Eurasian Academy of Sciences
Eurasian Econometrics, Statistics & Empirical Economics Journal
2022 Volume:21 S: 1- 24
Published Online May 2022 (http://econstat.eurasianacademy.org)
http://dx.doi.org/10.17740/eas.stat.2022-V21-01

# THE EFFECTS OF SUPPLY CHAIN DISRUPTIONS, INEQUALITY SHOCKS, AND INSTITUTIONAL INNOVATIONS ON THE PACE OF INDUSTRIALIZATION IN DEVELOPING COUNTRIES: A PANEL VAR ANALYSIS

**M. Sait ÇAKIR*** **Resul AYDEMİR****

*PhD Student, Istanbul Technical University, Institude of Graduate Studies, cakirmuhamm@itu.edu.tr, ORCID: 0000-0002-0615-7047
**Assoc. Prof., Istanbul Technical University, Department of Economics, resulaydemir@itu.edu.tr, ORCID: 0000-0003-1313-0464

Received Date:15.03.2022 Accepted Date:11.04.2022


## ABSTRACT

We empirically examine the effects of supply chain disruptions, inequality shocks, and institutional innovations on the pace of industrialization in developing countries by running a panel vector autoregressive model. We found that deterioration in income distribution unequivocally harms the developing countries' bid for industrialization while better institutions proxied by an improvement regulatory quality invariably foster it. On the other hand, the effects of supply chain disruptions on the pace of industrialization follow a nonlinear path, showing the great resilience of local industries in absorbing imported input bottlenecks through intermediate input import substitution. We also provide evidence that backward participation into GVCs and regulatory quality do not mutually Granger-cause each other, and suggest that the well-established link from better governance to GVCs may be missing in the developing country case.
**Keywords:** supply chains, Kuznets curve, industrialization, institutions, panel VAR

***JEL Classification:*** F63, O15, O14, O17

# TEDARİK ZİNCİRLERİ KESİNTİLERİ, EŞİTSİZLİK ŞOKLARI VE KURUMSAL YENİLİKLERİN GELİŞMEKTE OLAN ÜLKELERDE SANAYİLEŞME HIZINA ETKİLERİ: PANEL VAR ANALİZİ

## ÖZET

Bu çalışmamızda tedarik zincirleri kesintileri, eşitsizlik şokları ve kurumsal yeniliklerin gelişmekte olan ülkelerin sanayileşme hızına etkilerini panel VAR modeli ile incelemekteyiz. Bulgularımıza göre gelir bölüşümündeki bozulma gelişmekte olan ülkelerin sanayileşme çabalarına zarar verirken kurumsal faktörlerdeki iyileşmeler bu çabaları güçlü kılmaktadır. Diğer yandan, tedarik zinciri kesintilerinin sanayileşme üzerindeki etkisi doğrusal olmayan bir patika izlemektedir; bu da yerel endüstrilerin ithal girdi darboğazlarını aramalı ithal ikamesi yoluyla massedebildiğini göstermektedir. Küresel değer zincirlerine geriden katılım ile düzenleyici kurumsal nitelikler arasında herhangi bir Granger-nedensellik ilişkisinin bulunmaması literatürde sıklıkla işlenen yönetişimsel iyileşmelerin değer zincirlerine katılımı destekleyeceğine dair tezin gelişmekte olan ülke bağlamında geçerli olmayabileceğini göstermektedir.
**Anahtar Kelimeler:** tedarik zincirleri, Kuznets eğrisi, sanayileşme, kurumlar, panel VAR modeli
**Jel-Sınıflama:** F63, O15, O14, O17

## 1. INTRODUCTION

With the eruption of covid-19 pandemics, the long-simmering trends beneath the surface of economic reality became more visible. One of the immediate effects of the lockdowns which were, and still are part of the measures to prevent the virus from spreading has been a sudden disruption to highly complex supply chains as experienced by price surges in the advanced world. While the supply chains quickly sprawled all around the world during the 1990s and 2000s, encompassing the most of global trade in intermediate goods, many studies point to a sort of slowdown in its momentum after the great financial crisis in 2008-9 (Rodrik 2018). In this paper, we would like to examine the supply chain shocks to the pace of industrialization within the developing country context. To be more precise, we would like to examine how much resilient the manufacturing industry is to difficulties for securing high-quality imported inputs which might cause to decelerate its growth given the degree of integration into the global value chains.

The covid-19 pandemics also threw the deepening income inequality into sharp relief. Due to a sudden stop in business activities, many people got unemployed and ended up with having a meagre income to meet their ends. Since the manufacturing industry mainly operates on a mass production basis, a more skewed income distribution squeezes its market size (Foellmi and Zweimüller 2011). Given that the manufacturing industry basically provides basic necessary goods for ordinary people, an inequality shock to the national economy deprives the majority of the population of the financial means of absorbing mass production. However, an increased inequality might be associated with a lower wage share in national income, so the wage suppression would result in costs gains which could stimulate manufacturing production. As a result, two opposite forces linked with a more unequal income distribution work their effects out on the industrialization efforts of developing countries. The income distribution has thus dual nature, affecting both the cost of production as well as the composition of aggregate demand. We aim to analyze the overall effect of inequality shocks on the manufacturing growth in the developing world.

We also highlight the immense significance of the institutional quality in order to fight the collateral damage done to the industrialization rate in developing countries as a result of supply chain and inequality shocks. The literature abounds with studies showing that any improvement in regulatory quality ameliorates the efficiency of overall economic activity. While the relationship between institutional factors and economic growth is well examined (Acemoglu, et al. 2001), we would like to attract the attention to the fact that the link from better governance to an exhilarating manufacturing industry must be more pronounced because it is the sector which highly depends on complex contractual schemes. In other words, the manufacturing sector growth is more exposed to institutional shocks than traditional sectors and services. We also suggest that improvements in institutional quality is of utmost importance given the stalled industrialization process gripping the developing world.

We carry out an empirical analysis into the effects of supply chain disruptions, institutional innovations, growth shocks and skewed income distribution on the growth of manufacturing value-added share in national income for 18 developing countries from 1995 to 2018. We work with value-added shares rather than employment shares so we could treat the collective contribution of changes in total factor productivity and factor employment into manufacturing industry as our industrialization measure. We develop a comprehensive empirical framework within which the interrelationships among the principal factors affecting the trajectory of industrialization in developing countries could be identified by panel data methodology. We provide sound evidence regarding such disputed subjects in the literature as the nexus between inequality, participation into the supply chains, institutional quality and industrialization.

We use the GGDC database to obtain manufacturing value-added share in national income, the WB-WGI database for regulatory quality index and gini coefficient, the OECD-TIVA database for a proxy of participation into global value-added chains. Without a priori assumption about causal relationship among manufacturing output share, regulatory quality, fairness of income distribution, and participation into supply chains, we run a Panel VAR model using the Arellano-Bond GMM estimator. After implementing the Granger causality test to find that the direction of association runs from gini coefficient, regulatory quality index, and the degree of participation into supply chains to manufacturing output share, we use the Cholesky factorization to obtain orthogonalized impulse-response functions to examine the effects of one standard deviation positive shocks to the Granger-causes on the manufacturing output share.

We found that deterioration in income distribution unequivocally harms the developing countries' bid for industrialization while better institutions proxied by an improvement regulatory quality invariably foster it. Here, we provide a fresh evidence about the positive association between a fair income distribution and structural transformation favoring industrialization and the importance of institutional quality. However, the effects of supply chain disruptions and growth shocks on the pace of industrialization follow a nonlinear path. We show that local manufacturing industries exhibit great resilience in absorbing supply chain shocks which deprive developing countries of imported high-quality inputs after passing through a brief contraction period, suggesting a sort of intermediate input import substitution. Growth shocks also contain contradictory dynamics. While shocks affecting per capita income growth could expand industrial production through productivity or external income channel, they could hobble the growth of manufacturing due to their inequality-increasing nature in the absence of social mobility which is usually the case with many developing countries.

The rest of the paper is organized as follows. Section 1 reviews the literature. Section 2 develops the theoretical framework and explains our research hypotheses. Section 3 presents data and econometric methodology. Section 4 discusses empirical results. Section 5 concludes the paper.

## 2. LITERATURE REVIEW

In this section we mainly cover the literature on the global value chains (GVCs), inequality, and institutional quality through the lens of industrialization process in developing countries.

The literature on the relationship between participation into GVCs and developing countries' efforts at industrialization is far from being conclusive about the direction of association.

Beltramello et al. (2012) argue that GVCs help developing countries' bid for industrialization by providing them with vast exporting opportunities while Peneder and Streicher (2018) provide evidence that the net export channel which reflects GVC-based measure of revealed comparative advantage based on global input-output tables has negatively contributed to the manufacturing value-added share of developing countries in their sample between 2000-2014. Developing countries could have better access to information through the international production networks and develop new competencies and acquire technological skills by trying to live up to quality and business standards set by the GVCs (Gereffi 2018; Staritz et al. 2011). Participation in GVCs also lift the burden of building up a whole supply chains for developing countries so they could experience fast industrialization by focusing on a narrow set of competencies at which they would have competitive advantage (Baldwin 2013). They could also enhance their overall productivity by making an extensive use of high-quality imported inputs (Kummritz 2016; Taglionai and Winkler 2016; Amiti and Konings 2007; Topalova and Khandelwal 2011; Crino 2012). However, taking part in GVCs alone might not suffice to upgrade their economies unless accompanying policies targeting infrastructure, investment, trade, financial and labor markets, etc. are implemented by developing country governments (Kummritz, et al. 2017).

It, however, seems that these favorable effects of GVCs are confined only to a limited number of developing countries. Baldwin and Okubo (2019) build a model where the sprawling of supply chains and the associated outsourcing result in rapid deindustrialization of advanced countries like G7 and rapid industrialization of a few developing countries like China, South Korea, Mexico, and Thailand. However, some of those developing countries usually undertake the labor intensive parts of manufacturing production like assembly activities in automotive and machine industry, largely functioning as a platform for exports to rich markets in the case of China and Mexico.

Other skeptics in the literature also question the way the structure of GVCs affect the industrialization path of developing countries. Sumner (2019) identifies three channels through which the participation into global value chains might be associated with the premature deindustrialization. Trade liberalization would make developing countries import the price tendencies originated in the industrialized countries so the productivity gains in manufacturing translated into relative prices introduce deindustrializing dynamics into late industrializers (Rodrik 2015); developing countries might get trapped in the low value-added segments of the global value chains which are more accessible to them (UNCTAD 2016); the distribution of manufacturing activities across many competing developing countries would result in anemic industrial growth in host countries. Hence the main benefit of outsourcing to developing countries would practically be rendered ineffective by the sprawling of supply chains and the accompanying scramble for hosting manufacturing activities.

In order to truly assess the direct and indirect effects of GVCs, we have to examine their relation to income distribution and institutional framework within developing country context.

With respect to the inequality aspects of GVC participation, Timmer et.al. (2014) find that more than nine-tenths of the supply chains witness both a decline in the low-skilled labor share and a rise in the high-skilled labor share (including that of managers and CEOs) in value-added while the share of capital in value added has risen in two-thirds of the chains between 1995-2011. Hence, the industrialization through participation in global value chains involves a deterioration in income distribution.

The link between institutional quality and participation into GVCs is also far from being clear-cut. While it is being held true that countries engaged in complex value chains where trade flows cross borders at least twice (Wang, et.al. 2016) tend to be equipped with high-quality institutions since the industries involved are more sensitive to the quality of institutions, backward participants into GVCs, on the other hand, are generally found to have weak institutions (Dollar, et.al. 2016). As backward participants usually engaged in downstream sectors, developing countries depend on the importation of technology-intensive intermediate products. Nunn (2007) finds that the institutional sensitivity increases in direct proportion to the technological content of production. Hence, the availability of tech-intensive inputs is directly related to institutional quality (Jones 2011). It makes sense that backward participants into GVCs which extensively import sophisticated intermediate products from upstream countries happen to suffer from the lack of well-functioning institutions (Dollar and Kidder 2017, Rodrik 2008).

We witness a recent great shift in the literature on the nexus between industrialization and inequality. In his seminal paper, Kuznets (1955) found an inverted U-shape curve when inequality plotted against income per capita. The economic logic behind the geometry postulates that the structural transformation involving the shift of economic resources from agriculture to manufacturing comes with a rise in inequality first, and then a fairer income distribution could be obtained at a high stage of industrialization. His argument is based on the assumption that agriculture is a low-income sector with low inequality within itself while industry generates high income with huge income disparity. The reallocation of resources from agriculture to industry initially involves a deterioration in income distribution. The inequalities stemming from the difference between sectoral incomes decline and those originating within the sectors increase as the industry encompasses a higher share of population. At a certain point, the decline in between-sector inequality becomes more pronounced than the increase in within-sector component so we could obtain the usual hump-shaped curve.

However, recent empirical evidence casts large doubt on this argument (Baymul and Sen 2020**;** Ravindran and Babu 2021). First, in the era of hyper-globalization, the nature of structural transformation many developing countries have undergone is radically changed with the premature deindustrialization phenomena. It is shown that resources have increasingly transferred from agriculture to services, not to manufacturing industry at the early stages of economic development for many developing countries, a pattern radically different from the Kuznets' model. Second, industrialization is specifically associated with a fairer income distribution in contrast to the Kuznets' argument. Given the prevalence of informal enterprises and the wide range between low and high end of the pay-scale in services sector, manufacturing could be designated as the sector with lower within-sector inequality. It is a formal sector where its labor-force could be protected via the minimum wage regulations, trade unions, collective bargaining, etc. Industrialization also sets in motion forces towards better governance with the growth of organized working class and its accompanying political strength (Acemoglu and Robinson 2002). On the other hand, services sector carries great variability with respect to remuneration and largely involves informal employment with low-to-none protection for workers. Hence, we could establish a positive association between an amelioration in income distribution and industrialization (Sumner 2017; Sarma et al. 2017).

The literature is unequivocal about the importance of institutional quality in supporting the industrialization efforts of developing countries. The development of manufacturing industry is quite sensitive to the institutional quality since it largely involves contract-intensive production where contract enforcement and equitable protection of rights become an essential ingredient into the productivity gains (Rodrik 2008). Hence, complex transactions around infinitely many backward-forward linkages, and the production of highly differentiated goods requires a well-functioning regulatory system in the absence of which the manufacturing industry might greatly suffer from inefficiencies as a result of asymmetric information inherent in thinner markets. In this regard, it could be argued that the manufacturing is more sensitive to institutional quality than any other sector so the well-established link between growth and institutions mainly works through the mediation of manufacturing industry (Dollar and Kidder 2017, Rodrik 2008). The developing country context is also consistent with the fact that institutional quality and the related economic policy framework play great role in their industrial performance by promoting a stable macroeconomic environment (Martorano et al. 2017; Totoum et al. 2019). And poor institutions hamper the efforts at creating a robust manufacturing base by discouraging investments (Beji and Belhadj 2016).

## 3.THEORETICAL FRAMEWORK

We will develop a theoretical framework for analyzing the effects of inequality and growth shocks, supply chain disruptions, and regulatory innovations on the pace of industrialization in developing countries. We will formulate the growth of manufacturing output share as a function of participation into global value chains, regulatory quality, and income distribution as follows:

$$\frac{\Delta\, Mfg}{Mfg} = f[\overbrace{gini}^{-}, \overbrace{exgr\_dvashm}^{\pm}, \overbrace{rq}^{+}, \overbrace{growth}^{\pm}]$$

where Mfg, exgr_dvashm, rq, and gini represent the growth of manufacturing value-added share in nominal income, the share of domestic value added share in gross manufacturing exports (a proxy for the degree of participation into global supply chains), regulatory quality, and Gini coefficient which measure income inequality, respectively.

**Hypothesis 1: Inequality shocks are harmful for industrialization efforts**

We argue that a more unequal income distribution could drive developing countries into deindustrialization through the demand channel. Our hypothesis largely depends on the theoretical model developed by Foellmi and Zweimüller (2011).

Foellmi and Zweimüller (2011) constructs a model where monopolistic competition reigns in the exclusive goods and mass production sectors, implying the markup pricing in both. The price elasticity of demand for exclusive goods is assumed to be less than that for mass manufactured goods, meaning that higher markups prevail in the exclusive goods sector than mass production sector. Non-homothetic preferences hold such that the poor can consume only mass production goods or the subsistence goods if they are employed at that sector while the rich can consume only exclusive goods. All other things being equal, a more skewed income distribution against the poor reduces the demand for mass production along with their income. The mass production sector sees a contraction in terms of output and employment while the exclusive goods sector records an expansion in both accounts. Since markups and elasticities are different across the sectors, the expansion in the exclusive sector will be more than offset by the contraction in manufacturing sector, $|\Delta manufacturing| > |\Delta luxuries|$. The manufacturing sheds more labor than the exclusive sector hires, and loses more output than the latter gains because markups are higher in the exclusive goods sector. In the same vein, an increase in inequality in developed countries means a reduction in the size of export markets for manufacturing sector in developing countries (Grabowski 2017).

However, a deterioration in income inequality could be related to the suppression of wage share in total value-added. Then a worsening inequality could encourage more manufacturing output by providing a competitive advantage through lower costs of production. The wages seem to have dual economic nature, that is, they are one of the principal sources of aggregate demand while being a part of cost of production. As a result, the cost gains obtained at the expense of wage-incomes could to some extent counteract the depressing effects of a shrinking market size for manufactures, but they could be far from sufficient and sustainable to turn the tide. The wages as a generator of aggregate demand could have upper hand over the wages as a production cost item in terms of its effect on the industrialization process in the long run.

**Hypothesis 1.a: Growth shocks could have equivocal impact on the industrialization bid**

Growth shocks such as total factor productivity enhancements or a more favorable terms of trade are expected to encourage industrial expansion. A productivity rise could lead to an expansion in manufacturing output, and an improvement in export relative to import prices could have the potential to generate more revenue for manufacturing industry as a tradable sector. However, the growth shocks tend to be usually accompanied by a more unfair income distribution where the windfall gains do not trickle down from high to low income groups. While the growth shocks initially help accelerate the industrialization process, its side effects in the form of more inequality start to assert themselves later, hurting the growth of manufacturing sector through the demand channel.

**Hypothesis 2: The disruption to global supply chains is nonlinearly associated with the industrialization process**

Industrialization through participation in international supply chains provides an easier and faster way for developing countries because the usage of imported varieties raises the social value of marginal product of labor in manufacturing, thus making the industry less lumpy (Baldwin 2013). However, with a narrow domestic value-added margin due to the heavy use of imported components in production, backward participation in GVCs by developing countries did not serve the purpose of full-fledged industrialization.

A supply chain shock would manifest itself in the form of a wider domestic value-added margin of gross exports in the manufacturing industry. Given the volume of manufacturing output and exports, a higher local value-added content would be expected to favorably contribute to the share of manufacturing industry in national income. However, as long as the disruption to supply chains stays permanent, the difficulties at obtaining high-quality imported input could start to hurt the development of local manufacturing industries already well integrated into the global division of labor. Manufacturing activities could even be in danger of being interrupted in the face of disruption to supply chains due to their heavy dependence on the usage of imported intermediate goods for final production. The initial boost achieved by the value-added gains would run into the bottlenecks for imported inputs down the road.

As the lack of imported inputs would linger, local industries could look for ways of substituting imported high-quality components with their locally produced alternatives. By developing capabilities for producing some of the previously imported components, local manufacturing industries show their resilience before the supply chain shocks.

**Hypothesis 3: Regulatory quality encourages the industrialization bid**

We argue that the well-established nexus between institutional quality and economic growth can be formed by the intermediation of manufacturing industry. Since the manufacturing industry operates on a vast production network with infinitely many backward-forward linkages, it can be singled out as the most vulnerable sector to the notorious holdup problems, and any failure in contract enforcement. Better governance as captured by an improvement in regulatory quality disproportionately benefits the manufacturing industry which is a contract-intensive sector by clearing most of asymmetric information problems in the presence of strong protection of rights and credible contract enforcement (Dollar and Kidder 2017).

## 4. DATA AND METHODOLOGY

### *4.1. Estimation*

In the spirit of Sims (1980), we specify our reduced-form k-variate panel vector autoregressive (VAR) model of order p as follows:

$$Z_{it} = Z_{it-1}\boldsymbol{A_1} + Z_{it-2}\boldsymbol{A_2} + \cdots + Z_{it-p}\boldsymbol{A_p} + \mu_i + \varepsilon_{it}, , \mathrm{i} \in \{1,2,\ldots,\mathrm{N}\}, \mathrm{t} = \{1,2,\ldots,\mathrm{T}\} \quad (1)$$

where $Z_{it}$ is a k-variate row vector of endogenous variables for country i at time t and $Z_{it} \in \mathbb{R}^k$, $\mathbf{A_j}$ is k by k autoregressive coefficients matrix and $j \in \{1,2,\ldots,p\}$, $\mu_i$ is a k-dimensional row vector of equation-specific unobserved panel fixed effects and $\mu_i \in \mathbb{R}^k$, and $\varepsilon_{it}$ is a k-dimensional row vector of idiosyncratic errors and $\varepsilon_{it} \in \mathbb{R}^k$.

We made the simplifying assumption that there exist no exogenous variables in the model so all the variables which are simply treated as endogenous are expressed as a linear function of their predetermined values up to p lags. While we assume no serial correlation in error terms within an equation, $E[\varepsilon_{it}^T \varepsilon_{is}] = 0 \; for \; t > s$, contemporaneous correlations among them are allowable, that is, $E[\varepsilon_{it}\varepsilon_{it}^T] = \boldsymbol{\Sigma}$. We also assume that the same data generating process produces all the cross-sectional units, so $\mathbf{A_j}$ is common across the panels while systematic heterogeneity inherent in cross-section dimension is accounted for by panel-specific country fixed effects, $\mu_i$. Thus, we can apply traditional panel data methodology based on the assumption of homogenous slopes with heterogeneous intercepts.

However, estimating (1) is not as straightforward as it might seem at the first glance. We could use the within estimator or Least Squares Dummy Variable estimator or simple OLS after removing country fixed effect through some transformation but we know that the presence of lagged dependent variables on the right hand side might cause Nickell bias (1981). While we know that the within estimator yields consistent estimates as $T \longrightarrow \infty$, Judson and Owen (1999) prove that there exists a significant bias even when T = 30.

Anderson and Hsiao (1982) suggest using first-difference transformation to purge the panel fixed effects of the model. But again, the fact that $cov[\Delta Z_{it-1}, \Delta\varepsilon_{it}] \neq 0$ since $Z_{it-1}$ is a function of $\varepsilon_{it-1}$ by construction makes us to use the lagged values of $Z_{it}$ as instruments for $\Delta Z_{it-1}$ to overcome the endogeneity problem inherent in first difference transformation within the dynamic panel context. We usually start with using the second lag of the dependent variable as instrument because $cov[\Delta Z_{it-1}, \mathrm{Z}_{it-2}] \neq 0$ and $cov[Z_{it-2}, \Delta\varepsilon_{it}] = 0$. But $Z_{it-2}$ becomes a valid instrument if and only if $\varepsilon_{it} \sim iid\ (0, \sigma^2\mathbf{I})$. In the presence of serial correlation in idiosyncratic error terms, $Z_{it-2}$ also ceases to be a valid instrument. In this case, one must add the lagged values of dependent variable in level to the instrument matrix from the third lag on.

We must caution here that although the efficiency of the estimator increases with a large set of instruments derived from lagged values, we may run into the overfitting problem in the limit that the instruments get too weak to remedy the endogeneity bias as their number approaches the time dimension of the panels. A simple rule of thumb might be that the number of instruments should not exceed the cross-section dimension (Roodman 2009). Another issue which weakens the instruments is the autoregressive coefficient being near unit root in the case of univariate dynamic panel models. In the case of instruments getting weakened by a dependent variable close to random walk process, Blundell and Bond (1998) develop the system GMM approach to exploit new moment conditions. They propose to use lagged differences of the dependent variables as instruments for the level equation while retaining the original Arellano-Bond instruments for the first-difference equation and estimate both equations simultaneously. After the first-difference transformation we would be left with only idiosyncratic disturbance term in the case of a unit root process. Then the moment conditions become totally irrelevant since the lagged values of dependent variable would carry no information about the endogenous regressor (Abrigo and Love 2016). Hence, we have to make sure that the series is stationary.

Even when we could obtain consistent estimates of the panel VAR model parameters by applying the panel GMM estimator one equation at a time, Holtz-Eakin, et.al. (1988) show that multi-equation GMM would prove to be both efficient and consistent estimator. If we left multiply the model (1) by the instrument matrix $\mathbf{X}_{it}$ which includes from the second up to q[th] lag of the dependent variables in levels after the first-difference transformation, we obtain

$$\mathbf{X}_{it}^{\mathbf{T}}\Delta Z_{it} = \mathbf{X}_{it}^{\mathbf{T}}\,\widetilde{\boldsymbol{Z}_{it}}\mathbf{A} + \mathbf{X}_{it}^{\mathbf{T}}\Delta\varepsilon_{it} \quad (2) \text{ where}$$

$$\Delta Z_{it} = \begin{bmatrix} \Delta z_{it}^{1} & \dots & \Delta z_{it}^{k} \end{bmatrix}, \widetilde{\boldsymbol{Z}_{it}} = \begin{bmatrix} \Delta Z_{it-1} & \dots & \Delta Z_{it-p} \end{bmatrix}, \boldsymbol{X}_{it} = \begin{bmatrix} Z_{it-2} & \dots & Z_{it-q+1} \end{bmatrix},$$

$$\mathbf{A}^{\mathbf{T}} = \begin{bmatrix} \mathbf{A}^{\mathbf{T}}{}_{\mathbf{1}} & \dots & \mathbf{A}^{\mathbf{T}}{}_{\mathbf{p}} \end{bmatrix} \text{ and T denotes the transpose.}$$

The population moment conditions can be written as $E\left[\mathrm{X}_{it}^{\mathrm{T}}\Delta\varepsilon_{it}\right] = E\left[\mathrm{X}_{it}^{\mathrm{T}}\left(\Delta Z_{it} - \tilde{Z}_{\mathbf{it}}\mathbf{A}\right)\right] = 0$. It means that we have q equations from the columns of the instrument matrix $\mathbf{X}_{it}$ and p unknowns from the coefficient matrix $\mathbf{A}$ per equation. Whenever q>p, the model is considered as overidentified so the q-dimensional dependent variable vector is practically outside the column space of q by p matrix of $\mathbf{X}_{it}^{\mathbf{T}}\,\widetilde{\boldsymbol{Z}_{it}}$ whose rank is p at most.

We redefine the so-called collapsed instrument matrix stacked over t as follows:

$$\mathbf{X_i} = \begin{pmatrix} \mathbf{0} & \mathbf{0} & \cdots & \mathbf{0} \\ \boldsymbol{z_{i1}} & \mathbf{0} & & \\ \boldsymbol{z_{i2}} & \boldsymbol{z_{i1}} & & \\ \vdots & \vdots & & \\ \boldsymbol{z_{iT-2}} & \boldsymbol{z_{iT-3}} & \cdots & \boldsymbol{z_{iT-q+1}} \end{pmatrix}$$

After stacking over time-dimension, the population moment conditions become $E\left[\mathbf{X_i^T}\boldsymbol{\Delta\varepsilon_i}\right] = 0$ where $\Delta\varepsilon_i$ is (T-1) by k matrix of errors stacked over time and defined as $\Delta\varepsilon_i = \Delta Z_i - \sum_{\ell=1}^{p} \tilde{Z}_{i\ell}\,\mathbf{A}_{\boldsymbol{\ell}}$. $\mathbf{A}_{\boldsymbol{\ell}}$ is k by k parameter matrix for the l$^{th}$ lag of endogenous variables, and $\Delta Z_i$ and $\tilde{Z}_{i\ell}$ are (T-1) by k matrix as defined above. The corresponding sample moment conditions can be formulated as follows:

$$\hat{g}(\tilde{\delta}) = \frac{1}{N}\sum_{i=1}^{N} \hat{g}_i\,(\tilde{\delta})$$

$$\hat{g}_i(\tilde{\delta}) = \ (\boldsymbol{X_i} \otimes \mathbf{I_{kxk}})(\mathrm{vec}[\boldsymbol{\Delta\hat{\varepsilon}}_{\mathrm{i}}])$$

where $\otimes$ and vec denote the Kronoecker product and the vectorization of a matrix, respectively while $\boldsymbol{\Delta\hat{\varepsilon}}_{\mathrm{i}} = \Delta Z_i - \sum_{\ell=1}^{p} \tilde{Z}_{i\ell}\,\widetilde{\mathbf{A}_{\boldsymbol{\ell}}}$, $\tilde{\boldsymbol{A}}$ contains the true population parameters evaluated at some hypothetical value $\tilde{\delta}$ of $\delta$. While the population moment conditions hold theoretically, it would be practically impossible to satisfy sample moment conditions due to sampling error or noise in the data. Hence, our goal is to minimize this sampling error to obtain consistent estimator of the coefficient matrix **A**, a fact which makes Generalized Method of Moment an asymptotic or large sample estimator. We can characterize our objective function as follows:

$$\widehat{\boldsymbol{\delta_W}} = argmin_{\boldsymbol{A}} \left\|\frac{1}{N}\sum_{i=1}^{N} \hat{g}_i\,(\tilde{\delta})\right\| \equiv N\,\left(\sum_{i=1}^{N} \hat{g}_i\,(\tilde{\delta})\right)^{T} \boldsymbol{W}\left(\sum_{i=1}^{N} \hat{g}_i\,(\tilde{\delta})\right) \quad (2.a)$$

where **W** is the symmetric and positive semidefinite weighting matrix, $\|.\|$ denotes the Euclidean norm.

We can clearly establish that the GMM estimator is also a linear function of the weighting matrix **W**. The first order conditions of the objective function in (2.a) yield the formula for the GMM estimator. After stacking first over cross-sectional dimension and then over time dimension, we have

$$\hat{A}_{GMM} = \left[\left(\mathbf{X^T}\,\tilde{\boldsymbol{Z}}\right)^{\boldsymbol{T}}\boldsymbol{W}\left(\mathbf{X^T}\,\tilde{\boldsymbol{Z}}\right)\right]^{\mathbf{-1}}\left(\mathbf{X^T}\,\tilde{\boldsymbol{Z}}\right)^{\boldsymbol{T}}\boldsymbol{W}(\mathbf{X^T}\Delta Z) \quad (2.b)$$

Depending on the choice of the weighting matrix **W**, we could obtain consistent linear estimator of **A**. Now, the problem facing the researcher is reduced down to the optimal selection of the weighting matrix **W** which determines the efficiency of the estimator in (2.b). The lower bound for the asymptotic variance of the GMM estimator is achieved when the instruments are weighted in inverse proportion to their variance-covariance, $W = var\ [\mathbf{X^T}\Delta\varepsilon]^{-1}$

However, $var\ [\mathbf{X^T}\Delta\varepsilon]^{-1}$or equivalently $\left(\frac{1}{N}\sum_{i=1}^{N}\mathbf{X_i^T}\boldsymbol{\Omega}_{\mathbf{i}}\mathbf{X_i}\right)^{\mathbf{-1}}$ is unknown. To get a feasible estimator, we should first obtain the residuals from any consistent estimator in the initial stage of the estimation procedure for (2.b). Since the choice of the weighting matrix does not affect the consistency of $\hat{A}_{GMM}$, then any full-rank matrix does the trick.

We would like to keep it simple by choosing the identity matrix at the first step to get the so-called sandwich estimator for $\left(\frac{1}{N}\sum_{i=1}^{N}\mathbf{X}_{\mathbf{i}}^{\mathbf{T}}\boldsymbol{\Omega}_{\mathbf{i}}\mathbf{X}_{\mathbf{i}}\right)^{-\mathbf{1}}$. Then, at the second stage, we just set the weighting matrix as equal to the inverse of the covariance matrix obtained from the instrumental variable estimator or 2-Stages Least Squares estimator from the first-step. When we plug $\left(\frac{1}{N}\sum_{i=1}^{N}\mathbf{X}_{\mathbf{i}}^{\mathbf{T}}\widehat{\boldsymbol{\Omega}}_{\boldsymbol{i}}\mathbf{X}_{\mathbf{i}}\right)^{-\mathbf{1}}$ into (2b), and stacking all the terms in the expression first over panels and then time, we have

$$\hat{A}_{FEGMM} = \left[\left(\mathbf{X}^{\mathbf{T}}\,\widetilde{\boldsymbol{Z}}\right)^{\boldsymbol{T}}\left(\mathbf{X}^{\mathbf{T}}\,\widehat{\boldsymbol{\Omega}}\mathbf{X}\right)^{-\mathbf{1}}\left(\mathbf{X}^{\mathbf{T}}\,\widetilde{\boldsymbol{Z}}\right)\right]^{-\mathbf{1}}\left(\mathbf{X}^{\mathbf{T}}\,\widetilde{\boldsymbol{Z}}\right)^{\boldsymbol{T}}\left(\mathbf{X}^{\mathbf{T}}\,\widehat{\boldsymbol{\Omega}}\mathbf{X}\right)^{-\mathbf{1}}\left(\mathbf{X}^{\mathbf{T}}\Delta Z\right) \quad (2.c)$$

The feasible GMM estimator has the lowest asymptotic variance and standard errors robust to heteroscedasticity and autocorrelation within panels since the sandwich covariance estimator $\left(\mathbf{X}^{\mathbf{T}}\,\widehat{\boldsymbol{\Omega}}\mathbf{X}\right)^{-\mathbf{1}}$ takes care of arbitrary patterns of nonsphericity in errors through clustered block diagonal matrices $\widehat{\boldsymbol{\Omega}}_{\boldsymbol{i}}$ for each cross-sectional unit (Roodman 2009).

We could enhance the efficiency of the estimator in (2.c) by increasing the moment conditions. It means adding longer lags as instrumental variables for the first-difference equation within the GMM framework. Even before differencing, the autoregressive order of the panel VAR model costs us p observations per panel. To keep the discussion simple, we assume that p=1. After the first-differencing, we lose one more observation per panel to the transformation itself. When we include older lags in the columns of the instrument matrix, the model becomes overidentified but we would be losing as many observations per each cross-sectional unit as the number of extra columns of the instruments matrix.To avoid this additional loss of degrees of freedom, Holtz-Eakin et.al. (1988) suggest to replace missing values (dots) with zeros by noting that the moment conditions still hold, $E\left[\mathbf{X}_{\mathbf{it}}^{\mathbf{T}}\Delta\varepsilon_{it}\right] = 0$. Stata's *gmmstyle* command simply executes the Holtz-Eakin et.al.'s suggestion.

### *4.2. The Stability of the Panel VAR model*

Even though we could consistently estimate the Panel VAR model coefficients by the estimator in (2.c), it is hard to interpret them directly since we have just put the lags of dependent variables on the right hand side of each equation. However, if we guarantee that the panel VAR model of order p satisfies the stability conditions, then we could make causal inferences after converting the model into an-infinite order vector moving average (VMA) process.

We could more compactly write a panel VAR model of any order p as a first-order panel VAR model by means of the companion matrix.

$$\check{Z}_{it} = \begin{pmatrix} Z_{it} \\ Z_{it-1} \\ \vdots \\ Z_{it-p+1} \end{pmatrix} = \begin{pmatrix} \mu_i \\ 0 \\ \vdots \\ 0 \end{pmatrix} + \begin{pmatrix} \boldsymbol{A_1} & \boldsymbol{A_2} & & \boldsymbol{A_p} \\ \boldsymbol{I_k} & & & \\ & \ddots & & \\ & & \boldsymbol{I_K} & \boldsymbol{0} \end{pmatrix} \begin{pmatrix} Z_{it-1} \\ Z_{it-2} \\ \vdots \\ Z_{it-p} \end{pmatrix} + \begin{pmatrix} \varepsilon_{it} \\ 0 \\ \vdots \\ 0 \end{pmatrix} = \check{\mu}_i + \check{\boldsymbol{A}}\,\check{Z}_{it-1} + \check{\epsilon}_{it} \quad (3)$$

The companion matrix $\check{\boldsymbol{A}}$ has kp by kp dimension and the stability condition of the panel VAR (p) model depends on all of its kp eigenvalues having the moduli inside the unit circle.

$$Stability\ condition\text{: } \left|\check{\boldsymbol{A}} - \lambda\boldsymbol{I_{kp}}\right| = 0\ where\ |\lambda_i| < 1, \forall i, i = 1,2, \dots, kp \quad (3.a)$$

To see what would follow after the stability condition for the panel VAR model in (3.a) is satisfied, we show that the model can be reexpressed as a VMA (∞) by recursive substitution.

$$\check{Z}_{it} == \left(\boldsymbol{I_k} + \sum_{j=1}^{t-1}\check{\boldsymbol{A}}^{\boldsymbol{j}}\right)\check{\mu}_i + \check{\boldsymbol{A}}^{\boldsymbol{t}}\check{Z}_{i0} + \sum_{j=1}^{t-1}\check{\boldsymbol{A}}^{\boldsymbol{j}}\check{\epsilon}_{it-j} + \check{\epsilon}_{it} \quad (3.b)$$

When we take the conditional expectation of the VMA (∞) in (3.b) as the limit goes to t→∞, we have

$$E\left[\check{Z}_{it}|Z_{i0}\right] = \left(\boldsymbol{I_k} + \sum_{j=1}^{t-1}\check{\boldsymbol{A}}^{\boldsymbol{j}}\right)\check{\mu}_i + \check{\boldsymbol{A}}^{\boldsymbol{t}}\check{Z}_{i0}\ \text{ since } E[\check{\epsilon}_{it}|Z_{i0}] = 0 \text{ by assumption} \quad (3.c)$$

where $\check{Z}_{i0}$ represents the initial value of the vector process $\check{Z}_{it}$.

Now it becomes clear that the statistical properties of the panel VAR model depend on the matrix powers $\breve{\boldsymbol{A}}^{\boldsymbol{t}}$**.** We can check out the stability of the panel VAR model by the spectral decomposition of the companion matrix where $\breve{\boldsymbol{A}}^{\boldsymbol{t}} = \boldsymbol{S}\boldsymbol{\Lambda}^{\mathbf{t}}\boldsymbol{S}^{-\mathbf{1}}$**. S** is the eigenvector matrix, and **Λ** is the diagonal matrix with the eigenvalues being on the main diagonal. The matrix powers are convergent when $\lim_{t\to\infty} \breve{\boldsymbol{A}}^{\boldsymbol{t}} = 0$ since $\boldsymbol{\Lambda}^{\mathbf{t}} \longrightarrow \boldsymbol{zero\ matrix\ by}\ (\mathbf{3}.\boldsymbol{a})$. As a result,

$$\lim_{t\to\infty} E[\breve{Z}_{it}|Z_{i0}] = (\boldsymbol{I_k} - \breve{\boldsymbol{A}})\breve{\mu}_i \quad (3.d)$$

since $\left(\boldsymbol{I_k} + \sum_{j=1}^{t-1}\breve{\boldsymbol{A}}^{\boldsymbol{j}}\right) = \left(\boldsymbol{I_k} - \breve{\boldsymbol{A}}\right)$ when there exists $t \in \mathbb{N}\ such\ that\ \breve{\boldsymbol{A}}^{\boldsymbol{t}} = \mathbf{0}$.

The expected value of the vector process $\breve{Z}_{it}$ when t→ ∞ is equal to a vector of scalars. We can similarly extend these arguments into the covariance matrix of the vector process $\breve{Z}_{it}$. Hence the covariance-stationarity of the vector process $\breve{Z}_{it}$ is equivalent to all the moduli of eigenvalues of the companion matrix $\breve{\boldsymbol{A}}$ being strictly less than one.

With the transformation of the panel VAR model into the VMA (∞), we could obtain the impulse-response functions. However, the contemporaneous correlations among the idiosyncratic terms as captured by $E[\varepsilon_{it}\varepsilon_{it}^T] = \boldsymbol{\Sigma}$ prevents us from identifying shocks to each equation in the system. By construction, one shock to any equation is likely to have repercussions on other in the system. While being uncorrelated over time, the shocks might be correlated at a given point in time across the equations.

$$\boldsymbol{\Sigma} = E[\varepsilon_{it}\varepsilon_{it}^T|\mathcal{I}_{t-1}] = E\left[\begin{pmatrix}\varepsilon_{it}^1\\ \vdots \\ \varepsilon_{it}^k\end{pmatrix}(\varepsilon_{it}^1 \quad \dots \quad \varepsilon_{it}^k)|\mathcal{I}_{t-1}\right] = \begin{pmatrix}\Sigma_{11} & \Sigma_{12} & \dots & \Sigma_{1k}\\ \Sigma_{21} & \Sigma_{22} & \dots & \Sigma_{2k}\\ \vdots & & & \vdots\\ \Sigma_{k1} & \dots & & \Sigma_{kk}\end{pmatrix}$$

where $\mathcal{I}_{t-1}$is the information set at time t-1, $\mathcal{I}_{t-1} = \{Z_{it-1}, \dots, Z_{it-p}\}$.

**Σ** is k by k symmetric and positive definite matrix. It is symmetric because $\Sigma_{\mathrm{js}} = \mathrm{cov}\left(\varepsilon_{it}^j, \varepsilon_{it}^j\right) = \mathrm{cov}\left(\varepsilon_{it}^s, \varepsilon_{it}^j\right) = \Sigma_{\mathrm{js}}\ for\ j \neq s$. It is positive definite because the energy test yields $x^T(\varepsilon\varepsilon^T)x = (x^T\varepsilon)(\varepsilon^T x) = (\varepsilon^T x)^T(\varepsilon^T x) = \|\varepsilon^T x\|^2 > 0\ when\ x \neq 0$ (we just dropped the subscripts for convenience). The fact that **Σ** is symmetric and positive definite allows us to separate shocks through the Cholesky decomposition (Sims 1980) where $\boldsymbol{\Sigma} = \boldsymbol{P}\boldsymbol{P}^{\boldsymbol{T}}$**.** Here, **P** is the lower triangular Cholesky factor. We should in passing note that this factorization is not unique. For example, we could have applied the Singular Value Decomposition as well. If we pre-multiply the shocks by the Cholesky factor inverse, we could obtain a diagonal covariance matrix so that the shocks and their repercussions can be isolated from each other.

$$\dddot{\varepsilon}_{it} = \boldsymbol{P}^{-\mathbf{1}}\varepsilon_{it} \Longrightarrow E[\dddot{\varepsilon}_{it}\dddot{\varepsilon}^T{}_{it}|\mathcal{I}_{t-1}] = \boldsymbol{P}^{-\mathbf{1}}E[\varepsilon_{it}\varepsilon_{it}^T|\mathcal{I}_{t-1}](\boldsymbol{P}^{-\mathbf{1}})^{\boldsymbol{T}} = \boldsymbol{P}^{-\mathbf{1}}\boldsymbol{\Sigma}(\boldsymbol{P}^{\boldsymbol{T}})^{-\mathbf{1}} = \boldsymbol{I}. \quad (3.e)$$

With the diagonalized covariance matrix, we could work with the orthogonalized impulse-response functions using the structural form. However, we should be aware that the order in which the dependent variables enter into the vector process $Z_{it}$ reflects the identifying restrictions we impose on the error covariance matrix so as to make some causal inferences. For space consideration, let's examine the first order panel VAR model in its structural form.

$$\begin{pmatrix}1 & & & & \\ -\beta_{21} & 1 & & & \\ -\beta_{31} & -\beta_{32} & 1 & & \\ & & & \ddots & \\ -\beta_{k1} & -\beta_{k2} & \dots & & 1\end{pmatrix}\begin{pmatrix}Z_{it}^1\\ \vdots\\ Z_{it}^T\end{pmatrix} = \begin{pmatrix}\Pi_{11} & \Pi_{12} & \dots & \Pi_{1k}\\ \Pi_{21} & \Pi_{22} & \dots & \Pi_{2k}\\ \vdots & \vdots & \dots & \vdots\\ \Pi_{k1} & \Pi_{k2} & \dots & \Pi_{kk}\end{pmatrix}\begin{pmatrix}Z_{it-1}^1\\ \vdots\\ Z_{it-1}^T\end{pmatrix} + \begin{pmatrix}\dddot{\varepsilon}^1{}_{it}\\ \vdots\\ \dddot{\varepsilon}^k{}_{it}\end{pmatrix} \quad (3.f)$$

The first two equations will suffice to shed light on the interpretation of the orthogonalized impulse-response functions.

$$Z_{it}^1 = \Pi_{11}Z_{it-1}^1 + \dots + \Pi_{1k}Z_{it-1}^T + \dddot{\varepsilon}^1{}_{it}$$
$$Z_{it}^2 = \beta_{21}Z_{it}^1 + \Pi_{21}Z_{it-1}^1 + \dots + \Pi_{2k}Z_{it-1}^T + \dddot{\varepsilon}^2{}_{it}$$

The first equation is the usual panel VAR model where its shock $\dddot{\varepsilon}^{1}_{it}$ will have a direct impact on $Z^1_{it}$ and other variables in the system. The second equation is the Autoregressive Distributed Lag (ARDL) model into which $Z^1_{it}$ enters as an explanatory variable for $Z^2_{it}$. The third equation is also another ARDL model for $Z^3_{it}$ where both $Z^1_{it}$ and $Z^2_{it}$ now appear on the right hand side. The pattern applies to the rest of k-3 equations in the model. While the shocks on the first variable $\dddot{\varepsilon}^{1}_{it}$ have contemporaneous effect on all the variables in the model, the shock on the second variable $\dddot{\varepsilon}^{2}_{it}$ will affect the first variable $Z^1_{it}$ with a time lag ($\dddot{\varepsilon}^{2}_{it} \longrightarrow Z^2_{it} \longrightarrow Z^1_{it+1}$).
Since the orthogonalized impulse-response functions require a causal ordering, the Granger causality test might help us to arrange the vector process $Z_{it}$ in addition to the economic theory on the subject. For a 2-variate panel VAR model of order p, the equations and the null hypothesis to be tested are as follows:
$Z^1_{it} = \sum_{j=1}^{p} \gamma_{1j} Z^1_{it-j} + \sum_{j=1}^{p} \delta_{1j} Z^2_{it-j} + \varepsilon^1_{it} \Rightarrow H_0: \delta_{1j} = 0, \forall j, j = 1,2, \dots, p$. "$Z^2_{it}$ does not Granger cause $Z^1_{it}$."
$Z^2_{it} = \sum_{j=1}^{p} \gamma_{2j} Z^1_{it-j} + \sum_{j=1}^{p} \delta_{2j} Z^2_{it-j} + \varepsilon^2_{it} \Rightarrow H_0: \gamma_{2j} = 0, \forall j, j = 1,2, \dots, p$."$Z^1_{it}$ does not Granger-cause $Z^2_{it}$."
If one variable is the Granger-cause for other variable, and it is not the other way around according to the test results, we may place the former above the latter in the vector process $Z_{it}$.

### *4.3. Model specification and optimal lag length in moment conditions*

When we specify the panel VAR model, we need to decide both the optimal lag order while satisfying the moment conditions within the dynamic panel GMM framework. When it comes to the model specification, the inclusion of too many lags in the model might eat into an exponentially high degrees of freedom while a more parsimonious model which includes too few lags could easily be subject to the omitted variable bias. Regarding the moment conditions, the use of more moment conditions brings high efficiency to the GMM estimate while, on the other hand, adding too many moment conditions could lead to overfitting the endogenous variables so the Nickell bias could not be remedied by adding more instrumental variables. Andrews and Lu (2001) extends the standard GMM framework based on the Hansen's J statistics for overidentifying restrictions to the maximum-likelihood based model selection criteria (MMSC). The MMSC developed by Andrews and Lu (2001) contain "bonus terms" which reward the selection of fewer lag order for a fixed number of moment conditions and the inclusion of more lags of dependent variables in level as instruments for a given lag order of the panel VAR model.
Consider the model (2). The coefficient matrix **A** consists of p **A**$_i$'s with each **A**$_i$ having k x k parameters. The total number of parameters to be estimated comes out as $k^2p$ because for each equation there are k different endogenous variables with each having p lags and we have k equations in the system. If each distinct endogenous variable with p lags each is instrumented with its q lags in level starting with the second lag, we would have q x k moment conditions per equation and $k^2q$ moment conditions for the model as a whole. Whenever q>p, the Hansen's J statistics for overidentifying restrictions can be calculated since we have more equations than unknowns in the model.

$$MMSC_{BIC}(k,p,q) = J_n(k^2p, k^2q) - (|k^2q| - |k^2p|)\ln n$$
$$MMSC_{AIC}(k,p,q) = J_n(k^2p, k^2q) - 2(|k^2q| - |k^2p|)$$
$$MMSC_{HQIC}(k,p,q) = J_n(k^2p, k^2q) - Q(|k^2q| - |k^2p|)\ln\ln n \quad for\ Q > 2$$

where ln denotes the natural logarithm and n the sample size.
We would like to minimize $MMSC_{BIC}$, $MMSC_{AIC}$, $MMSC_{HQIC}$, and Hansen's J-statistics to specify optimal lag order while having the valid instruments for endogenous regressors. When the J statistics' probability value under the null hypothesis that the instruments are valid drops below 5 percent, we might suspect that the first-order autoregressive process might be present in the idiosyncratic error term which invalidates the moment conditions. In this case, we had

better back off one period and start using the third lag of the dependent variable in level as instrument for the first-difference equation.

### *4.4. Data*

When compiling our dataset, we use various sources such as World Bank's World Development Indicators (WB-WDI) and World Governance Indicators (WGI), Groningen Growth and Development Center/Economic Transformation Database (GGDC/ETD), and OECD's Trade in Value-added database (OECD/TIVA) (Table 1).

Our dataset cover 18 developing countries from Latin America, Africa, East Asia, and Europe for 1995-2018. Instead of working with the variables in levels, we prefer to calculate their growth rates by the formula $(X_t\text{-}X_{t-1})/X_{t-1}$ to address any possible nonstationarity in series and interpret results in a more convenient way. The variables measured in terms of their growth rates has the advantage of generating valid moment conditions within the GMM framework.

Since GDP per capita at current dollars exhibits a time trend, we demean the series from its time trend. Then we compute the growth rate of the detrended series to obtain the deviations from the historical growth trajectory. Hence, the growth shocks could easily be evaluated in terms of their effects on the structural characteristics of the national economy while controlling for the steady state growth path.

Domestic value-added share of gross manufacturing exports is used as a proxy variable for the degree to which a developing country takes part in the global supply chain chains as downstream producer since it typically operates as backward participant into GVCs. The further a country is integrated into the global value chains, the lower the domestic value-added share of its gross manufactures exports will be since it has access to the worldwide production network which provides them with high-quality intermediate goods entering the final product. Hence, a rise in domestic value added margin will be interpreted as a sign of disentanglement from the supply chains due to some disruption to them.

The construction of domestic value-added share of gross manufacturing exports is based on the OECD, Inter-Country Input Output tables (OECD 2019). The useful matrices are described as:

**W:** 1 by NK row vector of value-added content at basic prices
**X:** 1 by NK row vector of gross output at basic prices
**V:** 1 by NK row vector of value-added to output ratio
**Z:** NK by NK matrix of intermediate consumption at basic prices
**Y:** NK by N matrix of final demand
**A:** NK by NK matrix of input coefficients

We start with NK by NK matrix **Z** of intermediate consumption where there are K industries and N countries. Each entry in the matrix simply, $z_{ij}^{rs}$ shows the productive consumption of good i produced in country r by sector j in country s. When we postmultiply **Z** by $\mathbf{\hat{X}^{-1}}$, where $\mathbf{\hat{X}}$ is the diagonal matrix with the output vector X in its main diagonal, we obtain the input coefficient matrix **A**. Similarly, the value-added vector **V** is obtained by the matrix multiplication $\mathbf{W\hat{X}^{-1}}$. Now, the first equality yields the gross output vector as follows:

**Table 1: Descriptive statistics**

| Variable | Description | Source | Mean | Standard deviation | Range (Min-Max) | Mean Growth Rate |
|---|---|---|---|---|---|---|
| pcincome | GDP per capita, (current $) | WB/WDI, Release: 23 November 2021 | 5857,5 | 5292,2 | 268,9 – 31997,3 | 6% |
| outshare | Manufacturing value added share in nominal GDP | GGDC/ETD, Release: 17 February 2021 | 19,03% | 5,89% | 7,44%-34,96% | -0,3% |
| EXGR_DVASHM | Domestic value-added share in gross manufacturing exports | OECD/TIVA, Extracted on 5 December 2021 | 71,51% | 12,81% | 41,87% -93,6% | - |
| gini | GINI coefficient, | WB/WDI, Release: 30 July 2021 | 48,83 | 8,76 | 26,05-64,8 | - |
| rqe | Regulatory Quality | WB/WGI, Release: 30 July 2021 | 0,149 | 0,55 | -1,074-1,61 | - |

$$\boldsymbol{X} = \boldsymbol{AX} + \boldsymbol{Y}$$
$$\boldsymbol{X} - \boldsymbol{AX} = \boldsymbol{Y}$$
$$\boldsymbol{X} = (\boldsymbol{I} - \boldsymbol{A})^{-1}\boldsymbol{Y}$$

where **L**= $(\boldsymbol{I} - \boldsymbol{A})^{-1}$ is the global Leontieff inverse matrix. $\mathbf{L}_{c,c}$ is K by K diagonal block matrix of **L** which simply shows how much direct and indirect input is required to produce one more unit of output in country c. Thus K columns of $\mathbf{L}_{c,c}$ reflect the increase in the output of various industries as a result of one unit increase in the final demand for any industry in the country c. From the diagonal of block matrix **A**, we could construct $\mathbf{A}_\mathbf{D}$, the off-diagonal elements would form the block matrix $\mathbf{A}_\mathbf{F}$ where $\mathbf{A} = \mathbf{A}_\mathbf{D}+\mathbf{A}_\mathbf{F}$. Similarly NK by N block diagonal matrix $\mathbf{Y}_\mathbf{D}$ can be formed from the matrix **Y** where the main diagonal block include K by 1 $\mathbf{Y}_\mathbf{ii}$. NK by N matrix of $\mathbf{Y}_\mathbf{F}$ with al zeros on its main diagonal is simply equal to $\mathbf{Y}$-$\mathbf{Y}_\mathbf{D}$**.** When we plug $\mathbf{A} = \mathbf{A}_\mathbf{D}+\mathbf{A}_\mathbf{F}$ and $\mathbf{Y} = \mathbf{Y}_\mathbf{D}+\mathbf{Y}_\mathbf{F}$ into the first equation above, we would get

$$\boldsymbol{X} = (\boldsymbol{A_D} + \boldsymbol{A_F})\boldsymbol{X} + (\boldsymbol{Y_D} + \boldsymbol{Y_F})$$
$$\boldsymbol{X} - \boldsymbol{A_D X} = \boldsymbol{Y_D} + \boldsymbol{E} \text{ where } \boldsymbol{E} = (\boldsymbol{A_F X} + \boldsymbol{Y_F})$$

The vector **E** simply represents the total sum of gross intermediate and final good exports. We now extract a direct value-added coefficient matrix $\widehat{\mathbf{V}}$ which is NK by NK diagonal matrix with value-added shares for countries and industries being on the main diagonal. Domestic value-added share of gross exports for all countries and all industries can be calculated by $\widehat{\mathbf{V}}(\boldsymbol{I} - \boldsymbol{A})^{-1}\boldsymbol{E}$**.** To be more precise we now extract a direct value-added coefficient vector $\mathbf{V}_\mathbf{c}$ of 1 by K for country c from **V**. And we create K by 1 vector of $\widehat{\boldsymbol{E}}_{\boldsymbol{i}}$ with all entries being equal to zero except the one corresponding to the manufacturing industry. The domestic value-added share of gross manufacturing exports, the variable EXGR_DVASHM is nothing but $\mathbf{V}_\mathbf{c}\boldsymbol{L}_{\boldsymbol{cc}}\widehat{\boldsymbol{E}}_{\boldsymbol{i}}$**.** If we further decompose $\mathbf{V}_\mathbf{c}\boldsymbol{L}_{\boldsymbol{cc}}\widehat{\boldsymbol{E}}_{\boldsymbol{i}}$**,** we could easily see that it represents the exported value-added created not only by the manufacturing industry itself but also by any other local industries providing inputs to the manufacturing sector. When we continue from the last equation above, we isolate **X** on the left-hand side as follows:

$$\boldsymbol{X} = (\boldsymbol{I} - \boldsymbol{A_D})^{-1}\boldsymbol{Y_D} + (\boldsymbol{I} - \boldsymbol{A_D})^{-1}\boldsymbol{E}$$

where $\widehat{\boldsymbol{L}} = (\boldsymbol{I} - \boldsymbol{A_D})^{-1}$ is the local Leontief inverse which is NK by NK diagonal block matrix.

Direct domestic value added content of gross exports by the manufacturing industry itself can be calculated by $\widehat{\mathbf{V}}_{\mathbf{c}}\ \boldsymbol{diag}\ \widehat{\boldsymbol{L}}_{\boldsymbol{c}}\ \widehat{\boldsymbol{E}}_{\boldsymbol{i}}$ **.** We can read the direct production requirements off the main diagonal of the local Leontief inverse. Indirect domestic value added content which reflects the contribution of other domestic input-providing sectors to gross manufacturing exports can easily be calculated from $\widehat{\mathbf{V}}_{\mathbf{c}}\ \boldsymbol{offdiag}\ \widehat{\boldsymbol{L}}_{\boldsymbol{c}}\ \widehat{\boldsymbol{E}}_{\boldsymbol{i}}$. We can read the local value-added contribution of upstream sectors incorporated in the exports of manufacturing industry from the off-diagonal elements of the local Leontief inverse. The imported intermediate products entering the gross manufacturing exports could also contain a certain amount of domestic value added which had once been exported for the input-producing foreigners. The residual left, $\mathbf{V}_{\mathbf{c}}\boldsymbol{L}_{\boldsymbol{cc}}\widehat{\boldsymbol{E}}_{\boldsymbol{i}} - \widehat{\mathbf{V}}_{\mathbf{c}}\ \boldsymbol{diag}\ \widehat{\boldsymbol{L}}_{\boldsymbol{c}}\ \widehat{\boldsymbol{E}}_{\boldsymbol{i}} - \widehat{\mathbf{V}}_{\mathbf{c}}\ \boldsymbol{offdiag}\ \widehat{\boldsymbol{L}}_{\boldsymbol{c}}\ \widehat{\boldsymbol{E}}_{\boldsymbol{i}}$ just shows the reimported domestic value added content of gross manufacturing exports. It represents the domestic value added content embodied in imported intermediate goods.

The Gini coefficient is a relative measurement of income inequality. A coefficient of 0 denotes perfect equality whereas 100 reflects perfect inequality.

The regulatory quality index quantifies the capacity of government to carry out policies and regulations which improve business environment by preventing unfair competitive practices, and avoiding discriminatory taxation, etc. All the composite scores of 193 countries in the WGI database are standardized with mean zero and standard deviation one, assuming normality. The standard normal z-score has a range of -2,5 to +2,5. As the z-score approaches to +2,5, it means the regulatory quality has improved in that country.

## 5. EMPIRICAL RESULTS

To avoid any model misspecification, we should start out with the determination of optimal lag order for our panel VAR model while making sure that the instruments used satisfy the orthogonality condition. We set the maximum lag length at 3 and add up to 10 lags of the dependent variables as instruments for endogenous regressors (Table 2).

**Table 2: Selection order criteria**

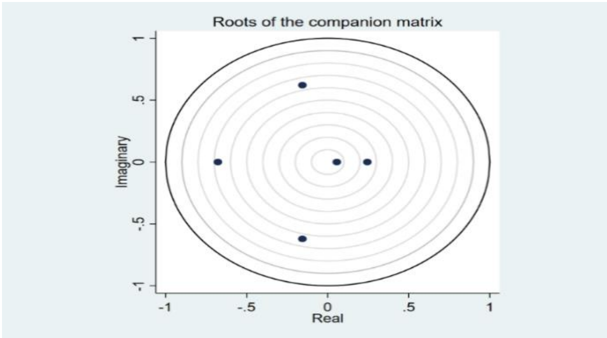
| Lag | CD | J | J p-value | MBIC | MAIC | MQIC |
|---|---|---|---|---|---|---|
| 1 | 0.9955911 | 129.337 | 0.6669048 | -567.6637 | -144.663 | -316.4077 |
| 2 | 0.9897379 | 92.40134 | 0.9114143 | -477.4095 | -131.5987 | -272.0031 |
| 3 | -23.95225 | 62.59136 | 0.9776236 | -380.0295 | -111.4086 | -220.4728 |

No. of obs = 162

Maximum likelihood based model selection criteria are minimized at the first lag so the correct model specification requires a panel VAR model of order one. On the other hand, the Hansen's J-statistic provides strong evidence that the instruments are valid.

Assuming no a priori causality among the variables, we run 5-variate panel VAR model of order one by applying the Arellano-Bond panel GMM estimator. The endogenous regressors in the first difference equation are instrumented with the predetermined values of dependent variables in levels from the second through the tenth lag. The reduced-form coefficients and their z-scores are given in Appendix 1.Since the reduced-form coefficients are hard to interpret due to its a-theoretical nature, we would like to transform the first-order panel VAR model into an infinite order vector moving average process. Since the stability of the VAR model is essential to the transformation, we obtain the eigenvalues of the companion matrix to verify that each has modulus strictly less than one (Graph 1).

**Graph 1: Eigenvalues of the companion matrix and the unit circle**




After the stability of the model is guaranteed, then we move on to estimating the impulse response functions to figure out the interactions among the dependent variables. Since the shocks or innovations in the reduced-form model are assumed to be correlated at a given point in time, a direct estimation of the impulse-response functions would not allow us to isolate one shock's effect from that of another. When we diagonalize the error covariance matrix, then we could single out the effect of shocks to one variable on the rest of the dependent variables. Since the diagonalization is quite sensitive to the order in which the dependent variables enter the model, we could run the Granger-causality test to help us to determine the causal ordering among the variables (Table 3).

Except a few cases, we could establish that all the variables mutually Granger-cause each other, indicating a high degree of predictive causality. Gini coefficient, regulatory quality z-score, domestic value-added share of gross manufacturing exports, and economic growth rate all do Granger-cause the growth of manufacturing value added share in national income, allowing us to treat the latter as "response" variable. The similar arguments could be extended to the growth rate with the caveat that regulatory quality rate does not Granger cause per capita income growth at one percent significance level.

It is interesting to note that we could establish one-way causality direction which runs from Gini coefficient to domestic value-added margin and regulatory quality. Inequality which might be related to the share of wages in national income could determine the degree to which a country takes part in somewhat labor-intensive segments of global value added chains. The income distribution has also impact upon the regulatory quality of business environment. The last point is not be as surprising as it might seem at first glance since a fair income distribution could lead to an improvement in overall institutional quality. Another intriguing point relates to the disassociation between institutional framework and backward participation into global supply chains as reflected by the domestic value-added margin in manufacturing exports. The spread of value chains into low-wage countries with poor institutional quality could plausibly bar us from establishing a direct link between them.

Since we would like to identify the factors quickening the industrialization process, we consider the response of the growth of manufacturing output share to the impulses associated with one standard deviation positive shock to domestic value-added share of gross manufacturing exports, regulatory quality z-score, gini coefficient, and per capita income growth (Graph 2).

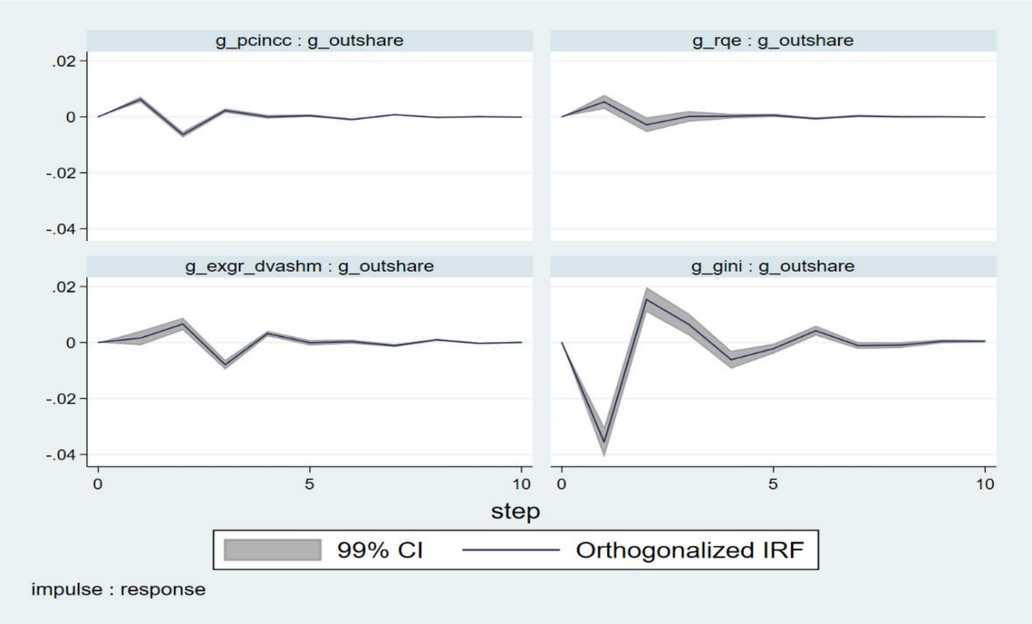
Table 3: Panel VAR Granger causality test

| Equation / Excluded | | Chi2 |
|---|---|---|
| g_outshare | | |
| | g_gini | 577.437*** |
| | g_rqe | 38.978*** |
| | g_exgr_dvashm | 29.333*** |
| | g_pcincc | 400.912*** |
| | ALL | 1085.116*** |
| g_gini | | |
| | g_outshare | 241.698*** |
| | g_rqe | 0.987 |
| | g_exgr_dvashm | 0.004 |
| | g_pcincc | 252.739*** |
| | ALL | 579.624*** |
| g_rqe | | |
| | g_outshare | 42.065*** |
| | g_gini | 14.688*** |
| | g_exgr_dvashm | 0.302 |
| | g_pcincc | 8.568*** |
| | ALL | 57.282*** |
| g_exgr_dvashm | | |
| | g_outshare | 350.076*** |
| | g_gini | 217.967*** |
| | g_rqe | 0.206 |
| | g_pcincc | 15.205*** |
| | ALL | 480.72*** |
| g_pcincc | | |
| | g_outshare | 110.314*** |
| | g_gini | 203.738*** |
| | g_rqe | 5.832** |
| | g_exgr_dvashm | 174.506*** |
| | ALL | 678.795*** |

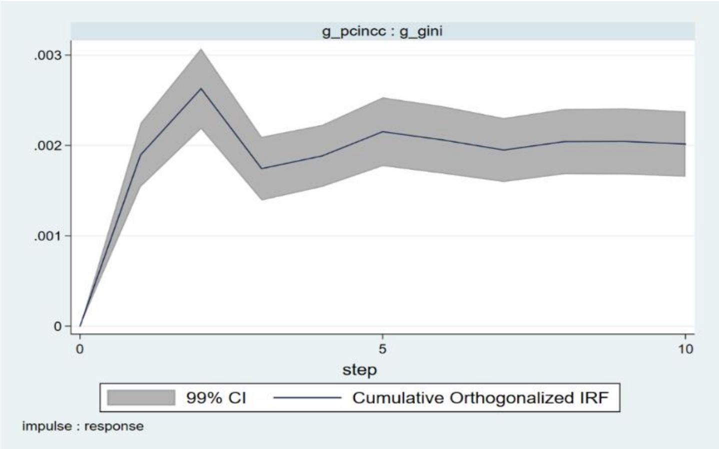
Notes: Asteriks indicate that robust chi square-statistics are significant at *10%, **5%, and ***1%.

According to the top left chart in Graph 2 growth shocks are nonlinearly associated with the rate of industrialization. Growth shocks such as total factor productivity enhancements or terms of trade improvements accelerate the pace of industrialization by up to 0,71%. But then the manufacturing output share starts to contract at a rate of 0,64% the next period, thus roughly neutralizing the initial gains achieved by growth shocks. This peculiar result could be ascribed to the inequality-increasing nature of growth shocks (Bandyopadhyay and Sun 2020; Halter et al. 2014, Barro 2000). When we isolate the effects of growth shocks on Gini coefficient, we argue that they could have deteriorating effects on income distribution over long-time horizon (Graph 3). Overall, we could claim that growth shocks positively contribute to the industrialization bid in the long-run but its contribution could be lessened by the deleterious effects of its inequality-increasing nature. Hence the government policies must make sure that each income group should get its own fair share in productivity gains or favourable international price trends.

**Graph 2: Orthogonalized impulse-response functions**




**Graph 3: Response of gini to growth shocks**




The left bottom diagram in Graph 2 shows that the supply chain shocks which result in a higher share of domestic value-added margin in one unit of gross exports is nonlinearly related to the pace of industrialization. Given the volume of gross exports, a widening domestic value added margin is expected to boost the manufacturing share in total value-added. The tailwind provided by higher local content could reach as far as 1% on cumulative terms in two years. However, when a supply chain shock occurs, the participant countries eventually face an immense difficulty in procuring highly needed imported intermediate products so the increase in domestic value added share is accompanied by the deceleration in the industrialization process with a contraction of almost 1 percent, nearly wiping out value-added gains. A higher value added share combined with a decline in national income share could be explained by a contraction in industrial production due to the essential imported input bottlenecks. It, however, seems that the malign effects of a disruption to supply chains is more or less compensated by the resiliency of domestic manufacturing industry the following period. Faced by the shortages of essential ingredients of production, the countries could start to develop new competencies corresponding to intermediate input import substitution. Hence, the developing countries could have a chance of escaping the worst thanks to the ability of their manufacturing industries to adapt to supply chain shocks. The countries doubtlessly could do even better with a well-designed industrial policy aimed at replacing imported intermediate goods with their local substitutes with matching quality and cost.

We have unequivocal evidence that any improvement in regulatory quality boost the industrialization process. A new policy paradigm which leads to a leap in the country's regulatory quality z-score could quicken the industrialization process by speeding its growth rate up to 0,8 percentage points. Hence, the countries could accelerate its manufacturing sector growth in national by ameliorating the business environment where the holdup problems are largely eliminated and the contracts are enforced by means of a supportive government. Hence, improving regulatory quality comes out as a policy recommendation to reverse the fate of premature deindustrialization.

But the greatest obstacle to the industrialization process in developing countries lies in the way the national income is distributed among population. Since it mostly produces necessary mass consumption goods purchased mainly by low to middle income groups, a more skewed income distribution squeezes the market size of manufacturing industry. An inequality shock astonishingly decreases the growth of manufacturing output share by as much as 4 percentage points. However, an increase in social inequality which might be caused by the suppression of wage income and which might mean a profit bonanza to entrepreneurs could seem to work out its effect to expanding the manufacturing the next period, giving it a total spin of 2%. However, these cost gains absolutely fall short of offsetting the depressing effects of a shrinking market size for manufactures, leaving the overall effects of a more unequal income distribution at a minus 2,5% over the medium to long term. Thus, secondary income distribution policies such as progressive taxation, social transfers, improvements and enlargements in public education, health care and pension system would help support the industrialization process by creating a wide domestic market for manufactures.

**Table 4: Forecast error variance decomposition**

| Response variable and forecast horizon | Impulse variable | | | | |
|---|---|---|---|---|---|
| | g_gini | g_rqe | g_exgr_dvashm | g_pcincc | g_outshare |
| g_outshare | | | | | |
| 0 | 0 | 0 | 0 | 0 | 0 |
| 1 | 0 | 0 | 0 | 0 | 1 |
| 2 | 0.2106723 | 0.0046678 | 0.000413 | 0.0063746 | 0.7778724 |
| 3 | 0.236876 | 0.0057199 | 0.0072287 | 0.0124609 | 0.7377146 |
| 4 | 0.2392633 | 0.0056242 | 0.0168744 | 0.013016 | 0.7252221 |
| 5 | 0.2415107 | 0.0055471 | 0.0181851 | 0.012823 | 0.7219341 |
| 6 | 0.2398954 | 0.0055337 | 0.0180093 | 0.0127212 | 0.7238405 |
| 7 | 0.2415402 | 0.005578 | 0.0179453 | 0.0128163 | 0.7221203 |
| 8 | 0.2416048 | 0.0055877 | 0.0181286 | 0.0128944 | 0.7217844 |
| 9 | 0.2416624 | 0.005586 | 0.0182607 | 0.0128984 | 0.7215925 |
| 10 | 0.2416314 | 0.0055847 | 0.0182723 | 0.0128955 | 0.7216161 |

We know that the stability of the panel VAR model and the validity of moment conditions depend on the stationarity of dependent variables, so we run panel unit root tests on them. Since we deal with a long panel with the time dimension (24 years) being greater than the cross-section dimension (18 countries), we apply Levin-Lin-Chu (LLC) panel unit roots test which does not suffer from size distortion as T/N ->0 asymptotically (Appendix 2). According to the LLC test statistics, we could strongly reject the null hypothesis that the panels contain unit roots. We would like to confirm this conclusion by the Hadri Lagrange Multiplier (LM) test. The Hadri test has stationarity as its null hypothesis. According to the test results, all the variables except outshare and gini are verified to be stationary. Since we work with the growth rates of manufacturing output share and gini coefficient, there is no reason for worrying about the random-walkness of them either. An analysis of the forecast error variance decomposition also confirms that except its own shocks the variability in the pace of industrialization is affected most by income inequality (Table 4). Almost a quarter of changes in the growth of manufacturing output share could be attributed to the inequality shocks.

## 6. CONCLUSION

We empirically examine the effects of supply chain, inequality, institutional and growth shocks on the pace of industrialization for developing countries. We construct a panel VAR model and adopt the Arellano-Bond approach into estimating it.

We found that supply chain disruptions are nonlinearly associated with the trajectory of industrialization. A shock suggesting a partial disentanglement from supply chains first accelerates the industrialization process since a wider domestic value-added margin in unit export helps local manufacturing industries gain a larger share in national income. After this initial impulse, the difficulties related to the supply bottlenecks of imported inputs rears its ugly head, leading to the contraction of manufacturing output share. As the supply chains disruptions turn out to be persistent, local industries start to adapt to them, developing particular competencies which can be referred to as intermediate input import substitution and recovering the value-added share lost to shocks. We claim that developing countries could do even better by means of industrial policies aimed at building up high-quality upstream sectors in the face of supply chain disruptions.

We also revisit the Kuznets curve by bringing fresh evidence to the literature that there is positive association between fair income distribution and industrialization. The long-run effects of inequality shocks on industrialization which work out through cost and aggregate demand channels are invariably and significantly negative. While inequality shocks seem to quicken the speed of industrialization via the cost channel, its positive effects are quite small and transitory. However, the aggregate demand channel totally dominates the cost channel throughout the whole process and completely retards the industrialization in developing countries by shrinking the markets for manufactures. This particular result also calls for secondary income distribution policies as an essential ingredient of industrialization efforts.

We also found an unequivocal evidence that better institutions via enhanced regulatory quality provides significant tailwind to the pace of industrialization in line with the literature.

We show that growth shocks have neutral effect on the bid for industrialization in the medium term since they contain contradictory elements. On the one hand, they could expand industrial production by positive impulses such as improved productivity and higher external relative prices. On the other hand, these productivity and net external income gains may not trickle down from high to low income groups due to the lack of social mobility characteristic of developing economies. The resulting rise in inequality could cripple the growth of manufacturing output share.

Another interesting result is the disassociation between institutional framework and backward participation into GVCs. We find that participation into GVC and regulatory quality do not mutually Granger-cause each other, suggesting that the well-established link from better governance to GVCs may be missing in the developing country case. The lack of high-quality institutions could prevent developing countries from building up domestic industries producing technology-intensive intermediate products, making them dependent on imports from upstream producers in GVCs. Hence, backward participation in GVCs could go hand in hand with weak institutional framework, a result theoretically developed in the literature. The one way causal relationship from inequality into backward participation into GVCs also suggest that a worsening income distribution indicative of lower labor costs might encourage the integration of developing countries into GVCs as downstream producers in labor-intensive segments.

**REFERENCES**


- Abrigo, M.R.M., and I. Love 2016. Estimation of panel vector autoregression in Stata. *The Stata Journal* 16(3): 778–804.
- Acemoglu, D., S. Johnson, and J.A. Robinson 2001. The colonial origins of comparative development: An empirical investigation. American Economic Review, 91(5): 1369-1401.
- Acemoglu, D., and J.A. Robinson 2002. The political economy of the Kuznets curve. *Review of Development Economics*. 6: 83–2002.
- Amiti, M. and J. Konings 2007. Trade liberalization, intermediate inputs, and productivity: evidence from Indonesia. *American Economic Review*. 97 (5): 1611-38.
- Anderson, T. W., and C. Hsiao. 1982. Formulation and estimation of dynamic models using panel data. *Journal of Econometrics* 18: 47–82.
- Andrews, D. W. K., and B. Lu. 2001. Consistent model and moment selection procedures for GMM estimation with application to dynamic panel data models. *Journal of Econometrics.* 101: 123–164.
- Baldwin, R. 2013. Trade and industrialization after globalization's second unbundling: How building and joining a supply chain are different and why it matters? NBER Chapters in *Globalization in an Age of Crisis: Multilateral Economic Cooperation in the Twenty-First Century,* pp. 165-212. National Bureau of Economic Research, Inc.
- Baldwin, R. and T. Okubo 2019. GVC journeys: Industrialization and deindustrialization in the age of second unbundling. *Journal of the Japanese and International Economies*. 52: 53-67.
- Bandyopadhyay, S., and R. Sun 2020. Size matters: Measuring the effects of inequality and growth shocks. World Institute for Development Economics Research, Working Paper No. 2020/177. United Nations University.
- Barro, R.J. 2000. Inequality and growth in a panel of countries. *Journal of Economic Growth*. 5: 5–32.
- Baymul, C., and K. Sen 2020. Was Kuznets Right? New evidence on the relationship between structural transformation and inequality. *The Journal of Development Studies*. 56(9): 1643-62.
- Beji S., Belhadj A. 2016, The determinants of industrialization: Empirical evidence for Africa. *European Scientific Journal*. (April): 219-239.
- Beltramello, A., K.D. Backer, and L. Moussiegt 2012. The export performance of countries within global value chains. *OECD Science, Technology and Industry Working Papers,* February 2012. OECD Publishing.
- Blundell, R., and S. Bond. 1998. Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics* 87: 115–143.
- Crino, R. 2012. Imported inputs and skill upgrading. *Labour Economics*. 6: 957-69.

- Dollar, D., Y. Ge, and X. Yu. 2016. Institutions and participation in global value chains. Global Value Chain Development Report Background Paper, World Bank, Washington, DC.
- D. Dollar, and M. Kidder 2017. Institutional quality and participation in global value chains. World Bank (Ed.), *Measuring and analyzing the impact of GVCs on economic development*. The World Bank, Washington, DC.
- Foellmi, R., and J. Zweimuller 2011. “Exclusive goods and formal-sector employment.” *American Economic Journal: Macroeconomics*, Vol. 3 No. 1, pp. 242-272.
- Gereffi, G. 2018. Global value chains and development: Redefining the countours of 21st century capitalism. *Cambridge University Press*. 2018. pp. 343-380.
- Grabowski, R. 2017. Premature deindustrialization and inequality. *International Journal of Social Economics*. 44 (2): 154-168.
- Halter, D., M. Oechslin, and J. Zweimüller 2014. Inequality and growth: The neglected time dimension. *Journal of Economic Growth*. 19: 81–104.
- Holtz-Eakin, D., W. Newey, and H. S. Rosen 1988. Estimating vector autoregressions with panel data. *Econometrica* 56: 1371–1395.
- Jones, C. 2011. Intermediate goods and weak links in the theory of economic development. *American Economic Journal*. 3 (2): 1–28.
- Judson, R. A., and A. L. Owen 1999. Estimating dynamic panel data models: A guide for macroeconomists. *Economics Letters* 65: 9–15.
- Kummritz, V. 2016. Do global value chains cause industrial development? *CTEI Working Papers 01- 2016*. Centre for Trade and Economic Integration, Graduate Institute Geneva.
- Kummritz, V., D. Taglioni, and D. Winkler. Economic upgrading through global value chain participation: Which policies increase the value added gains? *World Bank Policy Research Working Paper 6108*. Washington, DC: The World Bank.
- Kuznets, S. 1955. Economic growth and income inequality. *American Economic Review*. 45: 1-28.
- Martorano B., Sanfilippo M., Haraguchi N. 2017. What factors drive successful industrialization? Evidence and implications for developing countries. Inclusive and Sustainable Industrial Development Working Paper Series WP 7.
- Nickell, S. 1981. Biases in dynamic models with fixed effects. *Econometrica* 49: 1417–1426.
- Nunn, N. 2007. Relationship-Specificity, incomplete contracts, and the pattern of trade. *Quarterly Journal of Economics*. 122 (2): 569–600.
- OECD 2019. *Guide to OECD’s Trade in Value Added (TiVA) Indicators, 2018 edition*. Organization for Economic Cooperation and Development (OECD), Directorate for Science, Technology and Innovation, December 2019.
- Peneder, M. and G. Streicher 2018. De-industrialization and comparative advantage in the global value chain. *Economic Systems Research*. 30(1): 85-104.
- Ravindran, R., and S.M. Babu 2021. Premature deindustrialization and income inequality in middle-income countries. World Institute for Development Economics Research, Working Paper No. 2021/8, United Nations University.
- Rodrik, D. 2008. The Real exchange rate and economic growth. *Brookings Papers on Economic Activity*, Economic Studies Program, The Brookings Institution, 39(2): 365-439.
- Rodrik, D. 2015. Premature deindustrialization. *Journal of Economic Growth*, 21: 1-33.

- Rodrik, D. 2018. New technologies, global value chains, and the developing economies. *CESifo* Working Paper No. 7307.
- Roodman, D. 2009. How to do xtabond2: An introduction to difference and system GMM in Stata. *Stata Journal* 9: 86–136.
- Staritz, C., G. Gereffi, and O. Cattaneo, eds. 2011. *International Journal of Technological Learning, Innovation and Development* 4 (1-3). Special Issue on "Shifting End Markets and Upgrading Prospects in Global Value Chains."
- Sarma, V., S. Paul, and G. Wan 2017. Structural transformation, growth, and inequality: Evidence from Vietnam. ADBI Working Paper No. 681. Tokyo: Asian Development Bank Institute (ADBI).
- Sims, C. A. 1980. Macroeconomics and reality. *Econometrica* 48: 1–48.
- Sumner, A. 2019. Deindustrialization, tertiarization and development in a "GVC-world": What do new trajectories of structural transformation mean for developing countries? *Economic and Social Research Council Global Poverty and Inequality Dynamics Research Network* Working Paper No. 16.
- Sumner, A. 2017. *The developer's dilemma: The inequality dynamics of structural transformation and inclusive growth*. Working Paper No. 1. Global Poverty and Inequality Dynamics Research Network.
- Taglioni, D. and D. Winkler 2016. Making Global Value Chains Work for Development, Washington, DC: The World Bank.
- Timmer, M., A.A. Erumban, B. Los, R. Stehrer, and G. de Vries 2014. Slicing up global value chains. *Journal of Economic Perspectives.* 28(2): 99-118.
- Topalova, P., and A. Khandelwal 2011. Trade liberalization and firm productivity: The case of India. *The Review of Economics and Statistics*. 93(3): 995-1009.
- Totouom, A., H. F. Kaffo, and F. Sundjo 2019. Structural transformation of sub–Saharan Africa: Does the quality of institutions matter in its industrialization process? *Région et Développement*. 50:119-136.
- UNCTAD, 2016. Trade and Development Report, 2016: Structural Transformation for Inclusive and Sustained Growth. *United Nations* publication. Sales No. E.16.II.D.5. New York and Geneva.
- Wang, Z., S.-J. Wei, X. Yu, and K. Zhu 2016. Characterizing global value chains. Working Paper No. 578, Stanford Center for International Development, Stanford, CA.


## Appendix 1

Panel VAR GMM estimation

| | Coef. | Z |
|---|---|---|
| g_outshare | | |
| g_outshare (t-1) | -0.51495 | -24.59*** |
| g_gini (t-1) | -1.60587 | -24.03*** |
| g_rqe (t-1) | 0.003239 | 6.24*** |
| g_exgr_dvashm (t-1) | 0.127298 | 5.42*** |
| g_pcincc (t-1) | 0.000792 | 20.02*** |
| g_gini | | |
| g_outshare (t-1) | 0.143858 | 15.55*** |
| g_gini (t-1) | -0.03904 | -1.61 |
| g_rqe (t-1) | 0.000308 | 0.99 |
| g_exgr_dvashm (t-1) | -0.00058 | -0.06 |

| | | |
|---|---|---|
| g_pcincc (t-1) | 0.000243 | 15.9*** |
| g_rqe | | |
| g_outshare (t-1) | 1.848036 | 6.49*** |
| g_gini (t-1) | -3.41643 | -3.83*** |
| g_rqe (t-1) | 0.05306 | 2.23** |
| g_exgr_dvashm (t-1) | -0.2027 | -0.55 |
| g_pcincc (t-1) | -0.00104 | -2.93*** |
| g_exgr_dvashm | | |
| g_outshare (t-1) | -0.39192 | -18.71*** |
| g_gini (t-1) | 1.019447 | 14.76*** |
| g_rqe (t-1) | -0.00025 | -0.45 |
| g_exgr_dvashm (t-1) | -0.14534 | -3.74*** |
| g_pcincc (t-1) | 0.00014 | 3.9*** |
| g_pcincc | | |
| g_outshare (t-1) | 81.04983 | 10.5*** |
| g_gini (t-1) | -258.379 | -14.27*** |
| g_rqe (t-1) | 0.395225 | 2.42** |
| g_exgr_dvashm (t-1) | 202.0731 | 13.21*** |
| g_pcincc (t-1) | -0.0419 | -5.11*** |
| Number of observations | 378 | |
| Number of panels | 18 | |
| Hansen's J chi square (200) | 200.72 | p-value = 0.472 |
| Instruments | 1 (2/10). (g_outshare g_gini g_rqe g_exgr_dvashm g_pcincc) | |

Notes: Asteriks indicate that robust t-statistics are significant at the *10%, **5%, and ***1% level.

**Appendix 2**

**Levin-Lin-Chu unit-root test**

| Series | Lag | Trend | Constant | Adjusted t* |
|---|---|---|---|---|
| g_exgr_dvashm | 9 | No | No | -14.6062*** |
| g_outshare | 9 | No | No | -11.4589*** |
| g_gini | 9 | No | No | -3.0633*** |
| g_rqe | 9 | No | No | -13.8046*** |
| g_pcincc | 9 | No | no | -12.0222*** |

**Hadri LM test**

| Series | Lag | Trend | Constant | Z |
|---|---|---|---|---|
| g_exgr_dvashm | 3 | No | No | -0.4940 |
| g_outshare | 3 | Yes | No | 6.3150*** |
| g_gini | 3 | Yes | No | 5.8829*** |
| g_rqe | 3 | No | No | 0.2026 |
| g_pcincc | 3 | Yes | No | 1.3285 |