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Reaping Gains from Global Production Sharing: Domestic Value Addition and Job Creation by Indian Exports

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Abstract

Is it in the interest of a country to promote strong local linkages for domestic industries or to participate in global production sharing (GPS) activities wherein linkages are globally dispersed? This paper informs this debate by empirically analyzing which one of these strategies would result in higher levels of domestic value added (DVA) and employment in a developing country, India. A higher level of participation in GPS entails that, for any given country, DVA per unit of exports is smaller than when most inputs are sourced locally. However, owing to the scale and productivity effects of producing for the world market, participation in GPS can lead to higher absolute levels of DVA and domestic job creation. We test this hypothesis using a unique panel data on DVA and jobs tied to Indian exports from 112 sectors for the period 1999-2013. Our regression analysis confirms that participation in GPS, as measured by the sectoral ratio of DVA to gross exports, leads to higher absolute levels of gross exports, DVA and employment. These results are robust to alternative model specifications and estimation techniques. We conclude that developing countries can reap rich dividends by adopting policies aimed at strengthening their participation in GPS.

Keywords: Exports, Domestic Value Added, Employment, India, Global Production Sharing

JEL Code: 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 United States and Europe, developing countries like India and China are more 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. In this scenario, policy makers in India are grappling with the challenge of creating adequate employment opportunities for the masses. For example, the "Make in India" initiative by the Indian Government aims to create large number of jobs through the promotion of exports, particularly manufactured goods.

Against this background, whether exports offer a viable path to job creation is a question with significant policy implications. The relationship between exports and domestic job creation, however, is not straightforward, and often poorly understood, particularly in the current context of a high level of global production sharing (GPS) activities in several industries. The phenomenon of globally fragmented production processes, often described by the term GPS or vertical specialization, implies that intermediate inputs cross borders several times during the manufacturing process[1]. The proliferation of GPS poses certain challenges with respect to measurement of trade flows because, unlike the way domestic transactions are measured, trade data is usually collected and reported as gross flows at each border crossing rather than net value added between border crossings. This can lead to double (or multiple) counting, and also implies

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

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. Thus, a major difficulty in analysing the relationship between exports and job creation is concerned with the availability of appropriate data.

Participation in GPS also has a bearing on the mechanisms underlying the relationship between exports and employment. Furthermore, it raises an important policy question – that is, whether it is in the interest of a country to promote strong local linkages for domestic industries or to participate in GPS wherein linkages are globally dispersed. The present paper informs this debate by empirically analyzing which one of these strategies would result in higher levels of domestic value added (DVA) and employment in a developing country, India.

A higher level of participation in GPS entails that, for any given country, DVA *per unit* of exports is smaller than when most inputs are sourced locally. However, owing to the scale effect of producing for the world market, GPS participation can lead to higher *absolute* levels of DVA and hence higher job creation in participating countries[2]. The implication, if this indeed 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,

[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 for 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 et al 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 DVA tied to Chinese exports in 2008.

to test the hypothesis that greater participation in GPS leads to higher absolute levels of gross exports, DVA and employment. To the best of our knowledge, these relationships have not been studied before, using a multiple regression framework, in the context of developing countries.

In order to carry out the econometric analysis, we build a unique panel data on DVA and jobs tied to Indian exports from 112 sectors, covering the whole economy, during the period 1999-2000 to 2012-2013[3]. We obtain these estimates using Input-Output (IO) method, which enables us to disentangle the direct and indirect (backward and forward linkages) effects of exports from any given sector. To this end, we use all official IO Tables (IOT) and Supply Use Tables (SUT) available for the period under consideration. For the intervening years – the years for which official IOT and SUT are unavailable – we interpolate the relevant matrices by making use of detailed production and trade data from various official sources. Following Johnson and Noguera (2012), the ratio of DVA to gross exports (VAX ratio) is used as a proxy to quantify the extent of a country's participation in GPS. The rationale for this is that the VAX ratio measures how much domestic, as opposed to foreign, value-added is generated throughout the economy for a given unit of exports. In general, sectors with greater participation in GPS tend to record lower share of DVA in gross exports and vice versa (Johnson and Noguera, 2012).

Rest of the paper is organized as follows. Section 2 discusses the IO methodology used to estimate DVA and number of jobs tied to exports. Section 3 presents the estimates of DVA, VAX ratio and the number of jobs attributable to India's 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

[3] Indian financial year starts from 1st April to succeeding 31st March. For example, financial year 1999-2000 is from 1st April 1999 to 31st March 2000.

employment. Finally, Section 5 provides the concluding remarks. A detailed discussion of data, assumptions and methodology involved in the construction of year specific IO matrices is provided in the Appendix.

2. ESTIMATION OF DOMESTIC VALUE ADDITION AND JOB CREATION BY EXPORTS: METHODOLOGY

Driven by the concerns on the use (and misuse) of official international trade statistics, attempts have been made by different agencies to estimate value added content of exports. Estimates for India are available in World Input Output Database (WIOD) and OECD-WTO TiVA database. However, for the following reasons, WIOD and TiVA are not the ideal databases for our purpose. First, WIOD and TiVA estimates are only available for relatively aggregated sector categories[4]. Second, these estimates do not account for some of the important structural changes occurred in Indian economy (including inter-industry relationships) post 2007[5]. Third,

[4] In order to obtain comparable estimates across countries, WIOD and TiVA make use of harmonized inter-county IOT with a 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 Central Statistical Organization (CSO) is far more disaggregated (for example, 130 ×130 matrix for the year 2007-08). Based on the more disaggregated official IOTs, Goldar et al (2017) provide estimates of DVA share in India's gross exports, but only for selected years (1998-99, 2003-04 and 2007-08).

[5] The WIOD and TiVA estimates are based on a time series of IOT. In order to construct this time series, India's official IOT published by CSO (for the years 1998-99, 2003-04 and 2007-08) were benchmarked on the National Accounts Statistics (NAS), using an algorithm known as RAS method (Temurshoev and Timmer, 2011). However, the estimates for the post 2007 period do not capture certain important structural changes occurred in the economy. For example, the recent revision of NAS as well as SUTs shows that the share of manufacturing sector in India's GDP is significantly higher than what is reflected in the IOTs used for obtaining WIOD and TiVA estimates. For the year 2011-12, for example, the share

WIOD and TiVA do not provide estimates of employment tied to exports[6]. Addressing these gaps, we build an updated and more detailed panel data on DVA and jobs tied to Indian exports.

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

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

where $\boldsymbol{v}$ is a $1 \times n$ vector containing value added to output ratio for each sector *j*, $\widehat{\boldsymbol{X}}$ 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*[7]. $\boldsymbol{A^d}$ 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*. **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 value of DVA for broad sector groups (agriculture, manufacturing and services) and for the economy as a

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 obtaining our estimates of DVA (see Appendix for details). Indeed, we find that our estimates of VAX ratios differ significantly from the TiVA estimates for the years 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.

[6] 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] 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.

whole. Such aggregate estimates may be denoted as $\sum dva_{j1}$ where dva_{j1} 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 shown below.

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

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

where $\left(\boldsymbol{\widehat{I - A^d}}\right)^{\boldsymbol{-1}}$ 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 *j* as a result of its forward linkages with all downstream sectors *i*. For example, DVA is generated in 'iron and steel' sector as a result of exports from other sectors (such as, automobiles, machine tools etc) wherein 'iron and steel' is used as one of the inputs. Thus, based on a given sector's forward linkages with other sectors, DVA attributed to exports can be estimated as:

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

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

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

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

where $\widehat{\boldsymbol{V}}$ 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. The two approaches, however, give identical direct DVA estimates at the sector level– that is, the vectors dva_1^d and dva_2^d are identical for a given sector. On the other hand, dva_1^{bw} and dva_2^{fw} give different values for a given sector 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, no matter whether it is directly engaged in exports or not, if it supplies inputs to other exporting sectors.

The number of jobs tied to exports can also be computed, in an analogous manner, using the above approach. The relevant equations for estimation are:

$$\boldsymbol{e_1} = \boldsymbol{l}\left(\boldsymbol{I} - \boldsymbol{A}^{\boldsymbol{d}}\right)^{-1}\widehat{\boldsymbol{X}} \quad (3)$$

$$\boldsymbol{e_1^d} = \boldsymbol{l}\left(\widehat{\boldsymbol{I} - \boldsymbol{A}^{\boldsymbol{d}}}\right)^{-1}\widehat{\boldsymbol{X}} \quad (3a)$$

$$\boldsymbol{e_1^{bw}} = \boldsymbol{e_1} - \boldsymbol{e_1^d} \quad (3b)$$

based on backward linkages

$$\boldsymbol{e_2} = \widehat{\boldsymbol{L}}\left(\boldsymbol{I} - \boldsymbol{A}^{\boldsymbol{d}}\right)^{-1}\boldsymbol{x} \quad (4)$$

$$\boldsymbol{e_2^d} = \widehat{\boldsymbol{L}}\left(\widehat{\boldsymbol{I} - \boldsymbol{A}^{\boldsymbol{d}}}\right)^{-1}\boldsymbol{x} \quad (4a)$$

$$\boldsymbol{e_2^{fw}} = \boldsymbol{e_2} - \boldsymbol{e_2^d} \quad (4b)$$

based on forward linkages

Where l is $1 \times n$ vector containing employment coefficients (labor/output ratios) while $\boldsymbol{\hat{L}}$ 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 tied to exports from 112 sectors, covering the whole Indian economy, for the period 1999-2000 to 2012-13.

3. ESTIMATES OF DVA AND EMPLOYMENT TIED TO INDIAN EXPORTS

3.1. Aggregate Level Estimates

Table 1 reports the values of DVA (in billions of US$) tied to India's aggregate merchandise and services exports. These values are arrived at by summing the estimates for all 112 sectors for each year. Also reported in the table are a set of related indicators, namely, aggregate gross exports in dollars, VAX ratio and value of gross exports required to generate $ 1 billion worth of DVA. The average annual growth rates pertaining to these indicators for different periods are shown in Table 2.

(Table 1 and 2 about here)

It can be seen that India's gross exports stood at $53.3 billion in 1999-2000, of which the contribution of DVA was $46 billion with the rest being attributed to foreign value added. By 2012-13, the values of gross exports and DVA 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 the participation in GPS by Indian industries has increased over the years, especially since the second half of the 2000s. Did these changes translate into higher number of jobs in the country? Our descriptive statistics are consistent with an answer in the affirmative as we find that the number of jobs tied to India's total exports increased from about 34 million in 1999-00 to 62.6 million in 2012-13 (Table 3)[8]. Further, during this period, the number of jobs tied to exports grew faster than the size of total employment in the country (see Table 2) with the share of the former in the latter being increased from little over 9% in 1999-2000 to 14.5% in 2012-13[9].

(Table 3 about here).

Even as we observe a significant increase of export related jobs in absolute terms, the number of jobs generated per $1 million worth of exports declined steadily from 638 in 1999-2000 to 138 in 2012-13[10]. A similar trend of secularly declining number of jobs per million dollar worth of exports has been observed for a number of other countries (Cali et al, 2016).

[8] The additional number of export related jobs, being created during this 13-year period (1999-00 to 2012-13), is 28.6 million. This is far more impressive relative to India's past record. Based on the available estimate for 1975-76 (obtained from a comparable previous study by Chishti, 1981) and our estimate for the year 1999-2000, we find that only about 26.8 million additional export related jobs were created during 1975-76 to 1999-2000, a period spanning about quarter of a century. Other studies that provided estimates for selected years during the 1960s and 1970s include Taylor (1976), Banerjee (1975) and Nambiar (1979).

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

[10] Declining employment intensity of exports is partly driven by improvements in labor productivity over the years and partly as 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). 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.

Despite this decline, however, employment intensity of Indian exports is found to be perceptibly higher than similar estimates available for other major countries, including US and 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 (Chen et al 2012) as compared to 191 jobs for India for the same year.

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

As noted earlier, depending up on the type of linkages considered, two different approaches can be followed to estimate sector level DVA and employment attributed to exports. Between the two estimation 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 to understand the extent of a sector's dependence on exports, directly and indirectly, for growth and job creation. Our discussion below, keeping in mind the focus of this paper, primarily deals with the estimates based on backward linkages though we also briefly highlight the relative importance of the two types of linkages across sector groups.

Table 4 reports DVA $\left(\sum dva_{j1}\right)$ and employment $\left(\sum e_{j1}\right)$ attributed to Indian exports from each sector group – agriculture, manufacturing and services. The value of DVA tied to manufactured exports increased steadily from about $24 billion in 1999-2000 to $165 billion in 2011-12. At the same time, the number of jobs attributed to manufactured exports remained in the range of 17.5 to 25 million until the year 2009-10 before increasing sharply to 31.5 million in 2010-11 and 45 million in 2012-13. In contrast to these trends with respect to manufactured exports, DVA and employment attributed to agriculture exports recorded a significant decline during the second half of the 2000s as compared to the first half. Services sector exhibit a mixed trend in that the value of DVA attributed to exports from this sector recorded a consistent increase throughout the period (barring a one-off decline in 2009-10) while employment declined since 2008-09 following a steady increase in the previous years.

(Table 4 about here)

The ratio of $\boldsymbol{dva}_1$ to gross exports (VAX ratio) declined perceptibly for the manufacturing sector, from 0.81 in 1999-2000 to 0.53 in 2012-13 (see Figure 1, panel a). The VAX ratio, as noted earlier, captures the extent of a sector's participation in GPS; lower the ratio, greater is the foreign (as opposed to local) sourcing of intermediate inputs and vice versa. Clearly, the observed trends in VAX ratios suggest that India's manufacturing sector has strengthened its participation in GPS over the years. However, the VAX ratio remained quite high, throughout the period, both for agriculture (above 0.90) and services (above 0.85). In general, manufactured products are inherently more tradable and more amenable to global fragmentation as compared to most of the primary and services sectors. Furthermore, manufacturing has been the main focus of India's trade liberalization initiatives since the early 1990s while agriculture and services sectors have been subjected to a greater degree of trade policy restrictions. Viewed thus, the relatively higher participation in GPS by the manufacturing sector is as expected.

(Figure 1 about here)

In order to assess the relative importance of the two types of linkages across sector groups, Table 5 and 6 reports the estimates of DVA and job creation attributed to backward and forward linkages, respectively. Manufactured exports can be credited with accounting for the largest share of economy-wide employment as well as DVA generated through backward linkages (see Table 5). On the other hand, the bulk of export related jobs in agriculture and services sectors have been generated as a result of their forward linkages with the manufacturing sector (see Table 6 and 4). For the year 2012-13, for example, forward linkages accounted for 80% and 51% of total export related jobs in agriculture and services, respectively. Throughout the period, the ratio of $\sum dva_{j2}$ to gross exports is greater than 1 for agriculture as well as services sectors and less than 0.5 for the manufacturing sector (see Panel b, Figure 1). Values of these ratios reinforce our inference that exports from downstream manufacturing industries generates significant DVA and employment in upstream agriculture and services through linkages even though many of the upstream industries do not directly engage in export activities. Overall, it is clear that, exports of manufactured products offer the greatest potential to generate economy-wide value addition and employment, directly as well as indirectly through their backward linkages with agriculture and services.

(Table 5 and 6 about here)

4. REGRESSION ANALYSIS

The declining ratio of DVA to gross exports, as noted above, implies that India's participation in GPS has increased over the years. What are the consequences of this trend for value addition and job creation in the domestic economy? As alluded to earlier, what matters in determining the level of domestic employment generation is the absolute value of DVA, rather than DVA per unit of exported goods. In this section, we provide econometric evidence in support of the conjecture that a decline of the VAX ratio leads to higher absolute levels of gross exports, DVA and employment.

The theoretical basis for our hypothesis comes from the models that deal with the impact of offshoring on labor market outcomes[11]. Jones and Kierzkowski (1990, 2001) and Arndt (1997) were among the first to note that participation in GPS can achieve cost savings, increase productivity and cause the sector to expand. In these models, fragmentation acts as technological progress in final goods sectors – that is, trade in intermediate goods makes it possible to produce more final goods from any given stock of primary factors. Thus, fragmentation entails additional gains from trade beyond those achieved when trade is limited to final goods. Theoretical analysis by Arndt (1997, 1998), for example, shows that offshore sourcing in an industry increases employment and wages because of high net job creation – that is, the job growth in activities that are still performed at home more than compensate for the jobs lost due to sub-contracting.

Later, the seminal general equilibrium model of "trade in tasks" by Grossman and Rossi-Hansberg (2008) showed that offshoring induces a positive productivity effect in the home country, exerting an upward pressure on domestic wages and hence the level of DVA[12]. Extending this framework, Wright (2014) conceptualizes the impact of offshoring on domestic employment through three channels: (i) a direct negative displacement effect due to the decline

[11] See Gorg (2011) and Wright (2014) for an extensive review of theoretical and empirical literature. Previous studies, dealing with the impact of offshoring, are mostly in the context of developed countries.

[12] However, the net effect of offshoring on wages depends on the interplay between three forces: (i) positive productivity effect; (ii) negative relative price effect (for a large country, the relative price of the good, whose certain stage of production is being offshored, declines due to cost savings) and (iii) negative labor supply effect due to a decline in the domestic demand for the factor whose task is being offshored to a low cost location. Grossman and Rossi-Hansberg (2008) argue that in a number of situations the productivity effect can dominate the other effects leading to an overall positive benefit. They also provide some evidence to this effect.

in labor demand at home as firms move tasks overseas (ii) a positive scale effect connected to the productivity effect of offshoring and the resulting output expansion and (iii) an ambiguous effect due to the potential substitution between high and low skill factors and/or between domestic and foreign tasks. The net result of offshoring on employment is positive or negative, depending upon the relative importance of these different channels. Therefore, whether or not participation is GPS leads to higher DVA and job creation is primarily an empirical question to which we turn now.

4.1. Econometric Specification

Assuming that the scale and productivity effects outweigh any possible negative impact of offshoring, we hypothesize that the dollar value of gross exports from a sector (x_j) will increase with an increase in the participation of the sector in GPS. An increase in gross exports, in turn, implies that the absolute dollar value of total (direct plus indirect) DVA, tied to the sector's exports, would increase as well. For, with greater participation in GPS, even as the VAX ratio tends to decline, total DVA would increase due to the scale effect of producing for the world market. Finally, we hypothesize that an increase in the absolute value of DVA would cause an increase in the number of jobs tied to exports. In order to test these hypotheses, we estimate the following simultaneous equation model using 3SLS regression.

$$\boldsymbol{ln(x_{jt}) = \alpha_0 + \alpha_1 ln\left(\frac{dva_{j1}}{x_j}\right)_{t-1} + \alpha_2 ln(yd_{jt}) + \alpha_3 ln(rpo_{jt}) + \alpha_4 ln(wd_{jt}) + \alpha_5 J +}$$

$$\boldsymbol{\alpha_6 D(t) + u1_{jt}} \qquad (5a)$$

$$\boldsymbol{ln(dva_{j1t}) = \beta_0 + \beta_1 ln(x_{jt}) + \beta_2 ln(gvad_{jt}) + \beta_3 ln(rpv_{jt}) + \beta_4 J + \beta_5 D(t) + u2_{jt}}$$

(6a)

$$\boldsymbol{ln(e_{j1t}) = \gamma_0 + \gamma_1 ln(dva_{j1t}) + \gamma_2 ln(gvad_{jt}) + \gamma_3 ln(rw_{jt}) + \gamma_4 ln(l_{jt}) + \gamma_5 J +}$$

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

The notations *j*, *t* and *ln* 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 exports from India to rest of the world in sector *j* (x_{jt}); (ii) dollar value of direct plus indirect DVA attributed to Indian exports from sector *j* (dva_{j1}, individual elements of the vector $\boldsymbol{dva_1}$); and (iii) direct plus indirect employment attributed to Indian exports from sector *j* (e_{j1}, individual elements of the vector e_1).

In light of the hypotheses outlined above, the main coefficients of interest are α_1, β_1, and γ_1. The rest of the explanatory variables are included to control for other factors which may influence the dependent variables. In addition to sector and year dummies, each of the above equations includes appropriate control variables representing sector-specific levels of domestic activity and relative price. We use one year lagged value of VAX ratio $\left(\frac{dva_{j1}}{x_j}\right)$, rather than its contemporaneous value, assuming that the effect of GPS on gross exports may take time to manifest[13]. Coefficient of this variable, α_1, is expected to yield a negative sign in equation (5a) since greater participation in GPS is likely to cause an increase of gross exports in dollar terms. On the other hand, our hypothesis implies that the expected signs of β_1 in equation (6a) and that of γ_1 in equation (7a) are positive.

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[13] Our regressions exclude those observations where the values of both x and dva_1 are zeros as in such cases the ratio between the two (zero divided by zero) is undefined. For merchandise sectors, observations with zero export values account for less than 5% of total observations.

Domestic activity variables are included to capture the effect of domestic market size and supply capability on the dependent variables. The relevant domestic activity variable in equation (5a) is *yd*, defined as output value minus gross export value for each sector[14]. The variable *gvad*, defined as gross value added minus dva_{j1t}^{d}, is included as a domestic activity variable in equations (6a) and (7a)[15]. Based on the coefficient signs of domestic activity variables in these equations, we can infer 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 there are increasing returns to scale or if the strength in domestic market can be leveraged in international markets. Thus, the coefficient sign of domestic activity variable depends on which effect dominates. We treat the activity variables *yd* and *gvad* as endogenous explanatory variables in the simultaneous equations system.

The variable *rpo* (or *rpv*) represents sector level relative price adjusted for exchange rates, which is constructed by taking the ratio of sector level output (or value added) deflator for India to that of United States[16]. These ratios were then adjusted by dollar per rupee nominal exchange rate for each year, with an increase of the ratio being indicative of a deterioration of

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

[15] The variable *gvad* is included in equation (6a), instead of *yd,* because the dependent variable (dva_{j1t}) is measured in value added (rather than gross) terms. In order to avoid possible reverse causality, we subtract the value of direct domestic value added attributed to exports (dva_{j1t}^{d}) from total gross value added in the given sector.

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

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 (5a) while *rpv* is considered in equation (6a). The variable *rw* in equation (7a) is real wage rate, being computed using data on sector specific nominal wage rates and output deflators. As required data are not available for agriculture and services sectors, *rw* was computed only for manufacturing sectors. We expect *rw* to exert a negative influence on employment tied to exports.

Equation (5a) also includes *wd*, a variable representing the level of world demand for each sector. This variable is measured as the 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 relevant data are not available for services, *wd* was constructed only for merchandise sectors. The sign of *wd* is expected to be positive since Indian exporters may gain from higher world demand. Finally, in Equation (7a), we include labor-output ratio (*l*) to control for the effect of a sector's labor intensity on job creation. We expect this variable to yield a positive coefficient. For robustness check, we also run the following 3SLS regressions on first differences of the original variables.

$$\boldsymbol{Dln(x_{jt}) = \alpha_{0d} + \alpha_{1d}Dln\left(\frac{dva_{j1}}{x_j}\right)_{t-1} + \alpha_{2d}Dln(yd_{jt}) + \alpha_{3d}Dln(rpo_{jt}) + \alpha_{4d}Dln(wd_{jt}) + \alpha_{5d}J + \varepsilon 1_{jt}} \qquad (5b)$$

$$\boldsymbol{Dln(dva_{j1t}) = \beta_{0d} + \beta_{1d}Dln(x_{jt}) + \beta_{2d}Dln(gvad_{jt}) + \beta_{3d}Dln(rpv_{jt}) + \beta_{4d}J + \varepsilon 2_{it}} \qquad (6b)$$

$$\boldsymbol{Dln(e_{j1t}) = \gamma_{0d} + \gamma_{1d}Dln(dva_{j1t}) + \gamma_{2d}Dln(gvad_{jt}) + \gamma_{3d}Dln(rw_{jt}) + \gamma_{4d}Dln(l_{jt}) + \gamma_5 J +} \ \varepsilon\boldsymbol{3_{jt}} \qquad (7b)$$

where D is the first difference operator. While 3SLS is our preferred specification, as a further robustness check, we also consider dynamic panel data model (two-step system estimator) as well as fixed effect and random effect regressions. The Appendix provides further details pertaining to variable definition, variable construction, and data sources.

4.2. Regression Results

Before proceeding to the estimation of the above equations using 3SLS, we perform the Hausman specification test for simultaneity. The results show that simultaneity problem is indeed present in the system implying that the OLS estimators will not be consistent[17]. Therefore, we use the 3SLS econometric approach, which is asymptotically more efficient than 2SLS (Schmidt, 1976), to simultaneously estimate the equations. The 3SLS approach, a combination of seemingly unrelated regressions and 2SLS, obtains instrumental variable estimates taking into account the covariance across equation disturbances.

We estimate regressions for two separate sample groups – that is, (i) full sample consisting of all 112 sectors and (ii) manufacturing sub-sample consisting of 56 sectors. The regressions for the manufacturing sample include all explanatory variables introduced in the

[17] The test is carried out as follows. First, using the OLS method, we regress $\boldsymbol{ln(x_{jt})}$ on all explanatory variables (equation 5a) and obtain the residuals. Second, we run the OLS regression of $\boldsymbol{ln(dva_{j1t})}$ (equation 6a) 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 suggesting that the endogeneity problem does exist. In a similar fashion, we run an OLS regression of $\boldsymbol{ln(e_{j1t})}$ (equation 7a) with the residual obtained from the OLS regression of $\boldsymbol{ln(dva_{j1t})}$ on the exogenous variables being included as an additional regressor. These results also confirm the presence of endogeneity.

previous section while that for the full sample exclude the covariates *wd* (world demand) and *rw* (real wages) due to non-availability of relevant sector level data.

Table 7 reports the 3SLS regressions and Table 8 shows the results from alternative models - dynamic panel data models, fixed effect and random effect regressions. It may be noted, at the outset, that the 3SLS and other methods give broadly similar results, in terms of sign and statistical significance, particularly for the main variables of interest.

As expected, the VAX ratio $\left(\frac{dva_{j1}}{x_j}\right)$ shows statistically significant negative coefficient in equations 5a and 5b, for the full sample as well as for the sample of manufacturing sectors. In 3SLS specifications with levels, the elasticity of gross exports with respect to VAX ratio is 1.79 for manufacturing and 1.08 for the full sample. Thus, a 10% decline of the VAX ratio leads to an increase in the dollar value of manufactured products exports by 17.9%, which is quite large. 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 of the VAX ratio, causes the absolute dollar value of gross exports to increase.

The results corresponding to equation 6a confirm that higher value of gross exports, in turn, causes the absolute 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. Thus, a 10% increase of gross exports from manufacturing sectors causes DVA to increase by 4.3%. These results remain qualitatively the same if we instead use first differences of the original variables.

Does an increase of DVA, in turn, lead to higher employment creation? The results corresponding to equation 7a and 7b confirm that it does. The elasticity estimates from the level regressions suggest that a 10% increase of DVA tied to manufactured exports increases employment (direct plus indirect) by 17.2%. The elasticity estimate for the full sample suggests a stronger impact of 22% employment growth from a 10% increase of DVA.

The variables *yd* and *gvad* are included to capture the effects of domestic supply capacity on the respective dependent variables. In general, these variables fail to show statistically significant coefficients in full sample regressions while they show mixed results in regressions for the sub-sample of manufacturing sectors. The variable *gvad* yields statistically significant negative signs in employment regressions (equations 7a and 7b, manufacturing sample), which is indicative of a trade-off between selling in the domestic and foreign markets. For gross exports and DVA regressions, however, the domestic activity variables do not show consistent results across specifications (equations 5a, 5b, 6a and 6b, manufacturing sample), making it hard to arrive at an overall conclusion.

The variables representing exchange rate adjusted relative prices (*rpo* and *rpv*) always yield correct signs though their statistical significance is observed only in level regressions. As expected, the variable representing real wages (*rw*) show statistically significant negative coefficient in employment regressions, in both levels and first differences, suggesting that a decline of real wages would lead to an increase in employment. The results also confirm that labor to output ratio (*l)*, representing labor-intensity, is positively associated with the size of employment tied to exports. Finally, the variable *wd*, representing world demand conditions, yields statistically significant positive coefficient in the export equation 5a, implying that Indian exports respond positively to increase in world demand.

(Table 7 about here)

In order to assess whether our results are robust to alternative estimation methods, we run dynamic panel data model (two-step system GMM), fixed effect and random effect regressions.

The estimation results from these models, reported in Table 8, reinforce our main findings. The coefficient of the VAX ratio remains negative and statistically significant across all specifications of the regression equation 5a. When we compare the point estimates obtained for the two sample groups, we find that the elasticity of gross exports with respect to VAX ratio is generally higher for the full sample as compared to the manufacturing sub-sample (except for the 3SLS regression in level). This finding may imply that the marginal gains from GPS participation is higher for services and primary sectors as compared to manufacturing, which is not surprising as the current value of the VAX ratio is quite high for the former sectors compared to the latter.

Similarly, the variable x_{jt} (gross exports) consistently yield statistically significant positive coefficients in all DVA regressions in Table 8 with the point estimates of elasticity being significantly larger compared to the corresponding 3SLS estimates in Table 7. Finally, as in 3SLS specifications, the results in Table 8 show that the number of jobs tied to exports increases with an increase of DVA. The point elasticity of employment with respect to DVA is significantly larger in 3SLS than in the alternative specifications. Overall, notwithstanding some differences in point elasticity estimates, different regression specifications yield qualitatively similar results for our main variables.

The lagged dependent variables, appearing as explanatory variables, in dynamic panel regressions turn out to be significant in all cases. Among the remaining covariates, *wd* in gross export equation and *l* in employment equation generally yield expected positive coefficients with statistical significance. However, in general, the variables representing the level of domestic activity and relative prices do not show significant coefficients in Table 8.

(Table 8 about here)

5. CONCLUSIONS AND IMPLICATIONS

Using Input-Output (IO) analysis, we find that the domestic value added (DVA) content of India's exports (merchandise plus services) increased from US $46 billion in 1999-00 to US $295 billion in 2012-13. During this period, the total number of direct plus indirect jobs supported by aggregate Indian exports increased from about 34 million to 62.6 million, with the share of export-tied jobs in total employment being increased from little over 9% to 14.5%. Backward linkages, from manufacturing to agriculture and services, have become an important source of export related DVA and job creation in the country.

A higher level of participation in global production sharing (GPS) activities entails that, for any given country, DVA *per unit* of exports is smaller than when most inputs are sourced locally. We find that the ratio of DVA to gross exports (VAX ratio) for India has steadily declined from 0.86 in 1999-00 to 0.65 in 2012-13, with the decline being particularly sharp for the manufacturing sector during the second half of the 2000s. These trends suggest that participation in GPS by Indian industries has increased over the years. Using econometric analysis, we show that a greater participation in GPS, proxied by the VAX ratio, leads to higher absolute levels of gross exports, DVA and employment. This result is robust to a variety of specifications and implies that the positive scale and productivity effects of participation in GPS outweigh any possible negative impact of the same.

In the light of the above findings, the question that comes to the fore is: why has the manufacturing sector, despite its increased participation in GPS, not yet become the engine of India's growth unlike for China and other major East and South-East Asian countries? While a detailed study is needed to answer this question, a pertinent point to note at this juncture is that India's participation in GPS is still way below the level achieved by its counterparts in East and

South East Asia, the difference being more pronounced for sectors such as electronics and electrical machinery where GPS activities are generally more intense and ubiquitous (Veeramani and Dhir, 2017).

Our results imply that developing countries can reap rich dividends by adopting policies aimed at strengthening their participation in GPS. Using its abundant labor resources and imported capital-intensive intermediate inputs, India can emerge as a major assembly centre in several industries. Does participation in GPS imply that low wage countries are perpetually trapped at low value-added stage of the supply chain, such as assembly activities? This apprehension, often expressed by policy makers, is unwarranted as studies show that comparative advantage is not static, but changes throughout the process of accumulation of physical and human capital that characterizes development (Balassa, 1979, Ng and Yeats, 2001)[18].

For a country to become an attractive location for assembly activities, it is imperative that import tariff rates for intermediate inputs are zero or negligible. Viewed thus, the move by Indian government, since late 2017, to increase import duties for some of the intermediate inputs, partly in retaliation to the recent US tariff hikes and partly to boost the "Make in India" initiative is not a move in the right direction[19]. The import-weighted average tariff rates for intermediate inputs,

[18] Studies that analyze the process of economic and social upgrading within global production networks also report results that are consistent with the argument that comparative advantage is dynamic (see for example, Barrientos et al, 2012).

[19] The US-based company Apple, for example, has demanded duty free access to imported parts and components as a pre-requisite for its expansion in India. See the following links for details.
https://www.thehindu.com/business/apple-india-wrangle-over-tariff-on-parts/article21419854.ece)
https://economictimes.indiatimes.com/news/economy/policy/govt-hikes-import-duty-on-select-communication-items-to-20-pc/articleshow/66169958.cms

for the year 2017, stood high at 9.23 percent for India compared to 4.41 percent for China (Source: UNCTAD-TRAINS database).

While duty free access to imported intermediates is essential for the expansion of assembly activities, it is also imperative 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, its fast growing exports are either capital-intensive or skill-intensive (Kochhar et al., 2006, Panagariya, 2008, Krueger, 2010, Veeramani et al, 2018)[20]. Studies also show that a low level of service link costs (costs related to transportation, communication, and other tasks involved in coordinating the activity in a given country with what is done in other countries) is a pre-requisite for countries to strengthen their participation 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[21]. Policy measures in India should focus on reducing input tariffs, implementation of key factor market reforms, and reducing its high service link costs.

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[20] 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). 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.

[21] In terms of the World Bank's 2018 Logistics Performance Index, India ranks 44th and China ranks 26th in the World.

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TABLES

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

Year	DVA ($ billion)			Gross Exports ($ billion)	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 $=\sum \boldsymbol{dva_{j1}}$; Direct DVA = $\sum \boldsymbol{dva^{d}_{j1}}$; Indirect DVA=$\sum \boldsymbol{dva^{bw}_{j1}}$; Gross exports = $\sum \boldsymbol{x_j}$; VAX ratio = Ratio of total DVA to gross exports (ii) Estimates based on the two concepts of linkages give identical values for aggregate economy-wide DVA.

Source: Authors' estimation

Table 2: Average Annual Growth Rates of Aggregate DVA, Gross Exports and Employment (%) (1999-2000 to 2012-13)

Period	DVA Content of Exports ($ Billion)			Employment Tied to 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: (i) Growth rates are calculated using semi-logarithmic regressions (ii) The last column shows growth rates of employment attributed to total sales (exports plus domestic sales).

Source: Authors' estimation

Table 3: Employment Tied to India's Aggregate Exports (Merchandise Plus Services)

	Number of Jobs Tied to Exports (Millions)			Share of Export-Related Jobs in Total Employment (%)	Number of Jobs Per Million $ Worth of Exports
	Total	Direct	Indirect		
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

Note: (i) Total jobs $=\sum \boldsymbol{e_{j1}}$; Direct jobs $=\sum \boldsymbol{e_{j1}^{d}}$; Indirect jobs$=\sum \boldsymbol{e_{j1}^{bw}}$.

Source: Authors' estimation

Table 4: Total (direct plus indirect) DVA and Employment Attributed to Exports from Different Sector Groups (Agriculture, Manufacturing and Services)

	Total DVA: $\sum dva_{j1}$ ($ Billion)			Total Employment: $\sum e_{j1}$ (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
Growth Rate*	11.3	17.3	19.4	-4.0	5.4	3.4

Note: *Average annual growth rates, calculated using semi-logarithmic regression

Source: Authors' estimation

Table 5: DVA and Employment Attributed to Backward Linkages of Exports from Different Sector Groups (Agriculture, Manufacturing and Services)

	Indirect DVA: $\sum dva_{j1}^{bw}$ ($ Billion)			Indirect Employment: $\sum e_{j1}^{bw}$(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
Growth Rate*	14.8	17.2	19.3	2.1	6.4	4.0

Note: *Average annual growth rates, calculated using semi-logarithmic regression

Source: Authors' estimation

Table 6: DVA and Employment Attributed to Forward Linkages of Different Sector Groups (Agriculture, Manufacturing and Services) with Other Exporting Sectors

	Indirect DVA: $\sum dva_{j2}^{fw}$ ($ Billion)			Indirect Employment: $\sum e_{j2}^{fw}$ (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
Growth Rate*	18.1	15.9	18.1	7.3	3.7	3.2

Note: *Average annual growth rates, calculated using semi-logarithmic regression

Source: Authors' estimation

Table 7: Impact of GPS Participation on Gross Exports, DVA and Employment: Results of 3-SLS Regressions in Levels and First Differences

	Regressions in Levels		Regressions in First Differences	
	Manufacturing	Total	Manufacturing	Total
Dep. Variable: ln(x_{jt})	***Equation 5a***		***Equation 5b***	
$ln\left(\frac{dva_{j1}}{x_j}\right)_{t-1}$	-1.786***	-1.082***	-1.084***	-1.572***
	(0.114)	(0.222)	(0.292)	(0.356)
$ln(yd_{jt})$	-0.377***	0.283	1.152**	0.835
	(0.106)	(0.204)	(0.489)	(0.616)
$ln(rpo_{jt})$	-1.230***	-0.409**	-0.0628	-0.241
	(0.272)	(0.180)	(0.443)	(0.495)
$ln(wd_{jt})$	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)
Dep. Variable: $ln(dva_{j1t})$	***Equation 6a***		***Equation 6b***	
$ln(x_{jt})$	0.427***	0.236**	0.476***	0.652*
	(0.0478)	(0.110)	(0.135)	(0.402)
$ln(gvad_{jt})$	-0.361***	0.261	0.918***	0.794
	(0.0645)	(0.189)	(0.343)	(0.806)
$ln(rpv_{jt})$	-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)
Dep. Variable: $ln(e_{j1t})$	***Equation 7a***		***Equation 7b***	
$ln(dva_{j1t})$	1.718***	2.203***	2.481***	1.998***
	(0.449)	(0.313)	(0.408)	(0.374)
$ln(gvad_{jt})$	-1.485***	1.867	-2.412***	-1.442***
	(0.407)	(1.189)	(0.554)	(0.318)
$ln(rw_{jt})$	-0.374***		-0.174*	
	(0.119)		(0.100)	
$ln(l_{jt})$	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 3-SLS

Table 8: Impact of GPS Participation on Gross Exports, DVA and Employment: Results from Dynamic Panel Data Models (Two-Step System GMM), Fixed Effect and Random Effect Regressions

	Dynamic Panel		Fixed Effect		Random Effect	
	Manufacturing	Total	Manufacturing	Total	Manufacturing	Total
Dep.Variable: ln(x_{jt})						
$ln\left(\frac{dva_{j1}}{x_i}\right)_{t-1}$	-0.317***	-0.363**	-1.355***	-1.430***	-1.187***	-1.399***
	(0.125)	(0.136)	(0.308)	(0.407)	(0.267)	(0.387)
$ln(yd_{jt})$	0.045	0.038	-0.149	-0.145	-0.0173	0.0843
	0.049	0.025	(0.127)	(0.135)	(0.109)	(0.0837)
$ln(rpo_{jt})$	-0.242	-0.199**	-0.481	-0.261	-0.453	-0.337
	(0.155)	(0.103)	(0.400)	(0.422)	(0.411)	(0.422)
$ln(wd_{jt})$	0.075**		-0.0550		0.176**	
	(0.035)		(0.126)		(0.0877)	
$ln(x_j)_{t-1}$	0.831***	0.918***				
	(0.094)	(0.048)				
Constant	-0.214	0.092	21.54***	20.69***	13.89***	15.30***
	(0.720)	(0.588)	(4.163)	(3.553)	(2.936)	(2.686)
R^2			0.679	0.408	0.671	0.403
Hansen J statistic	0.949	0.328				
Dep.Variable: $ln(dva_{j1t})$						
$ln(x_{jt})$	0.650***	0.862***	0.949***	0.985***	0.955***	0.985***
	(0.112)	(0.055)	(0.0201)	(0.00557)	(0.0184)	(0.00526)
$ln(gvad_{jt})$	0.043*	0.040***	-0.0112	-0.00434	-0.000532	0.00558
	0.024	0.011	(0.0330)	(0.0189)	(0.0232)	(0.0103)
$ln(rpv_{jt})$	0.103	0.094*	0.110**	0.0436	0.120**	0.0478*
	(0.109)	(0.053)	(0.0534)	(0.0282)	(0.0567)	(0.0280)
$ln(dva_{j1})_{t-1}$	0.261**	0.075				
	(0.119)	(0.051)				
Constant	1.050	0.523	1.436*	0.391	1.147*	0.218
	(0.682)	(0.373)	(0.844)	(0.483)	(0.627)	(0.296)
R^2			0.982	0.993	0.982	0.993
Hansen J statistic	0.958	0.502				
Dep. Variable: $ln(e_{j1t})$						
$ln(dva_{j1t})$	0.470***	0.797***	0.994***	1.017***	0.994***	1.014***
	(0.103)	(0.058)	(0.0540)	(0.0197)	(0.0446)	(0.0171)
$ln(gvad_{jt})$	-0.103	-0.046**	0.0296	-0.0214	0.0257	-0.0302
	0.157	0.020	(0.0746)	(0.0425)	(0.0620)	(0.0294)
$ln(rw_{jt})$	0.129		-0.157		-0.153	
	(0.097)		(0.117)		(0.115)	
$ln(l_{jt})$	0.138**	0.420***	0.385***	0.534***	0.397***	0.533***
	(0.060)	(0.037)	(0.0625)	(0.0919)	(0.0546)	(0.0753)
$ln(e_{j1})_{t-1}$	0755***	0.229***				
	(0.127)	(0.060)				

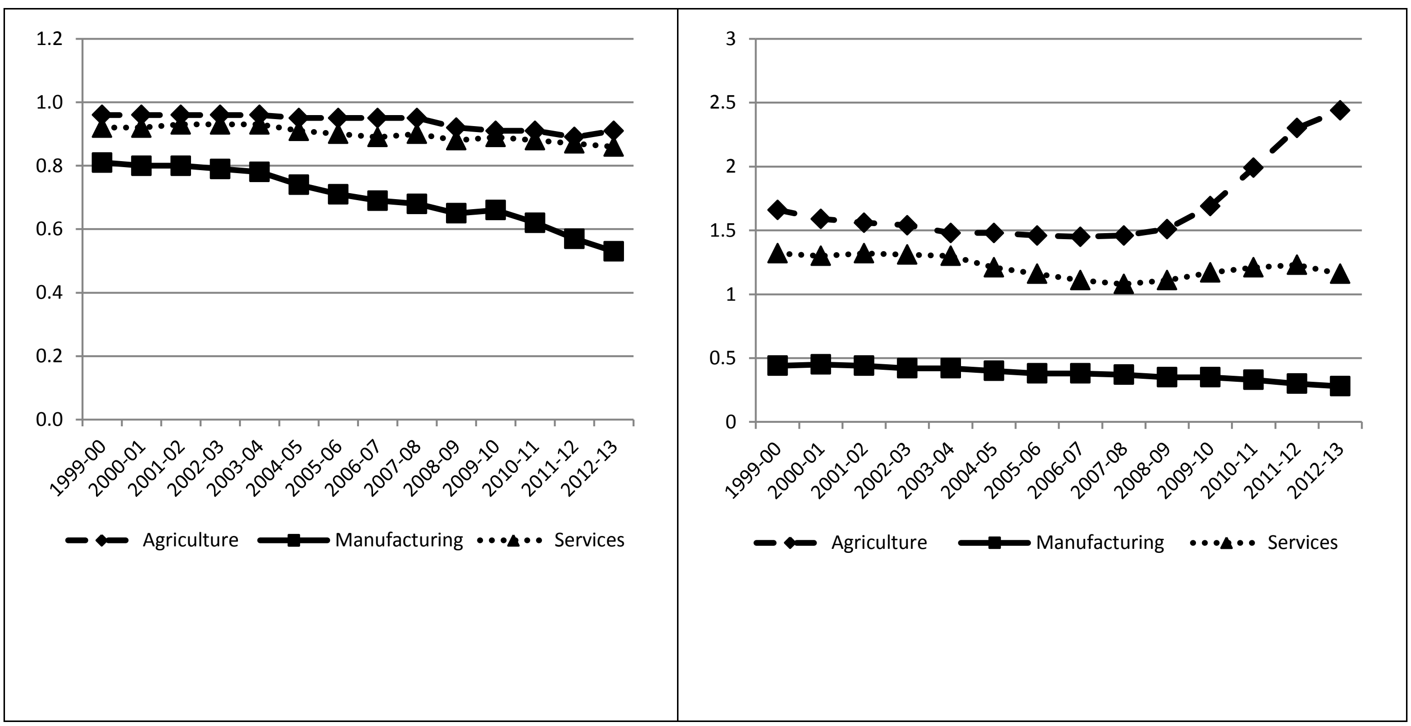
Constant	-4.419 (3.606)	-6.794*** (0.645)	-9.280*** (1.758)	-9.326*** (0.894)	-9.243*** (1.336)	-9.079*** (0.588)
Observations	726	1,242	781	1,348	781	1,348
R2			0.824	0.925	0.824	0.925
Hansen J statistic	0.435	0.531				

Notes: (i) All regression equations include year dummies; (ii) Robust 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. Dynamic panel regressions use 'two-step system GMM' based on the xtabond2 command in STATA.

Figure 1: DVA to Gross Export Ratio

(a) Ratio of $\sum dva_{j1}$ to Gross Exports

(b) Ratio of $\sum dva_{j2}$ to Gross Exports



Source: Authors' estimation

APPENDIX

In what follows, we provide a brief description of the method adopted for building the time series of annual domestic use tables (DUT) and various data sources used for this purpose (see Veeramani and Dhir (2017) and Exim Bank of India (2016) for further details).

(i) Method for Building the DUT Time Series

In order to construct the DUT time series, we start with all official Input Output Tables (IOT) and Supply Use Tables (SUT) available for the period under consideration. Official IOT are available for 1998-99, 2003-04 and 2007-08 while SUT are available only for 2011-12 and 2012-13[22]. As official IOTs and SUTs do not distinguish between imported and domestic inputs, we rely on a standard 'proportionality' assumption, discussed below, to separate the two types of inputs.

Looking across a given row in the absorption matrix of IOT, we can observe how the output of each product i (y_i) is used for intermediate use by various industries j (that is, sector i's forward linkages). On the other hand, 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

[22] A difference between IOT and SUT is that the former is a square matrix while the number of rows exceeds the number of columns in SUT.

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.

The ratio of total intermediate use to total availability (imports plus industry output) for a given sector i and year t (r_{it}) is defined as:

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

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 year t. 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 intermediate use ($DIIUSE_{it}$), as follows:

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

Next, we distribute the value of $DIIUSE_{it}$ across cells within a given 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 identity for each sector *i*[23].

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

Using 112×112 absorption matrices, we compute the ratios in (a.5) for all years for which official IOT and SUT are available. For the intervening years, we obtain them by linear interpolation. Multiplying these ratios for each row 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*.

The official IOT contains 115 sectors for 1998-99 and 130 sectors for 2003-04 and 2007-08. The SUT, unlike IOT, are not available as square matrices, with the number of rows being higher than the number of columns. By matching and regrouping these sectors across IOTs and SUTs, with the help of a concordance table provided by the Central Statistical Organization (CSO), we were able to identify 112 distinct sectors (covering the whole economy) for which we can generate a time series of DUT[24].

[23] 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: $IIUSE_{it} = DIIUSE_{it} + MIIUSE_{it}$

[24] Published SUTs contains 140 rows and 66 columns, which have been converted to 112×112 matrices. This conversion is done as follows (see EXIM Bank of India (2016) for further details). First, using a concordance table between 66 SUT column sectors and our 112 sector classification, the z_{ij} values

(ii) Data Sources

In order to construct DUT for the intervening years (that is, the years for which official tables are not available), we need consistent time series data on gross value of output (y_{it}), and imports (m_{it}) for 112 sectors. In addition, the analysis in this study requires sector level data on gross value added, employment and exports. The various sources and methods used in compiling these statistics are outlined below.

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

For the manufacturing sector, we use unit level data from two sources: (i) Annual Survey of Industries (ASI) for the formal enterprises; and (ii) 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

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appearing in each of the 66 cells of a given SUT row is apportioned into the corresponding sub-set of sectors within the whole set of 112 sectors. The apportioning of z_{ij} value is done on the basis of percentage share (as per official IOT for 2007-08) of individual sectors that correspond to a given SUT column sector group. Second, using a concordance table, 140 SUT rows have been aggregated into 112 sectors.

(formal plus informal) on *y* and GVA[25]. For the non-manufacturing sectors, we get data on *y* and *GVA* from National Accounts Statistics (NAS)[26].

(b) *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 (merchandise plus services) exports and imports, obtained from these two sources, matches exactly with the data reported in official IOTs and SUTs for the corresponding years. For each year, we apportion the total value of exports (and imports) across our 112 sectors, based on the percentage shares of these sectors in total. The percentages shares have been computed based on sector level trade data reported in official IOTs and SUTs. For the intervening years, the shares have been obtained through linear interpolation.

(c) *Employment*

[25]While ASI data is available for all years, NSSO surveys for informal sector were conducted only for selected years: 1999-00, 2000-01, 2005-06 and 2010-11. For the remaining years, we use output and GVA values reported by the NAS for about 21 broad informal manufacturing industry groups. Using a concordance table, the NAS values for each of the 21 industry groups have been apportioned (based on interpolated percentage shares) across the corresponding 5-digit NIC codes.

[26] For a few sectors, the NAS reports only *GVA* but not *y*. In such cases, we derived estimates of *y* by applying output to value added ratios, available in various official IOTs and SUTs. Values of sector level output and value added, in our final dataset, are in nominal terms and correspond to 2004-05 base year. All official IOTs and SUTs have been converted to 2004-05 base year. We validate and match our estimates of *y a*nd *GVA* with the data reported in official IOTs and SUTs for the corresponding years. At the economy-wide level, our values are identical to the values reported in the corresponding IOT/SUT. At the sector level, however, the match is not always perfect: for some of the individual sectors, we notice certain discrepancy (but always less than 1% where it occurs) between our estimates and the values reported in the corresponding IOT/SUT.

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[27]. The 5-digit level estimates were then aggregated to obtain a time series for our 112 sectors.

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[27] The surveys were conducted for the 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 India. For the period 2000-01 to 2003-04, we used employment estimates at 2-digit NIC level from different rounds of NSSO surveys on "Household Consumption Expenditure and Employment-Unemployment Situation in India". These estimates were apportioned across the corresponding 5-digit codes based on interpolated percentage shares. For rest of the years (2006-07, 2008-09, 2010-11 and 2012-13), estimates of aggregate employment were obtained through linear interpolation and extrapolation, which were then apportioned across the 5-digit level.