Steel Augmented Production Function: Robust Analysis for European Union

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Abstract

This study contributes to the empirical literature on augmented neo-classical production function. It is done by introducing steel production into macro-production function of the European Union. The data is collected from the World Development Indicators and the World Steel Association from the period of 1980–2014. We apply second generations of unit root tests to examine stationarity and panel cointegration with cross-sectional dependence to analyze long run relationship between national income and steel production. Robustness of tests is also reached by using 23 estimators and country specific slopes. Whereas, to detect the cause and effect, Granger and Dumitrescu-Hurlin causality tests are applied. Uni-directional causality from national income to steel production is found. Recommendations are made on the basis of empirical results.

Keywords

Steel production, national income, augmented mean group, panel causality

JEL code

D24, E01, C23

INTRODUCTION

Steel is not a nascent alloy, however, its manufacturing at commercial scale and organized trade started only after industrial revolution. Events related to changes of fuel industry and collection of technological advances during 1600s, 1700s and 1800s laid the foundation of the contemporary steel industry. During 1830 to 1860, steel was used as a semi-precious metal in expensive products. 'The Great Transformation' era (1860–1900) was mainly attributed to by low cost 'open hearth' and 'Bessemer' methods of steel production that spurred the growth of steel production by seventeen fold. Establishment of US steel companies led to consolidation period during 1900–1920. However, steel industry also felt depression during 1930s due to 'Great Depression' and the rise of labor movement. The revival of steel industry was triggered by World War-II during 1940-1945. Warring European countries used steel for manufacturing arsenals, tanks, trucks, ships and other war weapons rendering steel industry a giant industry. The post-war period (1946 to 1970) is called the 'period of prosperity' due to growth of steel industry, evolution of recycling segment of industry and development of substitute, such as aluminum.

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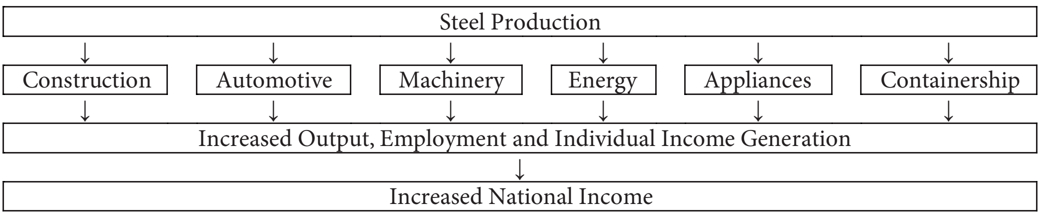
Alongside prosperity, steel also witnessed 'troubled times' during the period of 1970–1989, when many plants were closed, production declined and layoffs took place. The intensity of this trouble was mitigated during period of 1990–2001 which is called the era of 'uneasy trouble'.

The usage of steel is universal as the World Steel Association states, "steel is everywhere in your life". Related benefits include employment generation and infrastructural effects of providing infrastructure to industrial and modern sectors. In 1970 steel industry employed 531.196 people and even after its decline in 2000, it still had 225.000 on its payroll. Its backward & forward linkages play a significant role in development via providing critical inputs like machinery for developmental projects. In addition to assistance to developmental projects, public sector also gains from tax revenue by steel industry. Steel industry can also indirectly contribute to foreign exchange reserves by assisting industries in the production of exports. In addition, steel industry also contributes to agriculture sector by providing tractors, aerial spray, and harvesters etc. that increase the per acre yield of crops which will ultimately increase the national income.[4]

Figure 1 Mechanism of Contribution of Steel Industry in National Income



Source: Authors' formulation

Based on the pictorial explanation in Figure 1, this paper attempts to quantify the relationship between steel industry and national income in the European Union.

Hypothesis

Based on the objective, following hypothesis shall be tested:

H_A: There exists a causal and long run relationship between steel production and national income of the European Union.

1 LITERATURE REVIEW

Subject of this research has not been chosen by many of the researchers and it is due to the fact that there exists limited literature on it. Jeferrson (1990) using Chinese data investigated the productivity variation among enterprises within China's steel and iron industry. He found enhanced productivity growth during reform period within the industry. Labson and Crompton (1993) studied relationship between income and five industrial metals for Japan, OECD, USA and UK for the period of 1960–1987. However, they proposed slight explanation to support the existence of long run relationship between two variables. Hoechle (2007) studied the energy efficiency of China's steel and iron sector for the time span of 1994–2003 using Malmquist decomposition index. Provincial panel data was used permitting various energy inputs and outputs. Results revealed that empirical productivity of China's steel and iron sector increased by 60% from 1994 to 2003 which is a sign of technological progress.

Evans (2011) analyzed the long run relationship between crude steel and economic activity production in United Kingdom. He used integrated processes and allowed for the possibility of changes in equilibrium

[4] For more on sectoral contribution of steel industry, visit website of the World Steel Association.

path. Evidence is found in support the long term relationship. Huh (2011) studied the short run and long run relationship between steel production and GDP in Korea from 1975 to 2008. He used vector error correction and vector autoregressive models. He found a long term causal relationship, running from GDP to total steel production. He also found the bi-causal relationship between flat product consumption and GDP. Ozkan (2011) analyzed the relation between steel production consumption, import & export, GDP and industrial production. They applied error correction model, Engle-Granger cointegration and Granger causality test. Their results revealed a positive relation of steel export and production with GDP. A positive relationship was also found between industrial production and steel export. Both relations showed causality effects.

Siddique, Mehmood and Ilyas (2016) analyzed the relationship between economic growth and steel production in Pakistan. They used time series data to apply Philip Person (PP) and Augmented Dickey Fuller (ADF) test and Cointegration with Bai-Perron structural breaks test to check the long run relationship between the two variables. Their results show a positive relationship between steel production and economic growth with causality from economic growth to steel production.

Review shows that majority of studies are limited to a single country not allowing the benefits of panel data analysis. Moreover, possible effects of common shocks are not incorporated either. Important variables like capital and labor that play a critical role in any production are also missing in till-date empirical literature. Though steel industry is capital intensive, yet labor employment is also substantial due to need for manual labor in mega-structures. European Union (EU) is the largest producer of steel after China. Research on this sample should allow for improved policy directions. Current paper does so by choosing a sample of EU.

2 ESTIMABLE PRODUCTION FUNCTION

The estimable production function for testable prediction that steel production and national income have nexus in European Union countries is given as follows:

$$NI_{i,t} = f(ST_{i,t}, CP_{i,t}, LB_{i,t}), \tag{1}$$

where:

$NI_{i,t}$ = GDP (constant 2005 US$),
$ST_{i,t}$ = Steel production (thousand tones),
$CP_{i,t}$ = Gross fixed capital formation (constant 2005 US$),
$LB_{i,t}$ = Labor force, total,
i and t stand for cross-sections and time periods, respectively.

2.1 Methodology – Data Sources

Depending on the availability of data, 28 EU countries are selected while the number of years is 35 (1980–2014). Sample countries are Austria, Belgium, Bulgaria, Croatia, Republic of Cyprus, Czech Republic, Denmark, Estonia, Finland, France Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden and UK. Collection of data is done from World Development Indicators (WDI) and World Steel Association.

3 EMPIRICAL ANALYSIS

3.1 Static Estimations

In order to examine the empirical relationship of national income and steel production, following analysis is conducted. We estimated static models that are devoid of any lagged dependence of dependent variable. These include pooled OLS (POLS: $NI_{it} = \alpha + \beta_{ST}.ST_{it} + \beta_{CP}.CP_{it} + \beta_{LB}.LB_{it} + \varepsilon_{it}$), fixed effects (FE: $NI_{it} = \alpha_i + \beta_{ST}.ST'_{it} + \beta_{CP}.CP'_{it} + \beta_{LB}.LB'_{it} + \varepsilon_{it}$), random effects (RE: $NI_{it} = \alpha_i + \beta_{ST}.ST'_{it} + \beta_{CP}.CP'_{it} + \beta_{LB}.LB'_{it} + \beta_0 + \varepsilon_{it}$) and first differenced fixed effect (FD: $NI_{it} = \beta_{ST}.\Delta ST'_{it} + \beta_{CP}.\Delta CP'_{it} + \beta_{LB}.\Delta LB'_{it} + \Delta\varepsilon_{it}$). The estimated coefficients are statistically significant at 1% in POLS, FE, RE and at 5% in FD estimations, respectively. The range of statistically significant coefficients is from 0.0018 to 0.0731. Capital and labour also show desirable signs of their coefficients. R^2 also falls in reasonable range.

Table 1 Static Analysis – POLS, FE, RE and FD-FE Estimates

	POLS	FE	RE	FD
$ST_{i,t}$	0.0221[b] (0.011)	0.0293[a] (0.004)	0.0018[c] (0.001)	0.0731 (0.049)
$CP_{i,t}$	0.0023[b] (0.020)	0.0223[a] (0.006)	0.0024[b] (0.001)	0.1324[a] (0.038)
$LB_{i,t}$	0.7169[a] (0.024)	0.8099[a] (0.027)	0.7169[a] (0.024)	0.1321[a] (0.029)
Constant	–0.0731 (0.076)	0.9204[a] (0.142)	–0.0731 (0.076)	0.0693[a] (0.005)
Observations	887	910	887	884
Countries	26	26	26	26
R^2	0.50	0.35	0.50	0.24
CD[‡]	87.60[a]	87.60[a]	83.03[a]	17.06[a]

Note: [‡]CD is the cross-sectional dependence test by Pesaran (2004) and is calculated as $CD = \sqrt{\frac{TN(N-1)}{2}} \left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right)$. [a], [b] and [c] represent statistical significance at 1%, 5% and 10% respectively, whereas standard errors are in parentheses.

Source: Authors' estimates

3.2 Dynamic Analysis

3.2.1 Unit Root Test Results

Table 2 reports the results of unit root tests meant for investigating stationarity in the series, selection of the appropriate lag length was made using the Schwarz Bayesian Information Criterion.

Table 2 Unit Root Tests

	NI_{it}	ΔNI_{it}	ST_{it}	ΔST_{it}	CP_{it}	LB_{it}	ΔLB_{it}
LLC	–0.8	–6.4[a]	1.1	–12.0[a]	–5.4[a]	1.1	–12.0[a]
IPS	–0.6	–10.2[a]	–0.4	–17.9[a]	–2.2[a]	–0.4	–17.9[a]
	NI_{it} **is I(1)**		ST_{it} **is I(1)**		CP_{it} **is I(0)**	LB_{it} **is I(1)**	

Note: LLC and IPS stand for Levin, Lin and Chu (2002) and Im, Pesaran and Shin (2003) tests respectively. [a] represents statistical significance at 1%.

Source: Authors' compilation

3.3 Cointegration Tests

Results of LLC tests in Table 2 show that NI_{it}, ST_{it}, CP_{it} and LB_{it} have a mixed order of integration, i.e. *I(0)* and *I(1)*. Eberhardt and Teal (2010) suggest the use of macro-panel data techniques when time span is more than 20 years. Here $t = 35$, so we can resort to macro-panel data techniques. Since the series involved in our analysis is not integrated of same order, Pedroni and Kao tests cannot be applied. Therefore, we employ three econometric techniques that allow for mixed order of integration i.e. Mean Group (MG), Dynamic Fixed Effects (DFE) and Pooled Mean Group (PMG). Pesaran and Smith (1995) provided MG estimator of dynamic panels for large number of time observations and large number of groups. In this method separate equations are estimated for each group and distribution of coefficients of these equations across groups is examined. It provides parameter estimates by taking means of coefficients calculated by separate equations for each group. It is one extreme of estimation because it just makes use of averaging in its estimation procedure. It does not consider any possibility of same parameters across groups. For MG estimator, each parameter is taken as:

$$\bar{\hat{u}}_i = \frac{1}{N}\sum_{i=1}^{N} u_i \qquad \bar{\hat{\theta}}_i = \frac{1}{N}\sum_{i=1}^{N} \theta_i \qquad \bar{\hat{\phi}}_i = \frac{1}{N}\sum_{i=1}^{N} \phi_i \,, \tag{2}$$

where u_i, θ_i and ϕ_i denotes intercept, long run integrating vector and error correction term respectively.

For the averages of the parameters MG estimator will give consistent estimates. Thus allows all parameters to vary across countries, but it does not consider the fact that certain parameters may be the same across groups.

Pesaran and Smith (1997) suggested PMG estimator of dynamic panels for large number of time observations and large number of groups. Pesaran et al. (1997, 1999) added further in PMG and extended it. Pooled mean group estimator considers both averaging and pooling in its estimation procedure, so it is considered as an intermediate estimator. PMG allows variation in the intercepts, short-run dynamics and error variances across the groups, but it does not allow long-run dynamics

Table 3 Dynamic Analysis – Cointegration Estimation

	Mean Group	Dynamic Fixed Effects	Pooled Mean Group
	Long Run Parameters		
ST_{it}	0.0290 (0.046)	6.3398[a] (1.357)	1.0571[a] (0.089)
CP_{it}	0.4412 (0.275)	0.3295[b] (0.135)	1.7952[a] (0.239)
LB_{it}	0.4339 (1.492)	0.5074[c] (0.294)	7.5817[a] (0.952)
	Average Convergence Parameter		
φ_i	–0.4523[a] (0.035)	–0.0447[a] (0.008)	–0.0387[a] (0.011)
S.o.A	2.2 years	22.4 years	25.9 years
	Short Run Parameters		
ΔST_{it}	–0.0147 (0.015)	0.0061[a] (0.001)	0.0533[a] (0.012)
ΔCP_{it}	–0.0263 (0.038)	0.0039[a] (0.001)	0.0259 (0.016)
ΔLB_{it}	0.0325 (0.533)	–0.0628[a] (0.021)	–0.2920[a] (0.092)
C	4.1490[a] (1.588)	10.5039[a] (1.173)	3.2218[a] (1.008)
Observations	451	451	451
Groups	26	26	26
p-value	**$(\text{Hausman})_{MG/DFE} = 0.978$** **$(\text{Hausman})_{MG/PMG} = 0.746$**		
Remarks	**PMG is efficient & consistent**		
CD (MG)	**20.99[a]**		

Note: In parenthesis, standard errors of parameters are given while [a], [b] and [c] represent statistical significance at 1%, 5% and 10%, respectively. φ_i is the error correction term. S.o.A is the speed of adjustment.
Source: Authors' estimates

to differ across the groups. Adopting from Pesaran et al. (1997, 1999), PMG estimable model has an adjustment coefficient φ_i that is known as the error-correction term (ECT). In fact, explains what percentage of adjustments take place in each period. In addition to MG and PMG, DFE is also used to estimate the cointegrating vector. DFE specification controls the country specific effects, estimated through least square dummy variable (LSDV) or generalized method of moment (GMM). DFE relies on pooling of cross-sections. Like the PMG, DFE estimator also restricts the coefficient of cointegrating vector to be equal across all panels.

Results in the Table 3 reveal the comparison of panel cointegration estimation using MG, DFE and PMG. All three alternative methods of cointegration (MG, DFE and PMG) show the long run relationship between the national income and steel production. It is evident from error correction terms (φ_i), which are less than unity and negative in terms of sign with statistical significance at 1% level of significance. However, the most efficient of the three estimators should be relied upon. Its selection is done by employing the Hausman test. The results in Table 5 show statistical insignificance which implies superiority of PMG over MG and DFE. Therefore, the relationship is established under the assumption of absence of cross-sectional dependence.

3.4 Cross-Sectional Dependence

Results of CD test in Table 1 show the presence of cross-sectional dependence in the estimable model. Values of CD test are 87.60, 87.60, 83.03 and 17.06 for POLS, FE, RE and FD respectively. All are statistically significant at 1%, affirming cross-sectional dependence (CD) in residuals of the estimable models. In real life, CD is due to reasons like oil price shock, global financial crisis and local spill over and is common in most of panels.

We examined the CD in residuals and variables using further tests. Friedman (1937) proposed a nonparametric test (R_{ave}) based on Spearman's rank correlation coefficient. It helps in determining cross-sectional dependence. One of the most well-known cross-section dependence diagnostic is the Breusch-Pagan (1980) Lagrange Multiplier (LM) test statistic. Frees (1995) proposed a statistic (R^2_{ave}) which is based on the sum of the squared rank correlation coefficients. Pesaran (2004) proposed a standardized version of Breusch-Pagan LM test (LM_s) , suitable for large N samples. Since (LM) and (LM_s) are likely to exhibit worsening size distortion for small T_{ij} for larger N, Pesaran (2004) proposed an alternative statistic (CD_p) based on the average of the pairwise correlation coefficients. This test is already used in Table 1. The null hypothesis of this test is cross-sectional independence against the alternative hypothesis of cross-sectional dependence. More recently, Baltagi, Feng, and Kao (2012) presented a simple

Table 4 Tests for Cross-Sectional Dependence in Residuals of Estimable Model

Test	Statistic	Value
R_{ave}	$\frac{2}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{r}_{ij}$	322.62[a]
LM	$\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}T_{ij}\hat{\rho}_{ij}^2 \to \chi^2\frac{N(N-1)}{2}$	2804.49[a]
R^2_{ave}	$\frac{2}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{r}_{ij}^2$	5.30[a]
LM_s	$\sqrt{\frac{1}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}(T_{ij}\hat{\rho}_{ij}^2-1) \to N(0,1)$	97.25[a]
CD_P	$\sqrt{\frac{TN(N-1)}{2}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right)$	39.62[a]
LM_{BC}	$\sqrt{\frac{1}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}(T_{ij}\hat{\rho}_{ij}^2-1)-\frac{N}{2(T-1)} \to N(0,1)$	96.87[a]

Note: [a] represents statistical significance at 1%.
Source: Authors' estimates

asymptotic bias corrected scaled LM test (LM_{BC}). In Table 4, six statistics are estimated to scrutinize the presence of cross-sectional dependence in residuals of estimable model. All are statistically significant at 1% supporting the assumption of cross-sectional dependence in the residuals of estimable model.

Table 5 delves deeper by estimating four statistics, while considering the presence of cross-sectional dependence, in estimable model. All four tests are statistically significant at 1% showing cross-sectional dependence in the variables of estimable model.

Table 5 Tests for Cross-Sectional Dependence in Variables

		Value for			
Test	**Statistic**	$NI_{i,t}$	$ST_{i,t}$	$CP_{i,t}$	$LB_{i,t}$
LM	$\sum_{i=1}^{N-1}\sum_{j=i+1}^{N} T_{ij}\hat{\rho}_{ij}^2 \to \chi^2 \frac{N(N-1)}{2}$	8726.90[a]	3099.25[a]	6654.54[a]	10943.10[a]
LM_s	$\sqrt{\frac{1}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}(T_{ij}\hat{\rho}_{ij}^2-1) \to N(0,1)$	329.55[a]	108.81[a]	248.27[a]	416.48[a]
CD_P	$\sqrt{\frac{TN(N-1)}{2}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right)$	91.75[a]	14.51[a]	79.80[a]	104.58[a]
LM_{BC}	$\sqrt{\frac{1}{N(N-1)}}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}(T_{ij}\hat{\rho}_{ij}^2-1)-\frac{N}{2(T-1)} \to N(0,1)$	329.17[a]	108.43[a]	247.88[a]	416.09[a]

Note: [a] represents statistical significance at 1%.
Source: Authors' estimates

3.5 Stationarity Tests in Presence of Cross-sectional Dependence

Cross-sectional dependence has a strong presence in residuals as tested in Table 4 and Table 5. It calls for checking stationarity using second generation of unit root tests since first generation of unit root tests (Im et al., 2003; Levin et al., 2002) do not account for cross-sectional dependence in testing for stationarity.

Considering the evident cross-sectional dependence, we use second generation unit root tests proposed by Pesaran to shed light on the findings. Mathematically:

$$\Delta y_{i,t} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + \varepsilon_{i,t}\ , \tag{3}$$

where a_i is a deterministic term, $\bar{y}_t$ is the cross-sectional mean at time t and ρ is the lag order. $t_i(N,T)$ denotes the corresponding t-ratio of a_i and is known as cross-sectional ADF [CADF, attributed to Pesaran (2003)]. The average of the t-ratios gives the cross-sectional IPS [CIPS, attributed to Pesaran (2007)]. In Table 6, these tests are estimated with a constant term at level and first difference. Mutual consensus of both, CADF and CIPS tests, reveals that variables are stationary at level and at first difference i.e. *I(0) and I(1).*

3.6 Dynamic Analysis with Cross-sectional Dependence

Dynamic analysis is suitable in case of relationships where current values of the explained variable are inclined by past ones. Growth regressions, such as in this paper, are mostly characterized by a lagged term of explained variable ($NI_{i,t-1}$).

Table 6 Second Generation Unit Root Tests for Individual Variables

Cross-Sectional ADF (CADF) Test						
$NI_{i,t}$	$\Delta NI_{i,t}$	$ST_{i,t}$	$\Delta ST_{i,t}$	$CP_{i,t}$	$LB_{i,t}$	$\Delta LB_{i,t}$
–1.371	–3.300[a]	–2.362[a]	–	–3.352[a]	–0.691	–3.884[a]
Cross-Sectional IPS (CIPS) Test						
$NI_{i,t}$	$\Delta NI_{i,t}$	$ST_{i,t}$	$\Delta ST_{i,t}$	$CP_{i,t}$	$LB_{i,t}$	$\Delta LB_{i,t}$
–1.778	–2.857[a]	–1.858	–3.672[a]	–2.067[c]	–1.007	–2.953[a]
$NI_{i,t}$ is I(1)		$ST_{i,t}$ is I(1)		$CP_{i,t}$ is I(0)	$LB_{i,t}$ is I(0)	

Note: By definition: $CIPS = \frac{\sum_{i=1}^{N} t_i(N,T)}{N} = \frac{\sum_{i=1}^{N} CADF_i}{N}$, [a] and [c] represent statistical significance at 1% and 10%.

Source: Authors' estimates

In case of dynamic analysis, presence of CD requires implementation of improved versions of MG approach. In Table 1 and Table 3, CD tests have shown the presence of cross-sectional dependence in POLS, FE, RE, FD and MG estimates, respectively. Therefore, it is logical to deploy estimation techniques that cater cross-sectional dependence. Pesaran (2006) forwarded Common Correlated Effects Mean Group (CCEMG) model with estimator $\beta_j(= \beta + \omega_j)$ which implies a common parameter β across the countries while $\boldsymbol{\omega}_j \sim IID(0, V_\omega)$. CCEMG has the tendency to asymptotically eliminate CD. Moreover, it allows heterogeneous slope coefficients across group members that are captured simply by taking the average of each country's coefficient.

Attributed to Eberhardt and Teal (2010), Augmented Mean Group (AMG) is a surrogate for CCEMG, which also captures the unobserved common effect in the model. Moreover, AMG estimator also measures the group-specific estimator and takes a simple average across the panel. The highlight of AMG is that it follows first difference OLS for pooled data and is augmented with year dummies.

The estimable model can be written as follows:

$$NI_{it} = \alpha_i + c_i t + d_i \hat{\mu}_t^{va\bullet} + \beta_{i,1}(ST_{i,t}) + \beta_{i,2}(CP_{i,t}) + \beta_{i,3}(LB_{i,t}) + \varepsilon_{i,t}\ , \tag{4}$$

where, i stands for cross-sectional dimension $i = 1,\dots,n$ and time period $t = 1,\dots,t$ and α_i represents country specific effects and $d_i t$ denotes heterogeneous country specific deterministic trends. α_i is related with the coefficient of respective independent variables $\beta_{i1} = \frac{\alpha_{i1}}{1-\alpha_{i1}}$, $\beta_{i2} = \frac{\alpha_{i2}}{1-\alpha_{i2}}$ and $\beta_{i2} = \frac{\alpha_{i2}}{1-\alpha_{i2}}$ that are considered as heterogeneous across the countries. It is also assumed that the short run dynamics and their adjustment towards long run take place via error term $u_{i,t}(= \acute{r}_i f_t + \varepsilon_{i,t})$. f_t characterizes the vector of unobserved common shocks. f_t can be either stationary or nonstationary, which does not influence the validity of the estimation (Kapetanios, Pesaran, and Yamagata, 2011). AMG estimation finds an explicit estimate for f_t which renders $\hat{\mu}_t^{va\cdot}$ (common dynamic process) economic meaningfulness. Total factor productivity (TFP) is one of the plausible interpretations of $\hat{\mu}_t^{va\cdot}$. Its coefficient d_i represents the implicit factor loading on common TFP. In addition, the cross-sectional specific errors $\varepsilon_{i,t}$ are permissible to be serially correlated over time and weakly dependent across the countries (Cavalcanti, Mohaddes, and Raissi, 2011). However, the regressors and unobserved common factor have to be identically distributed.

3.6.1 Interpretation

In Table 7, the main variable of concern i.e. steel production shows statistically significant positive relationship using augmented mean group (AMG) as well as under common correlated effects mean group (CCEMG) estimation. CCEMG is estimated with 'without and with country specific trend' assumption.

Whereas AMG is estimated with an additional assumption of 'with and without common dynamic process (CDP)'. This allows for 4 variants of AMG. The significant positive relationship holds true for all variants 6 of CCEMG and AMG in Table 7. AMG being the most sophisticated is to be relied on.

Table 7 Dynamic Analysis with Cross-Sectional Dependence

Estimator	Common Correlated Effects Mean Group		Augment Mean Group			
Dependent variable	$NI_{i,t}$	$NI_{i,t}$	$NI_{i,t}$	$NI_{i,t}$	$NI_{i,t}-\hat{\mu}_t^{va\bullet}$	$NI_{i,t}-\hat{\mu}_t^{va\bullet}$
Trend Assumption	WoT	WT	WoT	WT	WoT	WT
$ST_{i,t}$	0.5479[b] (0.234)	0.5626[a] (0.199)	0.3353[a] (0.124)	0.4275[b] (0.174)	0.3964[a] (0.113)	0.3353[b] (0.150)
$CP_{i,t}$	0.1407[c] (0.077)	0.1572[b] (0.073)	0.2205[a] (0.058)	0.1867[b] (0.085)	0.0980 (0.060)	0.2040[b] (0.092)
$LB_{i,t}$	0.3826 (0.692)	0.3270 (0.468)	0.3528[a] (0.043)	0.3130[a] (0.057)	0.4679[a] (0.072)	0.3914[a] (0.047)
CDP	–	–	0.9682[a] (0.099)	0.7367[a] (0.200)	–	–
Country Trend	–	0.0005 (0.025)	–	0.0203 (0.019)	–	-0.00001 (0.010)
Constant	–3.4966[c] (2.040)	–3.2822 (3.627)	–5.4127[a] (1.953)	–7.3500[b] (2.964)	–6.3176[a] (1.806)	–5.6000[b] (2.440)
NST	–	13	–	13	–	21
RMSE	0.1468	0.1235	0.2207	0.1882	0.2439	0.2102
Observations	910	910	910	910	910	910
Groups	26	26	26	26	26	26
CD	3.84[a]	2.90[a]	4.30[a]	5.14[a]	7.38[a]	6.58[a]

Notes: WoT and WT stand for estimation without and with country specific trends. *CDP* is the common dynamic process. In parenthesis, standard errors are given whereas [a], [b] and [c] show statistical significance at 1%, 5% and 10%, respectively. NST stand for Number of Significant Trends. RMSE stands for root mean squared error and uses residuals from group-specific regression.
Source: Authors' estimates

3.7 Robustness Check

In Table 8, twenty-three (23) slopes are estimated using difference estimators and their variants and compared in order to check the robustness of results of hypothesis. These include Pooled Ordinary Least Squares (POLS), Fixed Effects (FE), Fixed Effects with Driscoll & Kraay standard errors (FE-DK), Random Effects (RE), Generalized Least Squares (GLS), First Differenced-Fixed Effects (FD), Pooled-Fully Modified Ordinary Least Squares (P-FMOLS), Weighted Pooled-Fully Modified Ordinary Least Squares (WP-FMOLS), Group Mean-Fully Modified Ordinary Least Squares (GM-FMOLS), Pooled-Dynamic Ordinary Least Squares (P-DOLS), Weighted Pooled- Dynamic Ordinary Least Squares (WP-DOLS), Group Mean-Dynamic Ordinary Least Squares (GM-DOLS), Difference Generalized Method of Moments (DIF-GMM), System Generalized Method of Moments (SYS-GMM), Dynamic Fixed Effects (DFE), Mean Group (MG), Pooled Mean Group (PMG), Common Correlated Effects Mean Group (CCEMG) and Augmented Mean Group (AMG).

CCEMG and AMG are further estimated with and without country specific trends (WoT and WT). In addition, AMG is further estimated without common dynamic process under the assumptions of with and without country specific trends {$(\text{WoT})_{\text{CDP}}$ and $(\text{WT})_{\text{CDP}}$}. In case of steel production, majority (83%) 19 out of 23 estimators give desirable results in terms of expected sign and statistical significance that adds to the robustness of the Steel production-growth relationship analyzed in this paper. Moreover, AMG – the most sophisticated of estimators – shows desirable results with all of its variants (with and without country specific trends and common dynamic process).

Table 8 Robustness Slope Parameters

Technique		Statistic of Estimator	Value	S.E
POLS		$\beta_{OLS} = \left(\sum_i X_i'X_i\right)^{-1}\left(\sum_i X_i'Y_i\right)$	0.0221[b]	0.011
FE		$\beta_{FE/DK} = \left(\sum_{i=1}^{N} X_i'QX_i\right)^{-1}\left(\sum_{i=1}^{N} X_i'QY_i\right)$	0.0293[a]	0.004
FE-DK			0.0293[a]	0.005
RE		$\beta_{RE/GLS} = \left(\sum_{i=1}^{N} X_i'\Omega_M^{-1}X_i\right)^{-1}\left(\sum_{i=1}^{N} X_i'\Omega_M^{-1}Y_i\right)$	0.0018[c]	0.001
GLS			0.0012[b]	0.001
FD		$\beta_{FD} = (\Delta X'\Delta X)^{-1}\Delta X'\Delta Y$	0.0731	0.049
P-FMOLS		$\beta_{FP} = \left(\sum_{i=1}^{N}\sum_{t=1}^{T} X_{it}X_{it}'\right)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(X_{it}\bar{Y}_{it}^{+} - \lambda_{12}^{+\prime}\right)$	0.1600	0.111
WP-FMOLS		$\beta_{FW} = \left(\sum_{i=1}^{N}\sum_{t=1}^{T} \bar{X}_{it}^{*}\bar{X}_{it}^{*\prime}\right)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\bar{X}_{it}^{*}\bar{Y}_{it}^{*} - \lambda_{12i}^{*\prime}\right)$	0.3308[a]	0.015
GM-FMOLS		$\beta_{FG} = \frac{1}{N}\sum_{i=1}^{N}\left\{\left(\sum_{t=1}^{T}\bar{X}_{it}\bar{X}_{it}'\right)^{-1}\sum_{t=1}^{T}\left(\bar{X}_{it}\bar{Y}_{it} - \lambda_{12i}'\right)\right\}$	1.0818[a]	0.215
P-DOLS		$\begin{bmatrix}\beta_{DP}\\ \gamma_{DP}\end{bmatrix} = \left(\sum_{i=1}^{N}\sum_{t=1}^{T}\bar{W}_{it}\bar{W}_{it}'\right)^{-1}\left(\sum_{i=1}^{N}\sum_{t=1}^{T}\bar{W}_{it}\bar{Y}_{it}'\right)$	0.1666	0.149
WP-DOLS		$\begin{bmatrix}\beta_{DW}\\ \gamma_{DW}\end{bmatrix} = \left(\sum_{i=1}^{N}\hat{\omega}_{1.2i}^{-1}\sum_{t=1}^{T}\bar{W}_{it}\bar{W}_{it}'\right)^{-1}\left(\sum_{i=1}^{N}\hat{\omega}_{1.2i}^{-1}\sum_{t=1}^{T}\bar{W}_{it}\bar{Y}_{it}'\right)$	0.2806[a]	0.099
GM-DOLS		$\begin{bmatrix}\beta_{DG}\\ \gamma_{DG}\end{bmatrix} = \frac{1}{N}\sum_{i=1}^{N}\left\{\left(\sum_{t=1}^{T}\bar{W}_{it}\bar{W}_{it}'\right)^{-1}\sum_{t=1}^{T}\bar{W}_{it}\bar{Y}_{it}'\right\}$	1.3661[a]	0.263
DIF-GMM		$\beta_{GMM} = argmin_{\beta}(\bar{v}'Z)A_N(Z'\bar{v}) = \frac{\bar{y}'_{-1}ZA_NZ'\bar{y}}{\bar{y}'_{-1}ZA_NZ'\bar{y}_{-1}}$	0.0247[a]	0.006
SYS-GMM			0.0198[a]	0.005
DFE		$\beta_{DFE} = \left(\sum_{i=1}^{N} X_{i,t-1}'QX_{i,t-1}\right)^{-1}\left(\sum_{i=1}^{N} X_{i,t-1}'QY_i\right)$	6.3398[a]	1.357
MG		$\beta_{MG} = \frac{1}{N}\sum_{i=1}^{N}\theta_i$	0.029	0.046
PMG		$\beta_{PMG} = -\left(\sum_{i=1}^{N}\frac{\hat{\phi}_i^2}{\hat{\sigma}_i^2}X_i'H_iX_i\right)^{-1}\left\{\sum_{i=1}^{N}\frac{\hat{\phi}_i}{\hat{\sigma}_i^2}X_i'H_i\left(\Delta Y_i - \hat{\phi}_iY_{i,t-1}\right)\right\}$	1.0571[a]	0.089
CCEMG	WoT	$\beta_{CCEMG} = J^{-1}\sum_{i=1}^{J}\hat{\beta}_j$	0.5479[b]	0.234
	WT		0.5626[a]	0.199
AMG	$(WoT)_{CDP}$	$\beta_{AMG} = \frac{\alpha_{i1}}{1-\alpha_{i1}}$	0.3353[a]	0.124
	$(WT)_{CDP}$		0.4275[b]	0.174
	WoT		0.3964[a]	0.113
	WT		0.3353[b]	0.15

Notes: WoT and WT show estimates without common dynamic process 'without trend' and 'with trend' argument. $(WoT)_{CDP}$ and $(WT)_{CDP}$ show estimates with explicit common dynamic process 'without trend' and 'with trend' argument. [a], [b] and [c] show statistical significance at 1%, 5%, and 10% respectively. S.E stands for standard error.
Source: Authors' estimates

3.8 Impetus of Relationship

At country level, robustness of the results is also affirmed by estimating country specific slopes $(\theta_i = \frac{\delta_i}{1-\lambda_i})$. Majority of countries show highly significant positive relationship between steel production and national income. Whereas remaining countries either give unexpected sign and/or statistical insignificance.

In similar veins, country specific error correction terms (ECT) are also estimated. Ones listed in the Table 9 fulfill the following conditions:

$$ECT_i < 1, |ECT_i| > 0 \; and \; (p - value)_{ECT_i} < 0.05. \quad (5)$$

These countries are major contributors to overall statistical long run relationship.

Table 9 Imputes of Relationship

Country Specific Slopes (θ_i)					
Country	θ_i	**S.E**	**Country**	θ_i	**S.E**
Croatia	0.1524[b]	0.060	Latvia	0.1152[a]	0.039
Czech Republic	0.4503[a]	0.102	Lithuania	0.1616[a]	0.041
Estonia	0.2168[a]	0.027	Netherlands	0.5482[b]	0.270
Finland	0.3160[b]	0.147	Romania	1.0623[a]	0.270
Germany	1.0492[a]	0.395	Slovakia	0.2631[a]	0.065
Greece	0.7258[a]	0.168	Slovenia	0.1895[b]	0.076
Italy	1.2976[a]	0.390	Spain	0.8162[a]	0.184

Country Specific Error Correction Terms (ECT_i)			
Country	ECT_i	**Country**	ECT_i
Austria	–0.0315[a]	Italy	–0.0448[a]
Belgium	–0.0116[a]	Latvia	–0.0402[a]
Croatia	–0.0621[a]	Lithuania	–0.0525[a]
Czech Republic	–0.0633[a]	Luxembourg	–0.0861[a]
Denmark	–0.0340[a]	Netherlands	–0.0182[a]
Estonia	–0.0423[a]	Poland	–0.0344[a]
Finland	–0.0118[a]	Portugal	–0.0296[a]
France	–0.0196[a]	Romania	–0.0366[a]
Germany	–0.0219[a]	Slovakia	–0.0240[a]
Greece	–0.0365[a]	Slovenia	–0.0559[a]
Hungary	–0.0703[a]	Spain	–0.0153[a]
Ireland	–0.0167[a]	United Kingdom	–0.0190[a]

Note: [a] and [b] show statistical significance at 1% and 5%. S.E stands for standard error. ECT_i are the country specific error correction terms.
Source: Authors' estimates

Countries including Croatia, Czech Republic, Estonia, Finland, Germany, Greece, Italy, Latvia, Lithuania, Netherlands, Romania, Slovakia, Slovenia and Spain show both expected significant slope as well as country specific significant ECT. These countries contribute to the overall positive sign and significance of relationship between national income and steel production.

3.9 What Causes What?

3.9.1 Panel Granger Causality Test

Work of Granger (1969) laid the foundation of causality test that uses the bivariate regressions in a panel data context:

$$\begin{aligned} y_{i,t} &= \alpha_{0,i} + \alpha_{1,i}\, y_{i,t-1} + \cdots + \alpha_{p,i}\, y_{i,t-p} + \beta_{1,i}\, x_{i,t-1} + \cdots + \beta_{p,i}\, x_{i,t-p} + \epsilon_{i,t} \\ x_{j,t} &= \alpha_{0,j} + \alpha_{1,j}\, x_{j,t-1} + \cdots + \alpha_{p,j}\, y_{j,t-p} + \beta_{1,j}\, y_{j,t-1} + \cdots + \beta_{p,j}\, y_{j,t-p} + \varepsilon_{j,t} \end{aligned} \quad (6)$$

Depending on the assumptions about homogeneity of the coefficients across cross-sections, there are two forms of panel causality test. First and conventional type treats the panel data as one large stacked set of data and performs the causality test in the standard way, that assumes all coefficients same across all cross-sections.

$$\begin{aligned} &\alpha_{0,i} = \alpha_{0,j}, \alpha_{1,i} = \alpha_{1,j}, \dots, \alpha_{p,i} = \alpha_{p,i}, \forall_{i,j} \\ &\beta_{1,i} = \beta_{1,j}, \dots, \beta_{p,i} = \beta_{p,i}, \forall_{i,j} \end{aligned} \quad (7)$$

Results of panel Granger causality are shown in Table 10.

Table 10 Panel Granger Causality Test Results

Causality	F-Statistic	Remarks
$ST_{i,t} \rightarrow NI_{i,t}$	0.1444	Uni-causal Relationship from macroeconomic performance to steel production.
$NI_{i,t} \rightarrow ST_{i,t}$	24.0905[a]	

Note: [a] shows statistical significance at 1%.
Source: Authors' estimates

Uni-causality from national income to steel production is evident from results in Table 10. Under the hypothesis in the Introduction, causal relationship is set for investigation. Siddique, Mehmood & Ilyas (2016) who explain the mechanism of causal linkages from the national income to steel production (demand following view) is showed in Figure 2. 'Demand following view' holds in case of EU since results in Table 10 show evidence of causality from national income to steel production. Due high growth rates of national income the need for innovation, industrialization and mechanization increases. Such raises the demand for steel that causes increased steel production. Same seems to be case of EU countries during the time span under consideration.

Figure 2 Demand Following Hypothesis for Steel Production and National Income

$$\boxed{Higher\ growth\ rates\ of\ national\ income} \longrightarrow$$
$$\boxed{Need\ for\ developmental\ projects\ (innovation, industrialization\ and\ mechanization)} \longrightarrow$$
$$\boxed{Increased\ demand\ for\ steel} \longrightarrow \boxed{Increased\ production\ in\ Steel\ Industry}$$

Source: Authors' formulation

3.9.2 Rationale for Dumitrescu-Hurlin Causality

However, one of the main issues specific to panel data models refers to the specification of the heterogeneity between cross-sections. To consider the heterogeneity across cross-sections, Dumitrescu-Hurlin (2012) made an assumption of allowing all coefficients to be different across cross-sections. In this causality context, the heterogeneity can be between the heterogeneity of the regression model and/or in terms of causal relationship from x to y. Indeed, the model considered may be different from an individual to another, whereas there is a causal relationship from x to y for all individuals. The simplest form of regression model heterogeneity takes the form of slope parameters' heterogeneity. More precisely, in a '*p*' order linear vectorial autoregressive model, four kinds of causal relationships are defined. Under the Homogeneous Non-Causality (HNC) hypothesis, no individual causality from x to y occurs. On the contrary, in the Homogeneous Causality (HC) and Heterogeneous Causality (HEC) cases, there is a causality relationship for each individual of the sample. To be more precise, in the Homogeneous Causality (HC) case, the same regression model is valid (identical parameters' estimators) for all individuals, whereas this is not the case for the HEC hypothesis. Finally, under the Heterogeneous Non-Causality (HENC) hypothesis, the causality relationship is heterogeneous since the variable x causes y only for a subgroup of $N–N_1$ units.

Authors based their version of causality test on the Granger (1969) and extended to non-causality test for heterogeneous panel data models with fixed coefficients.

Considering linear model:

$$y_{i,t} = \alpha_i + \sum_{k=1}^{K} \gamma_i^{(k)} y_{i,t-k} + \sum_{k=1}^{K} \beta_i^{(k)} x_{i,t-k} + \varepsilon_{i,t} \qquad i = 1, 2, \ldots, N: t = 1, 2, \ldots, T, \tag{8}$$

where x and y are two stationary variables observed for N individuals in T periods. $\beta_i = (\beta_i^{(1)}, \ldots, \beta_i^{(K)})'$ and the individual effects α_i are assumed to be fixed in the time dimension. It is assumed that there are lag orders of K identical for all cross-section units of the panel. Moreover, autoregressive parameters $\gamma_i^{(k)}$ and the regression coefficients $\beta_i^{(k)}$ are allowed to vary across groups. Under the null hypothesis, it is assumed that there is no causality relationship for any of the units of the panel. This assumption is called the Homogeneous Non-Causality (HNC) hypothesis, which is defined as:

$$\mathrm{H}_0: \beta_i = 0 \ \forall i = 1, \dots, N. \tag{9}$$

The alternative is specified as the Heterogeneous Non-Causality (HENC) hypothesis. Under this hypothesis, two subgroups of cross-section units are allowed. There is a causality relationship from x to y for the first one, but it is not necessarily based on the same regression model. For the second subgroup, there is no causality relationship from x to y. A heterogeneous panel data model with fixed coefficients (in time) in this group is considered. This alternative hypothesis is expressed as follows:

$$\begin{aligned} &\mathrm{H}_1: \beta_i = 0 \ \forall i = 1, \dots, N_1, \\ &\beta_i \neq 0 \ \forall i = N_1 + 1, \dots, N. \end{aligned} \tag{10}$$

It is assumed that β_i may vary across groups and there are $N_1 < N$ individual processes with no causality from x to y. N_1 is unknown but it provides the condition $0 \le N_1/\mathrm{N} < 1$.

The average statistic $W_{N,T}^{HNC}$, which is related with the null Homogeneous non-causality (HNC) hypothesis are proposed:

$$W_{N,T}^{HNC} = \frac{1}{N} \sum_{i=1}^{N} W_{i,T} \ , \tag{11}$$

where $W_{i,t}$ indicates the individual Wald statistics for the i$^{\text{th}}$ cross-section unit corresponding to the individual test $\mathrm{H}_0{:}\beta_i = 0$.

Let $Z_i = [e : Y_i : X_i]$ be the *(T, 2K+1)* matrix, where *e* indicates *a (T, 1)* unit vector and $Y_i =$ $Y_i = \left[y_i^{(1)} : y_i^{(2)} : \dots : y_i^{(K)}\right]$, $X_i = \left[x_i^{(1)} : x_i^{(2)} : \dots : x_i^{(K)}\right]$. $\theta_i = (\alpha_i \gamma_i' \beta_i')$ is the vector of parameters of the model. Also let $R = [0{:}\ I_K]$ be a *(K, 2K+1)* matrix.

For each *i =1,…,N*, the Wald statistic $W_{i,t}$ corresponding to the individual test $\mathrm{H}_0{:}\beta_i = 0$ is defined as:

$$W_{i,T} = \hat{\theta}_i' R' [\hat{\sigma}_i^2 R (Z_i' Z_i)^{-1} R']^{-1} R \hat{\theta}_i \ . \tag{12}$$

Under the null hypothesis of non-causality, each individual Wald statistic converges to a chi-squared distribution with K degrees of freedom for $T \to \infty$.

$$W_{i,T} \to \chi^2(K), \forall i = 1, \dots, N. \tag{13}$$

The standardized test statistic $W_{N,T}^{HNC}$ for $T, N \to \infty$ is as follows:

$$Z_{N,T}^{HNC} = \sqrt{\frac{N}{2K}} \left(W_{N,T}^{HNC} - K \right) \to N(0,1). \tag{14}$$

Also, the standardized test statistic $\tilde{Z}_N^{HNC}$ for fixed T samples is as follows:

$$\tilde{Z}_N^{HNC} = \sqrt{\frac{N}{2K} \times \frac{(T-2K-5)}{(T-K-3)}} \times \left[\frac{(T-2K-5)}{(T-K-3)} W_{N,T}^{HNC} - K \right] \to N(0,1), \tag{15}$$

where $W_{N,T}^{HNC} = \left(\frac{1}{N}\right) \sum_{i=1}^{N} W_{i,T}$.

In addition to presence of heterogeneity among cross-sections, if cross-sectional dependence exists in panel, Dumitrescu-Hurlin causality is suitable. Results of CD tests in Table 1, Table 3, Table 4 and Table 5 show the presence of cross-sectional dependence. Whereas, stationarity is a basic requirement of Dumitrescu-Hurlin causality test. Second generation unit root test named as Pesaran's CADF (2003) and CIPS (2007) statistic fulfills the objective of checking for stationarity in presence of cross-sectional dependence. Therefore, Dumitrescu-Hurlin causality test should be applied. Its results are as follows:

Table 11 Dumitrescu-Hurlin Causality Test Results

Causality	$W_{N,T}^{HNC}$	$\tilde{Z}_{N}^{HNC}$	p-value	Remarks
$ST_{i,t} \rightarrow NI_{i,t}$	2.6132	1.0068	0.314	Homogeneous Uni-causal relationship from macroeconomic performance to steel production.
$NI_{i,t} \rightarrow ST_{i,t}$	6.0121	8.4564	0.000	

Source: Authors' estimates

Table 11 represents statistical significance of first $\tilde{Z}_{N}^{HNC}$ test statistic showing that null hypothesis cannot be rejected that $ST_{i,t}$ do not homogeneously cause $NI_{i,t}$, whereas it gets rejected in reverse causality. It implies that the causality is homogeneous from national income to steel production. This specialized form of causality provides the insights into the causal relationship without contradicting the primary result of bi-causal Granger causality in Table 10. Homogenous causality can be attributed to 'uniform growth effects' of economic growth on steel industries in economies that are 'integrated' in a union known as European Union.

CONCLUSION

European Union was chosen for investigating relationship between steel production and national income. Using sophisticated econometric techniques, the relationship is found to be robust. The causality gives support to 'Demand Following Hypothesis'. Feedback effect of steel industry on national income can amplify the macroeconomic contribution of steel production. However, it is missing or too weak at this stage. Firm level studies can help in understanding the microeconomic foundations of causal linkage from steel production to national income. Such firm/industry specific studies are suggested for future. Role of substitute metals e.g. aluminum can also be investigated in terms of their macroeconomic contribution. In addition, to spur efficiency, state may increase the incentive and proportion of private sector in steel industry. Moreover, it may also re-allocate subsidies for steel industry and infrastructure sector. For reducing monopoly power, pricing policy can be effective.

References

BALTAGI, B. H., FENG, Q. AND KAO, C. A Lagrange Multiplier test for cross-sectional dependence in a fixed effects panel data model. *Journal of Econometrics*, 2012, 170(1), pp. 164–177.

BREUSCH, T. S., AND PAGAN, A. R. The Lagrange multiplier test and its applications to model specification in econometrics. *The Review of Economic Studies*, 1980, 47(1), pp. 239–253.

CAVALCANTI, T. V. D. V., MOHADDES, K. AND RAISSI, M. Growth, development and natural resources: New evidence using a heterogeneous panel analysis. *The Quarterly Review of Economics and Finance*, 2011, 51(4), pp. 305–318.

DUMITRESCU, E.-I. AND HURLIN, C. Testing for Granger non-causality in heterogeneous panels, *Economic Modeling*, 2012, 29, pp. 1450–1460.

EBERHARDT, M. AND TEAL, F. *Productivity analysis in global manufacturing production.* University of Oxford, Department of Economics, Economics Series Working Papers, 2010, p. 515.

EVANS, M. Steel consumption and economic activity in the UK: The integration and cointegration debate. *Resources Policy*, 2011, 36(2), pp. 97–106.

FREES, E. W. Assessing cross-sectional correlation in panel data. *Journal of Econometrics*, 1995, 69, pp. 393–414.

FRIEDMAN, M. The use of ranks to avoid the assumption of normality implicit in the analysis of variance. *Journal of the American Statistical Association*, 1937, 32, pp. 675–701.

GRANGER, C. W. Investigating causal relations by econometric models and cross-spectral methods. *Econometrica: Journal of the Econometric Society*, 1969, pp. 424–438.

HOECHLE, D. Robust standard errors for panel regressions with cross-sectional dependence. *Stata Journal*, 2007, 7(3), p. 281.
HUH, K.-S. Steel consumption and economic growth in Korea: Long-term and short-term evidence. *Resources Policy*, 2011, 36(2), pp. 107–113.
IM, K. S., PESARAN, M. H. AND SHIN, Y. Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, 2003, 115(1), pp. 53–74.
JEFFERSON, G. H. China's iron and steel industry: Sources of enterprise efficiency and the impact of reform. *Journal of Development Economics*, 1990, 33(2), pp. 329–355.
KAPETANIOS, G., PESARAN, M. H. AND YAMAGATA, T. Panels with non-stationary multifactor error structures. *Journal of Econometrics*, 2011, 160(2), pp. 326–348.
LABSON, B. S. AND CROMPTON, P. L. Common trends in economic activity and metals demand: Cointegration and the intensity of use debate. *Journal of Environmental Economics and Management*, 1993, 25(2), pp. 147–161.
LEVIN, A., LIN, C.-F. AND CHU, C.-S. J. Unit root tests in panel data: asymptotic and finite-sample properties. *Journal of Econometrics*, 2002, 108(1), pp. 1–24.
OZKAN, F. Steel industry and the sector's impact on economic growth in Turkey. *Regional and Sectoral Economic Studies*, 2001, 11(2).
PESARAN, M. H. A simple panel unit root test in the presence of cross section dependence. *Cambridge Working Papers in Economics 0346*, Faculty of Economics (DAE), University of Cambridge, 2003.
PESARAN, M. H. General diagnostic tests for cross section dependence in panels. *Cambridge Working Papers in Economics 0435*, Faculty of Economics, University of Cambridge, 2004.
PESARAN, M. H. Estimation and inference in large heterogeneous panels with a multifactor error structure. *Econometrica*, 2006, 74(4), pp. 967–1012.
PESARAN, M. H., SHIN, Y. AND SMITH, R. P. *Pooled estimation of long-run relationships in dynamic heterogeneous panels*. University of Cambridge, Department of Applied Economics, 1997.
PESARAN, M. H., SHIN, Y. AND SMITH, R. P. Pooled mean group estimation of dynamic heterogeneous panels. *Journal of the American Statistical Association*, 1999, 94(446), pp. 621–634.
PESARAN, M. H. A simple panel unit root test in the presence of cross-section dependence. *Journal of Applied Econometrics, 2007,* 22(2), pp. 265–312.
PESARAN, M. H. AND SMITH, R. Estimating long-run relationships from dynamic heterogeneous panels. *Journal of Econometrics*, 1995, 68(1), pp. 79–113.
SIDDIQUE, F., MEHMOOD, B. AND ILYAS, S. Steel production and macroeconomic performance in Pakistan: What does long-run data show? *Science International*, 2016, 28(4), pp. 95–97.