Reaping Gains from Global Production Sharing

Domestic Value Addition and Job Creation by Indian Exports

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Abstract

While greater participation in global production sharing (GPS) activities may imply that domestic value added (DVA) generated from *per unit* of the good produced is usually less than when inputs are sourced locally, the *total* DVA generation (and hence *total* domestic job creation) could be considerably high due to the scale effect of producing for the world market. We carry out a regression analysis, in a simultaneous equation framework, to test the hypothesis that greater participation in GPS, as measured by a declining share of DVA in India's gross exports, leads to higher absolute levels of gross exports, DVA and employment. To the best of our knowledge, these relationships have not been studied before in a multiple regression framework. In order to carry out this analysis, using the Input-Output (IO) analysis, we prepare a unique and consistent time series estimates of DVA and number of jobs supported by India's merchandise and services exports for the period 1999-2000 to 2012-13. We obtain these estimates for 112 sectors, covering the whole economy. The regression results show that greater participation in GPS, as measured by the declining share of DVA in gross exports, leads to higher absolute levels of gross exports, DVA and employment.

JEL Classification: C67, F14, F15

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1. Introduction

A cursory examination of current trade policy discussions reveals radically opposing trends across the groups of advanced and developing countries: while protectionist sentiments are on the rise in US and EU, developing countries like India and China are eager to use global trade as an instrument to support growth and job creation**.** By 2020, with the average age of its population being 29, India is projected to be the youngest nation in the world. This 'youth bulge' represents a major challenge for policy makers in terms of creating employment opportunities for the masses. The recently launched "Make in India" initiative by the Indian Government aims to create large number of jobs across the board by promoting exports, particularly from the manufacturing sector. In this context, whether exports offer a viable path to job creation is a question with significant policy implications for all countries. However, the relationship between exports and domestic job creation is not a straightforward one, and often poorly understood, particularly in a context in which production process in several industries are globally fragmented. The term global production sharing (GPS) or vertical specialization, often used to describe the phenomenon of globally fragmented production processes, implies that intermediate inputs cross borders several times during the manufacturing process[1]. However, unlike the recording of domestic transactions, trade data is usually collected and reported as gross flows at each border crossing rather than the net value added between border crossings. This leads to double (or multiple) counting, implying that official trade data does not accurately capture the domestic value added (DVA) content of exports. Yet, DVA is what really matters for job creation within a country.

The ratio of DVA to gross exports (VAX ratio) is often used as a measure to quantify the extent of a country's involvement in GPS. The rationale is that this ratio illustrates how much domestic, as opposed to foreign, value-added is generated throughout the economy for a given unit of exports. In general, countries (and sectors) with greater participation in GPS tend to record relatively low share of DVA in gross exports and vice versa (Johnson and Noguera, 2012).

As to the strategies for domestic job creation, a pertinent question is whether it is desirable to develop 'indigenous' industries with minimal reliance on imports but with significant potential for local linkages or to integrate domestic industries with global production networks wherein linkages and value added are globally dispersed. The present paper contributes to this important policy debate by analyzing which of these alternative strategies may help a country to maximize the absolute level of DVA and employment generation.

While greater participation in GPS may imply that DVA generated from *per unit* of the good produced is usually less than when inputs are sourced locally, the *total* DVA generation (and hence *total* job creation) could be considerably high due to the scale effect of producing for the world market[2]. The implication, if this indeed is the case, is that countries can reap rich dividends by adopting policies aimed at strengthening their participation in GPS. We carry out a regression analysis, in a simultaneous equation framework, to test the hypothesis that greater participation in GPS, as measured by a declining share of DVA in India's gross exports, leads to higher absolute levels of gross exports, DVA and employment. To the best of our knowledge, these relationships have not been studied before in a multiple regression framework.

In order to carry out this analysis, using the Input-Output (IO) analysis, we prepare a unique and consistent time series estimates of DVA, VAX ratio and number of jobs supported by India's merchandise and services exports for the period 1999-2000 to 2012-13. We obtain these estimates for 112 sectors, covering the whole economy. The major advantage of the IO framework is that, in addition to the direct effect of exports within a given sector, DVA and employment generated through indirect linkages – backward and forward – can be taken into consideration. The study makes use of the official I-O Tables (IOT) for the benchmark years 1998-99, 2003-04, 2007-08 as well as the recently published Supply Use Tables (SUT) for the years 2011-12 and 2012-13. The IOT and SUT, compiled by India's Central Statistical Organization (CSO), do not distinguish imported inputs from domestic inputs. We construct the 'domestic use tables' (DUT), separating domestic inputs from imported inputs, by relying on a standard 'proportionality' assumption. For the intervening years – that is, the years for which IOT and SUT are unavailable – we construct the DUT by making use of detailed production and trade data from various official sources. This enables us to use year-specific DUT for our estimation.

Rest of the paper is organized as follows. Section 2 discusses the IO methodology used to estimate DVA and number of jobs supported by India's exports. Section 3 presents the estimates of DVA, VAX ratio and the number of jobs attributable to exports at the aggregate and disaggregated levels. Section 4 carries out a regression analysis to answer our main question – that is, whether greater participation in GPS leads to higher absolute levels of gross exports, DVA and employment. Finally, Section 5 provides the concluding remarks. A detailed discussion of data, assumptions and methodology involved in the construction of our harmonized DUT is provided in Appendix A1 and A2.

2. Estimation of Domestic Value Addition and Job Creation by Exports: Methodology

Ideally, in order to avoid double counting, trade statistics should be collected and reported on value added basis rather than in gross terms. Driven by the concerns on the use (and misuse) of official international trade statistics, attempts have been made by different organizations (including OECD, WTO, and World Bank) to estimate value added content of exports. Estimates for India are available in World Input Output Database (WIOD) and OECD-WTO TiVA data base. However, a limitation of WIOD and TiVA is that the estimates are only available for relatively aggregated sector categories, rendering them inappropriate for our purpose as the variation across sectors for a given country is rather limited[3]. Further, these estimates do not account for some of the important changes in the structural characteristics of the Indian economy, including inter-industry relationships, since 2007-08. These changes in the Indian economy are evident from the recently brought out SUT by the CSO[4].

On the other hand, the estimates used in our study are free from these limitations as (i) they are based on harmonized annual time series of DUT with considerably more disaggregated sector classification than WIOD and TiVA, and (ii) they are based on DUT that have been constructed making use of information on the changing input-output relations and other structural features as reflected in the available official IOT since 1998-99 as well as the latest SUT for the years 2011-12 and 2012-13. Indeed, we find that our estimates of aggregate VAX ratios differ significantly from the TiVA estimates since 2007-08, though the two sets of estimates are very similar to each other until 2007-08, reinforcing the importance of accounting for the recent changes in the structure of the economy.

Based on the concept of backward linkages, the DVA content of exports from '*n*' sectors can be estimated as:

$$\boldsymbol{dva_1} = \boldsymbol{v}\left(\boldsymbol{I} - \boldsymbol{A^d}\right)^{\boldsymbol{-1}}\boldsymbol{\widehat{X}} \qquad (1)$$

where $\boldsymbol{v}$ is a $1 \times n$ vector containing value added to output ratio for each sector, $\boldsymbol{\widehat{X}}$ is a $n \times n$ diagonal matrix of exports from *n* sectors, $\left(\boldsymbol{I} - \boldsymbol{A^d}\right)^{\boldsymbol{-1}}$ is the inverse Leontief matrix that measures the total direct and indirect uses of each commodity *i* by each sector *j*[5]. $\boldsymbol{A^d}$ is $n \times n$ domestic coefficient matrix, whose elements (denoted as a_{ij}) measure the amount of domestic input from sector *i* required to produce one unit of output in sector *j*. $\mathbf{I}$ is an identity matrix with ones on the diagonal and zeros elsewhere. $\boldsymbol{dva_1}$ is the resulting $1 \times n$ vector of DVA content of exports. By summing the appropriate elements of this vector, we get the aggregate DVA for broad sector groups (agriculture, manufacturing and services) and for the economy as a whole. Such aggregate estimates may be denoted as $\sum dva_{i1}$ where dva_{i1} are the individual elements of the vector $\boldsymbol{dva_1}$.

The total DVA in (1) can be decomposed into direct and indirect (backward linkage) effects as given below.

$$\boldsymbol{dva_1^d = v\left(\widehat{I - A^d}\right)^{-1}\hat{X}} \qquad (1a)$$

$$\boldsymbol{dva_1^{bw} = dva_1 - dva_1^d} \qquad (1b)$$

where $\boldsymbol{\left(\widehat{I - A^d}\right)^{-1}}$ is a matrix consisting of the diagonal elements of $(I - A^d)^{-1}$ and zeros elsewhere; dva_1^d and dva_1^{bw} are respectively vectors of direct and indirect DVA content of exports from *n* sectors. Note that dva_1^{bw} in equation (1b) measures the DVA attributable to sector *j*'s backward linkages with all upstream sectors *i*. For example, exports of 'automobiles' generates domestic value addition within the automobile sector (dva_1^d) as well as in other upstream sectors (dva_1^{bw}), such as 'iron and steel', whose outputs are used as inputs by the automobile sector.

Following a slightly different approach, we can measure the extent of DVA generated in sector *i* as a result of its forward linkages with all downstream sectors *j*. For example, DVA is generated in 'iron and steel' sector as a result of exports from all sectors (such as, automobiles, machine tools etc) where 'iron and steel' is used as an input. Thus, based on a given sector's forward linkages with other sectors, DVA attributed to exports can be estimated as:

$$\boldsymbol{dva_2} = \boldsymbol{\widehat{V}}\left(\boldsymbol{I} - \boldsymbol{A^d}\right)^{-1}\boldsymbol{x} \qquad (2)$$

which can be decomposed into direct and indirect (forward linkage) effects as follows.

$$\boldsymbol{dva_2^d} = \boldsymbol{\widehat{V}}\left(\widehat{\boldsymbol{I} - \boldsymbol{A^d}}\right)^{-1}\boldsymbol{x} \qquad (2a)$$

$$\boldsymbol{dva_2^{fw}} = \boldsymbol{dva_2} - \boldsymbol{dva_2^d} \qquad (2b)$$

where $\boldsymbol{\widehat{V}}$ is $n \times n$ diagonal matrix of value added to output ratios and x is $(n \times 1)$ vector of exports from different sectors. Note that dva_1 and dva_2 give identical estimates for the economy as a whole (when aggregated for all sectors) but not for individual sectors. At the sector level, however, the two approaches give identical values for the estimates of direct DVA – that is, the vectors dva_1^d and dva_2^d are identical across sectors. On the other hand, dva_1^{bw} and dva_2^{fw} give different values across sectors due to differences in the type of linkages (backward versus forward) that they capture. It should be noted that a sector may record positive dva_2^{fw} value, even if its output is not directly exported, provided it supplies inputs to other sectors that export their outputs.

Employment supported by exports can be computed, in an analogous manner, using the two different concepts of linkages. The relevant equations for estimation are:

$$\left.\begin{array}{ll} \boldsymbol{e_1} = \boldsymbol{l}\left(\boldsymbol{I} - \boldsymbol{A^d}\right)^{-1}\boldsymbol{\widehat{X}} & (3) \\ \boldsymbol{e_1^d} = \boldsymbol{l}\left(\widehat{\boldsymbol{I} - \boldsymbol{A^d}}\right)^{-1}\boldsymbol{\widehat{X}} & (3a) \\ \boldsymbol{e_1^{bw}} = \boldsymbol{e_1} - \boldsymbol{e_1^d} & (3b) \end{array}\right\} \text{based on backward linkages}$$

$$
\left.
\begin{aligned}
&\boldsymbol{e_2} = \hat{\boldsymbol{L}}\left(\boldsymbol{I}-\boldsymbol{A}^{d}\right)^{-\boldsymbol{1}}\boldsymbol{x} && (4)\\
&\boldsymbol{e_2^d} = \hat{\boldsymbol{L}}\left(\widehat{\boldsymbol{I}-\boldsymbol{A}^{d}}\right)^{-\boldsymbol{1}}\boldsymbol{x} && (4a)\\
&\boldsymbol{e_2^{fw}} = \boldsymbol{e_2} - \boldsymbol{e_2^d} && (4b)
\end{aligned}
\right\} \quad \text{based on forward linkages}
$$

Where l is $1 \times n$ vector containing employment coefficients (labor/output ratios) while $\hat{\boldsymbol{L}}$ is the diagonal matrix of sectoral employment coefficients. The resulting vector of employment supported by exports is given by $\boldsymbol{e_1}$ and $\boldsymbol{e_2}$ where the former measures direct employment ($\boldsymbol{e_1^d}$) plus employment attributed to backward linkages ($\boldsymbol{e_1^{bw}}$) while the latter represents direct employment ($\boldsymbol{e_2^d}$) plus employment due to forward linkages ($\boldsymbol{e_2^{fw}}$). Following the approach outlined above, we estimate DVA and employment supported by India's exports for the period 1999-2000 to 2012-13.

3. Estimates of Export Related DVA and Employment

3.1. Aggregate Level Estimates

Table 1 provides the estimates of DVA content of India's aggregate merchandise and services exports, in billions of USD. For each year, these values are obtained by summing the estimates for all the 112 sectors. This table also reports a number of related indicators: aggregate gross exports in USD, VAX ratio and value of gross exports required to generate USD1 billion worth of DVA. The average annual growth rates pertaining to these indicators are shown in Table 2.

(Place Table 1 and 2 here)

India's gross exports stood at about \$53.3 billion in 1999-2000, of which the contribution of DVA was \$46 billion. By 2012-13, the value of gross exports and DVA content increased to

$452.1 billion and $295.4 billion, respectively. The VAX ratio declined consistently from 0.86 in 1999-2000 to 0.65 in 2012-13. Overall, the observed trends in VAX ratio suggest that Indian industries' participation in GPS activities have increased over the years, especially since the second half of the 2000s. Did this translate into higher number of jobs in the country? Our estimates provide an answer in the affirmative as the total number of jobs supported by Indian exports increased from about 34 million in 1999-00 to 62.6 million in 2012-13 (Table 3)[6]. Furthermore, throughout the period, export related jobs grew significantly faster than total employment (Table 2). As a result, the share of export-supported jobs in total employment increased from little over 9% in 1999-2000 to 14.5% in 2012-13[7].

(Place Table 3 here)

Even as the total number of jobs supported by exports recorded a significant increase, jobs per $1 million worth of exports declined steadily from 638 in 1999-2000 to 138 in 2012-13. Despite the observed decline, the employment intensity of Indian exports is perceptibly higher than the estimates available for other countries, including China. For example, $1 million worth of US exports supported only 6.6 jobs in 2009 and 5.2 jobs in 2014 (Rasmussen and Johnson, 2015). Available estimates for China suggest that $1 million worth of its exports supported 140 jobs in 2007 as compared to 191 jobs for India for the same year (Chen et al 2012). It may also be noted that the observed decline in the number of jobs per million dollar worth of exports is consistent with the general pattern observed for other countries (Massimiliano et al, 2016)[8].

3.2. Estimates for Sector Groups: Agriculture, Manufacturing and Services

3.2.1. Total DVA and Jobs Supported by Exports across Sector Groups

To start with, using data from official IOT and SUT, we provide a snapshot of the composition of gross exports across sector groups and over the years (Table 4). The share of manufacturing in total exports declined from 68.7% in 1998-99 to 42.7% in 2007-08 and then rebounded to 63.6% in 2012-13. Manufacturing accounted for the largest share of exports for all years, except for 2007-08. The share of services exports shot up from about 20% in 1998-99 to nearly 49% in 2007-08 and then declined to 32.5% in 2012-13. The export share of 'Agriculture, mining and allied activities' (henceforth agriculture) declined consistently over the years, from about 11% in 1998-99 to less than 4% in 2012-13. With these in background, we now turn to the estimates of export related DVA and employment at the sector group level.

As noted earlier, two different approaches can be followed to estimate sector level DVA (dva_1 and dva_2) and employment (e_1 and e_2). However, unlike at the aggregate economy wide level, the two approaches do not produce identical estimates at the sector level owing to differences in the type of linkages (backward versus forward) that they capture. Between the two approaches, which one to be chosen depends on the purpose at hand. The appropriate measures are the ones based on backward linkages (dva_1 and e_1) when the objective is to assess a given sector's ability to create DVA and employment across the board through linkages with other sectors. On the other hand, the appropriate measures are those based on forward linkages (dva_2 and e_2) if the main purpose is an understanding of the extent to which a sector depends on exports, directly and indirectly, for growth and job creation. In what follows, keeping in mind the focus of our paper, we primarily discuss the estimates based on backward linkages. However, in sub-section 3.2.2, in order to highlight the relative importance of the two types of linkages across sector groups, we also use the estimates based on forward linkages.

Table 5 reports DVA ($\sum dva_{i1}$) and employment ($\sum e_{i1}$) attributed to exports from each sector group. The value of DVA attributed to manufacturing exports increased steadily from about $24 billion in 1999-2000 to $165 billion in 2011-12 while job creation fluctuated within the range 17.5 million to 25 million until about 2009-10, before rising to 45 million in 2012-13. In contrast, both DVA and employment attributed to agriculture exports recorded a significant decline during the second half of the 2000s as compared to the first half. Turning to services, the value of DVA recorded a steady increase (barring a one-off decline in 2009-10) during the period though employment growth turned negative since 2007-08. Mirroring the observed changes in gross exports (see Table 5), the share of manufacturing in total export supported DVA and employment increased significantly since 2007-08 at the cost of services and agriculture (Figure 1)[9].

(Place Table 5 and Figure 1 here)

As noted earlier, sector level VAX ratios can be used as a proxy to measure the extent of a sector's participation in GPS. Clearly, $\boldsymbol{dva}_1$ is the appropriate measure for this purpose: a higher (lower) ratio of $\boldsymbol{dva}_1$ to gross exports implies that the given sector is mainly involved in the local (foreign) sourcing of intermediate inputs. Ratios of $\sum dva_{i1}$ to gross exports (VAX ratio) for the three sector groups is shown in Figure 2 (panel *a*). The VAX ratio remained quite high for agriculture (above 0.90) and services (above 0.85) throughout the period, notwithstanding a small decline from 2007-08. For the manufacturing sector, however, this ratio declined perceptibly, from 0.81 in 1999-2000 to 0.53 in 2012-13, at the rate of -3% per annum. Clearly, Indian manufacturing sector has strengthened its participation in GPS over the years. That the manufacturing sector tends to record generally lower VAX ratios, compared to agriculture and services, is expected as the former is more tradable and amenable to GPS compared to the latter[10].

(place Figure 2 and Figure 3 here)

3.2.2. Relative Importance of Backward and Forward Linkages across Sector Groups

In the light of growing importance of linkages for employment generation at the aggregate (economy-wide) level[11], a discussion on the relative importance of the two types of linkages across sector groups is in order. Table 6 shows the estimates of DVA ($\sum dva_{i1}^{bw}$) and job creation ($\sum e_{i1}^{bw}$) attributed to backward linkages of exports from each sector. It is evident that, throughout the period, manufacturing sector accounts for the largest share of employment and DVA created through backward linkages. Further, backward linkages have been responsible for more than 60% of total DVA and more than half of total employment tied to manufactured exports. In contrast, a greater part of DVA and employment attributed to agriculture and services exports have been induced by direct effects, notwithstanding the increasing significance of backward linkages for these sectors in recent years.

(place Table 6 and Figure 4 here)

Turning to forward linkages, Figure 2 (panel b) shows the ratio of $\sum dva_{i2}$ to gross exports across sector groups. Throughout the period, this ratio is above 1 for agriculture and services and less than 0.5 for manufacturing. Values of these ratios suggest that exports from downstream manufacturing industries generates significant DVA in upstream agriculture and services through linkages even though a number of upstream industries do not directly engage in export activities. Table 7 reports the estimates of DVA ($\sum dva_{i2}^{fw}$) and job creation $\left(\sum e_{i2}^{fw}\right)$ attributed to each sector j's forward linkages with all exporting sectors i. The DVA attributed to forward linkages grew at the rate of over 18% per annum for agriculture and services. Further, a large number of export related jobs created in the agriculture and service sector are due to their forward linkages with the manufacturing sector. For the year 2012-13, for example, forward linkages accounted for 80% of total export-tied jobs in agriculture and 51% of total export-tied jobs in services (see Figure 5). For the manufacturing sector, in contrast, forward linkages are less significant for job creation and value addition.

Exports of manufactured products offer the greatest potential to generate economy-wide value addition and employment, directly as well as indirectly through their strong backward linkages with agriculture and services. Our findings imply that even domestic market oriented industries sometimes may have heavy export dependence due to their forward linkages with export-oriented industries. A corollary is that domestic market-oriented industries are not necessarily protected from negative external shocks.

4. Impact of GPS Participation on Absolute Levels of Gross Exports, DVA and Employment

As seen in the previous Section, the ratio of DVA in India's gross exports has declined significantly during 1999-2000 to 2012-13. This implies that India's participation in GPS has increased over the years. As mentioned earlier, what really matters for employment generation within a country is the absolute value of DVA rather than DVA per unit of good exported. In this section, we analyze whether the decline in VAX ratio (implying greater participation in GPS) leads to an increase in the absolute dollar values of gross exports and DVA and hence the number of jobs created within the economy.

4.1. Econometric Specification

We hypothesize that the absolute dollar value of India's exports will increase with greater participation in GPS. This, in turn, will lead to an increase in the absolute dollar value of DVA, even as the VAX ratio falls. Total DVA generated from exports would increase due to the scale effect of producing for the world market under GPS participation. An increase in absolute value of DVA, in turn, would cause an increase in the absolute number of jobs linked to exports. In order to test these hypotheses, we estimate the following simultaneous equation model.

$$\boldsymbol{ln(x_{it}) = \alpha_0 + \alpha_1 ln\left(\frac{dva_{i1}}{x_i}\right)_{t-1} + \alpha_2 ln(yd_{it}) + \alpha_3 ln(rpo_{it}) + \alpha_4 ln(wd_{it}) + \alpha_5 J +}$$

$$\boldsymbol{\alpha_6\, D(t) + u1_{it}} \qquad \textbf{(5a)}$$

$$\boldsymbol{ln(dva_{i1t}) = \beta_0 + \beta_1 ln(x_{it}) + \beta_2 ln(gvad_{it}) + \beta_3 ln(rpv_{it}) + \beta_4 J + \beta_5 D(t) + u2_{it}}$$

(6a)

$$\boldsymbol{ln(e_{i1t}) = \gamma_0 + \gamma_1 ln(dva_{i1t}) + \gamma_2 ln(gvad_{it}) + \gamma_3 ln(rw_{it}) + \gamma_4 ln(l_{it}) + \gamma_5 J +}$$

$$\boldsymbol{\gamma_6} D(t) + \boldsymbol{u3_{it}} \qquad \textbf{(7a)}$$

The notations *i, t* and *ln* in the above equations stand respectively for sector, year and natural logarithm. *J* is the vector of sector dummies and *D*(t) is the vector of year dummies.

The endogenous dependent variables are: (i) dollar value of India's exports to the world from sector *i* (x_{it}); (ii) dollar value of total DVA attributed to exports from sector *i* (dva_{i1}), the individual elements of the vector $\boldsymbol{dva_1}$); and (iii) total employment attributed to exports from sector *i* (e_{i1} , the individual elements of the vector e_1).

In light of the hypotheses outlined above, the main coefficients of interest are $\alpha_1, \beta_1,$ and γ_1. The rest of the explanatory variables are included to control for other factors which may influence the values of the dependent variables. In addition to sector and year dummies, each of the equations includes appropriate control variables representing the level of sector-specific domestic activity and relative price. Note that we use one year lagged value of VAX ratio $\left(\frac{dva_{i1}}{x_i}\right)$, rather than its contemporaneous value, assuming that the effect of GPS on gross exports will be observed with one year lag[12]. Coefficient of this variable, α_1, is expected to yield a negative sign in equation (5a) since greater participation in GPS is likely to increase the absolute gross dollar value of exports. On the other hand, our hypotheses imply that the expected sign of β_1 in equation (6a) and that of γ_1 in equation (7a) are positive.

Domestic activity variables are included to capture the effect of domestic market size on the dependent variables. Relevant domestic activity variable in the gross export equation is *yd*, defined as value of output minus gross exports[13]. The variable *gvad*, defined as gross value added minus dva_{i1t}^{d}, is included as a domestic activity variable in equations (6a) and (7a)[14]. Domestic activity variables are included to examine whether foreign and domestic sales are complements or substitutes. A negative (substitutability) relationship may be expected if increasing domestic sales may come at the expense of export sales in the presence of capacity constraints. On the other hand, a positive (complementary) relationship may be expected if strength in the domestic market can be leveraged in international markets or if there are increasing returns to scale. Thus, the sign of the coefficients of domestic activity variable depends on which effect dominates. We treat the activity variables *yd* and *gvad* as endogenous explanatory variables in our simultaneous equations system.

The variable *rpo* (*rpv*), representing relative price, is constructed by taking the ratio of output (value added) deflator for India to that of United States for each IO sector[15]. These ratios were adjusted by dollar per rupee nominal exchange rate for each year -an increase in this ratio implies a deterioration of India's price competiveness in the given sector, and vice versa. Keeping in mind the way the dependent variable is measured, *rpo* is included in equation (5) while *rpv* is considered in equation (6). The variable *rw* in equation (7) is real wage rate computed using data on sector specific nominal wage rates and output deflators. As required data were not available for agriculture and services, *rw* was computed only for manufacturing sectors. We expect *rw* to exert a negative influence on employment tied to exports.

Equation (5) also includes *wd*, a variable representing the level of world demand for each sector. This variable is measured as a weighted average of total imports (in US dollars) in a given sector by the world from all countries, except from India. The share of each partner country in India's total exports in the given sector is taken as the weight. As required data were not available for services sectors, *wd* was constructed only for merchandise sectors. The sign of *wd* is expected to be positive since higher world demand would also mean higher demand for India's exports. Finally, in Equation (7), we include labor-output ratio (*l*) to control for the effect of a sector's labor intensity on export related job creation. Further details pertaining to variable definition, variable construction, and data sources are given in Appendix A1 and A2.

For robustness, we also run 3SLS regressions on first differences of the original variables.

$$\boldsymbol{Dln}(\boldsymbol{x_{it}}) = \boldsymbol{\alpha_{0d}} + \boldsymbol{\alpha_{1d} Dln}\left(\frac{\boldsymbol{dva_{i1}}}{\boldsymbol{x_i}}\right)_{\boldsymbol{t-1}} + \boldsymbol{\alpha_{2d} Dln}(\boldsymbol{yd_{it}}) + \boldsymbol{\alpha_{3d} Dln}(\boldsymbol{rpo_{it}}) + \boldsymbol{\alpha_{4d} Dln}(\boldsymbol{wd_{it}}) + \boldsymbol{\alpha_{5d}\, J} + \boldsymbol{\varepsilon 1_{it}} \quad (5b)$$

$$\boldsymbol{Dln}(\boldsymbol{dva_{i1t}}) = \boldsymbol{\beta_{0d}} + \boldsymbol{\beta_{1d} Dln}(\boldsymbol{x_{it}}) + \boldsymbol{\beta_{2d} Dln}(\boldsymbol{gvad_{it}}) + \boldsymbol{\beta_{3d} Dln}(\boldsymbol{rpv_{it}}) + \boldsymbol{\beta_{4d} J} + \boldsymbol{\varepsilon 2_{it}} \quad (6b)$$

$$\boldsymbol{Dln}(\boldsymbol{e_{i1t}}) = \boldsymbol{\gamma_{0d}} + \boldsymbol{\gamma_{1d} Dln}(\boldsymbol{dva_{i1t}}) + \boldsymbol{\gamma_{2d} Dln}(\boldsymbol{gvad_{it}}) + \boldsymbol{\gamma_{3d} Dln}(\boldsymbol{rw_{it}}) + \boldsymbol{\gamma_{4d} Dln}(\boldsymbol{l_{it}}) + \boldsymbol{\gamma_5 J} + \varepsilon\boldsymbol{3_{it}} \quad (7b)$$

where D is the first difference operator.

4.2. Regression Results

Before proceeding to the estimation, we perform the Hausman specification test for simultaneity. Results show that simultaneity problem is indeed present in the system and hence OLS estimators will not be consistent[16]. Therefore, we use a three-stage least squares (3SLS) econometric approach to simultaneously estimate equations (5a) through (7a) and (5b) through (7b)[17]. The regressions have been estimated for two sample groups: (i) all sectors and (ii) sub-set of sectors within manufacturing. While all explanatory variables were included in the regressions for the sample of manufacturing sectors, regressions for the full sample exclude the variables *wd* and *rw* due to non-availability of data.

The 3SLS regression results are reported in Table 9. While 3SLS is our preferred specification, for comparison and robustness, Table 10 also reports the results from alternative models, including dynamic panel data models (Arellano–Bover /Blundell–Bond system estimator), fixed effect and random effect regressions. It may be noted that the 3SLS and other methods give similar results, with respect to sign and statistical significance, particularly for the main variables of interest.

As expected, the VAX ratio shows statistically significant negative coefficient in equation 5a, for the full sample as well as for the sample of manufacturing. For the manufacturing group, the elasticity of gross exports with respect to $\left(\frac{dva_{i1}}{x_i}\right)_{t-1}$ is 1.79 in 3 SLS specification (column 1, Table 9). This implies that a 10% decline in the VAX ratio leads to an increase in the dollar value of gross exports in the range of 17.9% which is quite large. The elasticity value is relatively lower at 1.08 for the full sample[18]. The 3SLS regression on first differences (equation

5b) also yields statistically significant negative coefficients with respect to the VAX ratio. Overall, these results confirm that greater participation in GPS, as captured by a decline in VAX ratio, causes the absolute dollar value of exports to increase.

The results corresponding to equation 6a confirm that higher value of gross exports, in turn, causes the absolute dollar value of DVA to increase. The elasticity of DVA values with respect to gross exports are 0.43 and 0.24 for the manufacturing and full sample, respectively. The estimated elasticity value suggests that a 10% increase in gross exports of manufacturing causes 4.3% increase in the value of DVA. Qualitatively, these results remain the same if we use first differences of the original variables.

Does higher absolute dollar values of DVA, in turn, lead to higher employment creation? The results corresponding to equation 7a and 7b confirm that it does. The elasticity estimates obtained for the manufacturing sample suggest that a 10% increase in export related DVA increases employment by 17.2%. The elasticity estimate for the full sample is higher at 2.20% as compared to 1.72% for the manufacturing sample. Similar results are obtained when we use first differences.

Turning to the control variables, the variable *wd*, representing world demand conditions, yields statistically significant positive coefficient in equation 5a, implying that Indian exports respond positively to increase in world demand. The variables *yd* and *gvad* are included in equations 5a through 7a to capture the effects of domestic supply capacity. These variables do not show consistent results across manufacturing sample versus full sample and across regressions in levels versus regressions in first differences, making it hard to arrive at an overall conclusion[19]. The variables representing exchange rate adjusted relative prices (*rpo* and *rpv*) yield correct signs for regressions in levels as well as in first differences. As expected, the variable representing real wages (*rw*) yields statistically significant negative coefficient in the employment equation suggesting that a decline of real wages would lead to an increase in export related employment. Finally, the results confirm that labor to output ratio (*l*), representing labor-intensity, is positively associated with employment tied to exports.

In order to examine whether our results are robust to alternative estimation methods, we run dynamic panel data model (Arellano–Bover /Blundell–Bond system estimator), fixed effect and random effect regressions. The estimation results from these models, reported in Table 10, reinforce our major findings. The VAX ratio continues to show statistically significant negative coefficient in all variants of regression equation 5a. Similarly, the variable representing gross exports consistently yield statistically significant positive coefficients in all specifications where DVA is the dependent variable. Finally, the results from alternative specifications of regression equation 7a confirm that an increase of DVA, in turn, causes the absolute level of employment to increase.

5. Conclusions and Implications

Using Input-Output (IO) analysis, the present study reports that the domestic value added (DVA) of India's merchandise and services exports increased from US $46 billion in 1999-00 to US $295 billion in 2012-13, with a growth rate of 17.7% per annum. The total number of jobs supported by aggregate Indian exports increased from about 34 million in 1999-00 to 62.6 million in 2012-13, with a growth rate of 3.4% per annum. Export related jobs grew significantly faster than that of country's total employment- the share of export-supported jobs in total employment in the country increased from little over 9% in 1999-00 to 14.5% in 2012- 13. At the same time, ratio of DVA to gross exports (VAX ratio) steadily declined from 0.86 in 1999-00 to 0.65 in 2012-13.

Decline in VAX ratio has been particularly sharp for manufacturing sectors, suggesting that Indian industries have become more involved in global production sharing (GPS), especially since the second half of the 2000s. Backward linkages, particularly from manufacturing to agriculture and services, have become an important source of export related DVA and job creation in the country. An implication is that the industries which are less export oriented are not necessarily protected from negative external shocks.

Using an econometric analysis, we show that greater participation in GPS, as measured by the declining share of DVA in gross exports, leads to higher absolute levels of gross exports, DVA and employment. A pertinent question is, despite its increasing participation in GPS, why has the manufacturing sector not yet become the engine of India's growth unlike for China and other dynamic East and South-East Asian countries. For providing an explanation, we need to look at the extent of decline as well as the current level of VAX ratio in a proper comparative perspective. The VAX ratio available in TiVA database show that while India's participation in GPS has increased over the years, the level of its integration remains significantly less than that of other countries in East Asia (Veeramani and Dhir, 2017). For the year 2011, the VAX ratio for India's manufacturing sector was 0.64 as compared to 0.48 for Malaysia, 0.51 for Singapore and Vietnam, 0.52 for Thailand, 0.53 for Korea and 0.60 for China. The difference between India and other countries is starker for sectors such as electronics and electrical machinery, where GPS is more prevalent[20].

Our point in this paper is not to say that India has already exhausted the gains from GPS participation. Far from it, our argument is that the country can reap rich dividends by adopting policies aimed at strengthening its participation in GPS. Based on imported parts and components, India has a huge potential to emerge as a major hub for final assembly in several industries, particularly in electronics and electrical machinery. Since this strategy involves processing or assembly of imported parts and components, DVA *per unit* of exported good would be less. However, as the scale of operations is usually very large, potential for total domestic value addition and job creation is very high. Therefore, greater involvement of domestic industries in GPS must form a crucial part of the "Make in India" initiative. While it is essential to keep tariff rates low for intermediate inputs, it is also important to resist the temptation of extending tariff protection for final goods assembly as the latter will have detrimental effect of breeding inefficiencies. Viewed thus, the move by Indian government, since late 2017, to increase import duties for a range of products, partly in retaliation to the recent US tariff hikes and partly to boost the "Make in India" initiative is a move in the wrong direction.

It is important to create an ecosystem which will result in realignment of India's specialization patterns towards labor-intensive processes and product lines. A number of studies have noted an idiosyncratic nature of India's specialization patterns in that, despite being a labor-abundant country, fast growing exports are either capital-intensive or skill-intensive (Kochhar et al., 2006; Panagariya, 2008; Krueger, 2010, Felipe et al., 2013, Veeramani et al, 2017)[21]. Studies suggest that low level of service link cost - cost related to transportation, communication, and other related tasks involved in coordinating the activity in a given country with what is done in other countries within the production network - is critical for countries to participate in GPS. Supply disruptions in a given location due to shipping delays, power failure, political disturbances, labor disputes etc could disrupt the entire production chain. Clearly, the policy should focus on reducing India's high service link costs with other countries within the production network.

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Tables

Table 1: Domestic Value Added (DVA) Content of India's Total Exports, Merchandise plus Services ($ Billion).

Year	DVA			Gross Exports	VAX Ratio	Share of Direct DVA in Total DVA	Gross exports ($ billion) required to generate $1 billion worth of DVA
	Total	Direct	Indirect				
	(1)			(2)	(3)	(4)	(5)
1999-00	46.0	24.6	21.3	53.3	0.86	53.5	1.16
2000-01	53.0	29.2	23.8	61.8	0.86	55.1	1.17
2001-02	53.3	29.4	23.9	61.9	0.86	55.2	1.16
2002-03	63.7	35.5	28.2	74.5	0.85	55.7	1.17
2003-04	79.0	44.9	34.1	92.9	0.85	56.8	1.18
2004-05	105.7	61.5	44.3	128.1	0.83	58.2	1.21
2005-06	132.5	79.1	53.4	162.9	0.81	59.7	1.23
2006-07	163.7	100.4	63.3	202.6	0.81	61.3	1.24
2007-08	207.2	130.0	77.3	256.1	0.81	62.7	1.24
2008-09	229.4	137.4	92.0	296.0	0.77	59.9	1.29
2009-10	213.2	120.2	93.0	278.4	0.77	56.4	1.31
2010-11	278.1	150.1	128.0	380.8	0.73	54.0	1.37
2011-12	304.2	159.6	144.6	452.0	0.67	52.5	1.49
2012-13	295.4	160.1	135.3	452.1	0.65	54.2	1.53

Notes: (i) Total DVA $=\sum \boldsymbol{dva_{i1}}$; Direct DVA $= \sum \boldsymbol{dva_{i1}^{d}}$; Indirect DVA$=\sum \boldsymbol{dva_{i1}^{bw}}$; Gross exports $= \sum \boldsymbol{x_i}$ (ii) VAX ratio = Ratio of Total DVA to Gross Exports (iii) Estimates of DVA based on the two concepts of linkages give identical value for the whole economy.

Source: Authors' estimation

Table 2: Average Annual Growth Rates, Aggregate Values (%)

Period	DVA Supported by Exports ($ Billion)			Employment Supported by Exports, Number			Gross Exports ($ Billion)	VAX Ratio	Total Employment, Number
	Total	Direct	Indirect	Total	Direct	Indirect			
1999-2000 to 2012-13	17.7	17.7	17.7	3.4	1.6	5.8	20.1	-2.0	0.8
1999-2000 to 2005-06	19.3	21.3	16.8	7.6	8.4	6.5	20.5	-0.9	1.5
2006-07 to 2012-13	10.2	7.0	14.8	2.6	-1.9	8.4	14.5	-3.8	0.9

Note: Growth rates are calculated using semi-logarithmic regressions

Source: Authors' estimation

Table 3: Employment Supported by India's Merchandise plus Services Exports

	Export Supported Employment (Millions)			Share of Employment Supported by Exports in Total Employment (%)	No of jobs per million dollar worth of exports
	Total employment	Direct employment	Indirect employment		
1999-00	34.0	19.9	14.1	9.2	638
2000-01	37.9	23.0	14.9	10.3	614
2001-02	41.2	25.7	15.4	9.9	666
2002-03	43.5	26.8	16.7	11.0	584
2003-04	43.6	27.5	16.1	11.1	468
2004-05	52.1	32.6	19.6	12.8	406
2005-06	53.5	32.6	20.8	13.3	328
2006-07	53.5	33.0	20.5	13.2	264
2007-08	49.0	30.6	18.5	12.0	191
2008-09	54.1	31.1	23.0	13.4	184
2009-10	44.5	23.2	21.3	11.1	160
2010-11	49.3	23.6	25.7	12.0	129
2011-12	58.0	29.0	28.9	13.8	128
2012-13	62.6	31.4	31.2	14.5	138

Source: Authors' estimation

Table 4: Composition of Exports across Broad Sectors

Broad Sectors	Percentage share (%)			
	1998-99	**2003-04**	**2007-08**	**2012-13**
Agriculture, mining & allied activities	11.1	10.9	8.6	3.8
Manufacturing	68.7	53.7	42.7	63.6
Services	20.2	35.4	48.7	32.5
Total	100	100	100	100

Note: Percentage shares are reported for the years 1998-99, 2003-04, 2007-08 (years for which official IOTs are available) and for 2012-13 (the latest year for which SUT is available).

Source: Authors' estimation using IOT and SUT from CSO.

Table 5: Total DVA and Employment Generated by Exports from Each Sector Group

	Total DVA: $\sum dva_{i1}$ ($ Billion)			Total Employment: $\sum e_{i1}$ (Million)		
	Agriculture	Manufacturing	Services	Agriculture	Manufacturing	Services
1999-00	4.6	23.9	17.5	8.7	17.5	7.8
2000-01	5.6	27.1	20.3	9.5	19.9	8.5
2001-02	5.9	27.0	20.4	11.2	21.3	8.7
2002-03	7.5	31.7	24.5	11.4	22.5	9.6
2003-04	9.7	38.8	30.5	12.4	21.4	9.7
2004-05	12.6	48.1	45.1	14.4	24.8	12.9
2005-06	15.1	55.9	61.6	15.2	22.4	15.8
2006-07	17.6	63.8	82.3	14.4	20.9	18.2
2007-08	21.0	74.3	112.0	12.3	17.8	18.9
2008-09	20.5	93.1	115.9	12.0	24.1	18.0
2009-10	16.2	98.2	98.8	8.1	23.9	12.5
2010-11	18.1	140.4	119.7	6.7	31.5	11.0
2011-12	16.5	164.9	122.9	5.1	42.4	10.5
2012-13	16.0	153.8	125.6	6.3	45.1	11.2
r	11.3	17.3	19.4	-4.0	5.4	3.4

Note: r stands for average annual growth rates, calculated using semi-logarithmic regression

Source: Authors' estimation

Table 6: DVA and Employment Attributed to Backward Linkages of Exporting Sectors, Estimates for Sector Groups

	Indirect DVA: $\sum dva_{i1}^{bw}$ ($ Billion)			Indirect Employment: $\sum e_{i1}^{bw}$(Million)		
	Agriculture	Manufacturing	Services	Agriculture	Manufacturing	Services
1999-00	0.8	15.4	5.1	0.6	10.5	3.0
2000-01	1.0	17.3	5.5	0.8	10.9	3.2
2001-02	1.0	17.3	5.6	0.8	11.2	3.4
2002-03	1.2	20.3	6.7	0.9	12.1	3.8
2003-04	1.4	24.4	8.2	0.8	11.3	3.9
2004-05	1.9	30.5	11.9	1.1	13.5	5.0
2005-06	2.3	35.6	15.5	1.2	14.1	5.5
2006-07	2.6	40.9	19.7	1.2	13.6	5.8
2007-08	3.1	48.0	26.2	1.1	11.9	5.5
2008-09	3.8	59.8	28.5	1.2	16.3	5.6
2009-10	3.6	62.9	26.5	0.9	16.0	4.4
2010-11	4.1	90.3	33.6	0.9	20.3	4.5
2011-12	4.2	105.2	35.3	0.9	23.2	4.8
2012-13	3.8	95.7	35.9	0.9	24.8	5.5
r	14.8	17.2	19.3	2.1	6.4	4.0

Note: r stands for average annual growth rates, calculated using semi-logarithmic regression

Source: Authors' estimation

Table 7: DVA and Employment Attributed to Each Sector's Forward Linkages with All Exporting Sectors, Estimates for Sector Groups

	Indirect DVA: $\sum dva_{i2}^{fw}$ (\$ Billion)			Indirect Employment: $\sum e_{i2}^{fw}$ (Million)		
	Agriculture	Manufacturing	Services	Agriculture	Manufacturing	Services
1999-00	4.2	4.6	12.5	7.9	1.9	4.3
2000-01	4.7	5.4	13.7	8.1	2.2	4.6
2001-02	4.7	5.1	14.2	8.6	2	4.8
2002-03	5.6	5.6	16.9	9	2.3	5.4
2003-04	6.6	6.8	20.7	7.7	2.9	5.5
2004-05	8.8	8.6	26.9	10.2	2.7	6.7
2005-06	10.4	9.9	33.1	10.4	2.7	7.7
2006-07	11.9	11.9	39.5	9.9	2.7	8
2007-08	14.4	14.2	48.6	8.4	2.6	7.5
2008-09	16.8	17.0	58.3	11.8	2.7	8.5
2009-10	17.4	17.3	58.2	11.9	2.4	7
2010-11	25.9	23.8	78.4	16.4	2.7	6.6
2011-12	30.5	27.0	87.1	19.9	3.4	5.7
2012-13	30.6	23.5	81.2	21.2	3.9	6.1
r	18.1	15.9	18.1	7.3	3.7	3.2

Note: *r* stands for average annual growth rates, calculated using semi-logarithmic regression

Source: Authors' estimation

Table 9: 3 SLS Regression Results, Regressions in Levels and First Differences

	Regressions in Levels		Regressions in First Differences	
	Manufacturing	Total	Manufacturing	Total
Dependent Variable: ln(x_{it})	***Equation 5a***		***Equation 5b***	
$ln\left(\frac{dva_{i1}}{x_i}\right)_{t-1}$	-1.786***	-1.082***	-1.084***	-1.572***
	(0.114)	(0.222)	(0.292)	(0.356)
$ln(yd_{it})$	-0.377***	0.283	1.152**	0.835
	(0.106)	(0.204)	(0.489)	(0.616)
$ln(rpo_{it})$	-1.230***	-0.409**	-0.0628	-0.241
	(0.272)	(0.180)	(0.443)	(0.495)
$ln(wd_{it})$	0.254***		-0.0468	
	(0.0823)		(0.0731)	
Constant	17.72***	11.39**	0.316**	-0.209
	(1.335)	(5.271)	(0.144)	(0.187)
Dependent Variable: ln(dva_{i1t})	***Equation 6a***		***Equation 6b***	
$ln(x_{it})$	0.427***	0.236**	0.476***	0.652*
	(0.0478)	(0.110)	(0.135)	(0.402)
$ln(gvad_{it})$	-0.361***	0.261	0.918***	0.794
	(0.0645)	(0.189)	(0.343)	(0.806)
$ln(rpv_{it})$	-0.300***	-0.299**	-0.269	-0.390
	(0.0838)	(0.141)	(0.306)	(0.698)
Constant	17.14***	7.812	0.312***	-0.205*
	(0.802)	(5.274)	(0.0992)	(0.121)
Dependent Variable: ln(e_{i1t})	***Equation 7a***		***Equation 7b***	
$ln(dva_{i1t})$	1.718***	2.203***	2.481***	1.998***
	(0.449)	(0.313)	(0.408)	(0.374)
$ln(gvad_{it})$	-1.485***	1.867	-2.412***	-1.442***
	(0.407)	(1.189)	(0.554)	(0.318)
$ln(rw_{it})$	-0.374***		-0.174*	
	(0.119)		(0.100)	
$ln(l_{it})$	0.139	0.793***	0.325***	0.454***
	(0.119)	(0.142)	(0.0319)	(0.0348)
Constant	9.543***	-77.24**	0.323**	-0.254
	(1.769)	(30.04)	(0.162)	(0.162)
Observations	726	1,242	725	1,243

Notes: (i) All regression equations, in both levels and first differences, include sector dummies; (ii) All equations in levels include year dummies; (iii) Standard errors are in parentheses; (iv) *** p<0.01, ** p<0.05, * p<0.1; (v) R^2 values are not reported as it does not have the usual interpretation in 3SLS

Table 10: Results from Dynamic Panel Data Models (Arellano–Bover /Blundell–Bond system estimator), Fixed Effect and Random Effect Regressions

	Dynamic Panel		Fixed Effect		Random Effect	
	Manufacturing	Total	Manufacturing	Total	Manufacturing	Total
Dependent Variable: ln(x_{it})						
$ln\left(\frac{dva_{i1}}{x_i}\right)_{t-1}$	-0.484***	-0.989***	-1.355***	-1.430***	-1.187***	-1.399***
	(0.111)	(0.246)	(0.308)	(0.407)	(0.267)	(0.387)
$ln(yd_{it})$			-0.149	-0.145	-0.0173	0.0843
			(0.127)	(0.135)	(0.109)	(0.0837)
$ln(rpo_{it})$	0.0229	-0.399**	-0.481	-0.261	-0.453	-0.337
	(0.183)	(0.200)	(0.400)	(0.422)	(0.411)	(0.422)
$ln(wd_{it})$	0.215***		-0.0550		0.176**	
	(0.0472)		(0.126)		(0.0877)	
$ln(x_i)_{t-1}$	0.548***	0.672***				
	(0.0296)	(0.0229)				
Constant	4.568***	4.695***	21.54***	20.69***	13.89***	15.30***
	(1.161)	(0.872)	(4.163)	(3.553)	(2.936)	(2.686)
R^2			0.679	0.408	0.671	0.403
Dependent Variable: $ln(dva_{i1t})$						
$ln(x_{it})$	0.933***	0.993***	0.949***	0.985***	0.955***	0.985***
	(0.00579)	(0.00207)	(0.0201)	(0.00557)	(0.0184)	(0.00526)
$ln(gvad_{it})$			-0.0112	-0.00434	-0.000532	0.00558
			(0.0330)	(0.0189)	(0.0232)	(0.0103)
$ln(rpv_{it})$	-0.0102	0.0111	0.110**	0.0436	0.120**	0.0478*
	(0.0281)	(0.0140)	(0.0534)	(0.0282)	(0.0567)	(0.0280)
$ln(dva_{i1})_{t-1}$	0.0814***	-8.81e-05				
	(0.00630)	(0.00240)				
Constant	-0.497***	-0.0816	1.436*	0.391	1.147*	0.218
	(0.151)	(0.0619)	(0.844)	(0.483)	(0.627)	(0.296)
R^2			0.982	0.993	0.982	0.993

Dependent Variable: $\boldsymbol{ln(e_{i1t})}$						
$ln(dva_{i1t})$	0.881***	0.938***	0.994***	1.017***	0.994***	1.014***
	(0.0168)	(0.00843)	(0.0540)	(0.0197)	(0.0446)	(0.0171)
$ln(gvad_{it})$			0.0296	-0.0214	0.0257	-0.0302
			(0.0746)	(0.0425)	(0.0620)	(0.0294)
$ln(rw_{it})$	0.0299		-0.157		-0.153	
	(0.0431)		(0.117)		(0.115)	
$ln(l_{it})$	0.364***	0.601***	0.385***	0.534***	0.397***	0.533***
	(0.0137)	(0.0118)	(0.0625)	(0.0919)	(0.0546)	(0.0753)
$ln(e_{i1})_{t-1}$	0.240***	0.136***				
	(0.0173)	(0.00926)				
Constant	-9.831***	-10.23***	-9.280***	-9.326***	-9.243***	-9.079***
	(0.279)	(0.137)	(1.758)	(0.894)	(1.336)	(0.588)
Observations	726	1,242	781	1,348	781	1,348
R2			0.824	0.925	0.824	0.925

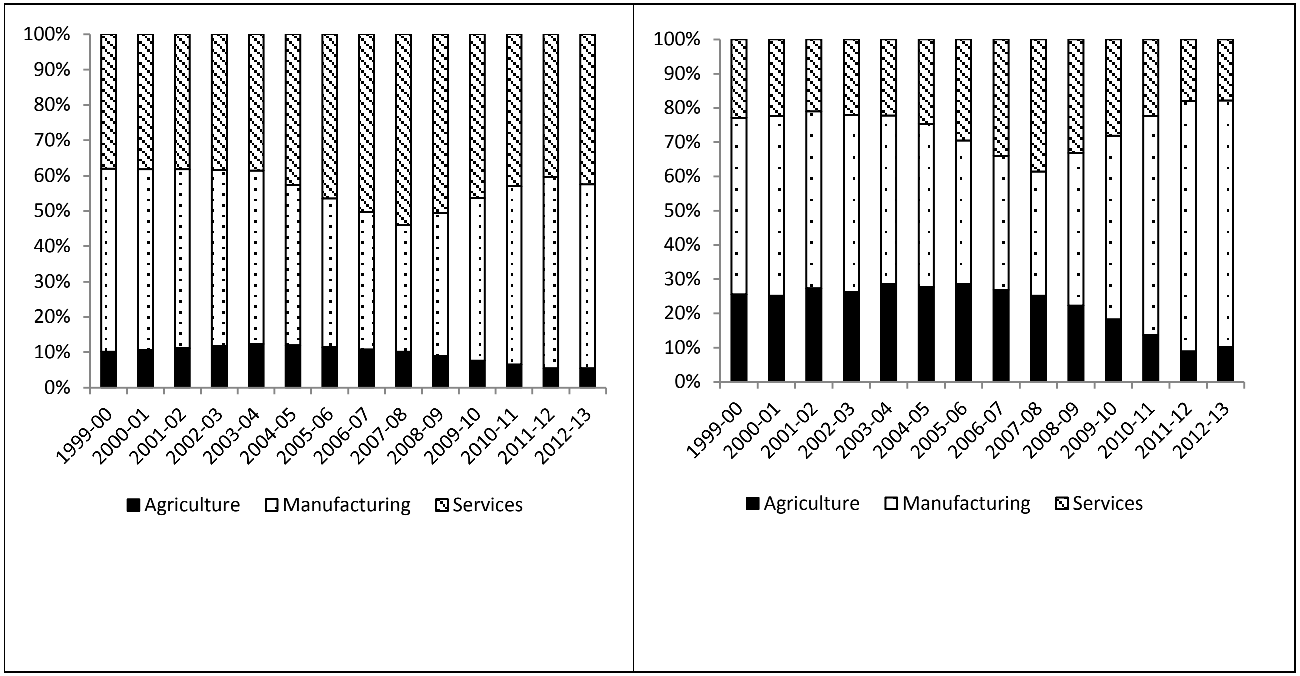
Notes: (i) All regression equations include year dummies; (iii) Standard errors are in parentheses; (iv) *** p<0.01, ** p<0.05, * p<0.1;

(v) R^2 values are not reported for dynamic panels as it does not have the usual interpretation

Figures

Figure 1: Composition of Total DVA and Employment across Sector Groups

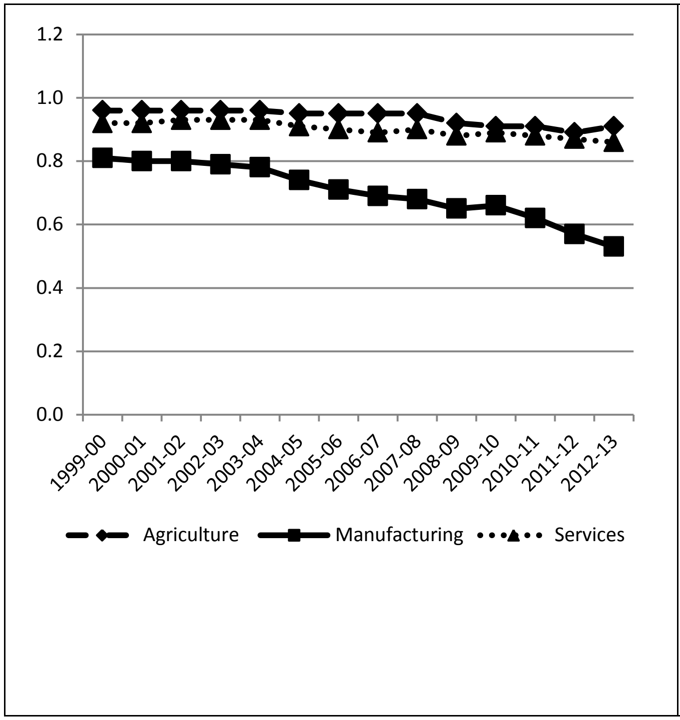
(a) Total DVA ($\sum dva_{i1}$) (b) Total Employment ($\sum e_{i1}$)



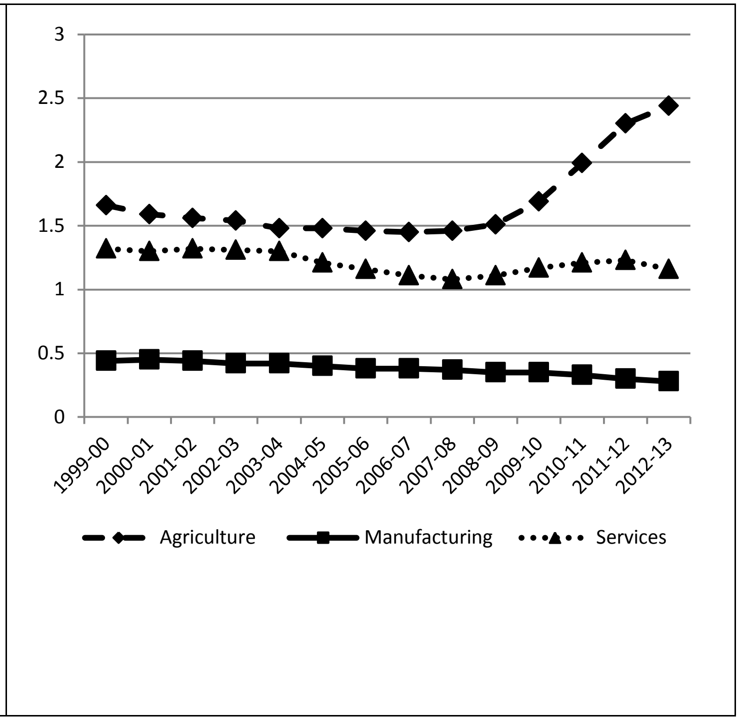
Source: Authors' estimation

Figure 2: DVA to Gross Export Ratio

(a) Ratio of $\sum dva_{i1}$ to Gross Exports

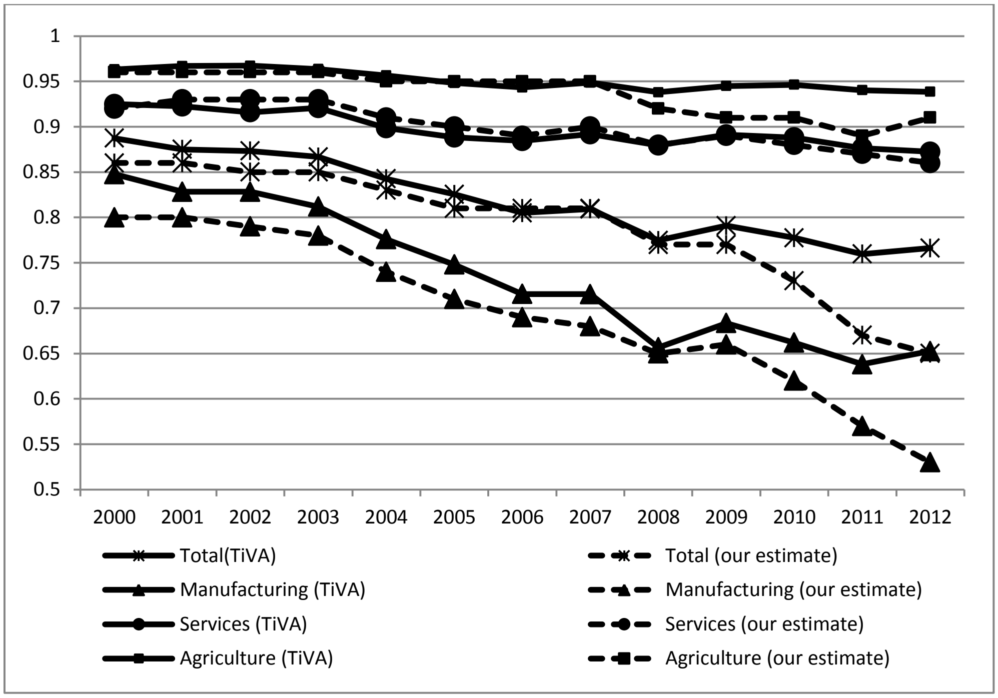


(b) Ratio of $\sum dva_{i2}$ to Gross Exports



Source: Authors' estimation

Figure 3: DVA to Gross Export Ratio (VAX Ratio): Comparison of Our Estimates with TiVA



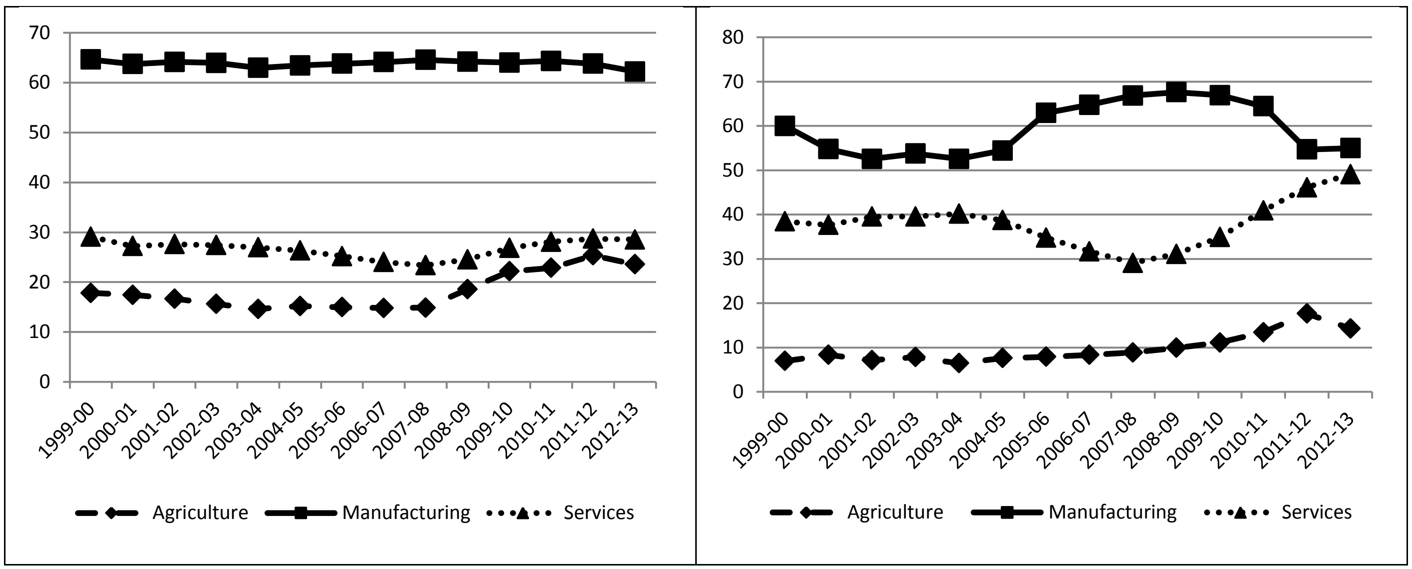
Note: Our estimates are for Indian financial years (1 April to 31 March) while the TiVA estimates are only available on calendar year basis (January 1 to December 31). Our estimate for a given financial year is compared with the TiVA estimate for the corresponding calendar year; for example, our estimate for 2000-2001 is compared with the TiVA estimate for the year 2000.

Source: OECD – TiVA Database and Authors' estimation

Figure 4: DVA and Employment attributed to Backward Linkages as a Share of Total DVA and Employment Generated by Exports from Each Sector Group

(a) Share of $\sum dva_{i1}^{bw}$ in $\sum dva_{i1}$ (%)

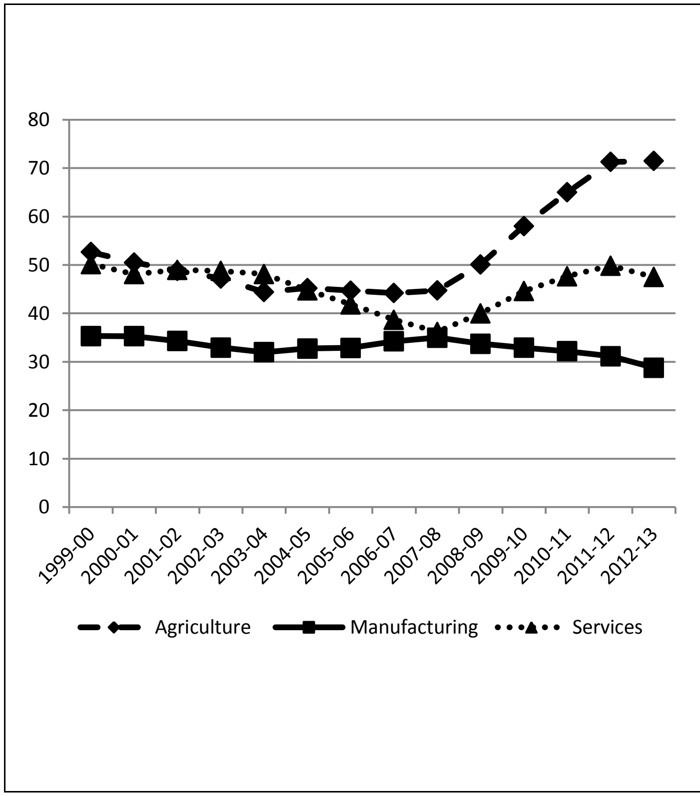
(b) Share of $\sum e_{i1}^{bw}$ in $\sum e_{i1}$ (%)



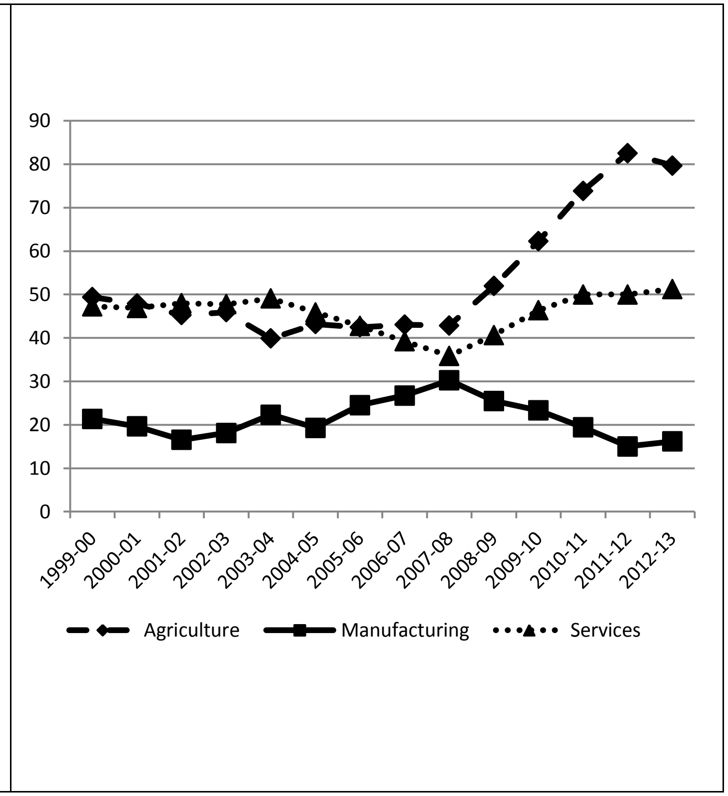
Source: Authors' estimation

Figure 5: DVA and Employment attributed to Forward Linkages as a Share of Total Export Related DVA and Employment in Each Sector Group

(a) Share of $\sum dva_{i2}^{fw}$ in $\sum dva_{i2}$ (%)



(b) Share of $\sum e_{i2}^{fw}$ in $\sum e_{i2}$ (%)



Source: Authors' estimation

Appendix A1: Methodology for Constructing Annual Domestic Use Tables (DUT)

The study uses official IOTs for the years 1998-99, 2003-04 and 2007-08 and SUTs for the years 2011-12 and 2012-13[22]. Looking across the rows in the absorption matrix of IOT, we can observe how the output of each product i (y_i) is used for intermediate consumption by various industries j (that is, sector i's forward linkages) and for final demand purposes. Each column records a given sector j's purchase of inputs from other sectors i (that is, sector j's backward linkages) for producing the output of sector j (y_j). Sector j's purchase of inputs represents total flows – that is, without distinguishing domestically sourced inputs from imported inputs.

Let z_{ij} denote the intermediate use of sector i's output by sector j, let F_i denote the final use of sector i's output and m_i denote total import of i for intermediate and final use. Note that F_i includes exports from sector i (x_i). Assuming that there are n sectors in an economy, the gross value of output from each sector i (y_i) can be obtained by subtracting the value of imports from the sum of all row entries (i.e., the sum of all z_{ij} and F_i in a given row). This can be expressed for year t as follows:

$$\boldsymbol{y_{it} = z_{i1t} + z_{i2t} + \ldots + z_{ijt} + \ldots + z_{int} + F_{it} - m_{it}} \qquad \text{(a.1)}$$

Similarly, from the supply perspective, output of each product j (y_{jt}) can be obtained by summing the column entries – that is, the sum of the value of all input purchases and value added in sector j

$$\boldsymbol{y_{jt} = z_{1jt} + z_{2jt} + \ldots + z_{jjt} + \ldots + z_{njt} + t_{jt} + v_{jt}} \qquad \text{(a.2)}$$

Where t_{jt} stands for net indirect taxes and v_{jt} stands for value added.

One of our tasks is to construct DUT for the years for which official IOT are not available. To this end, using available official IOT, we calculate the ratio of intermediate use to total availability (imports plus industry output) for each sector i and year t. This ratio (r_{it}) is defined as:

$$r_{it} = IIUSE_{it}/(y_{it} + m_{it}) \quad \text{(a.3)}$$

where $IIUSE_{it}$ stands for total intermediate use of sector i's output for year t – that is, the sum of all z_{ij}'s in equation a.1 for a given sector i and for a given year t[23]. We compute this ratio for 112 sectors and for all the years for which official IOT and SUT are available. For the intervening years, we obtain them by linear interpolation. Using these ratios, we obtain total domestic use ($DIIUSE_{it}$) – that is, the total of each sector i's value of output (net of imports) used by all j sectors for year t.

$$DIIUSE_{it} = r_{it} \times y_{it} \quad \text{(a.4)}$$

Next, we distribute the value of $DIIUSE_{it}$ across cells within a row on the basis of the share of each sector j in the total intermediate use of sector i's output – that is, by using the following identities for each sector i[24].

$$1 = \frac{z_{i1t}}{IIUSE_{it}} + \frac{z_{i2t}}{IIUSE_{it}} + \ldots + \frac{z_{iit}}{IIUSE_{it}} + \ldots \frac{z_{int}}{IIUSE_{it}} \quad \text{(a.5)}$$

Using 112×112 absorption matrices, we compute the ratios in (a.5) for all the years for which official IOT and SUT are available. For the intervening years, we obtain them by linear interpolation. For a given row, by multiplying each of these ratios by the respective $DIIUSE_{it}$ values, we obtain the annual time series of DUT (with dimension 112×112) for the period 1999-00 to 2012-13. The column entries in DUT are used to estimate the domestic technical coefficient matrix $(\boldsymbol{A^d})$, the elements of which (denoted as a_{ijt}) measure the amount of domestic input from sector i required to produce one unit of output in sector j.

Appendix A2: Database for Constructing DUT

The official IOT contains 115 sectors for 1998-99 and 130 sectors for 2003-04 and 2007-08. By matching and grouping these sectors across IOTs, with the help of a concordance table provided by CSO, we were able to identify 112 distinct sectors (covering the whole economy) for which we can generate a time series of IOTs. Unlike IOTs, the SUTs are not available as square matrices, with the number of rows (140) being higher than the number of columns (66). Following the procedure outlined in the endnote, we converted the SUTs into square matrices[25]. Hence, we obtain DUTs, with dimension 112×112, for all years for which official IOTs/SUTs are available. In order to construct DUT for the intervening years, however, we need consistent time series data on gross value of output (y_{it}), and imports (m_{it}) for 112 sectors. Once we have the complete time series of DUT, we can estimate DVA and employment tied to exports. For the latter, we also need sector wise time series data on gross value added (to compute value added to output ratio, v), employment (to compute labor to output ratios, l) and exports (x). A brief description of the various sources used for compiling these statistics is given below.

(i) *Gross Value of Output and Gross Value Added*

For the manufacturing sector, we use unit level data from two sources – that is, Annual Survey of Industries (ASI) for the formal enterprises and surveys conducted by the National Sample Survey Office (NSSO) for the informal enterprises. Using these sources, we retrieve value of output (y) and value added (GVA) at the 5-digit NIC (National Industrial Classification) level for the period 1999-2000 to 2012-13. These values are then aggregated, using concordance tables between different versions of NIC and our 112 sector classification, to obtain sector level data (formal plus informal) on y and GVA[26]. For the non-manufacturing sectors, we use disaggregated statements provided by India's National Accounts Statistics (NAS). For a large number of these sectors, we obtained data on both *y* and *GVA*: in some cases, where only GVA was available, estimates of *y* were derived by applying output to value added ratios, obtained from official IOTs and SUTs.

We validate our estimates of *y a*nd *GVA*, obtained as above, with official IOTs[27]. Our estimates are identical to the values reported in IOTs at the economy-wide level, though we notice certain discrepancy for some individual sectors. The discrepancy could be attributed to the possibility that the concordance tables that we use to assemble data at IO sector level are unlikely to match exactly with the ones used by the CSO. In any case, the observed aggregate discrepancies at the level of broad sector groups (agriculture, manufacturing and services) have been distributed across IO sectors based on the latters' weights within each of the sector groups. In this way, we ensure that any remaining mismatch with official IOT in our final dataset is less than 1% for a given sector.

(*ii*) *Exports and Imports*

For merchandise and services trade, we use official data published by Directorate General of Commercial Intelligence and Statistics (DGCI&S) and Reserve Bank of India (RBI), respectively. The value of total exports (merchandise plus services) and imports, obtained from these two sources, matches exactly with the data reported in official IOTs and SUTs. Percentage shares of 112 sectors in total exports has been computed using official IOTs and SUTs for the respective years while those for the intervening years have been obtained through linear interpolation. Using these shares, we apportion the total value of exports (and imports) for each year across our 112 sectors.

(*iii*) *Employment*

For estimating employment by sector, we use unit level data from various rounds of Employment and Unemployment Surveys (EUS) by NSSO. We obtain the estimates of employment at the 5-digit level of NIC for all years for which surveys were conducted. For the intervening years, we apportion each year's aggregate employment estimates, available from other sources, based on interpolated percentage distribution at the 5-digit NIC level[28]. The 5-digit level estimates were then aggregated to obtain a time series for our 112 sectors.

Endnotes

[1] See for example, Feenstra (1998), Hummels et al. (2001), Johnson and Noguera (2012), Athukorala (2012), Baldwin and Lopez-Gonzalez (2013), Koopman et al. (2014), Timmer et al (2014), Los et al. (2015) and Obashi and Kimura (2018).

[2] For example, the often-cited case study by Dedrick et al (2010) shows that although the factory-gate price of an assembled iPod from a Chinese factory is $144, only about $4 of this constitutes of Chinese value added with much of the rest being captured by US, Japan and Korea. However, despite the low DVA per unit, the aggregate DVA in China from iPod assembly could be very high due to the scale effect. Consider the following simple back-of-the-envelope calculation. In 2008 (close to the years for which Dedrick provided the estimates) Apple sold 54.83 million units of iPods. Assuming that the whole assembly was done in China, the aggregate DVA in China from the assembly of this single product was 219 million dollars ($4 × 54.83 million units), which accounts for 0.015% of China's gross merchandise exports and about 0.022% of aggregate export related DVA in China in 2008.

[3] In order to obtain comparable estimates across countries, WIOD and TiVA make use of harmonized inter-county IOT with rather aggregate level of sector classification. While WIOD and TiVA respectively make use of 35×35 and 34×34 IOT, India's official IOT from CSO is far more disaggregated (for example, 130 ×130 matrix for the year 2007-08). Based on more disaggregated official IOTs, Goldar et al (2017) provide estimates of domestic value added share in India's gross exports, but only for selected years -1998-99, 2003-04 and 2007-08.

[4] The WIOD and TiVA estimates are based on a time series of IOT. In order to construct this time series, India's official IOT (for the years 1998-99, 2003-04 and 2007-08) are benchmarked on the National Accounts Statistics (NAS), using an algorithm known as RAS method

(Temurshoev and Timmer, 2011). The estimates for the post 2007 period do not capture certain important structural changes in the economy, as reflected in SUT and the recent revision of NAS. For example, the recent revision of NAS shows that the share of the manufacturing sector in India's GDP is significantly higher than what was previously thought. For the year 2011-12, for example, the share of manufacturing sector in GDP was 14.7% as per the old NAS series (on which TiVA and WIOD are based) which was revised upward to 17.4% in the new series (for a detailed discussion, see Nagaraj and Srinivasan, 2016). These changes are captured in the recently published SUT, which we make use of for constructing the DUT (see Appendix A1 and A2 for details).

[5] Each element of Leontief inverse matrix indicates input requirement from i^{th} sector if there is a unit increase of the final-use (consumption, foreign trade, or investment) of j^{th} sector's output.

[6] To put these numbers in perspective, the additional number of export related jobs, being created during this 13-year period (1999-00 to 2012-13), is 28.6 million, which is impressive compared to India's past record. Using the estimates from a comparable previous study (Chishti, 1981), we note that only about 26.8 million additional export related jobs were created during the past period spanning about quarter of a century (1975-1999). Other studies that provided some estimates for the 1960s and 1970s include Taylor (1976), Banerjee (1975) and Nambiar (1979). To the best of our knowledge, similar estimates are not available for India for the post-1980 period. World Bank's 'Labor Content of Exports' dataset provides estimates for 66 countries for selected years but not for India (https://datacatalog.worldbank.org/dataset/labor-content-exports-database).

[7] Export related jobs accounted for only 4.3% of total employment in 1975-76 (Chishti, 1981).

[8] Declining employment intensity of exports is partly driven by improvements in labor productivity over the years. This can also be a result of a change in the composition of gross exports in favor of more skill and capital intensive products. While the share of capital-intensive products in India's merchandise exports increased consistently from about 32% in 2000 to nearly 53% in 2015, the share of unskilled labor-intensive products declined from about 30% to 17% (EXIM Bank, 2016; Veeramani et al, 2016). A similar trend was observed in services export basket with an increasing share of skill intensive software and business services at the cost of traditional services.

[9] The share of manufacturing sector in gross exports is relatively higher than its share in total DVA. This mismatch is mainly driven by two sectors: 'Petroleum Products' and 'Gems & Jewelry'. While both these sectors account for a high share in gross exports, their share in total DVA is relatively less owing to their high import dependence. For example, in 2012-13, these two sectors together accounted for about 24% of gross exports but only about 7% of total DVA attributed to exports.

[10] At this juncture, it may be of interest to compare our estimates of VAX ratios with those available for India in TiVA database (see Figure 3). We notice that our estimates are very close to TiVA estimates till the year 2007. Since 2007, however, our estimates are significantly lower (particularly for manufacturing) than the corresponding values reported in TiVA database. This difference is driven by the fact that our estimates for the post 2007 period account for recent changes in the structure of the economy (as captured by SUTs for the years 2011-12 and 2012-13) while the TiVA estimates do not capture these changes.

[11] At the aggregate level, the share of indirect jobs in total export-supported jobs increased from about 38% in 2007-08 to 52% in 2010-11 (see Table 3).

[12] Use of lagged ratio also enables us to treat this variable as exogenous. Our regressions exclude the observations where the values of both *x* and dva_1 are zero as in such cases the ratio between the two (zero divided by zero) is undefined. For merchandise sectors, the observations with zero export values account for less than 5% of total observations.

[13] The variable *yd* is measured in *gross* (rather than value added) terms, which is appropriate as the dependent variable in equation (5) is *gross* exports. The value of exports is subtracted from total output in order to overcome possible reverse causality.

[14] We include the variable *gvad* instead of *yd* in equation (6) as the dependent variable (dva_{i1t}) is measured in value added (rather than gross) terms. The value of direct domestic value added attributed to exports (dva_{i1t}^{d}) is subtracted from total gross value added in order to address possible reverse causality. Equation (7a) includes domestic value addition attributed to exports (dva_{i1t}) as well as value added from domestic sales (*gvad*) as separate explanatory variables.

[15] Output (value added) deflator for the United States is taken as a proxy for world prices.

[16] The test is carried out as follows. First, using the OLS method, we regress $\boldsymbol{ln(x_{it})}$ on all the exogenous variables and obtain the residuals. Second, we run the OLS regression of $\boldsymbol{ln(dva_{i1t})}$ (equation 6) with the residuals obtained in the first regression as an additional regressor. We find that the coefficient of the residual is statistically significant at 1% level which implies that endogeneity problem exists. In a similar fashion, we run an OLS regression of $\boldsymbol{ln(e_{i1t})}$ (equation 7) with the residual obtained from the OLS regression of $\boldsymbol{ln(dva_{i1t})}$ on the exogenous variables being included as an additional regressor. Again, the results confirm the presence of endogeneity.

[17] The 3SLS approach, a combination of seemingly unrelated regressions (SUR) and 2SLS, obtains instrumental variable estimates, taking into account the covariances across equation disturbances.

[18] Thus, the marginal gain from GPS participation is higher for manufacturing as compared to services and primary sectors. This is expected as manufactured products are generally more amenable to GPS as compared to services and primary products.

[19]The domestic activity variables in levels show statistically significant negative coefficients for the manufacturing sample. However, when we use the first differences, these variables yield positive coefficients in equations 5 and 6. In general, the domestic activity variables are not statistically significant for the full sample.

[20] It must be noted that the VAX ratio reported in TiVA is an overestimation for countries, such as China and Mexico, which are heavily involved in processing trade. This bias is because the calculation is based on the assumption that production techniques and input requirements are identical for exports and domestically absorbed final goods. This assumption would overstate the DVA content of exports for countries such as China and Mexico that have large export processing sectors (Koopman et al, 2010; Johnson and Noguera, 2012). For example, in China, processing exports account for about half of overall exports. Estimates for the year 2004 by Johnson and Noguera (2012) confirm that, once processing exports are separately taken into account, the aggregate VAX export ratio fall substantially from 0.70 to 0.59 for China and from 0.67 to 0.52 for Mexico.

[21]There are several reasons to believe that the general incentive structure is biased against labor-intensive industries in India. Many argue that India's rigid labor laws create severe exit barriers and discourage large firms from choosing labor-intensive activities and technologies (see Kochhar et al., 2006; Panagariya, 2007; Krueger, 2010). Another group of scholars, however, question this argument (see Bhattacharjea, 2006 and Nagaraj, 2011). Though there is no unanimity of opinion in this regard, a growing number of econometric studies suggest that the

role of labor laws cannot be ignored (see Hasan et al., 2007 and Aghion et al., 2008). Other constraints that stand in the way of labor-intensive manufacturing include inadequate supply of physical infrastructure (especially power, road and ports) and a highly inefficient and cumbersome land acquisition procedure. Faced with power shortages, capital and skill-intensive industries, such as automobiles and pharmaceuticals, might be in a position to rely on high-cost internal sources of power. But this option is unaffordable to firms in labor-intensive segments which typically operate with relatively low margin. Similarly, cumbersome land acquisition procedures create a bias against large scale labor-intensive manufacturing. – Do you want to write something about how these factors are improving – reflected in improvement in India's ease of doing business ranking.

[22] The SUT are not available for previous years. A major difference between IOT and SUT is that the former contains equal number of rows and columns (square matrix) while the number of rows exceeds the number of columns in SUT. The sectors represented by SUT columns are more aggregated than the sectors represented by SUT rows.

[23] For calculating this ratio, we have made appropriate adjustments for the Change in Stocks (CIS). Whenever CIS is negative we have proportionately subtracted CIS value from IIUSE on the basis of percentage shares of IIUSE in total (final plus intermediate) use. Note that output (y_{it}) values in IOT are already net of CIS whenever CIS is negative

[24] Note that $DIIUSE_{it}$ does not include imported intermediates. Total imported intermediate use $MIIUSE_{it}$ can be obtained in an analogous manner: $MIIUSE_{it} = r_{it} \times m_{it.}$. By summing the two, we get total use: $IIUSE_{it} = DIIUSE_{it} + MIIUSE_{it}$

[25]A square matrix is obtained by appropriately apportioning entries in each of the SUT column sectors and by aggregating some of the entries across SUT row sectors. Specifically, using a

concordance table between SUT column sectors and our 112 sector classification, the *zij* value appearing in each of the 66 cells of a given SUT row is apportioned into the corresponding sectors within the master list of 112 sectors. This apportioning of *zij* value is done on the basis of percentage share (as per official IOT for 2007-08) of sectors that correspond to a given SUT column sector. Similarly, using a concordance table, 140 SUT rows have been aggregated into 112 sectors in the master list. A detailed discussion on various assumptions, data sources and concordance tables used for the construction of this database is available in EXIM Bank (2016).

[26] While ASI data is available for all years, NSSO surveys for informal sector were available only for selected years: 1999-00, 2000-01, 2005-06 and 2010-11. The National Accounts Statistics (NAS), however, report a continuous time series on output and value added for about 21 broad industry groups in the informal manufacturing sector. For the years for which NSSO data was not available, we apportion the aggregate values from NAS across 5-digit codes within each of the 21 broad industry groups. This apportioning is done on the basis of interpolated percentage shares of 5-digit codes within each of the broad industry groups. Our procedure ensures that the value of output and GVA for the total manufacturing sector in our database is identical to those reported in NAS.

[27] Output and value added data are in nominal terms and correspond to 2004-05 base year. Further, all official IOTs and SUTs have been converted to 2004-05 base year.

[28] The surveys were conducted for the Indian financial years 1999-2000, 2003-2004, 2004-05, 2005-2006, 2007-2008, 2009-2010, and 2011-12. We use data based on 'Usual Principal and Subsidiary Status (UPSS), which is the commonly used measure for tracking employment trends. In order to obtain employment data for other years, we apportion available aggregate employment estimates across the corresponding 5-digit codes based on percentage shares. For

the period 2000-01 to 2003-04, we used the aggregate employment estimates at 2-digit NIC level from different rounds of NSSO surveys on "Household Consumption Expenditure and Employment-Unemployment Situation in India". For the rest of the years (2006-07, 2008-09, 2010-11 and 2012-13), the estimates of aggregate employment were obtained through linear interpolation and extrapolation.