

Product Innovation, Product Diversification, and Firm Growth:
Evidence from Japan's Early Industrialization

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Appendix—For Online Publication

A.1 Data construction

A.1.1. Product varieties data

Our data source for firm-level output by product varieties comes from bulletins (“Geppo”) published by the All-Japan Cotton Spinners’ Association (“Boren,” using its name’s abbreviation in Japanese). These bulletins were issued monthly, starting from 1889 (even earlier data are available from government statistics, starting from 1883), and they, in particular, contained firm-level input and output data for all members of the Association which was basically the universe of all firms operating in the industry at any time. The first time the breakdown of output by product varieties was added to the bulletins was May 1893. Since then, the data have been published continuously in dedicated tables in each issue. We have coded all such tables until December 1914 which is the end of our sample. Photo 1 presents a table showing output by product varieties by each firm for December 1906.

Photo 1. Output by product varieties table, December 1906.

The table is a detailed ledger showing the monthly production of cotton yarn in Japan for December 1906. It is organized into columns for each day of the month (1st to 31st) and rows for individual cotton mills. The mills listed include Nishikawa, Onoda, and many others. The data represents the number of bales (approximately 400 lbs) produced by each mill on each day. The table is divided into sections for different types of yarn and includes a total row at the bottom.

Source: Geppo, No. 173, Jan. 25, 1907.

A.1.2. Engineers data

The information about university-educated engineers was obtained from alumni lists, *Gakushikai Kaiin Shimeiroku* compiled by Gakushikai (The University Graduates’ Society), the association of the alumni of Imperial Universities, containing information about addresses and workplaces of the graduates. Until 1897 Tokyo Imperial University was the only one. In 1897 Kyoto Imperial University was founded and its first cohort graduated in 1901. Two more Imperial Universities were founded in 1907 and 1911 but there were no graduates of the last one available to the industry at the end of our sample (1914) as yet.

The above information was verified and supplemented, especially for earlier years, from chapters dedicated to the history of each firm in Kinugawa (1964) and from published company histories (Kanebo, 1988; Unitika, 1989; Toyobo, 1986; Fujibo, 1998, Shikibo, 1968, Kurabo, 1953). Engineers educated in British universities, in particular, were identified from these industry history sources and added to the list of graduates of Japanese Imperial Universities.

For technical college graduates, we used annual *Ichiran (Catalogs) (Tokyo Koto Kogyo Gakko Ichiran, Kyoto Koto Kogyo Gakko Ichiran, Osaka Koto Kogyo Gakko Ichiran, Nagoya Koto Kogyo Gakko Ichiran, Kumamoto Koto Kogyo Gakko Ichiran, and Sendai Koto Kogyo Gakko Ichiran)*, which contain the lists of alumni with their current workplaces, and picked up all graduates of mechanical engineering and dyeing departments who worked in one of the firms in our sample in any given year. The first technical college was established in Tokyo in 1881. By the end of our sample there were six technical colleges that already had alumni working in the industry; all those alumni data were coded and added to the database of educated engineers employed by cotton spinning firms.

A.1.3. Board members and merchants data

About 90 percent of firms in our sample (and all significant firms) were public (joint stock) companies, obligated to issue shareholders' reports every half a year (see Braguinsky et al., 2015, and Agarwal et al., 2020, for details). We have photocopied and processed 1,443 reports on 106 firms (Kokajo, 1883-1914), all such reports that we could find surviving until the present day.¹ Each report, in particular, contains a list of all shareholders and board members ("torishimariyaku") of the company issuing it. For privately held firms as well as in cases where some shareholders reports of incorporated firms were missing in the archival data, we supplemented this with information from the All-Japan Registry of Firms Executives ("Yakuinroku"), the first issue of which was published in 1893. We coded and reconciled the information on the members of the boards across these two sources, and also cross-checked the data by using information in company histories (Kinugawa, 1964; Kanebo, 1988; Unitika, 1989; Toyobo, 1986; Fujibo, 1998, Shikibo, 1968, Kurabo, 1953), and in Geppo.

The data published in "Yakuinroku" (above) were used to extract the names and addresses of board members of the four incorporated cotton yarn-related trade companies (Naigai Wata, Nihon Menka, Nitto Menshi and Mitsui Bussan), while the data contained in the 1943 brief history of Osaka Three Article Exchange ("Sampin Shoshi") were used to extract the names of board members and traders registered at this most important exchange dealing with cotton and cotton yarn in each year. The data in four available editions of *Nihon Zenkoku Shoko Jinmeiroku*, a nationwide registry of traders and manufacturers (for 1892, 1898, 1907, and 1914), were utilized to extract the names and addresses of individual merchants likely to play the most prominent role in cotton spinners' output markets; that is, traders in cotton yarn and cotton yarn-woven garments who paid business taxes exceeding a certain threshold (10-15 yen, depending on the year). We considered all these individuals to be potential providers of market knowledge ("market ties") for cotton spinning firms; hence, we matched their names and addresses to the names and addresses of cotton spinning firms' executives. Through this process (which involved both a computer algorithm and a manual re-check), we identified 55 executives of incorporated cotton yarn-related trade companies and board members and registered traders at the Osaka Three Articles Exchange, as well as 172 significant individual traders who were also board members in cotton spinning firms and created panel data reflecting their presence as an executive board member in firm i at time t . The variable "merchant as a board member" used in the main text takes value of one if at least one such merchant was identified to be a member of the executive board of firm i at time t and zero otherwise.

A.1.4. Machine capacity data

The data on machine capacity (the number of spindles installed by firm i at time t) were compiled and validated by cross-checking from three sources. The first source is the already mentioned semiannual shareholders' reports (Kokajo, 1883-1914), which often contained inventory of all property owned by the firm, including details about machines (number of spindles, their basic type—ring, mule or doubling—and the name of the manufacturer, such as Platt Brothers of Oldham, etc.). In some cases, however, those detailed inventories were not included, or the reports themselves may be missing. "Enkakukiji" (1901) contains the details of all installation and decommissioning of machines by cotton spinning firms from the inception of the industry and until 1901, while "Sankosho" (1903-1914), a semiannual bulletin published by Boren parallel to Geppo, contains the details about machines (number of spindles and their basic type, although not the name of the manufacturer) starting from 1903. Combining and manually cross-checking the data from these three sources, we were able to construct the full panel with the number of spindles installed by each firm at each point in time during our sample.

A.1.5. Machine orders from British manufacturers

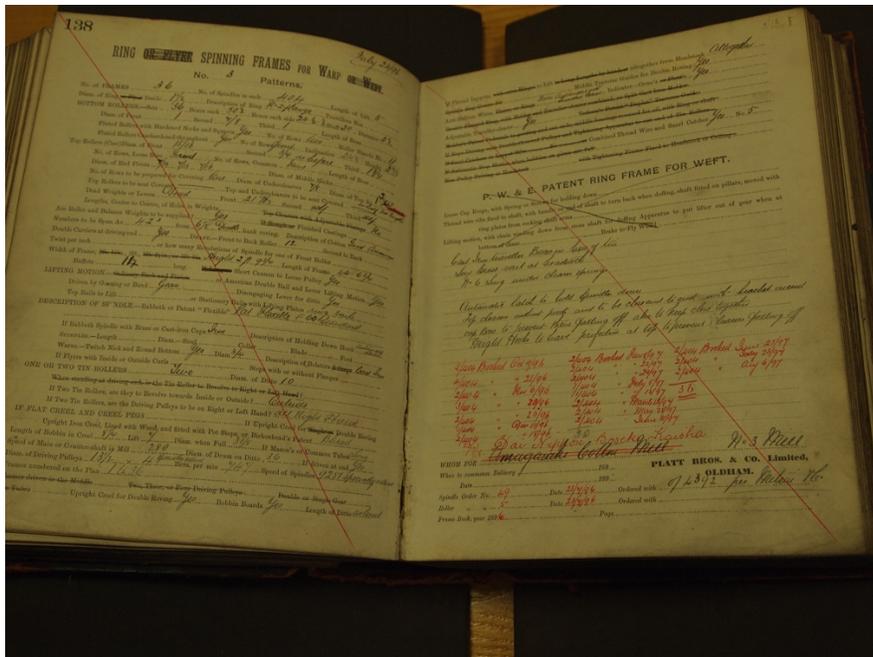
We collected and processed archival data on machine orders by Japanese cotton spinning firms placed with British textile machine manufacturers and preserved in Lancashire archives from the earliest such orders and until 1914. As mentioned in the main text, the same data collected by the late Gary Saxonhouse are archived

¹ We are grateful to Osaka University library and Prof. Takeshi Abe, its academic director at the time; to Yoshiyuki Murakami, head of the company history division of Toyo Boseki at the time (now retired); and to Kobe University Kanematsu Collection for their cooperation in allowing us to photocopy company reports used in this research.

on the ICPSR website (Wright, 2011). We had to collect and re-process these data once again because there were no original photos and firm names were missing from the ICPSR files, making it impossible to perform firm-level matching to Japanese sources of capacity data described above.² The total number of orders we collected and processed was 430. In Photos 2 and 3 below we present two representative orders placed with Platt Brothers of Oldham around the same time (Spring-Summer 1896) by two different Japanese firms. As can be seen, machines were custom-made, and each order contains the number of frames ordered, the number of spindles per frame (so that the total number of new spindles being ordered can be calculated), as well as detailed technical characteristics, additional hand-written notes taken by British engineers presumably during consultations with the client Japanese firms, the dates the order was taken and when machines were booked (shipped), in multiple installments.

The technical characteristics of machines specified in the orders allow us to differentiate between types of products they were designed to produce, types of inputs required, and other technological nuances. For example, the order in Photo 2 lists “Numbers to be Spun Av” as 42s. This is a “high-end” product in our classification and, hence, the machines that came with this order are high-end machines. We also know from the product varieties data (as well as from industry and firm history) that at the time, Amagasaki was beginning to scale its output of 42 count doubled yarn first introduced on trial basis only a few years earlier. We can also see from the same photo that cotton input is described as Good American and that hank roving is listed as 6 ½ double. Thus, we can indeed see that high-end machines designed for vertically upgraded products required dedicated inputs and technologies (compare to Photo 3 discussed immediately below). In the particular case of this order, we also have a description of how it actually happened in the company history (Unitika, 1989, p. 13). Amagasaki’s chief engineer, Kyozo Kikuchi (one of a few educated engineers employed by Japanese cotton spinning firms at the time), personally went to England to discuss the details of the order with the British engineers, traveling before that to the U.S. to examine the technology for producing 42 count doubled yarn, including comparing between Good and Middling cotton—and reaching the conclusion about using Good cotton.

Photo 2. High-end machines order placed by Amagasaki Spinning in July 1896

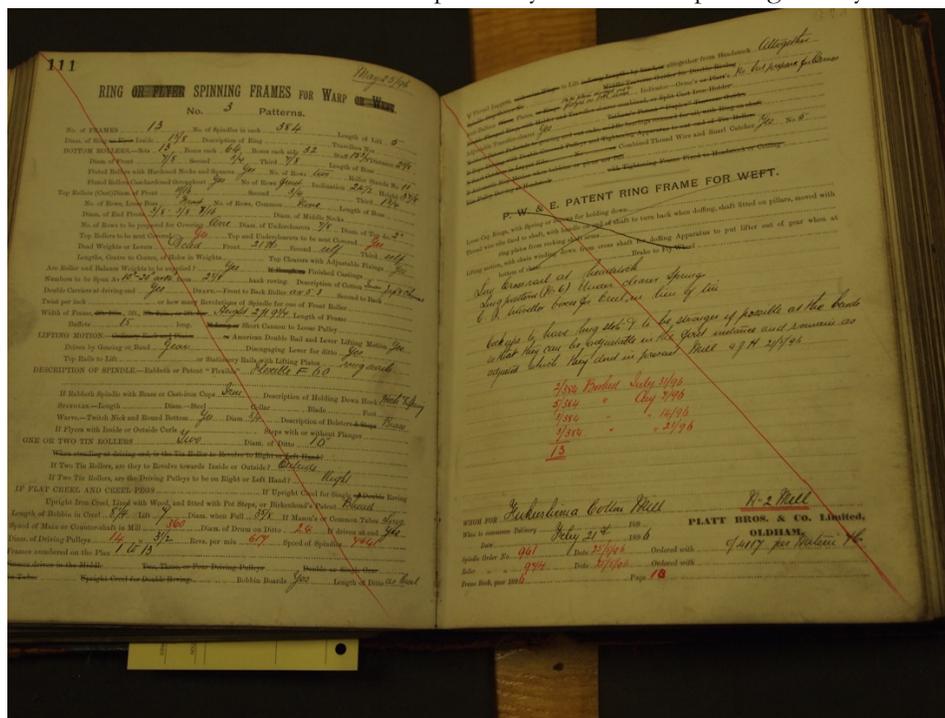


Source: The Platt Collection, Lancashire Archives, Lancashire City Council, Preston, U.K.

² Our newly collected and processed data, including photos of the originals, are publicly available from NBER Industry, Productivity and Digitalization Data Library (<http://www.nber.org/data>).

Photo 3 presents another typical order, by Fukushima Spinning, for 4,992 spindles (13 frames with 384 spindles in each frame). In this order, “Numbers to be Spun Av” are 10’s-20’s, with average 14’s. In line with this, cotton input is listed as Indian, Japanese, and Chinese while hank roving is 2 ⁵/₈ single. We therefore classify the machines in this order as “low-end machines” since they were not designed or intended to be used for high-end, vertically upgraded products. (Fukushima Spinning actually never produced high-end products during our sample.)

Photo 3. Low-end machines order placed by Fukushima Spinning in May 1896



Source: The Platt Collection, Lancashire Archives, Lancashire City Council, Preston, U.K.

A.1.6. Hand-matching machine capacity panel data with technical characteristics of machines

There were three major sources of changes to machine capacity owned by Japanese firms over the sample that are identifiable in the data. The first such source was the installation of new machines ordered from Britain. To illustrate how we matched orders to capacity changes in the Japanese firms that placed them, we work off Amagasaki Spinning 1897 capacity change.

Amagasaki Spinning’s spindle capacity was reported by Enkakukiji (1901) to be 27,036 spindles in the first half of 1897 (verified from Unitika, 1989; matched also with previous orders). The company shareholders report No. 15 (for the first half of 1898) indicates that the capacity had increased by 18,176 spindles to the total of 45,212 spindles by the end of the second half of 1897. Where did these new machines come from? The order presented in Photo 2 provides us with the bulk of the answer: in 1896 the firm placed an order with Platt Brothers of Oldham, for 14,544 “high-end” spindles (36 frames, 404 spindles in each frame). Another order (not shown), for 2,828 spindles, also for high-end machines (numbers to be spun 30s-42s, average 36s) was placed with Platt Brothers even earlier, in December 1894 and booked the next year, but was apparently installed together with the 14,544 spindles above, as part of the same expansion (verified also through company history). Out of the remaining 804 new spindles, 404 are accounted for by an order (not shown) placed in 1896 with another British manufacturer, Dobson & Barrow, also to spin 42 count yarn.³ This leaves 400 spindles (2.2

³ A hand-written annotation (apparently by a Dobson & Barrow employee) reads that “This is a sample trial order so let everything be finished with the utmost care, as further large order depends on the same being satisfactory.” Amagasaki Spinning

percent) of the total capacity increase in late 1897 “unaccounted for,” in the sense that we do not have a record of the corresponding order. From the firm inventory of property (not shown) we know that Amagasaki Spinning also added a 400-spindle frame manufactured by Brooks & Doxey at about the same time. Even though the actual order record is missing, due to its small size and timing, we can safely assume that this was another sample trial order, which in all probability should be similar to orders from Platt Brothers and Dobson & Barrow above. Hence, in this case, we have definitively matched 97.8 percent of the increase in installed capacity as reflected in property inventories to the corresponding orders, and we feel very confident that the remaining 2.2 percent of new capacity were of a similar design.

Applying the above procedure, we were able to hand-match all 437 orders whose records we found in Lancashire archives to corresponding changes in firms’ machine capacity using the timing,⁴ number of spindles, and the information about which of possibly multiple mills operated by the firm the order was slotted for (e.g., in Photo 2 machines are slotted for Amagasaki Mill No. 3—and company reports tell us that No. 3 was the mill constructed at the time to expand the output of the 42 doubled count yarn—the designated number of counts to be spun noted in the order is consistent with that).

The second source of changes to machine capacity owned by Japanese firms over the sample was acquisitions. Fifty eight firm-by-firm acquisitions were consummated during the period of our sample in the industry, involving 69 different mills (plants) (see Braguinsky et al., 2015; the number of acquisitions in there is listed as 73, involving 95 plants but 15 acquisitions involving 26 plants happened in 1915-20 which is outside of our current sample). As a result of these acquisitions, two-thirds of total industry capacity changed hands over the period, hence, it was imperative to trace machines from their original owners to subsequent (at times multiple) owners. Fortunately, all the acquisitions are well documented in company histories and company reports; the latter also reflect new machines acquired as a result of firm-by-firm acquisitions in the property inventories. Hence, we were able to create a script that reassigned machines (and technical characteristics thereof) through (possibly multiple consecutive) acquisitions to new owners, making sure that we updated the breakdown of machine capacity of acquiring firms each time they expanded their capacity through acquisitions.⁵

The third source of capacity changes were the removal of aging machines and their destruction in accidents such as fires or earthquakes. Fortunately, fires and other destruction were rare events, and those that did happen are documented in company histories, including the details of which machines were lost. As for machine removal, those were also uncommon (Japanese firms used their machines while conducting necessary repairs along the way for many decades). Inasmuch as the machines were decommissioned, such events concentrated in larger firms and in later years of our sample, where inventories of properties in company reports are especially detailed, so we had no problem identifying the machines that were being removed and updating the capacity breakdown of the remaining machines accordingly.

While we were thus able to match all orders available in Lancashire archives to firm capacity changes, and then follow those machines through acquisitions and possible destruction and removal as above, the converse is not always true. That is, not all firm capacity changes identified in our panel data using Japanese archival sources could be matched to orders placed with the British manufacturers. There are, broadly speaking, two reasons for that. One reason is that originals of the orders may be missing from Lancashire archives (such as the small order Amagasaki Spinning placed with Brooks & Doxey mentioned above). Rather than drop all such observations, we imputed machine characteristics (high-end or low-end) to new machine arrivals reflected in firms’ property inventories whenever we had unambiguous evidence allowing us to do that (once again, the case of 400 spindles of Brooks & Doxey machines added to Amagasaki Spinning capacity around 1897

never placed another order with Dobson & Barrow, preferring to continue working with Platt Brothers. The note, however, gives a glimpse of the competition among British textile machinery makers.

⁴ As can be seen from the Amagasaki example above, one-two or even more years would normally elapse between the placing of the order and the time the machines would be fully installed and reflected in firms’ property inventories. (Newly arrived machines were commonly included in property inventories after they were installed and ready to be operated; prior to that, new arrivals would be reflected in balance sheets in the “expansion account” but not in property inventories, which are the primary source of our panel data on firm capacity.)

⁵ In addition to firm-by-firm acquisitions, there was one plant-by-firm acquisition, in which a firm bought just one of the plants from another firm. We know exactly which machines were involved in this acquisition too.

mentioned above serves as an example). Such “imputed orders” comprise about 10 percent of the total orders we matched to firms’ property inventories, both in terms of the number of cases and the total number of spindles (Table A1).

Table A1. Machine orders: actual and imputed

	Number of orders	Number of spindles ordered
From Lancashire archives’ originals	437	2,443,886
Imputed	51	308,834
Fraction imputed	0.10	0.11

The second reason is second-hand market transactions where firms bought machines decommissioned by other firms. We do have several documented instances like that in company histories, and those are accounted for in our capacity breakdown. However, we do not have systematic records of purchases in the second-hand market, and in cases where we were also missing company reports, we had to drop observations where we could not know the origins of the machines, from the analysis that required machine characteristics. This affected 11 percent of all firms but only seven percent of all observations. Moreover, firms with unknown machine origins were generally small, so their fraction in the total number of capacity-weighted observations in our data is just about two percent (Table A2). Thus, dropping them from the analysis affects it only marginally.

Table A2. Total spindle-observations matched to underlying orders

	# of firms	# of observations	Capacity (# of spindles): Total	Of which: matched	Fraction matched
Matched sample	105	1,911	61,710,036	61,233,396	0.99
Unmatched sample	13	154	1,021,272	0	0.00
Fraction matched	0.89	0.93	0.98	0	0.98

As Table A2 shows, for firms for which we do have the data on how their machine capacity evolved through orders, acquisitions and removal/destruction (the “matched sample”), the correspondence between machine capacity changes recorded in Japanese archival sources (based on property inventories) and our calculated changes combining the data sources above is nearly perfect. Specifically, we were able to match 61.2 million spindle-observations out of 61.7 million total in the matched sample of 105 firms, the match rate of more than 99 percent. This brings the fraction of total industry capacity (including also firms for which matching turned out to be impossible) that we could match to the characteristics of the machines comprising it to 98 percent (Table A2).

A.2 Historical trends

Figure A1. Dynamics of the number of firms and industry output



Table A3. Imports, production, and exports, 1880-1900 (units: *koru*=0.18 ton)

Year	Imports from:		Total	Dom. production	Export	Dom. supply
	Britain	India				
1880	84,367	10,908	95,324			95,324
1881	73,515	17,932	92,421			92,421
1882	61,708	21,794	84,324			84,324
1883	55,687	26,448	82,135	2,326		84,461
1884	48,790	21,797	70,622	5,687		76,309
1885	40,437	30,887	71,324	3,370		74,694
1886	45,251	36,850	82,101	16,217		98,318
1887	54,103	56,884	111,096	25,273		136,369
1888	77,583	80,546	158,281	33,142		191,423
1889	62,194	80,488	142,929	69,959		212,888
1890	59,703	46,566	106,588	108,374	31	214,931
1891	42,624	15,560	58,123	160,207	108	218,222
1892	53,494	27,527	81,534	213,489	109	294,914
1893	48,426	16,216	65,174	222,223	1,053	286,344
1894	45,353	7,778	53,555	304,584	11,796	346,343
1895	44,157	4,472	49,876	383,565	11,776	421,665
1896	63,859	2,854	67,373	428,864	41,916	454,321
1897	52,380	355	54,555	544,461	140,116	458,900
1898	52,697	353	54,563	670,067	229,445	495,185
1899	27,101	252	28,339	785,612	341,202	472,749
1900	30,035	101	30,941	647,484	208,732	469,693

Source: Takamura (1971), Vol. 1, pp. 146, 183; Association data (dom. production in 1883-85).

Table A4. Imports and domestic production by variety 1891-93 (units: *kor*=0.18 ton)

Imports from:	Variety (count)	1891	1892	1893
India	10's-18's	2,449	4,507	1,164
	20's	17,570	17,657	12,376
	Subtotal	20,019	22,164	13,540
Britain	16's-24's	13,079	13,130	9,385
	28's-32's	13,727	14,967	8,737
	38's-42's	1,431	2,345	1,759
	32's doubled	2,506	10,827	12,045
	42's doubled	5,882		
	60's-120's gassed	5,377	7,809	8,532
	Subtotal	42,003	48,444	40,458
Total		62,022	70,608	53,998
<i>(Total import, stat.)</i>		<i>58,123</i>	<i>81,534</i>	<i>65,174</i>
Domestic production	<14's		43,677	43,052
	14's-15's		38,064	39,579
	16's		36,347	44,125
	17's-19's		8,918	10,617
	20's		49,919	68,604
	21's-24's		1,390	3,894
	25's-27's		104	31
	28's-32's		4,329	8,121
	33's-37's		113	131
	38's-42's		51	0.2
	Other		8,377	6,730
	Total		160,207	189,206

Source: Takamura (1971), Vol. 1, p. 184. Per source, import data come from port statistics in Kobe and Tokyo, therefore, does not correspond exactly to customs statistics data in Table 1 but captures most of it.

Table A5. Imports and domestic production by variety, 1898 (units: *kor*=0.18 ton)

Variety	Estimated import		Dom. production	Export	Domestic supply	
	min	max			min	max
<16's			160,355	3,246	157,109	157,109
16's-24's	4,248	4,248	453,936	198,246	259,938	259,938
16's			224,982	120,039	104,943	104,943
20's			208,479	77,905	130,574	130,574
28's-32's	3,186	3,186	22,032	45	25,173	25,173
38's-42's	531	531	2,115		2,646	2,646
60's gassed	6,372	7,434	19		6,391	7,453
80's gassed	9,558	10,620	3,044		12,602	13,664
100's gassed	2,655	2,655			2,655	2,655
120's gassed	1,593	1,593			1,593	1,593
doubled <32's			517		517	517
32's doubled	7,965	9,558	1,779		9,744	11,337
42's doubled	14,337	15,930	7,022		21,359	22,952
Total	50,445	55,755	650,819	201,537	499,727	505,037

Source: Takamura (1971), Vol. 1, p. 322.

A.3 Industry Association-mandated output cuts

Table A6 presents the details of Boren-mandated output cuts and (in the right column) our measure of their relative impact on low-end products. For output cuts imposed as mandated holidays, we converted those into percentage terms by dividing the number of holidays by 30 (e.g., 4/30=0.133). The numbers in the column “Implied fraction of lower counts mandated cuts” is the difference between the numbers in previous two columns.

Table A6. Mandatory output cuts during our sample period

year	month	Output of 20 count and lower	Output of 21 count and higher	Implied relative fraction of lower counts mandated cuts
		Policy detail		
1899	1	4 mandated holidays	4 mandated holidays	0
1899	2-12	None	None	0
1900	1-4	None	None	0
1900	5-7	4 mandated holidays	None	0.133
1900	8-12	40% of spindles to be idled or suspension of night shift	None	0.400
1901	1-3	40% of spindles to be idled or suspension of night shift	None	0.400
1901	4-12	None	None	0
1902	1-6	None	None	0
1902	7-12	4 mandated holidays	4 mandated holidays	0
1903	1-12	None	None	0
1904	1-12	None	None	0
1905	1-12	None	None	0
1906	1-12	None	None	0
1907	1-12	None	None	0
1908	1-4	5 mandated holidays	None	0.167
1908	5-12	27.5% of spindles to be idled or suspension of night shift	None	0.275
1909	1-12	27.5% of spindles to be idled or suspension of night shift	None	0.275
1910	1-4	20% of spindles to be idled or suspension of night shift	None	0.200
1910	5-9	None	None	0
1910	10-12	27.5% of spindles to be idled; or 12.5% of spindles to be idled, plus 4 days and 2 hours per workday mandated holidays	20% of spindles to be idled or 5 days and 2 hours per workday mandated holidays	0.075
1911	1-9	27.5% of spindles to be idled; or 12.5% of spindles to be idled, plus 4 days and 2 hours per workday mandated holidays	20% of spindles to be idled or 5 days and 2 hours per workday mandated holidays	0.075
1911	10-12	27.5% of spindles to be idled; or 12.5% of spindles to be idled, plus 4 days and 2 hours per workday mandated holidays	10% of spindles to be idled or 5 days mandated holidays	0.175
1912	1-3	27.5% of spindles to be idled; or 12.5% of spindles to be idled, plus 4 days and 2 hours per workday mandated holidays	10% of spindles to be idled or 5 days mandated holidays	0.175
1912	6-9	4 mandated holidays	4 mandated holidays	0
1912	10-12	None	None	0
1913	1-12	None	None	0
1914	1-7	None	None	0

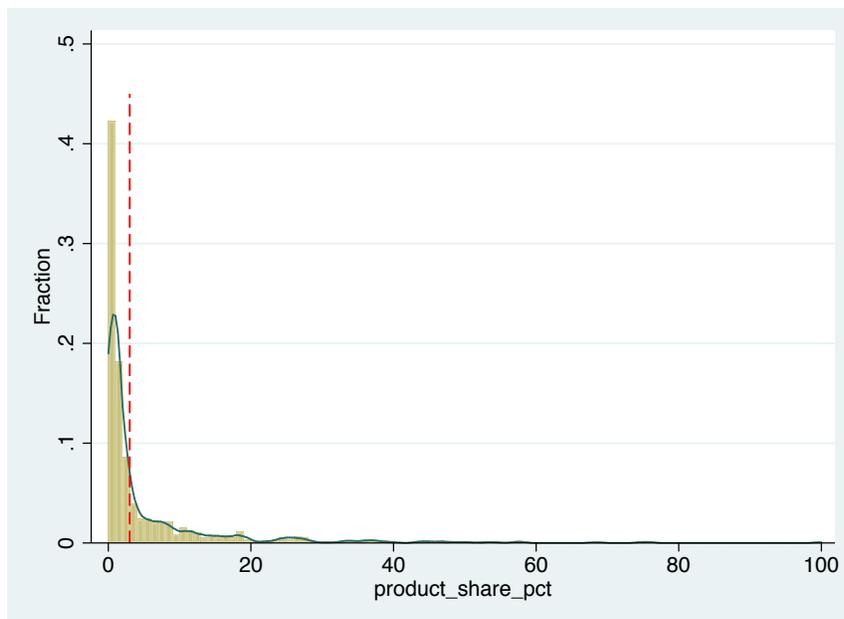
Source: compiled from Shoji, Otokichi, 1930. *Boseki Sogyo Tanshuku Shi* (History of Operational Curtailments in Cotton Spinning, in Japanese). Nihon Mengyo Kurabu, Osaka, Japan.

Since in the main text we use semi-annual data in our IV growth regression estimations, we converted the numbers from Table A6 into semi-annual data by multiplying the implied relative fraction of lower counts mandated output cuts by the number of months during which the restrictions were applied in any given semi-annual period, divided by 6. For example, 4 mandated holidays in the first half of 1900 were imposed for two months (May and June), hence our measure of mandatory output cuts impact on lower counts for the first half of 1900 is $0.133 \times 2/6 = 0.089$. For the second half of the same year it is $0.133 \times 1/6$ (July output cuts) + $0.4 \times 5/6$ (output cuts in the rest of the year) = 0.356, and so on.

A.4 Initial scale of new product introduction and definitions of product trials

Figure A2 presents the distribution of within-firm shares of newly introduced products. The mean and median within-firm shares are 5.27 percent and 1.39 percent, respectively. The majority of new products in our data are thus introduced as a small share of firm's total output, and new product introduction below three percent threshold are quite common. However, this initial small scale of new product introduction is much more pronounced among firms with high-end machines than for firms without such machines (the mean and median within-firm shares of newly introduced products for the first time for firms with high-end machines are 3.49 percent and 0.9 percent respectively, as opposed to 5.74 percent and 1.58 percent, respectively, for firms with no high-end machines).

Figure A2. Distribution of within-firm share of newly introduced products



mean	s.d.	10 th	25 th	50 th	75 th	90 th	N
5.27	10.43	0.08	0.33	1.39	4.91	15.21	793

Robustness to alternative definitions of trials: While in the main text we have used the three-percent cutoff of the within-firm share of newly introduced products as our empirical definition of a trial product, we conducted sensitivity analysis and confirmed that the findings are robust to using reasonable alternative thresholds (such as two percent or four percent). It is also possible to define trials in alternative ways. For example, we may consider a newly introduced product to be a trial if it was not produced in positive quantity for most of the time during the early stages after the firm tried producing it for the first time—that is, if its output was on an off during those early stages. To operationalize this concept, we use monthly production data and classify a new-to-the-firm product as a trial if its output was positive, regardless of scale, only for three months or less during the first 12 months following its introduction for the first time, and non-trial otherwise. Thus, a trial product is a product where the firm could not or would not continue producing it on a continuous

basis at least during the first year after launch. We count the number of all such products during any semiannual time period to arrive at the alternative count of the number of trials with new product varieties. Note that this makes the definition independent of the scale at which the product was introduced. As before, we define trials to be product upgrade trials if they involve a high-end product and if the firm had not produced of an even higher count before.⁶

Table A7. Firm Growth and complementarity between product innovation and diversification:
IV Estimation with an alternative definition of trials

VARIABLES	DV: number of upgrade trials started at t		DV: Ln(output) at $t+1$, minus Ln(output) at t	
	First stage	“Placebo test”	Second stage	
	(1)	(2)	(3)	(4)
Cumulative number of upgrade trials			0.013 (0.012)	-0.016 (0.015)
Fraction of low-end products in total number of products	-2.592*** (0.322)	-2.600*** (0.322)	-0.030 (0.029)	-0.079** (0.036)
Cumulative number of upgrade trials x fraction of low-end products				0.146*** (0.030)
Fraction of output cuts enforced at t x Logged installed high-end spindles in $t+1$, minus Logged installed high-end spindles in t	1.386*** (0.433)			
Fraction of output cuts enforced at t x Logged installed low-end spindles in $t+1$, minus Logged installed low-end spindles in t		-0.403 (0.562)		
Logged installed high-end spindles in $t+1$, minus Logged installed high-end spindles in t	-0.164 (0.118)	0.049 (0.073)	0.019*** (0.007)	0.019*** (0.007)
Logged installed low-end spindles in $t+1$, minus Logged installed low-end spindles in t	-0.126 (0.087)	-0.090 (0.107)	0.014 (0.016)	0.012 (0.016)
Dummy = 1 if university-educated engineer at t	-0.404 (0.402)	-0.400 (0.395)	0.065** (0.026)	0.078*** (0.027)
Dummy = 1 if merchant board member at t	0.285 (0.340)	0.336 (0.335)	0.026 (0.018)	0.024 (0.018)
Logged total firm output at t	0.309*** (0.117)	0.277*** (0.114)	-0.028** (0.014)	-0.048*** (0.014)
Firm age	0.051 (0.032)	0.053 (0.033)	-0.005*** (0.002)	-0.010*** (0.002)
Constant	-2.083*** (1.014)	-1.962* (1.008)	0.489*** (0.117)	0.697*** (0.131)
Semiannual time dummies	Included	Included	Included	Included
Observations	1,608	1,608	1,608	1,608
Log pseudolikelihood (R-squared)	-223.6	-225.1	0.195	0.203
Estimation	Poisson	Poisson	IV	IV

First stage: Poisson regression with robust standard errors clustered at the firm level. Second stage: OLS with standard errors clustered at the firm level from bootstrap (1,000 replications with a few non-convergent replications). *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Cumulative number of upgrade trials is an instrumented variable in the IV estimations. Note: mandated output cuts measure does not vary within periods and is therefore absorbed by the semi-annual time dummies.

⁶ Since firms may not know which new product varieties are going to be produced on a continuous basis and which are going to be discontinued at the time of their introduction, defining trial product varieties in this way gives rise to a “selection on outcome” concern potentially biasing our definition toward failed product introductions. Note that this definition also precludes us from looking at the second, third, and so on trials in the same product line.

Table A7 presents the results of the IV growth estimations as in Table 5 in the main text, using the afore-mentioned alternative definition of upgrade trials. In the first stage, we once again use a Poisson regression to obtain a predicted number of upgrade trials conducted by the firm in a particular period. The coefficient on the interaction term between mandated output cuts and high-end machines installation is still positive and statistically significant, although the instrument is somewhat weaker. The “Placebo test” once again finds no correlation between the interaction term and upgrade trials conducted by the firm when the interaction is with low-end, not high-end machines installations. The results from the second stage regression are also quite similar to the results presented in the main text. In particular, the coefficient on the interaction term between the instrumented cumulative number of upgrade trials and the fraction of low-end products in the firm product portfolio (statistically highly significant) implies that an additional (instrumented) upgrade trial at the mean low-end product fraction is associated with a 7.9-percentage-point higher output growth rate. We also repeated the estimations above using a definition of trials where we required that the new product was *both* introduced on a scale less than three percent of the firm’s total output *and* met the alternative definition above. The estimation results (not shown) once again look quite similar.

A.5 Decomposition and concentration of output, high-end machines, and product varieties

In this appendix we employ more formal decomposition analysis to quantify sources of change in the number of product varieties per firm we observe in Figure 1. We first decompose the market-share-weighted average number of products at time t as

$$\bar{y}_t \equiv \sum_{i=1}^{N_t} s_{it} y_{it} = \sum_{i=1}^{N_t} s_{it} \bar{y}_i + \sum_{i=1}^{N_t} s_{it} \tilde{y}_{it},$$

where N_t is the number of firms operating at time t ; y_{it} and s_{it} are firm i ’s number of products and market share at time t , respectively; $\bar{y}_i = \frac{1}{T_i} \sum_{t=1}^{T_i} y_{it}$ is the average number of products produced by firm i over the whole period it is observed in the sample (T_i), and $\tilde{y}_{it} = y_{it} - \bar{y}_i$. The change in the weighted average number of products between t and $t+1$ is then

$$\begin{aligned} \bar{y}_{t+1} - \bar{y}_t = & \left[\sum_{i=1}^{N_{t+1}} s_{it+1} \bar{y}_i - \sum_{i=1}^{N_t} s_{it} \bar{y}_i \right] + \left[\sum_{i \in C} s_{it} (\tilde{y}_{it+1} - \tilde{y}_{it}) \right] + \left[\sum_{i \in C} \tilde{y}_{it+1} (s_{it+1} - s_{it}) \right] + \left[\sum_{i \in EN} s_{it+1} \tilde{y}_{it+1} \right] \\ & - \left[\sum_{i \in EX} s_{it} \tilde{y}_{it} \right] \end{aligned}$$

where C , EN , and EX indicate continuing firms, entrants, and exiting firms, respectively.

We call the first term on the right-hand side the “composition effect.” It captures the change in the average number of products due to the difference in the composition of firms between t and $t+1$. This measures the difference, over their lifetimes, in the average number of products of new entrants versus exiting firms. The second term is the “expansion effect” of continuing firms. It captures within-firm changes in product variety counts between t and $t+1$, holding fixed firms’ base period market shares. The third term is the “allocation effect,” measuring the contribution of changes in the market shares of continuing firms between t and $t+1$. Finally, the fourth and fifth terms measure the contribution of entrants and exiting firms, respectively, coming from deviations in the first observation (for entrants) and the last observation (for exiting firms) from their own long-term average number of products. A positive (negative) number in the fourth term means that entrants’ average number of products varieties is greater (less) when they enter than in later periods of their operation. A positive (negative) number in the fifth term means that exiting firms’ average number of products is greater (less) right before they exit than in their earlier periods of operation. We label the sum of the last four terms in the decomposition the “overall within effect.”

Table A8 presents the results. The main takeaways are as follows. First, the decomposition shows there was an increase of 9.0 in the average number of all products per firm between 1893 and 1914. Of this, the within effect accounts for a greater share (5.6 products) than the composition effect (3.3 products). However, when we divide the sample before and after the spike in product varieties in 1907, there are stark differences. From 1893-1906, the overall increase of 2.5 products per firm is more modest, and the composition effect (1.6) contributes more than the within effect (0.9). Decomposition of the within effect also shows that it is entirely driven by allocation—changes in market shares (column (h) Table A8). We see a complete reversal from 1907-

1914. While the absolute magnitude of the composition effect remains roughly the same (1.7), the within effect (4.7) becomes a dominant contributor to the total growth in average products per firm of 6.4. Almost all of this within effect now comes from the expansion of continuing firms, while the allocation effect is much smaller.

Table A8. Decomposition analysis

Period	Total change	Composition	Within					
			Total	Continuing firms			Deviation from own average	
	(a)=(b)+(c)	(b)	(c)= (d) + (e)+(f)	Total (d)=(g)+(h)	Expansion (g)	Allocation (h)	Entrants (e)	Exiting firms (f)
1893.2-1914.2	9.0	3.3	5.6	6.7	5.4	1.3	-0.2	-0.8
1893.2-1906.2	2.5	1.6	0.9	1.0	0.02	1.0	-0.3	0.1
1907.1-1914.2	6.4	1.7	4.7	5.6	5.3	0.3	0.02	-0.9

Source: Our calculations using the data described in the main text and in the appendix.

Thus, during the first subperiod (1893-1906), which is the period of large-scale entry, followed by a shakeout and initial industry consolidation, the growth in number of product varieties was driven by new entry and by increasing market shares of continuing firms that produced more product varieties. In the second subperiod (1907-1914), while new entry still contributed to product variety growth at about the same magnitude as before, the number of product varieties produced by continuing firms swelled. This growth came to dominate the overall expansion of the number of product varieties produced by the industry. Separate decompositions of high- and low-end products present essentially the same picture in both cases, although with some nuanced differences. Thus, the big boost received by industry growth after 1907 from the expansion of the number of product varieties seen in Figure 1 in the main text resulted almost entirely from an increase in the number of both high-end and low-end products produced within continuing firms.

Table A9. Concentration of output, high-end machines, high-end and low-end products

Output quintile	High-end machine capacity			
	1893	1899	1907	1913
1	-	486	256	154
2	-	2,873	1,799	924
3	-	2,362	5,313	12,057
4	5,445	3,016	4,351	46,092
5	2,966	16,162	67,100	122,260
Output quintile	Number of high-end product varieties			
	1893	1899	1907	1913
1	0.0	0.5	0.4	0.3
2	0.1	1.1	0.8	0.3
3	0.3	0.6	0.9	1.9
4	1.1	0.1	1.2	2.9
5	1.1	1.2	3.2	6.5
Output quintile	Number of low-end product varieties			
	1893	1899	1907	1913
1	2.3	1.8	1.8	2.3
2	2.7	3.3	2.9	2.7
3	4.1	4.1	2.9	3.7
4	4.6	3.8	5.4	5.1
5	6.2	5.6	5.4	9.0

Source: Our calculations using the data described in the main text and in the appendix.

Table A9 presents high-end machine capacity (measured by the number of high-end machines spindles installed), the number of high-end product varieties and the number of low-end product varieties by quintiles

of total output (firm size measured by output scale, as in Figure 1 Panel A) at four points in time during our sample. The top panel shows that as high-end machine capacity increased from virtually zero at the start of our sample, it spread out across firms of different size, but remained heavily concentrated among the largest firms (even though the composition of the largest firms changed due to higher growth rates of firms with high-end machines). Not surprisingly perhaps, we can see the same pattern in the number of high-end product varieties in the middle panel. What is most interesting, however, is that the number of low-end product varieties (which do not require high-end machines for their production) also became heavily concentrated over time in the same set of firms. Thus, the same firms accounted for the expansion of both high- and low-end product varieties. Moreover, those were the firms that invested in high-end machines.

Table A10. Number of products and low-end products by firms with and without high-end machines

		Firms with high-end machines			Of which: firms above the median # of spindles in high-end machines	Firms with no high-end machines		
		1893.2-1914.2	1893.2- 1906.2	1907.1- 1914.2	1893.2-1914.2	1893.2- 1914.2	1893.2- 1906.2	1907.1- 1914.2
Number of products	Mean	7.81	6.77	9.56	10.22	3.99	3.89	4.33
	St. Err.	0.20	0.18	0.41	0.31	0.07	0.07	0.17
	# obs	743	465	278	363	1045	810	235
Number of low-end products	Mean	4.97	4.59	5.60	5.53	3.78	3.71	4.03
	St. Err.	0.13	0.14	0.26	0.23	0.06	0.06	0.15
	# obs	743	465	278	363	1045	810	235

Source: Our calculations using the data described in the main text and in the appendix. The difference in means between firms with and without high-end machines are highly statistically significant using double-sided t -test.

Table A10 looks at the same pattern from a slightly different angle. It presents the average numbers of all product varieties, and of low-end product varieties among those, produced by firms that did and did not have high-end machines at a given point in time. We present these statistics for the whole sample as well as for two subperiods corresponding to Table A8 above. Firms with high-end machines produced on average almost twice as many product varieties as firms that did not have such machines over the whole period, with the gap larger in the second period than in the first (all the differences in means in Table A10 are statistically highly significant). Even more interestingly, firms that had high-end machines produced more *low-end* product varieties compared to firms that only had low-end machines, and the gap, once again, is larger in the second subperiod than it is in the first. When limited to firms that had high-end capacity above the median in each period, the gap with firms with no high-end machines is even much larger.

A.6 Upgrade trials: regression analysis

Figure 2 in the main text showed the relationship between upgrade trials and new-to-firm high-end and low-end products in raw data. Here we confirm these relationships in a regression framework which also allows us to see the role played by high-end machines and other covariates. The regression below also demonstrates that only upgrade trials and no inside-the-envelope horizontal diversification trials contributed to persistent growth in firms' product varieties.

To relate product introductions to trials, we estimate the following specification:

$$\Delta y_{it+1} = \alpha + \beta_1 \text{cuml_upg_trials}_{it-1} + \beta_2 \text{cuml_div_trials}_{it-1} + \beta_3 X_{it} + \gamma_i + \delta_t + \zeta_\tau + \varepsilon_{it},$$

where Δy_{it+1} it is the change from t to $t+1$ in the number of products produced by firm i (total, high-end, or low-end, depending on the specification); $\text{cuml_upg_trials}_{it-1}$ and $\text{cuml_div_trials}_{it-1}$ represent the cumulative numbers of upgrade and diversification trials conducted by firm i by time $t-1$, respectively; X_{it} is a vector of controls, and ε_{it} is the error term. We include firm fixed effects γ_i and semi-annual period effects δ_t . In addition, we include a set of dummies ζ_τ to nonparametrically control the number of periods τ the firm has

been in the sample (the first equal to one for every firm's earliest period in the sample, the second equal to one for firms' second periods, and so on). We include these age indicators to ensure that our key variables of interest, the cumulative numbers of upgrade and diversification trials, capture accumulated experience with trials specifically and not simply how long the firm has happened to be in the data. As in the main text, we exclude each firm's first and last periods because they often cover less than a full six months.

The results, shown in Table A11, make clear that a firm's past product upgrade trials, but not diversification trials, are related to growth in its number of products of all types. The estimates in column (1) indicate that an additional past upgrade trial is associated with adding product varieties of all types in the following period. To give some sense of the magnitude of this relationship, conditional on past upgrade trials being positive, the 25th-percentile of cumulative past upgrade trials is one, while the 75th-percentile is five trials. Hence, the interquartile differential corresponds to about 1.3 (0.33x4) more new product varieties added during any given semi-annual period.⁷

Table A11. Product variety expansion as a function of past upgrade trials

VARIABLES	DV: # of all products at $t+1$, minus # of all products at t	DV: # of high-end products at $t+1$, minus # of high-end products at t	DV: # of low-end products at $t+1$, minus # of low-end products at t	DV: # of all products at $t+1$, minus # of all products at t	DV: # of high-end products at $t+1$, minus # of high-end products at t	DV: # of low-end products at $t+1$, minus # of low-end products at t
	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative number of upgrade trials at $t-1$	0.331*** (0.102)	0.172*** (0.062)	0.179** (0.085)	0.293*** (0.101)	0.148** (0.062)	0.162** (0.076)
Cumulative number of diversification trials at $t-1$	0.039 (0.044)	0.013 (0.008)	0.026 (0.039)	0.046 (0.041)	0.014** (0.007)	0.031 (0.037)
Dummy equal to 1 if high-end machine expansion between $t-1$ and t				0.818*** (0.175)	0.479*** (0.116)	0.344*** (0.115)
Dummy equal to 1 if low-end machine expansion between $t-1$ and t				0.122 (0.118)	-0.084 (0.074)	0.206* (0.117)
Dummy =1 if university-educated engineer employed at t				0.145 (0.228)	0.206 (0.134)	-0.045 (0.175)
Dummy =1 if merchant a member of board at t				0.178 (0.164)	-0.040 (0.063)	0.218* (0.124)
Number of all products at t	-0.381*** (0.040)			-0.397*** (0.039)		
Number of high-end products at t		-0.412*** (0.048)			-0.427*** (0.045)	
Number of low-end products at t			-0.383*** (0.044)			-0.392*** (0.045)
Constant	2.900*** (0.587)	0.788*** (0.257)	2.155*** (0.527)	2.657*** (0.595)	0.742*** (0.250)	1.924*** (0.534)
Semiannual time and observation	Included	Included	Included	Included	Included	Included
Firm FE	Included	Included	Included	Included	Included	Included
Observations	1,509	1,509	1,509	1,509	1,509	1,509
Within R-squared	0.221	0.235	0.228	0.237	0.256	0.236
Number of firms	95	95	95	95	95	95

Panel data estimation with firm fixed effects. Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

⁷ Columns (1)-(3) include the number of products (all, high-end, and low-end, respectively) produced by firm i at time t as a control in X_{it} . The total number of product varieties (and hence the potential number of products a firm can produce) is bounded from above in our data, so we control for the level of product diversification already attained. To check if the results are sensitive to including the lagged number of products, which also enters the dependent variable with a minus sign, we estimated an ordered logit with the dependent variable being -1, 0, or 1 if the firm respectively reduced, did not change, or increased its product varieties from t to $t+1$. The results were very similar; details are available upon request.

Columns (2) and (3) look at the relationship for high-end and low-end products separately. Past upgrade trials are associated not just with future growth of high-end products, but low-end products as well. Indeed, the magnitudes of the trial-associated high- and low-end product growth are similar. Because upgrade trials never involve low-end products by construction, the results in column (3) suggest there may be substantial connections tying firms' product upgrade attempts to their abilities to increase the number of seemingly unrelated low-end products. Diversification trials, on the other hand, have much smaller and statistically insignificant relationships to product additions.

Columns (4)-(6) of Table A11 include additional controls: an indicator for the firm installing new machines (whether high- or low-end) during the observation period, and indicator variables for the firm employing a university-educated engineer or having a board member who was a prominent cotton yarn or garments merchant (a proxy for "connectedness" to markets; see Braguinsky et al., 2015). The point estimates on past upgrade trials fall slightly but retain economic and statistical significance.

Among the covariates, high-end machine installation has an economically large and statistically significant association with both high-end and low-end product varieties expansion. Other things equal, expanding high-end machine capacity in the prior period relates to an additional 0.82 product introductions per period, about 59 percent (0.48/0.82) of which are new high-end products. The tie between growth in low-end products and high-end machine expansion (which could in principle be used for low-end production but rarely were because of their expense) is more suggestive evidence that pushing the technology frontier helped firms grow within the frontier as well.

On the other hand, low-end machine expansions do not exhibit patterns characteristic of a connection between such expansions and product innovation along the vertical dimension. They are statistically unrelated to the expansion of high-end product varieties. While they accompany growth in low-end products, the magnitude of this relationship is about 60 percent of the relationship with high-end machine expansion and only marginally significant statistically.

The relationships between high-end machine expansion and product growth hold even conditioning on past upgrade trials. As we saw in the main text, however, adoption and expansion of high-end machines (but not of low-end machines) is nevertheless significantly related to new product trials.

A.7 Formal model behind the conceptual framework in Section 3

Firms operate forever and time is continuous. Firms are endowed with an unobserved potential gross output parameter g^* which is bounded from above so that all firms have a finite present value. There is no strategic interaction among firms, so each firm's decisions emerge from a single-agent optimization problem. Initially, firms only know that g^* is distributed according to a Beta distribution with parameters (a, b) :

$$f(g^*) = \frac{\Gamma(a+b)g^{*a-1}(1-g^*)^{b-1}}{\Gamma(a)\Gamma(b)}, 0 < g^* < 1$$

If a firm conducts n trials at the time of its j -th opportunity, its success probability is given by the binomial distribution with parameter g^* (and therefore rises in g^*):

$$P(X_j) = \binom{n}{X_j} g^{*X_j} (1-g^*)^{n-X_j} \text{ for } X_j = 1, 2, \dots, n$$

where X_j is the number of successful upgrade product trials out of n trials in period j .

Product upgrade opportunities arrive discretely, separated by time intervals T_i where i denotes the i -th upgrade opportunity. Therefore, a firm undergoes its j -th trial opportunity at time $\sum_{i=1}^j T_i = T_1 + \dots + T_j$. We assume that T_i has an i.i.d. exponential distribution:

$$f(t) = \lambda e^{-\lambda t}, \quad t \geq 0$$

That is, T_j has mean $1/\lambda$. The parameter λ is the hazard rate of opportunity arrival process. For example, it could be the hazard rate of arrival of new high-end machines: as discussed in the main text and also further below, such an interpretation finds support in the data.

The firm pays a cost $c(n)$ to attempt n upgrade trials at any given time, where $c(0) > 0$, $c'(n) > 0$, $c''(n) > 0$, and $c(n)$ can vary across both firms and time. To ease notation, we omit time and firm subscripts. The expected discount factor is given by

$$\lim_{T_j \rightarrow \infty} E[e^{-rT_j}] = \int_0^\infty \lambda e^{-rt} e^{-\lambda t} dt = \frac{\lambda}{\lambda + r},$$

and the discounted cost of conducting n upgrade product trails at the j -th opportunity is given by

$$E \left[\int_0^{T_j} c(n) e^{-rt} dt \right] = c(n) \frac{1}{r} E(1 - e^{-rT_j}) = c(n) \frac{1}{r} \left(1 - \frac{\lambda}{\lambda + r} \right) = \frac{c(n)}{\lambda + r}.$$

We set the initial time to 0 when the first opportunity for upgrade product introduction arrives. As mentioned in the main text, we assume that the initial gross output of firms coincides with the prior mean of the potential growth rate:

$$g_0 \equiv E(g) = \frac{a}{a + b}$$

As firms conduct upgrade trials, their posterior expectation of g^* and their output decisions evolve in a Bayesian fashion, as in Jovanovic (1982). For example, a firm's gross output at the end of period T_1 is

$$g_1 = \frac{a + x_1}{a + b + n_1}$$

where n_1 is the number of trials conducted during period T_1 and x_1 is the number of successful trials among them. More generally, for a firm that has conducted upgrade product trials over j opportunities, the parameters of the Beta distribution are updated according to $(a + S_j, b + N_j - S_j)$, where $N_j \equiv \sum_{i=1}^j n_i$ is the cumulative number of trials and $S_j \equiv x_1 + \dots + x_j$ is the total number of successful trials. The actual output after the j -th trial (at time $\sum_{i=1}^j T_i$) is then given by

$$g_j = \frac{a + S_j}{a + b + N_j}$$

Output g_j evolves according to

$$g_{j+1} = \frac{a + S_j + x_{j+1}}{a + b + N_j + n_{j+1}}$$

where x_{j+1} is the number of successful upgrade trials conducted at opportunity $j+1$. Note that if $n_{j+1} = 0$, then $g_{j+1} = g_j$.

As mentioned in the main text, after each trial opportunity, firms observe the realization of g_j and choose among three actions: (a) continuing in the product upgrade trials regime, (b) stopping trials and focusing on expansion through horizontal product diversification, or (c) stopping trials and joining firms that never conducted upgrade trials in the first place. Choices (b) and (c) are irreversible.

Consider the last option. Denote as $\pi(g_j)$ the present discounted value of any firm with current realized output g_j that stops upgrade trials and exits at the lower boundary. For simplicity, as with the firms that never try product upgrades, we assume the value of output derived from such "exit" from trials is zero:

$$\pi(g_j) = 0 \quad \forall g_j$$

The second option, stopping upgrade trials and moving to horizontal product diversification by harnessing what has been learned so far, involves taking the following presented discounted value for a firm with current realized gross output g_j :

$$\tilde{\pi}(g_j) = -K + (1 + \alpha)g_j = -K + (1 + \alpha) \frac{a + S_j}{a + b + N_j} \quad (1)$$

where $K > 0$ and $\alpha > 0$. That is, the firm can retain the output it has already attained through successful upgrade product trials and add to this an extra boost from horizontal diversification. K is a fixed setup cost of starting horizontal diversification—purchasing extra equipment, setting up a marketing network for newly added diversified products, etc.

From (1), the firm enters horizontal diversification after the j -th opportunity if contemporaneous realized gross output is

$$\frac{a + S_j}{a + b + N_j} > \tilde{g}$$

where $\tilde{g} = \frac{K}{1 + \alpha}$ so that $\tilde{\pi}(\tilde{g}) = 0$.

Let $\Pi(g_j)$ denote the present discounted value of stopping upgrade trials and either taking the default or concentrating on horizontal product expansion given g_j :

$$\Pi(g_j) = \max[0, \tilde{\pi}(g_j)]$$

Further, let $V_j(g_j)$ denote the expected return from following an optimal policy at trial opportunity j if the current realized gross output (and the current point estimate of g^*) is g_j . Similar to McCardle (1985, p. 1377) this leads to the value function

$$V_j(g_j) = \max \left\{ \Pi(g_j), \frac{g_j - c(n_j^*)}{\lambda + r} + \frac{\lambda}{\lambda + r} E[V_{j+1}(g_{j+1})] \right\}, \quad (2)$$

where n_j^* is the optimal number of trials to be conducted at the j th opportunity. The first term on the right-hand side is the discounted return from stopping and the second term is the discounted expected return from continuation: specifically, $\frac{g_j - c(n_j^*)}{\lambda + r}$ is the discounted return from realized output, net of (the optimal number of) trial costs, while $E[V_{j+1}(g_{j+1})] = V_{j+1} \left(\frac{(a+b+s_j)g_j + E[x_{j+1}|n_{j+1}^*]}{a+b+N_j+n_{j+1}^*} \right)$ is the expected return from following an optimal policy at the $j+1$ th opportunity given the point estimate of g^* at j .

For sufficiently low values of g_j , $\tilde{\pi}(g_j) < 0$ in (1), so it is not worth stopping trials to focus on horizontal diversification. In such cases, the firm's choice is instead to continue upgrade trials, hoping to receive favorable future news that would justify a horizontal diversification focus, or instead to forgo such efforts, stop trials, and earn the default zero. The latter will occur if g_j is low enough so that future fixed costs $c(n)$ are too high to justify continuing to run upgrade trails.

The continuation set at j is given by

$$C_j = \left\{ g_j, n_j^* \mid \Pi(g_j) < \frac{g_j - c(n_j^*)}{\lambda + r} + \frac{\lambda}{\lambda + r} E[V_{t+1}(g_{j+1})] \right\}. \quad (3)$$

In particular, since at $j=0$, g_0 is the same for all firms, the set of firms that starts product upgrade trials depends on $c(n)$ in the initial period:

$$C_0 = \left\{ n_0^* \mid \pi(g_0) < \frac{g_0 - c(n_0^*)}{\lambda + r} + \frac{\lambda}{\lambda + r} E[V_1(g_1)] \right\}.$$

This set becomes smaller as average $c(n)$ values across firms increase, and as noted above, there is a $\bar{c}(0)$ such that this set is empty for $c(0) > \bar{c}(0)$. For the general case, it can be shown (see McCardle, 1985) that under certain parameters, there exist a pair of numbers \underline{g}_j and \bar{g}_j such that it is optimal to continue upgrade product trials if and only if the firm's current output is $\underline{g}_j < g_j < \bar{g}_j$. If $g_j \geq \bar{g}_j$, it is optimal for the firm to stop upgrade trials and focus on growth through horizontal diversification. If $g_j \leq \underline{g}_j$, it is optimal to stop upgrade trials without starting horizontal diversification. These thresholds can be defined as

$$\begin{aligned} \underline{g}_j &= \max\{g \mid E[V_t(g)] = 0\} \\ \bar{g}_j &= \min\{g \mid E[V_t(g)] = -K + (1 + \alpha)g\} \end{aligned}$$

These thresholds depend on the cumulative number of trials j because the firm's optimal choice depends on its realizations of past trials. As firms conduct more trials, \underline{g}_j rises and \bar{g}_j falls because the firm's posterior of its gross output potential becomes more precise. Eventually, these thresholds converge; by this point, every firm will halt product trials and choose either concerted growth through product proliferation if they have received sufficiently good news about their ability or, if news has been sufficiently pessimistic, take the default option.

A.8 Selection into high-end machine adoption

In the main text and appendix A.7 we examined the product variety choice behavior of firms conditional on having high-end machines. Here, we address the issue of selection into high-end machine adoption.

There are two, not mutually exclusive stories that can explain why only some firms adopt high-end machines. One is that of pure selection based on entrepreneurial ability or "awareness" which we alluded to in the main text. The other assumes that because high-end machines are expensive, even firms that potentially would consider pushing out the technological frontier want to make their decision not right away but after some smaller trials to avoid immediately committing to a big and costly investment (cf. Kerr et al., 2014). Both stories find support in our data.

Table A12 presents means of several metrics for two groups of firms: those that would adopt high-end machines at some point during our sample (“future adopters”), and those that never had high-end machines. It is similar to Table 2 in such a comparison. However, besides showing some different metrics than Table 2, it also computes the means of future high-end machine adopters using only the observations from periods prior to adoption. Therefore, any differences between the two groups of firms do not reflect post-adoption changes, whether causal or not.⁸

Future adopters introduced significantly more new products of all types on a trial basis, even before they placed their first order for high-end machines. They conducted almost 10 times as many upgrade trials (because this is before high-end machine installation, most of these trials would have to have been conducted by operating machines at least temporarily past their rated capabilities), and twice as many diversification trials. This renders support to the idea that future adopters were indeed more entrepreneurial in the sense of Kerr et al. (2014). They were also larger. Size at entry has been shown to be associated with the entrepreneurial ability both theoretically (Lucas, 1978) and empirically (Klepper, 2010), so perhaps this difference reflects future adopters’ advantages in the overall entrepreneurial ability of their management. Future adopters also had more market ties, as captured by the presence of merchants on boards. Interestingly, they were not systematically different from other firms in the number of educated engineers they employed before they had high-end machines. It appears that market knowledge from board member ties was important to the initial investment decision, while educated engineers were added later alongside high-end machines to help resolve the technology issues. Future adopters were also half as likely to have experienced a forced departure in their top management teams (TMTs), where we define “forced” as an executive departure for reasons not due to death, illness, or resignation for personal circumstances unrelated to the firm. Within-TMT conflicts that lead to forced departures have been found to strongly negatively affect firms’ capability to make major strategic decisions (see Agarwal et al., 2020).⁹

Overall, the evidence presented in Table A12 is consistent with future adopters exhibiting superior entrepreneurial ability and awareness as part of their self-selection process.

The second, machines-are-costly story is reflected in other metrics in the table. In our conceptual framework, firms that did not invest in high-end machines were those for which the fixed cost operating cost of running upgrade trials $c(0) > 0$ was prohibitively high. Suppose that the firm-specific fixed operating cost of running upgrade trials is initially unknown, but by making small investments in such trials while using the existing machinery, firms can form a better expectation about the cost function $c(n)$ they would face if they were to invest in high-end machines and start upgrade trials in earnest. A straightforward application of the same framework in McCardle (1985) (see appendix A.7 above) leads to a separating equilibrium where some firms (receiving bad realizations) drop out of the initial trials and never invest in high-end machines, while other firms (receiving good realizations) decide to go ahead with the investment.

A comparison of trial success rates and average durations across future adopters and non-adopters sheds some light on this potential mechanism. Future adopters were in fact more likely to have experienced success in their trials before machine adoption. Thus they both conducted more trials than non-adopters and were more successful in the trials they did conduct, in line with the predictions in McCardle (1985). In addition, successful trials conducted by future adopters were significantly shorter than those conducted by non-adopters, but the opposite is true of eventually failed trials. The first result is consistent with future adopters having better success odds (higher exponential arrival rate of success in any given trial). The latter result renders several (not necessarily mutually exclusive) possible interpretations. Two of the most likely are (a) future adopters had greater confidence in their chances, which made them persist longer despite a string of bad signals, and (b)

⁸ To err on the side of caution, we exclude not only observations after the high-end machines appear on firms’ balance sheets but also all observations pertaining to the period after firms placed their first high-end machines order. While this loses observations, it ensures that, especially when looking at trial production, we do not inadvertently pick up trials conducted with high-end machines that may have already been partially installed. That said, the results are similar if we use all observations prior to high-end machines appearing on the balance sheets.

⁹ While true on average, there were important exceptions. One such exception is Amagasaki Spinning which, as noted in the main text, was one of the earliest technology-pushing firms (it successfully challenged the monopoly of a British supplier over the 42-count doubled yarn market in the late 1890s). Placing its first order of high-end machines in 1893 had to be accompanied by firing of the company president (CEO) who had vehemently opposed the plan on the grounds that it was too risky.

future adopters placed higher value on trials as a means of accumulating technological and marketing knowledge, regardless of outcome.

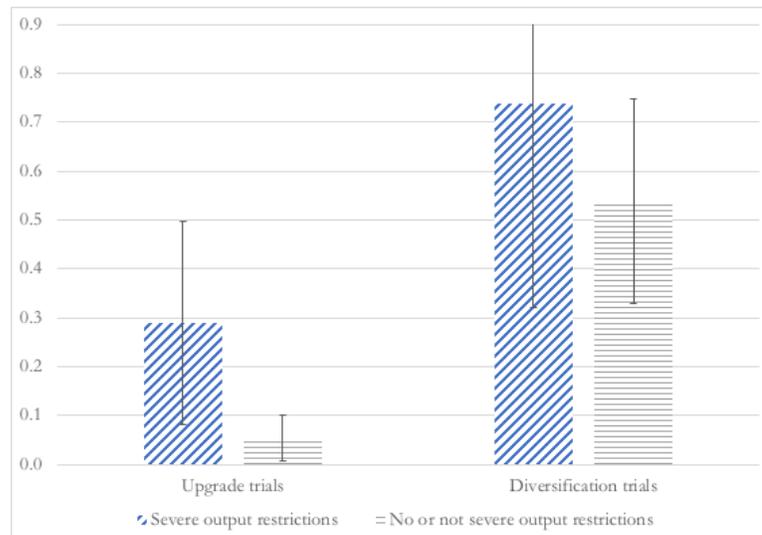
Table A12. Some comparisons between future high-end machine adopters and other firms *before* first high-end machine orders placed

	Future adopters	Other firms
Number of upgrade trials started	0.075	0.008
Number of diversification trials started	0.315	0.169
Fraction of successful trials among those started	0.373	0.287
Average duration of successful trials	1.64	3.82
Average duration of failed trials	4.68	2.64
Firm total output (in “kori” = 400 pounds)	4,957	2,842
Number of products	4.84	3.65
Merchant a board member	0.77	0.52
Number of university-educated engineers employed	0.09	0.13
TMT leader ousted in the previous two years	0.11	0.27
Added low-end machines	0.12	0.09
Firm age	7.78	8.88

Note: The table reports means across all observations. All mean differences are statistically highly significant using double-sided t-test with unequal variance, except for firm age (significant at the five percent level), fraction of successful trials among those started at t (not significant and conventional levels), the number of university-educated engineers employed (not significant and conventional levels), and whether the firm added low-end machines (not significant and conventional levels).

A.9 Relevance of the IV: evidence from raw data and excerpts from letters sent by Sanji Muto to plant managers in Section 4.2

Figure A3. Average number of new trials conditional on installation of new high-end machines



Note: “Severe” output restriction periods are defined as those where 10 percent or more of low-end capacity was mandated to be shut down. All observations pooled together. Bars represent 95-percent confidence intervals.

In Figure A3 we plot the number of new trials, separately by upgrade trials and diversification trials which firms start in the periods they installed high-end machines. The blue shaded bars are the periods when this coincides with mandated output restrictions where low-end machines were shut down by 10 percent or more. The vertical bars represent 95-percent confidence intervals.

The difference between the two bars in the left part of the figure illustrates how the first stage of the IV regressions in Table 5 looks in raw data. During the mandated output restriction periods, when installation of new machines coincides with mandated output restrictions, firms start on average about 0.29 new upgrade trials as opposed to just about 0.05 new upgrade trials if new machines are installed during periods of no mandated output restrictions. The 95-percent confidence intervals overlap a little bit but the results of the first-stage regression in Table 5 in the main text confirm that the instrument is relatively strong. Firms also start more diversification experiments during mandated output restriction periods but the difference is not that big and statistically not significant, in line with the results of the “placebo test” in Table 5.

The quotes below (in our translation from Japanese) are from letters sent by Sanji Muto, the general manager of Kanebo to factory heads in 1908 in relation to the installation of new machines in the gassed yarn plant (Tokyo plant No. 3) the plan for which was approved at the 1906 shareholders meeting (see appendix A.10 below) and which was about to be completed at that time. These letters are unpublished. They were originally held at Kracie Co. (Kanebo changed its name to Kracie in 2007), and are now at Kobe University archives. One of the authors took photos of the letters, while they were held at Kracie. Digital copies are available upon request from the authors.

Letter 1584, dated February 2, 1908:

“Tokyo plant No. 3 will start installing machines from March this year with the goal of finishing the installation by the end of June and starting full operations from July. However, we have not yet been able to secure the necessary number of female operators. Recruitment efforts are ongoing and we should see more joining the firm; however, silk worming season is coming, followed by busy agricultural season and hot weather which will probably lead to workers’ departures as well. Moreover, it may be hard to recruit experienced operators needed for full operation and even if it were possible, hard-push recruitment is quite expensive [Muto appears to be referring to head-hunting experienced operatives from other firms—authors]. Therefore, we would like to move operators from other plants to the Tokyo No. 3 plant and subsequently release them back in accordance with their wishes and the situation in other plants as the recruitment of new operators for the Tokyo No. 3 plant moves forward. ... Accordingly, we are asking plant managers to prepare the following number of operators to be ready to send to the Tokyo plant by the end of June:

Hyogo plant: 150 operators

Nakajima plant: 30 operators

Suminodo plant: 20 operators

Sumoto plant: 20 operators

Nakatsu plant: 20 operators

Hakata plant: 20 operators

Kurume plant: 30 operators

Miike plant: 75 operators

Kumamoto plant: 20 operators

Total: 385 operators ...

P.S. We are rushing full operation of the Tokyo plant No. 3 because the profitability of gassed yarn is high. I would like all plants to understand this goal and be careful not to lean too heavily on inexperienced workers when selecting female operators as above...”

Our comments: This appears to be quite an expensive plan necessary to secure the workforce of sufficient quality to operate the new machines. Removing a large number of experienced operators from those plants was going to be costly in terms of production in those plants. Muto appeared to be recognizing this in his plea to plant managers not to lean too much on inexperienced operators in the Post-Scriptum above. Also, plants from Hyogo to Sumoto were located in the Osaka-Hyogo area, more than 500km away from Tokyo, while the other plants were even further away, on the southern-most island of Kyushu, so the movement was also expensive in logistical terms. Muto also recognized that many of the moved operators would not want to stay in the Tokyo area (presumably far away from their hometowns) for a long time, so he was planning to return them back (another source of extra expenses to the firm) once the Tokyo plant were able to recruit enough new operators.

Letter 1621, dated April 10, 1908:

“As already reported in the press, the Executive Committee of the Industry Association is expected to decide at its meeting scheduled for May 1 to introduce output cuts on yarn of counts 20s and below over the period of six months until the end of October. It will consist either of the elimination of the night shift for three months, or of shutting down 27.5% of the machine capacity producing yarn of counts 20s and below. The meeting to finalize the decision has been scheduled for April 18 and the motion is expected to pass. ... [Once the output cuts are mandated] I request you not to lay off workers and to keep paying them salaries even for the days that the machines are shut down to avoid inflicting hardship on them. ... Especially with regard to workers who are being prepared to be sent to Tokyo No. 3 plant, please consider them to be in strategic reserve for that purpose. Full operation of the Tokyo No. 3 plant is now probably going to be possible from mid-June; therefore, the output cuts period is going to coincide exactly with the period when we are going to need workers in this plant, so we will be able to easily accommodate even more workers from your plants than originally planned. I will send you more information once the Association decides on the 18th.”

Our comments: Muto mentioned here that the new gassed plant would now be able to take even more workers from other plants as the opportunity cost of relocating them from those other plants was going to be low if not zero altogether because of planned output cuts.

Letter 1628, dated April 20, 1908:

“The Association Executive Committee has decided on output cuts. Detailed instructions on implementation will be coming soon, please be ready to act on them starting May 1. It hasn't been decided yet whether it will be elimination of the night shift or shutting down part of the machines. In any event, I want you to be aware that we will not be laying off any workers and will not be reducing their salaries despite reduced output.”

Letter 1636, dated April 25, 1908:

“As you already know, the Association Executive Committee had decided to implement output cuts, leaving the choice between abolishing the night shift and shutting down machines producing counts 20s and below to the member firms' discretion. Our firm made a cost-benefit calculation and decided to shut down 27.5% of our machines in counts 20s and below for six months, from May 1 to October 31. ... No male or female operative is to be laid off ... Machines to be shut down: Tokyo No. 1 plant [31 machines out of 95]; Tokyo No. 2 plant [no change in operation]; Hyogo No. 1 plant [18 machines out of 100] ... [Similar for other plants producing low-count yarns]”

Our comments: Muto did not mention if there were further changes to the workers' relocation plan to the gassed yarn plant which was just coming online. However, machines producing low-end yarn were being idled also in other parts of the Tokyo plant itself, with no workers being laid off. This should have made it possible to relocate some workers within the Tokyo plant itself, which would have been basically costless. According to our data, seven product upgrade trials were conducted at Kanebo in 1908-09, of which four resulted in scaling.

A.10 Historical evidence on the validity of the exclusion restriction in Section 4.2

To validate the exclusion restriction, we show that firms did not place high-end machine orders in anticipation of future mandated output cuts. We first present a narrative from a company report dealing with one of the largest high-end machine orders placed by the afore-mentioned Kanebo, one of the most important firms that pushed the frontier. We then supplement the narrative with regression estimation results.

As detailed in the previous appendix A.9, Kanebo constructed a new gassed yarn plant as an extension of its main Tokyo plant. This was a large expansion project, aimed at a big discrete push of the firm's technology frontier (it had never produced output of counts above 40s, let alone gassed yarn before that). The size of the machine order was 33,712 spindles, almost doubling the existing plant size. The project was completed (and the new machines listed in the balance sheets) in the second half of 1908 which turned out to be a period of output restrictions. However, the order itself was placed in the second half of 1906, which was a very good year for the industry. The following excerpts from the company report (in our translation from Japanese) provide the insights about the way the decision was made. All pages below are in reference to unpublished Kanegafuchi Spinning Company report to shareholders No. 40 (second half of 1906), available upon request as a digital copy from the authors.

“The 39th regular shareholders’ meeting held in Tokyo, Nibonbashi on July 17, 1906 at 1 pm ... Agenda item number 2. Concerning the Construction of Gassed Yarn Plant: Planned number of spindles — 33,712; Construction site — [address in Tokyo]; Construction budget — 1,250,000 yen.” (pp. 3-4)

[Construction plans for other plants are outlined next, then the report continues] *“These construction plans are to be implemented gradually, with consideration of the financial situation of the firm so as not to jeopardize operating funds. However, the construction of the Gassed Yarn Plant was deemed feasible to implement right away, based on the company’s current financial flows. Accordingly, this project will proceed without delay.”* (pp. 6-7)

Finally, *“State of the yarn market — The market for yarn remained strong in the reporting period [second half of 1906]... Post-war government finances are contributing to easy financial markets and strong domestic business conditions.”* (p. 11)

It is worth noting that, as this account demonstrates, any expansion plan contemplated by the management had to be presented to and approved by a shareholders meeting, not just in Kanebo but in all other firms (all firms that pushed the technological frontier in those years were joint stock companies and required shareholders’ approval for the actions by the top management). This alone makes it very unlikely, as we argued in the main text, that firms could strategically time high-end machine orders to coincide with mandated output cuts. In order to get approval from the shareholders, the management (in the example of Kanebo above) had to make an argument which would sound like “the business conditions are fine now but given the time needed for the machines to be delivered and installed, we suggest that you approve an investment in new high-end machines in anticipation of mandated output cuts exactly two years from now.” Not surprisingly, the actual company report quoted above makes no such reference; instead, it brims with optimism, although also cautions against placing too much strain on the firm’s finances. It also makes it very clear that the gassed yarn plant project is a strategic priority among all the future expansion plans. As mentioned above, the meeting that approved the investment was held on July 17, 1906; the actual order was entered into Platt Brothers’ order book on October 25, 1906 (two orders, both on the same day).

As it turned out, the stock market (which was soaring in 1906) crashed in the next year and the economy was plunged into a recession (leading to the Association imposing output restrictions in 1908). There is absolutely no indication that Kanebo could have anticipated that when making the above decision.

The delay of about two years between the placing of the order and the actual arrival and completion of the installation of the new machines in Kanebo’s case above is representative, if a little bit longer than usual due to the large size of the order. Both the mean and the median delay between the order and the time machines had been installed and appeared in firms’ balance sheets was two periods (one calendar year) for high-end machine orders, with more than a third of all orders delayed for three periods or more (up to five periods, that is, two and a half years). The delays were even longer for larger orders; for orders of 10,000 spindles or more (at or above the mean-sized order), the median delay was three periods. Perhaps even more importantly, those delays were hard to predict in advance. Regression analysis (not shown) confirms that time gap between the placement of the order and the timing when the machines actually were installed and became operational is not correlated with either current or future mandated output cuts, although it is significantly longer for larger orders.

In Table A13 we present the results of an estimation which directly tests for the presence of a link between the probability of placing a high-end machine order (and the order size) and the current and future state of demand. The sample consists of 265 firm-semi-annual observations on orders placed by Japanese firms with the British machinery manufacturers found in the Platt Collection. (The total number of orders in the sample is 465 but we combined together those that were placed in the same semi-annual period.) The dependent variable in columns (1), (2), (5), and (6) is the dummy equal to one if the order placed by firm i in period t included at least some high-end frames. The dependent variable in columns (3) and (4) is the IHS-transformed size (number of spindles) in the high-end machines included in the order. The variables of interest are a dummy equal to one if mandated output cuts were implemented in period t and zero otherwise in columns (1) and (3), and a dummy equal to one if mandated output cuts would be implemented in period $t+3$ (excluding those periods which overlapped with the start of mandated output cuts periods themselves which can happen if those periods lasted for more than 1.5 years) and zero otherwise in columns (2) and (4). We also repeated the same with estimation for dummies equal to one if there was a “demand boom” in period t and period $t+3$, respectively, in columns (5) and (6). The demand boom dummy captures the period of export boom in 1895-97 and the

Russo-Japanese War and immediate post-war boom in 1904-06. Both booms boosted the demand for low-end products (which were main export products as well as used to produce military uniforms) and thus increased the opportunity cost of pushing the technological frontier.

Table A13. High-end machine orders placement and the current and future demand

Estimation:	Logit		OLS		Logit	
VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	DV: probability of placing a high-end machine order at t		DV: IHS size of a high-end machine order at t		DV: probability of placing a high-end machine order at t	
Mandated output cuts at t	1.355*** (0.336)		3.149*** (0.750)			
Mandated output cuts at $t+3$		0.154 (0.348)		0.397 (0.785)		
Demand boom at t					-0.767*** (0.280)	
Demand boom at $t+3$						-0.075 (0.297)
Constant	-0.878*** (0.149)	-0.640*** (0.141)	2.724*** (0.291)	3.219*** (0.302)	-0.345** (0.159)	-0.596*** (0.149)
Observations	265	265	265	265	265	265
R-squared			0.071	0.001		

Robust standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

The estimation results show that both the probability of an order including high-end machines and the size of the high-end order (if any) were much larger for orders placed during mandated output cut periods. However, orders placed three periods before the onset of mandated output cut periods were not affected by future mandated output cuts. This is consistent with the anecdotal evidence from the Kanebo company report above. Firms' investment decisions into high-end machines may have been affected by the current state of demand but they did not make those decisions in anticipation of future state of demand. This is further confirmed by the estimation results in columns (5) and (6): here demand booms for low-end products significantly reduce the conditional probability of firms placing high-end machine orders but, once again, future demand booms have no impact. All historical evidence also indicates that both demand booms and sharp business downturns that triggered mandated output cuts were sudden and unpredictable macro events.

A.11 Timing of the scaling of new products (for Section 5)

In this section, we take a look at scaling of new products as a function of knowledge accumulated through upgrade trials and the state of high-end machine expansions to confirm, from a bit of a different angle, what was found in the main text related to growth patterns.

Table A14 presents marginal effects from a Poisson regression where the dependent variable is the number of scaled products started in period t (all products, and separately by upgrade and diversification products). This is defined as the number of all products produced at scale in period t and not produced at scale in $t-1$. The first two columns compare the number of all scaled products started in period t as a function of cumulative past upgrade and diversification experiments across two categories of firms: "non-expanders," which are the firms that installed high-end machines but never expanded them after that (that is, were "one-and-done" with moving into high-end machines) and "expanders," which are the firms that expanded high-end machines during our sample; that is, those firms that were *not* one and done with high-end machines installation. The sample is limited to firms that did or would have high-end machines at some point, so it excludes firms that never even tried to push the technology envelope. To make the two subsamples more comparable, we limit observations on expanders in the second column to the periods before they first expanded their high-end

machines. The last four columns zoom in on the “expander” subset and compare the number of scaled upgrade and diversification products started before and after those firms expanded their high-end machine capacity for the first time.

Table A14. Timing of the scaling of products: firms with high-end machines

DV	Products started at scale at t :					
	Non-expanders	Expanders				
		Before first expansion			After first expansion	
	All products	All products	Of which:			
			Upgrades	Diversification	Upgrades	Diversification
Cumulative # of upgrade trials by $t-1$	0.087* (0.046)	0.340*** (0.041)	0.310*** (0.101)	0.014 (0.065)	0.071** (0.031)	0.183*** (0.052)
Cumulative # of diversification trials by $t-1$	0.047*** (0.017)	-0.179*** (0.036)	-0.125*** (0.025)	-0.070* (0.037)	-0.006 (0.009)	0.006 (0.007)
Observations	416	152	152	152	356	356

Poisson regression with firm fixed effects, firm total output and fourth degree polynomial in calendar time as controls. Standard errors clustered at the firm level. Marginal effects (dy/dx) are shown. “Expanders” are firms that added more high-end machine capacity after installing such machines for the first time. “Non-expanders” are firms that installed high-end machines but never added more capacity later.

The estimation results in the first two columns show a stark difference between expander and non-expander subsamples, even before the expanders had a chance to add more to their high-end machine capacity. While both past upgrade and diversification trials are somewhat associated with scaling new products in the “one-and-done” subsample, the association is not very strong and, if anything, diversification experiments, at least statistically contribute more robustly to new scaled products. In the future expander subsample, however, cumulative past upgrade trials are the ones strongly associated with new product scaling already before they embark on expanding their high-end machine capacity. When we split those scaled products into upgrade products and diversification products (in columns three and four), we see that all the effect of cumulative upgrade trials is manifested in scaling new upgrade products before first high-end machine expansion in this subsample. That is, consistent with our theoretical framework in the main text, accumulated knowledge from cumulative upgrade trials is initially translated into the introduction of scaled upgrade products among those firms which will eventually be the successful in their high-end trials. In contrast, as the estimation results in the last two columns of Table A14 show, the impact of cumulative upgrade trials is much more strongly pronounced with respect to diversifying products after those firms expand their high-end machines. That is, the knowledge acquired through upgrade trials is utilized relatively more for scaling new diversification products later on. The “expander” subsample is comprised of firms that on average grow most in our sample; hence, we have another piece of evidence showing time complementarity between knowledge accumulated through upgrade trials and diversification of the whole product portfolio as it is related to firm growth.

A.12 Costs involved in changing direction and counts between adjacent counts (Section 6.1)

According to our interviews with Kanji Tamagawa (a prominent Japanese historian of cotton spinning technology), switching the direction of twist (from S to Z and vice versa) and/or changing the count to be spun between adjacent counts (say, from 16 to 18 or from 20 to 22) involved the following operations:

Operation	Required time
(1) Changing the draft (adjusting the draft change gear)	About 10 minutes
(2) Changing the twist number (adjusting the twist change gear)	About 10 minutes
(3) Changing the direction of the twist (changing the direction of the tin roller)	About 10 minutes
(4) Changing the spindles rotation speed (adjusting the gear)	About 10 minutes
(5) Changing the traveler (choosing a traveler of appropriate weight)	About 30 minutes

With appropriate skill, the first four operations could be completed during the time required to complete the fifth, so, under ideal conditions, the whole process would take about 30 minutes.

However, if the task was to change to a count of yarn that was further apart (such as from 16 count to 20 or from 24 count to 32 count), such a change also required a change in roving to be fed into the machine, taking about two hours, so such adjustment was much costlier. Thus, firms with a more diversified product portfolio could change counts more easily.

A.13 Demand system estimation in Section 6.2

Price variation: Table A15 compared within-period variation in 20-count price to within-period variation in female operative wages on average across all periods for firms that had a non-zero market share in 20-count yarn output, excluding (as always) the first and last observation on each firm. Variations in price are much smaller in magnitude.

Table A15. Comparing 20-count prices and female operative wages dispersion

	Coefficient of variation	Quartile coefficient of dispersion	90-10 percentile coefficient of dispersion
Prices of 20 count	0.027	0.014	0.030
Wages of female operatives	0.149	0.095	0.193

Note: The coefficient of variation is the ratio of the standard deviation over the mean. The quartile coefficient of dispersion is $(p75-p25)/(p75+p25)$. The 90-10 percentile coefficient of dispersion is $(p90-p10)/(p90+p10)$. All the metrics are measured within each semi-annual period and then averaged out over all periods.

Instrumenting for 20-count price: Because 20-count yarn is at the borderline between low-end and high-end products, we can instrument for its price using a plausible cost shifter that would be difficult to obtain for other product types in our data. Specifically, we use our portfolio rebalancing measure introduced in Section 6.1 in the main text, focusing on counts around 20, and interact it with the degree of industry-wide mandatory low-end product output cuts. Firms with more flexible production systems could respond more easily to mandated cuts by shifting their production to high-end products. This implies, especially in the face of having to meet short-run fixed costs, that more flexible firms would feel less pressure to raise revenue by cutting their 20-count prices during periods of slow demand.¹⁰ This gives us a supply-side source of price variation that is plausibly uncorrelated with quality (demand appeal). More precisely, our instrument for the price of 20-count yarn is the interaction of our across-count portfolio rebalancing measure for counts from 17 to 48 with the degree of mandatory output cuts the firm is subject to in a given period.

Demand system estimation: The first-stage estimates are in the first column of Table A16. Lower portfolio adjustment costs have a small, negative correlation with the firm's 20-count price during normal times. However, rebalancing is strongly positively associated with price during mandatory output cuts. Going from no portfolio rebalancing to its mean conditional on being positive and mandated output cuts being in place (0.38) is associated with 1.2 percent higher 20-count price. That is small in absolute size but is two-thirds of the interquartile dispersion during periods of output cuts.

We conducted a placebo test for this instrument using our other production flexibility measure, within-count portfolio rebalancing. While we found above this was associated with lower adjustment costs and firm growth, there is no reason why lower adjustment costs within the same count should be relevant for keeping up the price of 20-count yarn during mandatory output cuts. The results in the second column of Table A16 show this logic holds; the relationship is statistically and economically indistinguishable from zero.

¹⁰ The average price of 20-count yarn was significantly lower (between 2-9 percent) during mandatory output cut periods than in adjacent periods without cuts.

Table A16. 20-count demand estimation, First stage

Estimation	DV: Logged 20-count price	
	Instrumental regression	Placebo test
Number of across-count portfolio rebalancing (between 17-48 counts)	-0.002** (0.001)	
Number of across-count portfolio rebalancing (between 17-48 counts), interacted with mandatory output cuts	0.032*** (0.007)	
Number of within-count portfolio rebalancing (between 17-48 counts)		-0.001 (0.001)
Number of within-count portfolio rebalancing (between 17-48 counts), interacted with mandatory output cuts measure		0.005 (0.006)
Constant	4.897*** (0.027)	4.895*** (0.028)
Semiannual time dummies and firm dummies	Included	Included
Observations	743	743
R-squared	0.984	0.983

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Note: mandated output cuts measure does not vary within periods and is therefore absorbed by the semi-annual time dummies.

Table A17 shows the second stage regression of the firm's (logged) quantity of industry-wide 20-count output on the instrumented logged price. The estimated own-price elasticity is negative and large, about -5.4. This is consistent with high substitutability across horizontally differentiated brands. That said, the standard errors on these elasticity estimates are high, most likely because of low price variation in the sample discussed above.

Table A17. 20-count demand estimation, Second stage

	DV: Logged market share of 20 count
Instrumented logged 20-count price	-5.407 (6.136)
Constant	16.932 (30.047)
Semiannual time dummies and firm dummies	Included
Observations	743

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Instruments: number of across-count portfolio rebalancing and number of across-count portfolio rebalancing interacted with mandatory output cuts measure as explained in the main text.

For the sake of comparison, in Table A18 we present the results of an OLS estimation of firms' market shares of 20-count on own price. This "naïve" regression produces an own-price elasticity of -3.1, so the IV estimation, while imprecise, moves the point estimate in the theoretically predicted direction.

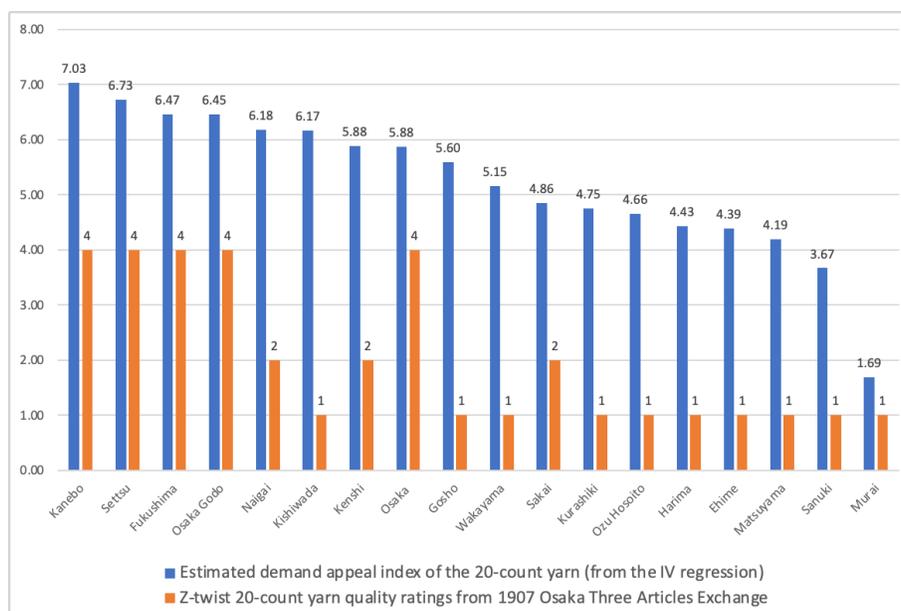
Table A18. OLS regression of logged market share of 20 count on logged 20-count price

	DV: Logged market share of 20 count
Estimation	OLS
Logged 20-count price	-3.056** (1.191)
Constant	7.132 (5.432)
Semiannual time dummies and firm dummies	Included
Observations	743
R-squared	0.732

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

External validity: Evidence from Osaka Three Articles Exchange

Figure A4. Estimated demand appeal index and historical quality ratings



Note: Quality rating is firm-level quality ratings of Z-twist 20 count in 1907 determined by the cotton yarn quality rating committee at the Osaka Three Articles Exchange (Arao, 1922, pp. 33-36). Rating 4 indicates the highest quality and rating 1 indicates the lowest quality. “Estimated demand appeal index” represents sample averages of our estimated demand appeal index for the same firms. The correlation between the two series is 0.69.

A.14 Historical evidence on input quality in low-end products (for Section 6.2)

We present plant-level data that show how push into high-end products accompanied input quality improvement in plants that were only producing low-end products (e.g., Verhoogen, 2008; Manova and Yu, 2017)¹¹. As mentioned above (appendix A.10), Kanebo started its push into the high-end product space around 1906 when the decision was made to add a brand-new gassed yarn-producing extension to its Tokyo plant.

As described above in appendix A.10, Kanebo started its push into high-end products by ordering new high-end machines and gassing equipment for its new Tokyo subplant No. 3 in October 1906. About a year later, it also placed orders for high-end machines to build a new subplant producing higher counts of yarn at its Sumoto plant (on a small island off the coastline of Osaka).

The installation of high-end machines came with the changes in complementary inputs (other than machines). In line with the general pattern noted in the main text of the paper, the decision to push the technology frontier was accompanied by an increase in hiring of formally educated engineers. In 1907 alone the company hired 14 graduates from the Engineering Departments of Imperial Universities and from several technical colleges such Tokyo Higher Technical School (the predecessor of the current Tokyo Institute of Technology). This increased the number of degreed engineers employed by the company by 30 percent in that year alone. Thirty five engineers were hired additionally in 1908-1910, doubling the number the company had at the start of 1908.

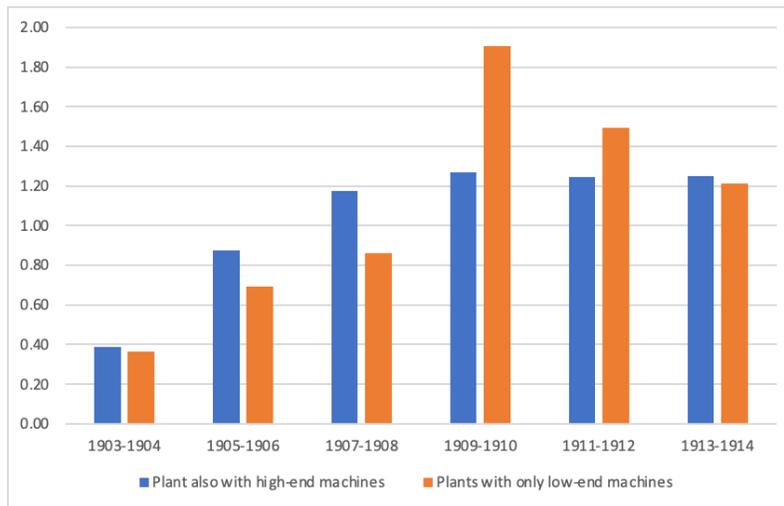
The changes in the allocation of those educated engineers across plants are also instructive. Prior to the start of the expansion into the high-end product space, at the beginning of 1906, Tokyo plant employed four educated engineers (17 percent of all engineers employed by the company). When the new gassed yarn

¹¹ Kanebo plant-level data are available in a series of unpublished documents, entitled *Eigyō Seiseki Hokokusho* [Report of Business Performance], which are different from company reports to shareholders, and contain more detailed information. The documents were originally held at Kracie Co., and now at Kobe University archives, as the letters by Sanji Muto.

subplant started operating in 1908, this number was up to seven (24 percent of all educated engineers working at various plants at Kanebo). The changes at Sumoto plant were even more dramatic. The plant employed a single degreed engineer until 1908. As new machines were being installed and the new, higher-end production was starting in 1909, Kanebo allocated five degreed engineers to the plant, and increased the number to seven in the next year. Clearly, a previously obscure island plant (which Kanebo acquired in 1900 from a company that went out of business) all of a sudden was given top priority in terms of allocating engineering talent as it was turned into a high-end products producing plant.

Similar patterns can be observed at Kanebo’s flagship Hyogo plant. For as long as it was only producing low-end products, the fraction of engineers employed at this plant in the total number of engineers working for the company was stable at about 20 percent. In 1912, however, the firm decided to add a high-end, gassed-yarn producing subplant to the Hyogo plant as well. As the new plant was coming online, the number of educated engineers employed by the Hyogo plant jumped from 12 in the first half of 1912 to 23 in the second half of 1913, and the plant was employing almost a third of all educated engineers working at Kanebo. Overall, as mentioned, the number of engineers employed by Kanebo went up dramatically during its push into high-end expansion: from 16 in the first half of 1905 to over 100 in 1914 (including engineers employed at headquarters). In a key development, this also affected the quality of engineers also in plants not involved in high-end expansion. Figure A5 below summarizes this impact using the data on all plants.

Figure A5. Average number of degreed engineers per 10,000 spindles in Kanebo plants



Since plants differ in size, in Figure A5 we present two-year average numbers of degreed engineers employed by Kanebo plants divided by the number of spindles (in tens of thousands) of machine capacity (dividing by the number of workers employed leads to very similar results). The figure shows the relative dynamics across plants of two types: those that already had high-end machines or were actively installing them (“Plants also with high-end machines”) and those that only had low-end machines and were not producing counts above 20s (“Plants with only low-end machines”). Plants in the former category clearly outpace plants in the latter category in terms of the engineering talent they employ per unit of capacity until 1908, which is the year in which Tokyo gassed yarn plant started operating. This is consistent with educated engineers being hired to help with pushing the technological frontier. After that, however, the relative numbers are reversed, and in 1909-10 it is plants with low-end machines that actually claim more educated engineers than plants with high-end machines. The numbers are then about the same for the rest of the sample.

Thus, increased hiring of educated engineers which picked up pace as the firm was about to push the frontier “spilled over” to plants that were not part of this push. The increased availability of degreed engineers across all plants was likely a contributing factor to the horizontal diversification and improved quality of low-end products in Kanebo in later years. As can be seen in Figure A4 above, Kanebo tops the rankings of the

quality index of low-end products we estimated over the sample, and it is among the highest-ranked firms in Z-twist 20 count yarn as determined by the Osaka Three Articles Exchange.

A shift to high quality raw cotton input also exemplifies how “vertical upgrading” facilitated better quality of low-end products. Products at the low end of the spectrum (counts 20 and below) were produced using Chinese or Indian raw cotton. Chinese cotton was cheaper, but more short-stapled and of inferior quality compared to Indian cotton, so the general trend in the industry was to move away from Chinese cotton and toward Indian cotton, with some American cotton added as well for even better quality.

Once Kanebo embarked on vertical product upgrading, it started using the highest-quality Egyptian cotton in its Tokyo subplant No. 3 and then also in Hyogo subplant No. 4 both of which produced gassed yarn of counts 60 and above. This did not directly affect plants with only low-end machines and producing counts 20s or lower—it did not make sense, from an engineering or economic perspective to use highest-quality, expensive Egyptian cotton for spinning low-end yarn. However, as new engineers arrived, the input mix in plants that did not participate in product upgrading nevertheless took a decisive turn away from using Chinese cotton and toward Indian cotton mixed with some American cotton. While, as mentioned, the shift from Chinese cotton to Indian and American cotton was a general trend in the industry as a whole, this trend accelerated in “low-end” Kanebo plants after the firm started product upgrading in its other plants, compared to firms that were not doing product upgrading.

Figure A6. Shares of Indian and American raw cotton inputs in Kanebo’s “low-end” plants and similar plants in the rest of the industry

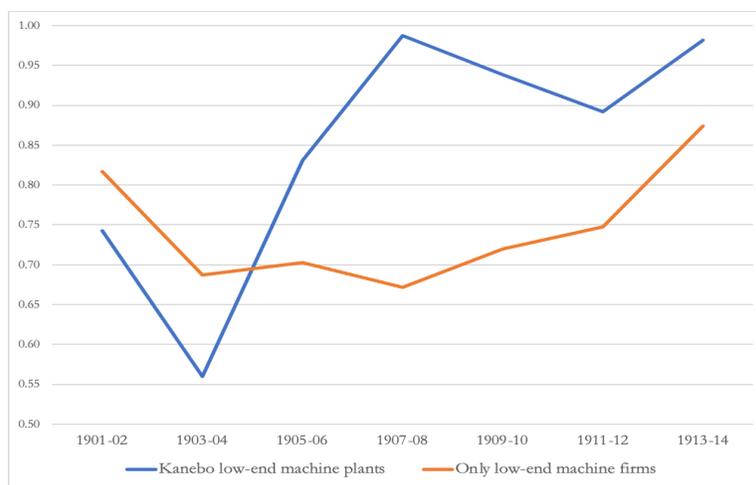


Figure A6 plots two-year averages of the fraction of Indian and American cotton in the total cotton inputs used in Kanebo plants that only had low-end machines and did not produce counts above 20s and the same fractions in all other firms in the industry which also only had low-end machines and did not produce counts above 20s either. Before the start of its product upgrading push and the hiring spree of educated engineers, Kanebo lagged behind the industry average in the fraction of Indian and American cotton input (that is, was relying relatively more on Chinese cotton). However, since 1907-08, “low-end” Kanebo plants decisively overtook the industry average and indeed, phased out Chinese cotton almost completely from its input mix. We interpret this as evidence that better (educated) engineers hired by the company to push the technology frontier, who, as noted, “spilled over” to other plants not involved in product upgrading, incentivized the firm to supply those plants (and engineers manning them) with higher-quality cotton inputs as well.

A.15 Alternative explanations in Section 7

Increasing Mean Growth or Increasing Variance? In Table A19 we present summary statistics on the status of firms at the end of our sample in 1914. A total of 33 firms survived to the end of the sample. Of these, 19 (58 percent) had high-end machines. This compares to 42 of 105 firms for which we have machine data (40

percent) having high-end machines over the entire sample. Firms with high-end machines therefore had a substantially higher probability of survival.

Table A19. Firm survival

Numbers of:		Surviving firms	Exiting firms; of which:		Total
			By acquisition	Shut down	
Had high-end machines	Yes	19	22	1	42
	No	14	31	18	63
Total		33	53	19	105

Moreover, among the 72 firms that left the sample, we can distinguish exits by acquisition (53 firms) and liquidation (19 firms). Firms that exit by acquisition are more likely to have high-end machines than firms that shut down, as seen in the table. High-end machines not only were associated with a greater chance of acquisition, but they also improved shareholders' returns conditional on being acquired. We have data on acquisition prices for 46 acquisition cases. In 18 of these cases, the acquired firm had high-end machines. We computed the "salvage fraction" of shareholders paid-in capital by dividing the acquisition price by the shareholders paid-in capital. The mean salvage fraction was 1.04 for acquired firms with high-end machines but only 0.70 for those that did not (a statistically significant difference at the 5 percent level)

Mergers and Acquisitions. As mentioned in the main text, new product introductions do increase by about 25 percent at the time of acquisition events but just 3.6 percent of new product introductions in our sample coincide with an acquisition event. Thus, while there is an uptick in new product introductions at the time of acquisitions, acquisitions played a minor role in product variety expansion during our sample. Also, if we include an acquisition event dummy in growth regressions like those in Table 5 in the main text, acquisitions are positively related to firm growth (as to be expected), but the effect of temporal complementarity between product upgrading and diversification on firm growth remains qualitatively unchanged even after controlling for merger and acquisition events.

Exporting. As has been observed in many other settings in the literature, firms that export in our sample are larger on average than non-exporting firms. However, in our sample, exports are negatively associated with the firm's number of product varieties, especially high-end varieties. The nature of industry exports during our sample explains this. Japanese cotton spinners successfully drove out imports and started exporting low-end products to East Asian markets during the 1890s. During those years, and to a large degree after that as well, exports were concentrated in a few low-end products (especially S-twist 16 count and Z-twist 20 count yarn). Major exporting firms tended to focus on scaling their output in and around these product varieties. More often than not, they chose to forgo opportunities in high-end markets.

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