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Measuring Robot Quality: Has quality improvement slowed down?[1]

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Abstract

This paper measures the extent to which the quality of robots has improved in Japan between 1990 and 2018, by using data from the "Production and Shipments of Manipulators and Robots" of the Japan Robot Association and the "Corporate Goods Price Index" of the Bank of Japan. We first calculate quality-unadjusted robot price indices applying three approaches: the traditional index number approach, the stochastic approach in the spirits of Edgeworth and Jevons, the structural approach. Then, we compute robot quality by dividing quality-unadjusted prices by the quality-adjusted industrial robot price index produced by the Bank of Japan. Based on three approaches, significant decline in improvement in the quality of robots in the last decade is found. The differences in the growth rates of the robot quality between the 2000s and the 2010s show substantially negative values around -3 percentage points *per annum*.

Keywords: robots, quality adjustment, homothetic demand system
JEL classification: C43, E22, E31, L15, O33

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1 Introduction

The question of whether machines will take human jobs away is not a new concern; it traces back at least 100 years. With significant progress in artificial intelligence and machine learning algorithms, this concern has now become an increasingly prominent fear. In response to this societal fear, academics tackle this issue from both theoretical and empirical angles.

In the theoretical strand, Benzell et al. (2015), Sachs et al. (2015), Berg et al. (2018), Graetz and Michaels (2018), Caselli and Manning (2019), and Acemoglu and Restrepo (2020) have explored the consequences stemming from technological progress in robotics from short to medium and long-run terms. Results of such studies are mixed, depending on the settings in the model, particularly, on the production side, which pins down whether robots are substitute or complement to labor.

Although data on robots are only available, at most, for the last two to three decades, Graetz and Michaels (2018), Acemoglu and Restrepo (2020), Dauth et al. (2018), Humlum (2019), Adachi et al. (2020), Adachi (2021), and Fujiwara and Zhu (2020) have estimated the impacts of the increased usage of robots on the labor market, eliciting somewhat mixed implications. For example, Graetz and Michaels (2018) and Dauth et al. (2018) have concluded that robotization increases labor productivity and real wage but causes no significant impact on labor inputs, whereas Acemoglu and Restrepo (2020) indicate that more automation leads to fewer labor inputs and lower real wages.

However, to the best of our knowledge, no study has specifically investigated the rate of technological progress; namely, quality improvement of robots.[1] For any attempt to predict how robots will affect the macroeconomy, in recognition of society's existing anxiety, it is vital to understand the progress of robot production and quality improvement path of robots. If the pace of quality improvement in robots slows down or has already diminished, fear regarding robots taking human jobs away may dissipate. This paper aims to fill in this gap.

The lack of research on robot quality can be traced to the lack of price information available in time series in typical datasets, such as "World Robotics," which is published annually by the International Federation of Robotics. Most studies examine how the number of robots; namely, the quality-unadjusted stock of robots, affects labor market variables.[2]

Two novel datasets that contain price information on robots are used in this study. The first is the "Production and Shipments of Manipulators and Robots" published by the Japan Robot Association (hereafter, JARA). JARA publishes sales data and the number of robots installed by industry and application. The 2018 table exhibits sales and the number of robots installed for 44 industries, reporting 36 applications. The price of robots by industry and application can be obtained by dividing sales by the number of robots installed. Note that prices computed in

[1]As a robustness check, Adachi et al. (2020) compute robot quality indirectly by assuming the exogenous shifter in the CES aggregator as unobserved quality following Khandelwal et al. (2013). Note that such an exogenous shifter can also be considered an unobserved demand shifter instead of quality as shown in Redding and Weinstein (2020). Contrary to Adachi et al. (2020), we aim to directly measure the quality of robots.

[2]Notable exceptions are Adachi et al. (2020), Adachi (2021), and Fujiwara and Zhu (2020). They all use data published by the Japan Robot Association, the details of which are discussed below.

this manner are not quality-adjusted.

The second dataset is the "Corporate Goods Price Index" (hereafter, CGPI), which is published by the Bank of Japan (hereafter, BOJ). BOJ began releasing the quality-adjusted price index of industrial robots as one of the components in CGPI in 1990. Therefore, we measure quality improvement of robots over time by dividing the quality-unadjusted price index of robots computed from JARA data by the industrial robot deflator produced by BOJ.

With this quality-adjusted price index of robots in hand, the key to measuring the quality of robots is determining how to calculate the quality-unadjusted robot price index from JARA data. A simple average of robot prices may well serve this purpose. However, the distribution of prices is found to be significantly positively skewed. While many are overly concentrated near median, some items have a small probability of eliciting a substantial inflation rate. It is not clear whether such outliers should be included or excluded in calculating a representative index of quality improvement in robots.

This question is reminiscent of classic arguments regarding the ideal presentation of price indices among giants of economics, such as Edgeworth, Frisch, Jevons, Keynes, and Walsh.[3] In the late 19th and early 20th centuries, a fierce debate occurred about two characteristics of prices. First, if only one price increases among many goods, should the representative price index increase? Second, are price indices stochastic variables? In other words, do they contain ambiguous fluctuations? Edgeworth and Jevons said no to the first question and yes to the second, whereas Frisch, Keynes, and Walsh argued strongly to the contrary.[4]

In our current view, the answer to the second question is, for sure, yes; most macroeconomic variables are assumed to be stochastic. The answer to the first question depends on the perception of what prices are intended to be. If prices are viewed as the *cost-of-living* for consumers, then prices should rise, as an increase in the price of one good raises cost for consumers. However, if prices are the target of monetary policy (*i.e.*, a measure of changes in the value of money), then changes in commodity prices, such as fresh food and energy prices, which vary considerably from other commodities, are excluded from the price index which is referred to as core inflation. This trimmed mean is considered a good measure of the core inflation rate and therefore is more related to other major macroeconomic variables with a better forecasting power. In constructing a price index for robots (*i.e.*, measuring the quality of robots), should extreme values be excluded or included? There is no prior knowledge on the impacts of extreme

[3] For the details, see Diewert (1993, 2010, 2020) and Abe (2019).

[4] For example, in Jevons (1884), "In drawing our averages the independent fluctuations will more or less destroy each other; the one required variation of gold will remain undiminished."; in Edgeworth (1887), "A third principle is that less weight should be attached to observations belonging to a class which are subject to a wider deviation from the mean."; in Keynes (1930), "What is the flaw in the argument? In the first place it assumed that the fluctuations of individual prices round the 'mean' are 'random' in the sense required by the theory of the combination of independent observations. In this theory the divergence of one 'observation' from the true position is assumed to have no influence on the divergences of other 'observations'. But in the case of prices, a movement in the price of one commodity necessarily influences the movement in the prices of other commodities, whilst the magnitudes of these compensatory movements depend on the magnitude of the change in expenditure on the first commodity as compared with the importance of the expenditure on the commodities secondarily affected."; in Walsh (1921), "Commodities are to be weighted according to their importance, or their full values."; in Frisch (1936), "We cannot assume that the "monetary factor" will manifest itself as a proportional change of all prices."

entries in robot prices on other macroeconomic variables, particularly employment, wage, and labor productivity.

In addition to the inclusion or exclusion of such extreme values, there are two other reasons why such an index cannot be narrowed down to a single price index. First, there is a composition effect; even if there is no change in the price of individual robots, the quality per robot will change when the composition changes. Again, we do not know whether accounting this composition effect would make a difference in the impact of robot adoption on labor markets and other macroeconomic variables.

Second, although BOJ (2009, 2020, 2021) offer detailed explanations on the quality adjustment, we still do not know how the quality adjustment is conducted by BOJ or on which items. BOJ (2021) says, "It is the principle of CGPI to survey product prices continuously with fixed quality." In contract, it also says that in reaction to product turnover, "*sample price replacement* is conducted to change reporting companies, surveyed products, and counterparties and terms of transactions, etc. which were set at the start of surveys." It is not possible to determine *a priori* whether a quality-unadjusted robot price index should be created only for products that have existed for a relatively continuous period or whether a robot price index should be created to cover a wide range of products.

Given the above three backgrounds – whether to include extremes, whether to take the composition effect into account, and whether to focus on a small number of representative robots – this paper will calculate several robot price indices, endeavoring to obtain robust results on robot quality, taking three approaches. The first is the classic *index number approach*. The second applies *the stochastic approach* in the spirits of Edgeworth and Jevons, aiming to capture the common trend of price fluctuations among individual robots. Finally, we seek to obtain a theoretical price index using the *structural approach*, which is explicitly based on firms' cost minimization problem.

For the index number approach, we calculate both arithmetic and geometric mean and median of robot prices. Since these are computed using sales as the weight, they represent rough measures of the theoretical price index, similar to the cost-of-living index.[5] Following Bryan and Cecchetti (1994) and Shiratsuka (1997), we also compute the trimmed means to reduce the impacts of extreme entries. As first demonstrated by Diewert (2010), trimmed means are closely related to the stochastic approach in that "less weight should be attached to observations belonging to a class which are subject to a wider deviation from the mean" as noted by Edgeworth (1887).[6] Trimmed means are effective for excluding outlier observations to render sample prices more homogeneous and representative. Therefore, these are more congruent with the *elementary price index* or *elementary aggregates* and likely to be more comparable to the industrial robot price index in CGPI. For this purpose, we also calculate robot price indices based on a simple average without using sales weights, and those only using items that have

[5]Notice that we consider firms' profit maximization problem instead of households' utility maximization problem.

[6]Notice that extreme entries have fewer weights in the geometric mean and median of the robot prices, so, computing these is also somewhat in congruence with the stochastic approach of Edgeworth and Jevons.

existed for the entire period.

In the stochastic approach, we estimate inflation rates of individual robots on time fixed effects in reference to the specifications proposed by Selvanathan and Prasada (1994). Estimated coefficients on the time dummies are considered the common trend, which is not susceptible to broader deviations from mean.

The CES aggregator is quite often estimated using the micro-founded structural approach. However, the CES function is broadly acknowledged as restrictive. There is no existing prior knowledge to justify the assumption behind the CES aggregator that all robots are subject to the same elasticity of substitution. In addition, JARA's robot data is intermittent; the number of available robot data is time-varying. To address these issues, Matsuyama and Ushchev (2017) propose a new and highly flexible homothetic preference. In what they coin the "homothetic demand system with a Single Aggregator" (hereafter, HSA), the theoretical price index can be estimated in the homothetic demand system with a minimal assumption that the expenditure share is the function of the relative price. In the structural approach, we estimate the aggregate robot price index under HSA using higher-order polynomials as examined in Kasahara and Sugita (2020).

Some heterogeneity exists among aggregate robot price indices computed by different approach. Nonetheless, robust findings are obtained regarding the quality of robots in the last three decades in Japan. The findings show that the quality per robot increased or leveled off in the 2000s and decreased in the 2010s. In all measures, growth rates in the 2000s elicit large positive values. Conversely, those in the 2010s are mostly negative. Most importantly, the difference in the growth rates between the 2000s and 2010s also takes negative values of around -3 percentage points *per annum*. According to the price information on robots from Japanese manufacturers, quality improvement in robots has significantly slowed down in the last decade.

These results agree with recent observations on the possibility of a slowdown in the investment-specific technological progress, which manifests itself as a slowdown in relative price declines. For example, Fernald (2014), Byrne and Pinto (2015), IMF (2019), and Takahashi and Takayama (2021) report a dramatic slowdown in the pace of relative price declines of capital goods over consumer goods. This implies a slowdown of the investment-specific technological progress, that may include robot quality. In a related study, Bloom et al. (2020) present evidence that "research effort is rising substantially while research productivity is declining sharply." This *ideas-are-getting-harder-to-find* hypothesis advocated by Bloom et al. (2020) may apply to robot production as well.

The remainder of this paper is structured as follows. Section 2 explains the details of data including the Production and Shipments of Manipulators and Robots published by JARA and the industrial robot price index in CGPI by BOJ. Section 3 discusses our strategies to compute the aggregate robot price index and the quality of robots. Sections 4, 5, and 6 explain the processes of computing the robot price index using the index number, the stochastic and the structural approaches, respectively. Results on quality improvement from each approach are also reported. In Section 7, we summarize the findings on quality improvement in Sections 4, 5,

Table 1: Numbers of industries and applications

year	Industry	Application	Total
1990 - 1997	26	31	806
1998 - 2001	26	34	884
2002 - 2013	22	34	748
2014 - 2018	26	34	884

and 6. We also confirm that the decline in quality improvement in the 2010s is a robust finding. Finally, Section 8 concludes.

2 Data

We first explain the "Production and Shipments of Manipulators and Robots" dataset from JARA, followed by the industrial robot price index in CGPI of BOJ.

2.1 JARA data

We use the Production and Shipments of Manipulators and Robots produced by JARA from 1990 to 2018.[7] Adachi et al. (2020) also use this database to gauge the impacts of robots on employment in Japan, offering comprehensive and detailed information about JARA data. The following will describe the main characteristics of JARA data that are of importance to our results.

JARA publishes two types of data. One is available on the JARA website.[8] The other is only available as a booklet in Japanese. The latter contains more detailed information by industry and application. Since we need to use data that are as disaggregated as possible to gauge quality improvement in robots, we decide to use the latter; in particular, Table B, which presents sales and the number of robots by industry and application.

In the 2018 table, 44 industries are covered with 28 major categories and their sub-categories in columns. Rows present 36 applications for 17 major categories with attending sub-categories. New robots are invented, and some old robots become obsolete. Therefore, industries and applications in the table change over time. As a result, the numbers of industries and applications available in JARA data in Table B across our sample from 1990 to 2018 become smaller. This is presented in Table 1. In total, there are potentially 23,400 (= 806 x 8 + 884 x 4 + 748 x 12 + 884 x 5) data points over industries, applications and years. There are, however, a considerable

[7] According to the Japanese Industrial Standards (hereafter, JIS), a robot is defined as "a locomotion mechanism that is programmed to operate on two or more axes, has a degree of autonomy, and operates in an environment to perform a desired task. Note 1: A robot includes a control system and an interface to the control system. Note 2: The classification of a robot as an industrial or service robot depends on its intended use." The industrial robot is defined as "A robot that is automatically controlled, reprogrammable, versatile manipulator, programmable in three or more axes, fixed in one place or with mobile functions, and used in industrial automation applications. Note 1: Industrial robots include the following – Manipulators (including actuators) including Control units [including pendants and communication interfaces (hardware and software)]. Note 2: Industrial robots include additional axes by integration." JARA is involved in the creation of JIS standards for robots and industrial robots.

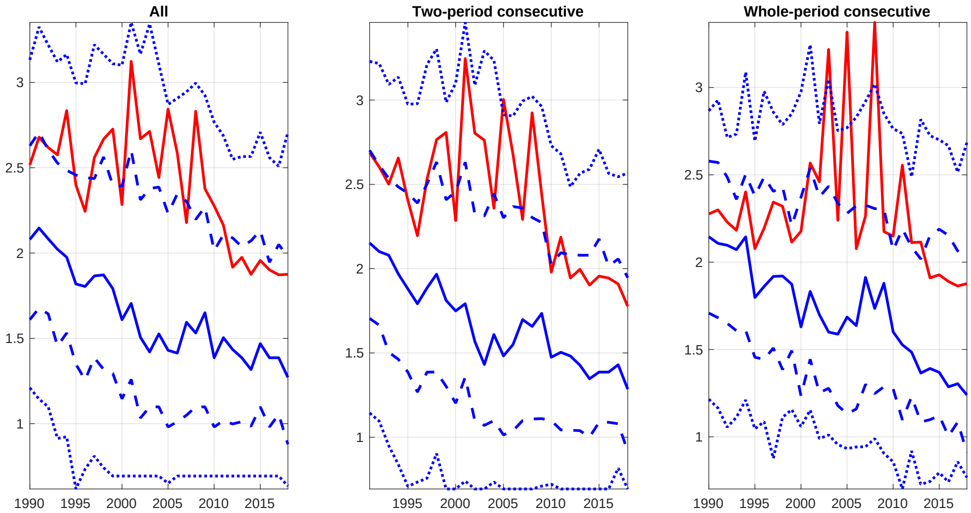
[8] https://www.jara.jp/e/data/index.html

Table 2: Descriptive statistics

	mean	variance	skewness	kurtosis
price	6.5	2949	25.8	833.9
quantity	134.0	315,358	8.9	109.9
sales	792.3	8,588,599	7.6	88.1

Note: Price is computed as the sales divided by the quantity. We normalize data so that median equals zero.

Figure 1: Distributions of prices over time



Note: All panels plot paths of prices in logarithmic scale. Red thick, blue thick, blue dashed, and blue dotted lines plot mean, median, 25 and 75 percentiles, and 10 and 90 percentiles, respectively.

number of empty spaces. In each year, around two-thirds of spaces are empty. As a result, the total non-zero entries are 8,266, resulting in a large number of disaggregated information on the prices, quantities, and sales.

2.1.1 Descriptive statistics

Table 2 presents the descriptive statistics for the prices, quantities, and sales in our dataset. To be comparable across time, we normalize all data so that median is zero. In 2018, median price was 3.6 million JPY, median quantity was 9, and median sales were 48 million JPY. Several characteristics are worth mentioning. First, variances in both price and quantity (and therefore in sales) are massive. Second, given median set as zero, mean is always positive. Skewness and kurtosis are also positive and considerably large. These altogether imply that distributions of price, quantity, and sales are concentrated around median, but significantly positively skewed. There are entries with a huge number but with minimal probabilities.

Figure 1 demonstrates how distributions of prices evolve. All data are used in the left panel, only data that exist for two consecutive periods are used in the center panel, and only data that exist for the whole sample are used in the right panel. In accordance with Table 2, means are simple average and computed with equal weights on all items.

Initially, it is apparent that the dynamics in mean differ from those in median. This observation is congruent with the characteristics found in Table 2. Very few robots are sold at very high prices, causing distributions to be significantly positively skewed. As a result, mean paths are always located above those of median and fluctuate around the upper 25 percentile. Second, while most series show declining trends, no clear declining trend in mean is identifed in the right panel. Also, the upper tail, the 90 percentile, is not in a declining trend. Note that there is no product turnover at the industry and application level in the right panel, whereas this is taken into acount in the left and the center panels. This observation implies that the prices of a few considerably costly robots that are always sold do not exhbit any trend. Therefore, product turnovers of high-end products are appear to be related to the declining trend in robot prices. This also implies that the downward trend in means observed in the left and center panels is primarily as a result of decreasing price of high-quality robots.

When gauging quality improvement in robots, or calculating the aggregate price index of robots, should the impacts from such a few very expensive entries be eliminated? To date, no consensus has been reached on this question. Therefore, we compute several aggregate price indices of robots in this paper, aiming to obtain a robust conclusion on quality improvement in robots. The trimmed means in the index number approach and the price indices based on the stochastic approach do not include those extreme values. This issue will be discussed in Section 3.

2.1.2 Relative prices

Table 3 presents relative prices by industry and application. Relative prices are calculated with a sample mean of unity. Significant heterogeneity exists in prices. The quality is quite different among various robot categories. For instance, those used for *measurement, inspection and test* and *mounting*, or in *Radio, TV, and communication equipment*, and *Iron and steel*, are considerably more expensive than others.

Figure 2 illustrates the dynamics of the number of robots installed by industry and application. The upper and lower panels plot paths of quantities in logarithmic scale by industry and application, respectively. All numbers are normalized to zero in 1990. The trend of volume change is distributed both by industry and by application. While most of the items show a gradual downward trend, some items present clear upward or significant downward trends. In addition, some items' quantities fluctuate wildly upward and downward.

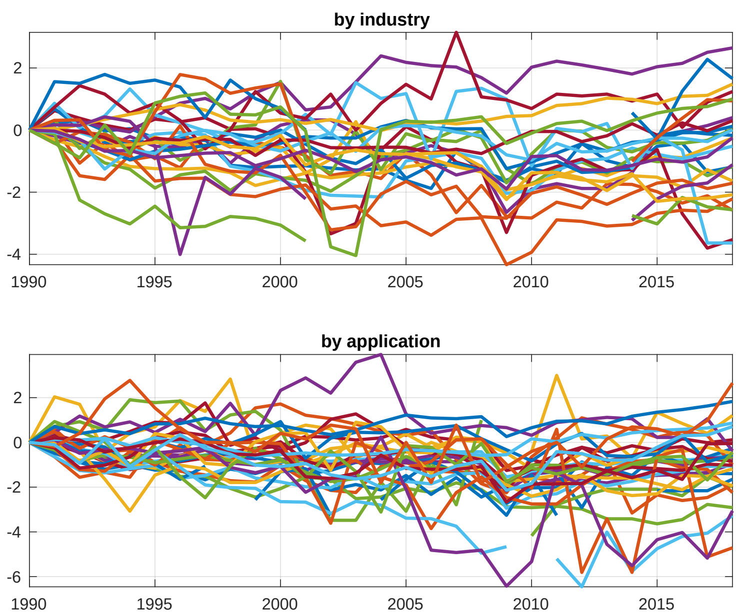
Table 3 and Figure 2 imply that the composition effect is not negligible. Even if there is no change in the price of individual robots, the quality per robot will change when the composition changes. However, whether the composition effect should be eliminated when considering the impacts of robots at a macroeconomic level is unknown. Therefore, several price indices are computed using JARA data. While the stochastic approach aims to remove this composition

Table 3: Relative prices by industry and application

Industry	Relative price
Iron and steel	1.78
Non-ferrous metals	0.62
Fabricated metal products	0.84
Other general machinery	0.71
Civil engineering and construction machine	0.88
Metal processing	0.91
Electronic computer	1.35
Household electrical equipment	1.17
Electric machinery	0.86
Radio, TV, and communication equipment	1.99
Other electric machinery	0.80
Precision / optics instruments and machinery	1.14
Ship manufacturing and repairing	1.49
Railroad vehicle	0.96
Automobile	0.92
Other transportation machinery	0.75
Beverages, tobacco and feed	1.36
Dry goods, apparel and leather goods	0.67
Lumber, wood and cork products	0.78
Paper and paper products / publishing and printing	0.84
Chemical and allied products	0.81
Petroleum coal products	0.83
Rubber products	0.51
Plastic products	0.81
Ceramic, stone and clay products	1.56
Other manufacturing	0.65

Application	Relative price
Die-casting	0.34
Other casting	0.92
Forging	1.15
Resin molding	0.88
Press	0.81
Arc welding	1.21
Spot welding	0.58
Laser welding	1.04
Other welding	0.66
Painting	0.73
Load / unload	0.80
Mechanical cutting	0.76
Polishing and deburring	0.61
Other machining	0.76
Gas cutting	1.15
Laser cutting	1.52
Water jet cutting	0.81
Other cutting	0.92
General assembly	0.83
Inserting	1.67
Mounting	2.39
Ponting	0.85
Soldering	0.49
Sealing and Gluing	0.41
Screw tightening	0.26
Other assembly	1.90
Shipment	0.94
Measurement, inspection and test	3.23
Material handling	0.49
Education and research	0.60
Clean room: flat panel display	1.05
Clean room: semi-conductor	0.51
Clean room: others	0.71
Others	2.03

Figure 2: Quantity by industry and application



Note: The upper and lower panels plot paths of quantities in logarithmic scale by industry and application, respectively. All numbers are normalized to zero in 1990.

effect, simple means from the index number approach and the theoretical price index computed from the structural approach incorporate the composition effects.[9] This issue will be further discussed in Section 3.

2.2 Industrial robot price index in CGPI

CGPI is the price index for goods traded in the corporate sector. As is usual with official price indices, CGPI is a quality-adjusted series. According to BOJ (2021), "The prices of products (goods) with the quality and contract terms fixed are continuously surveyed. ... At the time of sample price replacement, it is endeavored to reflect only "pure price change" to price indexes, after removing "price change resulting from quality changes" by using the following quality adjustment method":

$$\begin{aligned}&\text{price differencial between old and new product}\\&\quad = \text{price change resulting from quality change} \quad + \quad \text{pure price change,}\end{aligned}$$

where the first and second terms in the right hand side of the equation are used "for quality adjustment" and "to reflect to price index," respectively.

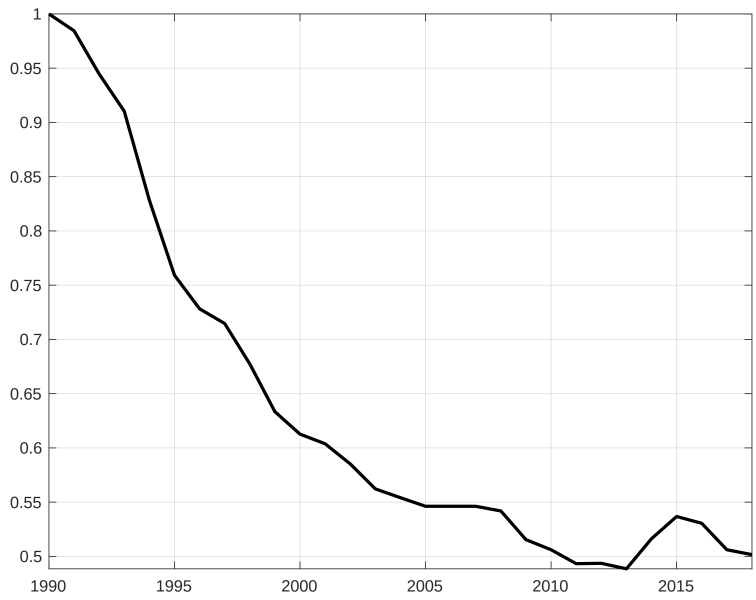
BOJ started releasing the industrial robot price index as one of the components in CGPI in 1990. Figure 3 plots the price index of the industrial robots in CGPI. The price of industrial robots was on a declining trend until 2010. The pace of decline was more significant in the 1990s than in the 2000s. The price index has remained almost flat since 2010. Since CGPI is a quality-adjusted index, it is not possible to determine from data alone whether the decline through 2010, for example, represents a decline in prices or quality improvement. Combined with the quality-unadjusted price index of robots to be computed from JARA data, we can measure the quality of robots through dividing it by the industrial robot price in CGPI. The details on how quality is calculated are given in Section 3.

According to BOJ (2021), CGPI continuously surveys product prices with a fixed quality. However, in reaction to product turnover, "sample price replacement is conducted to change reporting companies, surveyed products, and counterparties and terms of transactions, etc. which were set at the start of surveys." It is not possible to determine *a priori* whether a quality-unadjusted robot price index should be created only for products that existed for a relatively continuous period or whether a robot price index should be created to cover a wide range of products.

Thus, we calculate several robot price indices from JARA data. The trimmed means in the index number approach and the price indices based on the stochastic approach aim to capture prices with fixed quality that are continuously available. In excluding outlier observations to make sample prices more homogeneous and representative, these exercises are more congruent with the elementary price index and likely to be more comparable to the industrial robot price

[9]Note that we can exclude the composition effect at the industry and application level but not at the individual product level.

Figure 3: Industrial robot price - CGPI



Note: The index is in logarithmic scale and normalized to unity in 1990.

index in CGPI. For this purpose, we also calculate robot price indices based on simple averages without using sales weights, and those using only items that have existed for the entire period.

Regarding quality adjustment methods, BOJ (2021) employs nine quality adjustment approaches: (i) the direct comparison method, (ii) the unit price comparison method, (iii) the overlap method, (iv) the production cost method, (v) the hedonic regression method, (vi) the attribute cost adjustment method, (vii) the option cost method, (viii) the fuel efficiency method, and (ix) the webscraped prices comparison method.

Figure 7-25 in BOJ (2021) clarifies the procedure for selecting a quality control method. The selection flow works as follows: If the quality is considered constant, use (i) the direct comparison method; if not, and the only change in quality is in quantity, use (ii) the unit price comparison method; if not, and cost information can be obtained from reporting companies, use (iv) the production cost method; if not, and the new and old products are sold in parallel and the prices are moving in parallel, use (iii) the overlap method; if not, and the hedonic method is applied, use (v) the hedonic regression method; if not, and the prices of key parts causing quality changes are available, use (vi) the attribute cost adjustment method; if not, and the only change in quality is in the standardization of options, use (vii) the option cost method. Also, in this case, if monetary equivalent amounts of the fuel efficiency improvement effect are available, (viii) the fuel efficiency method can be employed together; if not, and prices in the retail market are available, and quality improvement is seen as a trend, use (ix) the webscraped prices comparison method.

Table 7-28 in BOJ (2020) demonstrates that, of the quality-adjusted items in CGPI, 35% are quality-adjusted using (i) the direct comparison method, 33% using (iv) the production cost method, 9% using (ii) the unit price comparison method, 8% using (v) the hedonic regression method, 2% using (iii) the overlap method, and the remaining 13% using other methods. Although it covers slightly older data (actual data from 2008), Figure 6 in BOJ (2009) shows, for General purpose machinery – a large category that includes industrial robots – 48% is quality-adjusted using (iv) the production cost method, 38% using (i) the direct comparison method, 3% using (v) the hedonic regression method, 2% using (iii) the overlap method, and the remaining 9% using other methods.

Further details regarding how the quality adjustment is conducted and which items is not available from BOJ. In addition, the coverage by BOJ is likely to differ from that by JARA. Thus, some caution in interpreting the results is necessary.

3 Measuring quality

This section discusses how the index number approach, the stochastic approach and the structural approach are linked to the structural equations with the micro-foundation. Note that the major advantage of the stochastic approach and the index number approach is that they do not rely on strong structural assumptions. However, here, we aim to demonstrate that they are not entirely without a theoretical basis.

3.1 A simple CES example

There are j industries and k applications. As a result, there are $n = j \times k$ categories. Consider a simple economy in a partial equilibrium, wherein a representative robot aggregator and the robot producers exist.[10]

A representative robot aggregator minimizes the total cost:

$$\sum_{i=1}^{n} \rho_{i,t} R_{i,t}, \tag{1}$$

subject to the CES aggregating technology:

$$R_t = \left[\sum_{i=1}^{n} \omega_i^{\frac{1}{\eta}} \left(a_t R_{i,t} \right)^{1-\frac{1}{\eta}} \right]^{\frac{\eta}{\eta-1}}. \tag{2}$$

ρ_t, R_t and a_t denote the price, the robot investment, the common quality, respectively.[11] The parameter, η, denotes the elasticity of substitution among different robots.

[10] The assumption that a *pseudo-single* economic agent represents the demand side may be considered strong. The stochastic approach, as shown below, does not require such an assumption.

[11] Theoretically, since robots are durable goods, their prices should be measured as rental costs. However, the industrial robot price index is calculated by BOJ as the flow price of robots in a similar manner to the calculation of the investment deflator in SNA. Thus, this study does not measure the robot price as a rental cost for consistency with the industrial robot price index in GGPI.

3.1.1 Measuring quality

By minimizing (1) subject to equation (2), we can derive the Hicksian demand function:

$$R_{i,t} = \omega_i \left(\frac{\rho_{i,t}}{\rho_t^*} \right)^{-\eta} R_t. \tag{3}$$

ρ_t^* denotes that the theoretical price index, which is quality-adjusted. Substituting equation (3) into equation (2) yields the theoretical price index:

$$\rho_t^* = \left[\sum_{i=1}^{n} \omega_i \left(a_t \rho_{i,t} \right)^{1-\eta} \right]^{\frac{1}{1-\eta}}, \tag{4}$$

which is equivalent to the cost-of-living index in households' utility maximization problem.

The JARA dataset offers individual robot price i, and ω_i as the sales share. However, the quality measure, a_t, is not available. The robot price index to be computed from JARA data is not quality-adjusted and therefore given by

$$P_t^{\text{JARA}} = \rho_t = \left(\sum_{i=1}^{n} \omega_i^{\frac{1}{\eta}} \rho_{i,t}^{1-\eta} \right)^{\frac{1}{1-\eta}}, \tag{5}$$

where P_t^{JARA} denotes the quality-unadjusted robot price index computed from the JARA database.

The industrial robot price index in CGPI, denoted by P_t^{BOJ}, is the quality-adjusted series. Therefore,

$$P_t^{\text{BOJ}} = \rho_t,$$

where the right-hand side is given by equation (4). Using equations (4) and (5), robot quality is given by

$$a_t = \frac{P_t^{\text{JARA}}}{P_t^{\text{BOJ}}}. \tag{6}$$

Robot quality can simply be computed by dividing the price index computed from the JARA database, P^{JARA}, by the price index of industrial robots by BOJ, P^{BOJ}.

Using this quality-adjusted series of robot price, the key to measuring the quality of robots is obtaining the quality-unadjusted price index for robots from the JARA dataset. Several issues must be considered.

1. The distribution of robot prices is significantly skewed positively, as shown in Table 2 and Figure 1. While many are overly concentrated near median, some items have a small probability of showing an enormous price or inflation rate. It is not evident whether such extremes should be included or excluded in calculating a representative index of robot quality improvement, which should have much to do with other major macroeconomic variables; particularly employment, wage, and labor productivity.

2. There is the composition effect, as hinted by Table 3 and Figure 2. Even if there is no

significant change in the price of robots by industry and application, the quality per robot will change when composition changes. We do not know how accounting for such a composition effect would make a difference in the impact of robot adoption on labor markets and other macroeconomic variables.

3. We do not know how BOJ conducts the quality adjustment on which items. BOJ (2021) indicates that CGPI continuously surveys product prices with a fixed quality. Conversely, it also says that BOJ conducts sample price replacement to alter reporting companies, surveyed products, and counterparties and terms of transactions, etc, that were set at the start of surveys, in reaction to product turnover. It is not possible to determine *a priori* whether a quality-unadjusted robot price index should be created only for products that have existed for a relatively continuous period, or whether a robot price index should be created to cover a wide range of products in the manner of a cost-of-living index.

Thus, the index cannot be narrowed down to a single price index. In this paper, several aggregate price indices of robots are computed in the interest of obtaining a robust conclusion on quality improvement in robots. To do so, we take three approaches, as previously described: the classic *index number approach*; *the stochastic approach* in the spirits of Edgeworth and Jevons, with which we aim to capture the common trend of price fluctuations among individual robots; the *structural approach*, with which we aim to obtain the theoretical price index being explicitly based on the cost minimization problem by firms.

As for the first point, the trimmed means in the index number approach and the price indices based on the stochastic approach are computed to exclude extreme values. Regarding the second point, the stochastic approach is applied to remove the composition effect, whereas the simple means from the index number approach and the theoretical price index computed from the structural approach include the composition effect. On the third point, the trimmed means from the index number approach and the price indices based on the stochastic approach aim to capture and gauge the underlying changes in product prices that are continuously available with fixed quality.

In addition, to get closer to elementary aggregates and therefore the industrial robot price index in CGPI by BOJ, we also calculate robot price indices based on simple averages without using sales weights, and those using only items that are tracked for the entire period. Outlier observations are excluded to render sample prices more homogeneous and representative.

3.1.2 Index number approach

When the elasticity of substitution, η, is unity, equation (5) collapses to the Cobb-Douglas aggregator:

$$\rho_t = \prod_{i=1}^{n} \rho_{i,t}^{\omega_i},$$

where

$$\sum_{i=1}^{n} \omega_i = 1.$$

These two equations show that ρ_t is given by the geometric mean of $\rho_{i,t}$. Thus, the geometric mean is considered a reasonable approximation of the theoretical price index in equation (5), particularly when the elasticity of substitution is close to unity.

Even when the elasticity of substitution is not unity, the price indices computed by the index number approach can be derived from the theoretical model. Suppose that the weights in the theoretical price index are the same across i and unity. Then, equation (5) collapses to

$$\rho_t = \left(\sum_{i}^{n} \rho_{i,t}^{1-\eta} \right)^{\frac{1}{1-\eta}},$$

or

$$\exp\left(p_t\right) = \exp\left[\frac{1}{1-\eta} \ln \left(\sum_{i}^{n} \exp\left(\left(1-\eta\right) p_{i,t}\right) \right) \right], \tag{7}$$

where we define $p_t := \ln\left(\rho_t\right)$ and $p_{i,t} := \ln\left(\rho_{i,t}\right)$. Taking the first order approximation of equation (7) around p_{t-1} and $p_{i,t-1}$ yields

$$\pi_t = \sum_{i}^{n} \frac{p_{i,t-1} R_{i,t-1}}{\sum_{k}^{n} p_{k,t-1} R_{k,t-1}} \pi_{i,t},$$

where we use the definition of inflation rates: $\pi_t{:=}p_t - p_{t-1}$. This equation expresses the definition of the inflation rate using the Laspeyres index.[12]

3.1.3 Stochastic approach

We next consider the problem of another economic agent. Robot producer i under the monopolistic competition maximizes the profit:

$$\rho_{i,t} R_{i,t} - r_t K_{i,t} - w_t h_{i,t}, \tag{8}$$

subject to the production technology:

$$R_{i,t} = Z_t z_{i,t} \left(K_{i,t}\right)^{\alpha} \left(h_{i,t}\right)^{1-\alpha}, \tag{9}$$

and the Hicksian demand function in equation (3). r_t, K_t, h_t, Z_t and $z_{i,t}$ denote the rental rate, capital, labor, the common technology, and i-specific technology, respectively. We assume that Z_t has a positive trend, whereas $z_{i,t}$ is stationary. The parameter, α, denotes the capital share.

[12]Similarly, the first order approximation of equation (7) around p_t and $p_{i,t}$ leads to the following:

$$\pi_t = \sum_{i}^{n} \frac{p_{i,t} R_{i,t}}{\sum_{k}^{n} p_{k,t} R_{k,t}} \pi_{i,t},$$

which denotes the inflation rate using the Paasche index.

From the first order necessary conditions, we have the condition for the optimal price setting:

$$\rho_{i,t} = \frac{\eta}{\eta-1}\frac{1}{Z_t z_{i,t}}\left(\frac{r_t}{\alpha}\right)^{\alpha}\left(\frac{w_t}{1-\alpha}\right)^{1-\alpha}.$$

Taking logs from both sides yields

$$\frac{p_{i,t}}{p_{i,t-1}} = \overbrace{\ln\left[\frac{Z_{t-1}}{Z_t}\left(\frac{r_t}{r_{t-1}}\right)^{\alpha}\left(\frac{w_t}{w_{t-1}}\right)^{1-\alpha}\right]}^{\text{common trend}} + \overbrace{\ln\left(\frac{z_{i,t-1}}{z_{i,t}}\right)}^{\text{idiosyncratic shock}}. \tag{10}$$

Equation (10) offers a micro-foundation of the stochastic approach in the spirits of Edgeworth and Jevons. We can estimate the common trend by the panel regression of inflation rates of individual robots on time fixed effects. As can be seen from equation (10), the stochastic approach is not subject to the composition effect because it uses inflation rates for estimation.[13]

3.2 HSA – structural approach

The price index obtained in the index number approach is theoretically valid in only a restrictive situation. For example, we do not have any prior knowledge to justify the assumption behind the CES aggregator that all robots are subject to the same elasticity of substitution. In addition, JARA's robot data is intermittent; the number of available robots is time-varying. The standard CES aggregator cannot handle such product turnovers.[14]

Matsuyama and Ushchev (2017) propose a new and highly flexible homothetic preference. With what they call the "homothetic demand system with a Single Aggregator" (hereafter, HSA), the theoretical price index can be estimated in a homothetic demand system with a minimal assumption that the expenditure share is the function of the relative price. With HSA, each factor can have its unique constant price elasticity, any number of essential and of inessential factors can be considered, and factors can be gross substitutes but essential.

HSA assumes that expenditure share is simply the function of the relative price:

$$s_{i,t} = m\left(\frac{\rho_{i,t}}{\rho_t}\right), \tag{11}$$

where $s_{i,t}$ denotes the nominal expenditure share of good i, and a function $m : \mathbb{R}_+ \to \mathbb{R}_+$ maps the relative price of good i denoted by $\frac{\rho_{i,t}}{\rho_t}$ to its expenditure share.[15]

[13]Notice that with the current data, the composition effect at the level of individual goods cannot be removed.

[14]When the time variation in the available set of robot varieties is allowed for, as in Feenstra (1994), the corresponding price index becomes the product of the conventional Sato–Vartia (SV) index, following Sato (1976) and Vartia (1976).

[15]Note that CES is a special case of HSA. With the CES aggregator, the expenditure share is given by the function of the relative price such that

$$s_{i,t} = \omega_i\left(\frac{\rho_{i,t}}{\rho_t}\right)^{1-\eta}.$$

Summing up equation (11) over i yields

$$\sum_{i=1}^{n_t} s_{i,t} = \sum_{i=1}^{n_t} m\left(\frac{\rho_{i,t}}{\rho_t}\right) = 1. \tag{12}$$

Equation (12) defines our HSA price index. HSA price index is the theoretical price index, similar to the cost-of-living index, and therefore incorporates the composition effect and extreme values.

The challenge in obtaining the price index from equation (12) is that we have two unknown components: the unknown function $m(\cdot)$ and a latent variable ρ_t. The details of our estimation strategy will be discussed in Section 6.

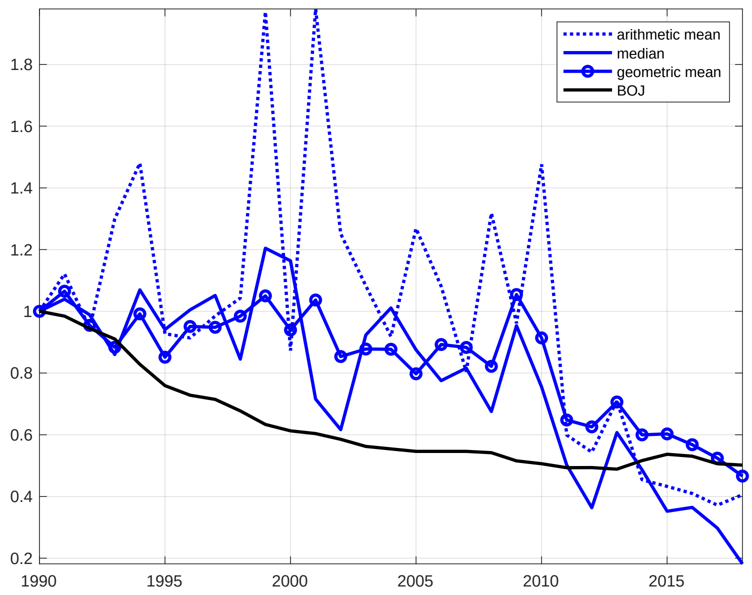
4 Index number approach

When gauging quality improvement in robots, or calculating the aggregate price index of robots, should we eliminate the impacts from a few but considerably expensive entries as observed in Table 2 and Figure 1? A popular approach in calculating the trend inflation rate is the trimmed mean approach following Bryan and Cecchetti (1994) and Shiratsuka (1997). To eliminate the influences from massive, but short-lived, fluctuations, we exclude a few percentiles' inflation rates at the top and bottom when computing the price index or the trend inflation rate. The rationale behind such a trimmed mean approach in the computation of trend inflation rates and the aggregate price index is that those fluctuations have very little to do with macroeconomic fundamentals. This is not a new idea, tracing back to the classic proposal known as the stochastic approach advocated by Jevons (1884) and Edgeworth (1887).

The answer hinges on how other macroeconomic variables are affected by the installation of robots, particularly whether the upper tail dynamics in the robot price distribution, as hinted by Table 2 and Figure 1, are critical, for instance, to the equilibrium of the labor market. If new, but only a few, high-end robots have significant impacts on firms' hiring or firing decisions, all data should be included when measuring the quality of robots. In contrast, if it is the adoption of robots close to the standard price range, (i.e., close to median price), that is important for determining other macro variables, the trimmed mean approach should be employed when computing the aggregate robot price index.

Rather than focusing on one index, in this section, we calculate several aggregate price indices using the traditional index number approach. In addition to averages using sales weights and median, we calculate the trimmed mean inflation rate of robots and then the aggregate price index by taking the integral of inflation rates over time. To get closer to elementary aggregates or the industrial robot price index in CGPI by BOJ, we also calculate robot price indices based on simple averages without using sales weights, and those using only items that were continuous for the entire period. We exclude outlier observations to make sample prices more homogeneous and representative.

Figure 4: Robot prices from levels



Note: All are in logarithmic scale and normalized to unity in 1990.

4.1 Mean and median

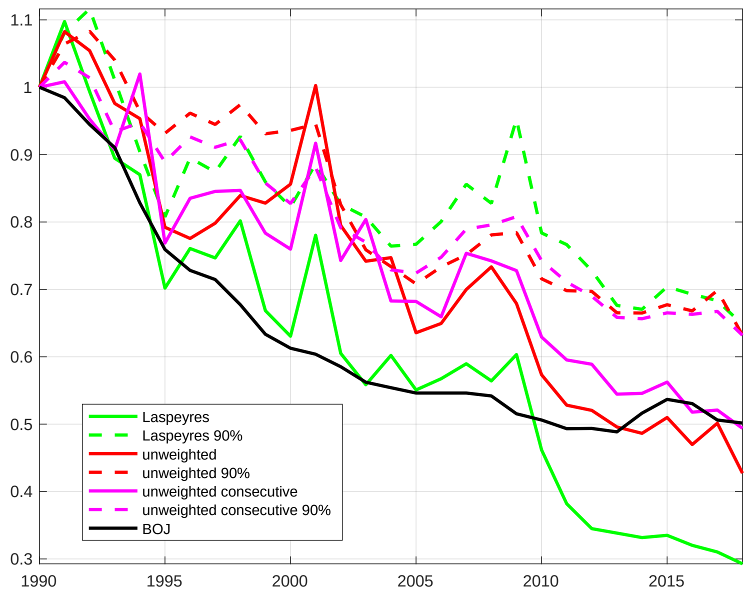
Figure 4 displays time series of mean and median of individual prices. All are in logarithmic scale and normalized so that the 1990 level is unity. When computing means, sales are used as the weight. The paths of both arithmetic and geometric means are plotted. The arithmetic mean presents the most volatile path, because it is the most susceptible to extreme fluctuations at tails. In this sense, the geometric mean and median also reflect the essence of the stochastic approach, as the tail portion has a more minor impact.

Declining trends in all measures are observed throughout the sample. The pace of decline was much faster in the 2010s compared to the previous two decades. These developments are in sharp contrast to those of the quality-adjusted CGPI industrial robot price denoted by "BOJ", which, in contrast, showed a higher pace of decline until 2010, remaining flat after 2010. Since data in Figure 4 is expressed in logarithmic scale, the vertical differences between values obtained from JARA data and CGPI industrial robot price represent the quality of robots. Even considering the simplest statistics, such as mean and median, it is clearly apparent that the pace of improvement in robot quality has been declining since around 2010.

4.2 Trimmed mean

Figure 5 plots the robot price indices computed from inflation rates. "Laspeyres" and "unweighted" indicate whether Laspeyres weights (weighted by sales in the previous period)

Figure 5: Robot prices from inflation rates



Note: All are in logarithmic scale and normalized to unity in 1990.

or equal weights are used to calculate the average inflation rate, respectively.[16] We call it Laspeyres in Figure 5, but since the weights are changed every period, it is the Laspeyres chain index. Unweighted indices are computed so that they are more comparable to elementary aggregates and therefore the industrial robot price index in CGPI by BOJ.

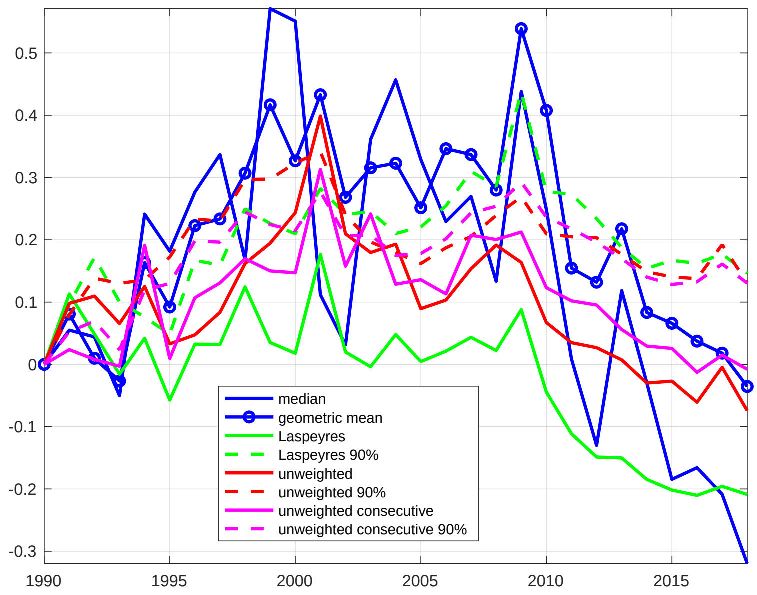
The difference between these and the arithmetic mean in Figure 4, of course, reflects the different weights, but also the fact that Figure 5 covers only those prices that are measured continuously for two periods. The sample size of Figure 5 is smaller than that of Figure 4 because it is not possible to calculate the inflation rate of individual robots without the availability of continuous data for two periods.

As measures that are less susceptible to tail movements, "Laspeyres 90%" and "unweighted 90%" represent robot price indices based on the trimmed mean inflation rates using Laspeyres and equal weights, respectively. Only price changes that fall in the 10% around median, with the top and bottom 45% symmetrically trimmed, are considered to capture the price changes of robots that are representative. We also calculate mean of equal weights. These are more congruent with the stochastic approach, particularly that of Edgeworth (1887); "less weight should be attached to observations belonging to a class which are subject to a wider deviation from the mean."

We can observe a similar tendency found in Figure 4. The pace of decline in the robot price index is higher in the 2010s, once again suggesting a slowdown in the pace of quality

[16] In using the sales weights, we calculate the inflation rate using only the Laspeyres index. For the reason and background, please refer to Appendix A.

Figure 6: Robot quality from index number approach



Note: All are in logarithmic scale and normalized to zero in 1990.

improvement. In Figure 5, the pace of decline is slower for the price index calculated using the trimmed mean. This suggests that, as implied in Figure 1, the prices of expensive robots have declined more.

Lines in magenta that are labeled "consecutive" plot means of prices for which data is available during the entire period. Again, these are for more comparable measures to the elementary price index. There is no significant difference between red and magenta lines. "unweighted consecutive" is slightly higher in recent years than unweighted, again reflecting the lower demand for high-end products implied in Figure 1.

4.2.1 Robot quality

Figure 6 presents the quality of robots computed from the index number approach. Robot quality is expressed as the robot price calculated from the JARA dataset divided by the CGPI industrial robot price index, as in Equation (6). Numbers in Figures 4 and 5 are expressed in logarithmic scale. In both charts, the vertical difference between each robot price represents robot quality.

Regardless of the methods examined in this section (i.e., whether the composition effect is considered, or whether only price trends of representative products are the focus), the results show that the quality per robot has been declining since around 2010. The quality calculated from median and the geometric mean presents a stronger downward trend in the 2010s than in other periods. This implies that cheaper robots have been selling better since around 2010, and as a result, the average quality per robot is shown to be in decline.[17]

5 Stochastic approach

Table 2 and Figures 1 and 5 suggest that the shape of the robot price index can vary depending on whether high-end products are included in the calculation. Also, Table 3 and Figures 2 and 5 imply that the composition effect is not negligible. To obtain robust results for robot quality, calculating the robot price index excluding the composition effect is also a sound approach. As shown in equation 10, the stochastic approach is not affected by the composition effect because it estimates inflation rates on the common factor.

In addition, since JARA data collects information from the supply side, it is unclear whether a price index can be estimated assuming that the demand side is represented by a *pseudo-single* economic agent as shown in Section 3. With this concern in mind, the current section sets the concept of the demand system aside for now and calculates an alternative price index without relying on the sales share information.[18]

In this section, we estimate a common trend among prices as a core measure of robot prices. We deliberately aim to measure the representative robot price index that is less susceptible to the outliers and the composition effect as well as structural assumptions. This approach is in line with the core inflation concept of Bryan and Cecchetti (1994) and the stochastic approach, which dates back to the classic proposal of Edgeworth and Jevons and is revived by Selvanathan and Prasada (1994).

5.1 Framework

Consider that the data generating process of logarithmic changes of individual robot prices, $\Delta p_{i,t}$, consists of a common trend component, g_t, and a zero-mean *i.i.d.* random component, $\epsilon_{i,t}$:

$$\Delta p_{i,t} = g_t + \epsilon_{i,t}, \tag{13}$$

where $E(\epsilon_{i,t}) = 0$ and $E(\epsilon_{i,t}^2) = \sigma^2$. If we are to make a structural interpretation, equation (13) corresponds to equation (10). We estimate equation (13) using a following econometric model with a panel of JARA's individual robot prices:

$$\Delta p_{i,t} = \overbrace{\sum_{s=1}^{T} \beta_s D_{s,t}}^{\text{common trend}} + \overbrace{\eta_i}^{\text{Individual fixed effect}} + \epsilon_{i,t}, \tag{14}$$

[17] Note also that if Paasche and Fisher weights are used, as implied in Figure 9 in Appendix A, quality decline in the 2010s becomes much more significant. Quality measures based on Paasche and Fisher weights exaggerate the declining quality of robots rather than weakening them.

[18] Section 3.1.3 shows that the stochastic approach can be derived from the demand system. However, the stochastic approach itself is a method that breaks down changes in individual prices into common and individual factors without assuming some structure *a priori*. For this reason, it can be viewed as a robust time-series analysis method that does not rely on theoretical assumptions.

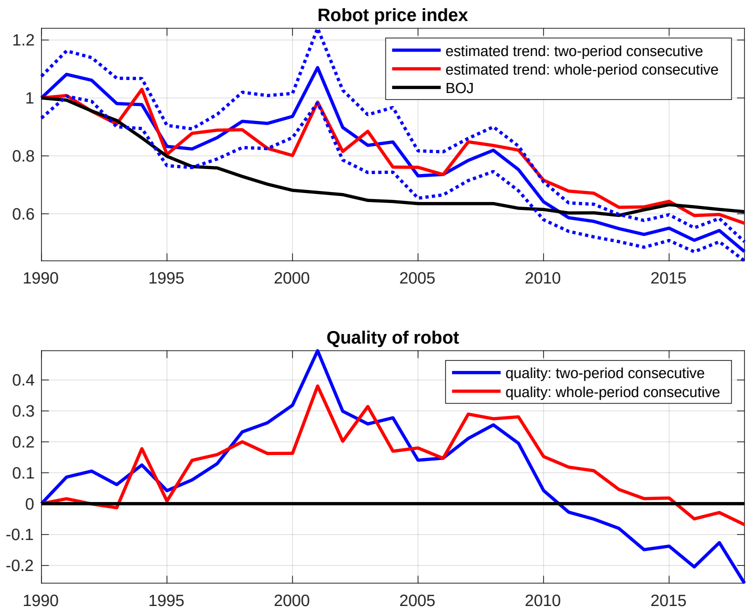
where β_s and $D_{s,t}$ are parameters of time fixed effects and a binary dummy of time s at time t. When estimating a variant of equation (14), Selvanathan and Prasada (1994) apply the weighted least square using sales share as a weight by postulating that the variance of price i's random component is inversely proportional to its sales share. However, Diewert (2010) criticizes this assumption because the variance assumption made in Selvanathan and Prasada (1994) is not consistent with the observed behavior of prices. Thus, the estimation in this section does not rely on the sales-share-weighted least square method. In this respect, price indices computed by the stochastic approach are closer to the elementary price index and therefore more comparable to the industrial robot price index in CGPI.

We estimate equation (14) using an unbalanced panel of JARA's individual robot prices. The sample period ranges from 1991 to 2018.

5.2 Empirical results

The upper panel of Figure 7 presents robot price indices computed using the stochastic approach. The blue solid line is the common trend in robot prices estimated using samples avail-

Figure 7: Price and quality: Stochastic approach



Note: All are in logarithmic scale. Prices in the upper panel and quality in the lower panel are normalized to unity and zero, respectively, in 1990. "estimated trend: two-period consecutive" and "estimated trend: whole-period consecutive" are the estimated trends using samples available for two consecutive periods and using samples available for the entire period, respectively. The 90% confidence intervals – dotted lines – are based on the robust standard error.

able for two consecutive periods. The blue dotted lines represent the 95% confidence interval. The narrowly estimated confidence interval suggests that the parameters are sharply estimated. The red solid line represents the common trend estimated using samples that are continuously available for the full period. For reference, BOJ's industrial robot price index is plotted in the black solid line.

The estimation result exhibits three critical points. First, the common movements in robot prices indicate a declining trend over the sample period. Second, the declining trend is more evident after around 2010. These findings are similar to those in the previous section. Interestingly, the different approaches – the trimmed mean and the stochastic approach – elicit the same conclusion. Third, the estimated trend using samples continuously available for the entire period is more stable than the estimated trend using samples available for two consecutive periods. The difference between these two series reflects the effect of product turnovers at the industry and application level; the former allows some samples to entry and exit, whereas the latter does not. Thus, it can be deduced that price declines are more pronounced for recently used robots. These are likely to be the high-end products, as implied in Table 3 and Figures 2 and 5.

The lower panel of Figure 7 presents the quality measure of robots, which is the log difference between the estimated common trend in robot prices and BOJ's quality-adjusted robot price index. The figure suggests that the quality per robot continued to improve until around 2000, but it slowed down in the 2000s, and started to decline in the 2010s. The representative robot index, which is less susceptible to the outliers and free from the composition effect, is significantly different from the industrial robot index by BOJ. This indicates that the trend in the lower panel of Figure 7 is significantly different from zero in the 2000s.

In summary, exercises in this section confirm the findings in the previous section; quality improvement progress in robot industries began declining in the 2010s. We can conclude that the declining trend in robot quality in the 2010s is not specific to particular types of robots. In addition, it is unlikely to be a matter of the methodological issues in construction of the conventional robot price index.

The stochastic approach used in this section still has some limitations, although they are deliberately ignored in this section to attain the representative index.[19] For example, this approach estimates common movements in prices, considering a relative price change as noise, though it may contain substantial information value. The following section attempts to measure a price index under a flexible demand system to utilize the information contained in relative price movements.

6 Structural approach

This section aims to compute the theoretical robot price index applying the structural approach. We estimate equation (11), which is based on a very general class of homothetic aggregator, HSA, proposed by Matsuyama and Ushchev (2017). We compute the HSA price index in reference to Kasahara and Sugita (2020), assuming that every robot producer engages in monopolistic competition taking the price index as given.

[19] General criticisms to the stochastic approach to index number are also found in Diewert (2010).

6.1 Framework

We assume that the share is additively separable into two components:

$$\ln\left(s_{i,t}\right) = m\left(\frac{\rho_{i,t}}{\rho_t}\right) + x'_{i,t}\beta,$$

where $x_{i,t}$ is a vector of controls which includes individual fixed effects by industry and application, and β is a vector of regression coefficients.[20] We proceed in two steps.

In the first step, we approximate the unknown function $m(\cdot)$ with a polynomial. This gives us the following nonparametric model:

$$\ln\left(s_{i,t}\right) = \tilde{m}_k\left(\frac{\rho_{i,t}}{\rho_t};\delta^k\right) + x'_{i,t}\beta + \tilde{e}_{k,i,t}, \tag{15}$$

where k denotes the order of polynomial, and e_k is the approximation error and hence depends on k, and δ^k are regression coefficients. Under the power series approximation, equation (15) can be transformed into

$$\begin{aligned} \ln\left(s_{i,t}\right) &= \tilde{m}_k\left(\frac{\rho_{i,t}}{\rho_t};\delta^k\right) + x'_{i,t}\beta + \tilde{e}_{k,i,t} \\ &= \sum_{l=1}^{k}\delta_l^k p_{i,t}^l + \sum_{l=1}^{k}\sum_{j=1}^{l}\underbrace{\begin{pmatrix} l \\ j \end{pmatrix}\delta_l^k}_{\equiv\delta_{l,j}^k} p_{i,t}^{l-j}\left(-p_t\right)^j + x'_{i,t}\beta + \tilde{e}_{k,i,t}. \end{aligned} \tag{16}$$

Since p_t is a time-varying unobserved variable, estimation of equation (16) is infeasible. However, time dummies can be used to absorb the effect of p_t. Rather than equation (16), we estimate the equation below:

$$\begin{aligned} \ln\left(s_{i,t}\right) &= \hat{m}_k(\rho_{i,t},\tau_t;\delta^k) + x'_{i,t}\beta + \hat{e}_{k,i,t} \\ &= \sum_{l=1}^{k}\delta_l^k p_{i,t}^{l-1} + \sum_{l=1}^{k}\sum_{s=t_0+1}^{T}\delta_{l,s}^k\tau_s p_{i,t}^{l-1} + \sum_{s=t_0+1}^{T}\delta_{\tau,s}^k\tau_s + x'_{i,t}\beta + \hat{e}_{k,i,t}, \end{aligned} \tag{17}$$

Notice that from equation (17), we can identify β and δ_l^k in equation (16).

In the second step, we use the identity:

$$\sum_{i=1}^{n_t} s_{i,t} = 1\,,\ \text{for all } t,$$

to solve for the price index p_t. By using the parameters estimated in the first step, we have

$$\bar{s}_{i,t} = \exp\left(\sum_{l=1}^{k}\hat{\delta}_l^k\left(\frac{p_{i,t}}{p_t}\right)^{l-1} + x'_{i,t}\hat{\beta}\right),$$

[20] Kasahara and Sugita (2020) show that HSA formalized in this manner can be derived from a unique preference by applying proposition 1 in Matsuyama and Ushchev (2017).

and we search for p_t by the nonlinear least square method:

$$\hat{p}_t = \underset{p_t}{\operatorname{argmin}} \left[1 - \sum_{i=1}^{n_t} \exp \left(\sum_{l=1}^{k} \hat{\delta}_l^k \left(\ln \frac{p_{i,t}}{p_t} \right)^{l-1} + x_{i,t}' \hat{\beta} \right) \right]^2 , \text{ for all } t.$$

6.2 Empirical results

In Table 4, we present the regression results from this nonparametric model. The improvement in fitting by increasing the order of the polynomial is marginal, at least, in the range of $k = 2$ to $k = 4$. All regressions include fixed effects by industry and application, and heteroskedasticity robust standard errors are reported.

Table 4: Polynomial regression

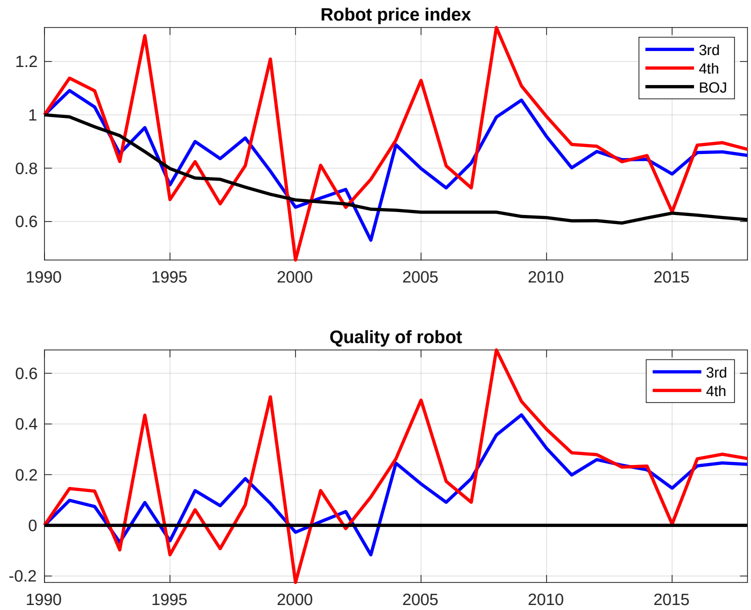
Variables	(1) $\ln(s_{i,t})$	(2) $\ln(s_{i,t})$	(3) $\ln(s_{i,t})$	(4) $\ln(s_{i,t})$
$p_{i,t}$	-0.699***	-1.843***	-2.534***	-3.551***
	(0.0843)	(0.243)	(0.369)	(0.547)
$(p_{i,t})^2$	0.237***	0.745***	1.275***	2.573***
	(0.0170)	(0.104)	(0.257)	(0.670)
$(p_{i,t})^3$		-0.0641***	-0.216***	-0.878**
		(0.0127)	(0.0709)	(0.344)
$(p_{i,t})^4$			0.0142**	0.158**
			(0.00663)	(0.0755)
$(p_{i,t})^5$				-0.0111*
				(0.00584)
Constant	-7.475***	-6.768***	-6.505***	-6.299***
	(0.105)	(0.171)	(0.177)	(0.174)
Observations	8,266	8,266	8,266	8,266
R-squared	0.757	0.761	0.763	0.765

Note: Robust standard errors are in parentheses. Fixed effect is considered at industry-purpose level. *** p<0.01, ** p<0.05, and * p<0.1.

The estimates of the price indices using the third and the fourth order power series approximation are shown in the upper panel of Figure 8.[21]

[21] We do not show the result from the second order approximation, as the difference between the second and the third order approximation is marginal; however, there is a huge increase in 2010 in the second order approximation.

Figure 8: Price and quality: HSA



Note: All are in logarithmic scale. Prices in the upper panel and quality in the lower panel are normalized to unity and zero, respectively, in 1990. "3rd" and "4th" are the estimated price indices using the third and fourth order approximation, repectively. The 90% confidence intervals – dotted lines – are based on the robust standard error.

All series are normalized so that $p_{1990} = 1$. Overall pictures are similar to those in Figures 4, 5, and 7. The aggregate robot price index demonstrates an upward trend until around 2010. The trend becomes flattened or somewhat declining after that.

The lower panel in Figure 8 illustrates the evolution of the quality per robot in both the third and the fourth order approximation. Results obtained here are congruent with our earlier findings in Figures 6 and 13, confirming that growth in robot quality slowed down after around 2010.

7 Discussion: has quality improvement slowed down?

Figures 6, 7, and 8 show that quality improvement in robots slowed down after around 2010. Table 5 summarizes the growth rate of the quality of robots illustrated in Figures 6, 7, and 8. The results regarding the quality of robots in Sections 4, 5, and 6 are divided into narrow and broad measures. The former is based on representative robot price indices that are less susceptible to outliers and the composition effect, in the spirit of the classic stochastic approach by Edgeworth and Jevons. Conversely, the latter views prices as a theoretical cost-of-living type index. Thus, the broad measures include the effects from both outliers and the composition effect when computing the quality of robots.

In all items examined in Sections 4, 5, and 6, the quality of robots improved in the 2000s compared to that in the 1990s. The growth rates in both narrow and broad measures are around

Table 5: Long-run trend in robot quality

		narrow measures					
		I-1	I-2	I-3	I-4	S-1	S-2
growth rate	2000-2009	1.09	1.40	0.63	0.99	1.48	1.55
	2010-2018	-4.05	-0.80	-1.33	-1.62	-5.58	-3.83
d(growth rate)		-5.14	-2.20	-1.33	-1.62	-5.58	-3.83

		broad measures					
		I-5	I-6	I-7	I-8	H-1	H-2
growth rate	2000-2009	1.92	0.08	1.01	1.07	0.78	1.15
	2010-2018	-2.47	-2.28	-2.21	-1.54	1.02	0.28
d(growth rate)		-4.39	-2.37	-3.22	-2.61	0.24	-0.87

Note: I-1 to I-8 correspond to quality measures in the index number approach: I-1 median; I-2 Laspeyres 90%; I-3 unweighted 90%; I-4 unweighted whole-period consecutive 90%; I-5 geometric mean; I-6 Laspeyres; I-7 unweighted; I-8 unweighted whole-periods consecutive. S-1 and S-2 correspond to those in the stochastic approach: S-1 for two-period consecutive S-2 whole-period consecutive. H-1 and H-2 correspond to those in the structural approach: H-1 3rd order polynomial; H-2 4th order polynomial.

1% *per annum*. In contrast, growth rates in the quality per robot in the 2010s compared to that in the 2000s are mostly negative. They are all negative, and the average is -2.87% *per annum*, in narrow measures. Even in broader measures, they are negative, except for those computed using the structural approach. The average growth rate in the 2010s is -1.20% *per annum*.

Numbers in d(growth rate) show the differences in growth rates between the 2000s and the 2010s. They take large negative values except for one case, the structural approach with the third order approximation. The average differences are -3.28 and -2.20 percentage points *per annum* in narrow and broad measures, respectively. Depending on the method to calculate the quality-unadjusted robot price index, the level and the growth rate of robot quality can differ. In particular, the structural approach using HSA shows relatively lower (higher) growth rates in robot quality in the 2000s (2010s) compared to the index number and the stochastic approaches. They all, however, show a significant slowdown in quality improvement in robots in the last decade.

Figures 6, 7, and 8, and Table 5 show the decline in the level of the quality per robot. It may be difficult to imagine that quality is declining in terms of level. As can be seen in Figures 4, 5, 7, and 8, the price per robot, whether narrowly or broadly defined, has been on a downward trend in the 2010s. This means that the quality of each robot is declining; thus, less expensive robots of lower quality are spreading.

This has some implications for the macroeconomic impact of robots, but it does not necessarily mean that the spread of cheaper robots will weaken their impact on the labor market. The conclusions in this paper suggest that robots may be as obsolete as conventional machines have ever been, but this study does not consider any technological advances on the software side that would expand the use and efficiency of robots. The benefits of the combination of versatility and the use of software to control robots can be seen as an improvement in the service flow of intangible capital rather than a traditional intermediate input, and understanding this from data and models is a major challenge for future research.

Detailed data for understanding the causes behind the decline in quality improvement in robots is not yet available. Our results hinting at the decline in the pace of robot quality seems to be congruent with recent observations in the slowdown in the pace of relative price declines of capital goods over consumer goods. Fernald (2014), Byrne and Pinto (2015), and Takahashi and Takayama (2021) report the dramatic slowdown in the pace of relative price declines of capital goods. This implies the slowdown of the investment-specific technological progress, which may include robot quality. In addition, in a related study, Bloom et al. (2020) present evidence that "research effort is rising substantially while research productivity is declining sharply." This *ideas-are-getting-harder-to-find* hypothesis advocated by Bloom et al. (2020) may also be applicable to robot production.

8 Conclusion

This paper investigates the extent to which the quality of robots has improved in Japan between 1990 and 2019, using novel datasets from JARA and BOJ that contain robot price information. We first show that the quality per robot increased or leveled off in the 2000s and decreased in the 2010s. We then report a drastic decline in improvement in robot quality in the last decade. The difference in the growth rates of robots' quality between the 2000s and the 2010s take substantial negative values, mostly around -3 percentage points *per annum*.

Naturally, there are several caveats in our results. First, the quality adjustment is solely dependent on BOJ's CGPI. Since the details of the kind of industrial robots that are covered are not available, caution is necessary in interpreting the results. According BOJ (2020), of the quality-adjusted items in CGPI, 33% are quality-adjusted using the production cost method. On actual data from 2008, BOJ (2009) shows that for General purpose machinery – a large category that includes industrial robots – 48% is quality-adjusted using the production cost method. Since this method assumes that quality change corresponds to the required production cost change between old and new product obtained from reporting companies, it is possible that quality has declined due to lowered prices of parts. Still, it seems unlikely that the markups of Japanese manufacturers increased in the 2010s. So, we believe that the quality of each robot decreased in some way. In addition, the coverage by BOJ is likely to differ from that by JARA. Micro data is needed to obtain a consistent quality adjustment measure with JARA data.

In this respect, the "mismeasurement hypothesis" coined by Syverson (2017) may apply to the observed slowdown in the quality of robots. Concerning the slowdown in labor productivity in the US, Syverson (2017) suggests that "the reasonable prima facie case for the mismeasurement hypothesis faces real hurdles when confronted with data." However, the quality of robots may no longer be determined by the robot itself, but by the software that expands the use of the robot. The latter seems to hardly be evaluated in currently available data.

Second, our analysis is based only on Japanese data. A decline in the robot price indices in the 2010s may reflect the Japanese robot industry's global competitiveness, resulting in a decline in the markups. For a long time, Japan was the largest producer of robots in the world. According to "World Robotics 2020" published by the International Federation of Robotics, China is the world's largest producer of robots, producing about three times as many robots as Japan. Singapore and South Korea also boast the highest robot density: the number of robots installed per worker, with numbers more than double that of Japan. Still, Japan remains the second-largest producer of robots and the third in robot density. Thus, something that is happening in Japan must not be orthogonal to the global market developments. For a proper analysis of the Japanese robot industry's relative competitiveness, price information of robots produced in foreign countries is needed.

Third, a deregulation of the safety standards for *collaborative robots* was implemented in 2013. Since collaborative robots are compact and cheaper, an increase in collaborative robots might place downward pressure on robot prices.[22] In the past, industrial robots with a motor output of more than 80W had to be separated from human workspace by a fence or enclosure. The Ministry of Health, Labor and Welfare issued a notice (Kihatsu 1224 No. 2) on December 24, 2013, to enforce the Ministerial Ordinance Partially Amending the Ordinance on Industrial Safety and Health, and ISO 10218-1/-2:2011 stipulates that industrial robots designed, manufactured, and installed under the conditions of use shall not be required to install fences or enclosures if they are correctly used. However, no significant structural break in the trends in robot prices around 2013 is evident. This may reflect the fact that the market for collaborative robots is still not large, making up only 4.8% of all industrial robots according to the International Federation of Robotics.

Careful analyses of each of these using new data and understanding the causes behind the slowdown of robot quality are left for our future studies.

[22]Even if this is true, quality per robot declines, which may impact macroeconomic variables; thus, we are ussure whether this deregulation is an issue for gauging robot quality.

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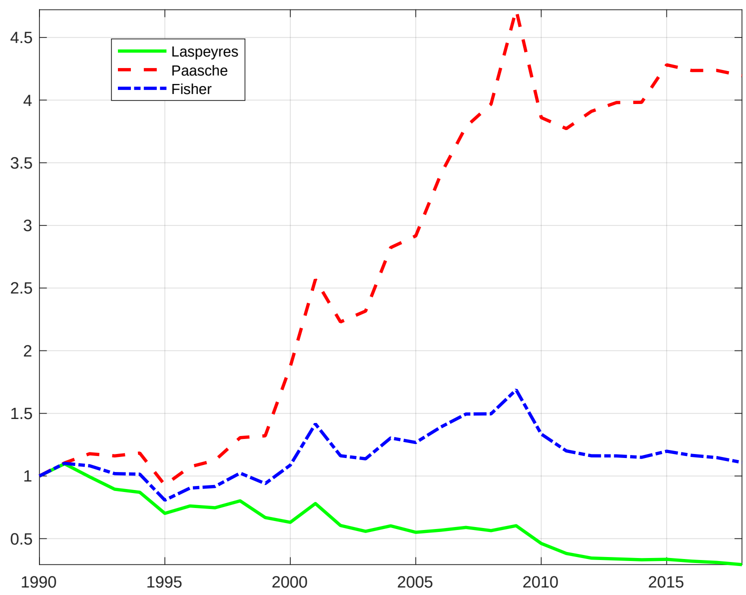
Appendix

A Why Laspeyres?

When computing price indices from inflation rates in Figure 5, we only report those using Laspeyres or equal weights. Figure 9 compares robot price indices calculated from inflation rates using Laspeyres, Paasche, and Fisher weights.[23] Since the robot price index calculated using Paasche and Fisher weights differ significantly from the trends shown in Figure 1 and 4, we decided to report those using Laspeyres weights.

Figure 9: Laspeyres, Paasche and Fisher indices



Note: All are in logarithmic scale and normalized to unity in 1990.

The divergence between the robot price indices calculated from the inflation rates using Laspeyres and Paasche weights has been widening over time. Bortkiewicz (1923) shows that when the covariance between price and quantity is negative (i.e., when there is a relationship between high price and low quantity), the Laspeyres-Paasche gap is negative (i.e., the Paasche Price Index is lower than the Laspeyres Price Index). For robots, the prices calculated using Paasche weights become higher. This implies that the covariance between price and quantity is positive, with higher-priced products having higher sales volume.

One potential source of this divergence is the demand switching behavior of Redding and Weinstein (2020) arguing that preference shifts among goods create a bias in the cost-of-living index. This bias is especially serious for the Paasche or Fisher index because the rise (fall)

[23] Since weights are changed every period in all measures, the Fisher index here is equivalent to the Törnqvist index, which is one of the *superlative* indices.

of relative prices caused by preference shocks incur the rise (fall) of current sales share. In contrast, the bias is less severe for the the Laspeyres index that does not rely on the current sales share information in the aggregation weight. To avoid the risk of this demand switching bias, we only adopt the Laspeyres index in the main text.[24]

[24]Note that if the quality of robots is computed using Paasche or Fisher indices, the decline in robot quality in the 2010s becomes more significant than that computed using the Laspeyres index shown in Figure 6.