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ITO, Keiko
RIETI

HAHN, Chin Hee
Gachon University

Research Institute of Economy, Trade & Industry, IAA
The Research Institute of Economy, Trade and Industry
https://www.rieti.go.jp/en/

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The Effect of Exporting on Product Compositional Changes and a Manufacturing Plant's Average Product Characteristics in Japan[1]

Keiko ITO
Chuo University

Chin Hee HAHN
Gachon University

Abstract

This paper examines whether exporting activity contributes to promoting product compositional changes and/or upgrading a plant's product portfolio. We first present evidence that exporters tend to produce, on average, products with higher product attributes than non-exporters do. Next, we find evidence that exporting improves a plant's average product attributes, utilizing propensity score difference-in-difference matching technique. Further examination of the mechanism reveals that the positive effect of exporting on a plant's average product attributes is realized through its effect of adding higher-attribute products and dropping lower-attribute products. Although exporting also promotes share changes among continuously produced products, the effects on product adding/dropping seem to be stronger. The results suggest that exporting might have contributed to the sustained economic growth of Japan by promoting creative destruction.

Keywords: creative destruction, exporting, introduction of new products, propensity score matching
JEL classification: F14, F61, O12

[1]This study is conducted as a part of the Project "East Asian Industrial Productivity" undertaken at the Research Institute of Economy, Trade and Industry (RIETI). This study utilizes the micro data of "the Census of Manufactures" and "the Economic Census for Business Activity" which are conducted by the Ministry of Economy, Trade and Industry (METI), and the Kogyo Tokei converter, which is provided by RIETI. The author is grateful for helpful comments and suggestions by Makoto Yano (RIETI), Masayuki Morikawa (RIETI), Kyoji Fukao (Hitotsubashi Univ., IDE-JETRO, and RIETI), Hyeog Ug Kwon (Nihon Univ. and RIETI), Toshihiro Okubo (Keio Univ.), and Discussion Paper seminar participants at RIETI.

I. Introduction

This research aims to examine empirically whether exporting improves a plant's average product characteristics and its mechanisms, utilizing plant–product matched datasets for the Japanese manufacturing sector. As well noted, the Schumpeterian creative destruction process is a quintessential element underlying sustained economic growth. In other words, many countries including Japan has been developing through a continual process of introducing new products and dropping old products.[1] As a result, the average product characteristics produced by firms have, by casual observation, shifted toward a more sophisticated range of products over the past decades in Japan.[2] Meanwhile, it has also often been argued that manufacturing export products played a crucial role in determining overall economy-wide growth performance in Japan. In contrast with the widely-believed important role of manufacturing export products in the economic growth, however, relatively little effort has been devoted to examining whether and how exporting contributes to product adding/dropping, i.e., creative destruction, and the upgrading of a firm's product portfolio. What, then, is the relationship between exporting on the one hand and the creative destruction and the upgrading of a firm's product portfolio on the other? Does exporting promote the creative destruction process and the upgrading of a firm's product portfolio? If so, what is the mechanism? These are the key questions that we address in

[1] Many previous studies show that resource allocation is one of the most important driving forces for economic development. There are studies that show that reallocation of resources from a less productive industry (firm) to a more productive industry (firm) contributes to productivity improvement at the macro (industry) level. For example, studies such as Foster, Haltiwanger, and Krizan (2006) and Nishimura, Nakajima, and Kiyota (2005) investigate how firms' entry and exit decisions affect productivity growth at the macro level. There are also studies that focus on product switching as an important source of resource reallocation. For example, Bernard, Redding, and Schott (2010) show that product switching contributes to a reallocation of resources within firms toward their most efficient use. Using Japanese manufacturing census data, Kawakami and Miyagawa (2013) find results consistent with Bernard, Redding, and Schott (2010), and they also show that product switching of incumbent firms is a crucial factor to output growth and productivity improvement in the Japanese manufacturing sector. However, these papers do not examine the relationship between firms' entry into the export market and product switching as we do in this study.

[2] Many previous studies have analyzed economic growth for various countries by looking at the sophistication of exported goods (e.g., Hausmann, Hwang, and Rodrik 2007, Jarreau and Poncet 2012, Thorbecke and Pai 2015).

this paper.

To examine these issues, we proceed in three steps. In the first step, we borrow the idea of Hausmann, Hwang, and Rodrik (2007) to measure quantitative indices of product attributes (PRAs) for each product in our dataset. We construct these measures by taking weighted averages of the characteristics of plants producing the product, such as plant productivity, wages, and capital and skill intensity, where the weights are the shipment share of each plant in the economy's total shipment of the product. Thus, if a product is produced mostly by high-productivity or high-capital-intensity plants, it is considered as a high-productivity or high-capital-intensity product. In this way, for each product, we generate an associated productivity level or a capital intensity level.[3] Then, borrowing the idea of Hausmann, Hwang, and Rodrik (2007) again[4], we construct measures of plant-average product attributes (PAPRAs) for each plant, by calculating the shipment-weighted average of PRAs. Thus, if a plant has a higher within-plant shipment share of high-productivity products, the productivity level of a plant *implied by the plant's product mix* is considered to be higher, other things being equal.

One important point to note here is that our measure of PAPRAs is not necessarily the same as the plant productivity or plant capital intensity measured in conventional ways. We focus on the productivity-based PAPRA measure of plants instead of the plant productivity measured in conventional ways, mainly because we are interested in the within-plant (firm) resource reallocation. By using this measure, we examine whether and through what mechanism exporting contributes to creative destruction and the upgrading of plants' product portfolios, which cannot be done if we use only the conventional plant-level productivity or

[3] Hausmann, Hwang, and Rodrik (2007) constructed a measure of "product productivity" by taking a weighted average of the per capita GDP of the countries exporting a product, where the weights reflect the revealed comparative advantage of each country in that product.
[4] Hausmann, Hwang, and Rodrik (2007) construct, for each country, a measure of income/productivity level that corresponds to a country's export basket, which they call EXPY. Thus, EXPY is the measure of a country's productivity level associated with its specialization pattern.

factor-intensity measures.

In the second step, we examine whether exporting causes PAPRAs to increase, utilizing propensity score difference-in-difference matching (PSM-DID) methodology as in Heckman, Ichimura, and Todd (1997). In the third step, we conduct several additional analyses to clarify the mechanism of the effect of exporting on PAPRAs. As will be explained in more detail below, the measured PRAs of this paper are time-invariant and the PAPRAs are constructed as the shipment-weighted average of PRAs. Thus, if we find that exporting has a positive effect on PAPRAs, it must be through its impact on either a plant adding or dropping a product, or shipment share reallocation among continuing products toward products with higher PRAs, or both. We are particularly interested in whether the product adding and dropping channel works, because this channel is likely to be closely related to the creative destruction process. Although the share reallocation across continuing products within a plant may be one important mechanism of how exporting increases PAPRAs or contributes to the upgrading of a plant's product portfolio, this channel does not involve export-driven product innovation (adding), which is a critical part of the creative destruction process. We assume that exporting is likely to increase product adding through learning-by-exporting, while fierce competition in international markets may force exporting plants to concentrate on core competence products. In order to clarify the mechanism, we first examine some general patterns in our dataset: 1) whether added products tend to have, in general, higher PRAs than dropped products, and 2) whether shipments of products with initially higher PRAs tend to become relatively larger than those with initially lower ones. As the main analysis to clarify the mechanism, we again utilize a PSM-DID methodology to examine the effect of exporting on a plant's adding and dropping of products as well as on a measure of share changes among continuing products.

In addition, given the fact that technological capabilities and competitiveness of information and communication technology (ICT) related industries have been attracting attention from researchers and policy makers, we conduct the same analyses as above, focusing on plants in ICT-intensive industries.

Our main empirical results are as follows. We first find significant exporter premia in PAPRAs: Exporters tend to produce, on average, products with higher PRAs. Second, we find evidence that exporting increases PAPRAs. The above two results tell us that exporting has an effect of upgrading a firm's product portfolio. Third, we find that exporting increases product adding, which is consistent with a learning-by-exporting effect. We also find the general patterns that added products tend to have higher PRAs than dropped products and that shipments of products with initially higher PRAs tend to become relatively larger than those with initially lower PRAs. However, our results suggest that the former channel is likely to be more strongly activated by exporting than the latter channel. Finally, plants' export market entry increases product dropping for Japan. This result may indicate that the concentration effect dominates the learning-by-exporting effect.

The organization of this paper is as follows. In the next section, we briefly introduce the literature related to our study. In Section III, we explain the data. Section IV explains the measurement of PRAs and PAPRAs and documents exporter premia in PAPRAs. Section V discusses the effect of exporting on PAPRAs using PSM-DID. Section VI discusses the mechanism. Section VII concludes.

II. Related Literature and the Scope of this Study

Our study relates to a number of papers that span the trade and development literatures. This paper is most directly related to empirical studies based on multiproduct firm trade theories.[5]

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[5] This paper is also broadly related to the extremely comprehensive literature on international trade and economic

One key prediction from these theories is that trade liberalization causes an adjustment of firms' product scope (the number of products produced) through a competition effect and a demand effect (i.e., trade liberalization is assumed to increase both international competition and demand), leading to an increase in productivity of the firm and the aggregate economy. According to these theories, however, firms' product scope may increase or decrease in response to liberalized trade depending on model specifics. In fact, most theories predict that firms' product scope decreases with trade liberalization as they drop marginal products and concentrate on the remaining products (Baldwin and Gu 2009, Eckel and Neary 2010, Bernard, Redding, and Schott 2011, and Mayer, Melitz, and Ottaviano 2014, 2016).[6] By contrast, Qiu and Zhou (2013) show that firms' product scope may increase as trade is liberalized.

Empirical results of existing studies on how firms' product scope responds to trade liberalization are also mixed. While there are studies finding product scope reduction in response to liberalized trade (Baldwin and Gu 2009, Bernard, Redding, and Schott 2011, Iacovone, Rauch, and Winters 2013), there are also studies finding a product scope expansion (Iacovone and Javorcik 2010, Berthou and Fontagne 2013, Qiu and Yu 2014).

Another strand of empirical studies related to this paper is that which assesses the effect of exporting on firm performance. Most studies along this line have been concerned with the effect of exporting on firm productivity: the learning-by-exporting effect.[7] Although many studies find some support for learning, most of these studies fail to show how exporters improve firm-level productivity or to identify the source of the productivity-enhancing effect of exporting. One exception is the study by Atkin, Khandelwal, and Osman (2017), which,

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growth, which will not be reviewed here.

[6] However, the specific mechanisms are varied among studies. For a comprehensive survey of literature on heterogeneous firm trade theories and their extension to multiproduct firm trade theories, see Redding (2010), Melitz and Redding (2012), and Melitz and Trefler (2012).

[7] Since the pioneering studies by Bernard and Jensen (1999a, 1999b), a large number of studies have been conducted on this issue. For a survey of this literature, see Greenaway and Kneller (2007).

conducting a randomized experiment, shows that export starters report higher profits and exhibit larger improvements in quality. Atkin, Khandelwal, and Osman (2017) find strong evidence of improvement in product quality and firm productivity in the case of rug producers in Egypt. Studies on multiproduct firms such as Eckel et al. (2015) for Mexico and Manova and Yu (2017) for China also find evidence of product-quality upgrading by exporters, using the product-level unit value and product ranking as measures of quality. These studies imply that productivity improvement through learning by exporting would be associated with quality upgrading. On the other hand, Ma, Tang, and Zhang (2014) find that in the case of China, new exporters tend to specialize in their core products and improve productivity by adding new products that are more labor-intensive and dropping existing exported products that are less labor-intensive, particularly in the case where a firm exports to a more capital-abundant country.

Thus, these previous studies suggest that exporting will affect firms' factor intensity, product scope, and productivity, through product churning. While there are several existing empirical studies that examine the effect of trade or trade liberalization on product scope, there are hardly any studies using micro data which directly examine the effect of trade on *both* product adding and dropping, which are core elements of creative destruction. An exception is Iacovone, Rauch, and Winters (2013), who examine the effects of increased competition from China on extensive and intensive margin adjustments to plants or products. However, they did not examine the effect on product adding, which is a crucial element of creative destruction.

Therefore, in this study, we hypothesize that exporting is likely to promote the creative destruction process and examine the effect of exporting on plants' product adding and dropping. How can exporting affect product adding and dropping? In our view, there are broadly two channels. One channel is, as mentioned above, learning by exporting. If plants learn from exporting activity and improve their productivity, their product scope is expected to increase because the marginal costs of producing all products are likely to be reduced. By this mechanism, exporting is expected to increase product adding and decrease product dropping. Another channel is the so-called concentration on core competence products in response to globalization, as shown in Eckel and Neary (2010). These authors show theoretically that firms drop marginally productive products and concentrate on their core competence products when oligopoly firms face larger foreign markets. By this mechanism, plants that enter the export market and face greater competition are expected to increase product dropping. If these two channels are operative, exporting is expected to increase plants' product adding, while it has an ambiguous effect on product dropping. The effect on the latter depends on the importance of the learning-by-exporting effect relative to the effect of concentration on core competences.

If exporting increases a firm's average PRAs mainly through adding of higher-attribute products or product innovation, it implies that exporting might have contributed to sustained economic growth in Japan during the periods of our analyses. If economic growth relies on learning and if the learning potential from a given product is bounded, for example, a continual shift to new products with higher learning potential is a necessary condition for a sustained economic growth.[8]

III. Data

We constructed the plant–product matched panel data for Japan for this study utilizing the micro data collected by the government. We define a product based on the most detailed product classification codes that the Ministry of Economy, Trade and Industry (METI) employs: 6-digit product code. The details of our data sources are as follows.[9]

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[8] See Stokey (1988) and Young (1993) for theoretical models of economic growth with learning by doing and introduction of new products.

[9] The information on export destination is not available in our dataset. Therefore, and unfortunately, we cannot analyze the export-destination mix.

The data are the plant–product matched data underlying the *Census of Manufacture* (hereafter CM) conducted every year by the METI.[10] The CM consists of two sub-censuses by size of establishment: Form A (*Kou Hyo* in Japanese) is for establishments with 30 or more employees, Form B (*Otsu Hyo*) is for those with 4 to 29 employees. Of the two types of censuses, we use Form A for this study because of various reasons. First, capital stock information is not available every year for Form B plants. Second, although export status information is also available for Form B plants, only one percent of the plants report non-zero positive export ratio while approximately ten percent of Form A plants are exporters. Moreover, export status information has been available since 2001, but the product classification has changed in 2002, 2008, and 2014. Therefore, we use the plant–product matched panel data for the period 2002–2007 and for the period 2008–2013 for this study.

Each plant reports the value of shipments (a breakdown into domestic shipments and exports is not available) by product, and the products – about 2,300 of which are reported – are classified at the six-digit basis. Each plant also reports the share of exports in the total shipment, and this information is used to identify a plant's export status.[11]

This study examines product adding and dropping at the plant level, not at the firm level. However, multi-plant firms may relocate production of one product from one plant to another, which cannot be considered as product adding or dropping at the firm level. In fact, we have the plant-firm linked identifier and we can identify single-plant or multi-plant firms. Although the permanent firm identifier is not officially available, we constructed the firm-level

[10] The data for 2011 are taken from the micro data of the *Economic Census for Business Activity* which is jointly conducted by the Ministry of Internal Affairs and Communications (MIC) and the METI. The compilation of the micro data of the *Census of Manufacture* and the *Economic Census for Business Activity* conducted as a part of the research project at the Research Institute of Economy, Trade and Industry (RIETI).
[11] For more details on plant–product-matched panel data for Japan, see Hahn, Ito, and Narjoko (2016).

panel dataset using the firm-level information such as telephone number, name, and address.

Therefore, although we can examine the firm-level product adding and dropping, we conduct the plant-level analyses in this paper focusing on Form A plants because we cannot calculate some capital stock-based measures at the firm level due to the data constraints explained above.

Nevertheless, we investigate to what extent the within-firm product relocation matters, using the firm-plant-product matched data for the periods 2002–2007 and 2008–2013. As shown in Appendix Table 1, in the case of the Form A plants for the period from 2002 to 2007 (Panel A), 80.6 percent of the newly added products (products not produced in year t but produced in year $t+1$) at the plant level are also newly added products at the firm level. Similarly, 80.7 percent of the dropped products (products produced in year t but not produced in year $t+1$) at the plant level are also dropped products at the firm level. When we take products produced by Form B plants into account, approximately 90 percent of the added (dropped) products at the plant level are also added (dropped) products at the firm level. Similarly, in the case of the period from 2008 to 2013, approximately 80–90 percent of the added/dropped products at the plant level are also added/dropped products at the firm level (Panel B). Therefore, it is not very likely that the plant-level investigation leads to seriously misleading results.

IV. PAPRAs: Exporter Premia?

IV.1 Measurement of PRAs and PAPRAs

In our previous study (Hahn, Ito, and Narjoko 2016), we found that export starters are more likely to change their product portfolio than non-exporters and showed some evidence that export starters likely shift toward products with higher attributes by actively adding and dropping their products. In this paper, we employ a more rigorous methodology to test whether export starters change their product portfolio differently from non-exporters.

This section first explains how to construct product-level measures that capture product quality or attributes and how to construct plant-level performance measures based on the product-level attribute measures.

It is not straightforward to measure product quality or PRAs. In the empirical international trade literature, product quality is often measured as the unit value for each product or as the weighted average of gross domestic product (GDP) per capita of the countries that export the product. However, in this study we refrain from using the quantity information and, alternatively, we construct product attribute measures in the following way.[12]

IV.1.1 PRA Measures

First, we assume that PRAs are associated with the characteristics of plants that produce the corresponding product. The idea comes from the quantitative index that ranks traded goods in terms of their implied productivity, constructed by Hausmann, Hwang, and Rodrik (2007). This measure is a weighted average of the per capita GDPs of the countries exporting a product, where the weights reflect the revealed comparative advantage of each country in that product. Therefore, each good has an associated income/productivity level. Then, Hausmann, Hwang, and Rodrik (2007) construct the income/productivity level that corresponds to a country's export basket by calculating the export-weighted average of the product-specific

[12] Although shipment quantity information is available at the product level, the unit of quantity varies across products; in particular, it is difficult to define the unit value for most parts and components. The unit of quantity is "pieces" for most parts and components, whereas the unit of quantity for homogeneous goods such as steel and textiles is "weight," such as tons or kilograms. Moreover, many kinds of unit are sometimes very specific to some products. For parts and components in particular, the definition of "pieces" is ambiguous, and it is thus, not appropriate to construct the unit value measure using this quantity information.

income/productivity measure for that country. This measure is interpreted as the productivity level associated with a country's specialization pattern.

Extending this idea to the product–plant level instead of the product–country level, we first calculate labor productivity, total factor productivity (TFP)[13], the capital–labor ratio, and the wage rate (all in logarithms) for each plant. We then calculate PRAs as the weighted average of the plant-level characteristics. We use the shipment share of each plant in the total shipment of a product as a weight.[14] Therefore, the PRA measures for product *j* and year *t* are expressed as:

$$PRA\_X_{jt} = \sum_{p \in P_j} \theta_{pjt} X_{pt} \tag{1}$$

$$\theta_{pjt} = \frac{Y_{pjt}}{Y_{jt}},$$

where PRA_X_{jt} is the time-variant product attribute measure for product *j* based on the plant-level characteristics *X*, X_{pt} is the plant-level characteristics for plant *p* in year *t*, θ_{pjt} denotes the share of plant *p*'s shipment of product *j* (Y_{pjt}) in the total shipment of product *j* in year *t* (Y_{jt}), and P_j denotes the set of plants that produce product *j*. Therefore, the PRA measure for product *j* in year *t* is the weighted average of plant-level characteristics for plants producing product *j* in year *t*. As a result, we obtain four kinds of PRAs measures for each product and for each year.[15]

To eliminate the effects of year-specific productivity shocks, we take the period average

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[13] Plant total factor productivity was estimated for each two-digit industry using the non-parametric index number method.

[14] We admit a possible causality problem of our PRA measure. This PRA measure can be increased if plants improve their performance as a result of adding high-attribute products or dropping low attribute products; that is, our measure may not be strictly exogenous to the product adding and dropping behavior of plants. One possible alternative is to measure PRAs only by using information on plants that introduced the corresponding product for the first time in the country. However, this methodology will substantially reduce the number of products for which the PRA measure can be calculated, and it is difficult to apply to old products that are dropped during the period of our analysis. Therefore, at present, we consider that the proposed PRA measure in this paper is the best possible option.

[15] Our PRA measure is constructed in a way similar to the PRODY measure in Haumann, Hwang, and Rodrik (2007).

of each product attribute measure and define it as the time-invariant PRA measure

$$\overline{PRA\_X}_j = \frac{1}{T}\sum_{t=1}^{T} PRA\_X_{jt.} \quad (2)$$

For the time-invariant product attribute measures, we use a deviation from the industry median of each PRA measure to eliminate the effects of differences in industry-specific characteristics and technologies, which we call a relative measure. We calculate the median of each time-invariant product attribute measure at the three-digit industry level. We also use the non-relative measure as the dependent variable. The time-invariant PRA relative to the 3-digit industry median value is defined as:

$$\overline{RPRA\_X}_j = \overline{PRA\_X}_j - med\left(\overline{PRA_{X}}_j\right). \quad (3)$$

IV.1.2 Plant's Average PRA

Next, using the PRA measures (*RPRA_X*), we calculate the PAPRA, which we use as a proxy for plant performance:[16]

$$PAPRA\_X_{pt} = \sum_j \omega_{pjt}\,\overline{RPRA\_X}_j, \sum_j \omega_{pjt} = 1, \quad (4)$$

where ω_{pjt} denotes the share of plant *p*'s shipment of product *j* in the total shipment of plant *p* in year *t*. Therefore, plants are assumed to perform better if they produce higher-attribute products more than lower-attribute products.

We should note that our PAPRA measure is interpreted as the plant characteristics associated with a plant's *specialization pattern*, as in Hausmann, Hwang, and Rodrik (2007). It is clear that the PAPRAs do not equal the plant-level productivity per se. We employ this measure and focus on the "specialization" pattern within a plant, because the main purpose of

[16] Our PAPRA measure is constructed in a way similar to the EXPY measure in Haumann, Hwang, and Rodrik (2007).

our study is to examine resource reallocation induced by the changes in a plant's export status, not to examine the plant-level productivity improvement and/or the product-level quality improvement.

IV.2 Exporter Premia

Many previous studies on various countries as well as our previous study on Japan, Korea, and Indonesia (Hahn, Ito, and Narjoko 2016) show that exporters outperform non-exporters. While these previous studies use plant productivity measures as a proxy for plant performance, we use the PAPRA as a proxy for plant performance and examine whether exporters perform better (i.e., producing higher-attribute products) than non-exporters. In order to examine the exporter premia, we estimate the following equation:

$$PAPRA\_X_{pt} = \alpha + \beta EXPDUM_{pt} + Ind_I + \pi_p + \tau_t + \varepsilon_{pt} \ , \qquad (5)$$

where $PAPRA\_X_{pt}$ is the plant-level average PRA for plant p in year t based on the plant-level characteristics X. $EXPDUM_{pt}$ is the exporter dummy variable which takes 1 for exporting plants in year t. Ind_I is the set of industry dummies and τ_t is the set of year dummies. The set of plant dummies, π_p, is also included in order to control for plant-specific fixed effects. We estimate the equation (5) using both annual cross-section data (without plant fixed effects) and annual panel data.

Table 1 shows the estimation results. Panels A1 and B1 show the results of cross-section estimations for year 2005 and for year 2011, respectively.[17] Panels A2 and B2 show the results of fixed-effect panel estimations for the periods 2002–2007 and for the periods 2008–2013, respectively. The estimated coefficient of the Exporter dummy (*EXPDUM*) is positive and statistically significant in most cases, suggesting that exporters tend to produce higher-

[17] We also estimated the equation using the cross-section data for other years, and we obtained similar results.

attribute products than non-exporters. Moreover, the fixed-effect panel estimation results indicate that plant's average PRAs are higher for plants that changed their status from non-exporter to exporter.

INSERT Table 1

V. Does Exporting Increase PAPRAs?

In the previous section, we showed that exporters have higher PAPRAs than non-exporters: exporter premia. The exporter premia may reflect a causal effect of exporting on PAPRAs, self-selection of plants with higher PAPRAs into the export market, or both.[18] In this section, we examine whether the higher PAPRAs of exporters reflect a causality running from exporting to PAPRAs.

V.1 Methodology

We employ a PSM-DID estimator, as in Heckman, Ichimura, and Todd (1997), in order to estimate the effect of exporting on a plant's average product characteristics. This methodology addresses the potential bias in the estimate of the effect of exporting on PAPRAs, which arises when there is a selection of unobservables in export market entry or when there exist time-invariant level differences in PAPRAs between exporters and non-exporters. To implement this methodology, we first estimate the following probit model:

$$\mathrm{P}(X_p) \equiv \Pr(d_p = 1 | X_p) = E(d_p | X_p), \tag{6}$$

where $\mathrm{P}(X_p)$ is the probability of participating in export markets conditional on the vector of

[18] When rich countries tend to import relatively more from countries that produce high-quality goods, as explained in Hallak (2006), we may expect that Japanese firms producing higher-quality goods are more likely to participate in export markets than those producing lower-quality goods insofar as Japanese firms targeted rich country markets.

characteristics of plant p, X_p , and d_p is a dummy variable that takes a value of 1 when plant p is an exporter and 0 otherwise. As plant characteristics, we include plant TFP (log), number of employees (log), a dummy variable for a young plant where a young plant is a plant aged five years or less[19], capital intensity (log), a multiproduct plant dummy variable. In order to control for the selection effect at least partially, we also included a dummy variable for product adding which takes a value of 1 if the plant added a new product during the past year and 0 otherwise, as well as a dummy variable for product dropping, similarly defined. All of the plant characteristics are values for one year before export participation.[20] The estimated probit model is presented in Table 2. For the both periods, plants that are more productive, larger, or more capital-intensive are more likely to participate in export markets. The estimate coefficients for the product adding and dropping dummy variables have different sign for the first period and the second period.

INSERT Table 2

Based on the estimated probability of participating in export markets, we match each export starter that started exporting during the sample period, with never-exporters that do not export at all during the sample period. Let T and C denote the set of export starters and never-exporters, respectively, and let y^T and y^C be the outcome variables of T and C. Let i and j be the index of export starters and never-exporters, respectively. The subscript t_0 denotes the year one year prior to export participation. The subscript s is the number of years that have passed after

[19] Plant age information is not available in the census. Therefore, based on the plant-level panel data that we constructed, we define a plant as a young one if it appeared for the first time in our panel dataset within the last five years.
[20] Following Bernard and Jensen (1999b), we chose mid-sample year as the artificial export market entry year for all plants, which is 2004 for the first sample period and 2010 for the second sample period.

export participation. Let us denote the set of never-exporters matched with the export starter i as $C(i)$, the number of never-exporters matched with export starter i as N_{iC},[21] and the number of export starters as N^T. Then, the effect of exporting at s years after export market entry is:

$$\hat{\beta}_s^{PSM-DID} = \frac{1}{N^T}\sum_{i\in T}\left(\left(y_{i,s}^T - y_{i,t_0}^T\right) - \sum_{j\in C(i)} w_{ij}\left(y_{j,s}^C - y_{j,t_0}^C\right)\right), \qquad (7)$$

where $w_{ij} = 1/N_{iC}$ if $j \in C(i)$ and zero otherwise.

For the plant-level outcome variables y^T and y^C, we use $PAPRA_X_{pt}$s as defined earlier in equation (4), where X_{pt} is a plant characteristic of plant p at year t. As before, we consider plant TFP, labor productivity (LP), capital intensity (KL), and wage rates as the plant characteristics, so that we consider four outcome variables in total. As shown earlier in equations (3) and (4), our plant-level outcome variables, $PAPRA_X_{pt}$s, are measured using the time-invariant PRA measure relative to the 3-digit industry median. As a robustness check, we also consider an alternative set of outcome variables that is based on the absolute level of time-invariant product attribute measure instead of the product attribute measure expressed relative to the industry median.

V.2 Results

Table 3 shows the estimated effect of exporting on various outcome variables we considered.[22] In Table 3, the outcome variables represented as X_dev are the plant-level outcome variables constructed from the PRA measures expressed relative to the industry median. The outcome variables represented as X are the plant-level outcome variables constructed from the absolute

[21] We used one-to-one nearest-neighbor matching, so that $N_{iC} = 1$ for each i.

[22] Although we report the results based on the observations matched using the one-to-one nearest matching technique, we also tried to employ other matching methods. We performed the radius matching technique using the caliper = 0.001 and caliper = 0.0001, and the results were very similar and consistent to those shown in Table 3.

level of time-invariant PRA measures. Panels A and B shows the results for the period 2002–2007 and for the period 2008–2013, respectively. Overall, we find some evidence that exporting increases PAPRAs. A positive and significant effect of exporting tends to be observed when outcome variables are based on absolute levels of PRA measures. However, such effects are not found in most of cases where relative PRA measures are used as the outcome variables. The result might suggest that plants are more likely to switch products toward those with higher attributes *across* industries than *within* an industry.

INSERT Table 3

So how does exporting increase PAPRAs? The way we constructed PAPRAs provides some answers to this question. We constructed the PAPRAs as a weighted average of time-invariant PRAs, so that the increase in PAPRAs must reflect export-driven reallocation across products within a plant. The reallocation across products within a plant occurs through two channels: 1) adding and dropping of products and 2) share changes among continuing products that a plant produced at both the beginning and end of a year. Which of the above two channels is more important when exporting increases PAPRAs? This is the issue that will be examined in the next section.

VI. Mechanism

In order to answer the question raised above, we first examine 1) whether product PRAs are different between added and dropped products, and 2) whether shipments of continuing products with high PRAs tend to increase more than shipments of continuing products with low PRAs. Then, we try to reveal which channel, product adding/dropping or share changes among continuing products, is more important to explain the improvement in a plant's average PRAs for export starters.

VI.1 Product Adding and Dropping

First, we examine whether PRAs are different between added and dropped products. Taking two adjacent years, *t* and *t+1*, we define, from a plant's point of view, "continuing products", "added products", and "dropped products." Added products are defined as products that were not produced in year *t* at a particular plant but were produced in year *t+1* at this plant. Similarly, dropped products are defined as products that were produced in year *t* at a particular plant but were not produced in year *t+1* at this plant. Continued products are products that were produced in both year *t* and year *t+1*. We construct a plant–product-level dummy variable (ADD) for added products that takes 1 for products added by a plant between year *t* and year *t+1*. Here, we focus only on added and dropped products and exclude continuing products, and estimate the following equation:

$$PRA\_X_j = \alpha + \beta ADD_{pjt} + \pi\tau_{pt} + \varepsilon_{pt}, \qquad (8)$$

where the dependent variable, *PRA_X*, denotes time-invariant PRA measures, $\pi\tau$ denotes the set of plant–year dummies that control for time-variant plant-specific characteristics. The coefficient β can be interpreted as the difference in PRA measures between the added and the dropped products in year *t*.

The estimation results are shown in Table 4.[23] Panels A and B show the results for the period 2002–2007 and for the period 2008–2013, respectively. The estimated coefficient of the ADD dummy is positive and statistically significant in most cases, particularly for the period

[23] We also ran the regressions including plant fixed effects and year fixed effects separately, instead of including plant–year fixed effects. We obtained results consistent with those in Table 4.

2002–2007, suggesting that added products tend to have higher PRAs than dropped products. Therefore, the results also suggest that product portfolio changes by adding and dropping products are likely to raise the PAPRAs.

INSERT Table 4

VI.2 Share Changes Across Continuing Products

Next, we examine whether shipments of continuing products with high PRAs increase more than shipments of continuing products with low PRA, by estimating the following equation:

$$\Delta Y_{pjt} = \beta \overline{RPRA\_X}_j + \gamma Y_{pjt} + \pi\tau_{pt} + \varepsilon_{pjt}, \tag{9}$$

where Y_{pjt} denotes the log of plant p's shipment of product j, and Δ denotes time difference between year t and year $t+1$. $\overline{RPRA\_X_J}$ denotes the time-invariant PRA measure relative to the industry median value as defined in equation (3). We also include the log of plant p's shipment of product j at year t in order to control for the initial shipment size of the product. $\pi\tau$ denotes the set of plant–year dummies that control for time-variant plant-specific characteristics. In addition, we also use the non-relative time-invariant PRA measure defined in equation (2) as an explanatory variable instead of the relative time-invariant PRA measure as a robustness check.

Alternatively, we also estimate the following equation (9') using the shipment share of product j in plant p's total shipments as a dependent variable instead of shipment growth rate.

$$\Delta\omega_{pjt} = \beta \overline{RPRA\_X}_j + \gamma Z_{pt} + \pi_p + \tau_t + \varepsilon_{pjt}, \tag{9'}$$

where ω_{pjt} is the shipment share of product j in plant p's total shipments in year t, as defined in equation (4), and Δ denotes time difference between year t and year $t+1$. For the plant characteristics, $Z_{pt,}$ we include TFP (log), number of workers (log), young plant dummy, capital–labor ratio (log), and multiproduct plant dummy. We also control for the plant-specific fixed effects and year-specific fixed effects.

Table 5 shows the estimation results for equation (9). We find that the estimated coefficient of the PRAs is positive and statistically significant for most cases, suggesting that products with higher PRAs tend to have a higher shipment growth rate. Although the estimated coefficient of the PRA variable in the alternative specification as in equation (9’) is not statistically significant in many cases as shown in Appendix Table 2, the results for equation (9’) do not contradict the results for equation (9) shown in Table 5.

INSERT Table 5

VI.3 Which Channel is Important?

The above analyses indicate that in general, products with higher PRAs are more likely to be added and that shipments of the products with higher PRAs tend to increase more than those of the products with lower PRAs within a plant. Then, which channel, product adding/dropping or share changes among continuing products, is more important to explain the improvement in PAPRAs for export starters?

In order to answer this question, we construct several measures that should capture the degree of product composition changes within the plant. As for the product adding/dropping channel, we construct the following four measures: the number of added products for each plant, the number of dropped products for each plant, the product adding rate, and the product dropping rate. For the share change channel, we compute the sum of the absolute share changes for a plant. Then, we conduct a PSM-DID estimation as explained in Section IV.1 using the measures of product compositional changes as the outcome variables.

We count the number of added products and dropped products between year *t-1* and year *t+s* for each plant, where year *t* denotes the export participation year and the subscript *s* is the number of years that have passed after export participation. The adding rate at year *t+s* is defined as total shipments of added products between year *t-1* and year *t+s* divided by total shipments of the plant at year *t+s*. Similarly, the dropping rate at year *t+s* is defined as total shipments of dropped products between year *t-1* and year *t+s* divided by total shipments of the plant at year *t-1*.

As for the share change channel, we compute the sum of the absolute share changes (ASCs) for a plant, which is defined as:

$$\sum_j \left| s_{pj,t+s} - s_{pj,t-1} \right|,$$

where $s_{pj,t}$ denotes the share of product *j* in the total shipments of plant *p* in year *t*. If a single-product plant drops a product or introduces a new product during the periods *t-1* and *t+s*, the share of dropped product at the ending year of the period should be zero while the share of introduced product at the beginning year of the period should be zero. The absolute share change of product *j* for plant *p* therefore takes a value between zero and two. We sum up the ASCs for all the products produced by each plant – the larger the value of the share changes, the more drastically plants change their product composition. Moreover, we calculate the sum of the ASCs only for continuing products for a plant in order to examine the shipment share changes for continuing products. This measure is defined as:

$$\sum_{j \in C_j} \left| s_{pj,t+s} - s_{pj,t-1} \right|,$$

where C_j denotes the set of continued products for each plant.

The PSM-DID results are shown in Table 6.[24] We find a strong positive effect of exporting on product adding. Export starters are also more likely to drop products than non-exporters. Probably reflecting the fact that export starters are more likely to both add and drop products, export starters also show higher shipment share changes (ASC).

The effect of exporting on ASC for continuing products is also significant in many cases. However, the magnitude of the effect on ASC for continuing products is much smaller than that on ASC including added and dropped products, implying that the continuing products' share change channel is likely to be activated by exporting but less strongly than the adding/dropping channel. That is, our results suggest that export starters are more likely to upgrade their product portfolio mainly through adding and dropping products. Although export starters are likely to upgrade their product portfolio through increasing the shipment share of continuing products with high PRAs, the adding/dropping channel seems to be stronger.

INSERT Table 6

VI.4 Differences across periods or industries

The above estimation results show that exporters tend to produce, on average, products with higher product attributes than non-exporters do. We also find that export starters are more likely to upgrade their product portfolio mainly through adding of higher-attribute products and dropping of lower-attribute products. Although the results for the period 2002–2007 and for the period 2008–2013 are broadly similar and consistent, in this sub-section, we will investigate whether there are any differences between the two periods. We also investigate whether plants

[24] Although we report the results based on the observations matched using the one-to-one nearest matching technique, we also tried to employ other matching methods. We performed the radius matching technique using the caliper = 0.001 and caliper = 0.0001, and the results were very similar and consistent to those shown in Table 6.

in ICT intensive industries perform differently compared to other plants, given the fact that ICT intensive industries are characterized by rapid technological progress and advancement.

Panels A and B of Figure 1 show the average changes in the relative PAPRAs and the non-relative PAPRAs, respectively. The figures show the mean value of the changes in PAPRAs after export participation. The horizontal axis of the figures indicates the export participation year (0), one year after (+1), two years after (+2), and three years after (+3) the export participation. We calculate the cumulative change in PAPRAs for each plant from one year before export participation, and then calculate the average value of the cumulative changes for each year after the event. Although the trajectories differ across PAPRA measures, PAPRAs tend to grow more for the period 2002–2007 than for the period 2008–2013. On the other hand, Panel C of Figure 1 and Table 7 indicate that product adding and dropping are equally or slightly more active for the period 2008–2013 than for the period 2002–2007.

INSERT Figure 1 & Table 7

How can we interpret such differences between the two periods? As we have already found in Table 4, added products tend to have higher PRAs than dropped products. However, the differences in PRAs between added and dropped products tend to be smaller for the period 2008–2013 than for the period 2002–2007, because the estimated coefficient of the ADD dummy variable in Table 4 tend to be smaller for the period 2008–2013 than for the period 2002–2007. Therefore, although plants are actively add and drop products during the period 2008–2013, the destruction might be less “creative” for the period 2008–2013 than for the period 2002–2007. In other words, for the period 2002–2007, plants may add much higher-attribute products and drop much lower-attribute products, compared to the period 2008–2013.

Although the above results suggest that starting exporting is likely to promote product adding/dropping and contribute to product portfolio upgrading for the both periods, the creative destruction process seems to be weaker for the period 2008–2013.

Moreover, as shown in Table 8, the share of export starters becomes lower for the period 2008–2013 than for the period 2002–2007, while the share of export stoppers becomes larger. Although the share of continuing exporters is larger for period 2008–2013, the decrease in the number of export starters and the increase in the number of export stoppers may also imply the fact that the exporting-induced creative destruction process has been somewhat weakened for the period 2008–2013.

INSERT Table 8

We also conduct the same analyses as above, focusing on plants in ICT-intensive industries.[25] The results for the plants in the ICT-intensive industries are shown in Appendix Figure 1 and Appendix Tables 3–6. The results for the plants in the ICT-intensive industries are broadly consistent to those for all the plants. However, as shown in Appendix Table 4, PRAs for added products are not significantly different from those for dropped products in the case of ICT-intensive industries. Moreover, the results in Panel B of Appendix Table 5 are somewhat weak, implying that in the case of the period 2008–2013, the shipment growth rate for continuing products with higher PRAs is not strongly higher. Therefore, although plants in the ICT-intensive industries tend to change their product compositions much more frequently than plants in other industries (Panel C of Figure 1 and Table 7), the creative destruction through product adding and dropping may not work very well.

[25] Based on the ICT investment by sector data taken from the JIP Database 2015, we define electrical machinery, computers and electronics, and precision machinery industries as the ICT-intensive industries.

It is beyond the scope of this paper to analyze possible reasons why the creative destruction process seems to be weakened in more recent period and in the ICT-intensive industries. However, one possible reason would be related to the quality or attributes of imported products. We calculated a sophistication measure for Japanese exports for years 2000–2015 using the same methodology as Hausmann, Hwang, and Rodrik (2008).[26] As in Hausmann, Hwang, and Rodrik (2008), we interpret EXPY in their paper as a proxy for the degree of sophistication of exported products. Although EXPY usually calculated using the export share of each product for each country, we also calculate EXPY using the import share, which we interpret as the degree of sophistication of imported products. Figure 2 shows the sophistication index for Japan from both the perspectives of exported and imported goods. Panel (a) of Figure 2 shows the index calculated using all the exported and imported goods while Panel (b) of Figure 2 shows the index calculated using only ICT-related products.[27] Looking at Figure 2, the sophistication index for ICT-related imported goods is slightly higher than that for ICT-related exported goods (Panel (b)), although the sophistication index for imported goods is much lower than that for exported goods when we take all the products into account (Panel (a)). Moreover, the sophistication index for imported goods seems to be increasing more than that for exported goods in both panels.

INSERT Figure 2

Thus, Figure 2 implies that Japan's imported goods has been increasingly sophisticated and such an increase in imported goods may have affected the choice of added and dropped

[26] We use the HS 6-digit level exports and imports data for all the countries in the world, which are taken from the Harvard Dataverse (The Growth Lab at Harvard University, 2019). We take the GDP per capita data from the CEPII's CHELEM GDP Database (De Saint Vaulry 2008). Using these data and the "prody" and "expy" programs for Stata (Huber 2017), we calculate the sophistication index for Japan.

[27] We follow the "ICT Goods Categories and Composition (HS1992)" defined by the United Nations Conference on Trade and Development (UNCTAD).

products at Japanese plants and firms. The impact of imported goods on the upgrading of product portfolio would require further scrutiny, particularly for the ICT-intensive industries.

VII. Summary and Concluding Remarks

The past economic growth process of Japan was undoubtedly accompanied by a Schumpeterian creative destruction process: the introduction of new goods and dropping of old goods. This paper examines whether exporting activity contributes to promoting product adding/dropping and the upgrading of a plant's product portfolio.

To do so, we measure product "attributes" using the productivity and factor intensities of plants that produce the corresponding product. We first examine whether exporters tend to produce, on average, products with higher PRAs than non-exporters, and we find significant and positive exporter premia. Next, we find evidence that exporting increases a plant's average PRAs (in other words promotes specialization toward products with higher attributes), utilizing the PSM-DID technique. Further examination of the mechanism reveals that the positive effect of exporting on a plant's average PRAs is realized through its effect on adding higher-attribute products, a key feature of creative destruction within a firm. However, we also find that such a creative destruction process seems to be weakened in the more recent period from 2008 to 2013, compared to the period 2002–2007, and that the process seems to be also weaker for plants in the ICT-intensive industries than for those in other industries.

To the best of our knowledge, this paper is unique in that it shows that exporting improves a plant's average PRAs, particularly through its effect on the adding of higher-attribute products. This paper's finding differs from existing studies in that the product scope expansion is in response to exporting. The empirical results of this paper imply that exporting has contributed to the *sustained* economic growth by promoting creative destruction, particularly if a continual shift to new products with higher learning potential is a necessary condition for sustained economic growth.

Last but not least, we should mention a couple of limitations of this study. First, we do not take export market conditions into account in this study because of various data constraints in the Japanese manufacturing census. We cannot identify which products are exported to which country, though we have information on the export share of total shipment at the plant level. The creative destruction can be promoted not only through supply-side technological development but also through demand-side factors such as learning from foreign customers. We need to pay more attention to demand-side factors to analyze the creative destruction process more thoroughly in the future studies. Second, as mentioned in the last section, the upgrading of imported products may affect the decision on product adding and dropping by a plant or a firm. Although we cannot take imports into account in this paper because information on imports is not available in the census, the impact of imports would be another important issue to be incorporated in the future study.

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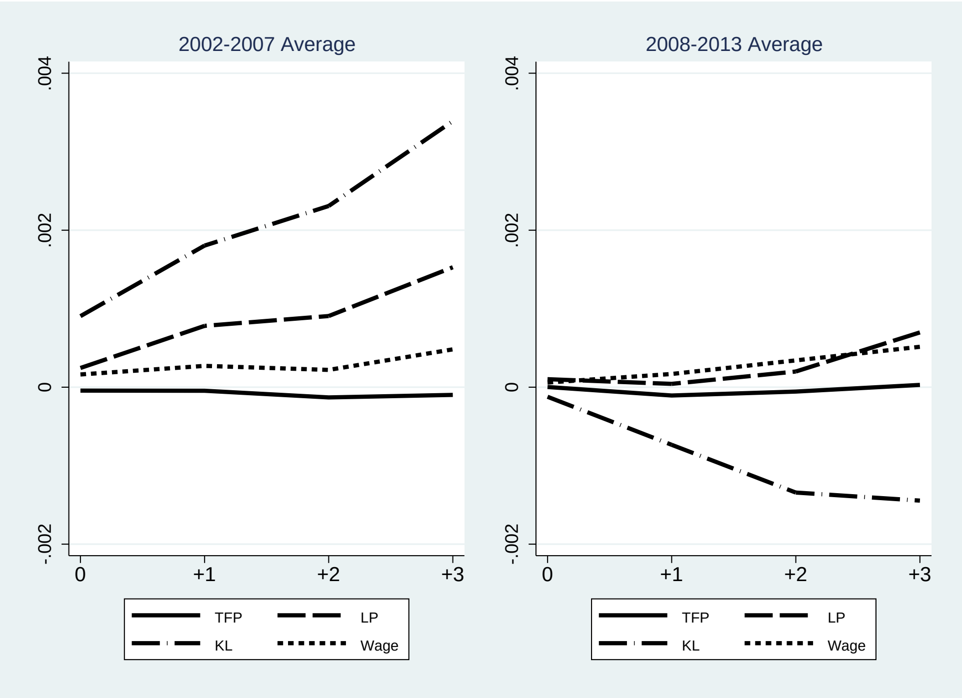
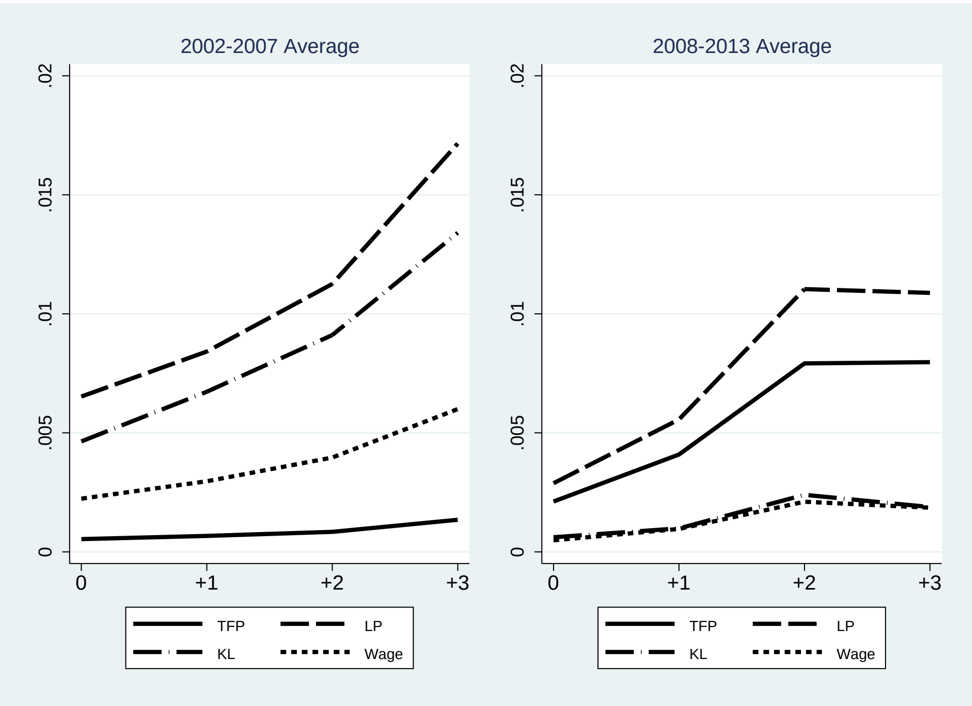
Figure 1. Comparison between Two Periods

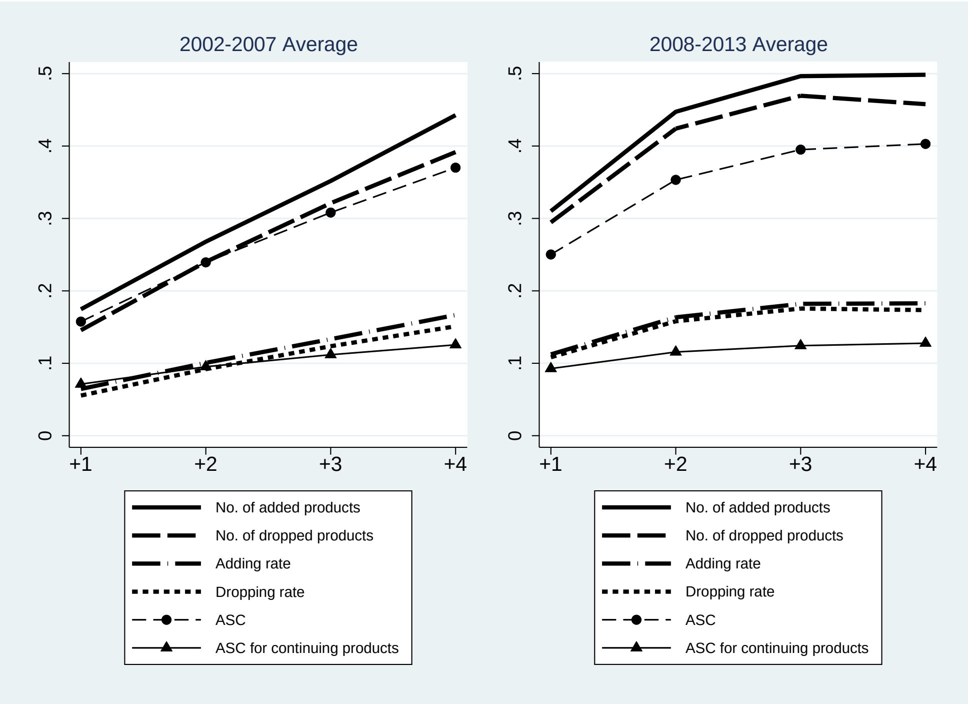
Panel A: Changes in Relative PAPRAs



Panel B: Changes in Non-Relative PAPRAs

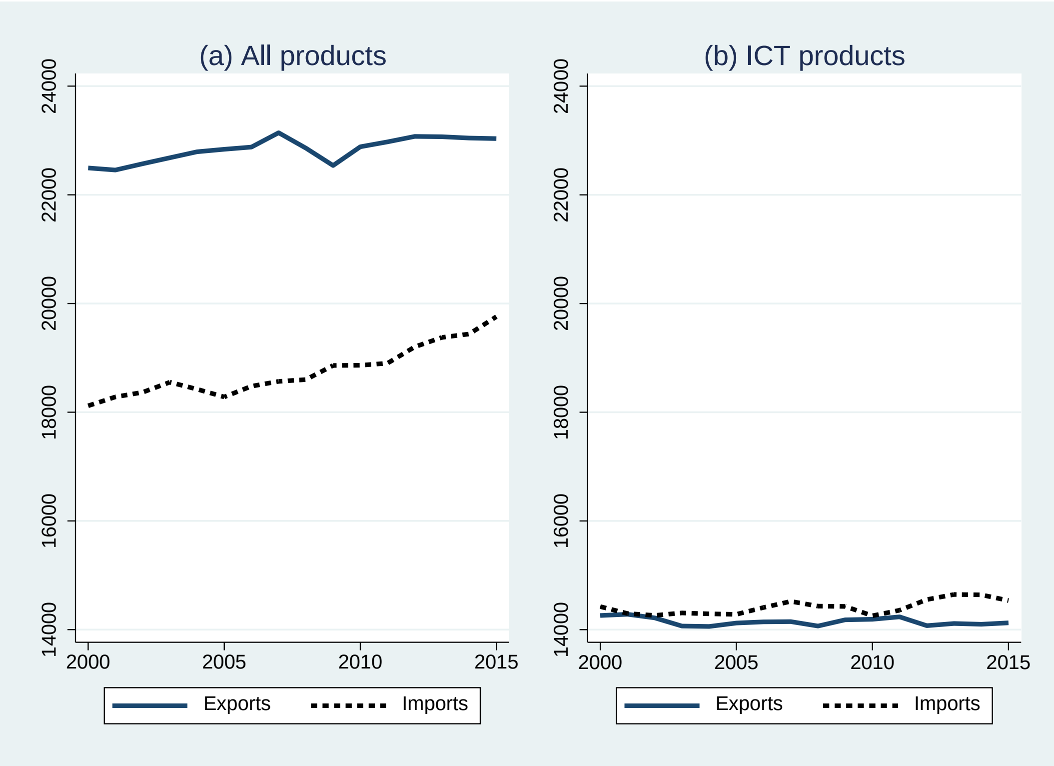


Panel C: Product Addition and Dropping



(Source) Authors' calculations based on the micro data underlying the *Census of Manufactures* conducted by the METI and the *Economic Census for Business Activity* jointly conducted by the MIC and the METI.

Figure 2. Product Sophistication Index for Japan: 2000-2015



(Source) Authors' calculations.

Table 1. Exporter Premia

Panel A1: Cross-section estimation for year 2005

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Relative to industry median and time-invariant				Non-relative and time-invariant			
PRA measured by:	TFP	LP	KL	Wage	TFP	LP	KL	Wage
EXPDUM	0.020***	0.144***	0.208***	0.067***	0.020***	0.146***	0.208***	0.069***
	(0.003)	(0.015)	(0.022)	(0.007)	(0.003)	(0.014)	(0.022)	(0.007)
Industry FE (4-digit)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No	No	No
Plant FE	No	No	No	No	No	No	No	No
SE clustering	Plant's industry							
N	46,028	46,028	46,028	46,028	46,028	46,028	46,028	46,028
r2	0.581	0.490	0.373	0.418	0.692	0.717	0.664	0.757

Panel A2: Fixed-effect panel estimation for 2002-2007

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Relative to industry median and time-invariant				Non-relative and time-invariant			
PRA measured by:	TFP	LP	KL	Wage	TFP	LP	KL	Wage
EXPDUM	-0.001*	0.003	0.004**	0.002**	-0.001	0.007***	0.006***	0.002***
	(0.000)	(0.002)	(0.002)	(0.001)	(0.000)	(0.002)	(0.002)	(0.001)
Industry FE (4-digit)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE clustering	Plant							
N	279,367	279,367	279,367	279,367	279,367	279,367	279,367	279,367
r2	0.160	0.144	0.135	0.136	0.197	0.183	0.163	0.142

Panel B1: Cross-section estimation for year 2011

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Relative to industry median and time-invariant				Non-relative and time-invariant			
PRA measured by:	TFP	LP	KL	Wage	TFP	LP	KL	Wage
EXPDUM	0.003	0.109***	0.172***	0.051***	0.037***	0.157***	0.192***	0.059***
	(0.003)	(0.008)	(0.014)	(0.003)	(0.005)	(0.011)	(0.015)	(0.004)
Industry FE (4-digit)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No	No	No
Plant FE	No	No	No	No	No	No	No	No
SE clustering	Plant's industry							
N	44,706	44,706	44,706	44,706	44,706	44,706	44,706	44,706
r2	0.562	0.485	0.437	0.483	0.376	0.603	0.680	0.779

Panel B2: Fixed-effect panel estimation for 2008-2011

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Relative to industry median and time-invariant				Non-relative and time-invariant			
PRA measured by:	TFP	LP	KL	Wage	TFP	LP	KL	Wage
EXPDUM	0.000	0.004**	0.003	0.001	0.014***	0.022***	0.010***	0.004***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.003)	(0.001)
Industry FE (4-digit)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE clustering	Plant							
N	265,997	265,997	265,997	265,997	265,997	265,997	265,997	265,997
r2	0.247	0.193	0.185	0.218	0.068	0.104	0.230	0.187

Notes: Standard errors in parentheses.
* p<0.10 ** p<0.05 *** p<0.01

Source: Authors' calculations based on the micro data underlying the *Census of Manufactures* conducted by the METI and the *Economic Census for Business Activity* jointly conducted by the MIC and the METI.

Table 2. Determinants of Starting Exporting: Probit Estimation Results

Dependent variable: Export starter dummy

Explanatory variables	(1) Period 2002-2007 Coef.		(2) Period 2008-2013 Coef.	
lnTFP (-1)	0.446	***	0.242	***
	(0.034)		(0.032)	
ln(employment) (-1)	0.265	***	0.234	***
	(0.014)		(0.017)	
Multi-product plant (-1)	0.100	***	0.018	
	(0.024)		(0.031)	
lnKL (-1)	0.108	***	0.093	***
	(0.011)		(0.013)	
YOUNG (-1)	0.057		0.249	***
	(0.040)		(0.043)	
Added(-1)	-0.146	***	0.103	**
	(0.047)		(0.046)	
Dropped(-1)	-0.170	***	0.214	***
	(0.046)		(0.044)	
2-digit industry dummies	Yes		Yes	
Number of obs.	33,796		27,764	
LR	2217.06		980.95	
Pseudo R2	0.1335		0.0988	
Log likelihood	-7197.9493		-4474.5711	

Notes: Standard errors in parentheses.
*, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.

Source: Authors' calculations based on the micro data underlying the *Census of Manufactures* conducted by the METI and the *Economic Census for Business Activity* jointly conducted by the MIC and the METI.

Table 3. Estimated Effects of Starting Exporting: Cumulative Effects on Product-Attribute-Based Plant Performance

Panel A: 2002-2007

Outcome variables	s=0	s=1	s=2	s=3
TFP_dev	0.000	0.000	0.000	0.000
LP_dev	0.003	0.005	0.003	0.005
KL_dev	0.005	0.007	0.006	0.005
wage_dev	0.001	0.003 *	0.002	0.002
TFP	0.001	0.001	0.000	-0.002
LP	0.022 ***	0.013 ***	0.010	-0.012
KL	0.015 ***	0.009 *	0.007	-0.003
wage	0.006 ***	0.003 *	0.004 *	-0.003

Panel B: 2008-2013

Outcome variables	s=0	s=1	s=2	s=3
TFP_dev	0.002	-0.008 **	0.001	-0.003
LP_dev	0.009	0.007	0.020 **	0.016
KL_dev	-0.001	0.010	0.005	-0.009
wage_dev	0.001	0.003	0.001	-0.002
TFP	0.012 ***	0.012	0.013 *	0.005
LP	0.028 ***	0.037 ***	0.041 ***	0.031
KL	0.013	0.026 **	0.023 *	-0.002
wage	0.005 **	0.008 **	0.003	-0.002

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.
Confidence intervals were calculated based on bootstrapping method with 1,000 repetitions.
Nearest neighbor matching with no common support restriction.
Source: Authors’ calculations based on the micro data underlying the *Census of Manufactures* conducted by the METI and the *Economic Census for Business Activity* jointly conducted by the MIC and the METI.

Table 4. Comparison of Product Attributes between Added and Dropped Products

Panel A: All plants for 2002-2007

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PRA	Relative to industry median and time-invariant				Non-relative and time-invariant			
	TFP	LP	KL	Wage	TFP	LP	KL	Wage
ADD	0.002*	0.010***	0.016***	0.003	0.008***	0.073***	0.061***	0.021***
	(0.001)	(0.004)	(0.005)	(0.002)	(0.001)	(0.005)	(0.006)	(0.002)
Year FE	No	No	No	No	No	No	No	No
Plant FE	No	No	No	No	No	No	No	No
Plant*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	49,680	49,680	49,680	49,680	49,680	49,680	49,680	49,680
r2	0.415	0.512	0.522	0.553	0.535	0.603	0.653	0.664
r2_within	0.000	0.000	0.000	0.000	0.001	0.006	0.003	0.003

Panel B: All plants for 2008-2013

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PRA	Relative to industry median and time-invariant				Non-relative and time-invariant			
	TFP	LP	KL	Wage	TFP	LP	KL	Wage
ADD	-0.001	0.001	-0.001	0.001	0.013***	0.022***	0.009**	0.004***
	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.004)	(0.004)	(0.001)
Year FE	No	No	No	No	No	No	No	No
Plant FE	No	No	No	No	No	No	No	No
Plant*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	94,930	94,930	94,930	94,930	94,930	94,930	94,930	94,930
r2	0.363	0.427	0.445	0.461	0.364	0.459	0.570	0.597
r2_within	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Added and dropped observations only. Continuous products are not included.
Standard errors in parentheses. Clustered for plants.
* $p<0.10$ ** $p<0.05$ *** $p<0.01$

Source: Authors’ calculations based on the micro data underlying the *Census of Manufactures* conducted by the METI and the *Economic Census for Business Activity* jointly conducted by the MIC and the METI.

Table 5. Shipment Growth for Continuing Products

Dependent variable: Annual growth rate of product shipments from 2002 to 2007

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Relative to industry median and time-invariant				Non-relative and time-invariant			
VARIABLES	TFP	LP	KL	Wage	TFP	LP	KL	Wage
PRA (j)	0.037***	0.023***	0.011***	0.048***	0.011	0.028***	0.037***	0.081***
	(0.011)	(0.004)	(0.003)	(0.009)	(0.010)	(0.003)	(0.002)	(0.008)
ln(product shipment) (pjt)	-0.037***	-0.037***	-0.037***	-0.037***	-0.036***	-0.037***	-0.037***	-0.037***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year dummies	No	No	No	No	No	No	No	No
Plant dummies	No	No	No	No	No	No	No	No
Plant*Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	324,174	324,174	324,174	324,174	324,174	324,174	324,174	324,174
r2	0.324	0.324	0.324	0.324	0.324	0.324	0.324	0.324
r2_within	0.012	0.012	0.012	0.012	0.011	0.012	0.012	0.012

Panel B: All plants for 2008-2013

Dependent variable: Annual growth rate of product shipments from 2008 to 2013

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Relative to industry median and time-invariant				Non-relative and time-invariant			
VARIABLES	TFP	LP	KL	Wage	TFP	LP	KL	Wage
PRA (j)	0.013	0.029***	0.016***	0.045***	-0.025*	0.018***	0.022***	0.036***
	(0.016)	(0.005)	(0.003)	(0.013)	(0.013)	(0.004)	(0.003)	(0.010)
ln(product shipment) (pjt)	-0.050***	-0.050***	-0.050***	-0.050***	-0.050***	-0.050***	-0.051***	-0.050***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Year dummies	No	No	No	No	No	No	No	No
Plant dummies	No	No	No	No	No	No	No	No
Plant*Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	125,617	125,617	125,617	125,617	125,617	125,617	125,617	125,617
r2	0.429	0.429	0.429	0.429	0.429	0.429	0.429	0.429
r2_within	0.018	0.018	0.018	0.018	0.018	0.018	0.019	0.018

Standard errors in parentheses. Clustered for plants.

*** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations based on the micro data underlying the *Census of Manufactures* conducted by the METI and the *Economic Census for Business Activity* jointly conducted by the MIC and the METI.

Table 6. Estimated Effects of Starting Exporting: Effects on Product Compositional Changes

Panel A: Period 2002–2007

Outcome variables	s=0	s=1	s=2	s=3
Number of Added Products	0.198 ***	0.198 ***	0.204 ***	0.070 *
Number of Dropped Products	0.061 ***	0.067 ***	0.096 ***	0.062 *
Adding Rate	0.061 ***	0.052 ***	0.049 ***	0.001
Dropping Rate	0.023 ***	0.022 ***	0.022 **	0.003
ASC	0.082 ***	0.066 ***	0.057 ***	-0.007
ASC for continuing products	0.025 ***	0.023 ***	0.020 ***	0.001

Panel B: Period 2008–2013

Outcome variables	s=0	s=1	s=2	s=3
Number of Added Products	0.477 ***	0.238 ***	0.482 ***	0.570 ***
Number of Dropped Products	0.272 ***	-0.126 ***	0.176 ***	0.119
Adding Rate	0.129 ***	0.022	0.088 ***	0.073 ***
Dropping Rate	0.100 ***	-0.023	0.064 ***	0.039 *
ASC	0.211 ***	0.020	0.136 ***	0.100 **
ASC for continuing products	0.040 ***	0.004	0.032 ***	0.013

Notes: *, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively.
Confidence intervals were calculated based on bootstrapping method with 1,000 repetitions.
Nearest neighbor matching with no common support restriction.

Source: Authors' calculations based on the micro data underlying the *Census of Manufactures* conducted by the METI and the *Economic Census for Business Activity* jointly conducted by the MIC and the METI.

Table 7. Average Product Adding & Dropping and Absolute Share Changes

Panel A: Period 2002−2007

	From 2003 to 2005 (Average of 2-year changes)		From 2003 to 2006 (Average of 3-year changes)	
	All industries	ICT industries	All industries	ICT industries
Number of Added Products	0.22	0.32	0.29	0.42
Number of Dropped Products	0.23	0.33	0.31	0.44
Adding Rate	0.09	0.13	0.11	0.17
Dropping Rate	0.09	0.13	0.12	0.18
ASC	0.23	0.34	0.29	0.43
ASC for continuing products	0.09	0.11	0.11	0.13

Panel B: Period 2008–2013

	From 2009 to 2011 (Average of 2-year changes)		From 2009 to 2012 (Average of 3-year changes)	
	All industries	ICT industries	All industries	ICT industries
Number of Added Products	0.32	0.70	0.43	0.58
Number of Dropped Products	0.33	0.72	0.39	0.55
Adding Rate	0.13	0.25	0.16	0.21
Dropping Rate	0.13	0.26	0.15	0.21
ASC	0.34	0.55	0.35	0.50
ASC for continuing products	0.11	0.14	0.12	0.15

Source: Authors' calculations based on the micro data underlying the *Census of Manufactures* conducted by the METI and the *Economic Census for Business Activity* jointly conducted by the MIC and the METI.

Table 8. Share of Plants by Export Status

Panel A: Period 2002−2007

	All industries		Non-ICT industries		ICT industries	
	Number of plants	Share (%)	Number of plants	Share (%)	Number of plants	Share (%)
Never exporters	52,739	(87.0)	45,597	(88.2)	7,977	(79.5)
Always exporters	3,394	(5.6)	2,483	(4.8)	986	(9.8)
Export starters	2,512	(4.1)	1,996	(3.9)	603	(6.0)
Export stoppers	711	(1.2)	562	(1.1)	172	(1.7)
Other	1,281	(2.1)	1,031	(2.0)	302	(3.0)
Total number of plants	60,637		51,669		10,040	

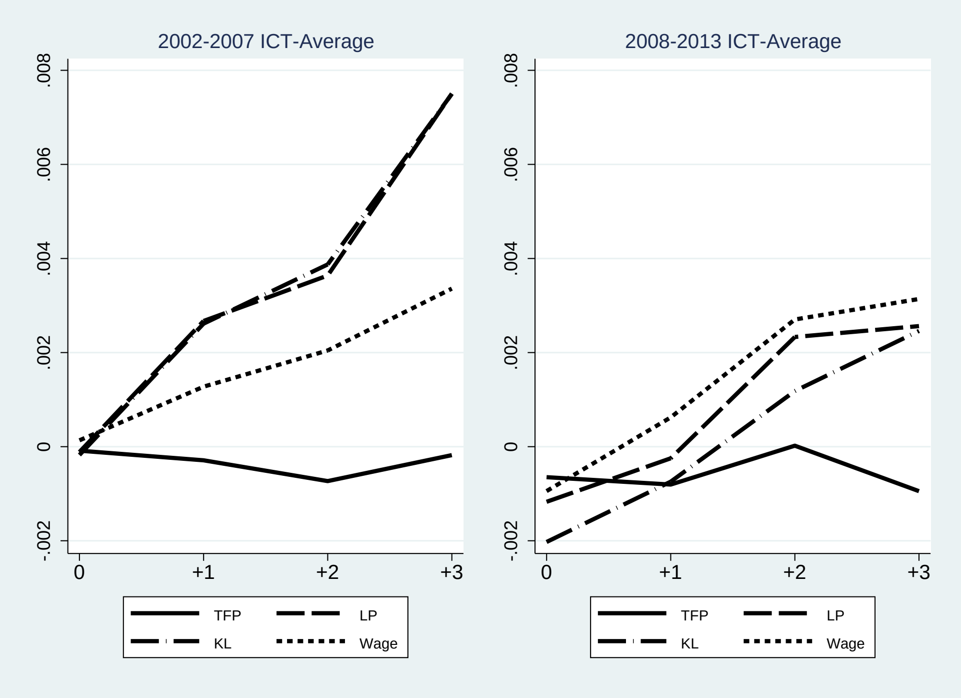
Panel B: Period 2008–2013

	All industries		Non-ICT industries		ICT industries	
	Number of plants	Share (%)	Number of plants	Share (%)	Number of plants	Share (%)
Never exporters	52,133	(84.6)	45,175	(85.9)	7,934	(76.8)
Always exporters	4,483	(7.3)	3,413	(6.5)	1,208	(11.7)
Export starters	1,495	(2.4)	1,217	(2.3)	337	(3.3)
Export stoppers	1,208	(2.0)	969	(1.8)	274	(2.7)
Other	2,271	(3.7)	1,817	(3.5)	574	(5.6)
Total number of plants	61,590		52,591		10,327	

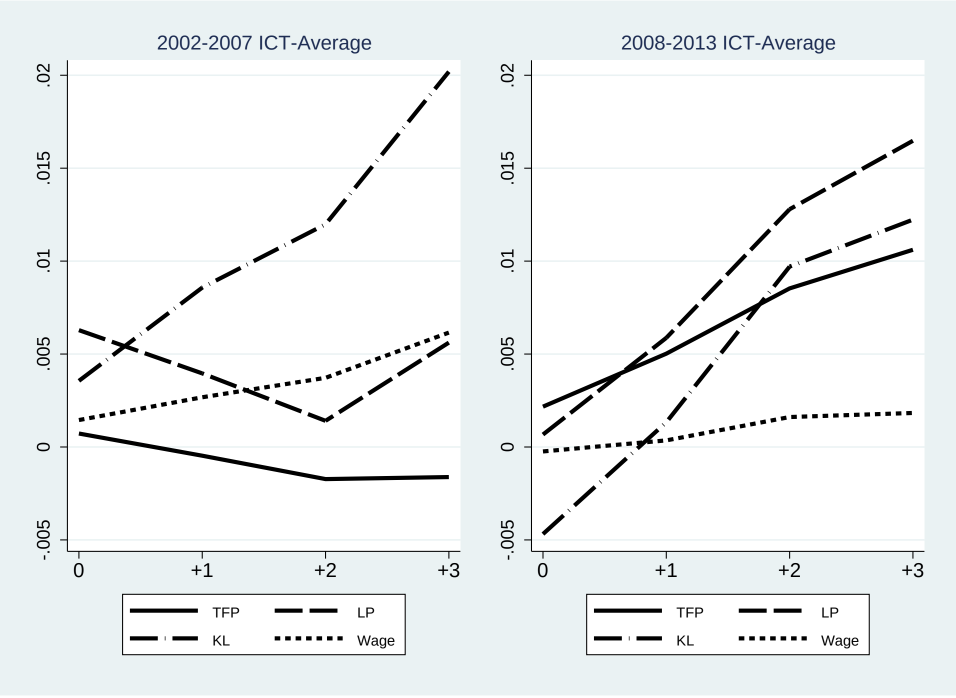
Source: Authors' calculations based on the micro data underlying the *Census of Manufactures* conducted by the METI and the *Economic Census for Business Activity* jointly conducted by the MIC and the METI.

Appendix Figure 1. Comparison between Two Periods (ICT intensive industries)

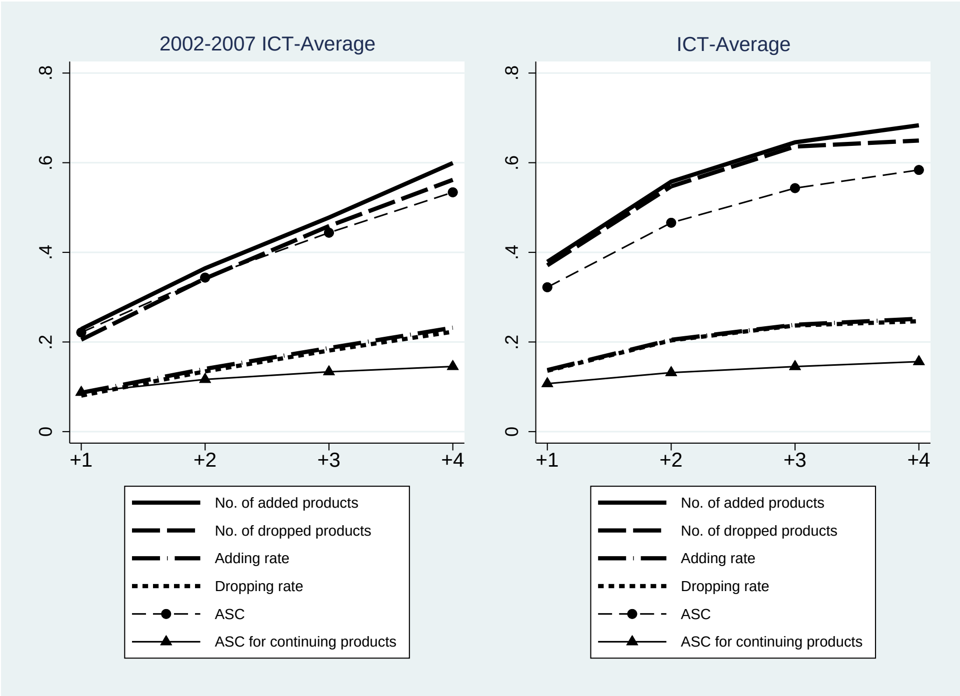
Panel A: Changes in Relative PAPRAs



Panel B: Changes in Non-Relative PAPRAs



Panel C: Product Addition and Dropping



Source: Authors' calculations based on the micro data underlying the *Census of Manufactures* conducted by the METI and the *Economic Census for Business Activity* jointly conducted by the MIC and the METI.

Appendix Table 1. Product Adding and Dropping at the Plant Level or at the Firm Level

Panel A: Period 2002−2007

	Number products for the period 2002–2007					
	Products produced at Form A plants used for the analyses in this paper (plants with 30 or more employees)			Products produced at Form A & B plants (plants with 4 or more employees)		
	Firm level (a)	Plant level (b)	Ratio (a)/(b) (%)	Firm level (a)	Plant level (b)	Ratio (a)/(b) (%)
Added	24,115	29,908	80.6	181,991	202,032	90.1
Dropped	19,061	23,631	80.7	166,142	182,874	90.9

Panel B: Period 2008−2013

	Number products for the period 2008–2013					
	Products produced at Form A plants used for the analyses in this paper (plants with 30 or more employees)			Products produced at Form A & B plants (plants with 4 or more employees)		
	Firm level (a)	Plant level (b)	Ratio (a)/(b) (%)	Firm level (a)	Plant level (b)	Ratio (a)/(b) (%)
Added	39,185	50,702	77.3	239,647	277,540	86.3
Dropped	37,807	45,269	83.5	231,307	246,121	94.0

Source: Authors' calculations based on the micro data underlying the *Census of Manufactures* conducted by the METI and the *Economic Census for Business Activity* jointly conducted by the MIC and the METI.

Appendix Table 2. Shipment Share Changes Across Continuing Products

Panel A: All plants for 2002-2007

Dependent variable: Shipment share changes (plant-product, from t to t+1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Relative to industry median and time-invariant				Non-relative and time-invariant			
	TFP	LP	KL	Wage	TFP	LP	KL	Wage
PRA	-0.002	0.000	0.000	0.001	-0.003**	0.000	0.002***	0.003***
	(0.002)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)
lnTFP	0.013***	0.013***	0.013***	0.013***	0.013***	0.013***	0.013***	0.013***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
lnemp	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
YOUNG	0.003**	0.003**	0.003**	0.003**	0.003**	0.003**	0.003**	0.003**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
MP	0.131***	0.131***	0.131***	0.131***	0.131***	0.131***	0.131***	0.131***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
lnKL	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	387,465	387,465	387,465	387,465	387,465	387,465	387,465	387,465
r2	0.098	0.098	0.098	0.098	0.098	0.098	0.098	0.098
r2_within	0.028	0.028	0.028	0.028	0.028	0.028	0.029	0.029

Panel B: All plants for 2008-2013
Dependent variable: Shipment share changes (plant-product, from t to t+1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Relative to industry median and time-invariant				Non-relative and time-invariant			
	TFP	LP	KL	Wage	TFP	LP	KL	Wage
PRA	0.001	0.001*	0.000	-0.001	-0.004**	0.001	0.001***	0.000
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.000)	(0.001)
lnTFP	0.024***	0.024***	0.024***	0.024***	0.024***	0.024***	0.024***	0.024***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
lnemp	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***	0.014***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
YOUNG	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
MP	0.166***	0.166***	0.166***	0.166***	0.166***	0.166***	0.166***	0.166***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
lnKL	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	166,317	166,317	166,317	166,317	166,317	166,317	166,317	166,317
r2	0.125	0.125	0.125	0.125	0.125	0.125	0.125	0.125
r2_within	0.053	0.053	0.053	0.053	0.053	0.053	0.053	0.053

Standard errors in parentheses. Clustered for plants.
* p<0.10 ** p<0.05 *** p<0.01

Source: Authors' calculations based on the micro data underlying the *Census of Manufactures* conducted by the METI and the *Economic Census for Business Activity* jointly conducted by the MIC and the METI.

Appendix Table 3. Exporter Premia (ICT Intensive industries)

Panel A1: ICT intensive industries (Electronics & Precision machinery) (Cross-section estimation for year 2005)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Relative to industry median and time-invariant				Non-relative and time-invariant			
PRA measured by:	TFP	LP	KL	Wage	TFP	LP	KL	Wage
EXPDUM	0.038***	0.274***	0.385***	0.140***	0.037***	0.268***	0.385***	0.141***
	(0.007)	(0.036)	(0.054)	(0.017)	(0.007)	(0.035)	(0.053)	(0.017)
Industry FE (4-digit)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No	No	No
Plant FE	No	No	No	No	No	No	No	No
SE clustering	Plant's industry							
N	7,022	7,022	7,022	7,022	7,022	7,022	7,022	7,022
r2	0.309	0.276	0.238	0.296	0.368	0.387	0.276	0.247

Panel A2: ICT intensive industries (Electronics & Precision machinery) (Fixed-effect panel estimation for 2002-2007)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Relative to industry median and time-invariant				Non-relative and time-invariant			
PRA measured by:	TFP	LP	KL	Wage	TFP	LP	KL	Wage
EXPDUM	-0.003**	0.003	0.010*	0.002	-0.004***	0.008	0.016**	0.004
	(0.001)	(0.004)	(0.006)	-0.002	(0.001)	(0.005)	(0.006)	(0.002)
Industry FE (4-digit)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE clustering	Plant							
N	43,057	43,057	43,057	43,057	43,057	43,057	43,057	43,057
r2	0.152	0.097	0.062	0.083	0.161	0.156	0.104	0.064

Panel B1: ICT intensive industries (Electronics & Precision machinery) (Cross-section estimation for year 2011)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Relative to industry median and time-invariant				Non-relative and time-invariant			
PRA measured by:	TFP	LP	KL	Wage	TFP	LP	KL	Wage
EXPDUM	0.017**	0.189***	0.287***	0.103***	0.063***	0.252***	0.309***	0.110***
	(0.007)	(0.017)	(0.027)	(0.008)	(0.011)	(0.023)	(0.028)	(0.008)
Industry FE (4-digit)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	No	No	No	No	No
Plant FE	No	No	No	No	No	No	No	No
SE clustering	Plant's industry							
N	6,740	6,740	6,740	6,740	6,740	6,740	6,740	6,740
r2	0.441	0.356	0.241	0.300	0.254	0.277	0.348	0.280

Panel B2: ICT intensive industries (Electronics & Precision machinery) (Fixed-effect panel estimation for 2008-2013)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Relative to industry median and time-invariant				Non-relative and time-invariant			
PRA measured by:	TFP	LP	KL	Wage	TFP	LP	KL	Wage
EXPDUM	0.000	0.007	0.014**	0.003*	0.015**	0.026***	0.022***	0.005***
	(0.002)	(0.005)	(0.006)	(0.002)	(0.006)	(0.009)	(0.007)	(0.002)
Industry FE (4-digit)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
SE clustering	Plant							
N	39,826	39,826	39,826	39,826	39,826	39,826	39,826	39,826
r2	0.226	0.143	0.107	0.116	0.076	0.097	0.199	0.125

Source: Authors' calculations based on the micro data underlying the *Census of Manufactures* conducted by the METI and the *Economic Census for Business Activity* jointly conducted by the MIC and the METI.

Appendix Table 4. Comparison of Product Attributes between Added and Dropped Products (ICT-intensive industries)

Panel A: Plants in ICT-intensive industries for 2002-2007

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PRA	Relative to industry median and time-invariant				Non-relative and time-invariant			
	TFP	LP	KL	Wage	TFP	LP	KL	Wage
ADD	-0.001	0.005	-0.002	-0.000	0.002	0.007	0.014	-0.001
	(0.003)	(0.011)	(0.013)	(0.005)	(0.003)	(0.012)	(0.014)	(0.005)
Year FE	No	No	No	No	No	No	No	No
Plant FE	No	No	No	No	No	No	No	No
Plant*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	9,441	9,441	9,441	9,441	9,441	9,441	9,441	9,441
r2	0.443	0.593	0.608	0.626	0.459	0.589	0.601	0.618
r2_within	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Panel B: Plants in ICT-intensive industries for 2008-2013

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PRA	Relative to industry median and time-invariant				Non-relative and time-invariant			
	TFP	LP	KL	Wage	TFP	LP	KL	Wage
ADD	-0.002	0.002	-0.005	0.001	-0.003	-0.005	-0.007	-0.003
	(0.003)	(0.007)	(0.009)	(0.003)	(0.003)	(0.007)	(0.009)	(0.003)
Year FE	No	No	No	No	No	No	No	No
Plant FE	No	No	No	No	No	No	No	No
Plant*Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	13,886	13,886	13,886	13,886	13,886	13,886	13,886	13,886
r2	0.388	0.502	0.535	0.576	0.390	0.499	0.543	0.576
r2_within	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Added and dropped observations only. Continuous products are not included.
Standard errors in parentheses. Clustered for plants.
* p<0.10 ** p<0.05 *** p<0.01

Source: Authors' calculations based on the micro data underlying the *Census of Manufactures* conducted by the METI and the *Economic Census for Business Activity* jointly conducted by the MIC and the METI.

Appendix Table 5. Shipment Growth for Continuing Products (ICT-intensive industries)

Panel A: Plants in ICT-intensive industries for 2002-2007
Dependent variable: Annual growth rate of product shipments from 2002 to 2007

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Relative to industry median and time-invariant				Non-relative and time-invariant			
VARIABLES	TFP	LP	KL	Wage	TFP	LP	KL	Wage
PRA (j)	0.081**	0.040***	0.035***	0.086***	0.061**	0.020**	0.037***	0.089***
	(0.032)	(0.012)	(0.009)	(0.023)	(0.031)	(0.010)	(0.009)	(0.023)
ln(product shipment) (pjt)	-0.052***	-0.054***	-0.054***	-0.054***	-0.052***	-0.053***	-0.054***	-0.054***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Year dummies	No	No	No	No	No	No	No	No
Plant dummies	No	No	No	No	No	No	No	No
Plant*Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	40,676	40,676	40,676	40,676	40,676	40,676	40,676	40,676
r2	0.361	0.361	0.361	0.361	0.361	0.361	0.361	0.361
r2_within	0.013	0.014	0.014	0.014	0.013	0.013	0.014	0.014

Panel B: Plants in ICT-intensive industries for 2008-2013
Dependent variable: Annual growth rate of product shipments from 2008 to 2013

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Relative to industry median and time-invariant				Non-relative and time-invariant			
VARIABLES	TFP	LP	KL	Wage	TFP	LP	KL	Wage
PRA (j)	-0.026	0.011	0.025*	0.062	-0.021	0.014	0.029**	0.075*
	(0.068)	(0.018)	(0.015)	(0.045)	(0.063)	(0.017)	(0.014)	(0.045)
ln(product shipment) (pjt)	-0.068***	-0.069***	-0.070***	-0.070***	-0.068***	-0.069***	-0.071***	-0.071***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Year dummies	No	No	No	No	No	No	No	No
Plant dummies	No	No	No	No	No	No	No	No
Plant*Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9,505	9,505	9,505	9,505	9,505	9,505	9,505	9,505
r2	0.462	0.462	0.462	0.462	0.462	0.462	0.462	0.462
r2_within	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021

Standard errors in parentheses. Clustered for plants.
*** p<0.01, ** p<0.05, * p<0.1

Source: Authors' calculations based on the micro data underlying the *Census of Manufactures* conducted by the METI and the *Economic Census for Business Activity* jointly conducted by the MIC and the METI.

Appendix Table 6. Shipment Share Changes Across Continuing Products (ICT-intensive industries)

Panel A: Plants in ICT-intensive industries for 2002-2007

Dependent variable: Shipment share changes (plant-product, from t to t+1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Relative to industry median and time-invariant				Non-relative and time-invariant			
	TFP	LP	KL	Wage	TFP	LP	KL	Wage
PRA	-0.004	0.000	0.001	0.003	-0.008*	-0.003**	0.001	0.001
	(0.004)	(0.002)	(0.001)	(0.003)	(0.004)	(0.001)	(0.001)	(0.003)
lnTFP	0.012**	0.012**	0.012**	0.012**	0.012**	0.012**	0.012**	0.012**
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
lnemp	0.008*	0.008*	0.008*	0.008*	0.008*	0.008*	0.008*	0.008*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
YOUNG	0.006	0.006	0.006	0.006	0.006	0.006	0.006	0.006
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
MP	0.151***	0.151***	0.151***	0.151***	0.151***	0.151***	0.151***	0.151***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
lnKL	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	56,627	56,627	56,627	56,627	56,627	56,627	56,627	56,627
r2	0.127	0.127	0.127	0.127	0.127	0.127	0.127	0.127
r2_within	0.031	0.031	0.031	0.031	0.031	0.031	0.031	0.031

Panel B: Plants in ICT-intensive industries for 2008-2013
Dependent variable: Shipment share changes (plant-product, from t to t+1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Relative to industry median and time-invariant				Non-relative and time-invariant			
	TFP	LP	KL	Wage	TFP	LP	KL	Wage
PRA	-0.008	-0.001	-0.002	-0.007	-0.003	-0.001	-0.002	-0.008
	(0.011)	(0.003)	(0.003)	(0.007)	(0.010)	(0.002)	(0.002)	(0.007)
lnTFP	0.021**	0.021**	0.021**	0.021**	0.021**	0.021**	0.021**	0.021**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
lnemp	0.019*	0.019*	0.019*	0.019*	0.019*	0.019*	0.019*	0.019*
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
YOUNG	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
MP	0.205***	0.205***	0.205***	0.205***	0.205***	0.205***	0.205***	0.205***
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
lnKL	0.004	0.004	0.004	0.004	0.004	0.004	0.004	0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Plant FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	15,986	15,986	15,986	15,986	15,986	15,986	15,986	15,986
r2	0.167	0.167	0.167	0.167	0.167	0.167	0.167	0.167
r2_within	0.062	0.062	0.062	0.062	0.062	0.062	0.062	0.062

Standard errors in parentheses. Clustered for plants.
* p<0.10 ** p<0.05 *** p<0.01

Source: Authors' calculations based on the micro data underlying the *Census of Manufactures* conducted by the METI and the *Economic Census for Business Activity* jointly conducted by the MIC and the METI.