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Quantifying heterogeneity in the relationship between R&D intensity and growth at innovative Japanese firms: A quantile regression approach

This paper focuses on innovative manufacturing firms in Japan in 2009–2020 and evaluates differences in the relationship between R&D intensity and firm growth. We use a longitudinal version of the conditional quantile regression model to estimate the augmented Gibrat's law equation for each of four innovative industries: chemicals and allied products; electronic and other electrical equipment; industrial and commercial machinery and computer equipment; and transportation equipment. The analysis reveals statistical differences in estimated coefficients for R&D intensity across low, median and high-growth firms within each industry and across pairs of industries. The results imply the presence of different patterns of R&D effectiveness which are discussed in the light of R&D management drawing on the experience of Sony and other fast-growing Japanese electronics firms. We also discover heterogeneity in the impact on growth of the age and size of firms.

Keywords: quantile regression; panel data; firm growth; innovation; R&D intensity.
JEL classification: C21; C22; D22; D24; O32; O47.

1. Introduction

Japan is a classic example of an innovative economy, where national policy is oriented to attaining economic growth by incentivizing R&D activity of firms (Lazonick, 2005). Overall, R&D expenditure is regarded as a prerequisite for innovation both by theoretical analysis (Osawa, Murakami, 2002; Klette, Kortum, 2004; Miyagawa et al., 2017) and by practitioners in US and Japanese companies (Gupta, Wilemon, 1996; Coad, 2007; Demirag, Doi, 2007). However, there is residual uncertainty about the outcome of R&D work: improper management of R&D expenditure may fail to produce innovation (Klette, Kortum, 2004) or the innovation may not prove a commercial success. Efficient linkage between R&D expenditure and company growth requires a combination of company-level managerial characteristics and favorable conditions on financial markets (Demirag, Doi, 2007; Suzuki, Takemura, 2016; Haneda, Ikeda, 2019; Iino et al., 2021).

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As there is a considerable variation between R&D management strategies (Song, Parry, 1993; Nobelius, 2004), it is plausible to expect that R&D expenditure will result in growth through innovation for some firms but may not lead to growth for others. Indeed, the association between growth and R&D intensity (defined as the ratio of R&D expenditure to the firm's sales) is not a generally accepted fact in the economic literature. Many empirical works find that there is no significant relationship between R&D intensity and firm growth in Japan (O'Mahony, Vecchi, 2000, 2009; Branstetter, 2001; Yasuda, 2005; Hosono et al., 2020) and in other countries (Coad, 2007; Charusilawong, 2014).

Arguably, the association between R&D intensity and growth is different for slow-growing and fast-growing firms (Coad, 2007). A seminal paper by Coad and Rao (2008)[2] proposes using a conditional quantile regression approach to quantify distinctions related to the effect of R&D intensity on growth for firms with different time profiles of growth. The quantile regression makes it possible to focus on low and high quantiles of the conditional distribution of the growth rate and to measure partial effects of R&D intensity on firm growth in each quantile (Koenker, Bassett, 1978; Koenker, 2004).

The estimation by Coad and Rao (2008) of the equation of Gibrat's law (analyzes the relationship between firm size and firm growth)[3], adding R&D intensity as one of the covariates, reveals that R&D intensity may be insignificant for median growth in an innovative manufacturing industry in the US, but shows that there is a positive and significant association between R&D intensity and firm growth in the highest quantiles of the growth distribution.

An emerging stream of empirical literature aims to quantify similar heterogeneity in the relationship between R&D intensity and growth across innovative firms in various countries in Europe and Asia (Goedhuys, Sleuwaegen, 2010; Falk, 2012; García-Manjón, Romero-Merino, 2012; Ebersberger, Herstad, 2013; Coad et al., 2016; Ahn et al., 2018; Zhu et al., 2021). However, to the best of our knowledge, analysis related to Japan is limited to estimates of average effect using mean-regression techniques (Charusilawong, 2014; Hosono et al., 2020).

The purpose of the present paper is to quantify heterogeneous association between R&D intensity and growth at Japanese firms. We use 2009–2020 data on the universe of Japanese firms (Orbis, Bureau van Dijk) and focus on the four most innovative manufacturing sectors: chemicals and allied products; electronic and other industrial equipment; industrial and commercial machinery and computer equipment; and transportation equipment. The analysis uses the conditional quantile regression approach of Coad and Rao (2008), and our methodological contribution consists in using the Parente and Santos Silva (2016) correction to account for intracluster correlation of errors in the longitudinal observations for each firm. Following the example of recent literature on the analysis of firm growth using conditional quantile regression, we add firm age as an important covariate (Falk, 2012; Distante et al., 2018).

Our approach leads to various interesting findings. Firstly, we find a negative and significant coefficient for the lagged value of firm size in median and high quantiles of the conditional growth distribution. This implies that, in a group of high-growth Japanese firms, small firms grow faster than large firms. Secondly, there is a negative coefficient for firm age in top quantiles and quantiles close to the median. But the effect of firm age is positive in the bottom quantiles. So, the stylized

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[2] With over 1250 citations in Google Scholar as of August 2022.

[3] See (Santarelli et al., 2006) for a review of the empirical literature on Gibrat's law. Recent uses of the quantile regression approach for such analysis can be found in (Distante et al., 2018) and (Leitão et al., 2010).

fact of the mean regression analysis, by which young firms grow faster than old ones, does not hold for slow-growing firms. Thirdly, we find that the coefficient for R&D intensity may be insignificant for explaining growth in the mean and median regressions. But the coefficient is positive and significant in high quantiles of the growth distribution. Our results show that the association between R&D intensity and growth is strongest in two of Japan's four highly innovative industries: transportation and electrical components.

Our results suggest that strategies for firm growth in Japan require a degree of nuance. Specifically, we find that R&D expenditure is vital for sustaining fast growth for firms in high-tech industries, but it may not be an engine of growth for slower-growing firms in less technology-intensive industries.

The remainder of this paper is structured as follows. Section 2 describes the quantile regression model, which is used in the paper for estimating a longitudinal version of conditional quantile regression. The explanation of data and variables is provided in section 3. Section 4 outlines estimation, inference and post-estimation analysis applied to the growth equation for Japanese firms. Section 5 presents findings on the values of R&D intensity, other firm-level variables and time effects for each industry. It points to statistical differences across low, median and high-growth firms within each industry and across pairs of industries. The results imply different patterns of R&D effectiveness which are discussed in section 6 using examples of R&D management at Sony and other high-growth Japanese electronics firms. Appendix A presents the results of the conditional quantile regression estimation.

2. Methodology

As was noted in the first, methodological part of this paper (Besstremyannaya, Golovan, 2021), the OLS regression is widely used in applied economics because "least-squares methods provide a general approach to estimating conditional mean functions" (Koenker, 2005, p. 1). However, conditional mean estimation has certain disadvantages. In particular, the researcher cannot use full information about the distribution of the dependent variable, and the conditional mean approach does not allow testing of the plausible supposition that "the partial effect of an explanatory variable can have very different effects across different segments" of the dependent variable y (Wooldridge, 2010, p. 449).

Quantile regression offers a convenient technique for identification of the impact of the covariates on these "segments": the analysis is applied to the conditional τ-th quantile of the dependent variable. Instead of extrapolating the estimates obtained in the mean regression to the tails of the distribution of the dependent variable, quantile regression makes it possible to obtain independent estimates for the impact of covariates in each conditional quantile of the dependent variable. Different values of the estimated coefficients of an explanatory variable at different values of τ in conditional quantile regression are often regarded as an indication of heterogeneous effect of this explanatory variable. So quantile regression is a helpful tool for analysis that aims to reveal heterogeneity. It identifies heterogeneity by establishing whether there is a statistical difference in partial effects of the explanatory variable on the dependent variable at different τ.

The simplest form of the longitudinal version for conditional quantile regression is a pooled model (Wooldridge, 2007).

$$Y_{it} = X_{it}'\beta\left(U_{it}\right),$$
$$\tau \mapsto X_{it}'\beta(\tau)$$

where τ is the value of a given quantile for conditional distribution of the dependent variable Y for observation i at period t, X denotes a vector of exogenous variables, and $U_{it} \perp \left(X_{it}\right) \sim U[0,1]$, $i = 1,...,n,\ t = 1,...,T$.

A consistent estimation procedure in this model involves minimization of the objective function of the quantile regression, where the sums are taken across the values of i and t:

$$W_{nT}(\tau,\beta) = \frac{1}{nT}\sum_{t=1}^{T}\sum_{i=1}^{n}\rho_\tau\left(Y_{it} - X_{it}'\beta\right)$$

where $\rho_\tau(\cdot)$ is the loss function (Koenker, Bassett, 1978).

It should be noted that pooling the data in conditional quantile regression entails the problem of a serial correlation of the error terms for each fixed value of i (i.e. each cluster of observations). The Wooldridge (2007) correction of the variance matrix in such a pooled model tackles the problem by accounting for serial correlation within the clusters of observations. Specifically, the scores of the objective function $s_{it}(\tau)$ are computed as a piecewise derivative:

$$s_{it}(\tau) = \frac{\partial\rho_\tau\left(\varepsilon_{it}(\tau)\right)}{\partial\beta'} = -\psi_\tau\left(\varepsilon_{it}(\tau)\right)X_{it},$$

and the asymptotic covariance matrix of the estimates is

$$\Sigma(\tau,\tau') = A(\tau)^{-1}B(\tau,\tau')\left[A(\tau')^{-1}\right]'.$$

The components of the matrix can be estimated as follows:

$$\hat{B}(\tau,\tau') = \frac{1}{n}\sum_{i=1}^{n}\sum_{t=1}^{T}\sum_{s=1}^{T}\hat{s}_{it}(\tau)'\,\hat{s}_{is}(\tau') = \frac{1}{n}\sum_{i=1}^{n}\sum_{t=1}^{T}\sum_{s=1}^{T}\psi_\tau\left(\hat{\varepsilon}_{it}(\tau)\right)\psi_{\tau'}\left(\hat{\varepsilon}_{is}(\tau')\right)X_{it}X_{is}',$$

$$\hat{A}(\tau) = \frac{1}{2nh_n(\tau)}\sum_{i=1}^{n}\sum_{t=1}^{T}\mathrm{I}\left(\left|\hat{\varepsilon}_{it}(\tau)\right| \le h_n(\tau)\right)X_{it}X_{it}'.$$

A similar approach to accounting for group-wise serial correlation is found in (Parente, Santos Silva, 2016), and it can be applied to time as a grouping dimension.

3. Data

We use Orbis (Bureau van Djik) data for the universe of firms in Japan in 2009–2020 and select active firms with non-missing values of firm sales (Table 1). The data is made up of 97% Japanese-owned firms and 3% foreign-owned firms.

In line with earlier literature that focuses on innovation in the manufacturing sector, we examine data at the level of 2-digit US SIC codes for manufacturing. We chose the four most innovative from 27 such industries (Table 2) using the following criteria.

1. The total number of firms in the industry is above 1000.

2. The share of firms with positive R&D expenditure is above the average in the economy and in the manufacturing sector.

3. The mean value of R&D intensity is above average in the economy and in the manufacturing sector.

The four industries are "Chemicals and allied products" ($SIC = 28$), "Industrial and commercial machinery and computer equipment" ($SIC = 35$), "Electronic and electrical equipment and components" ($SIC = 36$) and "Transportation equipment" ($SIC = 37$). The number of firms in the industries varies from 1285 to 5583, while the total number of observations in longitudinal samples is in the range of 6449 to 28332. Table 1 gives descriptive statistics and sample sizes.

Table 1. Descriptive statistics for 2010–2019

Variable	Observations	Mean	Standard deviation	Min	Max
		Chemicals and allied products ($SIC = 28$)			
log (*sales*)	9174	15.071	2.248	6.44	22.09
Δlog (*sales*)	9174	0.030	0.247	–3.01	5.54
R&D intensity	9174	0.031	0.360	0.00	19.22
age	9006	53.637	24.542	0	187
		Industrial and commercial machinery and computer equipment ($SIC = 35$)			
log (*sales*)	28332	13.915	1.814	4.67	22.28
Δlog (*sales*)	28332	0.040	0.329	–7.22	8.96
R&D intensity	28332	0.003	0.028	0.00	2.56
age	27641	43.225	20.061	0	166
		Electronic and other electrical equipment and components ($SIC = 36$)			
log (*sales*)	16084	14.185	2.109	1.61	23.03
Δlog (*sales*)	16084	0.029	0.351	–11.95	9.29
R&D intensity	16084	0.006	0.028	0.00	1.41
age	15593	40.965	20.466	0	116
		Transportation equipment ($SIC = 37$)			
log (*sales*)	6601	14.986	2.301	5.31	24.13
Δlog (*sales*)	6601	0.030	0.326	–6.11	5.26
R&D intensity	6601	0.003	0.012	0.00	0.24
age	6449	48.730	21.614	1	149

Notes. $\Delta\log(sales) = \log(sales_t) - \log(sales_{t-1})$. $R\&D\ intensity = R\&D\ expenditure / sales$. *age* denotes firm age (we follow (Ishikawa et al., 2015) to use date of incorporation in *Orbis* to infer the first year of firm's existence).

Table 2. R&D expenditure by Japanese manufacturing industries in 2010–2019

SIC code	Description	Observations	Companies with positive R&D	Share of companies with positive R&D	R&D/Sales, mean
35	Industrial and commercial machinery and computer equipment	28332	2508	0.089	0.00292
36	Electronic and other electrical equipment and components	16084	2245	0.140	0.00606
28	Chemicals and allied products	9174	2166	0.236	0.03105
20	Food and kindred products	17990	1067	0.059	0.00093
37	Transportation equipment	6601	1019	0.154	0.00348
34	Fabricated metal products	25840	838	0.032	0.00051
38	Measuring, photographic, medical and optical goods, and clocks	5374	814	0.151	0.01782
33	Primary metal industries	9054	724	0.080	0.00075
32	Stone, clay, glass, and concrete products	8486	528	0.062	0.00113
17	Construction — special trade contractors	292617	490	0.002	0.00003
30	Rubber and miscellaneous plastic products	12225	465	0.038	0.00092
16	Heavy construction, except building construction, contractor	77372	451	0.006	0.00002
15	Construction — general contractors and operative builders	30746	360	0.012	0.00005
22	Textile mill products	3548	315	0.089	0.00146
26	Paper and allied products	5454	314	0.058	0.00064
39	Miscellaneous manufacturing industries	5499	274	0.050	0.00179
27	Printing, publishing and allied industries	8163	222	0.027	0.00020
24	Lumber and wood products, except furniture	53390	186	0.003	0.00003
25	Furniture and fixtures	2149	113	0.053	0.00053
23	Apparel, finished products from fabrics and similar materials	2555	112	0.044	0.00048
29	Petroleum refining and related industries	981	96	0.098	0.00131
14	Mining and quarrying of nonmetallic minerals, except fuels	1556	33	0.021	0.00032
13	Oil and gas extraction	77	30	0.390	0.00046
31	Leather and leather products	510	26	0.051	0.00035
21	Tobacco products	10	10	1.000	0.02602
10	Metal mining	20	10	0.500	0.00671
12	Coal mining	15	0	0.000	0.00000

4. Empirical model

4.1. Specification

In this paper, we follow the approach by Coad and Rao (2008) and employ a longitudinal version[4] of the conditional quantile regression model. The specification is

$$Q_\tau\left(\Delta\log(sales)_{i,t+1} \mid X_{it}, ind_i, t\right) = \beta_1(\tau)\Delta\log(sales)_{it} + \beta_2(\tau)\log(sales)_{it} + \\ +\beta_3(\tau) R\&D\ intensity_{it} + \beta_4(\tau)\log(age)_{it} + \alpha_{ind_i}(\tau) + \delta_t(\tau), \quad (1)$$

where $X_{it} = \left(\Delta\log(sales), \log(sales)_{it}, R\&D\ intensity_{it}, \log(age)_{it}\right)$ is the vector of firm-level explanatory variables.

Here $\log(sales)_{it}$ is the log of sales, $\Delta\log(sales)_{it}$ is the annual change in the log of sales (rate of sales growth), $R\&D\ intensity_{it}$ is the ratio of R&D expenditure to sales, and $\log(age)_{it}$ is the log of firm age[5].

The specification includes $\alpha_{ind_i}(\tau)$, which are coefficients for sub-industry dummies (see 3-digit US SIC codes for sub-industries in each of the analyzed industries in Table 3), and also annual effects $\delta_t(\tau)$.

4.2. Estimation, inference and post-estimation analysis

For each industry, equation (1) is used to estimate the conditional quantile of firm growth for each value of τ. Such independent estimation avoids problems specific to multiple quantile models. For instance, the estimates in the top and bottom quantiles are not influenced by potential failure of the standard asymptotic theory to accurately represent the finite sample distribution.

We use the values of $\tau \in [0.2, 0.8]$, starting with $\tau = 0.2$ at the 0.05-step. It should be noted that as the size of our sample does not exceed 20000 observations, we avoid estimations at $\tau = 0.1$ and $\tau = 0.9$. Indeed, the asymptotic inference works poorly for extreme quantiles outside the $[0.2, 0.8]$ range, as demonstrated in (Chernozhukov, 2005).

The goodness-of-fit in each regression is assessed by the means of an equivalent of the R^2 statistic computed for pairs of quantile regressions: with constant only (restricted set of covariates) and with a full set of covariates (Koenker, Machado, 1999).

We extend the methodology of Coad and Rao (2008) regarding basic inference about the values of coefficients at each τ and we apply the Parente and Santos Silva (2016) correction for intracluster correlation of standard errors.

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[4] Use of the pooled version of the quantile regression model is justified by presence of the first lag of the dependent variable in the specification. The first lag would inevitably cause endogeneity in the model which considered the data as a panel with fixed effects, and such analyses are commonly avoided in the applications of quantile regression techniques.

[5] Our approach contrasts with that of Coad et al. (2016) who do not include firm age but have an interaction term of a young firm dummy and R&D intensity.

We do not use Wald tests in order to assess hypotheses about the differences between coefficients estimated in regressions for different values of τ within a given industry. Instead, this paper evaluates t-statistics based on the whole quantile regression process (Koenker, 2005)[6].

As regards testing whether coefficients at each τ are different in pairs of industries, we use the usual t-statistic and treat coefficients for different industries as independent.

Our post-estimation analysis considers the growth equation for high quantile values (0.75, 0.8) as an approximation of the high-growth trajectory (Bernini et al., 2004; Koenker, 2005) and we follow (Knox et al., 2007) to calculate the residual which enables ranking of the firms by growth. The value of the residual for each industry is computed as

$$\hat{u}_{it}(\tau)=\Delta\log(sales)_{i,t+1}-\hat{\beta}_1(\tau)\Delta\log(sales)_{it}-\hat{\beta}_2(\tau)\log(sales)_{it}-$$
$$-\hat{\beta}_3(\tau)\,R\&D\ intensity_{it}-\hat{\beta}_4(\tau)\log(age)_{it}-\hat{\alpha}_{ind_i}(\tau)-\hat{\delta}_t(\tau),$$

where higher values of the residual imply higher growth.

Table 3. Description of 3-digit industry codes for selected SICs

SIC code	Description
28	*Chemicals and allied products*
281	Industrial inorganic chemicals
282	Plastics materials and synthetic resins; synthetic rubber; synthetic and other manmade fibers, except glass
283	Drugs
284	Soaps, detergents, and cleaning preparations; perfumes, cosmetics, and other toilet preparations
285	Paints, varnishes, lacquers, and enamels
286	Industrial organic chemicals
287	Agricultural chemicals
289	Miscellaneous chemicals
35	*Industrial and commercial machinery and computer equipment*
351	Engines and turbines, and parts and accessories
352	Farm and garden machinery and equipment, and parts and attachments
353	Construction, mining, and materials handling machinery
354	Metalworking machines and equipment, and parts, accessories and attachments
355	Special industry machines and equipment and parts, accessories and attachments
356	General industrial machines and equipment and parts and attachments
357	Office, computing and accounting machines and parts and accessories
358	Refrigeration and service machinery, parts and attachments
359	Flexible tubing and piping of base metal and machine parts, nonelectric
36	*Electronic and other electrical equipment and components*
361	Electric transmission and distribution equipment and parts

[6] This approach not only reveals differences in coefficient values but also finds whether one coefficient is smaller or larger than another.

End of Table 3

SIC code	Description
362	Electrical industrial apparatus
363	Household appliances and parts
364	Electric lighting and wiring equipment
365	Radio and TV receiving sets; phonographs; recorders; microphones; loudspeakers; audio amplifiers; and other audio equipment and accessories
366	Communication equipment and apparatus
367	Electronic components and accessories
369	Electrical machinery, apparatus and parts
37	*Transportation equipment*
371	Motor vehicles and motor vehicle equipment and parts
372	Aircraft and parts
373	Ship and boat building and repairing
374	Railroad equipment
375	Motorcycles, motor scooters, motorbikes and cycles, not motorized and parts
376	Guided missiles and space vehicles and parts
379	Miscellaneous transportation equipment and parts

5. Results

The estimation results of equation (1) for different quantiles τ and different industries are given in Table 6 in Appendix.

Note that although our analysis says nothing about causality, it is plausible to assume that the link goes from R&D expenditure to growth. For instance, directors of Japanese companies tend decide on their annual R&D budget independently of the previous year's profit or sales, while company growth targets are among the main determinants of R&D expenditure (Demirag, Doi, 2007).

We reveal heterogeneity in the effect of R&D intensity on firm growth (as well as in the impact of other firm-level variables, 3-digit sub-industry effects and annual effects) in each industry by assessing whether there is a statistical difference in the values of the estimated coefficients in regressions for pairs of low- and high-output quantiles (0.2 and 0.8, 0.25 and 0.75). We also test whether the estimated coefficients in at least one of the low or high-output quantiles differ from the estimates in the median regression. The detailed results of estimation of equation (1) and the findings of pairwise tests are available from the authors upon request.

We start with results concerning R&D intensity, which correspond to the findings for innovative industries in other countries (Coad, Rao, 2008; García-Manjón, Romero-Merino, 2012; Ahn et al., 2018).

1. The association between R&D intensity and growth in the analyzed industries in Japan is in some cases statistically insignificant in bottom quantiles and at the median. Examples are, respectively, chemical and allied products ($SIC = 28$) and industrial and commercial machinery and computer equipment ($SIC = 35$).

2. The association between R&D intensity and growth at Japanese companies is occasionally negative in bottom quantiles ($SIC = 35$).

3. The coefficient for R&D intensity in growth equations increases with rise in the quantile index. This phenomenon is observed in all of the four Japanese industries that we considered.

To sum up, our analysis points to heterogeneity in the effect of R&D intensity on company growth. As is summarized in Table 4, at least two types[7] of growth pattern can be discerned at Japanese companies: low growth unrelated to R&D intensity and high growth related to R&D intensity.

Table 4. Differences across companies at low, median and high-growth quantiles at each industry

	Low vs High	Low vs Median	High vs Median
	Chemicals and allied products (*SIC* = 28)		
R&D intensity	+	+	+
log (*age*)	+	+	+
log (*sales*)	+	+	+
	Industrial and commercial machinery and computer equipment (*SIC* = 35)		
R&D intensity	+	+	+
log (*age*)	+	+	+
log (*sales*)	+	+	+
	Electronic and other electrical equipment and components (*SIC* = 36)		
R&D intensity	+		+
log (*age*)	+	+	+
log (*sales*)	+	+	+
	Transportation equipment (*SIC* = 37)		
R&D intensity	+	+	+
log (*age*)	+	+	+
log (*sales*)	+	+	+

Notes. The "+" mark the "Low vs High" cell in the row for each variable implies statistical difference of the estimated coefficients in at least one pair of regressions: for growth quantiles 0.2 and 0.8, or 0.25 and 0.75. The "+" mark in the "Low vs Median" cell (or respectively "High vs Median" cell) indicates statistical difference of the estimated coefficients in at least one pair of regressions: for growth quantiles 0.2 and 0.5, or 0.25 and 0.5 (or respectively 0.75 and 0.5, or 0.8 and 0.5).

As regards the effect of other firm-level variables, we discover negative and significant coefficients for the lagged value of firm size in median and higher quantiles of the conditional growth distribution. This implies that, in a group of high-growth Japanese firms, small firms grow faster than large firms. The phenomenon has already been demonstrated for European firms in an analysis which includes R&D intensity as a covariate of firm growth (García-Manjón, Romero-Merino, 2012) and for US and Portuguese firms in empirical works that do not include R&D intensity in the estimation (Leitão et al., 2010; Distante et al., 2018).

[7] The varied typology of Japanese company growth may be explained by the specific company management practices, which were discovered by Bloom and Van Reenen (2007) in several developed countries, including Japan. The typology also resembles the specific business-model typology at Japanese banks as regards cost efficiency (Besstremyannaya, 2017).

Secondly, there is a negative coefficient for firm age in top quantiles of firm growth in the four industries. In some industries a negative coefficient is observed in the median regression and in quantiles slightly below the median (e.g. 0.4 and 0.45 in electronics and transportation equipment). So, in the group of fast growing Japanese firms (and often, in the group of firms with median growth), young firms grow faster than old ones. However, we discover that the effect of firm age is positive for slow-growing Japanese firms. The finding of negative association between firm age and growth is often reported in empirical literature about Japanese firms that offers mean estimates (Yasuda, 2005; Hosono et al., 2020). However, our results point to heterogeneity in the effect of firm age on company growth. Similar conclusions are reached in the analysis with Austrian firms in Falk (2012), where the dummy for a young firm has a positive estimated coefficient only in median and high-growth quantiles, and in the work by Coad et al. (2016) with Spanish firms, where the interaction term of R&D intensity and a young firm dummy has a negative effect on growth in the bottom quantiles and a positive effect in top quantiles and quantiles close to the median. Note that heterogeneity of the effect of age on firm growth is also discovered for the US manufacturing firms in (Distante et al., 2018), but the analysis includes only age and size as correlates of growth.

We now move on to results for R&D intensity at our Japanese firms, which differ from the results observed at companies in other countries.

1. The coefficient for R&D intensity is significant in most quantiles for electronic and other electrical equipment and components ($SIC = 36$), while it is significant only in top quantiles of the conditional growth distribution for companies in Europe and South Korea (García-Manjón, Romero-Merino, 2012; Ahn et al., 2018).

2. The value of the coefficient for R&D intensity in a given quantile differs across pairs of Japanese industries whereas in other countries the coefficients for different industries are very similar (Coad, Rao, 2008; García-Manjón, Romero-Merino, 2012; Ahn et al., 2018).

The Japanese industries can be ranked as to value of the estimated coefficient for R&D intensity in top quantiles (0.75 and 0.8):

- Transportation equipment ($SIC = 37$) — the highest coefficient;
- Electronic and other electrical equipment and components ($SIC = 36$);
- Industrial and commercial machinery and computer equipment ($SIC = 35$);
- Chemicals and allied products ($SIC = 28$) — the lowest coefficient.

Similar ranking of industries by value of the coefficient for R&D intensity applies in most other quantiles. (See Figures 1–2; low-growth quantiles in $SIC = 28$ are the exceptions.) Moreover, it is possible to establish differences in the impact of other firm-level variables on growth for most pairs of industries in low, median and high-growth quantiles (Table 5).

Finally, we outline results related to annual effects in the growth equations for Japanese companies. For each industry, we find a negative coefficient for the 2019 dummy in regression at each quantile. (Year 2010 is used as the reference category.) Since the 2019 fiscal year comprises the period from April 2019 to March 2020, the finding arguably reflects the temporary recession due to COVID-19. The negative value of the 2019 dummy only varies across quantiles in electronics and other electrical equipment and components ($SIC = 36$), where it is larger in higher quantiles in absolute terms. So fast-growing electronics companies in Japan experienced a bigger decline of growth in 2019 than slow-growing companies.

A similar exogenous shock, the recession caused by the Great East Japan Earthquake, is reflected in the negative coefficient for the 2011 dummy, but is apparent in only two of the analyzed

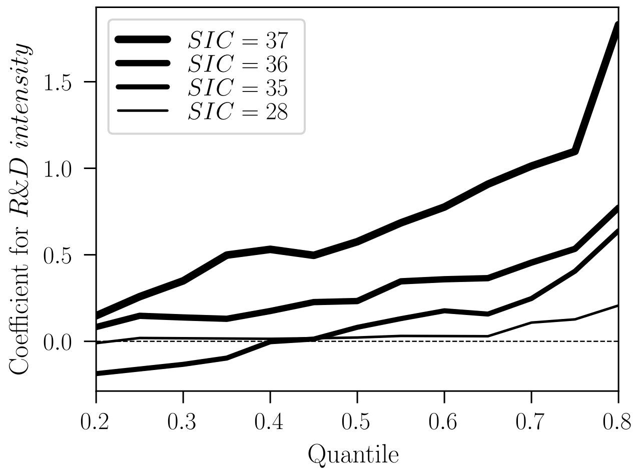
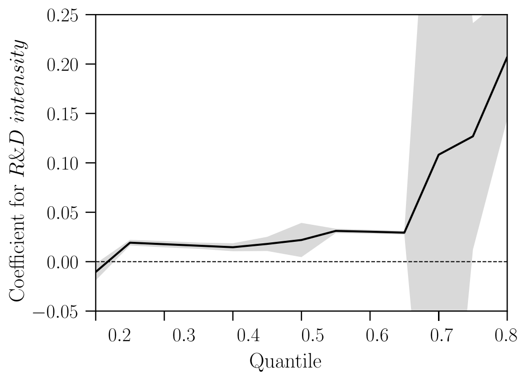
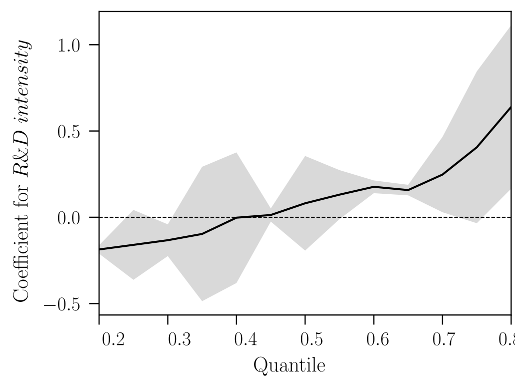


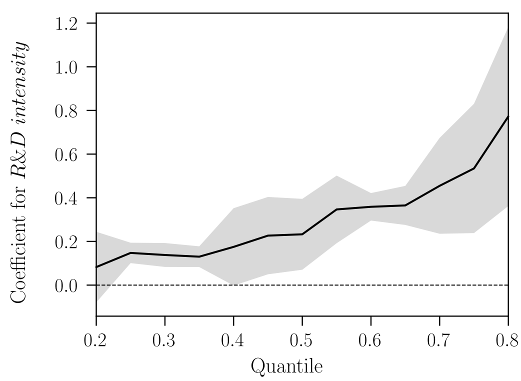
Figure 1. Coefficients for R&D intensity at each industry



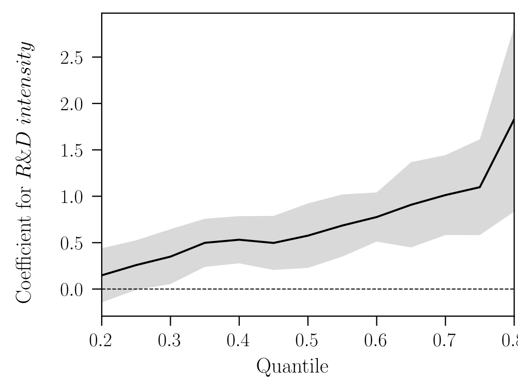
(a) Chemicals and allied products ($SIC = 28$)



(b) Industrial and commercial machinery and computer equipment ($SIC = 35$)



(c) Electronic and other electrical equipment and components ($SIC = 36$)



(d) Transportation equipment ($SIC = 37$)

Figure 2. Coefficients for R&D intensity at each industry with 90% confidence bands

Table 5. Differences across companies at low, median and high-growth quantiles at pairs of industries

	Low vs High	Low vs Median	High vs Median
Chemicals and allied products (*SIC* = 28) *vs Industrial and commercial machinery and computer equipment* (*SIC* = 35)			
R&D intensity	+		+
log (*age*)	+	+	
log (*sales*)	+	+	+
Chemicals and allied products (*SIC* = 28) *vs Electronic and other electrical equipment and components* (*SIC* = 36)			
R&D intensity	+	+	+
log (*age*)			
log (*sales*)	+	+	+
Chemicals and allied products (*SIC* = 28) *vs Transportation equipment* (*SIC* = 37)			
R&D intensity		+	+
log (*age*)			
log (*sales*)		+	+
Industrial and commercial machinery and computer equipment (*SIC* = 35) *vs Electronic and other electrical equipment and components* (*SIC* = 36)			
R&D intensity	+	+	
log (*age*)	+		
log (*sales*)	+		
Industrial and commercial machinery and computer equipment (*SIC* = 35) *vs Transportation equipment* (*SIC* = 37)			
R&D intensity	+		
log (*age*)			+
log (*sales*)	+		
Electronic and other electrical equipment and components (*SIC* = 36) *vs Transportation equipment* (*SIC* = 37)			
R&D intensity			
log (*age*)	+		
log (*sales*)			

Notes. The "+" mark in the cells "Low" (or respectively "High") in the row for each variable implies statistical difference of the estimated coefficients in at least one pair of regressions: for growth quantiles 0.2 or 0.25 (0.8 or 0.75, respectively). For median quantiles we check the statistical difference only at the pair of regressions at $\tau = 0.5$.

industries: industrial and commercial machinery and computer equipment (*SIC* = 35) and transportation equipment (*SIC* = 37). It should be noted that negative coefficients for other annual dummies are also observed in these industries.

Chemicals (*SIC* = 28) and electronics (*SIC* = 36) show sustainable growth in all years except for 2019: the effect of annual dummies for 2010–2018 is positive.

Analysis based on the results of our estimations produced a ranking of Japanese companies by rates of growth. The next section takes several of the fastest-growing companies in the Japanese electronics industry as examples of effective R&D management practice.

6. Discussion

The analysis in this paper established that innovative Japanese manufacturing companies show different association between R&D intensity and growth depending on whether the companies are slow-growing or fast-growing. This matches findings for other developed countries. Arguably, the differences may be due to more or less effective R&D management.

Greater or lesser efficiency of R&D management at Japanese companies is connected with specific features of R&D in Japan, which differ from practice in other countries. In this section we consider several high-growth Japanese electronics companies from our sample, including long-established corporations and young companies, and show in the light of our post-estimation analysis how these companies respond effectively to the challenges brought by specific features of R&D in Japan.

Firstly, Japanese companies show an economy of scale in R&D inputs, which is different from what is observed in the US (Mansfield, 1988; Wakasugi, Koyata, 1997). We conjecture that the fact makes it important for Japanese companies to focus on incremental innovation. The incremental innovation in Japan is noted by several economists (Rothwell, Gardiner, 1989; Gupta, Wilemon, 1996), and the electronics giant Sony is one example. Sony opened its overseas lab in San Jose, CA as early as in 1977, which enabled the company to benefit from the innovative environment of Silicon Valley. Moreover, Sony was unique among Japanese electronics companies in establishing bottom-up management of its overseas labs and still preserves many features of the original method (Arimura, 1999). To sustain high quality of its incremental innovation, the company uses a system of R&D performance evaluation and employs best-qualified R&D researchers and engineers (Wu, Haak, 2013). Sony is a world leader by the number of scientific papers per corporate scientist, number of external citations per paper, and number of patent citations (Furukawa, Goto, 2006). Good management of R&D has undoubtedly been crucial for maintaining Sony's position as flagbearer of the Japanese electronics industry with steady growth of sales (Arnaldi, 2016).

Secondly, Japanese companies pioneer new products and new product areas (the strategy is regarded as the most effective R&D pattern in Japan (Song, Parry, 1993)) and put strong emphasis on related commercialization of R&D (Arimura, 1999). The approach is more marked in Japan than among companies in the US, UK or Western Europe and is particularly evident in the electronics industry (Mansfield, 1988; Wakasugi, Koyata, 1997; Demirag, Doi, 2007). Almedio Inc. (specialized in test standards for audio, video, computer peripherals) has translated R&D expenditure into innovative growth by product diversification and an efficient commercialization strategy that includes the opening of overseas subdivisions in Asia[8]. A different management strategy used by Axell corporation has also proved effective: the company pursued R&D focused on new graphics technologies[9]. A relatively young company, Digital Development Systems (DDS, a government-supported

8 https://www.almedio.co.jp/en/cp-en/history-en/.

9 https://www.axell.co.jp/en/company/outline/#history.

startup), which specializes in new fingerprint technologies, drove its growth through open innovation opportunities and capital increase associated with overseas expansion[10].

Thirdly, multinational Japanese corporations tend to carry out in-house R&D and to centralize global R&D labs (Arimura, 1999; Reger, 1999; Demirag, Doi, 2007). Accordingly, successful innovation depends on effective leadership (including ability to manage diversity) and research collaboration (Suzuki, Takemura, 2016; Haneda, Ikeda, 2019). Nobelius (2004) has shown how these strategies are related to connectedness in R&D management. For example, Sony emphasizes connection between its global R&D strategy and the regional strategies of its local labs (Arimura, 1999). Unusually for Japan, Sony follows the Western European principle of contracting a large share of R&D out of house (80% at Sony, but less than 50% at other Japanese companies (Reger 1999)).

However, there are exceptions to the Japanese rule of reliance on in-house R&D. RVH Inc., established in 1996, has a diverse business including apparel, cosmetics and media and has made its way by a series of effective M&As of companies with high-quality R&D[11].

Finally, a specific feature of Japanese R&D is the establishment of strong links between basic and applied research (Mansfield, 1988; Kenney, Florida, 1994). The emphasis is on application-focused R&D, monitoring social interactions within the company and educating R&D personnel as generalists (Harryson, 1997; Arimura, 1999; Reger, 1999; Wu, Haak, 2013). For example, newly hired R&D researchers at Sony are required to undergo a one-month training in the company's production arm and a three-month training with sales and marketing (Harryson, 1997).

7. Conclusion

Our paper looks at differences in the relationship between R&D intensity and growth by using a conditional quantile regression approach to analyze growth equations at innovative Japanese manufacturing companies in 2009–2020. The paper contributes to the debate by revealing differences in the effect of R&D intensity on growth in four leading Japanese manufacturing industries: chemicals and allied products; electronic and other industrial equipment; industrial and commercial machinery and computer equipment; and transportation equipment. Heterogeneity also manifests itself in different values of other company characteristics, such as age and size. Although Japan is no exception to similar results on within-industry heterogeneity, observed in emerging empirical evidence from other countries (Coad, Rao, 2008; Falk, 2012; García-Manjón, Romero-Merino, 2012; Coad et al., 2016; Ahn et al., 2018), Japan offers a rare example of differences in the impact of R&D intensity on growth across pairs of the aforementioned industries.

We conjecture that heterogeneity in the relationship between R&D intensity and growth is largely attributable to differences in R&D management. In Japan, managerial differences are often related to commercialization of R&D. So we provide examples of effective R&D-marketing integration at high-growth Japanese electronics companies.

Our results on differential relationship between R&D intensity and growth support the idea that Japan should follow the examples of other countries (Ahn et al., 2018) and that the Japanese stock market requires further development. Equity financing in Japan would enable firms to be less

10 https://www.dds.co.jp/en/corporate-information/history/.

11 https://rvh.jp/en/corporate/data/.

dependent on internal cash flows and to boost their innovation output by profiting from favorable conditions on financial markets (Furukawa, Goto, 2006; Demirag, Doi, 2007).

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Appendix

Table 6. Regression coefficients for main explanatory variables in the growth equations for each industry

	Quantile							
	0.20	0.30	0.40	0.50	0.60	0.70	0.80	OLS
Chemicals and allied products (*SIC* = 28)								
Δlog(*sales*)	–0.063**	–0.034	–0.016	–0.010	–0.011	–0.013	–0.016	–0.165***
	(0.025)	(0.024)	(0.019)	(0.013)	(0.015)	(0.022)	(0.017)	(0.040)
log(*sales*)	0.007***	0.004***	0.003***	0.002**	0.000	–0.001	–0.004***	–0.002
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
log(*age*)	0.011***	0.001	–0.007***	–0.012***	–0.020***	–0.034***	–0.052***	–0.030***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)	(0.007)	(0.007)
R&D intensity	–0.010	0.018***	0.014***	0.020*	0.030***	0.040	0.196***	0.051**
	(0.006)	(0.001)	(0.003)	(0.010)	(0.001)	(0.296)	(0.042)	(0.021)
Industrial and commercial machinery and computer equipment (*SIC* = 35)								
Δlog(*sales*)	–0.237***	–0.221***	–0.215***	–0.209***	–0.202***	–0.206***	–0.216***	–0.262***
	(0.013)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)	(0.014)	(0.020)
log(*sales*)	0.013***	0.009***	0.004***	–0.001	–0.005***	–0.009***	–0.016***	–0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log(*age*)	0.010**	–0.011***	–0.016***	–0.022***	–0.030***	–0.042***	–0.057***	–0.025***
	(0.005)	(0.003)	(0.003)	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)
R&D intensity	–0.186***	–0.228***	–0.064	0.002	0.055	0.304	0.678***	–0.008
	(0.015)	(0.014)	(0.143)	(0.022)	(0.079)	(0.240)	(0.170)	(0.122)
Electronic and other electrical equipment and components (*SIC* = 36)								
Δlog(*sales*)	–0.128***	–0.100***	–0.089***	–0.075***	–0.081***	–0.089***	–0.105***	–0.265***
	(0.019)	(0.016)	(0.014)	(0.014)	(0.014)	(0.015)	(0.017)	(0.070)
log(*sales*)	0.010***	0.005***	0.001	–0.002**	–0.005***	–0.009***	–0.014***	–0.008***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
log(*age*)	0.019***	0.004	–0.007**	–0.018***	–0.027***	–0.038***	–0.050***	–0.015**
	(0.006)	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.006)
R&D intensity	0.112	0.122*	0.180	0.251**	0.342***	0.418***	0.710***	0.314***
	(0.090)	(0.064)	(0.110)	(0.119)	(0.036)	(0.126)	(0.183)	(0.121)
Transportation equipment (*SIC* = 37)								
Δlog(*sales*)	–0.049***	–0.063**	–0.055**	–0.053**	–0.072***	–0.073***	–0.105***	–0.228***
	(0.018)	(0.025)	(0.026)	(0.022)	(0.021)	(0.020)	(0.027)	(0.039)
log(*sales*)	0.007***	0.003***	0.000	–0.001	–0.004***	–0.006***	–0.012***	–0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.003)
log(*age*)	0.004	–0.003	–0.010**	–0.014***	–0.025***	–0.031***	–0.040***	–0.019***
	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.006)	(0.008)	(0.007)
R&D intensity	0.176	0.348*	0.503***	0.551***	0.688***	0.932***	1.517***	1.445***
	(0.192)	(0.180)	(0.162)	(0.199)	(0.143)	(0.277)	(0.550)	(0.424)

Note. *, ** and *** indicate significance at 0.1, 0.05 and 0.01 level, respectively.