# Impact of Backward Linkages and Domestic Contents of Exports on Labor Productivity and Employment: Evidence from Japanese Industrial Data

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**Abstract** This study examines how backward linkages (foreign value added [FVA] exports) and domestic value-added (DVA) exports impact industry-level labor productivity and employment in Japan by estimating a static and dynamic panel model using data drawn from the World Input-Output Dataset and Socio-Economic Accounts. We find that the domestic content of trade is a key driver of productivity and employment in Japan for all industries, while backward linkages lead to declining productivity and foster labor displacement. A sectoral analysis reveals that productivity benefits most of the backward linkages and domestic value-added exports in the manufacturing industry but weakens as the backward linkages increase in the service industry. We find that the DVA exports variable promotes employment, whereas the FVA variable displaces it.

**Keywords:** GVC participation, labor productivity, employment

# I. Introduction

Many researchers have attempted to explain the link between labor productivity, employment formation, and a country's involvement in the global supply chain (Amiti & Konings, 2007; Balsvik, 2011; Banga, 2016; Caselli & Wilson, 2004; Constantinescu et al., 2019; Feenstra et al., 1996; Kummritz, 2016). Global value chain (GVC) participation continues to increase. Economies integrate into GVCs through either imports of intermediates used in their exports and/or a supply of intermediate inputs to a third country's exports (Hummels et al., 2001).

The literature has examined the importance of international trade determinants and their effects on employment and productivity. Access to a wide range of cheap and high-quality intermediate inputs used in production may lead to higher productivity via the channel of knowledge spillovers. (Amiti & Konings, 2007) argue that access to cheap intermediate inputs contributes to productivity through "learning." (Kummritz, 2016) empirically examines the effects of GVC participation on productivity, finding that increasing the participation in GVCs leads to higher productivity. Balsvik (2011) suggests that labor mobility from multinational enterprises (MNEs) to domestic firms leads to higher productivity spillovers. (Caselli & Wilson, 2004) emphasize that technology embedded in capital imports can have a substantial effect on productivity.

The importance of international trade in employment has been discussed in the literature. (Feenstra et al., 1996) link the growing demand for skilled workers to increased trade in intermediates. (Banga, 2016) examines the impact of GVC integration using backward and forward linkages on employment in India and finds that higher backward linkages displace domestic labor.

The theoretical implication of access to cheap and varied products is a central concept in many endogenous growth models, and its impact on productivity, employment, and economic growth has become a common concern in the economics literature (Grossman & Helpman, 1991). The introduction of new trade measures, such as trade in value added and GVC income measures,[1] has made it easier to disentangle the importance of GVC participation in productivity and job creation.

Economies are increasingly interconnected via the GVC network. This is particularly true for East Asian countries, with their rapidly increasing GVC participation and deep integration of the Chinese economy, which is increasingly becoming a central hub of international trade. Criscuolo and Timmis (2018) argue that the Japanese economy has become less influential despite its important global role (mainly through increasing forward participation) and that Japanese industries and firms have lost their central role in the regional GVC network. This period of declining centrality coincides with low productivity growth among Japanese firms.

The variations in productivity and employment due to Japan's changing position in GVCs make it urgent to understand the underlying mechanism through which GVC integration, via backward linkages,[2] affects productivity and labor demand. In this study, Furthermore, the impact of domestic value-added exports is studied as well. International trade is the most important among the many factors affecting labor productivity and employment in Japan. Hence, examining the association between international trade and the labor market is critical for tailoring adequate labor market policies for Japan. This is the main purpose of this study.

Given the importance of understanding the associations between GVC participation and economic indicators in general and labor productivity and employment in particular, this study

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1)  GVC income measure developed by (Timmer et al., 2013)
2)  Also known as "vertical specialization" (OECD TiVA 2016 indicators-definitions).

empirically examines the effects of backward linkages and domestic content of exports on labor productivity and employment at the industry level in Japan.

This study is the first to use the WIOD 2013 and SEA databases at the sector level to examine the impact of backward linkages and domestic value-added (DVA) exports on labor productivity and employment in Japan. The study the most similar to ours is Nasserdine (2019), which uses a spatial econometric technique to account for the direct and indirect effects of GVC variables on employment in Turkey. However, our research differs from Nasserdine (2019) in several ways. For example, while Nasserdine (2019) derives both backward and forward linkages for Turkey, we focus on Japan to calculate FVA and DVA exports and examine their effects on employment and productivity. In addition, we account for possible endogeneity by using the first-difference GMM estimation method. Here, several related limitations should be addressed. This study uses a difference-GMM estimation to examine the association in a dynamic panel model. A common limitation of this approach is that when the number of used instruments increases over a long period, the estimates may be biased. Consequently, we employ a curtailing approach to limit the number of instruments used for the endogenous variables. Another limitation is that the assumptions required to use the WIOD are stringent, such as that of a production technique that is constant and unchanged over time in the production process and among firms within a given sector. These limitations are important to consider when interpreting the results.

We expect a significant association between backward linkages and domestic value-added exports on one hand and labor productivity and employment variables on the other. We expect a positive association between domestic value-added exports, labor productivity, and employment. We expect a positive association between backward linkages and labor productivity, in line with the argument that firms with import and export orientations grow faster and are more innovative than firms without internationalized activities (Constantinescu et al., 2019). However, the effects of backward GVC participation on employment may depend on different factors that influence employment formation, such as increasing competitiveness, access to cheap intermediate inputs, and substitution effects. For instance, we may anticipate that the effects on employment will be positive if the imported intermediates are complementary, while substitutive imported intermediates will damage employment formation.

This study contributes to the literature by investigating how GVC participation and domestic value-added exports at the industry level impact labor productivity and employment in Japan. Our main findings are as follows. DVA exports are key drivers of employment and labor productivity, which seems to be mainly driven by the positive impact of manufacturing DVA on exports. Productivity and employment weaken with the FVA variables. A sectoral analysis shows that productivity benefits most of the FVA and DVA variables in manufacturing but weakens with them in the service industry. Employment rises with the DVA variable and declines with FVA in the manufacturing industry. Employment rises with FVA and declines with DVA in the service industry.

The remainder of this paper is organized as follows. Section 2 introduces the study's methodology and empirical models. Section 3 presents the data used in the analysis. Section 4 presents and discusses the results and findings. Finally, Section 5 concludes the paper.

# II. Methodology and Empirical Models

## A. Methodology

This study uses WIOD and SEA data (Timmer et al., 2013) to calculate backward GVC participation and the domestic content of exports. In doing so, we combine two main datasets: the World Input-Output Database 2013 ("WIOD" hereafter), comprising a time series covering 35 industries in 40 countries, and the Socio-Economic Accounts (SEA), comprising industry-level data on employment, capital stocks, gross output, and value-added. The combined dataset covers 1995 to 2009.

We begin by calculating gross intermediate imports and exports. Then, we calculate the FVA and DVA in exports. We employ an empirical framework to examine the effect of the calculated variables on labor productivity and employment using two estimation methods: 1) a fixed-effects estimation of static panel data and 2) a difference generalized method of moments (GMM) estimation for a dynamic panel model. We group industries into three main categories: agriculture, manufacturing, and service. For each category, we examine the impact of trade-related variables on labor productivity and employment variables in Japan.

We begin by calculating the gross intermediate import and export variables. We then compute the variables for the FVA and DVA in exports. The FVA variable is known in the trade literature as a measurement of backward linkages (Hummels et al. 2001; Koopman et al., 2014). The DVA in exports reflects the value-added from domestically produced goods embedded in a country's exports. A detailed calculation of the FVA and DVA in exports is provided by (Aslam et al., 2017) and (Koopman et al. 2014).

Suppose there are $S$ industries and $N$ countries, and let $X$ be the ($SN \times SN$) of the input-output matrix, where row $(x_{i,.}(s))$ represents country $i$ industry's output of intermediates used as input either domestically or abroad, and Column $(x_{.,i}(t))$ represents the country $i$ industry's import of intermediates sourced either domestically or abroad.

### 1. Gross imports and exports of intermediates' variables

The intermediate export flows for industry $s$ of country $i$ equals all the intermediate exports used in foreign countries and industries. Likewise, intermediate import flows for industry $t$ of country $i$ consist of all the imports of intermediates sourced from abroad used domestically.

## 2. Foreign and domestic value-added in exports variables

We calculate the foreign and domestic values added to exports using the Leontief input-output model (Leontief, 1936). We calculate the Leontief inverse matrix; pre- and post-multiplication by the proper matrices allows us to trace the sources of all intermediates and intermediates' intermediates (and so on) involved in a country's exports. The calculation is as follows:

Let $y_i(s)$ be the output of industry $s$ of country $i$. We can write the output $y_i(s)$ as the sum of all intermediates and final demands used domestically and abroad $f_{ij}$:

$$y_i(s) = \Sigma_j \Sigma_t x_{ij}(s,\ t) + \Sigma_j f_{ij}(s) \tag{1}$$

$f_{ij}(s)$ stands for the final demand for the output of industry $s$ of country $i$ used in country $j$.

Let there be ($SN{\times}SN$) matrix A, whose elements are $a_{ij} = \dfrac{x_{ij}(s,t)}{y_j(t)}$, and vector $f$ of dimension ($SN{\times}1$), whose elements are $f_i(s) = \Sigma_j f_{ij}(s)$. Then, equation (1) can be written in matrix form as follows:

$$y = Ay + f \Leftrightarrow y = (I - A)^{-1} f \tag{2}$$

where $(I - A)^{-1}$ is the Leontief inverse (Leontief, 1936), whose elements $(a_{st})_{s,t}$ represent the quantity of the output in industry $s$ needed to produce one additional unit of output in industry $t$. To understand this, consider the final demand produced by, say, country-industry $k$, $f_k$. This requires the use of $A f_k$ intermediates, which in turn requires $A^2 f_k$, and so on. This process yields a geometric series that converges to $(I - A)^{-1} f_k$ which accounts for all the intermediates involved in the production of the final demand $f_k$.

The multiplication of the Leontief inverse by the proper matrices allows the investigation of the factors involved in production and exports. Let $p_i(s)$ be the value-added per gross output produced in industry $s$ of country $i$. Let $\hat{p}$ be the ($SN{\times}SN$) diagonal matrix whose elements are $p_i(s)$. Let $e_i(s)$ be the gross export of industry $s$ of country $i$:

$$e_i(s) = \sum_{j \neq i} \sum_t x(s,t)_{ij} + \sum_{j \neq i} f_{ij}(s) \tag{3}$$

Let $E$ be an ($SN{\times}SN$) diagonal matrix whose elements are $(e_i(s))_i$ if industry $s$ is in country $i$ and 0 otherwise.

Finally, let ($SN{\times}SN$) matrix $T$ be written as follows:

$$T = \hat{p}(I - A)^{-1}E \tag{4}$$

Given matrix $T$, the FVA of industry $s$ in country $i$ can be found by summing up the cross rows (countries and industries) and excluding the elements corresponding to the country of interest:

$$fva(s)_i = \sum_{j \neq i} \sum_t T_{ji}(t,s) \tag{5}$$

We calculate the FVA in exports variable for industry $s$ of country $i$ as a share:

$$fva\_\exp(s)_i = \frac{\sum_{j \neq i} \sum_t T_{ji}(t,s)}{Gross\_\mathrm{Exp}ort(i)} \tag{6}$$

where gross exports are measured as the country's overall exports for both intermediates and final goods. This measure is used to reflect the country-industry position in the global supply chain from an import perspective and is known as the "backward linkage" in the GVC network. It decomposes the value-added from the foreign intermediate imports involved in a country's exports (Hummel et al., 2001). It provides a rough picture of country/sector reliance on the intermediate inputs sourced from abroad used in exports, and hence measures a country's dependence on the global supply chain network. Meanwhile, the DVA of an industry $s$ and country $i$ is calculated as the sum of all value-added exports generated by domestic inputs involved in the country's exports. Hence, it can be calculated by summing up across columns and excluding all indirect value-added content generated abroad:

$$dva(s)_i = \sum_t T_{ii}(s,t) \tag{7}$$

The share of DVA in exports for industry $s$ of country $i$ is given by:

$$dva\_\exp(s)_i = \frac{\sum_t T_{ii}(s,t)}{Gross\_\mathrm{Exp}ort(i)} \tag{8}$$

DVA exports are of key importance, as they serve as a central measure of income derived from a country's trade and thus serve as an important tool for assessing a country's global competitiveness. Thus, understanding how changes in domestic value-added content in exports at the industry level affect productivity and employment formation is important for formulating

development policy.

## B. Empirical models

We develop an empirical framework to analyze the impact of the variables of backward linkages and domestic value-added exports on labor productivity and employment. We estimate a static model using fixed effects and a dynamic model with a first-difference GMM. We begin by estimating a pooled OLS and then control for industry and time fixed effects.

### 1. Fixed effects estimation

Our empirical specification follows Constantinescu et al. (2019) and relies on the industry-level production function, which expresses the value added in sector $i$ at time $t$, $V_{i,t}$, as a function of capital $K_{it}$ and labor $L_{it}$ in sector $i$ and time $t$. $A_{i,t}$, stands for the technology shifter driven by a range of trade-related determinants. We assume that $A_{i,t}$ is driven by FVA and DVA penetration, respectively:

$$V_{i,t} = A_{i,t}(\delta_1, \ \delta_2, \ \delta_3, \ \dots \delta_n) F(K_{it}, \ L_{it}) \tag{9}$$

The process of dividing by $L$, taking logs, and adding fixed effects and error terms yields *Model 1*:

$$\ln \ (labor-productivity_{it}) = a + \alpha\ln \ (FVA_{it-1}) + \beta\ln \ (DVA_{it-1}) \tag{10}$$
$$+ \gamma\ln \ (K_{it-1}) + \theta_i + \phi_t + \epsilon_{it}$$

where $labor-productivity_{it}$ is labor productivity calculated as the value-added divided by the labor variable in sector $i$ at time $t$. $\theta_i$ and $\phi_t$ control for industry and time fixed effects, and $\epsilon_{it}$ is an error term. The explanatory variables are first-order lagged, as we expect delayed reactions of outcomes to trade activity shocks. It might also address the counter-causality effect due to endogeneity in the explanatory variables.

Following Greenaway et al. (1997) and (Hasan et al., 2007), we estimate Model 2 accounting for the trade-related variables calculated in the previous section and considering gross value-added rather than the gross output of an industry:

*Model 2 :*

$$\ln \ (employment_{it}) = a + \alpha\ln \ (FVA_{it-1}) + \beta\ln \ (DVA_{it-1}) + \theta_i + \phi_t + \epsilon_{it} \tag{11}$$

*where* $K_{it}$ is the capital stock per employee, $\theta_i$ and $\phi_t$ control for industry and time fixed effects, and $\epsilon_{it}$ is an error term. Again, the explanatory variables are first-order lagged, as we expect delayed reactions of outcomes to trade activity shocks; and, again, this might address the counter-causality effect due to endogeneity in the explanatory variables.

### 2. Difference GMM approach

The FE models' assumption that the productivity variable is static might not hold true. Several factors contribute to productivity over time, including technology and innovation progress and knowledge accumulation. Therefore, the productivity variable can be assumed to be dynamic, and a dynamic model should be used to capture the effects properly. Likewise, the job creation process may depend on historical observations, and recruitment choices are considered accordingly. This study explores the dynamic process for both dependent variables, and uses a GMM estimation method to capture the associations between variables.

To do so, the study uses the first-difference GMM approach, which rules out heterogeneity in individuals and circumvents possible heteroscedasticity between transformed error terms and lagged dependent variables using lags of the dependent variable as instruments (Arellano & Bond, 1991). The correlation persists between the differenced error terms and the differenced dependent variable, which can be dealt with using the second lag and further lags of the dependent variable as instruments as long as the error terms are not serially correlated. The following assumptions are made in the study: The serial correlation of differenced errors is limited to the first lag, and there are no overidentification restrictions.

Furthermore, the FD-GMM estimation method can address under-identification due to omitted explanatory variables. The estimation methodology uses all available moment conditions and optimizes the weighted function to the minimum by allocating more weights to moments with smaller variances. Thus, the most efficient estimator corresponds to the estimator with the smallest variance-covariance matrix.

*Model 1:*

$$\ln\ (labor-productivity_{it})= a + \delta\ln\ (labor-productivity_{it-1}) \tag{12}$$
$$+\,\alpha\ln\ (X_{it})+ \beta\ln\ (Y_{it})+ \gamma\ln\ (K_{it})+ \theta_i + \epsilon_{it}$$

*Model 2:*

$$\ln\ (employment_{it})= a + \delta\ln\ (employment_{it-1}) \tag{13}$$
$$+\,\alpha\ln\ (X_{it})+ \beta\ln\ (Y_{it})+ \theta_i + \epsilon_{it}$$

In both models, $X_{it}$ and $Y_{it}$ stand for the FVA and DVA exports variable respectively.

## III. Data

The data used in this study are mostly obtained from the WIOD database and SEA.[3] We make use of a time series of world input-output tables covering 40 countries and a model for the rest of the world covering 1995 to 2011 for 35 industries,[4] which we use to calculate backward linkages and domestic value-added content for industries in Japan (Timmer et al., 2013). The WIOD table comprises a country-industry[5] matrix of intermediate inputs, wherein the matrix row elements are formed of country-industry intermediates used domestically and abroad; likewise, columns are formed of intermediate imports sourced either domestically or abroad. Additionally, data on demand for final goods are reported for all countries as a 1435 × 205 matrix, in which the rows account for exports of final goods absorbed both domestically and abroad. The columns indicate domestic and foreign use of final-good imports. Additional rows of value-added and gross output by industry are reported.
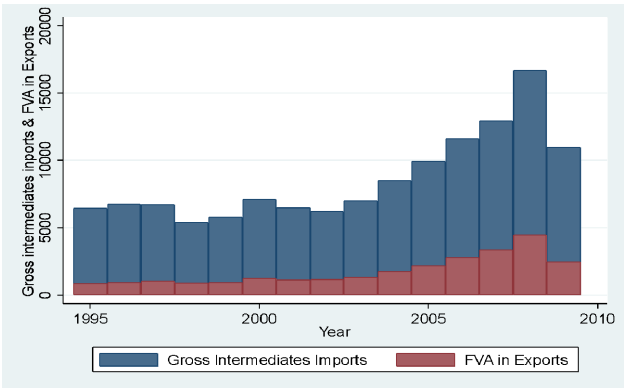
We restrict our sample to the 1995-2009 period because the employment variable, which we use to calculate labor productivity as well, is available only up to 2009. Figure 1 plots the FVA export variable for Japan, as well as the gross import of intermediates. The FVA exports and imports of intermediates both increased from 1995 to 2008. The FVA export variable is substantially smaller than the gross import of intermediates, suggesting that a large proportion of intermediate imports are used and absorbed domestically.

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3) The data are available at www.wiod.org.
4) Private households in the "employed persons" industry were dropped from the dataset because of many missing values.
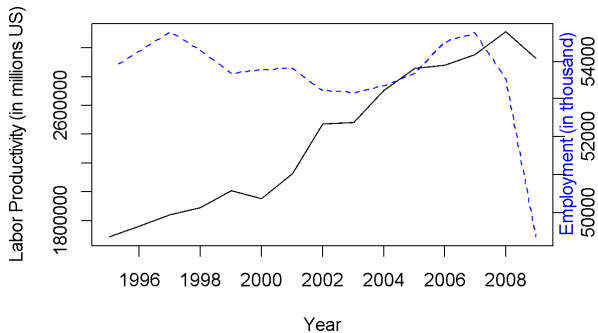5) We use industry and sector interchangeably.

**Figure 1.** Gross Intermediate Imports and FVA Exports in Japan, 1995-2009



(Source) Authors' calculation based on WIOD 2013 database.

Figure 2 illustrates the changes in employment and labor productivity during the study period. Labor productivity maintained steady growth from 1995 to 2008, while employment fluctuated over the same period and declined drastically after 2007.

**Figure 2.** Employment and Labor Productivity from 1995-2009



(Source) Authors' calculation based on SEA.

Figures 3 and 4 show graphs of the average of the observations for each industry's labor productivity and both FVA and DVA exports. As expected, productivity is positively correlated with DVA exports and negatively correlated with FVA exports.

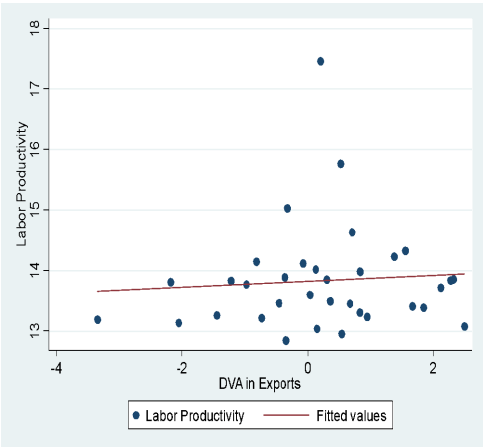**Figure 3.** Labor Productivity and DVA in Exports 1995-2009

**Figure 4.** Labor Productivity and FVA in Exports, 1995-2009



(Source) Authors' calculation based on WIOD and SEA.

Figures 5 and 6 illustrates the correlation between employment and FVA and DVA exports, respectively. Similar to the associations with productivity, employment is positively correlated with DVA exports and negatively correlated with FVA exports.

However, the relationships shown in Figures 3 to 6 are by no means an indication of a causal association between FVA exports, DVA exports, productivity, and employment, as other observable or latent factors might be causing these apparent relationships. Thus, a proper econometric analysis is required to disentangle the effects of the trade-related determinants of productivity and employment.

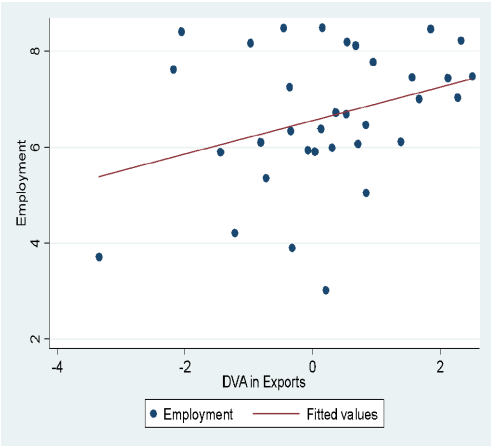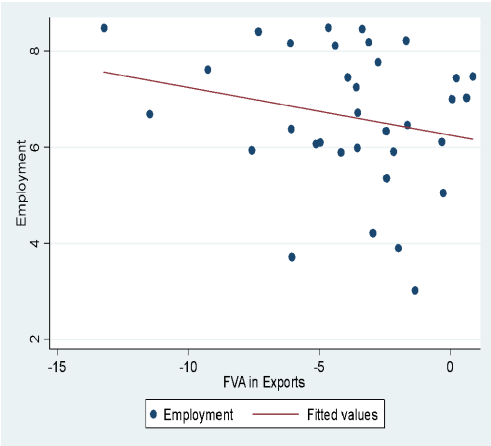**Figure 5.** Employment and DVA in Exports 1995-2009

**Figure 6.** Employment and FVA in Exports, 1995-2009



(Source) Authors' calculation based on WIOD and SEA.

# IV. Results

## A. Estimation results of static panel model

We first estimate the pooled OLS as a benchmark in Columns 1 and 2 of Tables 1 and 2. The results suggest that employment and productivity increase together with the import of intermediates, whereas employment declines with the export of intermediates. In Column 2 of Tables 1 and 2, we find that employment and labor productivity decline with FVA exports and increases with DVA exports. While the positive impact of DVA exports on the dependent variables is consistent with the "learning by exporting" assumption (De Loecker, 2013), the negative impact of FVA exports may suggest that the imported intermediates used in exports act as substitutes of locally produced goods, leading to declining productivity and employment. These results need to be interpreted with caution, however, as the estimation method does not account for time- and industry-specific effects. These are considered in Columns 3 and 4 of Tables 1 and 2. The positive impact of the import of intermediates persists after fixed effects are controlled for. In fact, (Amiti & Konings, 2007) find that increases in the imports of cheap intermediates raise productivity via learning. This seems to be the case here. However, our analysis of intermediate imports does not consider the multi-counting problem, wherein goods cross borders several times for further processing.

**Table 1.** *Estimates of Trade-related Activities' Effects on Labor Productivity*

| VARIABLES | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Lag.ln(Capital/Worker) | 0.379*** | 0.374*** | 0.125*** | 0.184*** |
| | (0.0216) | (0.0224) | (0.0415) | (0.0380) |
| Lag.ln(intermediates_exp) | -0.0106 | | -0.0230 | |
| | (0.0112) | | (0.0181) | |
| Lag.ln(intermediates_imp) | 0.275*** | | 0.194*** | |
| | (0.0285) | | (0.0447) | |
| Lag.ln(fva in exports) | | -0.0311*** | | -0.0485*** |
| | | (0.0120) | | (0.0163) |
| Lag.ln(dva in exports) | | 0.207*** | | 0.740*** |
| | | (0.0293) | | (0.0724) |
| Constant | 10.25*** | 12.34*** | 12.05*** | 12.92*** |
| | (0.270) | (0.0974) | (0.400) | (0.153) |
| Observations | 476 | 476 | 476 | 476 |
| No. of Industry | | | 34 | 34 |
| R-squared | 0.433 | 0.387 | 0.119 | 0.261 |
| Year FE | NO | NO | YES | YES |
| Industry FE | NO | NO | YES | YES |

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

In Column 3 of Table 2, the small negative effect of the export of intermediates on employment vanishes. Similar to the estimation of the pooled OLS, the effects of FVA exports on productivity and employment remain negative and significant, lending support to the substitutive nature of the imported intermediates used in Japanese exports. The variable for DVA exports is positive and significantly associated with productivity and employment, supporting the "learning by exporting" hypothesis.

**Table 2.** *Estimates of the Trade-related Activities on Employment*

| VARIABLES | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Lag.ln(intermediates_exp) | -0.073*** | | -0.00697 | |
| | (0.023) | | (0.0115) | |
| Lag.ln(intermediates_imp) | 0.29*** | | 0.156*** | |
| | (0.058) | | (0.0276) | |
| Lag.ln(fva in exports) | | -0.255*** | | -0.0212** |
| | | (0.0201) | | (0.0103) |
| Lag.ln(dva in exports) | | 0.685*** | | 0.506*** |
| | | (0.0485) | | (0.0442) |
| Constant | 4.67*** | 5.497*** | 5.471*** | 6.498*** |
| | (0.48) | (0.0998) | (0.219) | (0.0512) |
| Observations | 476 | 476 | 476 | 476 |
| No. of Industry | | | 34 | 34 |
| R-squared | 0.060 | 0.331 | 0.374 | 0.484 |
| Year FE | NO | NO | YES | YES |
| Industry FE | NO | NO | YES | YES |

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

These results contribute to shaping our understanding of how the integration of GVCs via backward linkages and DVA exports affect labor productivity and employment in Japan at the industry level.

## B. Estimations results of dynamic panel model

We estimate a dynamic panel data model for labor productivity and employment using first-difference GMM estimation. Difference GMM estimators work best in "large N, small T" situations in which the period of time is fairly large (more than seven or eight observations). An unrestricted set of lags introduces a large number of instruments, with a possible loss of efficiency. This can be addressed by specifying a limited and manageable number of lags for use in constructing the GMM instruments. We use the first to fourth available lags as instruments. Tables 3 and 4 show the estimation results for both dependent variables.

In Table 3, the significantly positive effect of the lagged dependent variable is suggestive of the dynamic process of productivity. The capital stock per employee becomes significant and positive after the variables for FVA and DVA exports are controlled for. Column 1 shows no significant association with the variables reflecting the exports and imports of intermediates. In Column 2 of Table 3, the impact of FVA exports on productivity is negative and significant, as in the fixed effects estimation, suggestive of the substitutive nature of the imported intermediates used in exports. Productivity increases together with DVA in exports, supporting the "learning by exporting" hypothesis, as discussed above.

**Table 3.** *Estimation of First Difference GMM for Productivity*

| VARIABLE | (1) | (2) |
|---|---|---|
| Lag.ln(labor-productivity) | 0.599*** | 0.521*** |
| | (0.0785) | (0.0800) |
| ln(Capital/Worker) | 0.0372 | 0.252*** |
| | (0.0628) | (0.0627) |
| ln(intermediates_exp) | -0.00719 | |
| | (0.00706) | |
| ln(intermediates_imp) | 0.0773 | |
| | (0.0672) | |
| ln(fva in exports) | | -0.0233* |
| | | (0.0126) |
| ln(dva in exports) | | 0.603*** |
| | | (0.105) |
| Observations | 442 | 442 |
| No. of Industry | 34 | 34 |

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4 shows that the lagged employment variable is significant across all models, suggesting the dynamic process of employment creation. Column 1 of Table 4 shows a significant relationship between the imports of intermediates and employment at the 10% level. Columns 2 and 3 show that DVA exports are a key channel through which employment is increased.

The results of the estimation of the dynamic panel model are consistent with those reported after time and industry fixed effects are controlled for.

**Table 4.** *Estimation of First Difference GMM for Employment*

| VARIABLES | (1) | (2) |
|---|---|---|
| Lagged.ln(employment) | 0.907*** | 0.818*** |
| | (0.0417) | (0.0390) |
| ln(intermediates_exp) | 0.00424 | |
| | (0.00316) | |
| ln(intermediates_imp) | 0.0842* | |
| | (0.0484) | |
| ln(fva in exports) | | -0.00191 |
| | | (0.00873) |
| ln(dva in exports) | | 0.259*** |
| | | (0.0540) |
| Observations | 442 | 442 |
| No. of Industry | 34 | 34 |

Standard errors in parentheses
*** p < 0.01, ** p < 0.05, * p < 0.1

One might question the validity of the instruments used in the FD-GMM estimates. Therefore, we run Hansen test statistics under the null hypothesis that the joint instruments are exogenous and valid. We fail to reject the null hypothesis for all estimates.[6] In addition, no significant autocorrelation is found at order 2 at the 5% significance level. These results confirm the validity of our instrumentation procedure.

## C. Sectoral analysis

The composition of labor and production technologies varies across industries. Agriculture industries employ a large share of low-skilled workers and production technology, whereas the share of low-skilled workers in manufacturing varies according to the production stage and value-added level. Service industries feature a large proportion of high-skilled workers and production technologies. Thus, examining the trade-related variables at the industry level may be important for understanding the channel through which productivity and employment levels are increased. Therefore, we disentangle industries' GVC participation and domestic value-added exports and their impacts on labor productivity and employment by classifying industries into three categories: (1) Agriculture, (2) Manufacturing, and (3) Services. We analyze each category separately and examine how its backward participation in GVCs and DVA exports impacts both labor productivity and employment; we create dummy variables for each category and calculate their interaction with GVCs integration and the variable for DVA exports. Tables 5 and 6 report

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6)  Hansen test Labor Productivity (Table 3). Column 1 P-Value = 0.88. Column 2 P-Val = 0.85. Column 3 P-Val = 0.84. Hansen test Employment (Table 4). Column 1 P-Value = 0.8. Column 2 P-Val = 0.88. Column 3 P-Val = 0.887.

the estimation results for labor productivity and employment.[7]

In Table 5, the estimation results show that productivity benefits significantly from the FVA and DVA exports in manufacturing and declines with the FVA and DVA exports in services. This suggests that imported intermediates are complementary in the manufacturing industries and are used in conjunction with domestically produced goods for exports, which leads to higher productivity. In addition, industries seem to benefit more from the export of domestically produced goods, as previously found by (De Locker, 2013).

The results differ for service industries, however, suggesting the substitutive nature of imported intermediates. The negative association between DVA exports and productivity may also suggest that domestic value-added increases more slowly than the number of workers in service industries.

**Table 5.** *Sectoral FVA and DVA in Exports' Effect on Labor Productivity*

| VARIABLES | Agriculture | Manufacturing | Services |
|---|---|---|---|
| | (1) | (2) | (3) |
| Lagged.ln(Capital/Worker) | 0.186*** | 0.228*** | 0.226*** |
| | (0.0379) | (0.0373) | (0.0373) |
| Lagged.ln(fva in exports) | -0.0533*** | -0.0573*** | 0.0925*** |
| | (0.0164) | (0.0161) | (0.0350) |
| Lagged.ln(dva in exports) | 0.770*** | 0.369*** | 0.948*** |
| | (0.0745) | (0.0977) | (0.0823) |
| Lagged.ln(agr-fva in exports) | 0.121 | | |
| | (0.123) | | |
| Lagged.ln(agr-dva in exports) | -0.0936 | | |
| | (0.358) | | |
| Lagged.ln(man-fva in exports) | | 0.133*** | |
| | | (0.0378) | |
| Lagged.ln(man-dva in exports) | | 0.621*** | |
| | | (0.119) | |
| Lagged.ln(serv-fva in exports) | | | -0.151*** |
| | | | (0.0357) |
| Lagged.ln(serv-dva in exports) | | | -0.573*** |
| | | | (0.127) |
| Constant | 12.91*** | 12.84*** | 12.94*** |
| | (0.162) | (0.148) | (0.147) |
| Observations | 476 | 476 | 476 |
| No. of Industry | 34 | 34 | 34 |
| R-squared | 0.268 | 0.321 | 0.319 |
| Year FE | YES | YES | YES |
| Industry FE | YES | YES | YES |

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

7) Estimates using intermediate gross indicators have been omitted. However, the estimates are available upon request.

**Table 6.** *Sectoral FVA and DVA in Exports' Effect on Employment*

| VARIABLES | Agriculture | Manufacturing | Services |
|---|---|---|---|
| Lagged.ln(fva in exports) | -0.0182* | -0.0101 | -0.110*** |
| | (0.0103) | (0.0101) | (0.0218) |
| Lagged.ln(dva in exports) | 0.500*** | 0.327*** | 0.645*** |
| | (0.0452) | (0.0619) | (0.0492) |
| Lagged.ln(agr-fva in exports) | -0.230*** | | |
| | (0.0776) | | |
| Lagged.ln(agr-dva in exports) | -0.446** | | |
| | (0.226) | | |
| Lagged.ln(man-fva in exports) | | -0.0941*** | |
| | | (0.0237) | |
| Lagged.ln(man-dva in exports) | | 0.335*** | |
| | | (0.0752) | |
| Lagged.ln(serv-fva in exports) | | | 0.109*** |
| | | | (0.0220) |
| Lagged.ln(serv-dva in exports) | | | -0.413*** |
| | | | (0.0790) |
| Constant | 6.429*** | 6.441*** | 6.470*** |
| | (0.0593) | (0.0510) | (0.0512) |
| Observations | 476 | 476 | 476 |
| No. of Industry | 34 | 34 | 34 |
| R-squared | 0.495 | 0.526 | 0.543 |
| Year FE | YES | YES | YES |
| Industry FE | YES | YES | YES |

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6 reports the estimation results for the employment-dependent variables. It shows that employment declines with both agricultural FVA and DVA exports. Manufacturing FVA exports displace labor in Japan, whereas DVA exports create jobs. The opposite holds true for service industries, where FVA exports increase employment and DVA exports reduce it.

# V. Conclusion

In this study, we examine how backward linkages and the domestic content of exports affect labor productivity and employment in Japan using panel fixed effects and difference GMM estimation using WIOD 2013 and SEA datasets. We begin by estimating the effects of variables reflecting gross intermediate imports and exports. We then consider more trade-specific

determinants: the FVA and DVA in exports. We examine the association between the trade-related variables and labor productivity and employment at the industry level.

After controlling for industry and time fixed effects, we find that gross intermediate imports have a significantly positive association with labor productivity and employment due to increased access to cheap and varied inputs (Amiti & Konings, 2007).

We also show that DVA in exports is a key driver of labor productivity and employment in Japan for all industries after controlling for industry-specific and time-fixed effects. Meanwhile, labor productivity and employment decline with FVA in exports. The difference GMM estimation supports our findings.

A sectoral analysis shows that productivity is boosted by FVA and DVA exports in the manufacturing industry and declines in the services industry. Employment declines with FVA exports in both agriculture and manufacturing and increases with them in the services industry. On the other hand, employment declines with DVA exports in both agriculture and services and increases with them in manufacturing.

Our findings reinforce the "learning by exporting" hypothesis proposed by the literature. Moreover, we find weaknesses related to GVC integration, suggesting job displacement patterns in some industries. These findings offer key policy implications. Most importantly, more emphasis should be placed on the domestic content of trade as a key determinant in promoting productivity and job creation in Japan. While our results suggest a substitution pattern for domestically produced intermediates via backward linkages, they also suggest that more focus should be placed on the gains associated with the impacts of the backward linkage of productivity at the sector level in Japan.

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