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The Employment Effects of Technology, Trade, and Consumption in Global Value Chains: Evidence for Developing Asia

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Global value chains (GVCs) have been a vehicle for job creation in developing Asia, but technology can also displace workers through automation or reshoring of production. We use an input–output approach to examine how employment responded to consumption, trade, and technological progress in 16 economies that accounted for about 95% of employment in developing Asia from 2008 to 2018. Structural decomposition analysis based on the Asian Development Bank's Multiregional Input–Output database combined with harmonized cross-economy occupation by industry data indicates that, other things being equal, technological change within GVCs and task relocation relate to a decline of routine manual, relative to nonroutine cognitive, occupations in manufacturing. We find no evidence of major shifts in labor

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demand due to reshoring. Domestic consumption expenditure of goods and services is associated with an increase in labor demand that is large enough to offset efficiency changes in GVCs.

Keywords: developing Asia, employment, global value chains, task relocation, technology

JEL codes: D57, F63, J21, O14

I. Introduction

Over the past 3 decades, developing Asia experienced rapid growth and several Asian economies underwent major structural transformation. Participation in global value chains (GVCs) was an important part of this success story (Baldwin 2018). Asia's GVC participation, approximated by the share of value-added to gross exports that is used for further processing in cross-border production networks, was already high at 66.9% in 2000 and rose to 68.1% in 2018 despite the economic shocks that affected the region during that time (Asian Development Bank [ADB] 2019).

At the micro-level, GVC participation has increased the productivity of participating firms and provided opportunities for the creation of better paid jobs (World Bank 2017); at the macro-level, it is associated with enhanced economic growth and higher income per capita (United Nations Economic and Social Commission for Asia and the Pacific [UNESCAP] 2015). However, Asian economies at different stages of development have engaged with GVCs in different ways (UNESCAP 2015). On one end of the spectrum are the higher-income economies that tend to specialize in the knowledge-intensive tasks on the value chain. On the other end are the lower-income economies whose firms tend to specialize in tasks that rely on low-wage labor (Timmer, Miroudot, and de Vries 2019).

While the academic and policy debates have often focused on how to foster developing economies' participation into GVCs and help them move up the value chain (Organisation for Economic Co-operation and Development [OECD] 2007, Cattaneo et al. 2013), a new challenge is on the horizon. As the Fourth Industrial Revolution (4IR) technologies such as digital manufacturing become more sophisticated and more effective, there is a risk that their adoption may result in job losses in developing Asia (ADB 2018). There are substantially two mechanisms through which this could happen. First, if machines replace workers at one or more of the production tasks in a GVC, this would lower the number of jobs needed in the GVC to meet the given demand. Second, the growing use of 4IR technologies may erode the labor cost advantage of emerging economies by making labor costs a smaller share of total costs

(United Nations Conference on Trade and Development 2016), thus encouraging reshoring production to advanced economies (De Backer et al. 2016).

Furthermore, to the extent that the technologies of 4IR are skill-biased, their adoption may shift the skill demand, thus widening inequality (Acemoglu 2002). This poses a problem for developing economies competing in low-to-medium-skill tasks, as using advanced technologies could create a shortage of high-skilled workers and a surplus of medium- and low-skilled workers.

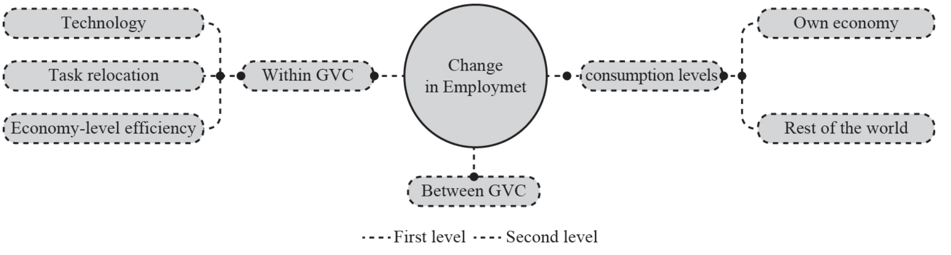
Understanding how 4IR technologies will affect employment along the value chain in developing Asia is as important as it is challenging. The first challenge relates to investigating a process that is only starting: a forecasting exercise requires heavy assumptions, and the results are quite sensitive to those assumptions. An additional challenge is that data on investment in new technologies in Asian economies are not as readily available. Finally, the location of a production task and technology adoption are not independent decisions, and their effect on the broader economy depends on the degree of exposure to a specific GVC.

In this paper, we aim to uncover the impacts of technological advances on jobs in developing Asia during the past decade. Our approach is to apply the structural decomposition analysis (SDA) framework developed in Reijnders and de Vries (2018) to the ADB Multiregional Input–Output (MRIO) tables to examine the relationship between technology and jobs along the value chains in 16 economies in developing Asia, covering 35 sectors, from 2008 to 2018. The 16 economies accounted for about 94.5% of employment in developing Asia in 2018. The analytical framework in Reijnders and de Vries (2018) has two important advantages: (i) it allows for macroeconomic analysis of GVCs; and (ii) it adheres to the national account series of gross output, value added, and employment.

The decomposition of change in an economy's number of jobs from 2008 to 2018 occurs on two levels (Figure 1). At the first level, the change in employment is decomposed into changes within a GVC (changes in employment within the production structure or GVC of a specific final product), changes between GVCs (the relative economic importance of GVCs), or changes from the shifts in consumer demand. Here, "consumption levels" refer to changes in employment associated with changes in the global demand for goods and services. In practice, higher consumption levels will increase the demand for goods and services, which in turn will increase employment.

At the second level, the SDA decomposes the within-GVC channel into: (i) technology within the GVC, or changes in employment associated with the changes in efficiency within a specific GVC; (ii) task relocation, or changes in employment as the location changes for one production task or more; and (iii) economy-level

Figure 1. **Decomposing Changes in Labor Demand**



GVC = Global value chain.
Source: Authors' illustration.

efficiency, or changes in employment from efficiency changes in the economy. Consumption levels are further decomposed into "own economy," or demand for goods and services originating within a specific economy, and "rest of the world," or demand from abroad for goods and services. The purpose is to see what fraction of employment depends on domestic demand and what fraction on foreign demand.

To preview our results, we have three key findings. First, many Asian developing economies benefited from the relocation of GVC tasks to their economies, but the effects of technological change account for a larger change in labor demand compared to task relocation. Second, both technological change within GVCs and task relocation tend to drive down routine manual occupations relative to nonroutine cognitive jobs in manufacturing, an observation that is not found in services. Third, we document that rising demand for goods and services finalized and consumed in the 16 Asian developing economies covered in the analysis induced a 9% increase in jobs within the region, which is suggestive of a rebalancing away from a manufacturing- and export-led growth model to a services- and consumption-led model. These patterns are observed in most economies.

It is helpful to place our paper in a broader context. There are several closely related empirical studies that juxtapose the role of technology and trade in explaining job polarization. For example, Autor, Dorn, and Hanson (2016) exploit the initial differences in exposure to competition with the People's Republic of China (PRC) across local labor markets in the United States (US) to explain subsequent changes in the employment structure. They find that import competition and technological change reduce the demand for routine production and clerical occupations relative to those that are intensive in abstract tasks (e.g., professionals and managers) and manual tasks (e.g., personal services). Other related studies include Goos, Manning, and Salomons (2014) and Reijnders, Timmer, and Ye (2021). But these studies focus on both advanced economies and several emerging economies. In contrast, this paper examines the drivers of labor demand in developing Asian economies.

The empirical concept of a GVC employed in this paper is based on Timmer et al. (2014) and consists of all activities that are directly or indirectly needed to produce a product that is used for final consumption. An example of a GVC is the production of garments whereby the final assembly stage takes place in Bangladesh, but with many of the inputs sourced from other economies (this example will be used throughout this paper). Developing economies in Asia are at different levels of development and differ in terms of their integration into GVCs. Moreover, it is likely that the impact of new technologies on labor demand differs between advanced and developing economies due to lower wages in developing Asia and hence less incentive to substitute automation for labor input. This makes it interesting to study the relation between technology, trade, and rising consumer expenditures in driving labor demand in Asian economies. Indeed, our findings suggest trends that appear specific to some economies, which calls for further investigation using economy-level case studies.

The rest of this paper is structured as follows. Section II provides an overview of the existing empirical literature, Section III presents the methodology, Section IV describes the data, and Section V discusses our findings. Finally, Section VI concludes with a discussion of the implications of our results, as well as potential avenues for future research.

II. Evidence from the Literature

The impact of technology on employment has been studied since the early 19th century, when the first generation of workers had the experience of being suddenly displaced by automation. The displacement often disproportionally affected workers on the lower end of the skill distribution, as machines could undertake mostly simple, repetitive tasks. But the technologies of 4IR are characterized by the convergence of a wide range of breakthroughs in the digital, physical, and biological spheres that are increasingly encroaching on high-skill occupations.

In this section, we discuss several approaches to studying the relationship between technology and jobs. One approach investigates how feasible it is to automate existing jobs given the current and presumed technological advances. Frey and Osborne (2017) conducted a feasibility study, and their findings made a big impact.[1]

[1]Several studies adapt (or build on) their methodology. See, for example, Chang and Huynh (2016), Citi and Oxford Martin School (2016), and Manyika et al. (2017).

They predicted that 47% of the total US-based employment is at a high risk of automation, with office and administrative support, sales, and other mostly middle-skilled services occupations taking the biggest hit. Their "occupation-based approach" links the O*NET database, which contains survey-based information on the task content of each occupation, with 2010 employment and wage data from the US Bureau of Labor Statistics, creating a dataset that distinguishes 702 occupations. With a group of researchers feeding a machine-learning algorithm, they label 70 occupations as automatable or not, and then they use a Gaussian process classifier to predict the probability of automation for the remaining 632, based on the features of the 70 occupations. They then distinguish between high (greater than 0.7), medium (between 0.3 and 0.7), and low (less than 0.3) risks of automation. Using the methodology from Frey and Osborne (2017), Chang and Huynh (2016) study the impact of technologies on employment in Cambodia, Indonesia, the Philippines, Thailand, and Viet Nam. They conclude that up to 56% of all employment in these economies is at a risk of displacement due to technology over the next decades.

This occupation-based approach has several shortcomings. First, automation does not target entire occupations, but specific tasks within an occupation. Second, the automation of one or more tasks in an occupation may be technically but not economically feasible. Third, even if it is both technically and economically feasible to automate one or more tasks, workers can adapt to the new division of labor by switching tasks. Furthermore, 4IR technologies, as with past technologies, could be complementary to workers, enabling them to increase productivity, leading to higher wages within sectors and productivity spillovers to other industries. This can support general economic and employment growth. Finally, by using Frey and Osborne's (2017) data on the probability of automation in the US, Chang and Huynh (2016) assume that the task content for each occupation is similar across economies. These shortcomings suggest the occupation-based approach of Frey and Osborne may overestimate the risk of automation for the entire occupations.

Arntz, Gregory, and Zierahn (2016) take a "task-based approach" to estimate the susceptibility of employment to automation for 21 OECD countries. They use individual survey data from the Programme for the International Assessment of Adult Competencies, which provides a list of tasks people actually perform at their workplace. They find that only 9% of jobs in the US are at high risk of automation, compared with the 47% estimated by Frey and Osborne (2017). This task-based approach has some of the same faults as the occupation-based approach: it is still based on technical feasibility rather than the actual adoption of new technologies, and it does not consider whether workers adapt to the new division of labor. Furthermore, it only analyzes existing occupations whereas new technologies create new jobs (Stewart, De, and Cole 2015). Nonetheless, task-based approaches show that the technical automation of jobs may be lower than feared under the occupation-based approaches—and lower still since these estimates do not consider economic feasibility and potential productivity gains.

An additional reason why the impact of 4IR technologies in developing Asia may not be as severe is that the region continues to undergo structural transformation—a movement of employment from mostly low-productivity, low-paying jobs in agriculture to higher-productivity, better-paying jobs in industry and services that expands the middle class and stimulates final demand. Developing Asia has created 30 million nonagricultural jobs annually over the past 25 years (ADB 2018), partly due to structural transformation as well as technology-driven improvements in productivity.

Another line of research estimates the effect of the increased use of a specific technology on employment, wages, and the broader economy. Such studies focus mostly on advanced economies because they require a wealth of data that is generally unavailable for developing economies. While some insightful studies focus on the impact of information and communication technologies on employment (see, for example, Autor, Levy, and Murnane 2003; Michaels, Natraj, and Van Reenen 2014; Chun and Tang 2018), industrial robots are the technology that perhaps best embodies the 4IR because of their capacity for autonomous movement and ability to perform an expanding set of tasks.

Acemoglu and Restrepo (2017) estimate the effect of the increase in industrial robot usage between 1990 and 2007 on employment and wages in the local US labor markets, which they proxy by commuting zones. They regress the change in employment and wages on the exposure to robots—defined as the sum over industries of the national penetration of robots into each industry times the baseline employment share of that industry in the labor market—and find large and robust negative effects of robots on employment and wages across commuting zones. When they incorporate trade between commuting zones, allowing the productivity gains from robot usage to spill over to other community zones, they find smaller negative employment effects and considerably smaller negative wage effects from robots.

Graetz and Michaels (2018) use an instrumental variables approach to estimate the effect of robot adoption within industries in 17 OECD countries from 1993 to 2007. They find that increased robot use contributed approximately 0.36 percentage points to the annual labor productivity growth, while at the same time raising the total factor productivity (TFP) and lowering the output prices. Interestingly, their estimates suggest that robots did not significantly reduce total employment, although they did reduce the employment share of low-skilled workers. Relatedly, de Vries et al. (2020) find that robot adoption lowered demand for the routine task-intensive jobs.

Finally, Reijnders and de Vries (2018) use the World Input–Output database to perform a structural decomposition analysis of the changes in the employment share of nonroutine jobs due to technological change and task relocation for a group of 40 advanced and emerging economies between 1999 and 2007. They find that technological change increased the number of nonroutine relative to routine jobs in all economies, and task relocation, albeit less strong, works in the same direction for advanced economies, but in the opposite direction for emerging economies.

In sum, the existing literature finds that technology affects both the level and composition of employment: increased use of technology tends to decrease overall employment, but the occupations traditionally considered low- and middle-skilled are more affected. However, these studies lean toward advanced economies. Therefore, we contribute to the literature by adopting the methodology in Reijnders and de Vries (2018) to investigate the relationship between technology and jobs in developing Asia.

III. Methodology

In the framework adopted here, the use of labor inputs is driven by demand. The production process of GVCs is modeled as consisting of different tasks. This aligns with the "task approach to labor markets," as described in Autor (2013), which enables an analysis of the interactions among technological capabilities, trade, and offshoring opportunities, as well as quantification of the effects of these forces on labor demand. Methodologically, we closely follow Los, Timmer, and de Vries (2014) and de Vries et al. (2019). Reijnders and de Vries (2018) introduce a methodological innovation by linking the task approach to the Leontief input–output framework extended to a multi-economy setting, which makes it possible to decompose changes in occupational labor demand into its several components.

In this framework, task outputs are produced using production factors (capital and labor), which are sourced either domestically or from foreign suppliers. As in Goos, Manning, and Salomons (2014), it is assumed that there is a one-to-one mapping between occupations and tasks, so that each task requires labor of a certain occupation, and each occupation only performs that specific task. It also assumes that tasks along a GVC are perfect complements (i.e., a fixed amount of each task, or

Figure 2. **Structure of a Multiregional Input–Output Table**

(Destination)

		Intermediate use				Final use				Gross output
		1	2	…	G	1	2	…	G	
(Source)	1	Z^{11}	Z^{12}	…	Z^{1G}	F^{11}	F^{12}	…	F^{1G}	y^{1}
	2	Z^{21}	Z^{22}	…	Z^{2G}	F^{21}	F^{22}	…	F^{2G}	y^{2}
	…	…	…	…	…	…	…	…	…	…
	G	Z^{G1}	Z^{G2}	…	Z^{GG}	F^{G1}	F^{G2}	…	F^{GG}	y^{G}
Value added		$w^{1\prime}$	$w^{2\prime}$	…	$w^{G\prime}$					
Gross output		$y^{1\prime}$	$y^{2\prime}$	…	$y^{G\prime}$					
Employment		$x^{1\prime}$	$x^{2\prime}$	…	$x^{G\prime}$					

Source: Authors' compilation.

occupational input, is required in the production of a final product).[2] Task outputs can either be sold to final consumers or be used as an input to production (at home or abroad).

We start by assuming that there are G economies and N industries within each economy. We define a GVC as an economy–industry pair that delivers a product for final use.[3] The basic structure of the ADB MRIO database (augmented with employment per economy–industry) for a given year is shown in Figure 2.

For the ease of exposition, we formally define source and destination economies and source and destination industries. In particular, we let i be the index for the source industry, j the destination industry, r the source economy, and s the destination economy. The $GN \times GN$ matrix

$$\mathbf{Z} = [\mathbf{Z}^{rs}] = \begin{bmatrix} \mathbf{Z}^{11} & \cdots & \mathbf{Z}^{1G} \\ \vdots & \ddots & \vdots \\ \mathbf{Z}^{G1} & \cdots & \mathbf{Z}^{GG} \end{bmatrix}$$

records the flows of outputs for intermediate use between the industries worldwide. $\mathbf{Z}^{rs}$ is an $N \times N$ block matrix whose typical element z_{ij}^{rs} gives the dollar value of output from industry i in economy r used as intermediate inputs to the production in

[2]Modeling task inputs as perfect complements in production implies that the task production functions in the empirical analysis take a Leontief (fixed proportions) functional form (Miller and Blair 2009).

[3]We use the term economy–industry to mean an industry in a particular economy, such as the Bangladesh textiles industry or the Japanese electronics industry.

industry j of economy s. The $GN \times GP$ matrix

$$\mathbf{F} = [\mathbf{F}^{rs}] = \begin{bmatrix} \mathbf{F}^{11} & \cdots & \mathbf{F}^{1G} \\ \vdots & \ddots & \vdots \\ \mathbf{F}^{G1} & \cdots & \mathbf{F}^{GG} \end{bmatrix}$$

of final demand contains, for each economy–industry, the output for final use in every economy.[4] $\mathbf{F}^{rs}$ is a $GN \times P$ vector whose typical element f_{ip}^{rs} gives the dollar value of output from industry i in economy r used to satisfy the final demand (in category p) in economy s. Gross output and value added per economy–industry pair are the $N \times 1$ vectors

$$\mathbf{y} = \begin{bmatrix} \mathbf{y}^1 \\ \vdots \\ \mathbf{y}^G \end{bmatrix} \quad \text{and} \quad \mathbf{w} = \begin{bmatrix} \mathbf{w}^1 \\ \vdots \\ \mathbf{w}^G \end{bmatrix}$$

for each economy, respectively. Each element of $\mathbf{y}^r$ ($\mathbf{w}^r$) describes the gross output (value added) of each industry in economy r.

Market-clearing conditions imply that total output of a particular economy–industry must tally with its total (i.e., intermediate and final) use domestically and globally. Therefore, the fundamental relationship between the matrices $\mathbf{Z}$, $\mathbf{F}$ and $\mathbf{y}$ is given by the following equation:

$$\mathbf{y} = \mathbf{Z1}_{GN,1} + \mathbf{F1}_{GP,1}, \tag{1}$$

where $\mathbf{1}_{\alpha,1}$ is a vector of 1s with length α. Put simply, the gross output vector $\mathbf{y}$ can be obtained from adding the row-sums of the matrices $\mathbf{Z}$ and $\mathbf{F}$.

We use this data to construct two new matrices. The first one is $\mathbf{A} = \mathbf{Z}\hat{\mathbf{y}}^{-1}$, the $GN \times GN$ matrix of intermediate-use coefficients.[5] A typical element of $\mathbf{A}$, a_{ij}^{rs}, refers to the dollar value of the intermediate inputs of industry i in economy r per dollar of output of industry j in economy s. Second, we add up across final demand categories and economies to derive the $GN \times 1$ vector $\mathbf{f} \equiv \mathbf{F1}_{GP,1}$. Using these two new matrices, we rewrite equation (1) as follows:

$$\mathbf{y} = \mathbf{Ay} + \mathbf{f}. \tag{2}$$

[4]Here, we represent the final demand as consisting of P categories, which can include final expenditure for consumption, government, and investment, as well as inventories.

[5]A hat (e.g., $\hat{\mathbf{y}}$) indicates a diagonal matrix, with the elements of the vector $\mathbf{y}$ on the diagonal.

Solving for $\mathbf{y}$, we obtain the fundamental identity by Leontief (1936):

$$\mathbf{y} = \mathbf{B}\mathbf{f}, \tag{3}$$

where $\mathbf{B} = (\mathbf{I}_{GN} - \mathbf{A})^{-1}$ is the so-called global Leontief inverse. Here, $\mathbf{I}_{GN}$ stands for the $GN \times GN$ identity matrix. A given column of $\mathbf{B}$ contains the dollar value of output of all industries and all economies required to produce one dollar of final output for the corresponding economy–industry pair.

Moving from output to occupational employment requires that we model the production process more explicitly. We can define l_{ki}^{r} as the quantity of employment in occupation k per unit of output in industry i of economy r: $l_{ki}^{r} = x_{ki}^{r}/y_{i}^{r}$ and then create the GN-column vector $\mathbf{l}_k$. We define another vector $\mathbf{x}_k$ which contains, for each economy–industry pair, the demand for labor in occupation k in all stages of production of final products by the GVCs worldwide:

$$\mathbf{x}_k = \hat{\mathbf{l}}_k \mathbf{B}\mathbf{f}, \tag{4}$$

where $\hat{\mathbf{l}}_k$ is a diagonal matrix containing labor requirements of occupation k per unit of gross output in each of the GN GVCs. A typical element of $\mathbf{x}_k$, x_{ki}^{r}, represents all labor of occupation k from industry i in economy r required to satisfy the worldwide final demand for goods and services. For instance, an element of $\mathbf{x}_k$ is all routine manual labor in the Bangladesh textiles industry required to satisfy the worldwide final demand. Since routine manual labor in the Bangladesh textiles industry may be contributing to the production of final goods and services in other economy–industries (not just Bangladesh textiles alone), all direct and indirect jobs demanded from it are captured in $\mathbf{x}_k$.

To analyze the relative impacts of trade, technology, and consumption levels on occupational labor demand, we further decompose equation (4). In particular, we specify three determinants of intertemporal changes in $\mathbf{x}_k$ that affect the product $\hat{\mathbf{l}}_k\mathbf{B}$ and three determinants that affect $\mathbf{f}$. The former set of determinants relate to changes within GVCs, while the latter are associated with changes in the relative weights of GVCs (Figure 1). We can express the employment in occupation k as follows[6]:

$$\mathbf{x}_k = \hat{\boldsymbol{\pi}}^{-1}\mathbf{R}_k\hat{\mathbf{l}}_k^{*}[\mathbf{T}^{*}\circ(\mathbf{S}^{*}\cdot\hat{\mathbf{c}})]\mathbf{u}. \tag{5}$$

In this equation, $\mathbf{c}$ is a G-vector. Its typical element, c^{s}, contains the total final demand exerted by the economy s (the destination economy). By construction, changes in $\mathbf{c}$

[6]The operator, $\circ$, is called the Hadamard product in matrix literature. It signifies element-by-element matrix multiplication. If $\mathbf{A} = [a_{ij}]$ and $\mathbf{B} = [b_{ij}]$ are matrices of the same size, $\mathbf{A}\circ\mathbf{B} = [a_{ij}b_{ij}]$ for all i and j.

would reflect changes in the demand for goods and services consumed in economy *s*. $\mathbf{S}^*$ is a $GN \times G$ matrix constructed by stacking G identical $N \times G$ matrices of final demand shares of each of the N industries. The rows of the $N \times G$ matrices that together form $\mathbf{S}^*$ are obtained by aggregating over final goods supplied by each of the trade partners. This matrix describes the relative distribution of final demand use across the GVCs worldwide. Thus, changes in this matrix would capture changes in the composition of consumption across GVCs. $\mathbf{T}^*$ is a $GN \times G$ matrix of final product trade coefficients. Its typical element t_i^{rs} represents the share of economy r in final demand for the products of industry i in economy s. Changes in this matrix would reflect changes in the relative share of GVCs in the production of final products. $\mathbf{u}$ is a G-element summation vector consisting of 1s.

If the production of final products is a fragmented process organized in (global) value chains, the GN vector $\mathbf{l}_k^{w\prime} \equiv \mathbf{l}_k'\mathbf{B}$ gives a more appropriate measure of the techniques used to produce the final products.[7] $\mathbf{l}_k^w$ gives the worldwide inputs of occupation k used to produce one unit of output from each of the GN GVCs, irrespective of the location of the activities required. Furthermore, we assume that Hicks-neutral, economy-level differences in the efficiency with which production factors are employed exist so that economies differ in their manner of transforming inputs to outputs. These Hicks-neutral, economy-level differences are captured in the GN productivity vector $\boldsymbol{\pi}$, of which a typical element π^s corresponds to the TFP level of economy s. To construct $\boldsymbol{\pi}$, we construct a measure of TFP for each economy and each year using the Penn World Tables (see Section IV). Introducing this efficiency correction term allows us to express the demand by a certain GVC for labor of occupation k in efficiency units, $\mathbf{l}_k^{*\prime} \equiv (\boldsymbol{\pi} \circ \mathbf{l}_k)'\mathbf{B}$. This more accurately describes the relative use of task inputs along the GVCs.

Since an input–output table represents GN industries in which labor is employed and GN global value chains to which this labor contributes, we can compute a $GN \times GN$-matrix, $\mathbf{R}_k = \{\hat{\boldsymbol{\pi}}\hat{\mathbf{l}}_k\mathbf{B}\}\hat{\mathbf{l}}_k^{*-1}$, with shares of each of the GN industries to total employment in occupation k per unit of the final demand produced. Rows correspond to industries of employment, while columns correspond to the GVCs to which the labor of type k contributes. Changes in the matrix reflect relative changes in the use of intermediate inputs by the GVCs.

By adding a time element in our framework, we are able to examine the determinants of occupational labor demand between two points in time. In particular,

[7]A prime ($\prime$) indicates matrix transposition. For example, if $\mathbf{A} = [a_{ij}]$ is a matrix, then $\mathbf{A}' = [a_{ji}]$ for all i and j. That is, the elements of the rows of $\mathbf{A}'$ correspond to the elements of the columns of $\mathbf{A}$.

we let $\mathbf{x}_{k1}$ and $\mathbf{x}_{k0}$ denote employments in occupation k at time 1 and time 0, respectively. Then, the difference between occupational labor demands at two points in time $(\mathbf{x}_{k1} - \mathbf{x}_{k0})$ can be written as follows:

$$
\begin{aligned}
\mathbf{x}_{k1} - \mathbf{x}_{k0} &= \hat{\boldsymbol{\pi}}_1^{-1}\mathbf{R}_{k1}\hat{\mathbf{l}}_{k1}^*[\mathbf{T}_1^*\circ(\mathbf{S}_1^* \cdot \hat{\mathbf{c}}_1)]\mathbf{u} - \hat{\boldsymbol{\pi}}_0^{-1}\mathbf{R}_{k0}\hat{\mathbf{l}}_{k0}^*[\mathbf{T}_0^*\circ(\mathbf{S}_0^* \cdot \hat{\mathbf{c}}_0)]\mathbf{u} \\
&= \frac{1}{2}\{\langle\hat{\boldsymbol{\pi}}_1^{-1} - \hat{\boldsymbol{\pi}}_0^{-1}\rangle\mathbf{R}_{k1}\hat{\mathbf{l}}_{k1}^*[\mathbf{T}_1^*\circ(\mathbf{S}_1^* \cdot \hat{\mathbf{c}}_1)]\mathbf{u} + \langle\hat{\boldsymbol{\pi}}_1^{-1} - \hat{\boldsymbol{\pi}}_0^{-1}\rangle\mathbf{R}_{k0}\hat{\mathbf{l}}_{k0}^* \\
&\quad \times [\mathbf{T}_0^*\circ(\mathbf{S}_0^* \cdot \hat{\mathbf{c}}_0)]\mathbf{u}\} \qquad \text{(6a)} \\
&\quad + \frac{1}{2}\{\hat{\boldsymbol{\pi}}_0^{-1}\langle\mathbf{R}_{k1} - \mathbf{R}_{k0}\rangle\hat{\mathbf{l}}_{k1}^*[\mathbf{T}_1^*\circ(\mathbf{S}_1^* \cdot \hat{\mathbf{c}}_1)]\mathbf{u} + \hat{\boldsymbol{\pi}}_1^{-1}\langle\mathbf{R}_{k1} - \mathbf{R}_{k0}\rangle\hat{\mathbf{l}}_{k0}^* \\
&\quad \times [\mathbf{T}_0^*(\mathbf{S}_0^* \cdot \hat{\mathbf{c}}_0)]\mathbf{u}\} \qquad \text{(6b)} \\
&\quad + \frac{1}{2}\{\hat{\boldsymbol{\pi}}_0^{-1}\mathbf{R}_{k0}\langle\hat{\mathbf{l}}_{k1}^* - \hat{\mathbf{l}}_{k0}^*\rangle[\mathbf{T}_1^*\circ(\mathbf{S}_1^* \cdot \hat{\mathbf{c}}_1)]\mathbf{u} + \hat{\boldsymbol{\pi}}_1^{-1}\mathbf{R}_{k1}\langle\hat{\mathbf{l}}_{k1}^* - \hat{\mathbf{l}}_{k0}^*\rangle \\
&\quad \times [\mathbf{T}_0^*\circ(\mathbf{S}_0^* \cdot \hat{\mathbf{c}}_0)]\mathbf{u}\} \qquad \text{(6c)} \\
&\quad + \frac{1}{2}\{\hat{\boldsymbol{\pi}}_0^{-1}\mathbf{R}_{k0}\hat{\mathbf{l}}_{k0}^*[\langle\mathbf{T}_1^* - \mathbf{T}_0^*\rangle\circ(\mathbf{S}_1^* \cdot \hat{\mathbf{c}}_1)]\mathbf{u} + \hat{\boldsymbol{\pi}}_1^{-1}\mathbf{R}_{k1}\hat{\mathbf{l}}_{k1}^* \\
&\quad \times [\langle\mathbf{T}_1^* - \mathbf{T}_0^*\rangle\circ(\mathbf{S}_0^* \cdot \hat{\mathbf{c}}_0)]\mathbf{u}\} \qquad \text{(6d)} \\
&\quad + \frac{1}{2}\{\hat{\boldsymbol{\pi}}_0^{-1}\mathbf{R}_{k0}\hat{\mathbf{l}}_{k0}^*[\mathbf{T}_0^*\circ(\langle\mathbf{S}_1^* - \mathbf{S}_0^*\rangle \cdot \hat{\mathbf{c}}_1)]\mathbf{u} + \hat{\boldsymbol{\pi}}_1^{-1}\mathbf{R}_{k1}\hat{\mathbf{l}}_{k1}^* \\
&\quad \times [\mathbf{T}_1^*\circ(\langle\mathbf{S}_1^* - \mathbf{S}_0^*\rangle \cdot \hat{\mathbf{c}}_0)]\mathbf{u}\} \qquad \text{(6e)} \\
&\quad + \frac{1}{2}\{\hat{\boldsymbol{\pi}}_0^{-1}\mathbf{R}_{k0}\hat{\mathbf{l}}_{k0}^*[\mathbf{T}_0^*\circ(\mathbf{S}_0^* \cdot \langle\hat{\mathbf{c}}_1 - \hat{\mathbf{c}}_0\rangle)]\mathbf{u} + \hat{\boldsymbol{\pi}}_1^{-1}\mathbf{R}_{k1}\hat{\mathbf{l}}_{k1}^* \\
&\quad \times [\mathbf{T}_1^*\circ(\mathbf{S}_1^* \cdot \langle\hat{\mathbf{c}}_1 - \hat{\mathbf{c}}_0\rangle)]\mathbf{u}\}. \qquad \text{(6f)}
\end{aligned}
$$

To reiterate, we identified six determinants of changes between the initial period 0 and final period 1 in the domestic demand for occupations k, related to changes within GVCs and the relative weights of these chains. We isolate the partial effects of these determinants, assuming that the other five partial effects were zero. The quantification thus assumes that determinants are independent, an issue to which we return in the empirical analysis below. It is also relevant to note that structural decompositions are not unique as they change with the weights applied to the expressions.[8] For that reason, we also compute its polar form (obtained by switching the initial and final year weights) and then take the average of the two. Dietzenbacher and Los (1998) argue this approach yields a close approximation to the average of the full set of possible decompositions.

[8]Dietzenbacher and Los (1998) show that if the number of components or determinants of a decomposition is n, then there are $n!$ equivalent ways of writing the decomposition.

Equation (6a) represents the changes in domestic demand for labor of occupation k that can be attributed to productivity catch-up to the US (changes in efficiency or TFP). Equation (6b) gives the employment in occupation k in the focal economy–industry in the final year if only the intermediate demand shares of GVCs as captured by economies would have changed (changes in location-of-intermediate stages). In a similar vein, equation (6c) shows what would have happened if technological change within global supply chains would have been the only source of change (changes in GVC technology). Equation (6d) indicates what would have happened in the counterfactual case in which final demand shares of GVCs would have changed, but everything else would have remained stable (changes in location-of-completion). Equation (6e) isolates the effects of changes in consumption patterns (changes in consumption composition), while equation (6f) focuses on the effects of differential rates of consumption growth in the G economies considered (changes in consumption levels). The changes regarding the composition and levels of consumption also include the effects of changing patterns and levels of investment demand. In our results, equation (6a) corresponds to "economy-level efficiency"; equation (6c) to "technology within GVC"; the sum of (6b) and (6d) to "task relocation"; equation (6e) to "consumption composition," which is the between GVC component in Figure 1; and equation (6f) to "consumption levels." Equation (6f) is further decomposed into "own economy" and "rest of the world."

IV. Data

The ADB MRIO database comprises input–output tables for the years 2000 and 2007–2020 for $G = 63$ economies—including an "economy" that captures the "rest of the world"—and $N = 35$ industries (see Tables A1 and A2 in Appendix for the lists of economies and industries, respectively).[9] Among the economies covered in the ADB MRIO database are 16 economies in developing Asia: Bangladesh; Cambodia; Fiji; India; Indonesia; the Kyrgyz Republic; Mongolia; Nepal; Pakistan; the Philippines; the PRC; the Republic of Korea; Sri Lanka; Taipei,China; Thailand; and Viet Nam. These economies are considered the developing members of ADB, although clearly there are substantial differences in the levels of economic development among them. We used input–output tables for the years 2008 and 2018, deflated to 2010 prices to ensure that

[9]The ADB MRIO database can be accessed at https://mrio.adbx.online/.

the relative magnitude of each component in our SDA is driven by changes in employment and output volumes, and not output prices.[10]

The second dataset provides occupational employment by economy–industry year. For Bangladesh, Fiji, India, Indonesia, Mongolia, Nepal, Pakistan, the Philippines, the Republic of Korea, Sri Lanka, Thailand, Viet Nam and Taipei,China, we used labor force surveys (LFSs), while the National Population Censuses of 2000 and 2010 provided occupational employment by industry data for the PRC. Moreover, the study benefited from occupational employment data sourced from the household surveys of Cambodia and the Kyrgyz Republic. These economies were selected based on the data available to us.

For each of the 35 industries in the 16 developing Asian economies, we developed time series information on occupations for the period from 2008 to 2018. Table 1 provides an overview of the sources and survey years. Constructing this dataset entails processing the surveys at the level of individual workers. Sampling weights were used to have a representative measure of occupational employment by 56 two-digit occupations in each of the 35 sectors. Throughout the analysis, we used persons employed as the measure of employment and not hours worked, because such data are not available for all economies in the dataset.

Because industry classifications vary from economy to economy, we first mapped the national industry classifications to the 35 International Standard Industrial Classification revision 3.1 industries. The sectors distinguished are agriculture, mining, construction, utilities, 14 manufacturing industries, telecom, finance, business services, personal services, eight trade and transport services industries, and three public services industries. Sectors are chosen such that the harmonized employment data can be merged with the ADB MRIO database and an SDA of the changes in occupational labor demand by economy–industry can be performed.

The two-digit occupations follow the 2008 International Standard Classification of Occupations (ISCO-08). However, there is substantial variation in the national occupational classifications across economies, which again poses the problem of

[10]The constant price series are constructed using the double deflation method, where gross value added is derived by deducting the intermediate consumption in volume terms from the total output in volume terms. Current values of gross industry outputs were all deflated using an appropriate price index (Paasche-type), which were all re-referenced to 2010 base prices (2010 = 100). For final demand, the aggregate deflators were implicitly derived (i.e., sum of final consumptions by industry in volume terms). Deflation of international input–output tables is not straightforward, as it requires proper deflation of all cells in the matrix of intermediate input flows between economy–industries and the matrix of final demand flows. Future releases of the ADB MRIO database may include tables in previous years' prices, taking advantage of recent methodological advances (see, for example, Rémond-Tiedrez and Rueda-Cantuche 2019, Timmer et al. 2021).

Table 1. **Sources of Occupational Data for the 16 Developing Asian Economies**

	Economy	Survey Name	Years
1	Bangladesh	Labor Force Survey (LFS)	2006, 2010, 2013, 2016
2	Cambodia	Cambodia Socio-Economic Survey (CSES)	2003/2004, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017
3	Fiji	Employment and Unemployment Survey (EUS)	2004, 2005, 2010, 2011, 2015, 2016
4	India	National Sample Survey–Employment and Unemployment Survey (NSS–EUS)	1999/2000, 2004/2005, 2011/2012
5	Indonesia	National Labor Force Survey (SAKERNAS)	2000, 2003, 2005, 2008, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017
6	Republic of Korea	Korea Labor and Income Panel Study (KLIPS)	1999–2017
7	Kyrgyz Republic	Kyrgyzstan Integrated Household Survey (KIHS)	2012, 2013, 2014, 2015, 2016, 2017, 2018
8	Mongolia	LFS	2002, 2003, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018
9	Nepal	Nepal Labor Force Survey (NLFS)	1999, 2008, 2017/2018
10	Pakistan	LFS	2001/2002, 2003/2004, 2005/2006, 2006/2007, 2008/2009, 2009/2010, 2010/2011, 2012/2013, 2013/2014, 2014/2015, 2017/2018
11	Philippines	LFS	Quarterly releases for 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2010, 2011, 2012, 2013, 2014, 2015, 2017
12	PRC	Population Census	2000, 2010, 2015
13	Sri Lanka	LFS	2002, 2003, 2004, 2005, 2006, 2007, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017
14	Taipei,China	Manpower Utilization Survey (MUS)	2000, 2001, 2002, 2003, 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018
15	Thailand	LFS	2000, 2005, 2010, 2011, 2012, 2013, 2014, 2015, 2016, 2017, 2018
16	Viet Nam	LFS	2007, 2009, 2010, 2012, 2013, 2014, 2016

PRC = People's Republic of China.
Notes: We drop the LFS in Indonesia before 2003 because of anomalies in the data. For the People's Republic of China, the year 2015 had an interim population census that is based on a more limited sample compared to a full census. Sources in years before the initial year of the analysis (i.e., before 2008) were included to improve upon trends in occupational groupings by economy–industry.
Source: Authors' compilation.

harmonization. The International Labour Organization (ILO) developed the ISCO, which provides an excellent basis for international reporting, comparison, and exchange of data about occupations. Some of our micro-datasets classified occupations using the older ISCO-88 version, in which case we converted them into the latest version, ISCO-08, using the correspondence tables provided by the ILO. Other economies, however, have national occupational classifications with structures that are quite different from ISCO. Where possible, we have used crosswalks from national classifications to ISCO-08 as provided by statistical offices to guide our mapping. Hence, for each year for which a labor force survey is available, we aimed at constructing an employment matrix that has the dimensions of 35 sectors x 56 occupations.[11]

For most economies, we have either a time series or data for a year close to the initial and final year of the analysis. Sources in years before the initial year of the analysis (i.e., before 2008) were included to improve upon trends in occupational employment by economy–industry. If we do not have information for a given year, we use interpolation or extrapolation while making sure that the employment shares always sum to one. These shares are subsequently multiplied with the number of persons employed per year by the economy–industry. This approach closely follows Reijnders and de Vries (2018).

The constructed occupational employment matrices are new and not readily available from public sources. Yet, more aggregate information on employment by broad sectors or employment by broad occupations is available from the ILO labor statistics database (ILO 2020). Data available at the ILO database were used to cross-check the accuracy at which our dataset has been constructed.

The new occupation dataset for developing Asian economies is based on an in-depth investigation of sources and methods on an economy-by-economy basis, described in greater detail in Gentile and de Vries (2021). Yet, the dataset is not without concerns. In particular, the accuracy is subject to data limitations in several Asian economies. Measurement error will be larger for those economies with more limited statistical capacity, especially if the statistical offices have a small budget and a limited experience in administering labor force surveys to cover an adequate and nationally representative portion of the workforce.[12]

[11]The number of two-digit occupations is less than 56 if an occupation is not observed in a particular sector, which does not pose a problem for the empirical analysis as occupations are aggregated (discussed below).

[12]See the World Bank's (2020) documentation of statistical capacity of economies at https://datatopics.worldbank.org/statisticalcapacity/SCIdashboard.aspx.

The next step is to investigate how demand for specific types of jobs changes in response to technological advances along the value chain. We adopt the taxonomy developed in Autor, Levy, and Murnane (2003), which classifies occupations as routine manual, routine cognitive, nonroutine manual, and nonroutine cognitive.

Based on these restrictions, we select the occupation groups that allow us to have as much detail as possible while minimizing the amount of classification errors. The occupation groups are reported with the corresponding two-digit ISCO-08 codes in Table 2 and classified as either routine or nonroutine, and either manual or cognitive. We multiply the occupation–industry year shares with the corresponding number of persons employed to obtain the employment levels.

As discussed in the previous section, we implement an efficiency correction using the economy–year TFP measures at constant national prices sourced from the Penn World Tables release 9.1 (Feenstra, Inklaar, and Timmer 2015). We normalize them by imposing the condition that TFP in the US in 2010 (corresponding to the base year of the constant-price ADB MRIO database) is equal to unity, so that economy-level efficiency is pegged to a numeraire economy at a fixed point in time.

The taxonomy developed by Autor, Levy, and Murnane (2003) to classify occupations as routine manual, routine cognitive, nonroutine manual, and nonroutine cognitive is not applicable to agricultural employment, since it is difficult to distinguish routine and nonroutine occupations in agriculture. As in Autor, Levy, and

Table 2. **Classification of Occupations**

	Routine	**Nonroutine**
Manual	Craft and related trade workers [71–75] Plant and machine operators and assemblers [81–83] Elementary occupations [91–96][a]	Services and sales workers [51–54]
Cognitive	Clerical support workers [41–44]	Managers [11–14] Professionals [21–26] Technicians and associate professionals [31–35]

[a]Elementary occupations involve the performance of simple and routine tasks which may require the use of hand-held tools and considerable physical effort.
Notes: The numbers in brackets refer to ISCO-08 codes, excluding Agriculture [61–63] and Armed forces [01–03]. The grouping of occupations in four categories (routine manual, routine cognitive, nonroutine manual, and nonroutine cognitive) is based on Autor, David, Frank Levy, and Richard Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *The Quarterly Journal of Economics* 118 (4): 1279–333, as described in Reijnders, Laurie S. M., and Gaaitzen J. de Vries. 2018. "Trade, Technology and the Rise of Non-Routine Jobs." *Journal of Development Economics* 135: 412–32.
Source: Authors' compilation.

Murnane (2003) and subsequent works, agricultural occupations are not considered in the analysis of changes in occupational labor demand. In advanced economies, this is innocuous as agricultural occupations typically constitute a small fraction of the workforce [e.g., it is less than 4% in the US as per Autor (2015)]. But in developing Asian economies, this is a substantial part of total employment (see the final column in Table A3 in Appendix for point estimates in the initial and final years).

V. Results

We perform structural decompositions at different levels of aggregation. First, we look at the relative impacts of technology, task relocation, and consumption levels on changes in total employment by economy and sector. Next, we split employment into the four occupational categories by sector. Finally, we look at the demand effects from domestic and foreign consumption expenditures.

Results for employment levels in subsections A and C pertain to all workers, including those with agricultural occupations. Subsection B examines the changes in routine and nonroutine employment associated with the changes in consumption, trade, and technology that pertain to nonagricultural occupations.

A. Aggregate Employment Effects of Technology, Trade, and Consumption

The SDA for total sectoral employment by economy is displayed in Table 3. Although we perform the SDA for all 63 MRIO economies, we focus on analyzing the results for the 16 developing Asian economies. Results for the other, mainly advanced, economies have been described in Reijnders and de Vries (2018). Columns (1)–(3) show the employment levels in 2008, 2018, and the percentage change in employment between 2008 and 2018, respectively. Columns (4)–(9) contain the six terms of the decomposition: the within-GVC channel (economy-level efficiency [4], technology within GVC [5], and task relocation [6]); the between-GVC channel (consumption composition [7]); and consumption levels (domestic demand for goods and services [8] and demand for goods and services from the rest of the world [9]). Table 3 is divided into three panels, displaying the SDA for manufacturing (Panel A), services (Panel B), and all sectors (Panel C).

Columns (1)–(3) of Table 3 document the structural transformation in developing Asia from 2008 to 2018. During this period, several Asian developing economies showed faster growth in manufacturing compared to services. This was observed in Bangladesh, Cambodia, the Kyrgyz Republic, Mongolia, Pakistan, Thailand, and Viet Nam.

Meanwhile, Fiji, India, Indonesia, the Republic of Korea, Nepal, the Philippines, the PRC, Sri Lanka, and Taipei,China displayed faster employment growth in services than in manufacturing. For instance, Fiji is a known banking and air transport services hub in the Pacific region, and its growth story is characterized by a rebalancing away from agriculture toward urban services (World Bank 2015). Services are also known to have led economic growth in the South Asian countries such as India, Nepal, and Sri Lanka (Noland, Park, and Estrada 2012). As a case in point, Dahal (2018) documents deindustrialization in Nepal, as indicated by the rising share of services in its economic output along with declining and stagnant shares of agriculture and manufacturing. Likewise, Indonesia, the Republic of Korea, the Philippines, the PRC, and Taipei,China commonly display a rapidly expanding services sector (in terms of job creation), albeit with differences in the historical development trajectories experienced by these economies. The pattern of structural transformation in employment in Indonesia, for instance, is characterized by a gradual decline of labor in agriculture accompanied by a rise in services employment (Majid and Sarma 2018). Employment in its manufacturing sector expanded during the review period, although much slower than the share of services employment. The PRC, on the other hand, witnessed a rapid increase in the share of employment in services in the past 2 decades (Hou, Gelb, and Calabrese 2017). This occurred alongside the development of a globalized network of manufacturing production prior to the global financial crisis. In 2008, the PRC started turning toward domestic factors of production to support its goods and services production.

Column (6) of Table 3 documents that task relocation to Viet Nam and Cambodia positively contributed to demand for workers in manufacturing in these two countries (accounting for 69% and 58% of the change, respectively). Positive task relocation effects in services, meanwhile, were the largest in Cambodia and Thailand (accounting for 23% and 13% of economy-specific labor demand change, respectively). In addition, our results indicate that many other Asian developing economies also benefited from the relocation of GVC tasks to their economies, with relatively larger effects in manufacturing than in services.

Moreover, it is apparent that GVC technological change (see column [5] of Table 3) generally accounts for a larger change in labor demand compared to task relocation. Indeed, technological progress has typically been substantial. For example, all else being equal, technological change within GVCs accounts for declines of 68%

Table 3. **Structural Decomposition Analysis of the Changes in Employment by Sector, 2008–2018**

	Employment (2018) (1)	Employment (2008) (2)	Change (3)	Economy-level Efficiency (4)	Technology within GVC (5)	Task Relocation (6)	Consumption Composition (7)	Consumption Levels: Own-Economy (8)	Consumption Levels: Rest-of-the-World (9)
				A. Manufacturing[a]					
Bangladesh	9,509	6,142	55	−19	−18	25	11	45	10
Cambodia	1,427	768	86	−18	−2	58	2	29	16
Fiji	23	31	−27	7	−30	−8	−12	10	7
India	56,125	48,360	16	−16	−56	12	5	66	5
Indonesia	18,263	12,629	45	−10	−9	8	5	39	11
Korea, Republic of	4,532	4,186	8	−2	−19	−4	0	13	21
Kyrgyz Republic	284	178	60	−112	179	−43	−4	18	23
Mongolia	98	63	57	−49	−5	−11	39	71	11
Nepal	2,449	1,138	115	−23	107	−63	18	67	10
Pakistan	11,096	6,936	60	−51	67	7	−3	34	7
Philippines	3,703	2,904	28	−19	−6	0	−8	49	11
PRC	156,382	161,491	−3	1	−68	−3	3	56	7
Sri Lanka	1,611	1,452	11	−18	−6	5	−12	33	8
Taipei,China	3,192	3,000	6	7	−24	−8	−2	6	28
Thailand	6,395	5,139	24	−18	10	16	−8	9	16
Viet Nam	9,297	6,836	36	−9	−58	69	−6	24	17
All Asian developing economies	284,386	261,252	9	−5	−53	4	3	53	8
				B. Services					
Bangladesh	24,295	18,479	31	−17	−29	0	−3	79	2
Cambodia	3,033	1,824	66	−16	6	23	−9	54	9

Continued.

Table 3. *Continued.*

	Employment (2018) (1)	Employment (2008) (2)	Change (3)	Economy-level Efficiency (4)	Technology within GVC (5)	Task Relocation (6)	Consumption Composition (7)	Consumption Levels: Own-Economy (8)	Consumption Levels: Rest-of-the-World (9)
Fiji	169	143	18	9	−24	8	6	13	7
India	139,754	107,586	30	−17	−45	1	15	72	5
Indonesia	60,939	41,805	46	−10	−4	−2	1	57	4
Korea, Republic of	18,816	16,288	16	−2	−8	−5	−1	24	8
Kyrgyz Republic	1,320	973	36	−99	103	11	−18	31	7
Mongolia	652	485	35	−44	−7	9	0	67	10
Nepal	7,608	2,856	166	−27	120	−5	−14	87	5
Pakistan	24,620	18,099	36	−46	30	0	12	37	2
Philippines	24,409	15,474	58	−21	−8	7	1	73	6
PRC	351,382	250,407	40	2	−48	−2	−3	88	4
Sri Lanka	3,642	2,990	22	−19	−10	4	−5	48	3
Taipei,China	7,036	6,208	13	7	−12	−7	1	18	8
Thailand	17,168	15,152	13	−17	−14	13	12	11	8
Viet Nam	13,495	14,801	−9	−7	−40	−3	−4	40	5
All Asian developing economies	698,339	513,572	36	−8	−35	−1	2	72	5
C. All Sectors									
Bangladesh	65,855	52,898	24	−16	−25	5	−13	71	3
Cambodia	8,838	7,242	22	−13	−19	15	−17	49	8
Fiji	272	341	−20	7	−36	0	−8	11	5
India	454,957	427,631	6	−15	−40	2	−14	70	3
Indonesia	126,754	103,319	23	−9	−21	−1	−1	49	5

Continued.

Table 3. *Continued.*

								Consumption Levels	
	Employment (2018) (1)	**Employment (2008) (2)**	**Change (3)**	**Economy-level Efficiency (4)**	**Technology within GVC (5)**	**Task Relocation (6)**	**Consumption Composition (7)**	**Own-Economy (8)**	**Rest-of-the-World (9)**
Korea, Republic of	26,956	24,191	11	−2	−11	−3	−4	22	9
Kyrgyz Republic	2,402	2,165	11	−86	54	3	4	27	8
Mongolia	1,237	1,068	16	−40	−33	6	8	63	11
Nepal	16,087	13,668	18	−16	−1	−13	−15	59	3
Pakistan	68,178	53,019	29	−44	35	2	−1	34	3
Philippines	42,839	33,265	29	−19	−21	4	−8	67	5
PRC	768,735	754,239	2	1	−67	−4	−8	75	4
Sri Lanka	8,196	7,571	8	−17	−20	4	−5	44	4
Taipei,China	11,772	10,657	10	7	−14	−6	−3	15	13
Thailand	38,395	38,076	1	−16	−12	16	−7	10	10
Viet Nam	50,574	48,394	5	−8	−49	19	−1	33	11
All Asian developing economies	1,692,045	1,577,745	7	−7	−46	0	−9	66	4

GVC = Global value chain, PRC = People's Republic of China.
[a]Manufacturing is derived by excluding electricity, gas and water supply, and construction from the industrial sectors. Instead, these are included in Panel C.
Notes: The first two columns represent absolute numbers, while the others pertain to percentage changes. Column (3) is equal to the sum of columns (4)–(9).
Source: Authors' calculations based on Asian Development Bank. 2020. "Multiregional Input–Output Tables." https://mrio.adbx.online/ (accessed May 4, 2020).

and 58% in the induced demand for manufacturing workers in the PRC and Viet Nam, respectively, between 2008 and 2018. For some economies—such as Pakistan and the Kyrgyz Republic—and some economy–sector pairs—such as Nepal and Thailand for manufacturing and Cambodia and Nepal for services—the findings suggest an increase in induced labor demand within the GVCs in which they participate. An examination of real labor productivity suggests these findings could be due to negative productivity growth in our data for these economies or economy–sector pairs between 2008 and 2018.[13]

The last columns of Table 3 compare the magnitude of changes in domestic employment levels associated with changes in consumption levels within the domestic economy and for the rest of the world. Meanwhile, the effects of own-economy consumption levels are generally much larger than those from the rest of the world. To illustrate, own-economy consumption accounted for a 66% change, all else being equal, in the overall labor demand across all economies studied. This contrasts with the 4% total labor demand change induced by the rest-of-the-world consumption levels.

A more nuanced analysis reveals that consumption from the rest of the world had a larger effect on labor demand than own-economy consumption in the manufacturing sector of some economies. This is true for the Republic of Korea, the Kyrgyz Republic, Thailand, and Taipei,China. In the Republic of Korea, for example, the increase in manufacturing labor demand associated with the demand for goods and services from the rest of the world is 21%, as opposed to 13% from the own-economy consumption channel. A large proportion of manufacturing employment generated by income effects in the four aforementioned economies relies on foreign demand, which may indicate their high forward participation in GVCs as suppliers of manufactured goods.

Column (7) of Table 3 suggests a general shift in consumer preferences toward manufactured goods and services, inducing moderate positive changes in manufacturing and services labor demand occurring through the consumption composition channel. This is an encouraging sign that a new class of consumers has emerged from the Asian

[13]For example, dividing the real value added from the ADB MRIO database by employment indicates that aggregate labor productivity declined by 2.6% (5.3%) annually in Pakistan (the Kyrgyz Republic) between 2008 and 2018. Confusingly, the TFP data in Penn World Tables 9.1 for Pakistan and the Kyrgyz Republic suggests an increase in country-efficiency (see column [4] in Panel C of Table 3). Moreover, alternative sources, such as the GGDC/UNU-WIDER Economic Transformation Database, indicate the real labor productivity growth was positive in Pakistan between 2008 and 2018. This suggests the approach to deflate value added for several economies in the ADB MRIO database requires further scrutiny (see also the discussion in Section IV).

developing economies, generating domestic demand for products and services (we will examine this further in Section V.C).

Finally, Table 3 shows that the increase in employment associated with own-economy and rest-of-the-world consumption levels is large enough to offset the decrease in employment associated with GVC technology. Aggregating changes across all sectors in the 16 developing Asian economies considered in the analysis, the combined own-economy and rest-of-the-world consumption effect accounted for a 70% increase in labor demand, while the countervailing negative employment impact associated with GVC technology stood at 46% of total employment. Strictly speaking, it thus seems desirable for a developing economy not to participate in GVCs if it aims to maximize job creation, because technological change within GVC lowers the induced labor demand whereas the domestic consumption raises it. However, such a strategy is misplaced. Innovation and technological change are essential for sustained economic growth. Indeed, economies that participate in GVCs characterized by rapid technological change also tend to experience a faster expansion of domestic consumption.[14] Yet, GVC participation has distributional implications that are examined in the next subsection.

B. The Demand for Routine and Nonroutine Jobs

Of great interest is whether certain occupations are more vulnerable than others to being displaced by technology. The results of the SDA by occupation type are presented for manufacturing in Table 4 and for services in Table 5. The overall trends are the same as in Table 3, but here the changes in sectoral employment are broken down by occupation types.

Examining employment changes across occupations for the 16 Asian developing economies taken together, the findings indicate that, in the manufacturing sector, nonroutine cognitive occupations showed the largest increase at 20% (Table 4).

In column (5) of Table 4 it can be observed that changes in employment associated with "technology within GVC" are mixed across economies and occupation types. Yet, assuming that only technology within GVCs changed between 2008 and 2018, we find (i) an increase in manufacturing employment of nonroutine cognitive occupations in eight developing Asian economies and a decrease in the other eight

[14] For example, the correlation coefficient between labor demand changes in all sectors due to technological change within GVCs (column [5] in Panel C of Table 3) and changes in domestic consumption levels (column [8] of Table 3) is -0.4.

Table 4. **Structural Decomposition Analysis of the Change in Manufacturing Employment by Occupation Type, 2008–2018**

								Consumption Levels	
	Employment (2018) (1)	Employment (2008) (2)	Change (3)	Economy-level Efficiency (4)	Technology within GVC (5)	Task Relocation (6)	Consumption Composition (7)	Own-Economy (8)	Rest-of-the-World (9)
A. Nonroutine Cognitive Occupations									
Bangladesh	1,280	1,090	17	−16	−43	9	13	46	8
Cambodia	27	7	316	−32	11	270	−5	34	39
Fiji	4	5	−18	7	−27	−3	−12	10	7
India	11,618	7,683	51	−18	−32	18	5	74	5
Indonesia	1,730	789	119	−13	24	41	2	49	15
Korea, Republic of	887	698	27	−2	−11	4	0	14	23
Kyrgyz Republic	42	29	45	−104	146	−31	−6	18	21
Mongolia	22	12	86	−55	4	10	35	81	11
Nepal	232	89	162	−27	143	−72	30	79	10
Pakistan	1,089	701	55	−50	62	4	−1	36	5
Philippines	850	547	55	−21	6	10	−7	55	12
PRC	24,004	23,164	4	1	−65	−3	3	59	7
Sri Lanka	190	191	−1	−17	−14	2	−11	32	8
Taipei,China	1,081	1,000	8	7	−26	−6	−2	6	30
Thailand	989	734	35	−19	12	21	−5	9	17
Viet Nam	768	550	39	−9	−41	47	−3	29	16
All Asian developing economies	44,814	37,288	20	−6	−48	4	3	57	8
B. Nonroutine Manual Occupations									
Bangladesh	251	122	106	−23	13	36	15	51	13
Cambodia	15	2	543	−47	97	374	6	60	53

Continued.

Table 4. *Continued.*

								Consumption Levels	
	Employment (2018) (1)	**Employment (2008) (2)**	**Change (3)**	**Economy-level Efficiency (4)**	**Technology within GVC (5)**	**Task Relocation (6)**	**Consumption Composition (7)**	**Own-Economy (8)**	**Rest-of-the-World (9)**
Fiji	1	2	−47	6	−32	−24	−13	9	6
India	1,766	1,390	27	−17	−42	11	1	69	5
Indonesia	1,303	899	45	−10	−10	9	4	39	13
Korea, Republic of	201	162	24	−2	−19	10	−1	13	22
Kyrgyz Republic	18	12	48	−106	165	−44	−6	18	21
Mongolia	8	6	32	−43	−40	5	29	73	7
Nepal	62	33	85	−21	76	−71	27	67	7
Pakistan	320	105	205	−84	192	41	−4	54	8
Philippines	184	76	142	−29	38	51	−5	73	14
PRC	8,814	9,725	−9	1	−71	−5	3	56	7
Sri Lanka	64	51	26	−19	10	9	−19	38	8
Taipei,China	89	90	−1	6	−18	−16	−3	9	22
Thailand	380	225	69	−22	28	41	−7	10	18
Viet Nam	343	239	43	−9	−44	57	−5	28	17
All Asian developing economies	13,818	13,140	5	−3	−56	0	2	54	8
				C. Routine Cognitive Occupations					
Bangladesh	95	64	48	−18	−7	5	9	49	9
Cambodia	15	1	1,697	−121	256	1,343	−41	117	143
Fiji	2	2	3	8	−12	4	−16	11	8
India	1,048	1,256	−17	−13	−66	−3	1	60	4
Indonesia	778	479	63	−10	4	13	3	39	13

Continued.

Table 4. *Continued.*

								Consumption Levels	
	Employment (2018) (1)	**Employment (2008) (2)**	**Change (3)**	**Economy-level Efficiency (4)**	**Technology within GVC (5)**	**Task Relocation (6)**	**Consumption Composition (7)**	**Own-Economy (8)**	**Rest-of-the-World (9)**
Korea, Republic of	1,045	740	41	−2	−5	10	0	14	25
Kyrgyz Republic	15	7	133	−152	271	−33	−3	22	29
Mongolia	2	1	73	−52	4	2	29	78	12
Nepal	47	30	54	−19	46	−93	53	60	7
Pakistan	141	99	43	−48	49	4	−2	34	5
Philippines	201	139	44	−20	1	6	−6	53	12
PRC	7,331	7,860	−7	1	−66	−9	3	56	7
Sri Lanka	48	45	8	−17	−7	2	−11	33	8
Taipei,China	349	298	17	7	−16	−7	−2	7	29
Thailand	356	276	29	−19	11	18	−6	9	16
Viet Nam	269	142	89	−11	−22	90	−15	27	21
All Asian developing economies	11,744	11,440	3	−3	−53	−4	2	50	9
D. Routine Manual Occupations									
Bangladesh	7,883	4,865	62	−19	−13	29	10	45	11
Cambodia	1,369	759	80	−17	−5	56	2	29	16
Fiji	16	23	−30	7	−31	−10	−12	10	7
India	41,692	38,030	10	−15	−61	11	5	64	5
Indonesia	14,451	10,461	38	−9	−13	6	5	38	11
Korea, Republic of	2,401	2,586	−7	−2	−23	−13	0	12	19
Kyrgyz Republic	209	130	61	−113	186	−49	−4	17	23
Mongolia	66	44	52	−48	−3	−18	42	68	12

Continued.

Table 4. *Continued.*

	Employment (2018) (1)	Employment (2008) (2)	Change (3)	Economy-level Efficiency (4)	Technology within GVC (5)	Task Relocation (6)	Consumption Composition (7)	Consumption Levels: Own-Economy (8)	Consumption Levels: Rest-of-the-World (9)
Nepal	2,108	986	114	−23	106	−61	15	66	11
Pakistan	9,546	6,032	58	−51	65	7	−3	33	7
Philippines	2,468	2,142	15	−18	−11	−4	−9	47	10
PRC	116,233	120,742	−4	1	−69	−2	3	56	7
Sri Lanka	1,308	1,165	12	−18	−5	6	−11	33	8
Taipei,China	1,673	1,612	4	7	−24	−10	−3	6	27
Thailand	4,669	3,903	20	−18	9	13	−9	8	15
Viet Nam	7,917	5,904	34	−9	−62	72	−6	24	16
All Asian developing economies	214,009	199,384	7	−6	−54	4	3	52	8

GVC = Global value chain, PRC = People's Republic of China.
Notes: The first two columns represent absolute numbers, while the others pertain to percentage changes. Column (3) is equal to the sum of columns (4)–(9).
Source: Authors' calculations based on Asian Development Bank. 2020. "Multiregional Input–Output Tables." https://mrio.adbx.online/ (accessed May 4, 2020).

Table 5. **Structural Decomposition Analysis of the Change in Services Employment by Occupation Type, 2008–2018**

								Consumption Levels	
	Employment (2018) (1)	Employment (2008) (2)	Change (3)	Economy-level Efficiency (4)	Technology within GVC (5)	Task Relocation (6)	Consumption Composition (7)	Own-Economy (8)	Rest-of-the-World (9)
A. Nonroutine Cognitive Occupations									
Bangladesh	13,194	9,539	38	−17	−25	1	−4	82	1
Cambodia	1,623	1,004	62	−16	−2	27	−9	52	10
Fiji	75	61	23	9	−25	7	12	14	6
India	84,131	64,370	31	−17	−49	0	19	72	5
Indonesia	33,689	21,357	58	−10	8	−1	−3	59	4
Korea, Republic of	7,994	7,170	12	−2	−12	−4	−2	24	7
Kyrgyz Republic	724	559	29	−96	94	7	−14	31	7
Mongolia	408	277	47	−47	1	13	0	70	9
Nepal	5,016	1,740	188	−29	140	−5	−15	94	4
Pakistan	15,052	10,623	42	−47	34	0	15	37	3
Philippines	13,662	10,004	37	−20	−25	2	5	69	5
PRC	211,238	156,928	35	2	−53	−1	−2	84	5
Sri Lanka	1,962	1,642	19	−18	−9	2	−7	49	2
Taipei,China	4,012	3,407	18	7	−11	−6	1	19	7
Thailand	9,752	9,428	3	−16	−25	12	15	11	8
Viet Nam	7,694	7,926	−3	−8	−34	−4	−5	43	5
All Asian developing economies	410,227	306,035	34	−7	−38	0	3	72	5
B. Nonroutine Manual Occupations									
Bangladesh	5,393	3,159	71	−20	6	−1	−4	88	2
Cambodia	852	211	304	−32	161	84	−14	87	17

Continued.

Table 5. *Continued.*

								Consumption Levels	
	Employment (2018) (1)	**Employment (2008) (2)**	**Change (3)**	**Economy-level Efficiency (4)**	**Technology within GVC (5)**	**Task Relocation (6)**	**Consumption Composition (7)**	**Own-Economy (8)**	**Rest-of-the-World (9)**
Fiji	41	34	20	9	−23	9	5	10	10
India	31,350	23,834	32	−17	−38	1	9	71	6
Indonesia	10,245	11,160	−8	−7	−48	−7	5	46	4
Korea, Republic of	6,367	5,401	18	−2	−3	−8	−1	24	8
Kyrgyz Republic	298	214	39	−101	104	22	−24	31	8
Mongolia	161	137	18	−40	−19	8	−5	63	11
Nepal	1,465	677	116	−23	77	−9	−10	75	7
Pakistan	5,975	2,863	109	−62	112	3	6	48	2
Philippines	6,817	3,092	121	−27	44	26	−15	86	7
PRC	63,544	36,037	76	2	−22	−3	−6	102	3
Sri Lanka	886	629	41	−20	−2	12	−2	50	4
Taipei,China	1,563	1,347	16	7	−11	−6	0	17	9
Thailand	4,201	2,480	69	−22	31	27	10	14	10
Viet Nam	3,634	2,411	51	−10	−36	20	23	44	10
All Asian developing economies	142,793	93,688	52	−9	−18	0	1	75	5
C. Routine Cognitive Occupations									
Bangladesh	880	860	2	−15	−45	−8	1	65	4
Cambodia	397	152	162	−22	89	17	−11	81	8
Fiji	21	15	34	9	−10	8	6	14	7
India	8,119	7,312	11	−15	−49	0	2	69	4
Indonesia	6,001	4,601	30	−9	−17	−2	0	55	3

Continued.

Table 5. *Continued.*

								Consumption Levels	
	Employment (2018) (1)	**Employment (2008) (2)**	**Change (3)**	**Economy-level Efficiency (4)**	**Technology within GVC (5)**	**Task Relocation (6)**	**Consumption Composition (7)**	**Own-Economy (8)**	**Rest-of-the-World (9)**
Korea, Republic of	3,249	2,654	22	−2	−3	−3	−2	25	8
Kyrgyz Republic	169	98	72	−119	162	10	−26	34	10
Mongolia	27	16	74	−53	25	18	−5	77	12
Nepal	421	186	126	−24	105	−13	−26	78	6
Pakistan	728	527	38	−47	11	2	32	39	1
Philippines	2,078	1,493	39	−20	−25	10	0	69	6
PRC	46,094	32,698	41	2	−51	−4	−3	95	3
Sri Lanka	272	255	7	−17	−19	2	−7	46	2
Taipei,China	887	784	13	7	−12	−9	1	17	9
Thailand	1,165	1,028	13	−17	−5	10	7	12	7
Viet Nam	658	525	25	−9	−29	1	8	49	5
All Asian developing economies	71,166	53,205	34	−4	−41	−3	−1	79	3
D. Routine Manual Occupations									
Bangladesh	4,828	4,920	−2	−14	−57	0	−2	71	1
Cambodia	161	457	−65	−8	−80	−10	−5	33	5
Fiji	33	33	−1	8	−28	6	−5	11	7
India	16,154	12,070	34	−17	−40	2	12	72	5
Indonesia	11,004	4,687	135	−13	59	4	7	73	5
Korea, Republic of	1,205	1,063	13	−2	−10	−5	−2	22	10
Kyrgyz Republic	129	102	27	−94	99	4	−19	30	8
Mongolia	56	55	2	−37	−28	−10	9	59	9

Continued.

Table 5. *Continued.*

								Consumption Levels	
	Employment (2018) (1)	**Employment (2008) (2)**	**Change (3)**	**Economy-level Efficiency (4)**	**Technology within GVC (5)**	**Task Relocation (6)**	**Consumption Composition (7)**	**Own-Economy (8)**	**Rest-of-the-World (9)**
Nepal	706	254	178	−28	117	−2	−3	84	10
Pakistan	2,865	4,087	−30	−31	−35	−2	8	28	2
Philippines	1,852	885	109	−26	24	9	11	84	7
PRC	30,506	24,744	23	1	−56	−5	−5	85	4
Sri Lanka	521	463	12	−18	−18	4	−4	45	3
Taipei,China	574	671	−14	6	−26	−16	−1	16	7
Thailand	2,049	2,216	−8	−15	−23	8	4	9	10
Viet Nam	1,510	3,938	−62	−5	−58	−14	−20	32	4
All Asian developing economies	74,153	60,645	22	−9	−38	−3	0	68	4

GVC = Global value chain, PRC = People's Republic of China.
Notes: The first two columns represent absolute numbers, while the others pertain to percentage changes. Column (3) is equal to the sum of columns (4)–(9).
Source: Authors' calculations based on Asian Development Bank. 2020. "Multiregional Input–Output Tables." https://mrio.adbx.online/ (accessed May 4, 2020).

economies; and (ii) an employment reduction of routine manual occupations in manufacturing, except in the Kyrgyz Republic, Nepal, Pakistan, and Thailand. As a result, our analysis suggests that technology within GVCs altered the occupational structure of the manufacturing sector in several Asian developing economies, shrinking the demand for routine manual occupations while exerting an upward pull on the contribution of nonroutine cognitive occupations. This lends support to the routine-biased job polarization hypothesis (Autor 2013).

The results in column (6) of Table 4 indicate sizable task relocation effects in manufacturing. Within manufacturing, the change in labor demand associated with task relocation is relatively larger (and often positive) in manual jobs (both routine and nonroutine). Other economies—such as Fiji, the Republic of Korea, the Kyrgyz Republic, Mongolia, Nepal, and Taipei,China—experienced a reduction in routine manual manufacturing employment that is attributable to task relocation. These observations may indicate a dynamic reorganization of manufacturing value chains in Asia.

In services, nonroutine manual occupations displayed the most sizable increase at 52% (Table 5). Aggregate results covering all 16 Asian developing economies suggest that technology within a GVC is associated with the largest relative contraction in routine cognitive occupations. Task relocation is associated with a modest decline in routine employment. The figure stands at 3% for both routine cognitive and routine manual occupations. The reduction in labor demand is most pronounced in routine cognitive occupations in Nepal and Taipei,China, and in routine manual occupations in Viet Nam and Taipei,China.

In sum, our findings exhibit two trends in task relocation: in manufacturing, it is associated with changes in demand for routine cognitive jobs, whereas in services, it is associated with reduced demand for routine cognitive and manual jobs. Overall, our findings suggests that task relocation in developing Asia induces a general orientation of labor demand toward cognitive and nonroutine jobs, potentially indicative of skill upgrading along the GVCs.

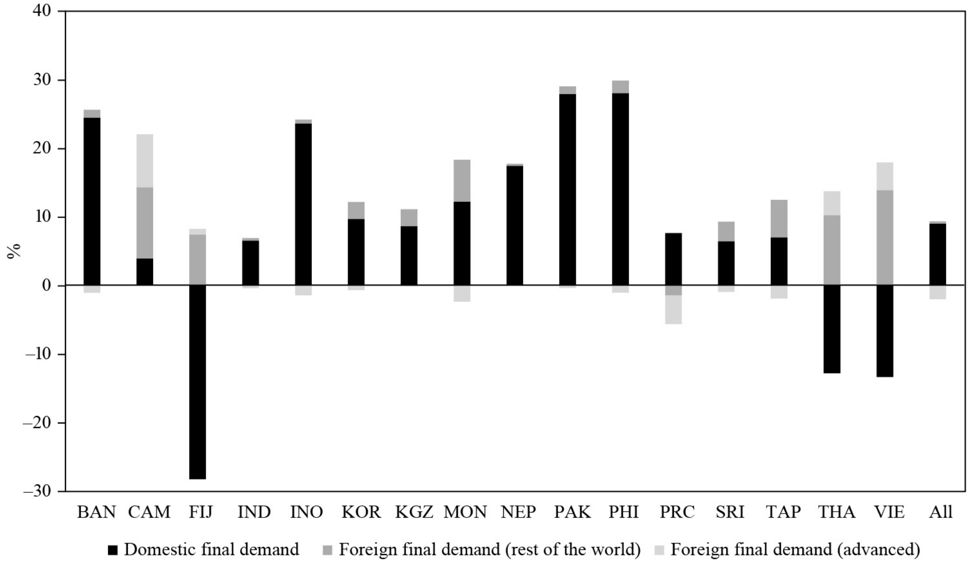
C. Foreign versus Domestic Expenditures and Labor Demand

The evidence thus far indicates that technological change within GVCs is associated with heterogeneous changes in employment across the Asian developing economies, although the general trends imply that its distributional impact corresponds to a rise of nonroutine cognitive occupations and a decline of routine manual occupations in manufacturing. This observation bears more weight when interpreted within the context of increasing affordability, flexibility, and use-of-production technologies such as industrial robots.

Developing economies that have benefited from offshoring of production tasks from advanced economies are now concerned about reshoring; that is, they fear that it could become economically feasible to move those production tasks back to the economy of origin (Barcia de Mattos et al. 2020). In an SDA, reshoring would appear as a sizable decrease in employment associated with task relocation. Indeed, Table 3 shows that at least for some developing economies there are some negative task relocation effects.

To determine whether employment in developing Asian economies is becoming increasingly less dependent on final demand from advanced economies, the approach adopted by Los, Timmer, and de Vries (2015) is utilized. Figure 3 shows the changes in the number of jobs induced by final demand from 2008 to 2018 as a fraction of total

Figure 3. **Changes in the Number of Jobs Induced by Foreign and Domestic Demands, 2008–2018**



All = 16 Developing Asian economies; BAN = Bangladesh; CAM = Cambodia; FIJ = Fiji; IND = India; INO = Indonesia; KGZ = Kyrgyz Republic; KOR = Republic of Korea; MON = Mongolia; NEP = Nepal; PAK = Pakistan; PHI = Philippines; PRC = People's Republic of China; SRI = Sri Lanka; TAP = Taipei,China; THA = Thailand; VIE = Viet Nam.

Source: Authors' estimates using data from the Asian Development Bank's Multiregional Input–Output database, Labor Force Surveys, and Socioeconomic Accounts of the World Input–Output Database.

jobs. It is decomposed into domestic final demand, final demand from advanced economies, and final demand from the rest of the world.[15]

Figure 3 shows that domestic final demand is associated with a 9% increase in employment for the 16 Asian developing economies as a whole. Fiji, Thailand, and Viet Nam show a decline in employment associated with domestic final demand, whereas Pakistan and the Philippines show the largest increases (28% for both economies).

Jobs induced by final demand from advanced economies decreased by 2% for the grouping of 16 Asian developing economies. Negative demand effects due to the global financial crisis and subsequent slow growth in final demand in advanced economies likely affected the results, especially for the PRC. Cambodia is the economy where final demand from advanced economies was the most important source of increased job demand at 8%, followed by Viet Nam (4%), and Thailand (3%).

The key advantage of reshoring is to move production close to customers, resulting in shorter time to market, lower transportation costs, and increased efficiency.[16] While consumer markets in advanced economies are increasingly saturated, the middle class in Asia expands, which raises the demand for goods and services. Perhaps the most interesting observation from Figure 3 is that, although the increase in employment associated with final demand from the rest of the world is negligible for all 16 Asian developing economies together, it is quite large for individual economies like Viet Nam (14%), Thailand (10%), and Cambodia (10%). Markets in the "rest of the world" have high potential for growth, and therefore the relative importance of final demand from advanced economies for employment in developing economies will likely decline over time.

VI. Conclusion

In many economies around the world, labor markets have seen a rise in nonroutine cognitive and nonroutine manual occupations relative to the routine

[15]The advanced economies in this decomposition are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Luxembourg, the Netherlands, Portugal, Spain, Sweden, the United Kingdom, and the US. For each of the 16 Asian developing economies in the chart, the "rest of the world" category includes the other 15 as well as other economies at various stages of development.

[16]"Time to market" is the time it takes from a product being conceived until it is being available for sale.

task-intensive occupations. So far, analysis of this phenomenon has been restricted to advanced and a select set of emerging economies. In this paper, we have expanded coverage to the developing Asian economies by studying the changes in the job structure in these economies. We have examined these changes through the lens of a GVC framework. In particular, for each supply chain we have looked at changes in the use of occupational labor per dollar of output (defined as GVC technology) and shifts in the share captured by each economy (defined as task relocation).

Our findings suggest that both technological change within GVCs and task relocation tend to drive down routine manual occupations relative to the nonroutine cognitive jobs in manufacturing. However, the increases in employment demand associated with own-economy increased expenditures of a rapidly expanding middle class are large enough to offset the decrease in employment associated with GVC technology.

These findings are based on a decomposition that is essentially an *ex-post* accounting exercise. The results are useful empirical findings, but we cannot claim to have determined a causal effect nor have isolated specific mechanisms for the observed changes in the structure of employment. In practice, technological change, task relocation, and consumption are interrelated. For example, an improvement in information technology may reduce labor demand throughout a supply chain, but it may also affect the ease at which a task can be relocated.

Yet, we believe the occupation-based analysis presented in this paper opens important avenues for future research that may uncover causal mechanisms. In particular, the measurement of occupations involved in GVCs provides a novel angle to study the effects of robot adoption on employment changes. The use of robots by lead firms in advanced economies may affect the demand for workers in developing economies participating in the value chain of the lead firm (Faber 2020).

Researchers may also use the approach put forth here and develop the data to examine the drivers of changes in the job structure in other developing economies, notably in Africa and Latin America. Finally, a critical open research question is the extent to which the occupational employment shifts documented here help to understand changes in wage inequality.

References

Acemoglu, Daron. 2002. "Technical Change, Inequality and the Labor Market." *Journal of Economic Literature* 40 (1): 7–72.

Acemoglu, Daron, and Pascual Restrepo. 2017. "Robots and Jobs: Evidence from US Labor Markets." NBER Working Paper No. 23285.

Arntz, Melanie, Terry Gregory, and Ulrich Zierahn. 2016. "The Risk of Automation for Jobs in OECD Countries: A Comparative Analysis." OECD Social, Employment and Migration Working Paper No. 189.

Asian Development Bank (ADB). 2018. *Asian Development Outlook 2018: How Technology Affects Jobs.* Metro Manila: Asian Development Bank.

_____. 2019. *Asian Economic Integration Report 2019/2020: Demographic Change, Productivity and the Role of Technology.* Metro Manila: Asian Development Bank.

_____. 2020. "Multiregional Input–Output." https://mrio.adbx.online/ (accessed May 4, 2020).

Autor, David. 2013. "The "Task Approach" to Labor Markets: An Overview." *Journal of Labour Market Research* 46 (3): 185–99.

_____. 2015. "Why are there still So Many Jobs? The History and Future of Workplace Automation." *Journal of Economic Perspectives* 29 (3): 3–30.

Autor, David H., David Dorn, and Gordon H. Hanson. 2016. "The China Shock: Learning from Labor-Market Adjustment to Large Changes in Trade." *Annual Review of Economics* 8 (October): 205–40.

Autor, David, Frank Levy, and Richard Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *The Quarterly Journal of Economics* 118 (4): 1279–333.

Baldwin, Richard. 2018. *The Great Convergence: Information Technology and the New Globalization*. Cambridge, MA: Harvard University Press.

Barcia de Mattos, Fernanda, Sukti Dasgupta, Xiao Jiang, David Kucera, and Ansel F. Schiavone. 2020. *Robotics and Reshoring: Employment Implications for Developing Countries*. Geneva: International Labour Organization.

Cattaneo, Olivier, Gary Gereffi, Sébastien Miroudot, and Daria Taglioni. 2013. "Joining, Upgrading and Being Competitive in Global Value Chains: A Strategic Framework." World Bank Policy Research Working Paper No. 6406.

Chang, Jae-Hee, and Phu Huynh. 2016. *ASEAN in Transformation: The Future of Jobs at Risk of Automation*. Geneva: International Labour Organization.

Chun, Natalie, and Heiwai Tang. 2018. "Do Information and Communication Technologies Empower Female Workers? Firm-level Evidence from Viet Nam." ADB Economics Working Paper Series No. 545.

Citi and Oxford Martin School. 2016. *Technology at Work v2.0: The Future is not What It Used to Be*. Oxford, UK: Oxford Martin School, University of Oxford.

Dahal, Madhav Prasad. 2018. "Stride of Service Sector in Nepal's Trajectories of Structural Change." *Economic Journal of Development Issues* 21–22 (1–2): 69–95.

De Backer, Koen, Carlo Menon, Isabelle Desnoyers-James, and Lauernt Moussiegt. 2016. "Reshoring: Myth or Reality?" OECD Science, Technology and Industry Policy Paper No. 27.

de Vries, Gaaitzen J., Quanrun Chen, Rana Hasan, and Zhigang Li. 2019. "Do Asian Countries Upgrade in Global Value Chains? A Novel Approach and Empirical Evidence." *Asian Economic Journal: Journal of the East Asian Economic Association* 33 (1): 13–37.

de Vries, Gaaitzen J., Elisabetta Gentile, Sébastien Miroudot, and Konstantin Wacker. 2020. "The Rise of Robots and the Fall of Routine Jobs." *Labour Economics* 66 (October): 101885.

Dietzenbacher, Erik, and Bart Los. 1998. "Structural Decomposition Techniques: Sense and Sensitivity." *Economic Systems Research* 10 (4): 307–24.

Faber, Marius. 2020. "Robots and Reshoring: Evidence from Mexican Labor Markets." *Journal of International Economics* 127 (November): 103384.

Feenstra, Robert C., Robert Inklaar, and Marcel P. Timmer. 2015. "The Next Generation of the Penn World Table." *American Economic Review* 105 (10): 3150–82.

Frey, Carl Benedikt, and Michael A. Osborne. 2017. "The Future of Employment: How Susceptible are Jobs to Computerisation?" *Technological Forecasting and Social Change* 114 (January): 254–80.

Gentile, Elisabetta, and Gaaitzen J. de Vries. 2021. "Accounting for Income Convergence by Developing Asian Economies: The Role of Jobs and Earnings from Fabrication and Knowledge Activities in Global Value Chains." Paper presented at the ASSA 2021 Virtual Annual Meeting. https://www.aeaweb.org/conference/2021/preliminary/paper/GrHfTGS2.

Goos, Maarten, Alan Manning, and Anna Salomons. 2014. "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring." *American Economic Review* 104 (8): 2509–26.

Graetz, Georg, and Guy Michaels. 2018. "Robots at Work." *The Review of Economics and Statistics* 100 (5): 753–68.

Hou, Jun, Stephen Gelb, and Linda Calabrese. 2017. "The Shift in Manufacturing Employment in China." Overseas Development Institute Supporting Economic Transformation Background Paper.

International Labour Organization. 2020. "ILOSTAT." https://ilostat.ilo.org/ (accessed May 4, 2020).

Leontief, Wassily W. 1936. "Quantitative Input and Output Relations in the Economic Systems of the United States." *The Review of Economics and Statistics* 18 (3): 105–25.

Los, Bart, Marcel Timmer, and Gaaitzen de Vries. 2014. "The Demand for Skills 1995–2008: A Global Supply Chain Perspective." OECD Economics Department Working Paper No. 1141.

_____. 2015. "How Important are Exports for Job Growth in China? A Demand Side Analysis." *Journal of Comparative Economics* 43 (1): 19–32.

Majid, Nomaan, and Nayantara Sarma. 2018. "Employment and Growth in Indonesia (1990–2015)." ILO Working Paper No. 239.

Manyika, James, Michael Chui, Mehdi Miremadi, Jacques Bughin, Katy George, Paul Willmott, and Martin Dewhurst. 2017. *A Future that Works: Automation, Employment, and Productivity*. New York: McKinsey & Company.

Michaels, Guy, Ashwini Natraj, and John Van Reenen. 2014. "Has ICT Polarized Skill Demand? Evidence from Eleven Countries over 25 Years." *The Review of Economics and Statistics* 96 (1): 60–77.

Miller, Ronald, and Peter Blair. 2009. *Input–Output Analysis: Foundations and Extensions* (2nd edition). Cambridge, UK: Cambridge University Press.

Noland, Marcus, Donghyun Park, and Gemma B. Estrada. 2012. "Developing the Service Sector as Engine of Growth for Asia: An Overview." ADB Economics Working Paper Series No. 320.

Organisation for Economic Co-operation and Development (OECD). 2007. *Staying Competitive in the Global Economy: Moving Up the Value Chain*. Paris: OECD Publishing.

Reijnders, Laurie S. M., and Gaaitzen J. de Vries. 2018. "Trade, Technology and the Rise of Non-routine Jobs." *Journal of Development Economics* 135 (November): 412–32.

Reijnders, Laurie S. M., Marcel P. Timmer, and Xianjia Ye. 2021. "Labour Demand in Global Value Chains: Is There a Bias against Unskilled Work?" *The World Economy* 44 (9): 2547–71.

Rémond-Tiedrez, Isabelle, and José Manuel Rueda-Cantuche. 2019. "EU Inter-country Supply Use and Input–Output Tables: Full International and Global Accounts for Research in Input–Output Analysis (FIGARO)." Eurostat Statistical Working Paper.

Stewart, Ian, Debapratim De, and Alex Cole. 2015. *Technology and People: The Great Job-Creating Machine*. London: Deloitte LLP.

Timmer, Marcel P., Abdul Azeez Erumban, Bart Los, Robert Stehrer, and Gaaitzen J. de Vries. 2014. "Slicing Up Global Value Chains." *Journal of Economic Perspectives* 28 (2): 99–118.

Timmer, Marcel P., Bart Los, Robert Stehrer, and Gaaitzen J. de Vries. 2021. "Supply Chain Fragmentation and the Global Trade Elasticity: A New Accounting Framework." *IMF Economic Review* 69: 656–80.

Timmer, Marcel P., Sébastien Miroudot, and Gaaitzen J. de Vries. 2019. "Functional Specialisation in Trade." *Journal of Economic Geography* 19 (1): 1–30.

United Nations Conference on Trade and Development. 2016. "Robots and Industrialization in Developing Countries." UNCTAD Policy Brief No. 50.

United Nations Economic and Social Commission for Asia and the Pacific. 2015. "Part II: Supporting Participation in Value Chains: Global Value Chains and Interconnectedness of Asia-Pacific Economies." In *Asia-Pacific Trade and Investment Report 2015: Supporting Participation in Value Chains*, 103–38. New York: United Nations.

World Bank. 2015. "Country Engagement Note for the Republic of Fiji for the Period FY2015-2017." Report No. 93706-FJ.

_____. 2017. "Jobs in Global Value Chains." Jobs Notes Issue No. 1.

_____. 2020. "Data: Statistical Capacity Indicator Dashboard." https://datatopics.worldbank.org/statisticalcapacity/SCIdashboard.aspx (accessed May 4, 2020).

Appendix. Additional Tables

Table A1. **The 63 Multiregional Input–Output Table Economies**

Australia	Norway
Austria	Poland
Belgium	Portugal
Bulgaria	Romania
Brazil	Russian Federation
Canada	Slovak Republic
Switzerland	Slovenia
China, People's Republic of	Sweden
Cyprus	Türkiye
Czech Republic	Taipei,China
Germany	United States
Denmark	Bangladesh
Spain	Malaysia
Estonia	Philippines
Finland	Thailand
France	Viet Nam
United Kingdom	Kazakhstan
Greece	Mongolia
Croatia	Sri Lanka
Hungary	Pakistan
Indonesia	Fiji
India	Lao People's Democratic Republic
Ireland	Brunei Darussalam
Italy	Bhutan
Japan	Kyrgyz Republic
Korea, Republic of	Cambodia
Lithuania	Maldives
Luxembourg	Nepal
Latvia	Singapore
Mexico	Hong Kong, China
Malta	Rest of the World
Netherlands	

Source: Authors' compilation.

Table A2. **The 35 Multiregional Input–Output Table Industries**

ISIC 3.1 Code	Description
AtB	Agriculture, Hunting, Forestry, and Fishing
C	Mining and Quarrying
15t16	Food, Beverages, and Tobacco
17t18	Textiles and Textile Products
19	Leather, Leather Products, and Footwear
20	Wood and Products of Wood and Cork
21t22	Pulp, Paper, Printing, and Publishing
23	Coke, Refined Petroleum, and Nuclear Fuel
24	Chemicals and Chemical Products
25	Rubber and Plastics
26	Other Non-Metallic Minerals
27t28	Basic Metals and Fabricated Metals
29	Machinery, Nec
30t33	Electrical and Optical Equipment
34t35	Transport Equipment
36t37	Manufacturing, Nec; Recycling
E	Electricity, Gas, and Water Supply
F	Construction
50	Sale, Maintenance, and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel
51	Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles
52	Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods
H	Hotels and Restaurants
60	Inland Transport
61	Water Transport
62	Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies
63	Air Transport
64	Post and Telecommunications
J	Financial Intermediation
70	Real Estate Activities
71t74	Renting of Machinery and Equipment and Other Business Activities
L	Public Administration and Defense; Compulsory Social Security
M	Education
N	Health and Social Work
O	Other Community, Social, and Personal Services
P	Private Households with Employed Persons

Nec = Not elsewhere classified.
Source: Authors' compilation.

Table A3. **Sources of Occupational Employment Data**

Economy	Source of Occupational Employment Data	Original Occupational Classification	Eight Mapped Occupations % of Nonagricultural Employment	Eight Mapped Occupations % of Total Employment
Bangladesh	Labor Force Survey 2010	ISCO-88	99.99	51.56
	Labor Force Survey 2016	BSCO 2012	99.98	57.17
Cambodia	Cambodia Socio-Economic Survey 2007	ISCO-88	99.02	40.72
	Cambodia Socio-Economic Survey 2017	ISCO-08	99.27	60.20
Fiji	Employment and Unemployment Survey 2010	FSCO 2007	99.26	55.68
	Employment and Unemployment Survey 2015–2016	FSCO 2007	98.90	84.12
India	National Sample Survey 2004/2005	NCO 1968	99.56	43.78
	National Sample Survey 2011/2012	NCO 2004	99.69	52.36
Indonesia	National Labor Force Survey (SAKERNAS), 2008	KJI 1982	98.66	59.62
	National Labor Force Survey (SAKERNAS), 2016	KBJI 2014	99.18	73.22
Korea, Republic of	Korea Labor and Income Panel Study (KLIPS) 2005	KSCO	100	92.25
	Korea Labor and Income Panel Study (KLIPS) 2018	KSCO	100	95.21
Kyrgyz Republic	Kyrgyzstan Integrated Household Survey 2012	ISCO-08	99.98	65.38
	Kyrgyzstan Integrated Household Survey 2018	ISCO-08	99.99	78.36
Mongolia	Labor Force Survey 2008/2009	ISCO-08	99.98	57.81
	Labor Force Survey 2018	ISCO-08	99.99	68.55
Nepal	Nepal Labor Force Survey 2008	NSCO 2001	99.84	34.62
	Nepal Labor Force Survey 2017/2018	NSCO 2017	98.88	76.43
Pakistan	Labor Force Survey 2008/2009	PSCO 1994	99.96	54.77
	Labor Force Survey 2017/2018	PSCO 2015	99.95	61.24

Continued.

Table A3. *Continued.*

Economy	Source of Occupational Employment Data	Original Occupational Classification	Eight Mapped Occupations % of Nonagricultural Employment	Eight Mapped Occupations % of Total Employment
Philippines	Labor Force Survey 2008	PSOC 1992	100	63.19
	Labor Force Survey 2017	PSOC 2012	99.99	74.30
People's Republic of China	Population census 2000	SOC	99.83	54.89
	Population census 2010 (shares applied to employment data for 2018)	SOC	99.85	75.87
Sri Lanka	Labor Force Survey 2007	SLSCO-88	99.42	67.20
	Labor Force Survey 2009	SLSCO-88	99.65	66.25
	Labor Force Survey 2017	SLSCO-08	99.85	72.97
Taipei,China	Manpower Utilization Survey 2008	TOC Rev 5	99.99	94.82
	Manpower Utilization Survey 2018	TOC Rev 6	99.99	95.08
Thailand	Labor Force Survey 2010	TSCO 2000	99.91	59.17
	Labor Force Survey 2018	ISCO-08	99.70	67.47
Viet Nam	Labor Force Survey 2007	ISCO-88	99.92	50.02
	Labor Force Survey 2009	VSCO 2009	98.19	51.46
	Labor Force Survey 2016	VSCO 2009	98.83	57.34

BSCO = Bangladesh Standard Classification of Occupations; FSCO = Fiji Standard Classification of Occupations; ISCO = International Standard Classification of Occupations; KBJI = Klasifikasi Basu Jabatan Indonesia; KJI = Klasifikasi Jabatan Indonesia; NCO = National Classification of Occupations; NSCO = Nepal Standard Classification of Occupations; PSCO = Pakistan Standard Classification of Occupations; PSOC = Philippine Standard Occupational Classification; SLSCO = Sri Lanka Standard Classification of Occupations; TOC = Taipei,China Occupational Classification; TSCO = Thailand Standard Classification of Occupations; VSCO = Viet Nam Standard Classification of Occupations.

Note: Only presented here are the sources of employment data that are closest to 2008 or 2018.

Source: Authors' compilation.