Do Capital Flows Cause (De)Industrialization?

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ABSTRACT

The conventional theory maintains that movement of capital from rich economies with lower rate of return to poor economies with higher rate of return provides efficient capital allocation, lowers the cost of capital and increases production. The recent literature, however, does not provide an empirical support to benefits of financial openness. In this context, this study aims to investigate the effect of capital flows on manufacturing industry which disaggregated as low- and high-technology. Our estimation results suggest that the impact of capital flows is to lower manufacturing in advanced (AE), emerging market and developing (EMDE) and Middle East and North Africa (MENA) economies. As consistent with the sectoral reallocation argument, this implies that capital flows lead to movement of resources out of the manufacturing sector. This effect appears to be the case for high-technology manufacturing industry in AE and EMDE whilst it seems to be hold for low-technology manufacturing industry in MENA. On the other hand, capital flows encourage low-tech manufacturing industries in all country groupings, except MENA. This empirical finding indicates that capital flows also lead to the allocation of resources within the manufacturing industry from high-tech to low-tech. All these imply that industrialization policy should include measures related with financial openness and policy makers should consider the use of capital flow management measures to protect the manufacturing industry from the side effects of capital flows.

Keywords: Capital Flows, Manufacturing, Industrialization, Sectoral Allocation, Allocation Puzzle

JEL Classification: F30, F32, F41, F62, F63, L60, O14

1. Introduction

Kaldor (1966) maintains that manufacturing industry is the engine of growth. Manufacturing industry has some unique characteristics that differentiated from the other sectors. These are briefly explained by Kaldor (1966), Szirmai (2012), and Rodrik (2013). Accordingly, manufacturing is a tradable and technologically dynamic sector, absorbs surplus labor, has higher productivity and provides positive externality to the other sectors. The recent literature in development economics investigates the causes of the declining trend in manufacturing, i.e., de-industrialization. Rodrik (2016) maintains that globalization -measured as trade and financial globalization- is amongst the factors that lead to deindustrialization. The literature often maintains that financial globalization i.e., openness to financial flows leads the allocation of sectors from tradable manufacturing to non-tradable sectors (Corden, 1994; Benigno et al., 2015; Kalantzis, 2015; Teimouri and Zietz, 2018). This study aims to investigate the impact of capital flows on manufacturing industry.

The conventional theory often maintains that capital moves[1] from rich economies with lower rate of return to poor economies with higher rate of return. The movement of capital provides efficient capital allocation, lowers the cost of capital, and increases production. Corden (1994) remarks that capital inflows cause higher domestic demand for tradable and non-tradable goods. The supply of non-tradable goods increases to eliminate the excess demand. This leads to an increase in the price of non-tradable goods and the real exchange rate appreciation. This is defined as financial Dutch disease by Palma (2005). Lartey (2008) finds that the Dutch disease effect is the case in fixed exchange rate regime prevailing economies. Benigno et al. (2020) remark that capital inflows from developing economies to US leads to global financial resource curse by increasing the demand for non-tradable goods, allocating resources to non-tradable sectors, mitigating innovative investment in tradable sector, and lowering global productivity growth.

International capital inflows often lead to synchronization of boom-and-bust business cycle episodes that may end up with financial crisis (Kalantzis, 2015). The boom episode causes domestic credit expansion. The bust episode, on the other hand, begins following the sudden stops and banking crisis. The literature often studies the drivers and consequences of

[1] However, Lucas (1990) maintains that capital does not flow from rich to poor countries. Gourinchas and Jeanne (2013) shows that capital flows to countries with less productivity growth.

international capital inflows. Recently, some studies have begun to examine the impacts of financial flows on manufacturing industry.

Gelos and Werner (2002) find that capital account openness alleviates the financial constraints for small Mexican manufacturing firms. Nonindustrial economies which attract less foreign capital inflows tend to have higher growth as indicated by Prasad et al. (2007). Rodrik (2006) notes that industrial policy aims to targeted new exportable products and maintain an exchange rate policy that encourages the production of tradable goods. Guzman et al. (2018) suggest that regulation of capital flows provides stable and competitive real exchange rate that is associated with long-run growth. Rajan and Subramanian (2011) find that aid inflows lead to real exchange rate appreciation that lowers the growth of manufacturing. Demir (2009) reports that capital flow volatility mitigates the profitability of Turkish manufacturing firms. The firm level evidence by Li and Su (2022) indicates that capital account openness increases total factor productivity, and this effect is much higher in sectors with external finance dependent. According to Aizenman and Sushko (2011), FDI inflows accelerate manufacturing growth especially in external finance dependent industries. Saffie et al. (2020) find that financial liberalization tends to increase the employment, value added and number of firms in Hungarian services sector.

Haraguchi et al. (2019) finds that openness to international financial flows encourages industrialization in the pre-1990 period whilst discourages industrialization in the post-1990 period. Their findings suggest that the differential effect of financial flows on industrialization is related with the volatility of capital flows which is more apparent in the post-1990 period. Asamoah et al. (2021) report that portfolio equity inflows accelerate but portfolio debt inflows decelerate manufacturing growth in Africa. The firm level evidence by Pan and Wu (2022) suggests that capital inflows mitigate financing costs of state-owned firms in China and foreign firms in Malaysia. Igan et al. (2020) investigate the relationship between industry growth and capital inflows by conditioning this to the external finance dependency degree of the industries. They find that external finance dependent industries tend to experience higher growth and this relation is driven by debt flows and this relation appears to be the case before the global financial crisis.

Benigno et al. (2015) employs an event study analysis and finds that capital inflows surges lead to the movement of production factors including capital and labor out of the manufacturing industry. Kalantzis (2015) studies the impact of capital inflows on sectors by constructing a small open economy. Accordingly, capital inflows lead to the movement of resources out of the manufacturing industry and a boom in domestic credits. Their overall effect tends to increase the incidence of crisis. Teimouri and Zietz (2018) employ local projection method to investigate the effect of surges on investment, unemployment, manufacturing output and employment. Their results suggest that surges accelerate de-industrialization especially in middle income Asia and Latin America countries than high income economies.

This paper aims to investigate the effect of capital inflows (measured as the sum of current account deficit and the change in reserves, as a percent of GDP) on manufacturing industry for a sample of advanced (AE) and emerging market and developing (EMDE) economies including Middle East and North Africa (MENA) economies over the 1986-2020 period. By considering the heterogeneity in technology intensity levels, we disaggregate the manufacturing as high and low technology industries based on the R&D intensities. To examine the sensitivity of manufacturing to capital inflows, we consider real income per capita, financial development, trade openness and *de facto* exchange rate regime as the important variables that effect manufacturing industry.

The literature often employs conventional panel data estimation procedures and ignores the unobserved common factors that may lead to cross-sectional dependence. The ignorance of this important issue may cause the inconsistent parameter estimates if the unobserved common factors are correlated with explanatory variables (Pesaran, 2006). Therefore, we employ common correlated effects mean group (CCE-MG) estimation procedure by Pesaran (2006). This estimation method considers the cross-sectional dependence and provides consistent parameter estimates. We also employ cross-sectionally augmented panel autoregressive distributed lag (CS-ARDL) estimation procedure to investigate the short-run and long-run effects of capital flows on manufacturing industry. To examine the dynamic response of manufacturing to capital flows, we employ local projection method by Jorda (2005).

Our empirical results suggest that capital flows tend to lower manufacturing industry in all country groupings. This is consistent with the sectoral allocation argument suggesting capital flows lead to the movement of resources out of the manufacturing. We find that this seems to be the case for high-tech manufacturing industries in AE and EMDE whilst this appears to be the case for low-tech manufacturing industry in MENA. This result also suggests that capital flows lead to the movement of resources within the manufacturing industry from high-tech to low-tech industries.

The rest of this paper is organized as follows. Section 2 introduces our data and reports some descriptive statistics. The estimation methodology is explained and estimation results are presented in Section 3. Section 3.1, 3.2 and 3.3, respectively, report CCE-MG, CS-ARDL and local projection method results. We evaluate and synthesize our main findings through concluding remarks in Section 4.

2. The Data

This study investigates the effect of capital flows on manufacturing for 22 advanced[2] (AE) and 56 emerging market and developing[3] (EMDE) including 10 Middle East and North Africa[4] (MENA) economies during the 1986-2020 period. Our sample is mainly restricted by data availability.

Table 1: Definition and data sources

HTech_MVA	Manufacturing value added in high and medium high technology sectors	United Nations Industrial Development Organization (UNIDO, INDSTAT 2, ISIC Rev.3)
LTech_MVA	Manufacturing value added in medium low and low technology sectors	
MVA	Natural logarithm of manufacturing value added (in constant prices)	United Nations Conference of Trade and Development (UNCTAD)
GDPpc	Natural logarithm of real income per capita	UNCTAD
FD	Financial development index	Financial development index database, IMF
Capital_Flows	The sum of current account deficit and change in reserves (as a percent of GDP)	International Financial Statistics, IMF
ERR	*De facto* coarse ERR classification	Ilzetzki et al. (2021)
TRADE	Sum of exports and imports (as a percent of GDP)	World Development Indicators, World Bank

Table 1 reports the definition and data sources for the variables. Our real manufacturing data are from UNCTAD. UNIDO, INDSTAT 2 database provides manufacturing data at the sectoral level. The sectoral manufacturing data enable us to classify the manufacturing industry

[2] AE are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, United Kingdom and United States.
[3] EMDE are Albania, Algeria, Argentina, Azerbaijan, Bahrain, Bangladesh, Belarus, Bolivia, Brazil, Bulgaria, Chile, China, Colombia, Costa Rica, Croatia, Czechia, Ecuador, Egypt, Estonia, Fiji, Georgia, Ghana, Hungary, India, Indonesia, Israel, Jordan, Kenya, Kyrgyz R., Latvia, Lithuania, Malaysia, Mexico, Moldova, Morocco, Nicaragua, Niger, North Macedonia, Oman, Paraguay, Peru, Philippines, Poland, Romania, Saudi Arabia, Senegal, Slovak R., Slovenia, South Africa, S. Korea, Sri Lanka, Tanzania, Thailand, Tunisia, Turkey and Uruguay.
[4] MENA are Algeria, Bahrain, Egypt, Israel, Jordan, Morocco, Oman, Saudi Arabia, Tunisia and Turkey.

based on the technology intensity levels as suggested by OECD (2011). Accordingly, we calculate the shares of high-technology[5] (sum of high-technology and medium-high-technology industries) and low-technology[6] (sum of medium-low and low-technology industries) manufacturing industries (as a percent of total manufacturing). Then, we multiply these shares with the real manufacturing data to obtain the real manufacturing value added in high and low technology industries. The data for real income per capita are from UNCTAD. IMF provides financial development index (FD) data based on the liquidity and efficiency of financial markets and institutions prepared by Svirydzenka (2016). The FD data are between 0 and 1, the proximity to 1 represents better financial development. Capital flows are proxied by the sum of current account deficit and the change in reserves (as a percent of GDP). Benigno et al. (2015) notes that this measure matters in explaining the allocation of resources among the sectors. The data for capital flows are obtained from IMF. We consider the *de facto* coarse exchange rate regime (ERR) classification provided by Ilzetzki et al. (2021). The ERR data lies between 1 and 6, with higher values representing more flexible ERR arrangements. Ilzetzki et al. (2021) notes that ERR5 and ERR6 represent the economies with severe macroeconomic instability and high inflation. Therefore, we restrict our sample of observations to include ERR classification up to ERR4. Our trade openness data are from World Development Indicators, World Bank.

Figure 1 shows the evolution of mean MVA, HTech_MVA and LTech_MVA in whole sample, AE, EMDE and MENA during the 1986-2020 period. The mean MVA tends to increase slightly in all country groupings. In the whole sample, the mean LTech_MVA is almost the same over the years, although the mean HTech_MVA tends to increase slightly especially during recent years. In AE, the mean of LTech_MVA tends to mitigate whilst the mean of HTech_MVA appears to increase over the years. In EMDE and MENA, the mean LTech_MVA is almost stable whilst the mean HTech-MVA tends to increase slightly.

[5] High-technology manufacturing industry consists of chemicals and chemical products; machinery and equipment; office, accounting and computing machinery; electrical machinery and apparatus; radio, television and communication equipment; medical, precision and optical instruments; motor vehicles, trailers and semi-trailers; other transport equipment.

[6] Low-technology manufacturing industries consist of the sum of food and beverages; tobacco products; textiles; wearing, apparel, furniture; leather, leather products and footwear; wood products; paper and paper products; printing and publishing; coke, refined petroleum products and nuclear fuel; rubber and plastic products; non-metallic mineral products; basic metals; fabricated metal products and recycling manufacturing industries.

Figure 1: Manufacturing Industry

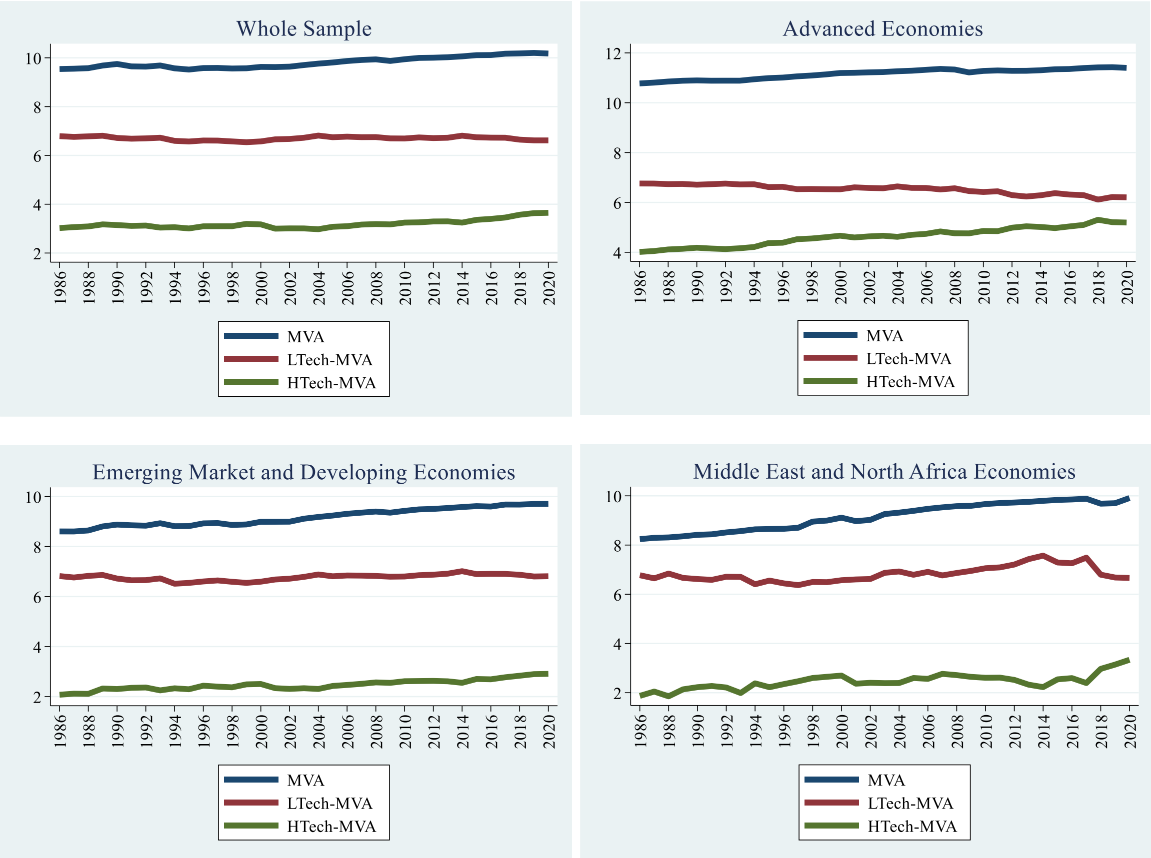


Figure 2 represents the evolution of mean capital flows over the 1986-2020 period. In the whole sample, capital flows tend to increase till global financial crisis (GFC). Then, it returns to the level before the GFC. In AE, capital flows are almost stable with around zero mean up to GFC. The crisis has led to sharp decrease in capital flows. Following the taper tantrum in 2013, there is a sharp increase in our capital flows measure due to the changes in reserves. Capital flows tend to return the pre-crisis level in the rest of the period. In EMDE, capital flows tend to increase up to 2000 and then they decrease slightly. There is a slight increase in capital flows during the 2002-2008 period whilst capital flows return to the pre-crisis level during the rest of the period. The volatility of capital flows appears to be much higher in the sample of MENA. In the beginning of the 1990s, capital flows appear to increase in MENA. This may be interpreted with an extreme caution. The increase in capital flows is most probably due to the decline in GDP caused by Gulf war. Except the beginning of the 1990s, the mean capital flows are almost stable with around 2 percent until the end of the 1990s, they decrease up to the half of the 2000s and they slightly increase and remain relatively stable during the rest of the period.

Figure 2: Evolution of Capital Flows

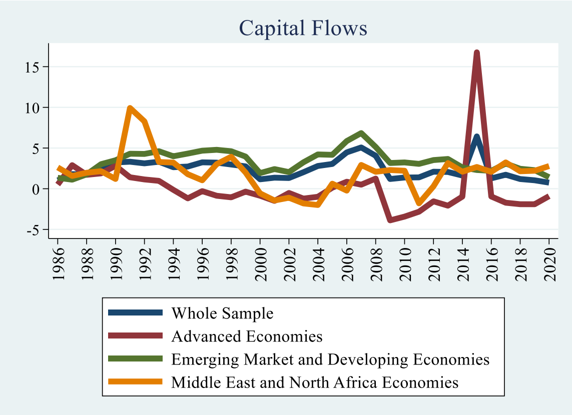


Table 2 reports the main descriptive statistics for our variables of interest. The mean of manufacturing (MVA, measured as natural logarithm of manufacturing in constant prices) is around 9.8 for the whole sample, 11.2 for AE, 9.2 for EMDE and MENA. As compared to AE, the mean of MVA is much lower both in EMDE and MENA. The mean of high-technology manufacturing industry (HTech_MVA) is around 3.2 for the whole sample. Among all country groupings, the mean of HTech_MVA is much higher and less volatile in AE. On the other hand, the low-technology manufacturing industry (LTech_MVA) has almost the same mean and volatility in all country groupings. The mean real income per capita is almost 9.05 for whole sample, 10.48 for AE, 8.40 for EMDE and 8.86 for MENA. In AE, the mean of real income is much higher and the volatility is considerably lower than EMDE and MENA. The mean of financial development (FD) is 0.39 for whole sample, 0.65 for AE, 0.28 for EMDE and 0.33 for MENA. In comparison to the whole country groupings, the mean of FD is substantially higher and less volatile in AE. The average of net capital flows (Capital_Flows) is around 2.4 for the whole sample, -0.02 for AE, 3.5 for EMDE and 1.9 for MENA. The mean of Capital_Flows is much higher in EMDE, whilst the volatility is substantially much higher in AE. For all country groupings, the mean of trade openness (TRADE) is almost around 80 (as a percent of GDP), albeit the volatility of TRADE is much higher in AE.

Table 2: Descriptive Statistics							
	MVA	HTech_MVA	LTech_MVA	Real GDP per capita	FD	Capital_Flows (% of GDP)	TRADE (% of GDP)
	Whole Sample						
Mean	9.82	3.20	6.70	9.05	0.39	2.43	79.21
St. Dev.	1.95	2.05	1.22	1.31	0.23	10.89	49.72
CoV	0.20	0.64	0.18	0.14	0.60	4.49	0.63
NT	2475	2357	2357	2475	2538	2362	2465
	Advanced Economies						
Mean	11.16	4.63	6.52	10.48	0.65	-0.02	83.33
St. Dev.	1.53	1.96	1.37	0.35	0.16	16.86	68.62
CoV	0.14	0.42	0.21	0.03	0.24	-936.9	0.82
NT	770	770	770	770	770	699	770
	Emerging Market and Developing Economies						
Mean	9.22	2.51	6.78	8.40	0.28	3.45	77.34
St. Dev.	1.82	1.71	1.13	1.04	0.17	6.74	38.04
CoV	0.20	0.68	0.17	0.12	0.59	1.95	0.49
NT	1705	1587	1587	1705	1768	1663	1695
	Middle East and North Africa Economies						
Mean	9.18	2.47	6.85	8.86	0.33	1.86	82.88
St. Dev.	1.28	1.41	0.97	0.99	0.13	7.11	35.05
CoV	0.14	0.57	0.14	0.11	0.40	3.81	0.42
NT	333	296	296	333	333	310	323
Note: St. Dev., CoV and NT represent, respectively, standard deviation, coefficient of variation (standard deviation over the mean) and number of observations.							

3. Empirical Methodology

To study the effect of capital flows on manufacturing industry, we consider the following benchmark equation:

$$MVA_{it} = \alpha_i + \alpha_1 Capital\_Flows_{it} + \alpha_2 GDPpc_{it} + \alpha_3 FD_{it} + \alpha_4 ERR_{it} + \alpha_5 TRADE_{it} + u_{it} \quad (1)$$

In eq. (1), i and t represent, respectively, country and years, MVA is natural logarithm of real manufacturing value added, Capital_Flows is net capital flows proxied with the sum of current account deficit (as a percent of GDP) and the change in official reserves (as a percent of GDP), GDPpc is natural logarithm of real GDP per capita, FD is financial development index, ERR is the *de facto* coarse exchange rate regime classification by Ilzetzki et al. (2021) and TRADE is trade openness measured as the sum of exports and imports (as a percent of GDP).

To examine the relationship between manufacturing and capital flows, we control the impacts of income per capita, financial development, *de facto* exchange rate regime and trade openness as suggested by literature. To capture the cross-country differences in development process, we include the level of real income per capita (Haraguchi et al., 2019). The importance of financial development for investment and growth has been emphasized by Schumpeter (1911). Levine (1997) notes that financial development provides the allocation of liquid unproductive funds to productive investment projects for resource constrained firms. The results by Szirmai (2012) and Colacchio and Davanzati (2017) suggest that financial development plays a key leading role in investment and growth. Also, we consider the impact of prevailing exchange rate regime which is important to explain the evolution of manufacturing. Rogoff et al. (2004) maintains that credible managed ERRs import monetary policy credibility of the anchor currency country, mitigates both inflation and transaction costs and enable exchange rate guarantee. On the other hand, flexible ERRs provide the independency in macroeconomic policies that led the countries to accommodate external shocks (Edwards, 2011). Rodrik (2006) remarks that exchange rate policy that promotes the development of tradable manufacturing industry is one of the most important targets for industrial policy. Martorano and Sanfilippo (2015) notes that both stable and competitive exchange rates foster the development of tradable manufacturing industry. Trade openness is also amongst the important drivers of manufacturing industry because it leads to higher productivity (Dowrick and Golley, 2004), provides both specialization (Chandran and Munusamy, 2009) and efficient allocation of resources (Baldwin and Lopez-Gonzalez, 2015).

The literature has shortcomings of the conventional estimation procedure to investigate the effect of capital flows on manufacturing industry. For instance, the literature often ignores the unobservable dependence among the cross-sections that led to autocorrelation and biased parameter estimates. Also, the literature often ignores the cross-section dependence in explaining the short and long run effects of capital flows on manufacturing industry. This study aims to provide an empirical contribution to the literature by considering the cross-sectional dependence and employing common correlated effects mean group (Pesaran, 2006), cross-sectional dependence autoregressive distributed lag estimation procedures (Chudik and Pesaran, 2015) and local projection method (Jorda, 2005) to examine the dynamic response of capital flows to manufacturing.

3.1 Common Correlated Effects Mean Group Estimation Procedure and Results

The reparametrized version of benchmark eq. (1) can be represented as follows:

$$MVA_{it} = \alpha_i + \beta_i' x_{it} + u_{it}$$

$$\text{where } u_{it} = \gamma_i' f_t + e_{it} \quad (2)$$

In (2), f_t is an observed common factor, γ_i is a heterogenous factor loading and α_i is country-specific fixed effects. Here, e_{it} is the error term that satisfies the independent and identical distribution (IID) assumption. The random distribution with a common mean for the heterogenous parameters can be represented as $\beta_i = \beta + v_i$, where v_i~IID $(0, \Omega_v)$. Pesaran (2006) suggests that unobserved common factors can be proxied with the cross-sectional averages and introduces the common correlated effects (CCE) estimation procedure. Chudik and Pesaran (2013) and Chudik et al. (2011) remark that CCE method is better than two-way fixed effects because the former considers the prevailing differences among the countries, global and country-specific shocks that irrespective of stationary properties and their homogenous or heterogenous effects on countries. Chudik and Pesaran (2015) shows that CCE estimation procedure provides consistent parameter estimates only in non-dynamic panels. The incorporation of cross-sectional averages also prevents the endogeneity bias as suggested by Fuleky et al. (2017). Juodis (2022) notes that CCE method is applicable in nonlinear and nonstationary models. Coakley et al. (2001) finds that mean group estimators are more robust than pooled estimators. Therefore, we prefer to employ common correlated effects mean group (CCE-MG) estimation procedure.

The initial step of CCE estimation method is to test the cross-sectional dependence. Pesaran (2015) introduces the test that maintains the weak cross-sectional dependence under the null hypothesis. Table 3 reports the cross-sectional dependence (CD-Test) results for the variables. Accordingly, all variables have weak cross-sectional dependence.

Table 3: Cross-Sectional Dependence Test

	MVA	HTech_MVA	LTech_MVA	GDPpc	FD	Capital_Flows	TRADE
CD-Test	0.815 [0.42]	0.094 [0.93]	0.96 [0.34]	-1.69 [0.09]	-1.78 [0.08]	1.329 [0.18]	-1.984 [0.05]

Notes: The value in square brackets are the p-values.

Then, we investigate whether our variables of interest contain unit root or not. We employ Im, Pesaran and Shin (2003) test that maintains the existence of unit root under the null hypothesis. Table 4 reports the results. Accordingly, MVA, GDPpc, FD and TRADE are nonstationary in levels, whilst they stationary in first differences. The rest of all variables are stationary in levels.

Table 4: Im, Pesaran, Shin Unit Root Test Results		
	Level	1^{st} Difference
MVA	-0.76 [0.22]	-29.21 [0.00]
HTech_MVA	-5.70 [0.00]	-41.56 [0.00]
LTech_MVA	-2.85 [0.00]	-42.24 [0.00]
GDPpc	-0.08 [0.47]	-17.12 [0.00]
FD	-1.53 [0.06]	-40.03 [0.00]
Capital_Flows	-12.37 [0.00]	-49.65 [0.00]
ERR	-2.22 [0.01]	-13.87 [0.00]
TRADE	-0.28 [0.39]	-33.55 [0.00]
Notes: The values in square brackets are p-values. Im, Pesaran and Shin (2003) panel unit root test maintains the unit root null hypothesis. The unit root test equations include a constant term. The lag lengths are chosen based on the AIC.		

Considering the panel unit root test results, our estimated model with stationary variables is as follows:

$$\Delta MVA_{it} = \alpha_i + \alpha_1 Capital\_Flows_{i,t-1} + \alpha_2 \Delta GDPpc_{it} + \alpha_3 \Delta FD_{it} + \alpha_4 ERR_{it} + \alpha_5 \Delta TRADE_{it} + u_{it} \quad (3)$$

Given the fact that the impact of capital flows on manufacturing industry may take some time[7], we prefer to use lagged capital flows. Table 5 provides the CCE-MG estimation results. In all the estimated equations, Pesaran CD-test rejects the null of weak cross-sectional dependence. Also, all the estimated equations pass the autocorrelation test. The estimated coefficient for income per capita is positive and statistically significant, albeit it is much lower in MENA. This empirical result suggests that an increase in income per capita leads to higher manufacturing industry. There is a negative and statistically significant relationship between capital flows[8] and manufacturing industry. The estimated parameter for capital flows is much higher in MENA while it is much lower in AE. In contrast to the conventional theory maintaining openness to international financial flows is beneficial, our findings suggest that financial openness leads to lower manufacturing industry (i.e., de-industrialization) which is the engine of growth. Consistent with the Dutch disease argument by Palma (2005), our result may suggest that capital flows lead to the allocation of resources from tradable manufacturing

[7] Thanks to referee for pointing this crucially important point.

[8] In the appendix, Table A1 reports the CCE-MG estimation results for the whole sample. In the first column, we consider net capital flows (sum of portfolio, foreign direct investment (FDI) and other investment flows, as a percent of GDP). We find that there is a negative association between net capital flows and manufacturing. The literature often maintains that FDI is more beneficial than the other types of flows. Therefore, we decompose aggregate net capital flows as FDI and non-FDI flows to understand which component of capital flows drive the estimation results. Accordingly, the relationship between manufacturing and FDI is insignificant whilst there is a negatively significant association between manufacturing and non-FDI flows. Therefore, we can say that the negative impact of capital flows on manufacturing comes from non-FDI flows.

to non-tradable sectors. The impact of financial development on manufacturing is negatively significant in the whole sample and advanced economies, albeit it is insignificant in EMDE and MENA. According to the descriptive statistics reported in Table 2, financial development is substantially much higher in AE than EMDE and MENA. As consistent with this fact, we may maintain that further increases in financial development boosts the services sector. On the flip side, this may also cause de-industrialization. The effect of ERR on manufacturing is positive and statistically significant except the sample of AE. This suggests that ERR flexibility tends to increase manufacturing industry. As consistent with the remarks by Edwards (2011), our findings indicate that flexible ERR led the countries to accommodate external shocks and thus encourages manufacturing. There is a positive and significant association between trade openness and manufacturing. Accordingly, trade openness increases productivity, provides specialization and efficient resource allocation and their overall effect is to encourage industrialization.

Table 5: CCE-MG Estimation Results

	Whole Sample	AE	EMDE	MENA
$\Delta GDPpc_{it}$	1.261*** (0.094)	1.713*** (0.178)	1.136*** (0.113)	0.833** (0.336)
$Capital\_Flows_{i,t-1}$	-0.141** (0.057)	-0.068* (0.048)	-0.118* (0.067)	-0.274* (0.150)
ΔFD_{it}	-0.137* (0.094)	-0.099* (0.060)	-0.072 (0.176)	-0.278 (0.449)
ERR_{it}	0.018* (0.012)	0.145 (0.145)	0.027* (0.016)	0.069* (0.045)
$\Delta TRADE_{it}$	0.199*** (0.035)	0.310*** (0.063)	0.133*** (0.039)	0.188* (0.124)
Constant	-0.001 (0.008)	-0.003 (0.028)	-0.004 (0.014)	-0.020 (0.029)
N	78	22	56	10
NT	2072	633	1439	275
F-test [p-value]	0.00	0.00	0.00	0.00
R^2	0.37	0.20	0.41	0.43
Root MSE	0.04	0.02	0.05	0.05
CD-test[p-value]	0.00	0.00	0.00	0.00
AC-test[p-value]	0.15	0.88	0.21	0.07

Notes: *** <1%, ** <%5, * <%10. N and NT represent, respectively, the number of countries and observations. The values in parentheses are the robust standard errors. AC-test maintains the null hypothesis of there is no first order autocorrelation.

The aggregate manufacturing industry contains heterogeneity in terms of technology levels of the sectors. Considering this important issue, we estimate eq. (3) for high and low technology manufacturing industries. The estimation results are reported in Table 6. CD-test results strongly reject the null of weak cross-sectional dependence. Also, our estimated equations pass the serial autocorrelation test.

Table 6: CCE-MG Estimation Results

	High-Technology MVA				Low-Technology MVA			
	Whole Sample	AE	EMDE	MENA	Whole Sample	AE	EMDE	MENA
$\Delta GDPpc_{it}$	-0.231 (0.571)	-0.313 (1.461)	-0.175 (0.602)	-0.183 (1.469)	1.232** (0.609)	0.864 (1.413)	0.953* (0.604)	0.193 (1.335)
$Capital\_Flows_{i,t-1}$	-0.815** (0.408)	-1.251* (0.790)	-0.540* (0.300)	0.049 (0.884)	1.385** (0.601)	1.954* (1.256)	0.767* (0.519)	-1.915* (1.346)
ΔFD_{it}	0.274 (1.022)	-0.903 (1.400)	0.513 (1.399)	-2.129*** (0.755)	0.630 (1.155)	0.268 (0.671)	-0.401 (1.099)	-3.861 (4.068)
ERR_{it}	1.436* (1.018)	4.897* (3.383)	0.316* (0.210)	0.615* (0.451)	1.486*** (0.435)	0.125 (1.337)	1.125*** (0.318)	2.936*** (0.765)
$\Delta TRADE_{it}$	0.104* (0.071)	0.466* (0.324)	0.447** (0.227)	0.667* (0.418)	0.346 (0.286)	0.786* (0.505)	0.026 (0.383)	0.375 (1.161)
Constant	0.016 (0.138)	0.043 (0.169)	-0.058 (0.115)	0.615 (0.952)	0.084 (0.185)	0.008 (0.245)	0.116 (0.154)	-0.101 (0.373)
N	77	22	55	10	77	22	55	10
NT	1977	633	1346	250	1977	633	1346	250
F-test [p-value]	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
R^2	0.51	0.51	0.64	0.48	0.36	0.30	0.43	0.39
Root MSE	0.32	0.30	0.30	0.46	0.38	0.29	0.35	0.52
CD-test[p-value]	0.07	0.54	0.08	0.31	0.12	0.05	0.07	0.03
AC-test[p-value]	0.42	0.17	0.77	0.79	0.39	0.20	0.74	0.79

Notes: *** <1%, ** <%5, * <%10. N and NT represent, respectively, the number of countries and observations. The values in parentheses are the robust standard errors. AC-test maintains the null hypothesis of there is no first order autocorrelation.

According to the results in Table 6, capital flows tend to lower high-tech manufacturing industries. However, capital flows appear to increase low-tech manufacturing industries[9], except the sample of MENA. This may suggest our results in Table 5 reporting that there is a negative relationship between capital flows and manufacturing is due to high-tech manufacturing industry in AE and EMDE whilst this relationship is due to low-tech manufacturing industry in MENA. In addition to capital flows cause movement of resources out of the manufacturing, our findings also indicate that capital flows lead to the movement of resources within the manufacturing industry from high-tech to low-tech. This empirical finding may also be interpreted as the conventional benefits of financial openness appear to be hold in low-tech manufacturing sectors whilst the Dutch disease argument as suggested by the empirical literature appears to be valid in high-tech manufacturing sectors. Our findings showing the positive association between capital flows and low-tech manufacturing industry is consistent with the recent literature indicating that capital flows to firms with lower productivity (Gopinath et al., 2017). On the other hand, our findings suggesting a negative relationship between capital flows and high-tech manufacturing industry is consistent with the fact that high-tech manufacturing industry requires long investment cycles (Yu and Quayyum, 2021). Therefore, investment decisions in high-tech manufacturing industry may be delayed until accumulating sufficient level of reserves (Gopinath et al., 2017).

Our results in Table 6 also indicate that there is a positive and significant relationship between income per capita and low-tech manufacturing industry. Accordingly, an increase in income per capita increases low-tech manufacturing industry in EMDE and whole sample. Financial development lowers high-tech manufacturing industry in MENA. Flexible ERR appears to be one of the most important drivers of both high-tech and low-tech manufacturing industries. Trade openness encourages high-technology manufacturing industry. This may also be the case in low-tech manufacturing industries in AE.

[9] In the appendix, Table A2 reports the CCE-MG estimation results for the whole sample. We divide our observations into pre-GFC (1986-2007 period) and post-GFC (2010-2020 period) period. Accordingly, our empirical findings appear to be valid when we consider the effect of GFC. In the appendix, Table A3 provides generalized method of moments (GMM) estimation results for the whole sample. We obtain almost the same results. Therefore, we can say that our estimation results are robust to different estimation procedures.

3.2 Cross-Sectionally Augmented Autoregressive Distributed Lag Model Estimation Results

To investigate the short and long run drivers of manufacturing, we can introduce the dynamics into the benchmark eq. (2). Considering the cross-sectional dependence, the autoregressive distributed lag model representation of eq. (2) is as follows:

$$MVA_{it} = \alpha_i + \sum_{j=1}^{p} \lambda_{ij}\, MVA_{i,t-j} + \sum_{j=0}^{q} \delta_{ij}\, x_{i,t-j} + u_{it}$$

$$u_{it} = \gamma_i' f_t + \varepsilon_{it}$$

$$x_{it} = a_i + b_i y_{i,t-1} + \Gamma'{}_i f_t + v_{it} \tag{4}$$

where α_i and a_i are the fixed effects that control country invariant factors, f is unobserved common factors, γ_i' and Γ_i' are the factor loadings, p and q are the determined lag orders to eliminate the autocorrelation concerns and ε and v are uncorrelated idiosyncratic errors. Under the condition of cross-section independence ($\gamma_i' = \Gamma_i'$), we can employ conventional autoregressive distributed lag model estimation procedure whether the variables are exogenous or endogenous as well as whether the variables are I(0) or I(1). The reparametrized version of eq. (4) can be specified as;

$$\Delta \mathrm{MVA}_{it} = \alpha_i + ecm_i\left(MVA_{i,t-1} - \beta_i x_{i,t-1}\right) + \sum_{j=1}^{p-1} \theta_{ij} \Delta MVA_{i,t-j} + \sum_{j=0}^{q-1} \zeta_{ij} \Delta x_{i,t-j} + \varepsilon_{it} \tag{5}$$

In eq. (5), ecm is the speed of adjustment term, β_i shows the long-run relationship whilst θ_{ij} and ζ_{ij} represent the short-run relationship between our variables of interest. The presence of cross-sectional dependence reported in Table 3 invalidates the estimation of eq. (5) with mean group and pooled mean group estimation procedures. Chudik and Pesaran (2013) notes that the incorporation of cross-sectional averages eliminates the cross-sectional dependence problem. Chudik et al. (2016) introduces the cross-sectionally augmented autoregressive distributed lag (CS-ARDL) procedure to estimate the short and long run parameters for the variable of interest.

Table 7 reports the CS-ARDL estimation results of eq. (4). CD-test results strongly reject the null of weak cross-sectional dependence in all the estimated equations. Also, our estimated equations pass the autocorrelation test. Kao test results indicate the presence of cointegration in all estimated equations.

Table 7: CS-ARDL Estimation Results				
	Whole Sample	AE	EMDE	MENA
Long-run coefficients				
$ECM_{i,t-1}$	-0.765*** (0.040)	-0.886*** (0.052)	-0.764*** (0.050)	-0.518*** (0.097)
$GDPpc_{i,t-1}$	1.222*** (0.083)	1.437*** (0.309)	1.256*** (0.097)	0.684*** (0.229)
$Capital\_Inflows_{i,t-1}$	-0.199* (0.120)	-0.308* (0.203)	-0.304* (0.170)	-0.510 (0.531)
$FD_{i,t-1}$	-0.365 (0.305)	-0.083 (0.086)	-0.522 (0.490)	1.439 (1.546)
$TRADE_{i,t-1}$	0.206*** (0.055)	0.194** (0.081)	0.153*** (0.058)	0.272* (0.186)
$ERR_{i,t-1}$	0.027** (0.012)	0.001 (0.009)	0.039*** (0.015)	0.047* (0.032)
Short-run coefficients				
$\Delta MVA_{i,t-1}$	0.235*** (0.040)	0.114** (0.052)	0.236*** (0.050)	0.482*** (0.097)
Δ $GDPpc_{it}$	0.949*** (0.081)	1.262*** (0.295)	0.940*** (0.087)	0.477*** (0.169)
$\Delta Capital\_Inflows_{it}$	-0.052 (0.053)	-0.154 (0.134)	-0.062 (0.063)	-0.201* (0.128)
$\Delta Capital\_Inflows_{i,t-1}$	-0.153*** (0.056)	-0.189* (0.125)	-0.163*** (0.053)	-0.054 (0.109)
ΔFD_{it}	-0.241* (0.157)	-0.095* (0.056)	-0.252* (0.163)	1.153 (1.168)
$\Delta TRADE_{it}$	0.160*** (0.040)	0.173** (0.071)	0.135*** (0.043)	0.073 (0.073)
ΔERR_{it}	0.012** (0.006)	0.003 (0.007)	0.014** (0.007)	0.017* (0.011)
Statistics	N=77 NT=2157 F[p-value]=0.00] R^2 =0.14	N=21 NT=641 F[p-value]=0.00 R^2 = 0.12	N=56 NT=1516 F[p-value]=0.00 R^2 = 0.16	N=10 NT=288 F[p-value]=0.00 R^2= 0.19
Kao-test[p-value]	0.00	0.00	0.00	0.04
CD-test[p-value]	0.00	0.00	0.00	0.01
AC-test[p-value]	0.32	0.93	0.72	0.78
Note: N and NT represent, respectively, number of countries and observations. The values in parentheses and square brackets are, respectively, the robust standard errors and p-values. CD-test maintains the null hypothesis of weak cross-sectional dependence. AC-test maintains the null hypothesis of there is no first order autocorrelation. Kao (1999) test maintains the null of no cointegration.				

The error correction term (ecm) is estimated as -0.77 in whole sample, -0.89 in AE, -0.76 in EMDE and -0.52 in MENA. The negative and statistically significant ecm coefficients suggest that manufacturing industry adjusts to the deviations from long-run equilibrium. This also provides an empirical support to the conditional manufacturing convergence by representing that any differences in the long-run equilibrium are transitory. Considering ecm term is much lower in MENA, we may suggest that adjustment to the deviation from long-run equilibrium is relatively slower than the other country groupings.

The estimated coefficient for income per capita is positive and statistically significant both in the long-run and in the short-run, albeit it is much lower in MENA. As compared to the short-run, the parameter of income per capita is slightly higher in the long-run. This can indicate that an increase in income per capita leads to higher manufacturing industry. This appears to be the case for all country groupings. The effect of capital flows on manufacturing is negative and statistically significant in the whole sample, AE and EMDE in the long-run, whilst this effect is negative and statistically significant in the short-run for all country groupings. The magnitude of the estimated coefficient for capital flows is almost the same. This result may imply that the short and long run impacts of capital flows are to allocate the resources out of the manufacturing industry, albeit these impacts are invariant to the country groupings. There is a positive and significant association between trade openness and manufacturing in all equations, although the estimated parameter is almost the same not only in the short but also in the long run. This empirical finding indicates that trade openness leads to industrialization both in the short and long-run. ERR appears to be positively associated with manufacturing, except the sample of AE. Also, the impact of ERR is much higher in the long run. This result can suggest that flexible ERR tends to encourage industrialization both in the short and long run.

Table 8 reports our CS-ARDL estimation results for high-tech and low-tech manufacturing industries. According to the CD-test results, there is no sign of cross-sectional dependence. Also, our estimated equations do not suffer from autocorrelation. Kao-test results indicate that there is cointegration among our variables of interest. Considering the results for high-tech manufacturing industry, the ecm term is estimated as -0.72, -0.51, -0.88 and -0.84, respectively for whole sample, AE, EMDE and MENA. The negatively significant ecm term suggests that high-tech manufacturing industry tends to adjust to the deviations from the long-run equilibrium.

In the long-run, capital flows appear to be negatively associated with high-technology manufacturing industry, except MENA. This negative relationship seems to be hold also in the short run. As compared to the short run, the magnitude of the estimated coefficient is much higher in the sample of AE. This empirical result suggests that capital flows tend to lower high-tech manufacturing industry.

Table 8: CS-ARDL Estimation Results

	High-Tech Manufacturing Industry				Low-Tech Manufacturing Industry			
	Whole Sample	AE	EMDE	MENA	Whole Sample	AE	EMDE	MENA
				Long-run coefficients				
$ECM_{i,t-1}$	-0.721*** (0.040)	-0.505*** (0.048)	-0.876*** (0.050)	-0.836*** (0.090)	-0.880*** (0.038)	-0.484*** (0.066)	-0.720*** (0.052)	-0.596*** (0.116)
$GDPpc_{i,t-1}$	0.139 (2.071)	1.004 (1.472)	0.509 (0.407)	0.331 (1.124)	-1.019 (1.790)	-3.422 (2.628)	1.161** (0.571)	1.571 (2.959)
$Capital\_Inflows_{i,t-1}$	-3.054* (2.081)	-4.158* (2.206)	-1.297* (0.736)	-2.944 (2.794)	1.180* (0.548)	1.156* (0.544)	3.649** (1.689)	-7.622 (5.426)
$FD_{i,t-1}$	3.743 (3.194)	1.242 (0.950)	2.902 (2.428)	-3.296** (1.410)	4.919 (6.075)	-8.119 (12.255)	-5.443* (3.202)	3.944 (3.964)
$TRADE_{i,t-1}$	0.834* (0.574)	2.271* (1.377)	0.228* (0.113)	1.214** (0.514)	0.359* (0.155)	0.306* (0.207)	0.551* (0.230)	2.130* (1.084)
$ERR_{i,t-1}$	3.082* (1.958)	1.252* (0.692)	2.989* (1.870)	5.708* (2.714)	1.425* (0.718)	5.687* (2.201)	-0.886 (2.536)	0.615* (0.403)
				Short-run coefficients				
$\Delta HT\_MVA_{i,t}$	0.279*** (0.040)	0.495*** (0.048)	0.124** (0.050)	0.164* (0.090)				
$\Delta LT\_MVA_{i,t}$					0.210*** (0.038)	0.516*** (0.066)	0.280*** (0.052)	0.404*** (0.116)
Δ $GDPpc_{it}$	0.447 (0.503)	0.132 (0.559)	0.597* (0.373)	0.413 (1.054)	1.084** (0.421)	-0.361 (0.481)	0.683** (0.323)	0.185 (0.865)
$\Delta Capital\_Inflows_{it}$	-0.188 (0.396)	-0.129 (0.996)	-1.024** (0.388)	-2.210 (1.627)	0.062 (0.349)	0.396 (1.022)	0.930** (0.437)	0.371 (1.220)
$\Delta Capital\_Inflows_{i,t-1}$	-0.606* (0.332)	-0.879* (0.532)	-0.343 (0.383)	0.212 (1.178)	0.431 (0.484)	1.066 (0.905)	0.242 (0.410)	-1.437* (0.741)
ΔFD_{it}	1.997 (1.510)	0.525 (0.366)	3.278* (2.029)	-2.572** (1.136)	-2.038 (1.740)	-1.562 (1.545)	-3.800* (2.168)	0.041 (0.997)
$\Delta TRADE_{it}$	0.798** (0.375)	0.674* (0.400)	0.045* (0.021)	0.955** (0.394)	-0.236 (0.308)	0.436* (0.239)	0.166 (0.250)	0.189 (1.648)
ΔERR_{it}	7.555* (4.913)	3.136* (2.161)	1.457* (0.760)	6.529* (3.645)	0.278 (1.782)	0.920* (0.584)	1.023 (1.413)	0.992* (0.685)
CD-test[p-value]	0.04	0.03	0.04	0.03	0.01	0.01	0.05	0.05
AC-test[p-value]	0.38	0.91	0.78	0.79	0.43	0.90	0.75	0.9
Kao-test[p-value]	0.00	0.00	0.00	0.01	0.00	0.01	0.00	0.02
Statistics	N=75 NT=2059 F[p-value]=0.00 R^2=0.39	N=22 NT=655 F[p-value]=0.00 R^2= 0.38	N=54 NT=1390 F[p-value]=0.00 R^2= 0.47	N=9 NT=232 F[p-value]=0.01 R^2= 0.39	N=72 NT=1897 F[p-value]=0.00 R^2=0.20	N=22 NT=655 F[p-value]=0.00 R^2= 0.29	N=55 NT=1404 F[p-value]=0.00 R^2= 0.33	N=10 NT=258 F[p-value]=0.00 R^2= 0.43

Note: N and NT represent, respectively, number of countries and observations. The values in parentheses and square brackets are, respectively, the robust standard errors and p-values. AC-test maintains the null hypothesis of there is no first order autocorrelation. Kao (1999) test maintains the null of no cointegration.

In the long run, there is a positive association between trade openness and high-tech manufacturing in all the estimated equations. This appears also be the case in the short run. As compared to the short run, the impact of trade on high tech manufacturing is much higher in the long run. Accordingly, an increase in trade openness leads to industrialization by increasing high-tech manufacturing. There is a positive relationship between ERR and high-tech manufacturing. This tends to be the case for both short and long run. This empirical finding indicates that exchange rate regime flexibility appears to support high-tech manufacturing. In addition to all these findings, high-tech manufacturing industry is procyclical in the short run for the sample of EMDE. Also, the short run impact of financial development is to encourage high-tech manufacturing in EMDE, whilst it mitigates industrialization in MENA.

Considering the results for low-tech manufacturing, the ecm term is estimated as -0.88 in whole sample, -0.48 in AE, -0.72 in EMDE and -0.59 in MENA. The negatively significant coefficient for ecm suggests that low-tech manufacturing adjusts to deviations from long-run equilibrium. Low-tech manufacturing is procyclical both in the short and long run for the sample of EMDE. The long-run impact of capital flows is to increase the low-tech manufacturing, except MENA. In the short-run, capital flows tend to raise low-tech manufacturing in EMDE whilst mitigates low-tech manufacturing in MENA. Considering the estimation results for high-tech manufacturing, we can say that capital flows tend to allocate the resources out of the high-tech manufacturing. According to our results, this appears to be the case in the long run.

The long run and short run impacts of financial development on low-tech manufacturing are negative and significant in EMDE. Accordingly, an improvement in financial development tends to allocate the resources out of the low-tech manufacturing. There is a positive and significant association between trade openness and low-tech manufacturing industry in the long run. This positive relationship holds in the short run for the sample of AE. This result suggests that an increase in trade openness leads to higher low-tech manufacturing. ERR is positively associated with low-tech manufacturing, except EMDE. This positive association appears to be the case both in the long run and short run.

3.3 Local Projection Method Estimation Method and Results

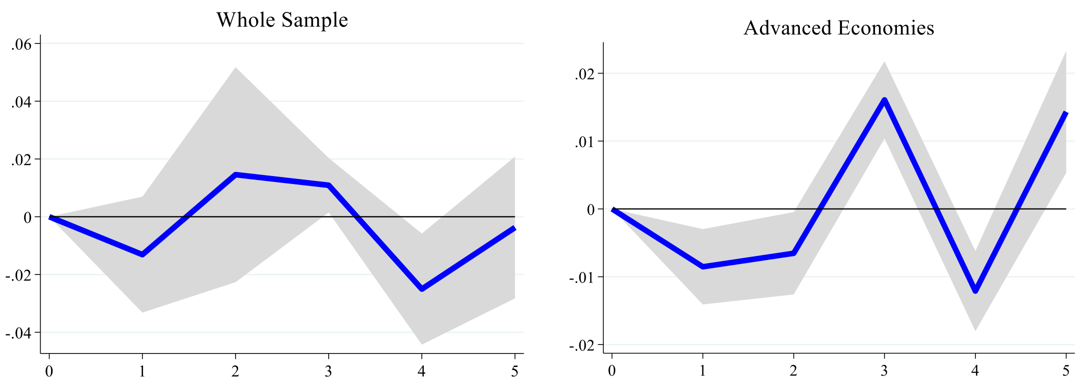
This section aims to investigate the dynamic response of manufacturing industry to capital flows. To study this important issue, we employ local projection method by Jorda (2005). We prefer to use local projection method to investigate the dynamic response of manufacturing industry to capital flows because this method is robust to a misspecification of the data generating process, reconciles nonlinearities and provides impulse response functions in a simple univariate framework. Our estimated equation is as follows:

$$\Delta MVA_{i,t+k} - \Delta MVA_{i,t} = \alpha_i + \gamma_t + \sum_{j=1}^{q} \phi_{jk} \Delta MVA_{i,t-j} + \beta_k Capital_{Flows_{i,t}}$$

$$+\varphi_k Controls_{i,t} + \varepsilon_{i,t} \tag{6}$$

In eq. (6), i represents countries, t denotes years and k=0,1,2,3,4,5 shows the k^{th} year after the shock in capital flows. We incorporate the lagged dependent variable to eliminate the autocorrelation concerns. We also include the country and time fixed effects. Considering our earlier results, we control the impacts of income per capita, financial development, trade openness and *de facto* exchange rate regime. All these variables are included as Controls in eq. (6). For each k, we estimate eq. (6). β_k measures the cumulative impact of the shock in capital flows to manufacturing for each one of the k. In other words, β_k shows the cumulative percentage change in manufacturing relative to its value in k = 0 which is the beginning of the shock in capital flows. Impulse response functions are obtained by plotting the estimated coefficient for β_k with respect to k = 0,1,2,3,4,5. The dynamic responses are represented within the 90 percent confidence intervals.

Figure 3: Response of Manufacturing to Capital Flows



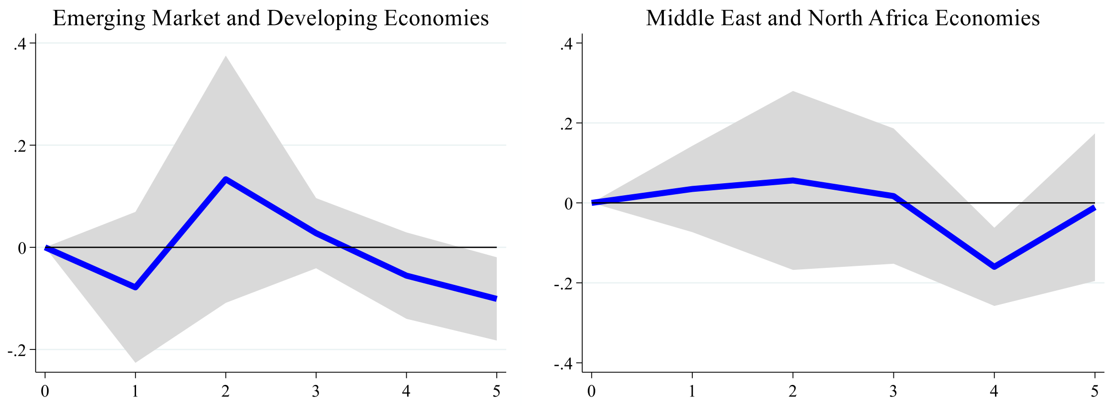
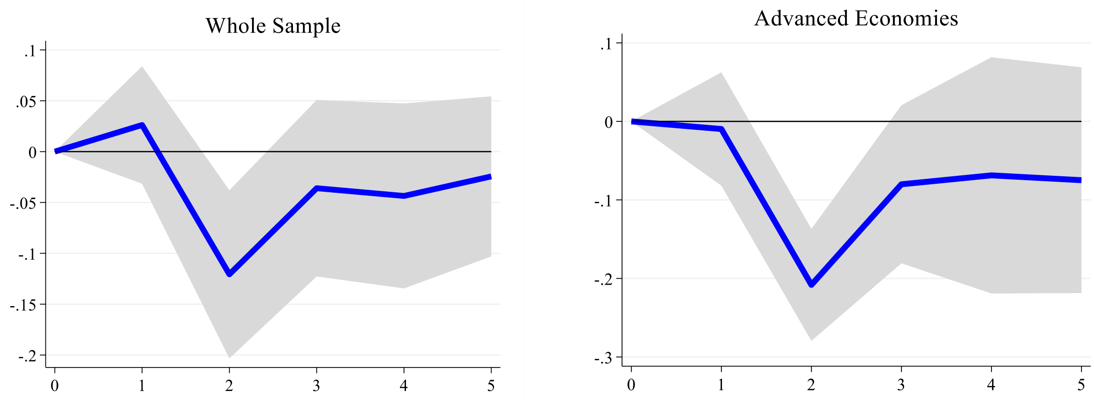


Figure 3 represents the dynamic response of manufacturing industry[10] to capital flows. Accordingly, the dynamic response of manufacturing industry tends to follow an inverted-N shaped relationship. For the whole sample, the initial impact of capital flows is to lower manufacturing. The recovery begins after the first year. Manufacturing tends to diminish following the second year, but it appears to recover towards the end of the period. AE and EMDE seem to follow the similar pattern. However, EMDE does not show any recovery sign towards the end of the period. On the other hand, the pattern for MENA is different than the other country groupings. The initial impact of capital flows is to increase manufacturing, albeit the deterioration begins following the second year. Towards the end of period, manufacturing seems to fully recover in MENA.

Figure 4: Response of High-Tech Manufacturing to Capital Flows



[10] In appendix, Figure A1 represents the impulse response of aggregate manufacturing and low- and high-tech manufacturing to 1 standard deviation shock to capital flows for the whole sample. We obtain essentially the same results.

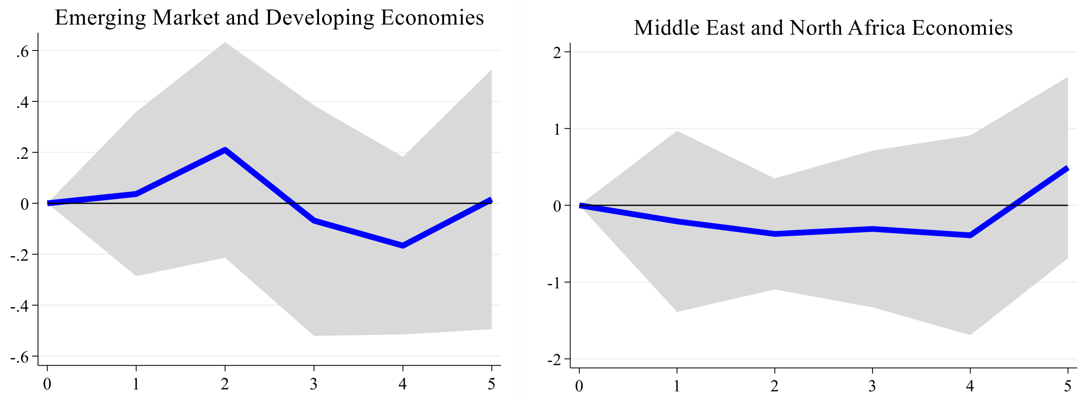
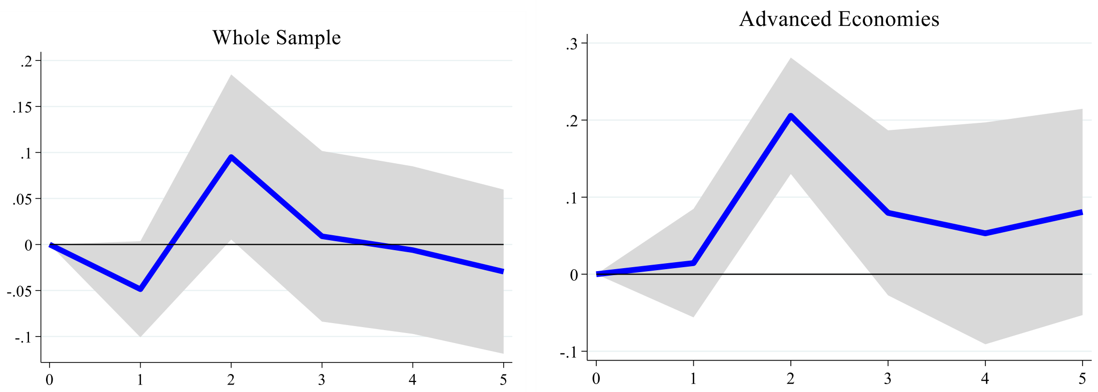


Figure 4 shows the dynamic response of high-tech manufacturing to capital flows. The response of manufacturing tends to follow V-shaped pattern in all country groupings, except EMDE. The pattern for EMDE appears to have N-shaped. In the whole sample, the initial impact of capital flows is to increase high-tech manufacturing. It deteriorates substantially following the first year and does not recover during the rest of the period. The similar pattern appears to be the case in AE. However, the magnitude of the deterioration is much higher in AE. In EMDE, high-tech manufacturing appears to increase following the first two years of capital flows. Although high-tech manufacturing tends to diminish following the second year, it recovers at the end of the period. In MENA, high-tech manufacturing decreases slightly, albeit it fully recovers towards the end of the period.

Figure 5: Response of Low-Tech Manufacturing to Capital Flows



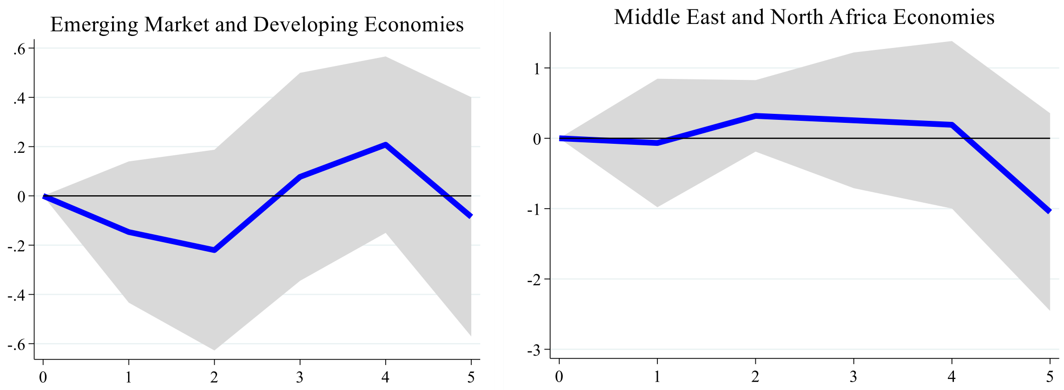


Figure 5 shows the dynamic response of low-tech manufacturing to capital flows. The response follows an inverse-N shaped relation in whole sample, EMDE and MENA whilst N-shaped pattern in AE. In the whole sample, low-tech manufacturing first decreases then increases and it exhibits a diminishing trend during the rest of the period. This appears also be the case in EMDE and MENA. However, the duration and magnitude of the variation is substantially much higher in EMDE than MENA. In AE, there is a substantial increase in low-tech manufacturing during the first two years of capital flows, albeit the magnitude of low-tech manufacturing tends to diminish for the rest of the period.

4. Conclusion and Policy Implications

Manufacturing has often been considered as the main engine of growth. The recent literature maintains that globalization, especially financial globalization, is one of the reasons that explain the declining trend in manufacturing. Conventionally, the movement of capital from rich to poor economies is beneficial because this leads to efficient allocation of capital, mitigates the cost of capital, and encourages production. However, the empirical literature does not provide convincing evidence on this issue. This paper investigates the relationship between manufacturing and capital flows for advanced (AE), emerging market and developing (EMDE) and Middle East and North Africa (MENA) economies over the 1986-2020 period.

Our empirical findings suggest that there is a negative and significant association between capital flows and manufacturing in AE, EMDE and MENA. This result indicates that capital flows lead to deindustrialization by lowering manufacturing industry. Our empirical findings suggest also that deindustrialization caused by capital flows is the case both in the short and long run. This is consistent with the remarks by Rodrik and Subramanian (2009) noting that capital flows appreciate the domestic exchange rates, mitigate profitability and investment opportunities in tradable manufacturing sector. Our results are also in line with the financial Dutch disease argument by Palma (2005). The recent literature points that financial openness leads to the movement of resources from tradable to nontradable sectors (Benigno et al., 2015; Kalantzis, 2015; Teimouri and Zietz, 2018). As consistent with the sectoral allocation argument, our findings indicate that capital flows lead to the movement of resources out of the manufacturing industry. Considering the development stages of economies, the movement of resources out of the manufacturing can also correspond to higher services value added i.e., servicification.

Manufacturing industry contains heterogeneity in technology intensity levels among the sectors. Therefore, we disaggregate manufacturing industry as high-tech and low-tech manufacturing. Our results suggest that there is a negative relationship between high-tech manufacturing and capital flows, except the sample of MENA. This relationship appears to be the case both in the short and long run. Accordingly, our findings suggest that capital flows lead the movement of resources out of the high-tech manufacturing sector. We find also that low-tech manufacturing and capital flows are positively associated in the long run, except MENA. In MENA economies, capital flows lead to the allocation of resources out of the low-tech manufacturing industry in the short run. The positive relationship between capital flows and low-tech manufacturing implies that capital flows lead to movement of resources within the manufacturing industry i.e., from high-tech to low-tech manufacturing.

Our empirical finding is consistent with the allocation puzzle implying that capital flows to economies with less productivity growth (Gourinchas and Jeanne, 2013). Gopinath et al. (2017) points that the allocation puzzle seems to hold at the firm level. They find that capital flows to firms that have higher net worth but less productive. Based on these arguments, we can suggest that capital flows to low-tech manufacturing industries and access to additional funding leads to higher low-tech manufacturing industry. On the other hand, capital flows impede the investment in high-tech manufacturing products that have long investment cycles (Yu and Qayyum, 2021). This is also consistent with an argument that high-tech manufacturing industries may prefer to delay their investments till they accumulate necessary levels of funds.

The empirical findings indicate that capital flows cause deindustrialization by impeding manufacturing industry which is the engine of economic growth. This is more apparent in high-tech manufacturing industry which has higher productivity. Considering this, the evolution of capital flows should be monitored carefully by policy makers. A recent report by IMF (2022) suggests the use of pre-emptive capital flow management measures like capital controls as the permanent part of policy toolkit to reap the benefits of capital account openness while minimizing macroeconomic and financial stability risks. In this context, policy makers may direct capital flows to low-tech manufacturing industry. In addition, effective sterilization policies may prevent the impact of financial Dutch disease on high-tech manufacturing industry. As consistent with the remarks by Aiginger and Rodrik (2020), policy makers may design and implement economic and social policies that place the industrialization at the core. These policies may also incorporate the collaboration between public and private sectors. Also, the movement from “turbo globalization” to “responsible globalization” along with the international cooperation and solutions to globalization related problems may increase the success of policies. The empirical results in this paper indicate that it is possible to finance manufacturing investment with capital flows, but it could be risky.

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APPENDIX

Table A1: CCE-MG Estimation Results for Whole Sample			
$\Delta GDPpc_{it}$	1.295*** (0.088)	1.252*** (0.087)	1.284*** (0.088)
$Net\_Capital\_Flows_{i,t-1}$	-0.064* (0.033)		
$Net\_FDI\_Flows_{i,t-1}$		0.016 (0.080)	
$Net\_Non\text{-}FDI\_Flows_{i,t-1}$			-0.077* (0.043)
ΔFD_{it}	-0.225** (0.118)	-0.285* (0.200)	-0.243** (0.122)
ERR_{it}	0.009* (0.006)	0.046* (0.030)	0.009** (0.004)
$\Delta TRADE_{it}$	0.238*** (0.039)	0.245*** (0.034)	0.238*** (0.036)
Constant	-0.087 (0.826)	-0.007 (0.016)	-0.002 (0.006)
N	77	77	77
NT	2061	2061	2061
F-test [p-value]	0.00	0.00	0.00
R^2	0.37	0.37	0.38
Root MSE	0.04	0.04	0.04
CD-test[p-value]	0.05	0.00	0.00
AC-test[p-value]	0.11	0.16	0.16

Notes: Dependent variable is ΔMVA. *** <1%, ** <%5, * <%10. N and NT represent, respectively, the number of countries and observations. The values in parentheses are the robust standard errors. AC-test maintains the null hypothesis of there is no first order autocorrelation.

Table A2: CCE-MG Estimation Results for Whole Sample						
	Before Global Financial Crisis (1986-2007 period)			After Global Financial Crisis (2010-2020 period)		
Dependent Variable:	ΔMVA	HTech_MVA	LTech_MVA	ΔMVA	HTech_MVA	LTech_MVA
$\Delta GDPpc_{it}$	1.186*** (0.134)	0.217 (0.689)	2.402** (1.209)	1.718*** (0.251)	0.124 (5.278)	1.031 (6.118)
$Capital\_Flows_{i,t-1}$	-0.105* (0.071)	-0.624* (0.311)	0.773* (0.379)	-0.432** (0.187)	-2.418* (1.384)	2.770* (1.636)
ΔFD_{it}	-0.115 (0.141)	0.864 (0.630)	2.217* (1.311)	0.380 (0.447)	0.998* (0.607)	-0.837 (0.746)
ERR_{it}	0.002 (0.011)	0.191* (0.093)	0.916*** (0.266)	0.522 (1.458)	0.392** (0.178)	0.265* (0.142)
$\Delta TRADE_{it}$	0.133** (0.070)	0.292* (0.166)	0.099 (0.284)	0.120* (0.064)	0.928* (0.459)	0.670 (1.597)
Constant	-0.005 (0.022)	0.013 (0.070)	0.047 (0.118)	-0.102 (0.306)	2.548** (1.069)	-0.099 (0.768)
N	63	57	57	71	65	65
NT	1064	958	958	710	650	650
F-test [p-value]	0.00	0.00	0.00	0.00	0.00	0.00
R^2	0.33	0.42	0.24	0.14	0.18	0.20
Root MSE	0.04	0.24	0.31	0.03	0.33	0.37
CD-test[p-value]	0.29	0.12	0.55	0.09	0.46	0.51
AC-test[p-value]	0.61	0.06	0.26	0.13	0.05	0.16

Notes: *** <1%, ** <%5, * <%10. N and NT represent, respectively, the number of countries and observations. The values in parentheses are the robust standard errors. AC-test maintains the null hypothesis of there is no first order autocorrelation.

Table A3: Difference GMM Estimation Results for Whole Sample			
Dependent Variable:	MVA	HTech_MVA	LTech_MVA
Lagged Dependent Variable	0.078*** (0.00)	0.779*** (0.001)	0.634*** (0.001)
$\Delta GDPpc_{it}$	1.308*** (0.002)	0.436*** (0.006)	2.345*** (0.015)
$Capital\_Flows_{i,t-1}$	-0.033*** (0.002)	-0.475*** (0.009)	0.138*** (0.004)
ΔFD_{it}	-0.008*** (0.002)	0.116 (0.189)	-0.262*** (0.010)
ERR_{it}	0.006*** (0.001)	0.124*** (0.001)	0.012*** (0.001)
$\Delta TRADE_{it}$	0.169*** (0.004)	0.026*** (0.002)	0.007* (0.004)
N	79	79	79
NT	2066	2022	2022
Hansen-Sargan Test [p-value]	0.36	0.28	0.45
AR1-test[p-value]	0.19	0.00	0.05
AR2-test[p-value]	0.35	0.76	0.98

Notes: *** <1%, ** <%5, * <%10. N and NT represent, respectively, the number of countries and observations. The values in parenthesis are robust standard errors. Hansen-Sargan test is the instrument validity test. AR1 and AR2 are, respectively, first and second order serial autocorrelation test.

Figure A1: VAR Results