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1. Introduction

Many observers of the Japanese economy feel its import behavior had undergone a fundamental shift during the 1980s.[1] To what degree this was due to changes in Japanese consumer demand (more moderately priced imports) and producer's expenditure patterns (increased outsourcing), unilateral liberalization on the part of the Japanese government, or simply the result of overall structural change in the economy has been much debated. It is likely due to a combination of all of these factors. A more important question may be: what was the *effect* of this apparent change in import behavior on the Japanese economy? The gains from (more) trade manifest themselves in a number of ways: gains from exchange, gains from specialization, increased competition, and gains from variety. It is this last channel in which we are interested. That is, what was the effect on increased variety of imports on the productivity of various sectors in Japan?

In the past two decades, the term "product variety" has become more common in the economic growth literature. Although the definitions of product variety vary across papers, the impact of product variety on economic growth is commonly accepted. That theoretical implication is a crucial idea in many endogenous growth models (Romer, 1990; and Grossman and Helpman, 1991): new or higher quality

[1] See Ceglowski (1996) who asserts this most strongly and also Krugman (1991) and Hamori and Matsubayashi (2001) to some extent.

products have significant impacts on productivity and economic growth. At the same time, the tools to measure increases in variety have seen some major advances not only in the microeconomic theory of new goods (see Bresnahan and Gordon, 1997), but also in the field of empirical trade, most notably by Feenstra (1994). In this paper, we apply Feenstra's measure of variety to determine which sectors, if any, benefited from the change in import behavior that occurred over the 1980-2000 period.

A handful of empirical studies (see below) on product variety have been carried out for the OECD, East European countries and some Asian countries, but none have studied the effects of increased *import* variety as the channel for gains in productivity. As such, the case of Japan not only offers an opportunity to document and test the relationship between import variety and productivity for the second largest country in the world, but also offers a complement to perhaps the most well-known study of the gains from variety (Broda and Weinstein, 2006) for the US. While the US is a mature economy now and was during the period of Broda and Weinstein's study, Japanese was undergoing far more change both in the nature and volume of imports as well as internal restructuring. In the 1980s Japanese firms were still experiencing large increases in productivity in the manufacturing sector (Marston, 1987).

This paper looks at the impact on the increased availability in the variety of imported intermediate goods on the productivity of these industries. Moreover, we assess whether this effect, if any, changed in the 1990s during the stagnant years.[2] These questions are explored with a newly constructed variety data set applied to TFP data for 21 industries over 21 years. The findings vary across industries, and over time,

[2] Kuroda, Motohashi and Shimpo (2007) found that aggregated TFP growth rate for Japan in 1980's was 2.57%, while that in 1990's it fell to 0.77%.

but the overall message is clear. Many Japan industries had significant gains in productivity which can be attributed to increased access to a larger variety of goods.

There are four major contributions of this paper. First, a careful documentation of the change in import variety by both simple count measures and construction of the far more sophisticated Feenstra variety index has been done for the 1980-2000 period for 21 industries in Japan. Such a unique, new data set has many possible empirical uses. Second, the relationship between *import* variety and productivity for Japan has been econometrically tested. While in some ways this is similar to Feenstra, Madani, Yang and Liang (1999), who examined Korea and Taiwan, export data was used in that study.[3] Third, input-output (I-O) tables are used to give a weighted average of the changes in variety of the inputs used by each of the 21 industries. This has also not been done elsewhere. Fourth, and more generally, this study complements the relative few extant papers which examine the link between variety and productivity for Japan, the second largest economy in the world, and a country which saw both great changes in import demand and great stagnation over the 20 year period.

The remainder of the paper is as follows. Section 2 will explain the theoretical underpinnings and describe the methodological approach of this paper. In section 3, we will describe how we assembled the data and constructed the new variety indices, and the source of the TFP data for 21 industries. Section 4 presents the econometric specification and discusses the empirical results of the estimation. Section 5 summarizes the results and concludes with some policy implications and questions for future research.

[3] Funke and Ruhwedel (2001a, 2001b, 2005) also use Feenstra's measure of export variety to examine the effect on economic growth and/or exports, but this is done at a national level across many OECD, East Asian and East European countries, respectively.

2. Methodology

The variety index created by Feenstra (1994) can be used to measure the impact of new inputs (or outputs) on economic growth or productivity. In short, the wider availability of inputs in the CES production function allows for a tangency at a lower point on a given isoquant. This implies lower unit costs. This results in, almost by definition, an increase in productivity. Graphically, this can be seen most clearly in Figure 1 of Feenstra and Kee (2007), and is developed more rigorously in his earlier work, most clearly presented perhaps in Feenstra (2004). This idea fits well with the theory that if one firm or economy can have access to a greater variety of inputs, it can produce more efficiently. We also expect that industries which purchase large amounts of inputs from upstream industries will be affected more by the variety of those upstream industries than by variety in their own industry. In order to capture these effects, we will calculate a weighted-average of the variety of the upstream industries for each of the 21 industries.

As mentioned above, import variety has not been studied broadly in empirical papers. Among the few papers dealing with import variety, Broda and Weinstein (2006) study how the import of new varieties contributed to national welfare gains in the United States. The authors applied and extended the variety index created by Feenstra (1994) using disaggregated data of U.S. imports. They show that over the last three decades (1972-2001), the number of imported product varieties of the U.S. increased by a factor of three and estimates that welfare gains for the U.S. consumers from cumulative variety growth in imports were 2.6 per cent of GDP in 2001.

In this paper, we also study import variety of Japan during period 1980-2000, but instead of estimating consumer welfare gains from variety as in Broda and Weinstein (2006), we estimate the impact of import variety on Japan’s TFP. As mentioned above, Feenstra, Madani, Yang and Liang (1999) studied the relationship between variety and TFP but they used export data and only for South Korea and Taiwan. Feenstra, Yang and Hamilton (1999) studied the relationship between product variety and business groups in Korea, Taiwan and Japan. Elsewhere, Feenstra and Kee (2007) use export variety as a proxy for total variety of inputs in the economy. Our interpretation here is somewhat different, and in a sense, more straightforward. By using imports instead, the majority of which are intermediate goods and therefore imported inputs, we hope to better capture the increase in inputs available to Japanese industry over this time.[4] In particular, we hope to get a better understanding of how Japan's changing import structure in the late 1980s affected productivity in Japan.

Feenstra's (1994) variety index is briefly explained below. There are two periods *t* and *t-1*. The set of inputs changes over time, but there are some inputs available in both periods $I = I_0 \cap I_1$. The change in variety between two periods is measured by:

$$\Delta VAR_{t-1,t} = \ln\left(\frac{\lambda_{t-1}(I)}{\lambda_t(I)}\right) = \ln\left(\frac{\sum_{i \in I_t} p_{it}x_{it} \Big/ \sum_{i \in I} p_{it}x_{it}}{\sum_{i \in I_{t-1}} p_{it-1}x_{it-1} \Big/ \sum_{i \in I} p_{it-1}x_{it-1}}\right) \qquad (1)$$

where x_{it} is the input of good *i* in period *t*, I_t is the set of input available in period *t* at price p_{it} and similar for period *t-1*. As Feenstra (2004, p. 365) shows, with

[4] Very roughly speaking, intermediate goods were about two-thirds of all Japanese non-energy imports according to Ceglowski, 1996 (table 2). This fell over the period of this study. However, our import data *does* include oil and other energy, most certainly intermediate goods which should, in theory, benefit from a greater variety of inputs. Thus, we conclude that the majority of Japanese imports over this time were intermediate goods. There would be, of course, large consumer gains as well from increased variety, though here we are focusing on the production function interpretation of the Feenstra index.

a constant elasticity of substitution (CES) production function, TFP is a function of the change in input variety and the elasticity of substitution, σ

$$TFP = \frac{1}{(\sigma - 1)} \Delta VAR_{t-1,t} \tag{2}$$

Given σ >1, it is apparent that the increase in variety, reflected as the increase in $\Delta VAR_{t-1,t}$, will lead to an increase in TFP. As such, the above equation provides us with a direct way to test the endogenous model with expanding variety.

The calculated variety indices will be used to estimate their effects on TFP. However, as mentioned above, inputs for one industry include not only inputs from its own industry but also inputs from other industries as intermediates. Therefore, it is not enough to include only variety indices for each industry (called "VAR" in this paper) into our estimation equation. As such, we have calculated another I-O-weighted variety index ("VARS") for each of the 21 industries. As an oversimplified example, suppose for example, "motor vehicles" one of the 21 industries, was comprised of 50% "fabricated metal", 30% "electrical machinery" and 20% "rubber". Then, the VARS variety index applicable to the motor vehicle industry would be a weighted average of the three separately constructed Feenstra import variety indices for metal, electrical machinery and rubber. We feel this more accurately captures the multiple channels in which an increase in a variety of inputs can result in higher productivity.[5]

[5] It is also possible that the variable VAR, has a more direct competitive effect on TFP. That is, as an increase in the import variety of goods likely implies more direct competition with the Japanese made good, possible reducing market power and increasing efficiency in that way.

3. Data

We use disaggregated imports of Japan for the period 1980-2000 to construct the product variety indices. In reality, the input variety includes not only imports but also the domestically-produced inputs in the country. Unfortunately, domestic industrial data for Japan, the US, and elsewhere is very aggregate, the equivalent of say, the two or three digit level in trade data, at best. This typically gives less than one hundred "goods" (industries), thereby aggregating and masking a wide range of subcategories. However, imports account for a significant portion of total inputs in a heavily trade dependent Japan. Thus, the increase in import variety should also, at least partially, explains changes in productivity.

To maintain consistency in the classification of goods, we use disaggregated UN COMTRADE trade data at the five-digit level (SITC revision 2) for Japan from 1980-2000. The classification distinguishes 1,473 commodities according to the Standard International Trade Classification (SITC Revision 2). We define a *good* to be a four or five digit SITC-2 category, and a *variety* as the import of a particular good from a particular country as in Armington (1969) and Broda and Weinstein (2006). 21 variety indices were constructed from the UN trade data in a concordance with the already defined 21 sectors for the TFP data constructed by the Japanese RIETI project. This, of course, was no light task, but for the most part trade data for the major manufacturing sectors examined here usually fell neatly into one category or another, and few arbitrary decisions were needed. For more details see Nguyen (2009). These 21 sectors are further delineated in this paper as either primary or secondary industries. (See table 1 for a list. Primary industries are in italics.) Secondary industries are defined, as in Feenstra, Madani, Yang and Liang (1999) as those industries which require more inputs from upstream industries than from themselves.

Before discussion of the more sophisticated variety indices, a simple “count-measure” of the increase in variety of goods imported to Japan over time may be useful. We see in table 1 that by the simple count measure, import variety has increased in all 21 industries.[6] However, in order to understand whether there is a link between increased import (and input) variety and productivity, a more precise measure of variety is needed. Here is where the Feenstra “exact” index is far superior. By generating an expenditure-share, weighted average which incorporates prices as well as new goods into the optimization problem of the firm, we obtain a far better relative weighting of the increase in inputs (or imports) than a simple count (sum) of import varieties could provide.

To compare the changes of variety between two years *t* and *t-1*, we calculate $\Delta VAR_{t-1,t}$ by using equation (1) and multiplying it by 100.

[6] Interestingly, this is not the case for exports. By the simple count measure, variety in all of the 21 industries actually declined over time. Using the Feenstra variety index, however, export variety is shown in the various industries to have sometimes increased and sometimes decreased over this period. See Anh Thu Nguyen (2009).

Table 1. Simple count-based variety in Japan's imports (1980-2000)

	Industry	1980	2000
1	*Agriculture*	1607	2292
2	Food and kindred products	1536	2330
3	*Textile mill products*	2363	3146
4	Apparel	2036	4015
5	*Lumber and wood*	648	891
6	Furniture and fixtures	237	354
7	Paper and allied	499	742
8	Printing, publishing and allied	398	444
9	Chemicals	2977	4364
10	*Petroleum and coal products*	278	337
11	Leather	419	462
12	*Stone, clay, glass*	1047	1696
13	*Primary metal*	1427	1960
14	Fabricated metal	1174	1699
15	Machinery, non-electrical	2780	4402
16	Electrical machinery	1382	2466
17	Motor vehicles	220	417
18	Transportation equipment and ordnance	147	213
19	Precision instruments	630	1617
20	*Rubber and misc. plastics*	534	859
21	Misc. manufacturing	1546	1978
	Total	**23885**	**36684**

Source: UN's Comtrade database; counts compiled by the authors. Industries in italics are primary sectors, as defined in the text.

In order to smooth the variety indices we calculate a 3-year moving average ($MA\Delta VAR_{jt} = 1/3(\Delta VAR_{jt-2} + \Delta VAR_{jt-1} + \Delta VAR_{jt})$. Another reason for calculating the moving average is that TFP in one year can be affected by the variety of the previous years. The increase (or decrease) in import variety in one year, meaning the changes in intermediates input, may take some time to influence TFP.

The data on TFP for Japan are taken from the ICPA project launched by RIETI (Research Institute of Economy, Trade and Industry). This project provides us with TFP for 33 sectors, 21 of which are analyzed in this paper (services and some other industries such as mining and construction are excluded). This project is based on the EU KLEMS framework, i.e., industry level data on capital (K), labor (L), energy (E), material (M), service (S) as well as gross output to produce the TFP values. TFP is measured as a Divisia index, i.e. the rate of growth of output minus a weighted average of the growth of inputs.

The increase in variety means the appearance of new products or, in this case, at least new sources/countries of products. While more, and perhaps better, inputs for Japanese firms may increase productivity (TFP) there are likely many other reasons why TFP may rise over time. R&D activity in the industry is clearly one likely source of TFP growth. As such, it is also included as an additional right-hand side variable.[7] R&D data is taken from the ESRI-HISTAT-JIP project launched by Economic and Social Research Institute (ESRI) and the statistics of the Ministry of Internal Affairs and Communications of Japan.[8] An R&D variable for each industry is calculated as the expenditure on R&D over output of that industry. R&D may have lagged effects

[7] There is also the possibility that while R&D may increase TFP in an industry, it may also cause increased specialization in that industry. That is, they may tend to produce less variety of goods than before, *ceteris paribus*. In this case, an increase in R&D may decrease variety in that industry, thus econometric estimation may overstate any positive relationship between variety and TFP. R&D, of course, could also increase variety, by generating new goods. As we do not have a strong *a priori* here, and it would certainly differ across industries, we do not explore this any further here. Moreover, this effect, if any, would only be strong in own-industry variety, not variety in the upstream industries. Nonetheless, the relationship between R&D, TFP and variety should be explored further.

[8] The TFP data can be found at www.rieti.go.jp/en/database/d03.html while the R&D data was taken from two Japanese government sources found at www.esri.go.jp/index-e.html and www.stat.go.jp/english/index.htm.

on TFP because research and development may take some time to become realized in production so we adjusted R&D indices with 3-year moving averages, similar to that done for import variety.[9]

4. Empirical specification and results

From equation (2), which represents the relationship between TFP and variety, we estimate the relationship between TFP and import variety as follows:

$$TFP_{jt} = \alpha_j + \beta_j STAGDUMMY + \gamma_j MAVAR_{jt} + \mu STAG \times MAVAR_{jt} + \lambda_j MAVARS_{jt} + \eta_j MAR\&D_{jt} + \varepsilon_{jt} \qquad (3)$$

where α_j is a constant term for each industry *j*, β_j is the estimated impact of the slowdown in Japan during its "lost decade" (starting from 1993). γ_j reflects the estimated relation between the change in own import variety (VAR) and the growth in TFP in one industry, and λ_j is the estimated effects of the changes in other upstream industries' varieties (VARS) on industry *j*'s TFP. μ_j is an interaction term for variety and the stagnation on TFP, and η_j is the coefficient for the R&D variable. Variety and R&D are both 3-year moving averages as explained above.

TFP_{jt} is the dependent variable, and is calculated as the growth of TFP between two years *t-1* and *t*. VAR_{jt} is the import variety index, calculated as described in the previous section and presents the change in variety between two years *t-1* and *t*. The above equation is consistent with equation (2), where γ_j equals $1/(\sigma_j - 1)$, where σ_j is the elasticity of substitution between differentiated products in industry *j*.

[9] We are grateful to Eiichi Tomiura for suggesting both inclusion of the R&D variable and the use of moving-averages.

All the regressions were estimated by simple OLS, with standard errors corrected for heteroskedasticity in the pooled estimation. The data are time-series data, which means they have potential non-stationarity issues. However, with only 21 years of data of annual data, any unit root test, let alone cointegration test, would be unreliable (see Toda, 1994 *inter alia*). Visual inspection of the series, both variety and TFP, shows no apparent trending, and so we feel satisfied with this straightforward estimation, given the limitations of the data.

Table 2 presents the parameter estimates on 21 separate industry regressions for the own-industry variety variable, VAR (or rather the MA of VAR or "MAVAR"). Most of the industries have positive coefficients on import variety. 11 coefficients in bold in this table are positive and significant at a 10% level. Among them, 10 industries have positive and significant coefficients of variety and only one industry - electrical machinery- has a negative and significant coefficient of variety. However, the measurement of import variety of this industry at the 4 and 5-digit level may not fully reflect the full range of differentiated products and its changes over time.

Table 2. Coefficients for own industry's variety (moving average of "VAR")

	Industry	MAVAR	t-stat	R^2
1	*Agriculture*	1.35	1.49	0.07
2	Food and kindred products	**3.72**	**2.19**	0.32
3	*Textile mill products*	-0.95	-0.57	0.23
4	Apparel	**5.73**	**2.96**	0.43
5	*Lumber and wood*	**2.33**	**2.64**	0.55
6	Furniture and fixtures	**4.23**	**2.25**	0.49
7	Paper and allied	**2.86**	**4.03**	0.64
8	Printing, publishing and allied	1.71	0.68	0.23
9	Chemicals	-0.28	-0.46	0.45
10	*Petroleum and coal products*	0.95	0.72	0.18

11	Leather	**3.01**	**3.08**	0.51
12	*Stone, clay, glass*	**2.13**	**2.69**	0.46
13	*Primary metal*	0.92	0.94	0.36
14	Fabricated metal	**1.81**	**2.06**	0.42
15	Machinery, non-elect	0.47	0.50	0.44
16	Electrical machinery	**-3.19**	**-2.17**	0.52
17	Motor vehicles	**2.14**	**2.04**	0.37
18	Transportation equipment and ordnance	0.60	1.07	0.13
19	Precision instruments	-0.04	-0.06	0.18
20	*Rubber and misc. plastics*	**3.40**	**2.69**	0.49
21	Misc. manufacturing	0.39	1.07	0.49
	n = 18 for each of the 21 regressions			

Note: The values in bold indicate significance at the 10% level or more.

Of the ten industries that have positive and significant effects between variety and TFP, seven are secondary industries. For secondary industries, Feenstra et al. (1999) argue that the expansion of input variety plays a more important role in increasing TFP. That is, the endogenous growth model may apply more to secondary industries than primary industries, which rely heavily on natural resources. The results here are in line with Feenstra et al. (1999).

We also expect the coefficients of variety of other industries (MAVARS) to be positive and significant for secondary industries. The separate industry estimates of this variable are presented in table 3. Six coefficients (again, in boldface) are positive and significantly different from zero at a 10% level or more. Five of these industries are secondary industries.

Most of these industries purchase large amount of inputs from upstream industries rather than from themselves. The positive and significant coefficients of MAVARS of these industries confirm the idea that secondary industries' TFP rely on the variety of upstream industries. Only the lumber and wood industry, which can be defined as a primary industry, has a positive and significant coefficient of MAVARS. For electrical machinery, the coefficient of its own industry's import variety is negative and significant, whereas the coefficient of other industries' import variety is positive and significant. This confirms the role of differentiated inputs from other industries for this industry's production.

Table 3. Coefficients for other industries' variety (moving average of "VARS")

	Industry	MAVARS	t-stat	R^2
1	*Agriculture*	-0.98	-0.89	0.07
2	Food and kindred products	0.08	0.14	0.32
3	*Textile mill products*	-2.20	-0.98	0.23
4	Apparel	2.40	1.25	0.43
5	*Lumber and wood*	**3.39**	**2.35**	0.55
6	Furniture and fixtures	0.98	0.83	0.49
7	Paper and allied	-1.29	-1.53	0.64
8	Printing, publishing and allied	0.55	0.51	0.23
9	Chemicals	1.39	1.47	0.45
10	*Petroleum and coal products*	-1.48	-0.59	0.18
11	Leather	**3.09**	**2.00**	0.51
12	*Stone, clay, glass*	1.76	1.38	0.46
13	*Primary metal*	0.03	0.05	0.36
14	Fabricated metal	**1.86**	**1.73**	0.42
15	Machinery, non-elect	**4.80**	**2.48**	0.44
16	Electrical machinery	**5.34**	**3.49**	0.52
17	Motor vehicles	0.20	0.18	0.37
18	Transportation equipment and ordnance	1.23	0.43	0.13
19	Precision instruments	1.90	1.08	0.18
20	*Rubber and misc. plastics*	-1.95	-1.40	0.49
21	Misc. manufacturing	**1.73**	**2.47**	0.49

n = 18

Note: The values in bold indicate significance at the 10% level or more..

We found no evidence of a relationship between TFP and variety (both MAVAR and MAVARS) in eight industries, including agriculture, textile mill products, printing, publishing and allied, chemicals, petroleum and coal products, primary metal, precision instruments, rubber and miscellaneous plastics. Six of these industries are primary industries. In general, most industries' TFP are more affected by their own industries' import variety than other input industries' import variety. This fact is illustrated by the number of positive and significant values of coefficients in table 2, which is larger than that number of table 3 (11 compared to 6). This may suggest that the direct competition effect of increased import variety is stronger than the Feenstra-style, increased variety inputs effect. And naturally, the degree to which this is occurring (or not) differs across industries.

To see how TFP may have differed in the pre-stagnation and stagnation years, we refer to the estimates of STAGDUMMY and STAG*MAVAR in table 4. We see that all of the coefficients of STAGDUMMY are not significant. For the STAG*MAVAR variable, there are only three significant coefficients. Among them, one industry has a positive and significant value for its coefficient and only two industries have negative and significant value of coefficients, as we expected. Economic intuition might suggest the stagnant years would have caused TFP to fall, *ceteris paribus*. Empirical analysis seems to back this up, at least at the aggregate level. Kuroda et al. (2007) found aggregated TFP growth rate for Japan in the 1980's to be 2.57%, while in the 1990's it was 0.77%. Furthermore, there certainly seems to be a significant change in TFP at the sectoral level over the two periods as seen in figures 1 and 2. Over the 1980-1992 period, only three industries had, on average, a negative TFP growth rate. However, in many of the industries, TFP growth rate turns negative in the post-bubble period. In the stagnation years, only textile mill products and electrical machinery industries show strong TFP growth. However, both the direct and interacting dummies show virtually no effect in the regression results of this paper.

This inability to derive any explanatory power for TFP in the pre- and post-bubble years is, of course, somewhat disappointing. But at a more detailed sectoral level, what happened to individual industries (and firms) during the "lost decade" is full of puzzles and paradoxes. Nishimura, Nakajima and Kiyota (2005), for example, find that in a detailed firm level study of entry, exit, and TFP for Japanese firms in the 1990s, more often *efficient* firms (as measured by TFP) went out of business and inefficient ones survived. This, coupled with the effect (often lagged) of increased import variety on TFP makes the task of unbundling these effects a difficult one and one unfortunately not captured here with the simple year-dummies on industry-level regressions.

Table 4. Coefficients of STAGDUMMY, STAG*MAVAR

	Industry	STAGDUMMY	t-stat	STAG*MAVAR	t-stat	R^2
1	*Agriculture*	0.50	0.16	-0.10	-0.04	0.07
2	Food and kindred products	-0.87	-0.80	-2.89	-0.92	0.32
3	*Textile mill products*	-0.21	-0.09	4.47	1.08	0.23
4	Apparel	-0.91	-0.33	-3.84	-1.06	0.43
5	*Lumber and wood*	-3.72	-1.49	-0.88	-0.37	0.55
6	Furniture and fixtures	1.79	1.26	-2.77	-1.53	0.49
7	Paper and allied	-0.45	-0.45	**-2.95**	**-1.94**	0.64
8	Printing, publishing and allied	-2.00	-1.15	-1.16	-0.37	0.23
9	Chemicals	0.72	0.41	1.18	0.82	0.45

10	*Petroleum and coal products*	-3.21	-1.15	-1.08	-0.56	0.18
11	Leather	0.19	0.14	**-2.77**	**-1.94**	0.51
12	*Stone, clay, glass*	0.19	0.14	0.09	0.05	0.46
13	*Primary metal*	1.38	1.16	2.05	1.32	0.36
14	Fabricated metal	-0.08	-0.05	1.51	0.48	0.42
15	Machinery, non-elect	-0.93	-0.48	-0.78	-0.40	0.44
16	Electrical machinery	0.71	0.36	**4.56**	**3.49**	0.52
17	Motor vehicles	-0.88	-0.90	-1.84	-1.02	0.37
18	Transportation equipment and ordnance	-1.15	-0.54	-3.17	-0.89	0.13
19	Precision instruments	0.72	0.18	-0.66	-0.20	0.18
20	*Rubber and misc. plastics*	1.11	0.60	-1.24	-0.84	0.49
21	Misc. manufacturing	**6.24**	**2.95**	1.80	1.47	0.49
	n = 18					

Note: The values in bold indicate significance at the 10% level or more.

Figure 1. Average TFP growth (1980-1992)

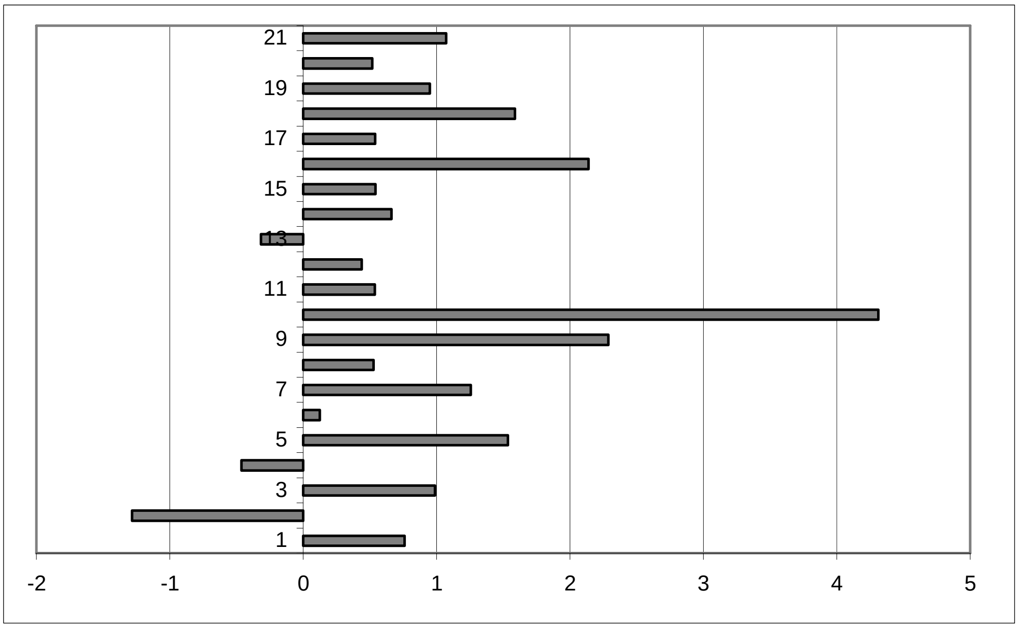
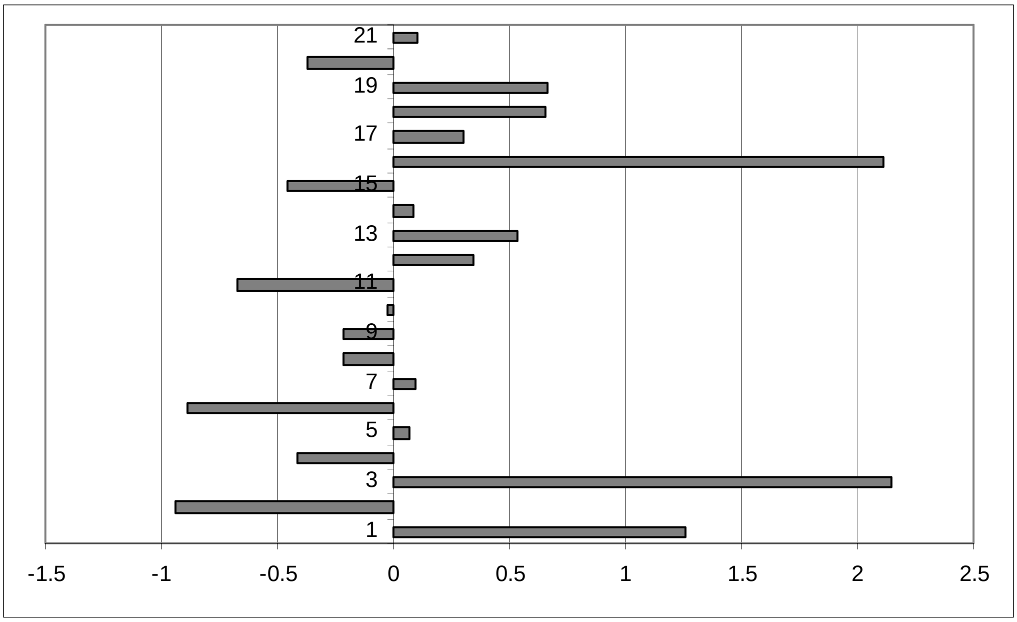


Figure 2. Average TFP growth (1993-2000)



Source: ICPA project conducted by RIETI (2007), http://www.rieti.go.jp/en/database/d03.html
Note: rates are percentages.

Table 5 presents the estimates of the R&D coefficient indices for each of the 21 industry regressions. While the *a priori* is a positive coefficient, most of the coefficients are not significant. Only two coefficients (in bold) are significant at 10% level or more, but one of them has negative sign. This result may arise from the possibility that our separate regressions for each industry might not cover the long term effect of R&D on TFP. This issue is further exacerbated by the short time series for each of the industry-level regression.

Panel Regression Results

To address the weakness of the short time series, as well as the paucity of explanatory variables in the basic regression, a fixed-effect panel regression was conducted. The results are presented in table 6. [10] The results are more compelling than

[10] The fixed effects coefficients were found to be significant, but not reported here. Hausman tests indicated that a fixed effects rather than random effects model was more suitable.

the individual industry regressions, though the stagnation dummies are still not significant.[11] Table 6 shows that both MAVAR and MAR&D have positive and significant coefficients. The result proves again the strong effect of import variety on productivity, as also illustrated in the separate regressions, at least for most secondary industries. Differing with the separate regressions' results, the R&D variable in the fixed effects panel regressions is now positive and significant. This result may have benefitted from the larger pooled sample as well as the inclusion of individual, unobservable industry-specific effects. This result confirms our expectation that the increase in R&D expenditure contributes to the improvement of productivity. [12]

Table 5. Coefficients of MAR&D in import variety regressions

	Industry	MAR&D	(t-statistics)	R2
1	*Agriculture*	-38.95	-0.28	0.07
2	Food and kindred products	3.22	1.46	0.32
3	*Textile mill products*	-2.32	-0.60	0.23
4	Apparel	1.56	0.37	0.43
5	*Lumber and wood*	-11.50	-1.00	0.55
6	Furniture and fixture	**3.53**	**1.77**	0.49
7	Paper and allied	5.23	1.21	0.64
8	Printing, publishing and allied	6.94	0.64	0.23
9	Chemicals	-1.07	-1.27	0.45
10	*Petroleum and coal products*	-2.33	-0.34	0.18
11	Leather	-0.81	-0.54	0.51
12	*Stone, clay, glass*	1.63	0.93	0.46
13	*Primary metal*	-1.55	-0.27	0.36
14	Fabricated metal	-0.07	-0.01	0.42

[11] Both stagnation dummies were also included, but both were insignificant, jointly and separately, and are not reported here.
[12] Kwon (2004) also finds a positive relation between R&D and TFP of Japan during the period 1970-1998.

15	Machinery, non-elect	0.02	0.02	0.44
16	Electrical machinery	-0.18	-0.36	0.52
17	Motor vehicles	0.19	0.20	0.37
18	Transportation equipment and ordnance	0.46	0.42	0.13
19	Precision instruments	-0.03	-0.14	0.18
20	*Rubber and misc. plastics*	-2.26	-0.24	0.49
21	Misc. manufacturing	**-3.07**	**-2.59**	0.49
	n = 18			

Note: The values in bold are the coefficients that are significant at a 10% level or more.

Table 6. Fixed effects least squares regression (pooled across 21 industries)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.04	0.17	0.23	0.82
MAVAR	**0.93**	0.20	**4.69**	0.00
STAG*MAVAR	0.10	0.42	0.23	0.82
MAVARS	**0.51**	0.14	**3.55**	0.00
MAR&D	**0.03**	0.02	**1.90**	0.06

Total panel (balanced) observations: 378

R-squared: 0.17

Note: The values in bold are the coefficients that are significant at a 10% level or more.

5. Conclusion

This paper has demonstrated the importance that increases in import variety can play in productivity increases. The regression results are based on Japanese TFP data for more than 20 years matched with a newly constructed data set measuring the variety of imports over the same period. The documentation of the change of import variety during Japan transitional years is an important contribution in and of itself. Moreover, the regression results, both individually and in the panel regression, generally confirm the prediction of endogenous growth theory; that is, an increase in a variety of inputs increased productivity. However, in this paper we focused on import variety, which suggests that not only domestic variety (the kind envisioned in most growth models) but imported variety can also be a source of productivity gains. However, the channels by which this occurs, in reality, are less clear. In this study, we found that own-variety affected TFP more often than an increase in variety of inputs from other industries. Here, the novel use of the input-output tables to calculate the weighted-varieties of other industries provided a more complete measurement of input varieties and helped distinguish between these two channels.

This may mean that the stronger gains from variety in increased imports were from more competition, rather than an increase in the mix of available in inputs. Moreover, both of these effects were far stronger in secondary industries than in primary ones. While Japan is already a very open country, any further liberalization (to be interpreted very broadly as reductions in NTBs, increased arms-length imports rather than intra-firm, increased flexibility in general) may see larger benefits in secondary industries and few in primary industries. R&D was also found to increase productivity, but only in the panel regression. This reflects both the weakness of the short time-series for individual industries, but also the difficulty in capturing the very irregularly timed benefits that come from R&D efforts.

As a first step, this paper has answered some important questions, but more can be done with respect to (import) variety and productivity. Certainly, we would benefit from a Broda and Weinstein-style study for Japan, focusing on consumer gains, for a country whose consumption patterns may have changed substantially over this time. Also, the interplay between import (and export) variety, which exploits very detailed trade data, and detailed firm level should be explored, if possible.

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