2011)
Venezuela, RB	1,960	2,005		M&R (2011)
Country	Time coverage			Source
	From	Until		
Viet Nam	1,996	2,006		WDI and ILO KILM7
Yemen, Rep.	1,991	1,999		WDI and ILO KILM7
Zambia	1,990	2,005		M&R (2011)
Zimbabwe	1,999	2,004		WDI and ILO KILM7

Annex IV. Countries for the econometric estimates

High income (35)	**Upper middle income (23)**	**Lower middle income (18)**	**Low income (4)**
Australia	Argentina	Bolivia	Ethiopia
Austria	Azerbaijan	Egypt	Kenya
Belgium	Brazil	El Salvador	Kyrgyz Republic
Canada	Bulgaria	Ghana	Malawi
Chile	China	Georgia	
Croatia	Colombia	Ghana	
Cyprus	Costa Rica	Honduras	
Czech Republic	Cuba	India	
Denmark	Dominican Republic	Indonesia	
Estonia	Ecuador	Moldova	
Finland	Hungary	Mongolia	
France	Jamaica	Morocco	
Germany	Jordan	Nicaragua	
Greece	Kazakhstan	Nigeria	
Hong Kong	Malaysia	Pakistan	
Ireland	Mauritius	Paraguay	
Italy	Mexico	Philippines	
Japan	Panama	Pakistan	
Korea	Peru		
Latvia	South Africa		
Lithuania	Thailand		
Luxembourg	Turkey		
Malta	Venezuela		
Netherlands			
Norway			
Poland			
Portugal			
Singapore			
Slovak Republic			

Slovenia			
Spain			
Sweden			
Trinidad and Tobago			
United States			
United Kingdom			

Annex V. Ranking of countries in terms of GDP growth, intensive industrialization and extensive industrialization (compounded annual growth rate). Period 1990 – 2005

Country	Economic growth		Country	Intensive industrialization growth rate		Country	Extensive industrialization growth rate
China	0.099		China	0.115		Honduras	0.049
Malaysia	0.067		Korea, Rep.	0.064		Ireland	0.046
Singapore	0.064		Malaysia	0.061		Trinidad and Tobago	0.043
Ireland	0.063		Ireland	0.059		Costa Rica	0.042
India	0.058		Thailand	0.059		Malaysia	0.038
Korea, Rep.	0.054		Indonesia	0.053		Ghana	0.037
Chile	0.054		Finland	0.051		South Africa	0.034
Nigeria	0.051		Sweden	0.051		Luxembourg	0.030
Costa Rica	0.050		Singapore	0.047		Ecuador	0.029
Mauritius	0.050		Sri Lanka	0.046		Pakistan	0.029
Hong Kong SAR, China	0.048		India	0.046		Singapore	0.029
Sri Lanka	0.048		Turkey	0.041		Colombia	0.028
Trinidad and Tobago	0.047		Pakistan	0.040		Chile	0.027
Luxembourg	0.046		Trinidad and Tobago	0.037		India	0.027
Indonesia	0.046		Egypt, Arab Rep.	0.034		El Salvador	0.027
Thailand	0.045		Peru	0.034		Sri Lanka	0.026
Pakistan	0.043		Mauritius	0.023		Philippines	0.026
Peru	0.041		Costa Rica	0.022		Bolivia	0.026
Egypt, Arab Rep.	0.040		United States	0.022		China	0.025
El Salvador	0.038		El Salvador	0.022		Nigeria	0.023
Honduras	0.037		Chile	0.021		Mexico	0.022
Ghana	0.037		Argentina	0.019		Spain	0.022
Turkey	0.037		Austria	0.017		Venezuela,	0.022

						RB	
Philippines	0.035		Japan	0.016		Korea, Rep.	0.022
Australia	0.035		Canada	0.014		Zambia	0.018
Argentina	0.033		Ghana	0.012		Indonesia	0.018
Norway	0.032		France	0.012		Malawi	0.017
Bolivia	0.031		Mexico	0.009		Brazil	0.017
Ecuador	0.030		Philippines	0.007		Thailand	0.017
United States	0.029		Norway	0.006		Mauritius	0.017
Spain	0.029		Brazil	0.005		Australia	0.016
Colombia	0.029		Netherlands	0.005		Canada	0.015
Mexico	0.028		Portugal	0.004		Netherlands	0.015
Canada	0.028		Belgium	0.003		United States	0.012
Greece	0.027		Nigeria	0.003		Greece	0.012
Zambia	0.025		Bolivia	0.003		Argentina	0.011
South Africa	0.025		Denmark	0.000		Norway	0.010
United Kingdom	0.025		Australia	-0.001		Hong Kong SAR, China	0.009
Malawi	0.024		United Kingdom	-0.002		Peru	0.008
Netherlands	0.024		Italy	-0.003		Austria	0.008
Sweden	0.024		Ecuador	-0.006		Belgium	0.008
Finland	0.023		Honduras	-0.007		Kyrgyz Republic	0.008
Austria	0.022		Spain	-0.007		France	0.007
Portugal	0.022		Colombia	-0.008		Portugal	0.006
Brazil	0.019		Luxembourg	-0.012		Turkey	0.005
Belgium	0.019		Greece	-0.017		Italy	0.004
France	0.018		Venezuela, RB	-0.017		United Kingdom	0.004
Denmark	0.018		South Africa	-0.025		Egypt, Arab Rep.	0.003
Venezuela, RB	0.018		Hong Kong SAR, China	-0.035		Denmark	0.003
Japan	0.015		Zambia	-0.049		Japan	0.000
Italy	0.012		Malawi	-0.050		Finland	-0.003
Kyrgyz Republic	-0.015		Kyrgyz Republic	-0.067		Sweden	-0.004

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