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# **Effects of external capital inflows on industrialization in developing countries**

## **Evidence from ASEAN-4 economies**

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# Effects of external capital inflows on industrialization in developing countries: Evidence from ASEAN-4 economies

John Paul Corpus\* and Danny Cassimon†

## Abstract

We examine the effect of net capital inflows on industrialization in the ASEAN-4 countries of Indonesia, Malaysia, Philippines, and Thailand. Using panel data covering 1980–2018, we estimate the influence of both aggregate and disaggregated net capital inflows on the manufacturing sector's share in employment and real output. We find that aggregate net capital inflows have a negative influence on the manufacturing share of employment. Disaggregating capital inflows reveals that the negative effects emanate from non-FDI inflows, particularly portfolio investment and portfolio debt inflows. Meanwhile, FDI inflows have a positive effect on the manufacturing share of output. Our findings are consistent with existing evidence on the effects of aggregate capital inflows and non-FDI inflows on the manufacturing sector. We make a novel contribution for the ASEAN-4 by tracing the negative effects of non-FDI inflows to portfolio investment and portfolio debt, and uncovering the positive effect of FDI on manufacturing's output share. Our findings imply that policymakers in developing countries must pay attention to the influence that capital inflows exert on structural change and their industrialization efforts.

**Keywords:** capital inflows, structural change, premature deindustrialization, ASEAN-4

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# 1 Introduction

Financial globalization has increased inflows of external capital to developing countries. In the immediate pre-COVID-19 pandemic years (2017-2019),<sup>1</sup> the annual volume of net capital inflows<sup>2</sup> to developing countries amounted to an average of USD 1.2 trillion,<sup>3</sup> equivalent to 3.5% of developing countries' GDP. A substantial body of literature has been devoted to examining whether external capital flows foster economic development, particularly economic growth (for instance, as reviewed in Kose et al., 2009). Relatively less attention has been paid to the effect of these flows on structural change, or the movement of a country's labor and resources from low-productivity sectors to higher-productivity sectors, or broadly, from agriculture to modern industry and services. The nexus between capital inflows and structural change merits greater attention since economic development is predicated not simply on economic growth but on the transformation and upgrading of developing countries' economic structures and production capabilities.

For developing countries, of particular interest is a specific pattern of structural change, namely, industrialization, whereby an economy transforms from being predominantly agricultural into one with diverse and technologically dynamic manufacturing industries. It was through industrialization that practically all of today's advanced economies developed, save for a few oil-rich economies, tax havens, and small city states (Hauge and Chang, 2019). Industrialization powered rising incomes and economic development in Western Europe, North America, and Japan during the long 19<sup>th</sup> century. In the 20<sup>th</sup> century, manufacturing emerged as a major activity in many developing countries, serving as an important engine of economic growth especially following independence and the Second World War (Szirmai, 2012). Industrialization paths in the Global South, however, have been diverse. Few developing countries, namely Korea, Taiwan, and Singapore in East Asia, reached levels of industrialization and per capita incomes attained by the early industrializers. Most other developing countries have not experienced the same transformation, instead seeing their manufacturing sectors (as a share of output and/or employment) stagnate at modest levels or prematurely decline before reaching high levels of income (UNCTAD, 2016). Premature deindustrialization is a significant concern because it hinders the main channel of economic convergence for developing countries (Rodrik, 2016). Indeed, premature deindustrialization has been empirically associated with growth slowdowns in middle-income countries (Ravindran & Manalaya, 2022), thus hindering efforts to break out of the so-called middle-income trap.

The relationship between external capital inflows and industrialization in Southeast Asia's four largest developing economies—namely, Indonesia, Malaysia, the Philippines, and Thailand—is an interesting case to explore. Collectively called the ASEAN-4,<sup>4</sup> these economies have reached varying stages of middle-income status<sup>5</sup> and have each achieved respectable levels of industrialization. Malaysia, Thailand, and Indonesia, in particular, belong to the second tier of the so-called East Asian “miracle”

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<sup>1</sup> We exclude the years 2020 onwards from the analysis to avoid the effects of the COVID-19 pandemic.

<sup>2</sup> Throughout this paper, “net capital inflows” are defined as a country's net incurrence of external financial liabilities, *not* as the difference between capital inflows and capital outflows (i.e., net incurrence of external liabilities minus the net acquisition of external assets, or net capital *flows*).

<sup>3</sup> Current US dollars.

<sup>4</sup> ASEAN refers to the Association of Southeast Asian Nations, a political and economic bloc of 10 countries in Southeast Asia which includes the ASEAN-4 countries, Singapore, Vietnam, Laos, Cambodia, Myanmar, and Brunei Darussalam.

<sup>5</sup> Based on these countries' gross national income per capita, the World Bank classifies Indonesia, Malaysia, and Thailand as upper middle income and the Philippines as lower middle income.

or “tiger” economies<sup>6</sup>—countries that achieved rapid economic growth, poverty reduction, and industrial development since the 1960s (Jomo K. S. et al., 1997).

Despite considerable variations in economic and institutional structures, ASEAN-4 economies share some broad characteristics that distinguish them from other Southeast Asian countries. Firstly, the ASEAN-4 countries have had roughly comparable levels of development (measured in terms of income per capita) during the previous four decades (Figure 1.1). With few years in exception, all four countries have been considered middle income economies since the World Bank began classifying countries into income categories in 1987. In comparison to the ASEAN-4 economies, other countries in the Southeast Asian region have either been much more prosperous or (traditionally) less developed.<sup>7</sup>

Secondly, ASEAN-4 economies share broadly similar levels of institutional financial openness and integration with the rest of the world relative to other Southeast Asian countries (Figure 1.2). After Singapore, ASEAN-4 countries have traditionally exhibited the most open policies for cross-border financial flows in the region especially in the 1980s and 1990s. However, there has been a notable convergence in de jure financial openness between the ASEAN-4 and CLMV economies (particularly Cambodia and Vietnam) since the 2000s.

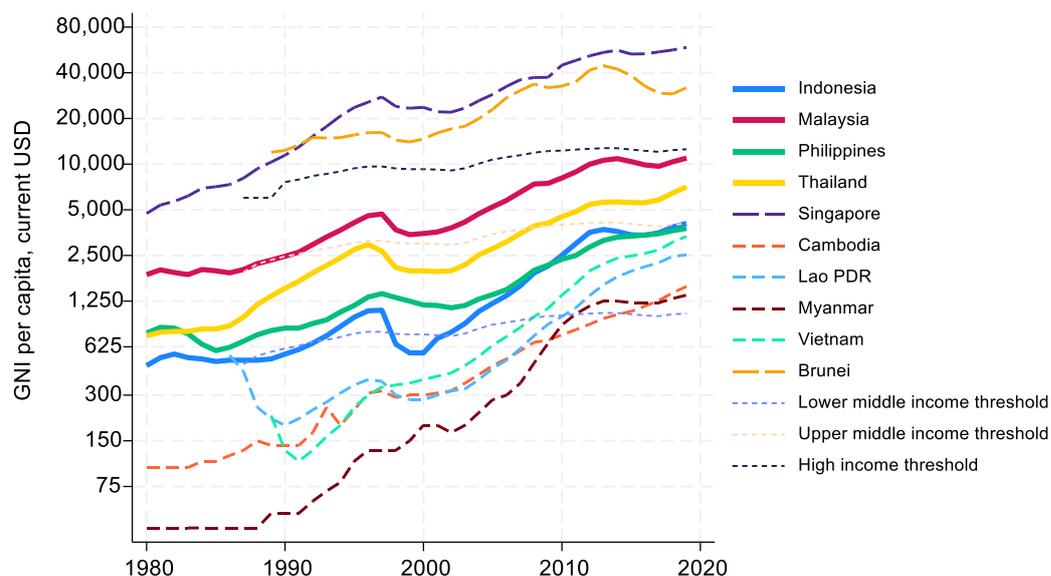
Thirdly, ASEAN-4 economies have traditionally received a significant share of capital inflows to the developing world, as well as most of the capital flows to developing Southeast Asia (Figure 1.3). In the 1980s and 1990s, this bloc of four countries collectively accounted for about 15% and 12%, respectively, of cumulative net capital inflows to all developing countries. The surge in capital inflows during the 1990s in the ASEAN-4 and other East Asian economies famously preceded the Asian Financial Crisis of 1997-1998, demonstrating the risks carried by financial globalization. The share of ASEAN-4 economies to developing-country-bound net capital inflows dipped to 3% in the 2000s and 7% in the 2010s. Nevertheless, during the 2010s, ASEAN-4 countries still accounted for over 75% of all capital inflows received by Southeast Asian developing countries.

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<sup>6</sup> The so-called East Asian miracle countries also include Japan, and the so-called first tier newly industrializing economies of South Korea, Taiwan, Hong Kong, and Singapore.

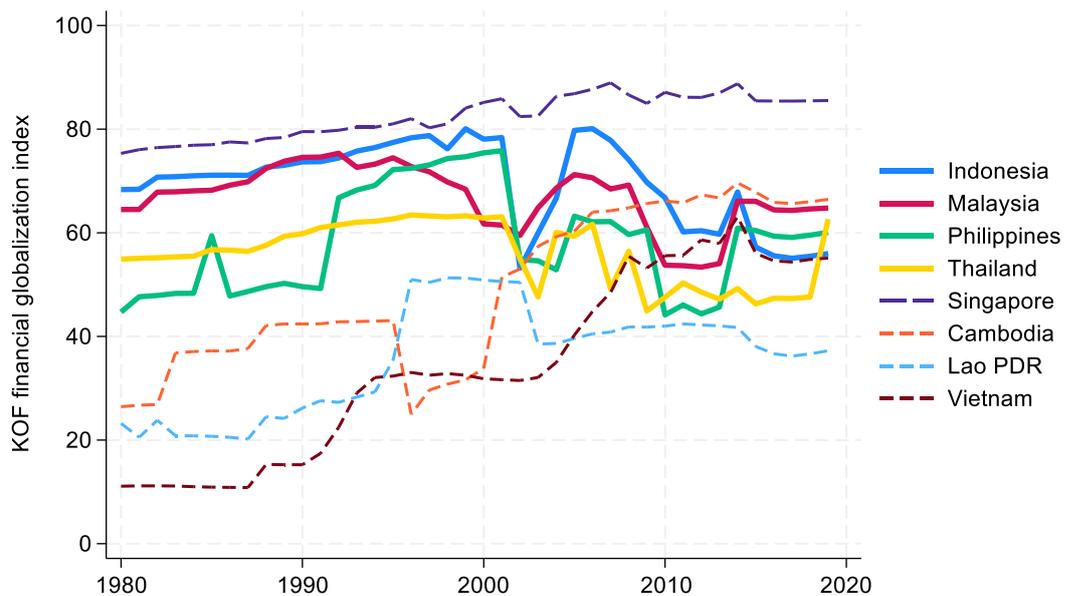
<sup>7</sup> Singapore and Brunei—both geographically small, high-income economies—are the region’s two wealthiest countries, the former being based on financial services, logistics, and high-technology exports, and the latter on oil and gas resources. Meanwhile, the so-called CLMV economies (Cambodia, Laos, Myanmar, and Vietnam) were originally centrally planned economies which embarked on economic liberalization beginning in the mid-1980s and 1990s (OECD, 2013). Although traditionally poorer than the ASEAN-4, CLMV economies (particularly Vietnam) have shown signs of convergence with the former due to their rapid economic growth since the 1990s.

**Figure 1.1. Gross national income per capita of Southeast Asian countries, 1980–2019**



Source: Authors' illustration using World Bank data.

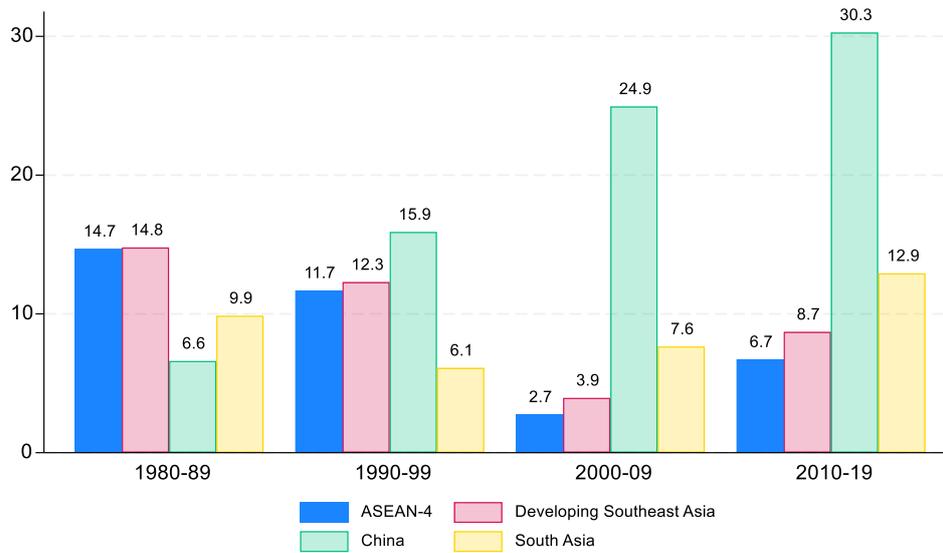
**Figure 1.2. KOF de jure financial globalization index in Southeast Asian countries, 1980–2019**



Note: The KOF de jure financial globalization index combines indicators consisting of investment restrictions, capital account openness, and international investment agreements (Gygli et al., 2019).

Source: Authors' illustration using the KOF Globalization Index (Gygli et al., 2019).

**Figure 1.3. Share of selected Asian regions to cumulative net capital inflows to developing countries**



Source: Authors' calculations and illustration using IMF Balance of Payments data.

In contrast to their Northeast Asian counterparts, industrialization in the Southeast Asian tigers is described as having either stalled or being in premature decline (UNCTAD, 2016; Rasiah, 2020). What role have external capital inflows played in this development? This paper sets out to investigate the effects external capital inflows on industrialization (particularly the share of manufacturing in employment and real value-added) in the ASEAN-4 economies. In addition to analyzing the effects of aggregate capital inflows, we also explore the effects on industrialization of different types of capital inflows, namely, foreign direct investment (FDI), portfolio investment (i.e., portfolio equity and portfolio debt flows) and other investment. These questions are addressed through an econometric analysis of panel data from 1980 to 2018.

The rest of the paper is organized as follows. Section 2 provides an overview of the patterns of structural change in, and net capital inflows into, ASEAN-4 economies. Section 3 reviews the literature on the relationship between external capital flows and structural change in developing countries. Section 4 describes our empirical methodology and data. Section 5 discusses our results, while Section 6 presents our conclusions and draws policy implications.

## 2 Structural change and capital inflows in ASEAN-4 economies

### 2.1 Structural change

Structural change is characterized by three stylized facts about the evolution of the structure of employment and output across broad economic sectors (i.e., agriculture, manufacturing, and services) over the course of economic development. These are that, as per capita incomes increase: (1) the share of agriculture falls; (2) the share of services rise; and (3) the share of manufacturing follows an inverted-U or hump-shaped path, i.e., rising at lower levels of income, reaching a peak, and declining at higher levels of income (Herrendorf et al. 2014; Sen, 2023).

ASEAN-4 economies have seen significant transformation in their employment and production structures since the 1970s, exhibiting to varying degrees certain aspects of the classic pattern of structural change (Figures 2.1 and 2.2). In all four countries, employment shifted from being predominantly agricultural to predominantly services-oriented. By the 2010s,<sup>8</sup> agriculture's employment share had dropped to just about one-tenth in Malaysia, over a quarter in the Philippines, and about one-third in Indonesia and Thailand. Over the same period, services employment steadily increased, reaching, by the 2010s, 60% of employment in Malaysia, 54% in the Philippines, and 44–45% in Indonesia and Thailand.<sup>9</sup> Shifts in these sectors' value-added shares followed trends that are broadly similar to their employment shares. Due to lower labor productivity in agriculture relative to services, services surpassed agriculture much earlier in terms of its contribution to output compared to its contribution to employment. By the 2010s, agriculture's real output share had fallen to just around one-tenth of total output in all countries. The services sector, on the other hand, accounted over 40% of output in Indonesia, and well over half in the three other countries.

Meanwhile, industrialization has taken different trajectories in the four countries. Between the 1970s and 1990s, the employment share of manufacturing saw robust growth in Malaysia, Thailand, and Indonesia, before peaking at 24% in 1997 and declining in subsequent decades in the case of Malaysia, while appearing to stagnate at modest levels in both Thailand (at around 15-16%) and Indonesia (at 13%). The real output share of manufacturing showed a similar dynamic in the three countries, rising rapidly from the 1970s to the 1990s, before peaking at around 24-25% in Indonesia and Malaysia (in the 2000s) and at 30% in Thailand (in 2010), and stagnating or slightly declining thereafter. The Philippines' manufacturing sector stands out in the group as its contribution both to employment and real output has been declining since the 1970s, indicating that it had peaked much earlier than its neighbors. Philippine manufacturing's employment share declined from 13% in the 1970s to just 9% in the 2010s, while its output share declined from a peak of 27% in 1973 to around 20% in the 2010s.

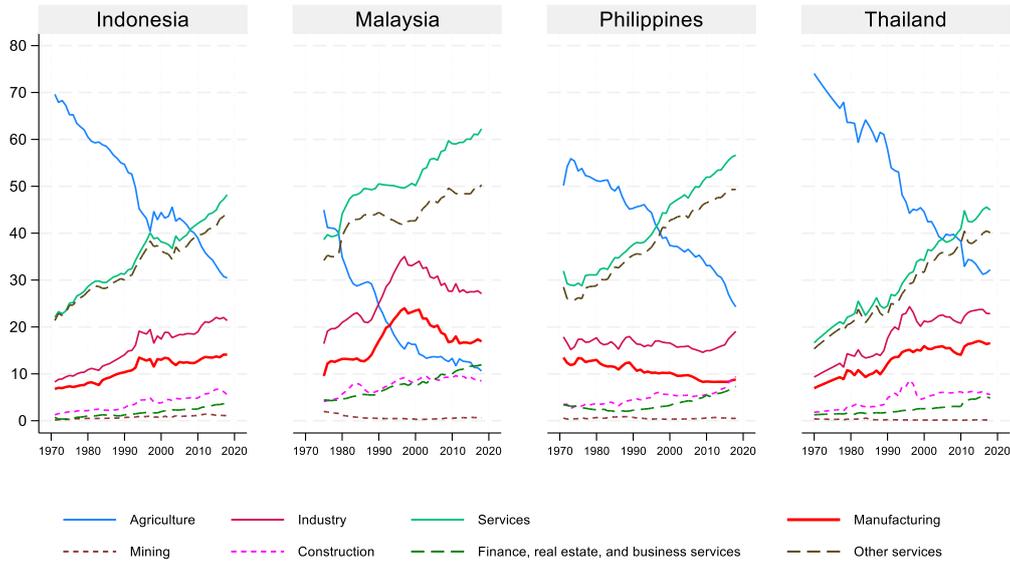
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<sup>8</sup> In this section, “2010s” cover 2010 to 2018 only, as the panel dataset for industrial structure used here only goes up to 2018.

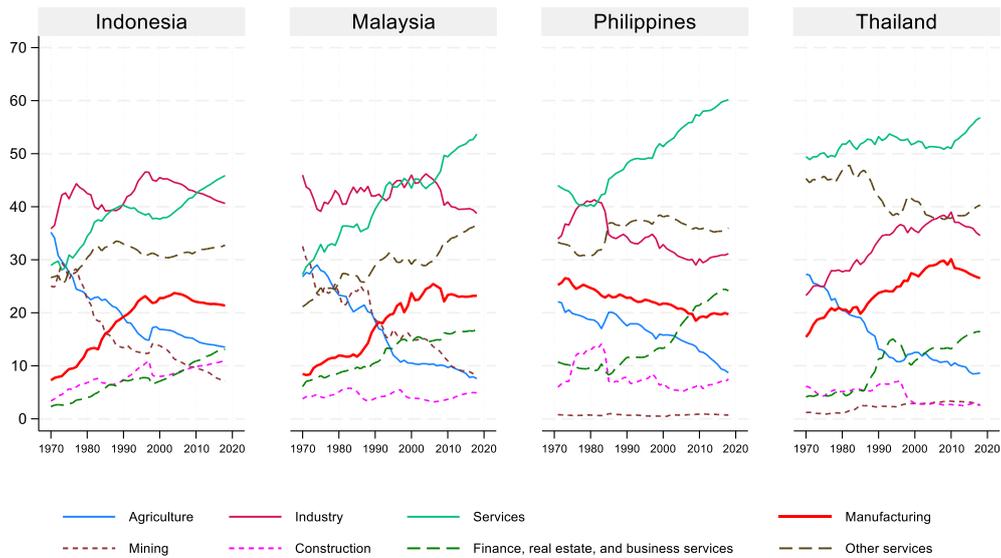
<sup>9</sup> Services employment is dominated by employment in relatively lower productivity services sectors, i.e., trade, transportation, government, and other services, which we refer to as “other services”. The higher productivity services sectors of finance, real estate, and business services account for much smaller shares in total employment (typically less than 10%).

**Figure 2.1. Structural change in ASEAN-4 economies, 1970–2018**

**A. Employment shares (percent)**



**B. Real value-added shares (percent)**



Note: Industry includes manufacturing, mining, construction, and utilities. Other services include trade, transportation, government, and other services.

Source: Authors' illustration using data from the Economic Transformation Database of the Groningen Growth and Development Centre (GGDC) (Kruse et al., 2023) (see <https://www.rug.nl/ggdc/>).

A notable feature is the large contribution of mining to real output in Indonesia and Malaysia. Both countries are rich in mineral resources and are important exporters of mineral fuels such as petroleum and natural gas as well as mineral ores. In the 1970s, mining in Indonesia and Malaysia contributed around a quarter of total output (on average), but this share had fallen to (a still substantial) 10% by the 2010s. Mining contributes a much smaller share of real output in Thailand (3%) and the Philippines (0.8%).

Figure 2.2 compares the relationship between industrialization and per capita incomes in the ASEAN-4 with that in the so-called first-tier newly industrializing countries (NICs) of South Korea and Taiwan from 1970 to 2018.<sup>10</sup> In Panel A, we observe that in 2018, the output share of manufacturing in ASEAN-4 countries, except the Philippines, were about as large than those in Taiwan or Korea when they were at similar levels of income. However, manufacturing's share in Thailand and Korea continued to rise past an income level of \$20,000 per person, while those in Thailand, Malaysia, and Indonesia had already peaked at lower income levels (between \$6,000 and \$13,500) during the 2000s and appear to be declining since (Table 2.1). For its level of income, the Philippines had a larger manufacturing output share in the early 1970s than any of the other comparator countries in East Asia, but this share only diminished in subsequent decades after passing an income of less than \$3,200 per person.

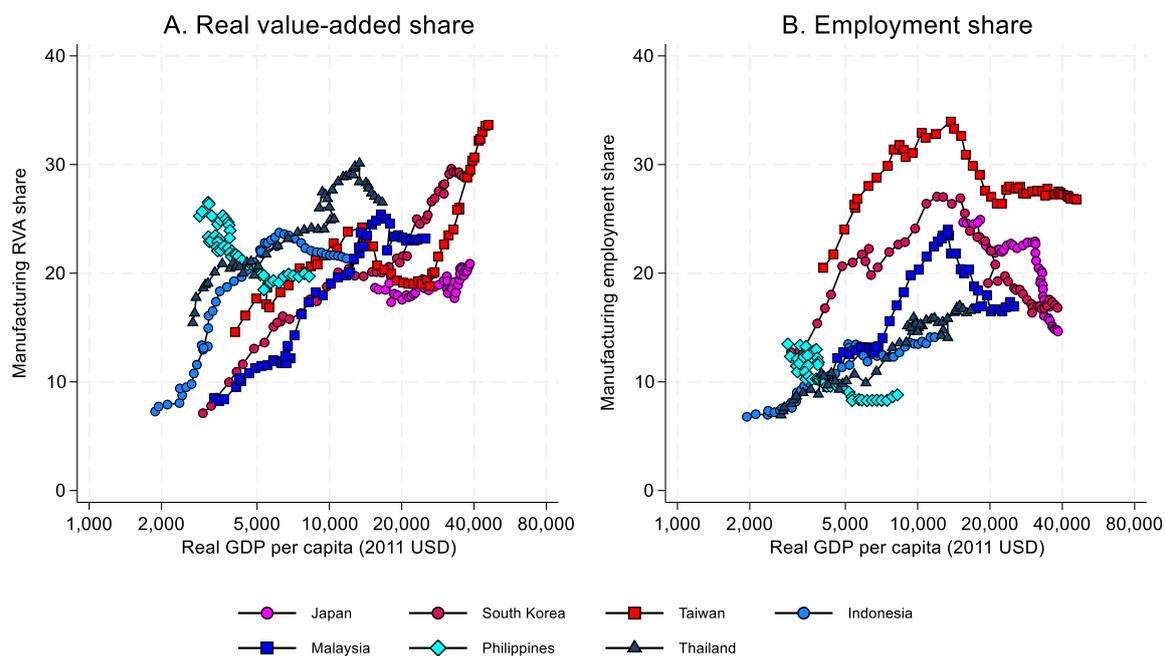
In Panel B, we find that ASEAN-4 economies achieved much lower levels of employment industrialization relative to their Northeast Asian counterparts. Malaysia, Thailand, and Indonesia have all employed a smaller share of workers in manufacturing compared to Taiwan or South Korea at any income level during the period in consideration. In Malaysia, while manufacturing employment crested at an income level that is comparable with South Korea's and Taiwan's when their manufacturing employment peaked (at around \$12,000-14,000 per person), it did so at a considerably lower share of total employment (at 24%, versus 27% in South Korea and 34% in Taiwan) (Table 2.1). Around these same income levels, manufacturing employment in Thailand and Indonesia appear to stagnate at even lower shares (17% and 14%, respectively). Philippine manufacturing's behavior again deviates from the group; its share in employment shrank while those of its neighbors increased, ending up by 2018 with a much smaller manufacturing workforce than did its East Asian peers when they were at a similar stage of development.

These comparisons point to signs of premature deindustrialization in the ASEAN-4. The observation that manufacturing employment in the ASEAN-4 economies was unable to grow as large as those in the first-tier NICs is critical, as analysis by Felipe et al. (2019) shows that *employment* industrialization is a better predictor of future economic prosperity than *output* industrialization. They show that virtually all wealthy countries had manufacturing employment shares that peaked at 18% or higher, and that most countries that crossed this threshold are rich, whereas high manufacturing output shares are not as important (Felipe et al., 2019).

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<sup>10</sup> The name "newly industrializing countries", which dates back to the 1980s, is anachronistic in current times as these countries have already industrialized. Singapore and Hong Kong are usually considered to belong to the first-tier NICs, but they are distinct from South Korea and Taiwan in that the former countries are small city states that did not begin their development with a large agrarian base.

**Figure 2.2. Manufacturing share vs. income per capita in the ASEAN-4, Northeast Asia, and other developing regions**



Source: Authors' illustration using GGDC data (Kruse et al., 2023).

**Table 2.1. Year and income per capita when manufacturing output and employment shares peaked**

	Year of peak	Peak manufacturing share (percent)	Income per capita at peak (2011 USD)
<b>A. Employment share</b>			
Taiwan	1987	34.0	13,705
South Korea	1988	27.0	12,040
Malaysia	1997	24.0	13,345
Thailand	2015	17.0	14,961
Indonesia	2017	14.1	11,292
Philippines	1971 or earlier	13.5	2,882
<b>B. Real value-added share</b>			
Taiwan*	-	33.6	45,818
Thailand	2010	30.1	13,344
South Korea	2011	29.6	32,225
Philippines	1973	26.5	3,131
Malaysia	2006	25.4	16,354
Indonesia	2004	23.7	6,181

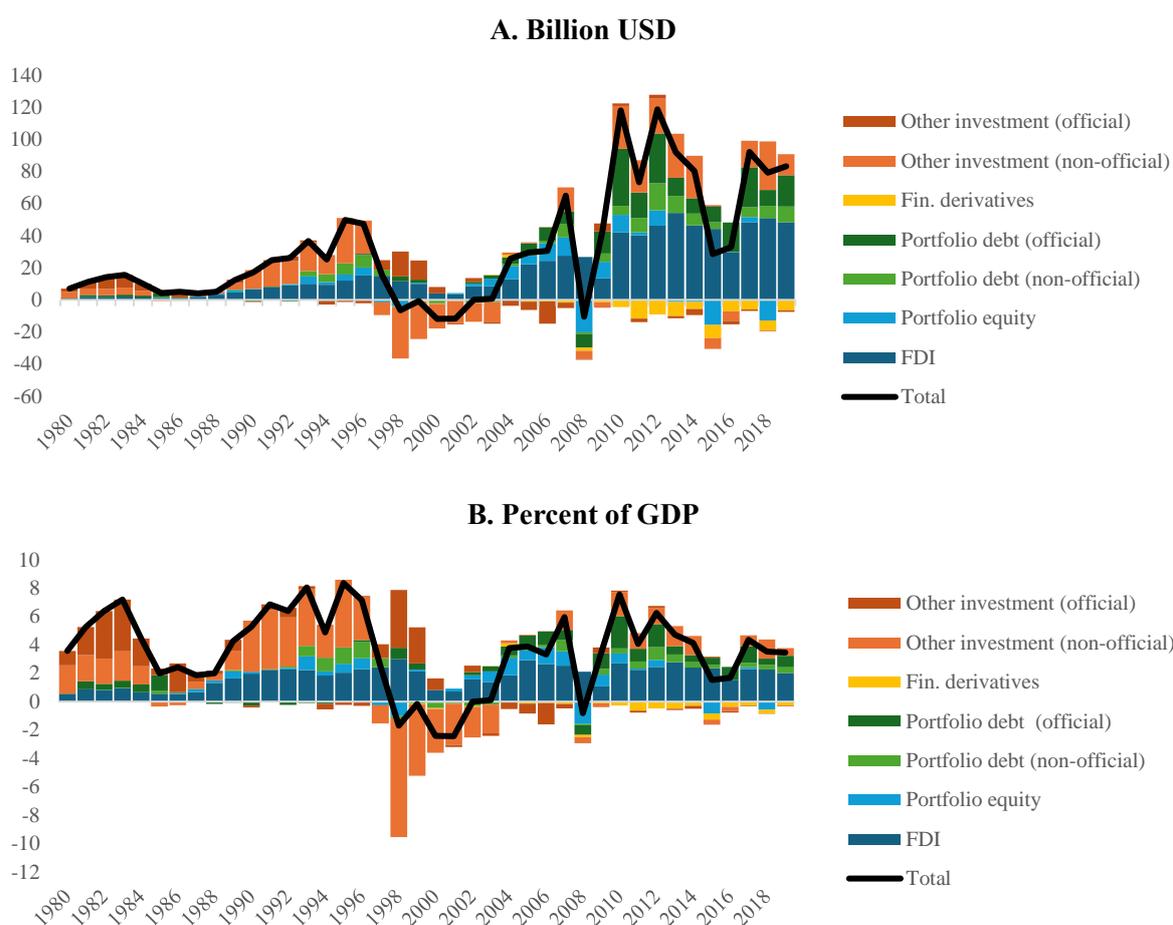
Note: \* Taiwan's manufacturing real value-added share had not peaked in 2018, the year when the dataset ends.

Source: Authors' calculation using GGDC data (Kruse et al., 2023).

## 2.2 Net capital inflows

Net capital inflows are defined as a country’s net incurrence of external liabilities as recorded in the financial account of its balance of payments. These inflows come in the form of foreign direct investment (FDI), portfolio investment (portfolio equity and portfolio debt), other investment,<sup>11</sup> and financial derivatives. Net capital inflows to ASEAN-4 economies over the last four decades have undergone cycles of upswings and downswings. This is evident from Figure 2.3, which depicts the evolution of aggregate net capital inflows to the region as a whole, as well as composition of these flows, from 1980 to 2019.<sup>12</sup>

**Figure 2.3. Evolution and composition of total net capital inflows to ASEAN-4, 1980–2019**



Source: Authors’ illustration using IMF Balance of Payments and World Economic Outlook data.

Between 1980 and 2019, four episodes of surging or elevated levels of capital inflows to ASEAN-4 economies can be identified, punctuated by bouts of capital flow reversals or slowdowns.

<sup>11</sup> The IMF defines “other investment” as a “residual category that includes all financial transactions not considered direct investment, portfolio investment, or reserve assets” (IMF, 1996, p. 124). Other investment includes trade credit, IMF credit and loans, other loans, and currency and deposits (IMF, 1996). Although changes in foreign reserve assets form part of the financial account, they are excluded from the definition we adopt as these flows arise from foreign exchange interventions of central banks.

<sup>12</sup> We exclude the years from 2020 onwards to avoid the years affected by the COVID-19 pandemic.

The early 1980s were at the tail end of heightened capital flows to developing countries that began in the mid-1970s. Private capital flows primarily took the form of commercial bank lending, with developing country governments often acting as borrowers or guarantors (World Bank, 1996). This period of rising external indebtedness came to an end as monetary policy in advanced economies severely tightened, setting off a wave of debt crises in many heavily indebted developing countries. Most emerging economies in East and Southeast Asia had borrowed prudently and were able to weather the worst of the debt crisis while maintaining high growth rates (World Bank, 1996). The exception was the Philippines, which suffered from an external debt crisis and a severe recession in 1984–1985.

The late 1980s through to the mid-1990s saw a resurgence of net capital inflows to the region, rising from USD 12 billion (4% of regional GDP) in 1989 to a peak of USD 50 billion (8% of regional GDP) in 1995. This upswing was driven by higher FDI inflows together with higher non-official lending. Net FDI inflows notably increased from USD 3 billion (1.3% of regional GDP) in 1989 to USD 15 billion in 1996 (2.3% of regional GDP). A major contributor was the growth of Japanese FDI in Southeast Asia, as Japanese multinational firms relocated their labor-intensive production activities to less developed neighboring countries in response to the appreciation of the Japanese yen against the US dollar following the 1985 Plaza Accord (Thorbecke & Salike, 2011). Currency appreciation in other first-tier newly industrialized economies in Northeast Asia (i.e., South Korea and Taiwan) also led to an increase in FDI inflows from these countries to Southeast Asia (Jomo K. S. et al., 1997). Portfolio investment flows started play a significant role at around 1993.

This period also saw a large increase in foreign bank loans incurred by the private sector. The biggest recipient of such flows was Thailand, where financial institutions borrowed large amounts of foreign capital at short maturities, taking advantage of lower interest rates abroad and the fixed exchange rate at home (Montiel, 2014). The inflows caused the rapid expansion of domestic credit, which financed tradable industries but also to non-tradable sectors such as construction and real estate (Montiel, 2014). The erosion of investor confidence due to a combination of factors<sup>13</sup> triggered a massive reversal of these capital flows (most prominently in Thailand and Indonesia), helping set off the Asian Financial Crisis of 1997–1998. While ASEAN-4 economies had recovered by 2000, overall net capital inflows to the region remained negative until 2002 as the bursting of the dot-com bubble and subsequent recession in the United States dampened investor sentiment (Kawai & Lamberte, 2010).

Net capital inflows to the region surged once more starting in 2003, reaching USD 65 billion (6% of regional GDP) in 2007. This revival was facilitated by the benign and stable macroeconomic environment that prevailed during the period (Villafuerte & Yap, 2015). FDI and portfolio investment played a dominant role in driving the upswing in capital flows, in contrast to previous surge episodes wherein other investment flows played a more prominent role. In particular, the rise in portfolio equity inflows after the Asian Financial Crisis is ascribed to the reduction of barriers to equity investment to help recapitalize troubled banks and corporations (Kawai & Lamberte, 2010). This surge episode came to an end in 2008 as the Global Financial Crisis sparked a flight to safety.

Quantitative easing by advanced economies after the Global Financial Crisis resulted in record levels of liquidity and the search for higher yields, fueling another surge in capital flows to emerging markets including ASEAN-4 economies from 2010 to 2012. Net capital inflows in 2010 reached USD 118 billion (7.5% of regional GDP). The period saw large net inflows of portfolio investment particularly into official debt securities, alongside substantial net inflows of FDI and non-official lending. However, from 2013 to 2016, the region experienced diminished net capital inflows driven by reversals of portfolio equity and other debt flows. The unwinding of expansionary monetary

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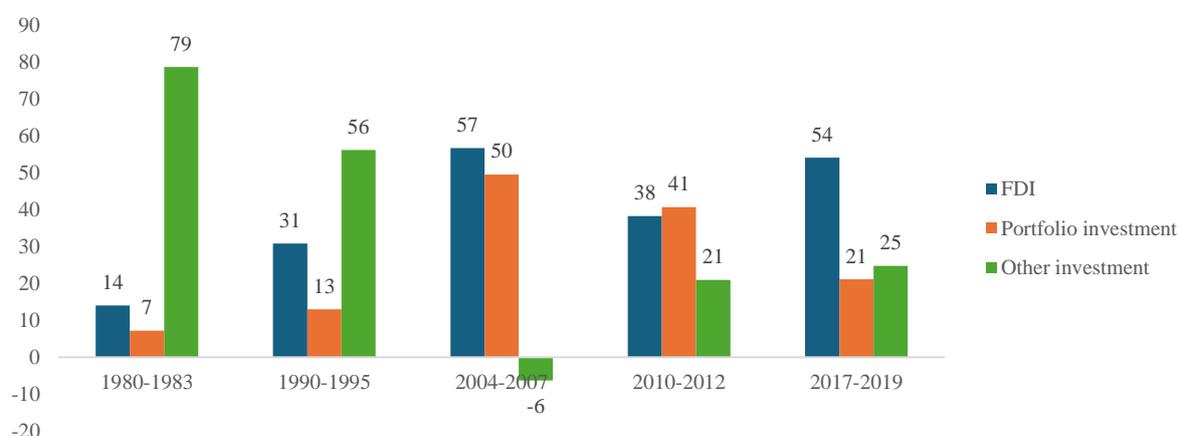
<sup>13</sup> Including faster inflation, disappointing export growth, a widening current account deficit, and belief that domestic currencies (e.g., the Thai baht) were overvalued (Montiel, 2014).

policies in advanced economies (particularly the United States) and slower economic growth in emerging economies were factors behind the slowdown in capital inflows (IMF, 2016).

The years preceding the COVID-19 pandemic (2017–2019) saw renewed net capital inflows to the region, albeit reaching lower levels than the peak previously achieved in the early 2010s (USD 92 billion of 4% of regional GDP in 2017). The resurgence owed to higher portfolio inflows into official debt (particularly into official securities) and non-official lending. Net inflows of portfolio equity investment, however, remained muted overall.

Figure 2.4 illustrates the contribution of each of the three major sources of foreign capital (FDI, portfolio investment, and other investment) to cumulative net capital inflows during surge episodes between 1980 and 2019. Capital flows were dominated by other investment flows in the 1980s and 1990s, but the latter’s importance diminished over time, being superseded by FDI (and portfolio investment during some periods) since the 2000s.

**Figure 2.4. Composition of cumulative net capital inflows during surge periods (percent of total)**



Note: Excludes financial derivatives.

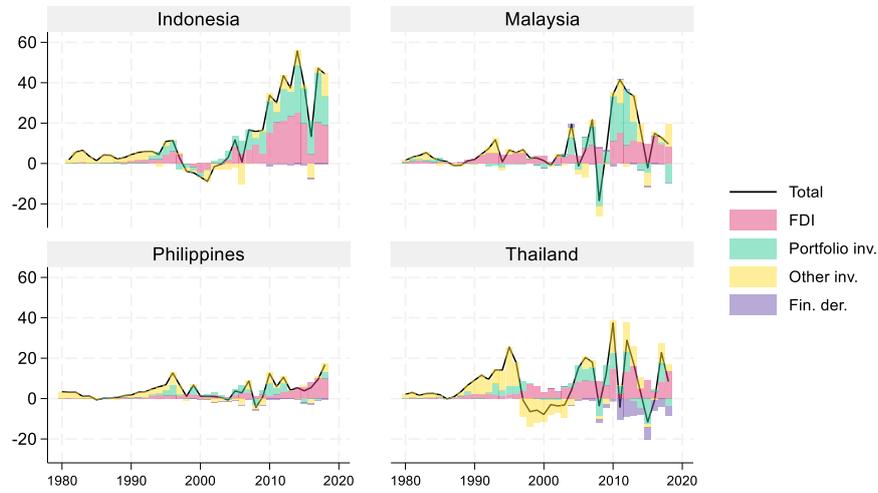
Source: Authors’ calculation using IMF Balance of Payments data.

Turning to country-level capital net inflows, differences and similarities can be observed in Figure 2.5, which illustrates the evolution of net capital inflows for each of the four countries from 1980 to 2019. Summary statistics of these flows are presented in the Appendix (Table A1).

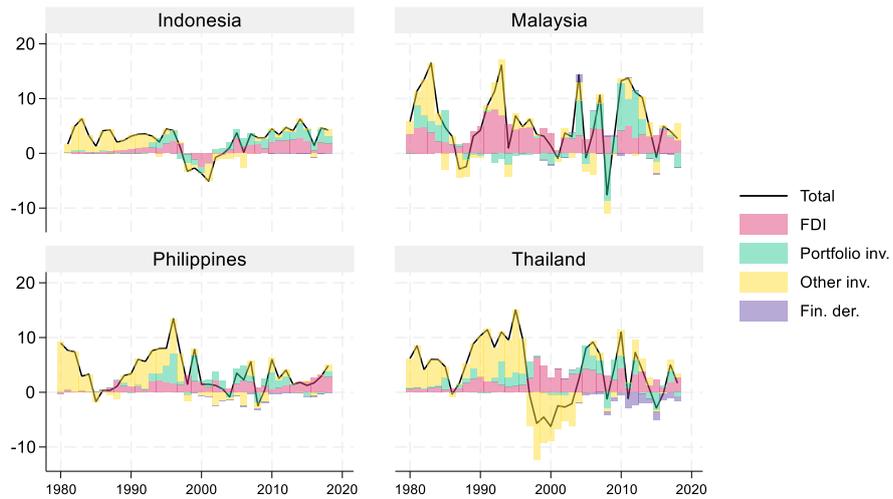
In dollar terms (Figure 2.5 Panel A), annual net capital inflows tend to be smallest for the Philippines (perennially below USD 20 billion since the 1980s), and largest for Indonesia (breaching USD 40 billion in some years) at least during the 2010s. The volume of FDI and portfolio investment flows to Indonesia were the largest in the region in the past decade. Malaysia and Thailand also saw large aggregate capital inflows in the 2010s (reaching USD 20–40 billion in some years), but these flows have been notably volatile due to swings in inflows of non-FDI capital particularly portfolio investment. Meanwhile, relative to GDP (Figure 2.5 Panel B), average net capital inflows from 1980 to 2019 were actually smallest for Indonesia (2.4%) and largest for Malaysia (5.6% on average, and over 10% of GDP in some years). Moreover, Malaysia and Thailand have been the two largest recipients of FDI relative to GDP (3.6% and 2.2% on average, respectively).

**Figure 2.5. Evolution and composition of net capital inflows to individual ASEAN-4 countries, 1980–2019**

**A. USD billion**



**B. Percent of GDP**



Note: Fin. der. = financial derivatives.

Source: Authors' illustration using IMF Balance of Payments and World Economic Outlook data.

There is a substantial degree of co-movement in net capital inflows among ASEAN-4 countries (see Appendix Table A2). Net capital inflows in each country are found to have a statistically significant positive correlation with capital inflows to every other country in the region. The exception is the co-movement between inflows to Indonesia and the Philippines when scaled by GDP, which seems to have no statistically significant relationship.

### 3 Literature review

What role does finance play in structural change? Griffith-Jones and Ocampo (2021) argue that (domestic and external) finance affects structural change through two channels. The first channel is through the sectoral destination or allocation of finance. Finance promotes positive structural change when it is directed to more productive and innovative sectors of the economy.

The second channel is through the effect of these financial flows on financial stability. Financial flows that generate financial instability and crises undermine economic growth. The authors were not explicit about how this leads to undesirable sectoral shifts in the economy. Presumably, this happens when manufacturing and other higher-productivity sectors experience worse contractions than lower-productivity sectors from tighter credit conditions and lower demand during crises, and if these sectors then suffer persistently lower investment and production capacity.

Griffith-Jones and Ocampo (2021) add that whether the “increase in investment is channeled to sectors that have higher-productivity or faster-productivity growth generally depends on domestic economic structures rather than on capital flows as such” (p. 477). They highlight the role of government policies to attract investment into desired sectors, but this also speaks to the idea that economies can attract certain types of financing based on their existing (or emerging) sectoral structure.

Botta et al. (2022) offer a framework to understand the various channels through which non-FDI capital flows can influence structural change. The first channel is through the exchange rate or Dutch disease channel. Large capital inflows lead to currency appreciation and diminished export competitiveness, inducing sectoral reallocation away from tradables towards non-tradables. The second channel is through balance sheet or investment effects. Currency appreciation fueled by capital inflows can (temporarily) strengthen the balance sheets of domestic firms with foreign currency liabilities and reduce the cost of importing capital goods, thus encouraging firms to increase their productive investment. The third channel is through macroeconomic instability. Periods of surging capital flows and foreign debt accumulation are usually followed by capital flow reversals and currency depreciation, creating unsustainable debt burdens that lead to financial turmoil and a drop in productive investment. The fourth channel is through the sectoral orientation of credit expansions that capital inflows encourage. Credit booms that channel credit to non-tradables over tradables lead to unfavorable structural change.

Several cross-country empirical studies examine the influence of capital inflows on the size of manufacturing sector. One strand of the literature focuses on the dynamic or short-run effects of aggregate capital inflow surges on the share of manufacturing employment and/or output.

Benigno et al. (2015) explore the effect of capital surge episodes on sectoral composition for a sample of 70 high- and middle-income countries spanning 1975–2010. The authors measure capital inflows as the sum of the current account deficit and the change in foreign exchange reserves.<sup>14</sup> Using an

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<sup>14</sup> Identifying capital surges as periods wherein inflows rise by more than one standard deviation above the long-run standard deviation, the authors identified 155 episodes of large capital inflows in the sample.

event study approach, they find that capital surges are usually accompanied by a rise in output followed by a slump. Moreover, manufacturing's share in output, employment, and investment were all found to decline below their trend levels in the middle and end stages of capital surges.

Teimouri and Zietz (2018) investigate the dynamic response to surges of net capital inflows of key macroeconomic variables, including the employment and output share of manufacturing, for 45 high-income and middle-income countries spanning 1970–2010. The authors define “net capital inflows” as gross capital inflows (relative to trend GDP) minus gross capital outflows (relative to trend GDP).<sup>15</sup> Using the local projection method (Jorda, 2005), their analysis shows that in middle-income countries, manufacturing's share in output and employment both decline for several years following a capital surge. For Latin American middle-income economies, the manufacturing sector's share in output experiences an immediate and persistent decline after a surge, while for Asian middle-income economies, the decline occurs in the medium and long run. Surges in middle-income countries also tend to be followed by lower investment-GDP ratio and higher unemployment.

Another strand of the literature focuses on the long-run effect of surges or flows of aggregate or specific types of capital on the manufacturing sector's employment or output share in the context of its inverted-U relationship with income per capita.

Gui-Diby and Renard (2015) examine the relationship between inward FDI and industrialization (measured as manufacturing's output share) in Africa. Using a panel of 47 African countries spanning 1980–2009, the authors find no significant association between aggregate FDI flows and industrialization in Africa.

Botta et al. (2022) empirically examine the long-run relationship between surges of *non-FDI* capital inflows and sectoral allocation on a panel 36 developed and developing countries covering 1980–2017.<sup>16</sup> The authors estimate the effect of financial boom episodes on manufacturing using the model specification of Rodrik (2016), which is based on the inverted-U relationship between manufacturing share and income. Using pooled OLS estimation that accounts for cross-sectional dependence between countries, the authors find that for the subsample of developing countries, financial booms have a negative effect on manufacturing's share in employment and nominal value-added.

Finally, Özçelik and Özmen (2023) analyze the effect of trade openness and financial openness (measured as gross financial assets and liabilities over GDP) on the output share of manufacturing for a sample of 80 advanced, emerging, and developing economies spanning 1970–2011. They find that financial openness has had a positive effect on the output share of manufacturing in emerging and developing economies and in Africa, but a negative effect in East Asia and Latin America. The authors argue that financial openness enables the financing of manufacturing investments in developing and African economies which suffer from greater domestic financial constraints, but enhances deindustrialization in regions such as East Asia and Latin America with a relatively larger industrial base.

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<sup>15</sup> Episodes of large capital inflows are identified as those wherein net capital inflows are (1) in the top 30th percentile of the country's own distribution and (2) in the top 30th percentile of the entire sample's distribution. The authors identified 309 surge episodes in their data.

<sup>16</sup> Capital inflow surge episodes are identified as those wherein net non-FDI inflows are (1) non-zero or non-negative; (2) positive for three consecutive years; and (3) higher than the country average by 10% of the standard deviation. Using this definition, 60 boom episodes were identified in the sample.

## 4 Methodology and data

To estimate the effect of net capital inflows on industrialization, we closely follow the empirical model used by Botta et al. (2022). The model specification we adopt embeds capital inflows within the long-run inverted-U-shaped path of manufacturing shares with respect to income per capita.

Our baseline specification is stated in the following static panel regression equation:

$$m_{it} = \alpha + \beta cap_{it} + \lambda_1 y_{it} + \lambda_2 y_{it}^2 + \lambda_3 pop_{it} + \lambda_4 pop_{it}^2 + \lambda_5 reer_{it} + \lambda_6 trade_{it} + \lambda_7 rent_{it} + \tau_t + c_i + \varepsilon_{it} \quad (1)$$

where the subscripts  $i$  and  $t$  represent country and time dimensions, respectively; and the dependent variable,  $m$ , stands for either the share of manufacturing in total employment ( $memp$ ), or the share of manufacturing in total real value-added ( $mva$ ). Manufacturing shares are constructed using data from the Economic Transformation Database of the Groningen Growth and Development Centre (or GGDC of the University of Groningen) (Kruse et al., 2023). The parameter  $\alpha$ , meanwhile, is a constant term.

The explanatory variable of interest is  $cap$ , which stands for net capital inflows (as a percentage of GDP), defined as the summed net inflows of foreign direct investment, portfolio investment, and other investment. Alternative specifications of the model use the individual components of net capital inflows in order to disentangle the effects of different types of capital flows on the share of manufacturing. We exclude net inflows of financial derivatives in the calculation of aggregate net capital inflows because such flows only began to appear in the ASEAN-4 in the 2000s. Moreover, inflows of financial derivatives have only been substantial for one country in the region (i.e., Thailand) while being relatively small for other countries individually as well as for the region as a whole. Data on net capital inflows and nominal GDP are obtained from the International Monetary Fund's Balance of Payments database and World Economic Outlook database, respectively.

The other explanatory variables are as follows:

- $y$  and  $y^2$  are, respectively, the natural logarithm of real income per capita (in 2011 US dollars) and its square. These variables are meant to capture the inverted-U relationship between income per capita and the share of manufacturing in employment and GDP. Thus, the coefficients on  $y$  and  $y^2$  are expected to be positive and negative, respectively. This is the case in the estimations performed by Botta et al. (2022), Felipe et al. (2019), Kruse et al. (2023) and Rodrik (2016) using a larger set of counties. However, such expectations may not be borne by the data for ASEAN-4 economies. As shown in Section 2, the hump-shaped relationship between income per capita and manufacturing employment share is present only in Malaysia during the sample period (1980–2018). The downward-sloping phase had yet to occur by 2018 for Thailand and Indonesia, while the Philippines had already passed the upward-sloping phase by 1980 and has only shown downward movement since. Income data are obtained from the Maddison Project Database (Bolt & Van Zanden, 2024).
- $pop$  and  $pop^2$  are, respectively, the natural logarithm of population and its square. At least in the literature reviewed, no theoretical grounds are presented to explain the relationship between population and manufacturing share.<sup>17</sup> Intuitively, since population and per capita incomes are positively correlated, a hump-shaped relationship between population and manufacturing share might be expected. But in estimations performed by Botta et al. (2022),

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<sup>17</sup> One possibility is that a larger population could support a larger domestic manufacturing sector due to economies of scale, implying a positive relationship. But opportunities for export-oriented manufacturing means that a small population need not necessarily constrain the expansion of manufacturing.

Kruse et al. (2023), and Rodrik (2016), this is not necessarily the case: coefficients on  $pop$  and  $pop^2$  imply either a concave (inverted-U) or convex (U- or J-shaped) relationship depending on the sample, timeframe, or dependent variable. Thus, we do not have prior expectations about the direction of these variables' coefficients. Population data are obtained from the Maddison Project Database (Bolt & Van Zanden, 2024).

- $reer$  is the natural logarithm of the real effective exchange rate (REER). The REER is expected to have a negative relationship with manufacturing share, as a higher exchange rate reduces the price competitiveness of manufactured exports vis-à-vis those of other countries, and raises the relative price of tradables compared to non-tradables, thus encouraging greater resource allocation towards (and the expansion of) the latter sector (i.e., the Dutch disease effect). Empirical support for this relationship is found, for instance, in Rodrik (2008), which shows real exchange rate undervaluation to be positively associated with a larger share of industry in GDP and employment. Data for REER are obtained from Bruegel (Darvas, 2021).
- $trade$  represents a country's de facto trade openness, measured as the sum of exports and imports as a percentage of GDP. There is no a priori assumption about the relationship between trade openness and the share of manufacturing. In Botta et al. (2022), for instance, a positive and statistically significant association between trade openness and manufacturing shares is found for their full sample of countries and its subset of developed countries, but not for the subsample of emerging and developing economies. However, given the significant role that export-oriented manufacturing production has played in the economic development of major Southeast Asian economies, a positive relationship between trade openness and manufacturing share could be expected from our sample. Data are obtained from the World Bank's World Development Indicators.
- $rent$  stands for natural resource rents as a percentage of GDP. This variable is included to capture the effect of natural resource abundance and the importance of natural resource extraction in the economy. Large natural resource rents can encourage patterns of resource allocation that favor resource extraction over manufacturing development. Moreover, foreign exchange inflows from natural resource exports induce currency appreciation and, in turn, Dutch disease effects. Thus, we expect natural resource rents to be negatively associated with the size of manufacturing in the economy. Data are obtained from the World Bank's World Development Indicators.

Finally,  $\tau_t$  are time fixed effects meant to capture country-invariant, time-specific effects;  $c_i$  are country fixed effects intended to account for time-invariant, country-specific effects such as geography, resource endowments, institutions, and history that uniquely impact each country's level of industrial development (Kruse et al., 2023); and  $\varepsilon_{it}$  is the idiosyncratic error term.

We use annual panel data for the ASEAN-4 economies covering 1980 to 2018. The length of the sample period is determined by the coverage of the main data sources (capital flows data from the IMF commonly start in 1980, while manufacturing shares data from the GGDC end in 2018).

We perform tests to help diagnose whether the residuals obtained from the regression of equation (1) suffer from autocorrelation, heteroskedasticity, and cross-sectional dependence. The results of these tests are shown in the Appendix (Table A3). When the model is estimated with manufacturing employment share as the dependent variable, the tests find evidence for first-order serial correlation, but not for groupwise heteroskedasticity or cross-sectional dependence. Using manufacturing real-value-added as the dependent variable, the tests find evidence for serial correlation, heteroskedasticity, and cross-sectional dependence.

Given these diagnostic results, we use pooled OLS and fixed effects estimation with Driscoll and Kraay standard errors (using the user-written `xtscc` command in Stata), which allow for heteroskedasticity, autocorrelated errors of the general form (up to  $m$  lags), and error correlation across panels (Cameron & Trivedi, 2022; Hoechle, 2007).

As noted in Section 3, capital inflows may be endogenous due to reverse causality (i.e., an economy attracts capital inflows or certain types of it because of its industrial structure). To address the potential endogeneity of capital inflows, we pursue two-stage least squares (2SLS) estimation with Driscoll and Kraay standard errors. We closely follow the instrumentation strategy used by Blanchard et al. (2017). In estimating the effects of bond and non-bond capital inflows on credit growth and GDP growth in emerging economies, they instrument for capital inflows to a specific country using capital inflows received by other countries. Capital inflows to other countries are arguably relevant because they are correlated with capital inflows to a specific country due to the “global financial cycle”, which is driven, for instance, by monetary policies in advanced economies or shifts in market sentiment (Blanchard et al., 2017). Meanwhile, capital inflows to other countries are arguably exogenous because they are unlikely to influence or be correlated with economic developments (including structural change) in any particular country.

In our study, we use regional capital inflows as instrumental variables. For each country in our sample, regional capital inflows are defined as the sum of net capital inflows to the three other ASEAN-4 countries, scaled by the combined GDPs of those countries. Instruments for inflows of FDI, portfolio investment, and other investment are constructed in a similar manner. Since the effects of regional capital flows to each particular country varies, we interact the regional capital flow variables with country-specific dummies, as done by Blanchard et al. (2017). Letting  $rcap_{it}$  be regional capital inflows constructed for each country  $i$ , and  $D_{it}$  be country dummy variables, the set of instrumentals for estimating equation (1) is:

$$D_{IDN}rcap_{IDN,t}, D_{MYS}rcap_{MYS,t}, D_{PHL}rcap_{PHL,t}, D_{THA}rcap_{THA,t}$$

$$i = IDN, MYS, PHL, THA$$

As the number of endogenous variables (capital flow types) included in the model increases, the number of instruments also increase by a multiple of four.

## 5 Results

We estimate four specifications of equation (1) using different disaggregations of net capital inflows. Model (1), the baseline model, uses aggregate net capital inflows. In model (2), these inflows are broken down into FDI and non-FDI inflows. Model (3) retains FDI inflows and disaggregates non-FDI inflows into portfolio investment and other investment inflows. Finally, model (4) retains FDI and other investment inflows while splitting portfolio investment into portfolio equity and portfolio debt. We estimate each specification using four methods: pooled OLS, pooled 2SLS, fixed effects (FE), and FE-2SLS. All specifications are run with year dummies.

The estimated effects of net capital inflows on manufacturing employment share ( $memp$ ) and in manufacturing real value-added share ( $mva$ ) are presented in Tables 5.1 and 5.2, respectively. Both tables are organized into two sections. Section A presents results from pooled OLS and 2SLS regressions, corresponding to columns 1.1–1.4 and 2.1–2.4, respectively. Meanwhile, Section B presents results from FE and FE-2SLS regressions, corresponding to columns 3.1–3.4 and 4.1–4.4, respectively. Suffixes of the column numbers correspond to our four regression models.

**Table 5.1. Effect of net capital inflows on manufacturing employment share**

**A. Pooled OLS and 2SLS**

VARIABLES	OLS				2SLS			
	(1.1)	(1.2)	(1.3)	(1.4)	(2.1)	(2.2)	(2.3)	(2.4)
Net capital inflows	-0.082** (0.039)				-0.088** (0.038)			
FDI/GDP		0.107 (0.138)	0.136 (0.132)	0.165 (0.114)		0.069 (0.143)	0.091 (0.140)	0.114 (0.116)
Non-FDI/GDP		-0.096** (0.039)				-0.103** (0.040)		
Portfolio investment/GDP			-0.201** (0.075)				-0.154** (0.070)	
Portfolio equity/GDP				-0.032 (0.197)				-0.005 (0.222)
Portfolio debt/GDP				-0.260* (0.131)				-0.235 (0.149)
Other investment/GDP			-0.047 (0.053)	-0.042 (0.057)			-0.072 (0.053)	-0.064 (0.056)
log(GDP per capita)	-15.351 (13.269)	-17.710 (13.918)	-18.195 (14.420)	-18.100 (16.024)	-15.449 (13.224)	-17.534 (13.662)	-17.698 (13.923)	-17.737 (15.636)
log(GDP per capita) squared	1.030 (0.738)	1.154 (0.771)	1.189 (0.802)	1.174 (0.882)	1.035 (0.736)	1.145 (0.756)	1.159 (0.773)	1.153 (0.860)
log(population)	-60.541*** (13.510)	-59.984*** (13.722)	-60.579*** (12.629)	-58.528*** (14.283)	-60.830*** (13.636)	-60.592*** (14.074)	-60.609*** (13.605)	-58.922*** (15.438)
log(population) squared	2.748*** (0.584)	2.731*** (0.597)	2.754*** (0.548)	2.666*** (0.624)	2.760*** (0.590)	2.756*** (0.610)	2.755*** (0.589)	2.682*** (0.674)
log(REER)	-3.095 (3.025)	-3.436 (2.717)	-3.268 (2.731)	-4.043 (2.437)	-3.067 (3.038)	-3.334 (2.839)	-3.275 (2.862)	-3.980 (2.512)
Trade/GDP	0.068*** (0.013)	0.068*** (0.012)	0.064*** (0.014)	0.065*** (0.014)	0.068*** (0.013)	0.068*** (0.012)	0.066*** (0.013)	0.066*** (0.014)
Resource rents/GDP	-0.256*** (0.080)	-0.259*** (0.075)	-0.257*** (0.073)	-0.237*** (0.080)	-0.258*** (0.080)	-0.262*** (0.077)	-0.259*** (0.077)	-0.239*** (0.083)
Observations	154	154	154	148	154	154	154	148
R-squared	0.927	0.930	0.932	0.925	0.913	0.916	0.918	0.907
Country FE	NO							
Year dummies	YES							
Underid test p-val					0.069	0.251	0.512	0.742
Weak id F-stat					227.201	42.617	53.404	64.901
Overid p-val					0.132	0.170	0.426	0.735
Endog test p-val					0.467	0.904	0.998	0.917

## B. Fixed effects and FE-2SLS

VARIABLES	Fixed effects				FE-2SLS			
	(3.1)	(3.2)	(3.3)	(3.4)	(4.1)	(4.2)	(4.3)	(4.4)
Net capital inflows	-0.078** (0.034)				-0.093** (0.037)			
FDI/GDP		0.015 (0.133)	0.050 (0.120)	0.067 (0.102)		-0.047 (0.151)	-0.022 (0.145)	-0.015 (0.117)
Non-FDI/GDP		-0.083** (0.032)				-0.101*** (0.036)		
Portfolio investment/GDP			-0.194*** (0.063)				-0.168*** (0.058)	
Portfolio equity/GDP				-0.022 (0.121)				0.012 (0.131)
Portfolio debt/GDP				-0.262*** (0.094)				-0.263** (0.100)
Other investment/GDP			-0.029 (0.045)	-0.024 (0.046)			-0.061 (0.048)	-0.051 (0.047)
log(GDP per capita)	-15.129 (26.097)	-13.475 (24.424)	-11.141 (24.002)	-13.879 (24.675)	-18.310 (26.259)	-18.432 (25.084)	-15.915 (24.882)	-19.039 (25.106)
log(GDP per capita) squared	1.245 (1.511)	1.139 (1.408)	1.001 (1.378)	1.128 (1.409)	1.429 (1.522)	1.431 (1.449)	1.283 (1.434)	1.431 (1.435)
log(population)	-74.215*** (24.157)	-70.500*** (21.421)	-67.795*** (20.843)	-69.412*** (21.923)	-78.269*** (24.321)	-77.549*** (22.570)	-74.558*** (22.364)	-77.155*** (22.569)
log(population) squared	2.903** (1.328)	2.729** (1.185)	2.558** (1.127)	2.635** (1.152)	3.109** (1.338)	3.080** (1.242)	2.906** (1.214)	3.024** (1.196)
log(REER)	-0.700 (1.800)	-0.942 (1.763)	-0.791 (1.732)	-1.518 (1.600)	-0.602 (1.786)	-0.702 (1.865)	-0.630 (1.862)	-1.329 (1.649)
Trade/GDP	0.063*** (0.013)	0.063*** (0.012)	0.057*** (0.011)	0.058*** (0.010)	0.064*** (0.013)	0.064*** (0.013)	0.060*** (0.012)	0.061*** (0.010)
Resource rents/GDP	-0.300*** (0.067)	-0.303*** (0.063)	-0.309*** (0.058)	-0.296*** (0.061)	-0.300*** (0.067)	-0.302*** (0.063)	-0.305*** (0.060)	-0.294*** (0.062)
Observations	154	154	154	148	154	154	154	148
R-squared	0.828	0.831	0.842	0.840	0.827	0.829	0.839	0.837
Country FE	YES							
Year dum	YES							
Hausman p-val	0.000	0.000	0.000	0.000				
Underid test p-val					0.072	0.252	0.542	0.743
Weak id F-stat					177.296	39.330	57.798	54.562
Overid p-val					0.314	0.410	0.594	0.777
Endog test p-val					0.360	0.778	0.821	0.891

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Driscoll-Kraay standard errors in parentheses. Underidentification test null: equation is identified (instruments are relevant). Overidentification test joint null: instruments are valid (i.e., uncorrelated with the error term) and excluded instruments are correctly excluded from the estimated equation. Endogeneity test null: endogenous regressors can be treated as exogenous. Source: Authors' calculations.

**Table 5.2. Effects of net capital inflows on manufacturing real value-added share**

**A. Pooled OLS and 2SLS**

VARIABLES	OLS				2SLS			
	(1.1)	(1.2)	(1.3)	(1.4)	(2.1)	(2.2)	(2.3)	(2.4)
Net capital inflows	-0.015 (0.042)				-0.039 (0.041)			
FDI/GDP		0.331** (0.148)	0.333** (0.156)	0.332** (0.143)		0.328** (0.130)	0.326** (0.143)	0.335** (0.125)
Non-FDI/GDP		-0.039 (0.043)				-0.062 (0.041)		
Portfolio investment/GDP			-0.046 (0.078)				0.002 (0.077)	
Portfolio equity/GDP				0.023 (0.193)				0.078 (0.204)
Portfolio debt/GDP				-0.094 (0.125)				-0.082 (0.134)
Other investment/GDP			-0.036 (0.060)	-0.029 (0.069)			-0.071 (0.059)	-0.058 (0.069)
log(GDP per capita)	14.184 (18.979)	9.866 (19.491)	9.834 (19.616)	14.017 (20.717)	13.735 (19.083)	9.233 (19.296)	9.751 (19.170)	13.595 (20.497)
log(GDP per capita) squared	-0.475 (1.048)	-0.248 (1.081)	-0.246 (1.089)	-0.477 (1.139)	-0.449 (1.053)	-0.213 (1.070)	-0.246 (1.062)	-0.458 (1.125)
log(population)	61.280*** (12.840)	62.299*** (13.010)	62.259*** (13.044)	61.407*** (13.125)	59.951*** (12.736)	61.145*** (12.999)	62.210*** (13.336)	61.066*** (13.787)
log(population) squared	-2.645*** (0.531)	-2.675*** (0.541)	-2.673*** (0.543)	-2.626*** (0.547)	-2.587*** (0.527)	-2.624*** (0.541)	-2.669*** (0.557)	-2.609*** (0.578)
log(REER)	-9.106** (3.614)	-9.731*** (2.897)	-9.720*** (2.890)	-10.095*** (2.811)	-8.978** (3.594)	-9.647*** (2.918)	-9.800*** (2.905)	-10.219*** (2.734)
Trade/GDP	0.016 (0.021)	0.017 (0.019)	0.016 (0.020)	0.021 (0.020)	0.016 (0.021)	0.016 (0.019)	0.019 (0.019)	0.022 (0.019)
Resource rents/GDP	-0.077 (0.060)	-0.083 (0.053)	-0.082 (0.054)	-0.086 (0.056)	-0.084 (0.060)	-0.090 (0.053)	-0.086 (0.055)	-0.088 (0.057)
Observations	154	154	154	148	154	154	154	148
R-squared	0.879	0.888	0.888	0.893	0.812	0.826	0.826	0.835
Country FE	NO							
Year dummies	YES							
Underid test p-val					0.069	0.251	0.512	0.742
Weak id F-stat					227.201	42.617	53.404	64.901
Overid p-val					0.356	0.233	0.469	0.647
Endog test p-val					0.435	0.794	0.814	0.997

## B. Fixed effects and FE-2SLS

VARIABLES	FE				FE-2SLS			
	(3.1)	(3.2)	(3.3)	(3.4)	(4.1)	(4.2)	(4.3)	(4.4)
Net capital inflows	-0.009 (0.028)				-0.039 (0.028)			
FDI/GDP		0.202** (0.095)	0.215** (0.092)	0.207** (0.090)		0.161 (0.113)	0.164 (0.111)	0.165 (0.100)
Non-FDI/GDP		-0.020 (0.034)				-0.051 (0.033)		
Portfolio investment/GDP			-0.059 (0.071)				-0.034 (0.072)	
Portfolio equity/GDP				0.068 (0.140)				0.139 (0.124)
Portfolio debt/GDP				-0.122 (0.089)				-0.152* (0.089)
Other investment/GDP			-0.001 (0.040)	0.006 (0.045)			-0.040 (0.039)	-0.024 (0.045)
log(GDP per capita)	8.279 (29.311)	12.014 (26.727)	12.840 (25.998)	17.838 (28.486)	1.900 (28.866)	5.091 (26.131)	7.593 (26.609)	12.148 (28.817)
log(GDP per capita) squared	-0.054 (1.741)	-0.292 (1.568)	-0.341 (1.526)	-0.615 (1.655)	0.315 (1.712)	0.110 (1.531)	-0.034 (1.559)	-0.292 (1.673)
log(population)	38.876 (29.300)	47.266* (26.530)	48.223* (25.800)	49.450* (28.530)	30.747 (28.644)	38.278 (25.842)	41.334 (25.997)	41.744 (28.892)
log(population) squared	-2.587 (1.605)	-2.980** (1.429)	-3.041** (1.391)	-3.083** (1.513)	-2.174 (1.578)	-2.525* (1.400)	-2.680* (1.400)	-2.694* (1.534)
log(REER)	-6.027*** (1.843)	-6.572*** (1.523)	-6.519*** (1.503)	-6.981*** (1.473)	-5.830*** (1.819)	-6.339*** (1.586)	-6.407*** (1.579)	-7.002*** (1.442)
Trade/GDP	0.002 (0.015)	0.000 (0.013)	-0.002 (0.013)	0.002 (0.013)	0.003 (0.015)	0.002 (0.013)	0.002 (0.012)	0.005 (0.014)
Resource rents/GDP	-0.215*** (0.079)	-0.223*** (0.066)	-0.225*** (0.065)	-0.223*** (0.057)	-0.216*** (0.077)	-0.223*** (0.065)	-0.223*** (0.067)	-0.222*** (0.055)
Observations	154	154	154	148	154	154	154	148
R-squared	0.844	0.854	0.855	0.865	0.843	0.853	0.853	0.864
Country FE	YES							
Year dum	YES							
Hausman p-val	0.000	0.000	0.000	0.000				
Underid test p-val					0.072	0.252	0.542	0.743
Weak id F-stat					177.296	39.330	57.798	54.562
Overid p-val					0.842	0.573	0.705	0.767
Endog test p-val					0.028	0.349	0.607	0.935

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Driscoll-Kraay standard errors in parentheses. Hausman test null: panel effects are not correlated with regressors. Underidentification test null: equation is identified (instruments are relevant). Overidentification test joint null: instruments are valid (i.e., uncorrelated with the error term) and excluded instruments are correctly excluded from the estimated equation. Endogeneity test null: endogenous regressors can be treated as exogenous. Source: Authors' calculations.

## 5.1 Instrument validity

Before discussing the results, we reflect on the validity of using 2SLS and FE-2SLS over the standard OLS and FE estimators. Results of statistical tests on instrument validity and regressor endogeneity are reported at the bottom rows of Tables 5.1 and 5.2.

Test results corresponding to our 2SLS estimations (Columns 2.1–2.4 of Tables 5.1 and 5.2) indicate that across four models, our instruments cannot be considered weak (based on the weak identification test),<sup>20</sup> and are exogenous and correctly excluded from the estimated equation (based on the overidentification test).<sup>21</sup> However, only in model 1 are the instruments found to be relevant or correlated with the endogenous regressor (based on the underidentification test).<sup>22</sup> Moreover, the regressor endogeneity test indicates that net capital inflows (whether aggregated or disaggregated) can in fact be treated as exogenous.<sup>23</sup>

Similar information about our instruments and endogenous regressors are obtained from running the corresponding tests for FE-2SLS (Columns 4.1–4.4 of Tables 5.1 and 5.2). The only exception is the FE-2SLS estimation of model 1 with *mva* as the dependent variable (Column 4.1 of Table 5.2). In this lone case, the instruments are found to be relevant (at the 10% level), not weak, exogenous and correctly excluded, and capital inflows could not be treated as exogenous (at the 10% level)—results which justify the use of instrumental variables.

Thus, taking the results of the endogeneity tests on their own (i.e., almost uniform non-rejection of the null that our endogenous variable can be treated as exogenous), it appears that we should prefer standard OLS and FE estimators over their 2SLS counterparts, except in the singular case discussed above. Nevertheless, we report the results obtained from the 2SLS and FE-2SLS estimations along with those from standard OLS and FE.

## 5.2 Effects of net capital inflows on manufacturing

Table 5.1 presents the results of our estimations with *memp* as the dependent variable across our four models and four estimation methods. For greater clarity, we visualize the estimated effects of capital inflows in Figures 5.1 and 5.2.

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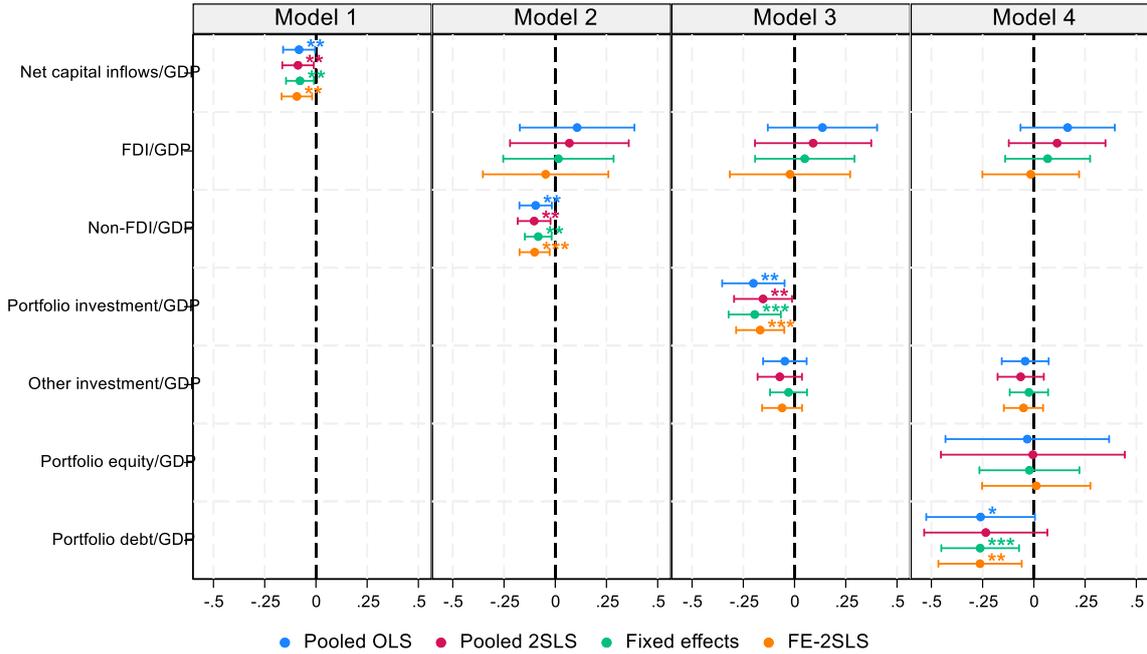
<sup>20</sup> Our weak identification tests report Kleibergen-Paap Wald  $rk F$  statistic which are robust to violations of errors being i.i.d. (Baum, 2000a, 2000b).

<sup>21</sup> The Sargan-Hansen test of overidentifying restriction has the joint null that (1) the instruments are exogenous or uncorrelated with the error term, and (2) the instruments are correctly excluded from the estimated equation (Baum, 2000a, 2000b).

<sup>22</sup> The underidentification test is a Lagrange multiplier (LM) test of whether the equation is identified, i.e., the excluded regressors are relevant or correlated with the endogenous regressors (Baum, 2000a, 2000b).

<sup>23</sup> The endogeneity test has the null that the endogenous regressor can be treated as exogenous (Baum, 2000a, 2000b).

**Figure 5.1. Effects of net capital inflows on manufacturing employment share**



Note: Markers and capped bars represent coefficient point estimates and 95% confidence intervals, respectively. Asterisks denote significance levels (\*\*\*)  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ ). Source: Authors' illustration.

In the baseline model, we find that aggregate net capital inflows have a statistically significant negative association with *memp*. This holds true across all estimation methods. Our point estimates are relatively small, ranging from  $-0.078$  to  $-0.093$ . This means that a 1-percentage-point increase in net capital inflows (% of GDP) is associated with a decrease in the employment share of manufacturing of about 0.08–0.09 percentage points.

Disaggregating capital inflows uncovers the types of flows driving the negative estimates. In models 2 through 4, FDI inflows are found to have positive influence on *memp* across all methods (except FE-2SLS), but none of its estimated effects are statistically significant. By contrast, in model 2, non-FDI inflows (in aggregate) are estimated to have a statistically significant (albeit small) negative influence, with point estimates ranging from  $-0.083$  to  $-0.103$ .

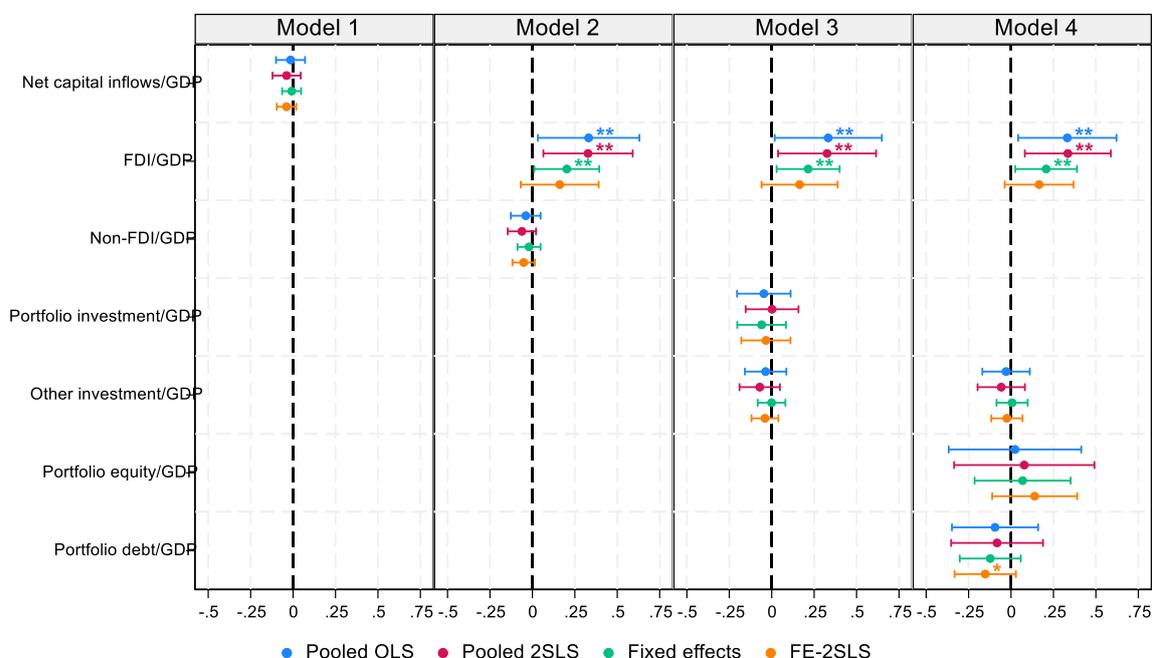
Further disaggregating non-FDI flows in model 3 reveals that the negative influence of non-FDI flows on *memp* stem particularly from the effects of portfolio investment. Our point estimates for portfolio investment inflows (which are statistically significant across all estimation methods) are in the range of  $-0.154$  to  $-0.201$ . These imply a reduction in the share of manufacturing employment of about 0.15–0.2 percentage points for every percentage-point increase in net portfolio investment inflows (% of GDP). On the other hand, the estimated effects of other investment flows, while also consistently negative, are statistically insignificant across estimation methods.

Within portfolio investment, the negative effects on *memp* appear to emanate specifically from portfolio debt inflows. In model 4, our point estimates for portfolio debt (all statistically significant at least at  $\alpha = 10\%$  except for pooled 2SLS) are close to  $-0.26$ . This implies that a percentage point increase in net portfolio debt inflows (% of GDP) is associated with about a quarter of a percentage point decline in *memp*. Meanwhile, we find inflows of portfolio equity to have no statistically

significant effects on *memp* across estimation methods, although all point estimates appear to be centered around zero or close to it.

The results of our estimations with *mva* as the dependent variable are reported Table 5.2, with the coefficient estimates for capital flows visualized in Figure 5.2.

**Figure 5.2. Effects of net capital inflows on manufacturing real value-added**



Note: Markers and capped bars represent coefficient point estimates and 95% confidence intervals, respectively. Asterisks denote significance levels (\*\*\*)  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ ). Source: Authors' illustration.

We observe a striking similarity in the sign or direction (but not statistical significance) of our point estimates for net capital inflows in the *mva* regressions with those from the *memp* regressions. Inspecting the signs of the point estimates alone, we find our estimates in the *mva* regressions to be positive across all estimation methods for FDI; negative across all estimation methods for net capital inflows, non-FDI, and portfolio debt; and negative for most estimation methods for other investment.

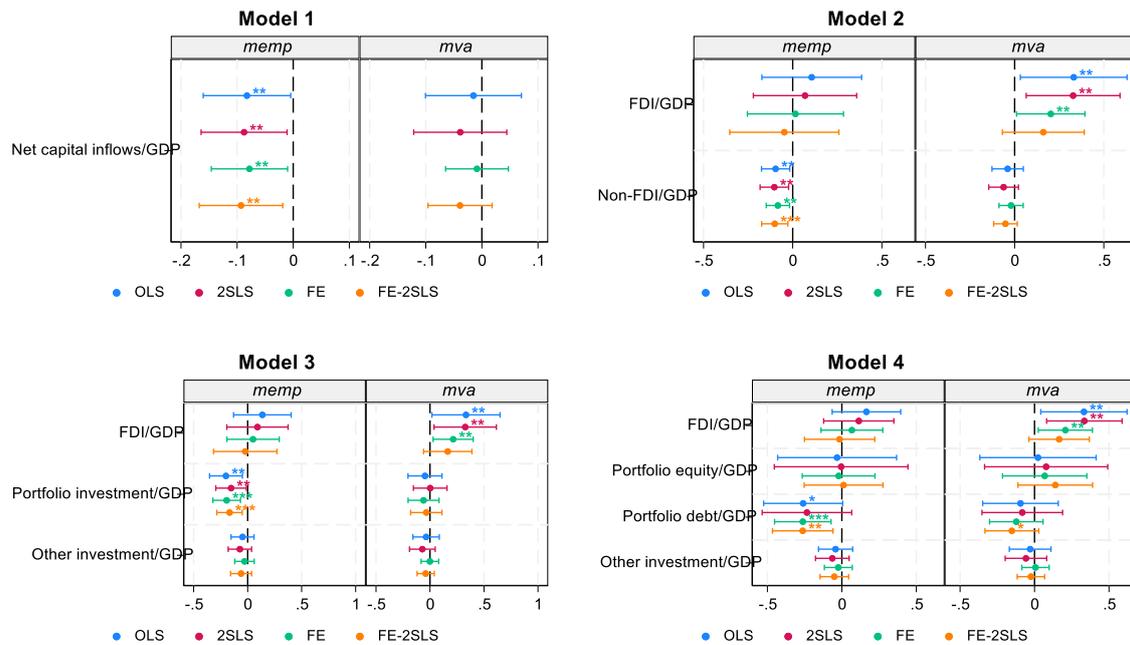
Indeed, in visualizing the coefficient estimates for capital inflows from the *memp* and *mva* regressions side by side (Figure 5.3), we find the difference between the two to be mainly one of magnitude. Estimates for our capital inflow variables when regressed on *mva* consistently appear to be slightly less negative, or more positive, than the corresponding estimates for capital inflows when regressed on *memp* (which is equivalent to saying that estimates for *mva* lie to the right of those for *memp*). Since our point estimates are all quite close to zero (within +/-1 percentage point), the implication is that estimates for some capital flows lose statistical significance while others gain significance as we move from *memp* to *mva*.

In particular, across all estimation methods, capital inflows, non-FDI, portfolio investment, and portfolio debt are estimated to have no statistically significant influence on *mva*.<sup>24</sup> Only FDI inflows are found to have a statistically significant positive effect on *mva* across all relevant models and

<sup>24</sup> Except for the FE-2SLS estimation of model 4, wherein portfolio debt remains statistically significant albeit at a lower level.

estimation methods (except FE-2SLS), with point estimates ranging from 0.202 to 0.335. This implies that a percentage-point increase in net FDI inflows (% of GDP) is associated with about a 0.2–0.3 percentage points increase in *mva*. Meanwhile, portfolio equity inflows continue to have no statistically significant effect on *mva* (similar to its estimated influence on *memp*), although point estimates for the variable are now all positive.

**Figure 5.3. Effects of capital inflows, *memp* vs. *mva***

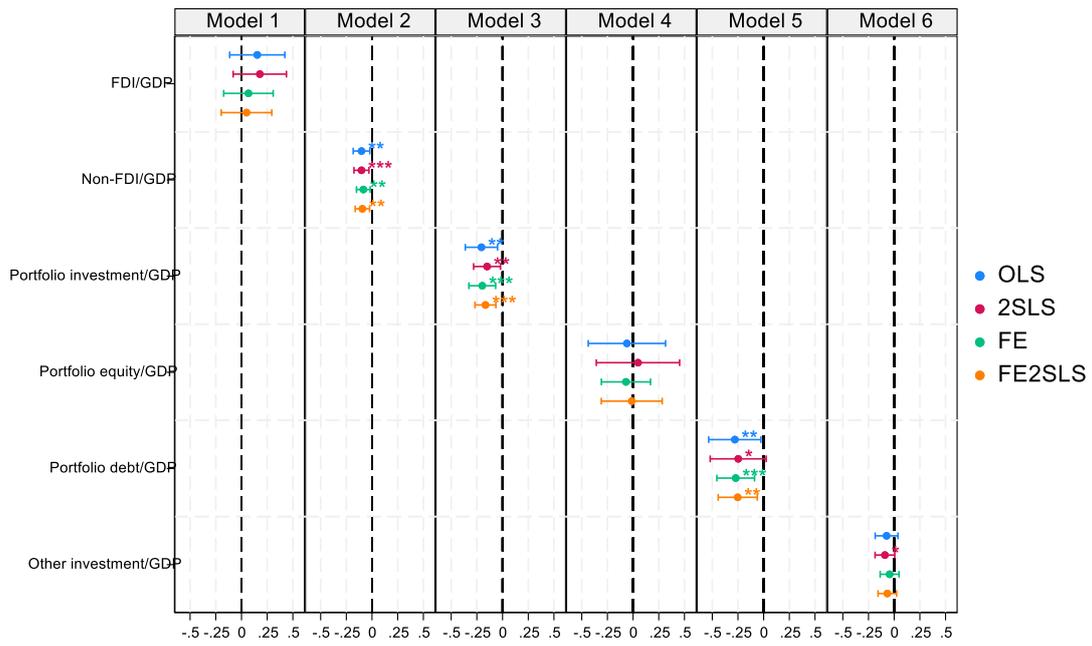


Note: Markers and capped bars represent coefficient point estimates and 95% confidence intervals, respectively. Asterisks denote significance levels (\*\*\*)  $p < 0.01$ , (\*\*)  $p < 0.05$ , (\*)  $p < 0.1$ ). Source: Authors' illustration.

To check for robustness, we perform the regressions with just one type of capital flow in each model. The full regression tables are in the Appendix (Tables A4 and A5), but the main coefficient estimates are visualized in Figures 5.4 and 5.5.

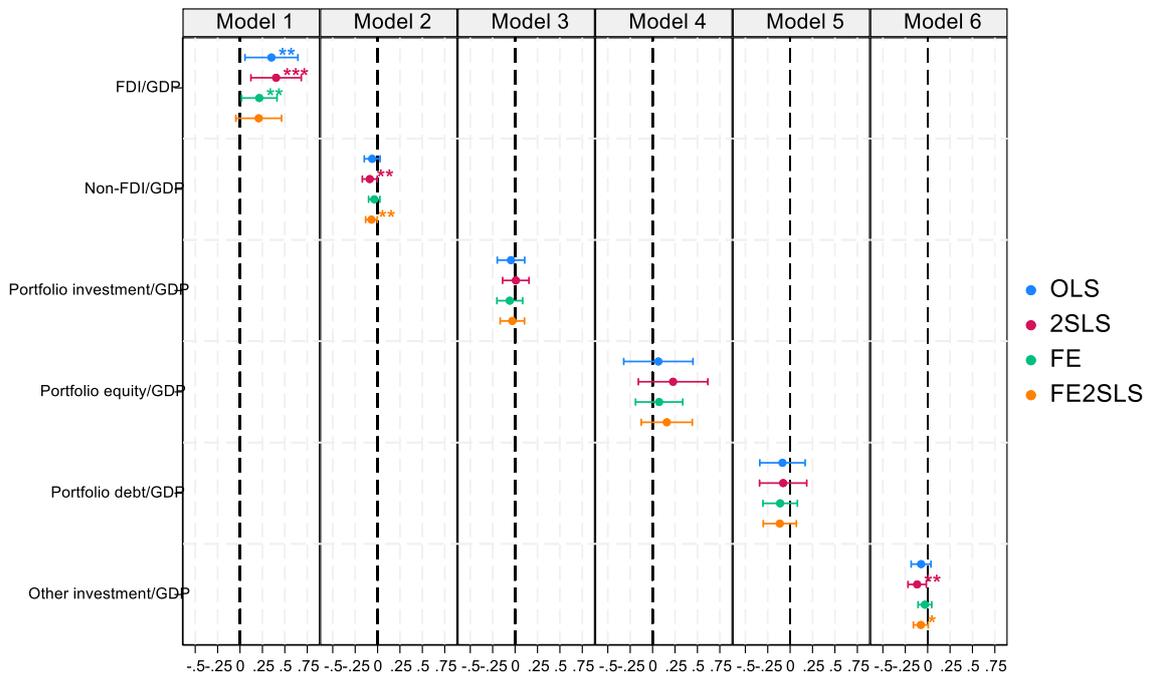
The effects capital flows on the share of manufacturing, when estimated separately, are very similar to those in the main regressions. In the *memp* regressions, non-FDI inflows, portfolio investment, and portfolio debt are each estimated to have a statistically significant negative effect on the employment share of manufacturing across estimation methods. Meanwhile, in the *mva* regressions, FDI is estimated to have a positive effect on the output share of manufacturing. The alternative regressions detect a statistically negative effect of non-FDI flows and other investment flows on *mva* when using instruments, which were otherwise absent in the main regressions (although the point estimates are directionally similar).

**Figure 5.4. Effects of net capital inflows on manufacturing employment share**



Note: Markers and capped bars represent coefficient point estimates and 95% confidence intervals, respectively. Asterisks denote significance levels (\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ ). Source: Authors' illustration.

**Figure 5.5. Effects of net capital inflows on manufacturing real value-added share**



Note: Markers and capped bars represent coefficient point estimates and 95% confidence intervals, respectively. Asterisks denote significance levels (\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ ). Source: Authors' illustration.

### 5.3 Effects of explanatory variables

Our point estimates for per capita income conform with the expected signs in the *mva* regressions (positive for  $y$  and negative for  $y^2$ ) but not in the *memp* regressions (negative for  $y$  and positive for  $y^2$ ). In both *memp* and *mva* regressions, estimates for  $y$  and  $y^2$  are statistically insignificant across all models and estimation methods. The large standard errors indicate substantial variation in the data. The counterintuitive signs for  $y$  and  $y^2$  in the *memp* regressions could simply stem from the fact that in the ASEAN-4, only Malaysia exhibits the inverted-U relationship between the two variables in the years covered by our data, as we conjectured in the previous chapter. Running our model using data that goes back further than 1980 (to capture the rising phase and peak of the inverted-U relationship between *memp* and  $y$  for the Philippines) and ends later than 2018 (to capture the turning point and decline occurring for Indonesia and Thailand) could yield estimates for per capita income in the expected direction.

Estimates for *pop* and  $pop^2$ , which are statistically significant in most regressions, follow the direction of the point estimates for  $y$  and  $y^2$  (i.e., implying a convex relationship with manufacturing share in the *memp* regressions, and a concave relationship in the *mva* regressions). As mentioned in the previous chapter, the literature reviewed provides no strong grounds to expect the influence of population on the share of manufacturing to go in one direction or another.

Finally, the coefficients on *reer*, *trade*, and *rent* follow the expected signs (negative, positive, and negative, respectively) in all estimations based on the reasons provided in the previous section, although these estimates are not uniformly statistically significant.<sup>25</sup>

## 6 Conclusion, discussion, and policy implications

This paper aimed to estimate the effects of net capital inflows on industrialization in ASEAN-4 countries. We contribute to the incipient empirical literature on the consequences of capital inflows on structural transformation. In the current era of financial globalization, this is a particularly relevant question for developing countries, as historical experience has shown industrialization to be tightly intertwined with economic development. Our study is significant for being, to our best knowledge, the first to explore this topic for the ASEAN-4 region. It also stands out in its attempt to disentangle the effects of different types of capital flows on manufacturing share within a single empirical framework, going further than existing studies which consider the effects of aggregate capital flows or just one type of it.

Analyzing panel data from 1980 to 2018 through a variety of estimation methods (pooled OLS, pooled 2SLS, fixed effects, and FE-2SLS), we find evidence that in the aggregate, net capital inflows have a negative (though rather small) influence on the manufacturing share of *employment* in ASEAN-4 countries. Disaggregating capital flows uncovers heterogeneous effects. The negative effects emanate specifically from non-FDI inflows, with FDI inflows being found to have an opposite (albeit statistically insignificant) positive effect. Within non-FDI inflows, the strongest negative forces originate from portfolio investment, and within it, portfolio debt. Net capital inflows and its components have directionally similar effects on the *real value-added* share of manufacturing—the

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<sup>25</sup> *reer* is significant only in the *mva* regressions. *trade* is significant only in the *memp* regressions. *rent* is not significant in the pooled OLS and 2SLS regressions for *mva*.

difference being that among different types of capital flows, only FDI has effects that are found to be statistically significant.

Our findings are consonant with those from recent empirical work on this subject. Similar to Benigno et al. (2015), Taşdemir (2023), and Teimouri and Zietz (2018), we find *aggregate* net capital inflows to be negatively associated with the share of manufacturing in output or employment. And similar to Botta et al. (2022), we find *non-FDI* capital inflows to be negatively associated with the share of manufacturing output and employment. The novelty of our contribution is twofold. First, we are able to pin down the source of these negative associations in ASEAN-4 countries to inflows of portfolio investment, particularly portfolio debt. Second, we are able to uncover the positive effect of FDI inflows on the share of manufacturing in output in the ASEAN-4—an opposite effect that would have otherwise remained hidden if capital flows were considered only in the aggregate.

The estimated positive effect of FDI inflows on manufacturing output is rather unsurprising given the role that FDI has played in (to varying degrees for different countries) promoting export-oriented manufacturing production in Southeast Asia since the 1980s. The inflows of manufacturing FDI into Southeast Asia thus reflect the region's integration into regional/global production networks for manufactured products. FDI's positive effect on manufacturing potentially works through the channel of investment altering the sectoral allocation of production.<sup>26</sup>

What accounts for the negative effects of portfolio investment, specifically portfolio debt, on manufacturing's share particularly in employment? The literature identifies three mechanisms through which portfolio investment (and capital flows in general) can affect structural change: sectoral allocation, Dutch disease effects, and macroeconomic instability. The Dutch disease and macroeconomic instability channels could potentially be empirically tested, but this exercise is outside the scope of this paper.<sup>27</sup> Meanwhile, given the absence of readily available data on the sectoral distribution of portfolio investment, evidence on its sectoral allocation effects can be established through in-depth country studies on the sectors receiving portfolio investment and portfolio debt inflows. These gaps in our analysis provide scope for future research in this area.

Our study offers several policy insights. First, while attention on the development impacts of capital inflows has been mostly focused on economic growth, policymakers must not neglect the effects that these flows have on structural change. As historical experience has shown, structural change and industrialization are integral parts of sustained economic development in almost all countries that are considered development successes. Thus, policymakers must consider not just whether capital inflows are generating economic growth, but also whether these flows are facilitating the long-term reallocation of resources and labor into more productive and more technologically dynamic job-creating sectors such as manufacturing.

Second, our findings suggest that different types of capital flows have different effects on structural transformation, particularly on the share of manufacturing. Some types of flows may promote industrialization (such as FDI in the case of ASEAN-4 economies), while others may have the ultimate effect of diminishing it. For middle-income economies such as ASEAN-4 countries which have achieved respectable levels of industrial development, this implies that certain types of capital

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<sup>26</sup> Manufacturing is not the only recipient of FDI in the ASEAN-4, however. ASEAN countries have received substantial FDI inflows into services sectors such as finance, wholesale and retail trade, transportation, and information and communication (ASEAN Secretariat, 2023). Indonesia, meanwhile, receives substantial FDI in the mining sector (Jomo K. S. et al., 1997). The fact that non-manufacturing FDI is incorporated in the aggregate FDI inflows data we used in our estimations probably contributed to the imprecision (relatively large standard errors) of our estimates for FDI.

<sup>27</sup> The negative coefficient estimates on REER in our regressions, however, appear to indicate the presence of the Dutch disease mechanism.

flows may be contributing to their premature deindustrialization, which, in turn, may ultimately trap them in “middling” income levels. Policymakers must therefore be mindful of the different and potentially conflicting effects that these capital inflows have on their industrialization efforts.

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## Appendix

**Table A1. Mean and standard deviation of net capital inflows in the ASEAN-4 (% of GDP), 1980–2019**

Country		Net capital inflows (% of GDP)	FDI (% of GDP)	Non-FDI (% of GDP)	Portfolio investment (% of GDP)	Other investment (% of GDP)	Financial derivatives (% of GDP)
Indonesia	n	40	39	40	39	40	10
	Mean	2.41	0.96	1.49	0.78	0.74	-0.07
	SD	2.65	1.20	1.93	1.08	1.81	0.03
Malaysia	n	40	40	40	40	40	21
	Mean	5.61	3.63	1.98	0.87	1.12	-0.01
	SD	5.51	1.66	4.84	3.23	3.23	0.36
Philippines	n	40	40	40	40	40	21
	Mean	3.64	1.34	2.39	0.87	1.52	-0.17
	SD	3.33	0.89	3.38	1.43	2.93	0.08
Thailand	n	40	40	40	40	40	27
	Mean	3.93	2.24	2.09	0.86	1.23	-0.59
	SD	5.33	1.44	5.79	1.65	5.20	0.77
ASEAN-4	n	160	159	160	159	160	79
	Mean	3.90	2.05	1.99	0.84	1.15	-0.26
	SD	4.49	1.67	4.21	2.01	3.49	0.54

Source: Authors' calculation.

**Table A2. Pairwise correlation of net capital inflows in ASEAN-4 countries, 1980–2019**

<b>A. Net capital inflows in USD billion</b>				
	Indonesia	Malaysia	Philippines	Thailand
Indonesia	1			
Malaysia	0.5554 (0.0003)	1		
Philippines	0.5739 (0.0002)	0.5259 (0.0006)	1	
Thailand	0.3851 (0.017)	0.4748 (0.0023)	0.5591 (0.0002)	1

<b>B. Net capital inflows relative to GDP</b>				
	Indonesia	Malaysia	Philippines	Thailand
Indonesia	1			
Malaysia	0.3152 (0.0539)	1		
Philippines	0.186 (0.2635)	0.3604 (0.0242)	1	
Thailand	0.5377 (0.0005)	0.3754 (0.0185)	0.5043 (0.0011)	1

Note: Figures in parentheses are p-values.

Source: Authors' calculation.

**Table A3. Preliminary residual diagnostic tests**

	Dependent variable	
	Manufacturing employment share	Manufacturing value-added share
<b>Wooldridge autocorrelation test for panel data</b>		
Null hypothesis: no serial first-order serial correlation		
F statistic	28.11	25.77
Prob>F	0.01	0.01
<b>Modified Wald test for groupwise heteroskedasticity</b>		
Null hypothesis: $\sigma_i^2 = \sigma^2$ for all $i$		
Chi-squared statistic	5.89	11.91
Prob>Chi-squared	0.21	0.018
<b>Breusch-Pagan LM test for cross-sectional correlation</b>		
Null hypothesis: cross sectional independence		
Chi-squared statistic	8.09	36.38
Prob>Chi-squared	0.23	0.00

Note: The tests for panel data autocorrelation, heteroskedasticity, and cross-sectional correlation were respectively performed using the following user-contributed Stata programs: xtserial (Drukker, 2003), xttest3 (Baum, 2000b), and xttest2 (Baum, 2000a).

Source: Authors' calculation.

**Table A4. Effects of net capital inflows on manufacturing employment share**

**A. Pooled OLS and 2SLS**

VARIABLES	OLS						2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
FDI/GDP	0.154 (0.133)						0.178 (0.128)					
Non-FDI/GDP		-0.102** (0.040)						-0.103*** (0.036)				
Portfolio investment/GDP			-0.206** (0.077)						-0.151** (0.065)			
Portfolio equity/GDP				-0.061 (0.186)						0.047 (0.200)		
Portfolio debt/GDP					-0.280** (0.126)						-0.247* (0.135)	
Other investment/GDP						-0.074 (0.055)						-0.090* (0.047)
log(GDP per capita)	-15.374 (13.368)	-16.798 (13.601)	-15.926 (13.483)	-13.559 (13.836)	-15.842 (14.189)	-15.189 (13.323)	-15.633 (13.263)	-16.808 (13.382)	-15.352 (13.085)	-13.372 (13.856)	-15.518 (14.014)	-15.493 (13.174)
log(GDP per capita) squared	1.023 (0.742)	1.107 (0.755)	1.071 (0.755)	0.933 (0.759)	1.055 (0.795)	1.013 (0.739)	1.036 (0.737)	1.108 (0.743)	1.036 (0.731)	0.917 (0.759)	1.037 (0.785)	1.029 (0.731)
log(population)	-54.895*** (12.553)	-61.009*** (13.621)	-60.180*** (11.352)	-52.884*** (14.351)	-59.387*** (12.997)	-58.046*** (13.844)	-54.735*** (12.814)	-61.026*** (13.476)	-59.033*** (11.777)	-52.748*** (14.229)	-58.612*** (13.773)	-58.513*** (13.750)
log(population) squared	2.510*** (0.545)	2.772*** (0.591)	2.729*** (0.487)	2.410*** (0.626)	2.696*** (0.560)	2.644*** (0.601)	2.504*** (0.556)	2.772*** (0.585)	2.680*** (0.506)	2.407*** (0.621)	2.662*** (0.595)	2.665*** (0.597)
log(REER)	-3.857 (2.808)	-3.195 (2.795)	-3.017 (2.988)	-3.672 (2.965)	-3.748 (2.850)	-3.481 (2.884)	-3.908 (2.819)	-3.194 (2.792)	-3.157 (3.011)	-3.932 (2.846)	-3.756 (2.886)	-3.468 (2.845)
Trade/GDP	0.068*** (0.012)	0.068*** (0.012)	0.062*** (0.014)	0.065*** (0.012)	0.064*** (0.015)	0.070*** (0.012)	0.068*** (0.012)	0.068*** (0.012)	0.064*** (0.014)	0.067*** (0.013)	0.064*** (0.015)	0.071*** (0.012)
Resource rents/GDP	-0.229*** (0.070)	-0.262*** (0.077)	-0.248*** (0.070)	-0.214** (0.084)	-0.232*** (0.077)	-0.247*** (0.078)	-0.229*** (0.070)	-0.262*** (0.077)	-0.243*** (0.071)	-0.210** (0.081)	-0.229*** (0.080)	-0.250*** (0.077)
Constant	384.098*** (101.793)	423.175*** (113.412)	413.298*** (99.714)	364.401*** (106.469)	412.258*** (112.088)	400.221*** (110.573)						
Observations	154	154	154	148	151	154	154	154	154	148	151	154
R-squared	0.925	0.929	0.929	0.913	0.923	0.925	0.910	0.915	0.915	0.892	0.908	0.910
Number of groups	4	4	4	4	4	4						
Country FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Underid test p-val							0.102	0.080	0.098	0.232	0.086	0.161
Weak id F-stat							85.113	419.254	121.152	148.819	149.961	313.354
Overid p-val							0.274	0.216	0.339	0.738	0.243	0.175
Endog test p-val							0.778	0.718	0.089	0.042	0.628	0.856

## B. Fixed effects and FE-2SLS

VARIABLES	FE						FE-2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
FDI/GDP	0.068 (0.119)						0.049 (0.121)					
Non-FDI/GDP		-0.084** (0.033)						-0.094** (0.035)				
Portfolio investment/GDP			-0.198*** (0.064)						-0.167*** (0.050)			
Portfolio equity/GDP				-0.070 (0.118)						-0.013 (0.146)		
Portfolio debt/GDP					-0.272*** (0.091)						-0.252** (0.094)	
Other investment/GDP						-0.045 (0.045)						-0.067 (0.045)
log(GDP per capita)	3.204 (21.334)	-14.136 (27.790)	-8.819 (23.449)	-1.770 (25.526)	-12.310 (22.178)	-4.594 (27.357)	2.690 (21.144)	-15.856 (27.859)	-7.221 (22.963)	-1.233 (25.520)	-11.431 (21.699)	-7.498 (27.991)
log(GDP per capita) squared	0.177 (1.217)	1.179 (1.608)	0.874 (1.346)	0.465 (1.454)	1.043 (1.274)	0.632 (1.580)	0.209 (1.207)	1.278 (1.612)	0.782 (1.319)	0.429 (1.453)	0.994 (1.250)	0.799 (1.617)
log(population)	-49.747*** (17.560)	-71.575*** (26.371)	-66.118*** (20.448)	-54.258*** (23.335)	-69.260*** (20.613)	-60.070*** (26.078)	-50.706*** (17.499)	-73.614*** (26.187)	-64.091*** (19.904)	-53.654*** (23.533)	-68.076*** (20.336)	-63.419*** (26.480)
log(population) squared	1.669* (0.988)	2.781* (1.434)	2.455** (1.118)	1.894 (1.245)	2.605** (1.101)	2.198 (1.418)	1.715* (0.979)	2.886* (1.432)	2.357** (1.095)	1.862 (1.255)	2.549** (1.086)	2.376 (1.451)
log(REER)	-1.396 (1.816)	-0.894 (1.668)	-0.672 (1.727)	-1.277 (1.903)	-1.374 (1.625)	-1.162 (1.776)	-1.344 (1.876)	-0.859 (1.632)	-0.756 (1.751)	-1.418 (1.836)	-1.380 (1.653)	-1.140 (1.733)
Trade/GDP	0.058*** (0.012)	0.063*** (0.013)	0.055*** (0.011)	0.056*** (0.013)	0.057*** (0.010)	0.062*** (0.014)	0.058*** (0.013)	0.063*** (0.013)	0.056*** (0.012)	0.057*** (0.013)	0.057*** (0.010)	0.063*** (0.014)
Resource rents/GDP	-0.300*** (0.063)	-0.303*** (0.065)	-0.307*** (0.060)	-0.284*** (0.073)	-0.295*** (0.060)	-0.298*** (0.067)	-0.299*** (0.063)	-0.303*** (0.065)	-0.305*** (0.061)	-0.283*** (0.072)	-0.295*** (0.062)	-0.298*** (0.067)
Observations	154	154	154	148	151	154	154	154	154	148	151	154
R-squared	0.816	0.831	0.839	0.803	0.838	0.817	0.816	0.830	0.839	0.802	0.838	0.817
Country FE	YES											
Year dum	YES											
Hausman p-val	0.000	0.000	0.000	0.000	0.000	0.000						
Underid test p-val							0.147	0.075	0.139	0.207	0.112	0.101
Weak id F-stat							106.388	398.692	174.869	300.824	219.496	272.942
Overid p-val							0.169	0.200	0.889	0.516	0.931	0.138
Endog test p-val							0.932	0.693	0.052	0.104	0.582	0.857

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Driscoll-Kraay standard errors in parentheses. Underidentification test null: equation is identified (instruments are relevant). Overidentification test joint null: instruments are valid (i.e., uncorrelated with the error term) and excluded instruments are correctly excluded from the estimated equation. Endogeneity test null: endogenous regressors can be treated as exogenous. Source: Authors' calculations.

**Table A5. Effects of net capital inflows on manufacturing real value-added share**

**A. Pooled OLS and 2SLS**

VARIABLES	OLS						2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
FDI/GDP	0.350** (0.146)						0.402*** (0.139)					
Non-FDI/GDP		-0.060 (0.044)						-0.087** (0.041)				
Portfolio investment/GDP			-0.046 (0.076)						0.008 (0.073)			
Portfolio equity/GDP				0.064 (0.191)						0.228 (0.191)		
Portfolio debt/GDP					-0.085 (0.125)						-0.078 (0.130)	
Other investment/GDP						-0.073 (0.055)						-0.117** (0.050)
log(GDP per capita)	10.826 (19.147)	12.697 (19.627)	13.993 (18.873)	19.056 (19.230)	14.081 (19.306)	13.071 (19.244)	10.284 (19.100)	11.903 (19.647)	14.558 (18.511)	19.340 (19.113)	14.156 (19.332)	12.235 (19.201)
log(GDP per capita) squared	-0.302 (1.064)	-0.393 (1.083)	-0.462 (1.045)	-0.744 (1.053)	-0.476 (1.071)	-0.419 (1.060)	-0.274 (1.061)	-0.349 (1.084)	-0.497 (1.023)	-0.769 (1.047)	-0.480 (1.072)	-0.375 (1.057)
log(population)	64.389*** (12.656)	59.120*** (12.715)	61.174*** (11.800)	61.406*** (11.812)	59.209*** (11.997)	59.987*** (12.727)	64.724*** (12.996)	57.775*** (12.519)	62.301*** (11.855)	61.613*** (11.787)	59.388*** (12.313)	58.708*** (12.738)
log(population) squared	-2.766*** (0.530)	-2.549*** (0.525)	-2.641*** (0.485)	-2.638*** (0.493)	-2.551*** (0.494)	-2.585*** (0.528)	-2.778*** (0.546)	-2.490*** (0.517)	-2.688*** (0.491)	-2.643*** (0.493)	-2.559*** (0.508)	-2.527*** (0.528)
log(REER)	-9.904*** (2.950)	-8.984** (3.497)	-9.071** (3.560)	-9.451** (3.567)	-9.274** (3.574)	-9.126** (3.463)	-10.010*** (2.939)	-8.892** (3.426)	-9.209** (3.529)	-9.847*** (3.401)	-9.275** (3.581)	-9.090** (3.367)
Trade/GDP	0.017 (0.019)	0.016 (0.021)	0.015 (0.022)	0.022 (0.022)	0.018 (0.023)	0.018 (0.020)	0.017 (0.019)	0.016 (0.020)	0.016 (0.021)	0.024 (0.021)	0.018 (0.023)	0.019 (0.020)
Resource rents/GDP	-0.070 (0.058)	-0.091 (0.060)	-0.076 (0.056)	-0.079 (0.063)	-0.084 (0.062)	-0.089 (0.062)	-0.070 (0.059)	-0.099 (0.059)	-0.072 (0.057)	-0.073 (0.060)	-0.084 (0.063)	-0.099 (0.061)
Constant	-372.619** (148.524)	-354.034** (152.370)	-371.431** (144.316)	-395.363*** (144.282)	-359.593** (146.964)	-359.965** (150.442)						
Observations	154	154	154	148	151	154	154	154	154	148	151	154
R-squared	0.887	0.880	0.879	0.884	0.880	0.880	0.825	0.815	0.812	0.819	0.815	0.814
Number of groups	4	4	4	4	4	4						
Country FE	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Underid test p-val							0.102	0.080	0.098	0.232	0.086	0.161
Weak id F-stat							85.113	419.254	121.152	148.819	149.961	313.354
Overid p-val							0.130	0.936	0.175	0.304	0.066	0.265
Endog test p-val							0.540	0.180	0.215	0.087	0.778	0.268

## B. FE and FE-2SLS

VARIABLES	FE						FE-2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
FDI/GDP	0.215** (0.098)						0.208 (0.126)					
Non-FDI/GDP		-0.037 (0.031)						-0.068** (0.032)				
Portfolio investment/GDP			-0.059 (0.071)						-0.031 (0.067)			
Portfolio equity/GDP				0.072 (0.130)						0.158 (0.141)		
Portfolio debt/GDP					-0.111 (0.095)						-0.115 (0.091)	
Other investment/GDP						-0.031 (0.038)						-0.076* (0.041)
log(GDP per capita)	16.030 (22.806)	3.375 (28.665)	7.085 (26.641)	17.576 (29.263)	5.499 (26.132)	6.036 (28.042)	15.840 (23.035)	-2.388 (27.889)	8.542 (26.748)	18.394 (29.289)	5.341 (25.729)	0.044 (28.484)
log(GDP per capita) squared	-0.524 (1.346)	0.226 (1.687)	0.013 (1.586)	-0.565 (1.728)	0.090 (1.546)	0.074 (1.655)	-0.512 (1.363)	0.557 (1.634)	-0.070 (1.594)	-0.619 (1.728)	0.099 (1.524)	0.417 (1.669)
log(population)	52.262** (21.867)	33.226 (27.966)	37.372 (26.606)	45.659 (28.390)	34.394 (27.020)	36.514 (26.856)	51.907** (22.582)	26.394 (27.007)	39.220 (26.753)	46.579 (28.489)	34.182 (26.610)	29.604 (27.062)
log(population) squared	-3.236*** (1.177)	-2.294 (1.519)	-2.521* (1.464)	-2.898* (1.528)	-2.382 (1.480)	-2.457* (1.455)	-3.219** (1.213)	-1.942 (1.468)	-2.610* (1.474)	-2.946* (1.530)	-2.372 (1.462)	-2.090 (1.455)
log(REER)	-6.681*** (1.585)	-5.947*** (1.775)	-5.924*** (1.784)	-6.382*** (1.867)	-6.158*** (1.754)	-6.052*** (1.816)	-6.662*** (1.672)	-5.830*** (1.694)	-6.000*** (1.788)	-6.597*** (1.798)	-6.157*** (1.751)	-6.006*** (1.723)
Trade/GDP	-0.001 (0.012)	0.003 (0.014)	0.000 (0.014)	0.005 (0.014)	0.002 (0.016)	0.003 (0.014)	-0.001 (0.012)	0.005 (0.014)	0.001 (0.014)	0.006 (0.014)	0.002 (0.016)	0.006 (0.014)
Resource rents/GDP	-0.222*** (0.069)	-0.217*** (0.074)	-0.218*** (0.076)	-0.214*** (0.075)	-0.221*** (0.069)	-0.215*** (0.077)	-0.222*** (0.069)	-0.219*** (0.071)	-0.216*** (0.077)	-0.213*** (0.074)	-0.221*** (0.069)	-0.216*** (0.075)
Observations	154	154	154	148	151	154	154	154	154	148	151	154
R-squared	0.854	0.846	0.846	0.852	0.850	0.845	0.854	0.845	0.845	0.851	0.850	0.843
Country FE	YES											
Year dum	YES											
Hausman p-val	0.000	0.000	0.000	0.000	0.000	0.000						
Underid test p-val							0.147	0.075	0.139	0.207	0.112	0.101
Weak id F-stat							106.388	398.692	174.869	300.824	219.496	272.942
Overid p-val							0.605	0.599	0.249	0.211	0.266	0.450
Endog test p-val							0.370	0.038	0.235	0.213	0.949	0.052

Note: \*\*\* p<0.01, \*\* p<0.05, \* p<0.1. Driscoll-Kraay standard errors in parentheses. Underidentification test null: equation is identified (instruments are relevant). Overidentification test joint null: instruments are valid (i.e., uncorrelated with the error term) and excluded instruments are correctly excluded from the estimated equation. Endogeneity test null: endogenous regressors can be treated as exogenous. Source: Authors' calculations.



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