Japanese Programmer and Technology Adoption

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Abstract

This paper investigates the role of labor market institutions in shaping human capital investment and technology adoption by focusing on the IT sectors of Japan and China. Leveraging online job posting datasets, we find that Japanese IT firms are more inclined to offer on-the-job training and rely on older technologies, while Chinese firms prioritize hiring skilled workers and adopting newer technologies. We develop a two-period model that encapsulates the interactions between human capital investment, technological shifts, and labor market frictions. Contrary to conventional models positing that firms and workers are perfect substitutes in investing in human capital, we argue that their roles are asymmetrical and influenced by the technological regime and labor market structure. The model reveals that the rigidity of Japan's labor market suppresses workers' incentives but enhances firms' incentives for human capital investment and technology adoption, despite its technical efficiency, while the fluidity of China's labor market does the opposite. We further utilize our model to explain how labor market institutions can be both cause and consequence of technology adoption and economic development by suggesting that labor market structures could be aligned with the dominant technological regime for optimal human capital investment, and that a misalignment due to technological change afterwards could lead to significant economic inefficiencies.

Keywords: technology adoption, human capital, training, labor market institution

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1 Introduction

Human capital, exemplified by the various skill levels of the labor force, is often identified as a crucial driving force of economic growth. This argument is particularly relevant in recent decades, given the rise of skill-biased technological progress and the Information Technology (IT) boom, which underscore the significance of labor acquiring new IT-related skills, be it through individual learning or firm-sponsored training. Becker (1964) posits that, within a competitive market and for general skills, firms lack the incentive to bear any training costs due to frictionless labor mobility and the risk of free-riding, whereas workers, being the full residual claimants of the returns from skill investments, are incentivized to invest in themselves. Paradoxically, empirical studies contradict this prediction, finding abundant evidence of firm-sponsored training in real-world labor markets. Addressing this discrepancy, Acemoglu and Pischke (1998, 1999a,b) propose that under labor market imperfections, the worker's incentive to invest in general skills is stifled, whereas firms may find it beneficial to provide costly training and elevate their workers' skill levels. Notably, in these and other economic models, firms and workers are perfectly substitutable in terms of investing in workers' human capital. Thus, it does not matter who provides human capital investment as long as one party is sufficiently incentivized. In practice, however, firms and workers often command significantly different resources and face unique positions and incentive issues. If there are technological differences in the productivity of human capital investment from both parties, a specific type of labor market institution that provides sufficient incentives to one side may be effective in certain technological regimes, but inappropriate in others. Moreover, in the comprehensive analyses by Acemoglu and coauthors, the non-competitive labor market and resulting wage compression is attributed to exogenous labor market frictions. However, labor market institutions that create an imperfect labor market and wage compression can be endogenous, corresponding to technological regimes. Also, their effect on dampening workers' incentives for skill investment could potentially generate large market failure in overall human capital investment when the inputs from firms and workers are imperfect substitutes and workers play an pivotal role in this investment.

In this paper, we delve into these issues by juxtaposing the labor markets and technological adoption behaviors within the IT industry in Japan and China. Despite Japan's rapid post-war economic growth and its successful transition into a welfare state, its IT sector hasn't been at the forefront of the digital age, and Japanese IT jobs have often been regarded as not high-skilled and high-pay jobs. Conversely, China, which has experienced similar rapid growth in recent years, has fostered a robust IT sector, housing numerous globally recognized 'superstar' firms, who has been know as pay extraordinarily well for its workers.[1] We first lend empirical support to these informal or anecdotal observations by utilizing two datasets of online job postings from Japan and China. These datasets enable comparisons that would otherwise be unfeasible due to the absence of comprehensive census data, particularly for China. One major advantage of these online vacancy data lies in its ability to yield insights into training provisions and technology usage through the detailed job descriptions provided by employers. Our analysis reveals a divergence in labor market behaviors and technology adoption practices between IT firms and workers in China and Japan. Japanese IT firms tend to set lower education and experience requirements for their workers compared to their Chinese counterparts. Instead, Japanese IT firms are more inclined to offer on-the-job training, while Chinese firms generally prefer candidates who already possess the required skills. When it comes to technological adoption, our findings suggest that Japanese firms are more likely to utilize legacy programming languages or those declining in popularity. In contrast, Chinese firms tend to favor newer, more popular programming languages and are significantly more likely to employ the latest technologies in machine learning and data science. Finally, our study shows a noticeable wage disparity between IT workers in the two countries. Chinese IT workers, especially those employed in jobs involving the latest technologies in machine learning or data science, enjoy a significant wage premium comparing to other jobs. Conversely, wages for Japanese IT workers align more closely with national average levels, and the premium associated with new technologies is relatively limited. In summary, IT workers and firms in Japan and China exhibit marked differences in their roles in human capital investment, technology adoption decisions, and resulting wage structures.

Could labor market structures or institutions explain these observed empirical differences? If so, what led these two countries to develop such distinct labor market institutions? Furthermore, under what technological contexts does a particular labor market structure result in efficiency or inefficiency—i.e., market failure—with respect to human capital investment and technological adoption, as appears to be the case in Japan's IT industry? To address these questions, we propose a simple yet encompassing theory encapsulating the interactions between human capital investment, technological shifts, and labor market institutions. Our model is a simple two-period construct of training and production, building on the seminal works by Acemoglu (1996, 1997) and Acemoglu and Pischke (1999b,a). In the first period, firms and workers match in pairs and co-invest in the worker's general

[1] One indicator of the divergence in the evolution of the IT industries between Japan and China can be gleaned from the stark differences in the number of unicorn companies, that is, privately held IT companies valued at more than 1 billion dollars. See for example: https://howmuch.net/articles/the-worlds-unicorn-companies-2017.

human capital under a non-cooperative investment regime. Hence, they optimize their human capital investment decisions based on their individual value functions. In the second period, new firms armed with advanced technology and superior productivity enter the market, competing with incumbent firms for workers in a frictional labor market. A fluid labor market, where workers are at high chance of matching with new firms, would motivate workers' human capital investment since they can benefit from the combined effects of increased productivity and enhanced human capital in the event of a successful on-the-job search. Conversely, firms would favor a less fluid labor market, as their investment in workers' human capital would only pay off if they retain their workforce. The key deviation and innovation in our model lies in our assumption of imperfect substitution of inputs from firms and workers in the joint human capital investment function, with the factor share or productivity of firms and workers contingent on the prevailing technological regime. Consequently, this will generate mismatches between technological regimes and labor market structures. In a technological regime where the worker plays a pivotal role in investing in human capital, a fluid labor market is appropriate as it maximizes incentives for workers. Conversely, a less fluid labor market stimulates firms' incentives, promoting predominant investment by firms, even if it's technologically inefficient.

Our model helps to elucidate the divergent empirical findings within the IT industry in Japan and China. The IT sector epitomizes a technological regime wherein workers play a crucial role in human capital investment, facilitated by easy access to the latest technologies on the internet. As a result, the renowned rigid labor market in Japan hampers workers' self-driven learning, yet spurs firm-sponsored training despite its relative inefficiency. Consequently, firms do not prioritize workers' education and experience, providing modest wages as they anticipate encountering workers with low human capital levels. Conversely, the frictionless labor market in China proves ideal for the IT industry, maximizing workers' incentives to acquire knowledge of productive or cutting-edge technologies. Firms in the Chinese labor market refrain from training their workforce, instead poaching competent workers by offering higher wages. Our model, utilizing the same framework, can also account for why Japanese society developed their distinctive labor market institutions, characterized by lifetime employment, firm-sponsored training, and restrictive tenure-based job ladders. These institutions were established during the rapid economic growth and industrialization period of the 1950s and 1960s when the manufacturing industry was dominant in the Japanese economy. With its heavy reliance on large-scale facilities and capital expenditures, manufacturing typifies a technological regime wherein firms play the primary role in workers' human capital investment. To address the hold-up problem faced by firms and to provide sufficient incentives for investing in workers, the so-called Japanese labor market systems were needed to mitigate the risk of free-riding. However, when structural transformations and the IT revolution shifted the economy toward a technology regime that favored worker-intensive human capital investment, incumbent labor market institutions posed significant resistance, as enhanced labor market turnover and/or increased productivity from new innovations yielded limited benefits for incumbent firms. China, conversely, avoided this scenario by resolving the hold-up problem faced by manufacturing firms during modernization through a distinct wage strategy. Rather than establishing national labor market institutions through social norms, China consolidated its heavy manufacturing industries into a state-owned sector with a highly rigid labor market, and simultaneously allowed its private sector to remain highly fluid, accommodating the needs of the emergent IT industry. Beyond the Japan-China IT industry comparison, our model can also reconcile the non-monotonic relationship between labor market turnover and economic prosperity across different stages of development.

Related Literature. Our study links and contributes to several distinct yet interrelated strands of literature. Firstly, we are related to the literature on the impact of human capital and labor market on technology adoption (Nelson and Phelps, 1966; Greenwood and Yorukoglu, 1997; Chari and Hopenhayn, 1991; Adão, Beraja, and Pandalai-Nayar, 2021; Galor and Moav, 2000; Krueger and Kumar, 2004a,b; Acemoglu and Zilibotti, 2001), and especially those related to the holdup problem (Acemoglu, 2003; Acemoglu, Aghion, and Zilibotti, 2006). While previous studies have primarily emphasized the impact of firm-level technology adoption and the related hold-up problems faced by firms, we propose a different perspective. We argue that workers themselves can also significantly contribute to technological adoption, and this introduces another hold-up problem that operates in a direction inverse to the one experienced by firms. Our empirical investigation into the IT industries of Japan and China also adds to the empirical literature in this area (Bloom, Sadun, and Van Reenen, 2012; Arora, Branstetter, and Drev, 2013; Michaels, Natraj, and Van Reenen, 2014).

Secondly, our model is built on the literature on modelling training and human capital investment under non-Walrasian markets (Acemoglu, 1996, 1997; Acemoglu and Pischke, 1998, 1999b; Acemoglu and Shimer, 1999; Moen and Rosén, 2004; Wasmer, 2006; Doepke and Gaetani, 2020; Engbom, 2022). Our main divergence and contribution lies in exploring the possibility that firms and workers are not perfect substitutes within the joint human capital investment function, and that their factor share within this process may vary across different technological regimes.

Thirdly, we contribute to the literature on endogenous labor market institutions (Acemoglu et al., 2006; Acemoglu, Robinson, and Verdier, 2017), especially those focusing on the emergence of Japanese labor market institutions Hashimoto (1979); Hashimoto and Raisian (1985); Morita (2001); Owan (2004). Instead of suggesting better usage of specific human capital by Japanese firms, we demonstrate that the interplay of labor market friction and different technological regimes can account for both the historical success of Japanese manufacturing firms and their more recent struggles within the IT industry.

Finally, our work adds to recent literature exploring the cross-country relationship between labor market turnover and economics development as well as factors like training or lifecycle wage growth (Blinder and Krueger, 1996; Donovan, Lu, Schoellman, et al., 2022; Ma, Nakab, Vidart, et al., 2021; Engbom, 2022). We do so by documenting the empirical discrepancy within the Japanese and Chinese labor markets using a novel data source, the job vacancy data, and by constructing a theory predicting a U-shaped relationship between labor market turnover and economics development.

2 Motivating Facts

In this section, we elucidate a comparative analysis of the labor markets in the Information Technology (IT) industries of China and Japan by scrutinizing the distinct patterns disclosed in their respective online job postings. Empirical findings reveal clear and systematic divergences between the two countries' IT job postings in terms of worker requirements, technology utilization, training policies, and wage structures. These distinctive labor market behaviors illuminate the potential interrelations between the underlying labor market institutions and firms' technological adoption strategies. Recognizing this connection is paramount, as it carries significant implications for technological evolution, labor productivity and industry competitiveness, and labor market inequality in the respective countries.

The primary datasets used for our analysis are procured from two online job boards - 'Doda.com' for Japan and 'Lagou.com' for China. Each platform stands as the most leading and national-wide IT-focused job site within their respective countries, although their scale varies substantially due to the differing sizes and turnover rates of the two countries' labor markets. From "Doda.com", we collected approximately 216,000 job postings of all types between June 2019 and March 2020, of which 34,000 were specifically related to IT engineers. From 'Lagou.com', we gathered around 909,000 job postings of all types from January to December 2019, with a substantial subset of 278,000 being IT occupations.[2] While

[2] These two time periods were selected to allow for a parallel comparison while circumventing potential disruptions arising from the COVID-19 pandemic. For "Doda.com", we classify those jobs pertain to IT engineers by directly using the classification of the job board. For "Lagou.com", we classify all jobs into the U.S.

'Lagou.com' caters primarily to the IT-intensive sector, with non-IT jobs largely from roles such as design, operation, or administration that IT-producing or IT-using firms post alongside their IT vacancies, 'Doda.com' showcases a broader spectrum of job opportunities, thus incorporating a wider range of non-IT positions. Consequently, our comparison between IT occupation and other occupations in the markets mainly involves those occupations that frequently appear on 'Doda.com'. As part of our data cleaning process, we removed duplicate job postings and filtered out part-time positions, thus concentrating exclusively on regular jobs in our sample.[3] Due to the unique recruitment system in Japan that separates fresh graduates with other workers (see e.g. Genda, Kondo, and Ohta (2010)), our dataset from 'Doda.com' does not include postings for fresh graduate vacancies. Such listings, however, are present in the Chinese data from 'Lagou.com.' Nevertheless, this disparity does not impact the qualitative validity of our findings. In fact, if we were to exclude fresh graduate jobs from the Chinese data, the observed differences between the job postings from these two countries would appear even more pronounced. Moreover, in a qualitative sense, this divergence in the recruitment of fresh graduates serves as an illustration of the differing labor market institutions in these two countries—a key aspect that this study aims to highlight.

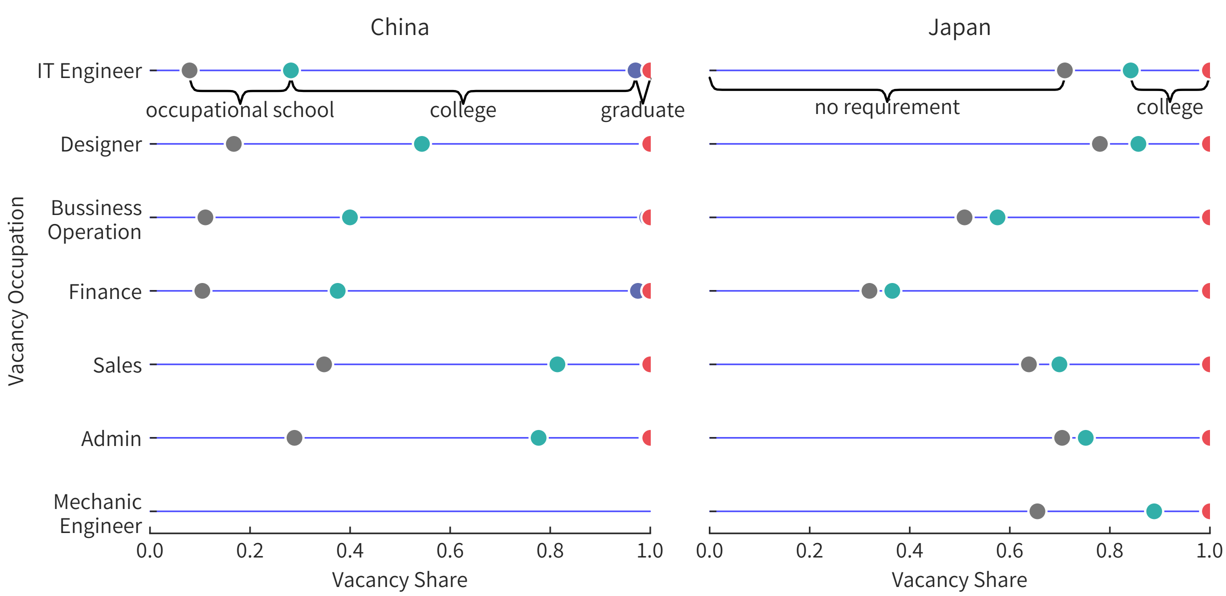
Our analysis commences by comparing job requirements pertaining to education and experience. Figure 1 displays the percentage of postings with various education requirements for occupations of IT Engineer, Design & Media, Business Operation, Finance, Sales, Administrative, and Mechanic Engineer in both countries. In our Chinese online job market, the majority of job postings for IT engineers mandate a college degree (over 70 percent). A smaller fraction of these postings (around 20 percent) specify the need for an occupational college degree, which generally requires two- or three- years education post-high school and is considered a level below a university degree. Additionally, less than 3 percent of postings seek candidates with postgraduate degrees, and around 6 percent do not stipulate any education requirements. In fact, IT Engineer positions stand out as the most education-intensive compared to other occupations in our Chinese dataset, with the highest likelihood of requiring a college degree, surpassing the 60 percent in Business Operations and Finance, and far exceeding the roughly 20 percent in Sales and Administrative occupations. On the other hand, in Japan, the education requirements for IT engineer jobs are

Standard Occupational Classification (SOC) by using a simple machine learning algorithm (see Zhu (2022)), and refer the Computer occupations there to IT occupations in our paper .

[3] Notably, within the Chinese dataset, we also discarded job postings with minimal job description content. This action was necessitated by the significantly lower cost of job postings on the Chinese job board compared to the Japanese one, leading to a subset of Chinese job postings that were deficient in information or of lower quality.

substantially lower. Less than 18 percent of Japanese IT job vacancies require a college degree, and almost no vacancies require a postgraduate degree. An additional 14 percent of job postings demand a vocational college education, while close to 70 percent of job postings do not specify any education requirements. Perhaps interestingly, IT Engineer jobs in Japan are less education-intensive than even Sales and Administrative occupations, which mandate a college degree in around 20 to 30 percent of cases, larger than in the Chinese data. Also, for occupations such as Business Operations and Finance, the share of postings demanding a college degree in Japanese data is close to the Chinese case, ranging from 40 to 60 percent. The only other occupation in our dataset showing a similar large discrepancy in educational requirements between the Japanese and Chinese datasets is the Design & Media occupation. For the occupation of Mechanical Engineer, for which we only have data in the Japanese dataset, the composition is similar to the IT engineer case.

Figure 1: Job Requirements on Education



Notes. This figure displays the proportions of various educational requirements for different occupations in two online job boards of China and Japan. "Occupational College" refers to a two- or three-year post-high-school occupational education, which is inferior to a university or bachelor degree. "College" denotes a standard bachelor's degree from a university. "Graduate" represents postgraduate degrees, including both master's and doctoral degrees. "No Requirement" signifies job postings that do not specify any educational qualifications.

The requirement discrepancies between two countries are also evident in the experience required for IT jobs, as illustrated in Figure 2. In China, nearly half of the job postings demand 3 to 5 years of experience, while over 20 percent require 1 to 3 years, and approximately 16 percent necessitate more than 5 years. Positions requiring no experience or less than one year experience constitute the remaining 10 percent. Similar to the education scenario, IT jobs are the most experience-intensive positions in the Chinese dataset. Other occupations such as Design, Business Operations, and Finance require somewhat less experience, whereas Sales and Admin show a significant decline in experience requirements, with over 50 percent of positions necessitating no prior experience. In contrast, the experience data in the Japanese dataset is more ambiguous, with the majority of postings across occupations vaguely requiring 'some experience' instead of delineating clear experience prerequisites.[4] Despite this vagueness, a clear trend emerges in Japan: irrespective of occupation, a small proportion—no more than 15 percent—of postings call for over 3 years of experience. This feature aligns with the well-documented Japanese lifetime employment system, characterized by firms' preference for hiring fresh graduates, offering lifetime employment, managing adjustments through internal labor markets, and rarely directly hiring highly experienced candidates from external labor markets (see the reviews in Morita (2001); Owan (2004)).[5] In summary, our initial comparison of IT positions in the online job markets of China and Japan reveals a distinctive dichotomy: IT engineers in China are typically high-education and high-experience jobs, whereas in Japan, these positions are typically low-education and low-experience jobs.

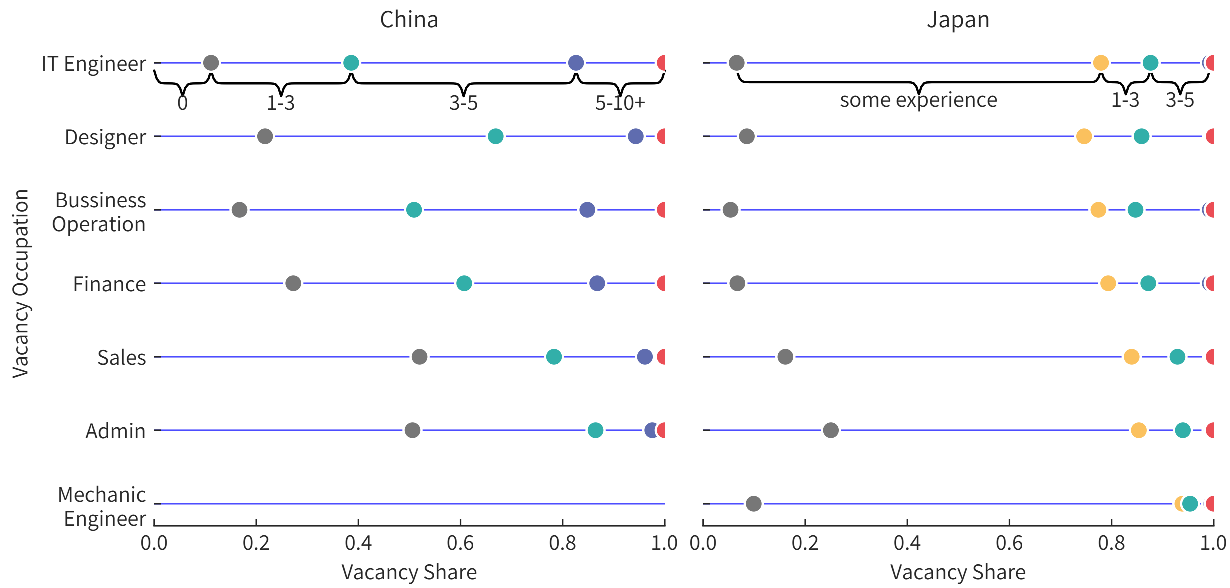
We proceed to investigate the training opportunities mentioned in the job postings. For the Chinese dataset, a job is defined as offering training if the job text includes any terms related to training. In contrast, the Japanese dataset has a designated column for employers to detail training provisions. We consider a job to offer training if the content in this column exceeds ten words.[6] The resulting training ratios across various occupations in both countries are depicted in Figure 3. In the Chinese job postings, a mere 12 percent mention training, ranking among the lowest across all occupations. Conversely, nearly 80 percent of Japanese job postings contain more than ten words related to training, a figure that

[4] This ambiguous requirement could encompass a range of experience, from knowledge gained through formal education or personal endeavors to exposure to relevant tasks in previous roles. Consequently, we suggest that this type of requirement arguably indicates a relatively low-experience requirement, likely falling somewhere between no experience and 1-3 years of experience, and it is unlikely to suggest a need for over 3 years of experience.

[5] Another perhaps noticeable trend is that IT engineers are not among the least experience-intensive occupations in Japan, with over 12 percent of IT postings requiring 3 to 5 years of experience, fewer than those in Design, Business Operations, and Finance occupations, but significantly more than those in Sales, Admin, and Mechanical Engineering.

[6] By setting this length threshold, we classify postings with no (often two or three words) or very brief training information (often under ten words) as jobs without training. This method may underestimate jobs with training but aims to counterbalance potential measurement error in the Chinese dataset, where firms might offer training but deem it inconsequential and thus not mention it in the job postings. Our qualitative findings remain robust even with a significant increase in the word threshold, given that the distribution of training text length is close to uniform between 10 and 100 words (Figure A1).

Figure 2: Job Requirements on Experience

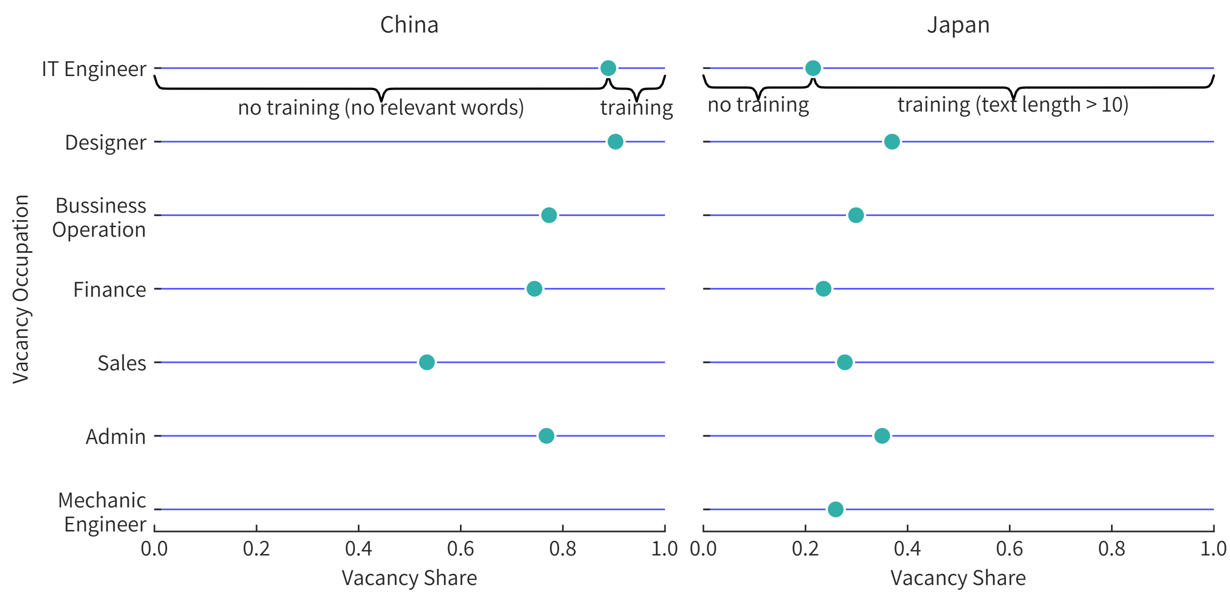


Notes. This figure showcases the distribution of experience requirements across different occupations in two online job boards of China and Japan. The categories of experience include "No Experience", "Less than 1 year", "1-3 years", "3-5 years", and "More than 5 years". "Some experience", a frequently used term in Japanese job postings, implies a range of experience from having gained relevant knowledge during education or personal time to having worked in similar roles previously. Given the ambiguity of this requirement, it is considered to indicate a relatively low-experience requirement and is represented accordingly in the figure.

is among the highest across all occupations. In general, our datasets reveal that Chinese firms are significantly less likely to provide training for their employees than their Japanese counterparts. Interestingly, even within all the occupations in our data, it is the IT jobs that demonstrate the most disparate training provisions between the two countries. This discrepancy suggests the potential existence of differing determinants influencing training provision by firms in China and Japan.

Next, we investigate the IT skills and technologies specified in the job postings. Our focus on the IT engineer jobs makes this investigation particularly amenable, since IT technology usages can largely be identified through the utilization of distinct programming languages and computer science tools—which are clearly defined, publicly accessible, and thus convenient for research. In particular, we study two broad and important categories of IT technologies. Firstly, we consider programming languages. We select approximately twenty of the principal languages featured both in our data and on the internet, comparing the prevalence of each language in IT job postings between China and Japan. We further divide these programming languages into groups based on their online popularity. The results of this comparison are displayed in Panel A of Figure 4. For the six predominant pro-

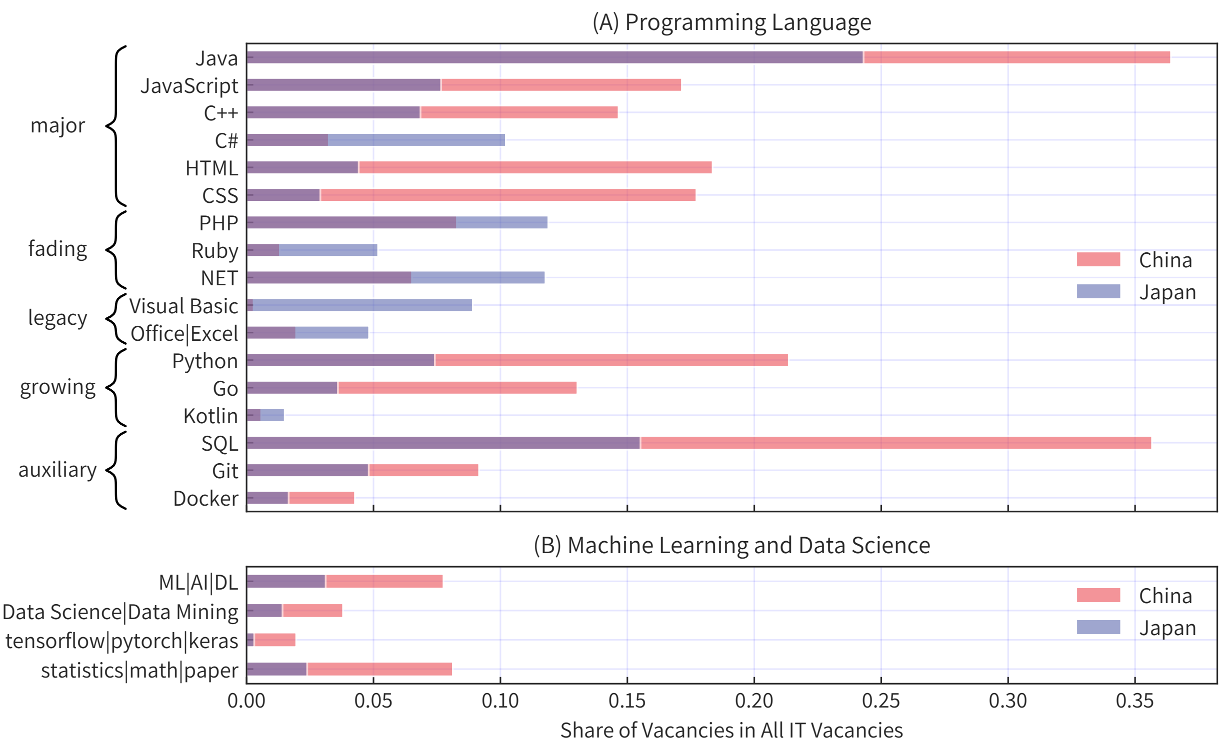
Figure 3: Provision of Training



Notes. This figure displays the ratio of job postings mentioning training opportunities across different occupations in two online job boards of China and Japan. For the Chinese dataset, a job is defined as offering training if the job text includes any training-related terms. Conversely, in the Japanese dataset, a job is considered to offer training if the training column content exceeds ten words.

gramming languages on computer occupations (Java, JavaScript, C++, C#, HTML, CSS), we note that, except for C#, Chinese job vacancies mention these languages significantly more frequently. For three growing languages (Python, Go, and Kotlin), Chinese vacancies predominantly cite Python and Go more often (21% vs 7%; 13% vs 4%), while Kotlin, being relatively less popular, is more frequently cited in Japanese job postings. Conversely, for all five legacy or declining programming languages (PHP, Ruby, NET, Visual Basic, Office|Excel), Japanese vacancies are significantly more likely to reference them, often at more than double the rate compared to their Chinese counterparts. For auxiliary programming tools such as SQL, Git, and Docker, we once again find that Chinese job postings are twice as likely to mention these tools. The second category of IT skills and technologies we explore are recently developed machine learning and data science tools or concepts. These emerging technologies can provide an indication of how new technological adoptions are conducted in these two countries. We identified the presence of such technologies using key terms, such as "machine learning", "deep learning", "artificial intelligence", "data science", "data mining", and their Chinese and Japanese abbreviations or equivalents. We also used specific package names like "tensorflow", "python", "keras", or more academic terms like "statistics", "math", "papers". Regardless of the type of keywords used, our data indicates that Chinese job postings are more than twice as likely to mention these new technologies than Japanese postings, particularly in the case of specific package names, which are almost ten times more likely to be mentioned in Chinese postings (Panel B of Figure 4). This disparity suggests that Chinese IT firms appear more inclined to adopt new technologies, whereas Japanese IT firms seem to persist with legacy or declining IT technologies, lagging behind in the uptake of emerging ones.

Figure 4: IT Skills and Technologies Mentioned



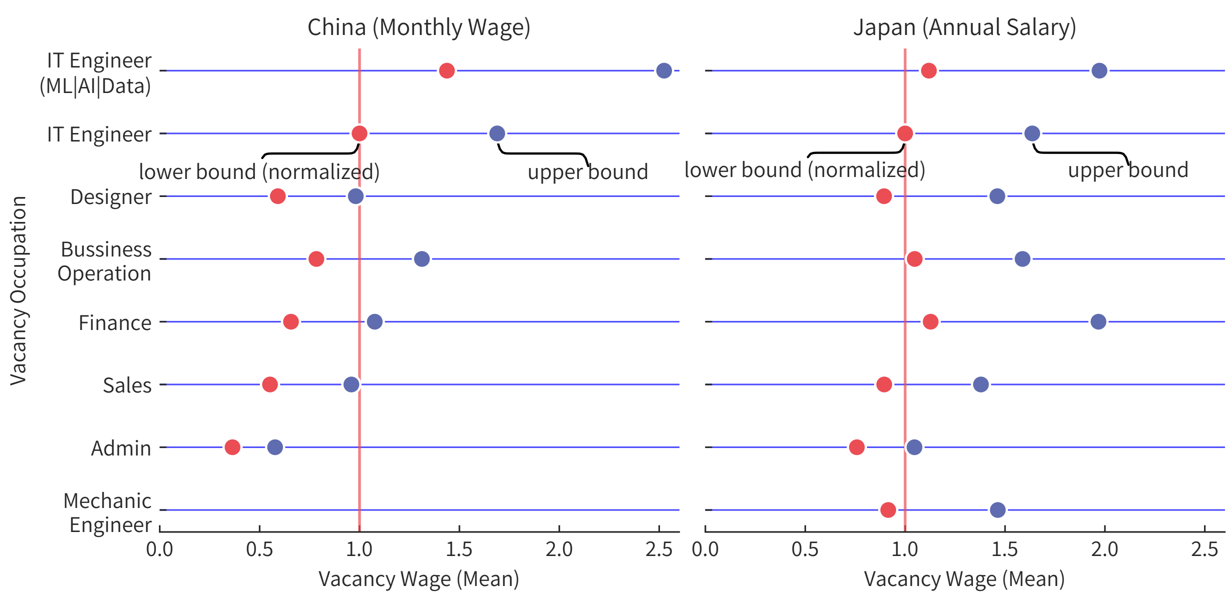
Notes. The figure presents a comparison of the prevalence of various IT skills and technologies as stated in the job postings for IT engineer positions in two online job boards of China and Japan. Skills and technologies have been grouped into two categories: (A) major programming languages, further categorized based on their online popularity, and (B) newly emerging machine learning and data science tools or concepts.

Lastly, we examine the wage structure in these two structures, focusing on the relative wage premiums for IT Engineer jobs in comparison to other professions. The results of this comparison are illustrated in Figure Figure 5, where we plot the averages of both the upper and lower bounds of salary ranges reported in job postings, with the lower bound for IT occupations normalized to 1 for ease of comparison.[7] We also examine a subset of

[7] Notably, while we utilize monthly wage data for the Chinese dataset, as it's the only available wage information for Chinese job postings, we use yearly wage data for the Japanese dataset as yearly wages are more typically used as standard wage information in Japan. However, as shown in Figure A2, using monthly wage data for Japanese firms does not alter our results at all.

IT job postings—those containing terms related to machine learning and data science—to represent the IT jobs that incorporate the most recent technologies. Figure 5 makes it clear that, in our Chinese dataset, IT engineer positions boast substantial wage premiums compared to other occupations, with both the average lower and upper bounds nearly triple those of the lowest-paid administrative positions. Furthermore, jobs relevant to machine learning and data science command even higher premiums, with both bounds 50 percent above those of the average IT engineer jobs. Contrastingly, our Japanese dataset reveals that wages for IT positions are quite moderate when compared to other professions. Wage disparities between different occupations are relatively small, with the lower wage bound for the lowest-paid administrative jobs only 20 percent less than those of IT positions, and the upper wage bound 40 percent less. Moreover, IT positions mentioning machine learning and data science see limited wage premiums—only about 10 and 20 percent greater on the lower and upper bounds, respectively, than average IT roles. This finding suggests significantly lower skill premiums for IT workers in Japan than in China, with new technologies largely not reflected in wage compensation.

Figure 5: Mean Posted Wage



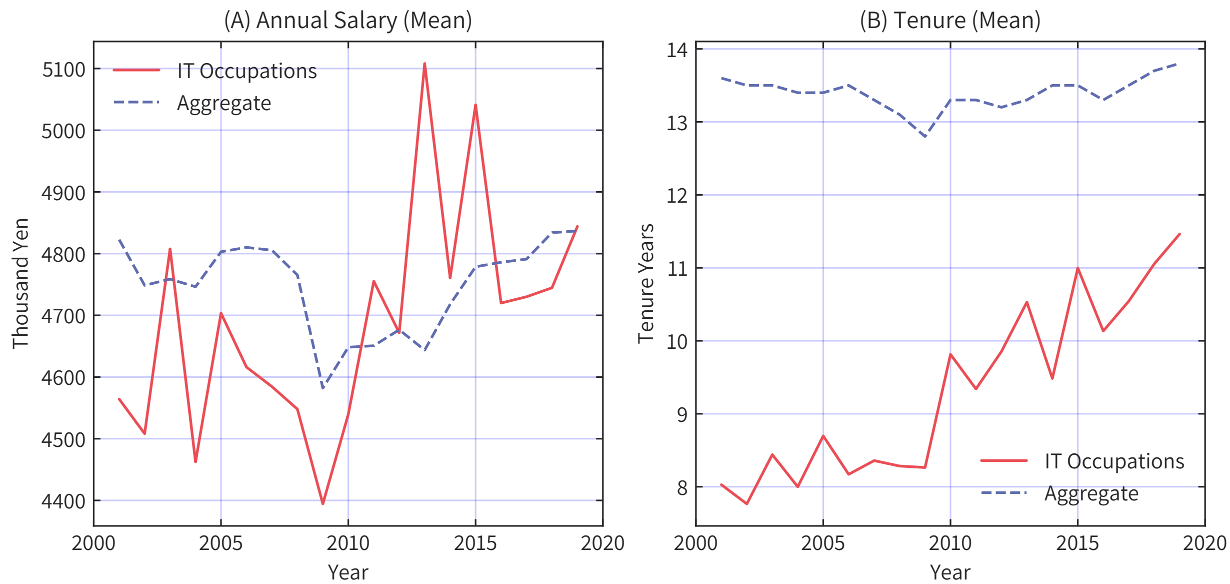
Notes. This figure compares the relative wage premiums of IT Engineer jobs to other occupations in two online job boards of China and Japan. The average upper and lower wage bounds sourced from the salary ranges provided in the job postings are plotted for each occupation, with the lower wage bound for IT roles normalized to 1 for comparative purposes. A subset of IT job postings that mention machine learning and data science terms, regarded as jobs incorporating recent technologies, are included in the comparison.

One limitation of our vacancy data is the possibility that the composition of online jobs may differ from the real labor market, and that the wages posted may deviate from the real wages due to various reasons. Additionally, our vacancy data lacks information regarding worker tenure or worker turnover rates, which is an important aspect of the labor market.[8] To address these limitations, we supplement our analysis with the Basic Survey on Wage Structure (BSWS) provided by the Japanese statistics bureau to verify the wage structure we observed in our job posting data and to illustrate the tenure patterns for Japanese IT workers. The results illustrating wage and tenure evolution trends of IT occupations and the national average, derived from BSWS data, are shown in Figure 6. Panel A demonstrates that the annual income of IT occupation workers closely mirrors the national pay level in 2019, consistent with our findings in the vacancy data. Tracing back two decades to 2001, we observe that IT worker wages were around 5 percent lower than the national average before 2011 and then shifted to being 5 percent higher than the national average until 2016, when IT worker pay realigned with the national average, without significant growth thereafter. Furthermore, Panel B reveals that during the same period, the average tenure of workers in IT occupations increased from approximately 8 years to about 11.5 years, converging to the national average tenure of 13-14 years. While we were unable to find similar census data for China, we reference the average weekly earnings and tenure for U.S. IT workers using data from the U.S. Current Population Survey (CPS). The U.S. data is deemed a useful point of comparison given the close alignment of the Chinese IT industry with the U.S. IT industry, as well as the comparatively light labor market regulations in the U.S. and China versus Japan and European countries. The results in Figure A3 illustrate a substantial wage premium for U.S. IT workers, with a notable surge between 2016 and 2020, and a decline in average tenure from 7 years in 2008 to 6 years in 2019, with a pronounced drop after 2016. Hence, the evidence from census data supports our findings from vacancy data, indicating that Japanese IT workers receive limited wage premiums compared to other occupations, whereas in China and the U.S., IT workers earn significantly higher relative wages. Moreover, Japanese IT workers tend to have increasingly longer tenures with their employers, often staying with the same employer for over ten years. This contrasts with the U.S. IT industry (and potentially the Chinese IT industry), where rapid evolution of new technologies seems to lead to shorter tenures with the same employer, typically not exceeding 6 years.

In summary, our empirical findings reveal several distinctive differences between the labor markets for IT engineers in China and Japan. We observe that Chinese IT firms demand

[8] Though the quantity of firm-level postings can act as an indicator of labor market turnover, issues such as the relative importance of online postings and the possibility of multiple postings for one job largely prevents a rigorous comparison using only online job posting data.

Figure 6: Mean Salary and Mean Tenure from Census Data



Notes. This figure presents trends in average wage and tenure for IT occupations versus the national average in Japan, derived from the Basic Survey on Wage Structure (BSWS). The IT occupation data aggregates from two occupation categories: System Engineers and Programmers.

more formal education and working experience than their Japanese counterparts. Moreover, Japanese IT firms are found to more likely provide firm-based training, while Chinese IT firms appear to emphasize more on workers' self-learning, presumably acquired through formal education and past work experience. In terms of technology adoption, our analysis shows that Japanese IT firms lag behind Chinese firms in embracing new and advanced technologies. Perhaps as a result of these divergences in skill and task requirements, we find Japanese IT workers enjoy less skill premium than their counterparts in China, with wage levels only at national average. In contrast, IT workers in Japan have notably longer tenure (compared to those in U.S. and presumably in China), suggesting sluggish job mobility and labor market turnover. These observations are in line with prior research that conduct cross-country comparisons on IT usages. Bloom et al. (2012) report that European affiliates of US multinationals show higher productivity in using IT capital than non-US multinationals, especially those Japanese ones. This productivity difference is attributed to variations in people management practices, including aspects such as promotions, rewards, hiring, and firing. In terms of technological innovation, Arora et al. (2013) provide evidence that Japanese firms lagged behind US firms in IT-related invention during a software-biased shift in the innovation process in IT sectors, supporting our finding of a slower adoption of advanced technologies among Japanese IT firms. Furthermore, Michaels et al. (2014) demonstrate a positive correlation between the demand and wages for high-skill (educated) workers and ICT adoption across countries and industries, where Japanese industries locate close to the bottom.

Our empirical findings suggest potential links between firms' labor market behaviors and their technology adoptions. Japanese IT firms appear to prefer hiring less-educated and less-experienced new workers, subsequently training them to work with relatively outdated technologies. These firms maintain low wage structures, yet ensure a longer tenure for their IT employees. Conversely, Chinese IT firms tend to hire workers with higher levels of education and experience, who are capable of using frontier technologies without any further formal training. These high-skilled workers are compensated with significantly higher wages and presumably frequently poached by competing firms. In essence, the responsibility of human capital investment in the IT industry is allocated to different market players in these two countries: firms in Japan and workers in China. This choice of different modes of human capital investment seems to result in varying technologies utilized in the jobs and distinct wage levels and tenure lengths offered by firms in these two nations. In the following section, we develop a model of human capital investment that can account for these two distinct paths within a simple framework.

3 A Simple Model

Our model is a simple two-period model of training and production, following in the spirit of seminal studies by Acemoglu (1996), Acemoglu (1997), and Acemoglu and Pischke (1999b), as reviewed in Acemoglu and Pischke (1999a). Similar to the key arguments in these studies, frictional labor markets provide incentives for firms to offer training for even general human capital, thus circumventing the classical result of only workers investing in it, as described by Becker (1964). The key departure in our model is that wet assume the inputs of firms and workers are no longer perfect substitutes in the human capital investment function, and their factor share or productivity in the co-investment function depends on the technology of the industry in which they are located. We demonstrate that this seemingly "physical" difference in human capital production functions can interact with labor market institutions and generate a flexible impact on human capital investments and wage levels in equilibrium.

The economy consists of a continuum of firms and a continuum of workers, both of a measure one. For simplicity, we assume that all agents are risk-neutral and there is no discounting over periods. Workers are endowed with their initial human capital h_0, and firms draw productivity z upon entry. To ease derivation, we simplify the model by assuming both workers and firms are homogenous, normalizing the initial worker human capital such that $h_0 = 1$, and denoting $z = z_1$. In the first period, firms and workers match randomly into one-to-one pairs, producing homogenous final goods (with price normalized to 1) following a simple production function: $f(z, h) \equiv zh$.[9]

In addition to production, in the first period, a firm and a worker in a match can jointly invest in the worker's general human capital h. Human capital is considered general in the sense that it is not firm-specific (though it can be occupation-specific). This is a plausible assumption given that in the IT industry cases, most technologies, even those newest ones like machine learning or artificial intelligence, are public knowledge and can be utilized commonly. We assume that investments from the firm and worker sides fall under a non-cooperative regime; they cannot form perfect contracts and conduct joint maximization. This is a reasonable assumption since both firm investment (i.e., training) and worker investment (i.e., self-learning), whether on-the-job or off-the-job, often cannot be verified by third parties, making them non-enforceable in contracts. The human capital production function is assumed to be

$$\Delta h(k, l) = A k^{\alpha} l^{(1-\alpha)} \tag{1}$$

, where k represents the firm's input, l represents the worker's input, A is a productivity term, and α is the factor share of the firm's input. The key aspect here is that the firm's input and the worker's input are imperfect substitutions, so the Cobb-Douglas form in Equation (1) can be easily generalized into a CES form. Moreover, we will allow α to vary across industries. The idea behind this is to acknowledge that firms and workers play different roles in training and investing in human capital, depending on the technological nature of skill and human capital accumulation. For example, in heavy manufacturing industries, training requires expensive machinery that can only be procured by firms. In contrast, in modern IT industries, especially software-intensive ones, the hardware requirement for developing computer skills is minimal, and workers can simply self-train at home using personal computers. We assume that the worker's input incurs a cost of $\kappa \frac{l^{1+\gamma}}{(1+\gamma)}$ in the unit of numeraire. This cost could either be pecuniary costs on equipments or learning materials or direct utility costs like effort, or indirect utility costs like leisure as in the classical lifecycle human capital growth model. We also assume no credit constraint problem on worker investment, though the level of $1 - \alpha$ can be regarded as a reduced form of such problems. On the other hand, the firm's input is simply capital, with a unit cost r exogenously given.

[9] With this setting, we only model the production and human capital accumulation post formal education, despite our empirical work showing distinguished job requirements at the level of formal education. However, it is straightforward to add a period 0 where workers can self-invest in their human capital based on their expectations on future labor market matching outcomes, so that the initial human capital z_1 could vary across different labor market structures or institutions.

Assume that at the beginning of the second period, there is a large mass of potential firm entrants, who can pay an entry cost c to open a vacancy and draw productivity $z_2 > z_1$, due to technological progress. These new entrants will contend with incumbent firms to hire workers, while all employed workers engage in on-the-job searches in order to match with new firms. Given that the labor market is frictional, the number of meetings depends on market thickness, i.e.

$$m = M(v, s) = \xi v^{\phi} s^{1-\phi} \tag{2}$$

, where v represents the vacancies per worker, s denotes aggregate search efficiency per worker, ξ is matching efficiency, and the constant return of scale form aligns with the job search literature. Thus the matching rate for a worker searching for a new firm is $p = \xi(v/s)^{\phi}$, and the matching rate for a new firm poaching workers is $q = \xi(v/s)^{\phi-1}$. To simplify the model setting, we normalize s to 1, and v will be determined in the equilibrium. Wages paid to workers are determined through Nash bargaining at both periods, with worker's bargaining power assumed to be β.

Under this setting, we can write the worker's present value at the beginning of period 1 as

$$W(l; k, v) = \beta z_1 - \kappa \frac{l^{1+\gamma}}{(1+\gamma)} + \left[(1 - p(v))\, \beta z_1 + p(v)\, (z_1 + \beta(z_2 - z_1))\right] (1 + \Delta h(l, k)) \tag{3}$$

, where the first two terms represent the worker's wage and learning investment cost in the first period, and the last term corresponds to the worker's expected return in the second period. In the second period, with probability $(1 - p(v))$, the worker fails to find a firm with new technology, hence staying with her previous employer and receiving $\beta z_1(1 + \Delta h(l, k))$. Alternatively, with probability $p(v)$, the worker successfully matches with a new firm, and obtain a second-period wage of $p(v)\,(z_1 + \beta(z_2 - z_1))\,(1 + \Delta h(l, k))$, with the first period wage share βz_1 serving as the worker's outside option during her wage bargaining with the new firm. Similar, for an active firm in the first period, its present value will be

$$F(k; l, v) = (1 - \beta) z_1 - rk + (1 - p(v))(1 - \beta) z_1 (1 + \Delta h(l, k)) \tag{4}$$

, where the first two terms denote the firm's profit and training investment in the first period, and the last term indicates the expected profit in the second period. With probability $p(v)$, its matched worker will be poached by a new firm with new technology, yielding zero profits for it in the second term. Otherwise, the firm receives $(1 - \beta) z_1 (1 + \Delta h(l, k))$. Lastly, potential entrants, upon considering enter or not, face a free entry condition:

$$q(v)(1-\beta)(z_2-z_1)(1+\Delta h(l,k)) \geq c \tag{5}$$

.

Next, we characterize the market equilibrium. The equilibrium of this economy is defined as the optimal investments by workers and incumbent firms in the first period, l^* and k^*, along with a vacancy posting intensity in the second period, $v*$, such that workers and firms maximize their values in Equations (3) and (4), respectively, and the free entry condition in Equation (5) holds in equality. To characterize the equilibrium outcomes, we first derive the optimal investment levels using the first order conditions of firms' and workers' value functions:

$$\begin{aligned} \Gamma_l(1-\alpha)Ak^{*\alpha}l^{-\alpha} &= \kappa l^{\gamma} \\ \Gamma_k A\alpha k^{(\alpha-1)}l^{*(1-\alpha)} &= r \end{aligned} \tag{6}$$

, where $\Gamma_l = (1-p)\,\beta z_1 + p\,((1-\beta)z_1 + \beta z_2)$ and $\Gamma_k = (1-p)(1-\beta)z_1$. The left hand sides in the FOCs of Equation (6) are the marginal benefits of increasing human capital investment for workers and firms. For the worker side, the marginal benefit increases in p, as greater chance of matching with a new firm increases their second period wages through the better match with higher productivity. Conversely, for the firm side, the marginal benefit decreases with p, as greater chance of undergoing poaching diminishes their expected profits in the second period. In essence, workers favor a fluid labor market as they can reap benefits from new technology and high productivity through their on-the-job search. Incumbent firms, however, perceive a liquid labor market as a risk, as their investment in employees' human capital is less likely to rewarded under the free-riding of new entrants. Solving the first order conditions, the optimal human capital investments by workers and firms are respectively

$$\begin{aligned} l^*(p) &= \left(\Gamma_l^{1-\alpha}\Gamma_k^{\alpha}A\alpha^{\alpha}(1-\alpha)^{1-\alpha}r^{-\alpha}\kappa^{\alpha-1}\right)^{\frac{1}{\gamma(1-\alpha)}} \\ k^*(p) &= \left(\Gamma_l^{1-\alpha}\Gamma_k^{\alpha+\gamma}A^{1+\gamma}\alpha^{\alpha+\gamma}(1-\alpha)^{1-\alpha}r^{-(\alpha+\gamma)}\kappa^{\alpha-1}\right)^{\frac{1}{\gamma(1-\alpha)}} \end{aligned} \tag{7}$$

. Combining these two optimal investments, we obtain the equilibrium human capital increase in the first period to be:

$$\Delta h^*(p) = \left(\Gamma_l^{1-\alpha}\Gamma_k^{\alpha(1+\gamma)}A^{1+\gamma}\alpha^{\alpha(1+\gamma)}(1-\alpha)^{1-\alpha}r^{-\alpha(1+\gamma)}\kappa^{\alpha-1}\right)^{\frac{1}{\gamma(1-\alpha)}} \tag{8}$$

.

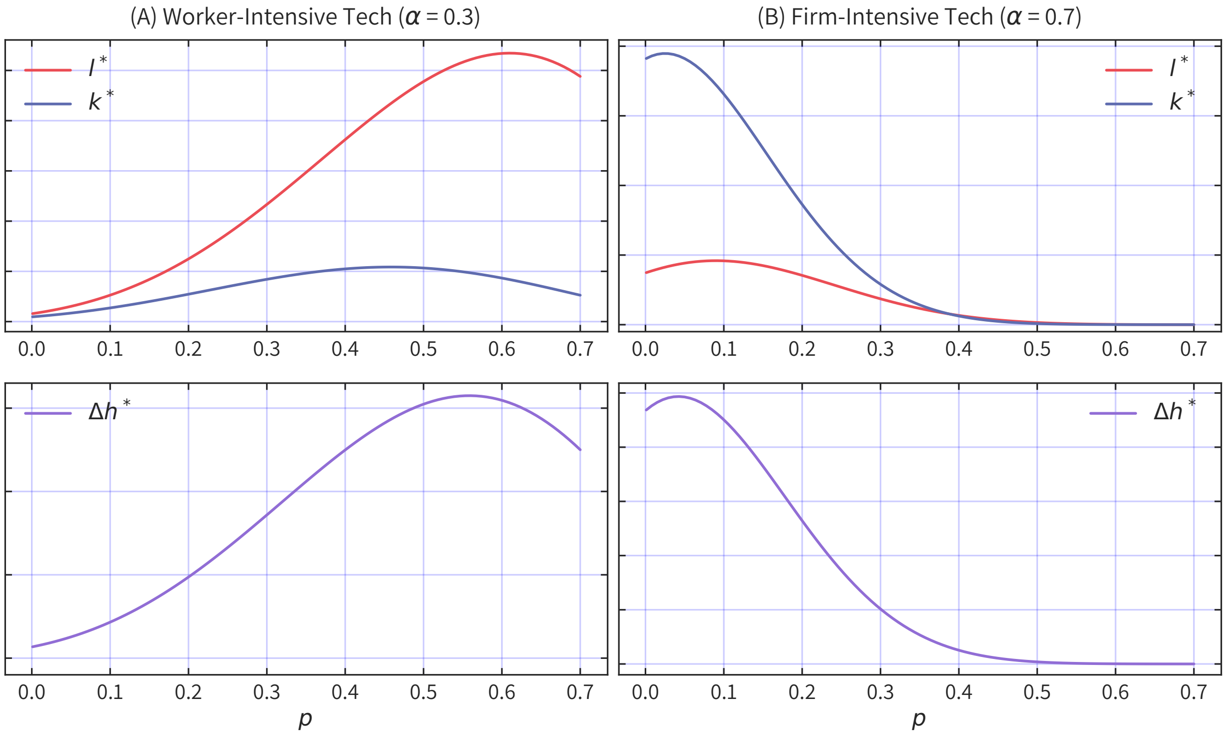
Notably, the optimal investments l^* and k^*, as well as the equilibrium human capital increase Δh^*, are now non-monotone functions of the matching probability in the second period, p. Instead, given that an increase in p generates opposing effects for firms' and workers' incentives for human capital investment, its impact now depends on the factor share parameter, α. We illustrate the equilibrium results for two different cases in Figure 7. In Panel A, we set $\alpha = 0.3$, interpreting this as a worker-intensive technology in human capital investment. In this case, an increase in p significantly boosts human capital investment from the worker side, but only moderately affecting the firm side, as the risk of poaching by new entrants discourages firms' investment in their workers' general human capital. However, as the worker side plays a more important role in this technology's human capital investment, a high level of p in the labor market is required to achieve socially optimal human capital investment, i.e. the highest Δh^*.[10] In contrast, Panel B of Figure 7 set $\alpha = 0.3$, interpreting this as a firm-intensive technology in the human capital investment function. In this case, the firm side has a higher factor share and productivity in the human capital investment function, hence a low chance of workers being poached and ending up without an employee encourages large-scale investment from the firm side. Conversely, the effect on the worker side is largely muted in this case as workers now play a relatively small role in human capital investment, and a low p dampens workers' incentive for investing human capital, counteracting the positive effect on firms' investment. As a result, in this case, we see a very low level of p is necessary to achieve the social optimal level of human capital investments in firm-worker matches.[11]

The key variable affecting firms' and workers' investment incentives, p, is an endogenous result of the equilibrium. We thus now characterize the market equilibrium by combing the optimal investment equation in Equation (8) and the free entry equation in Equation (5). These two equations are depicted in the $\Delta h - v$ diagram in Figure 8 for the two cases described above, with the intersection of these equations indicating the equilibrium outcomes. As the worker matching probability p increases monotonically with the vacancy intensity

[10] An allocation in the economy is (constrained) efficient if it maximizes the net output of the economy subject to search frictions. In particular, in our setting a social planner chooses training investment and vacancy opening to maximize the output in the second period $\max_{l,k,v}[(1-p(v))z_1 + p(v)z_2](1+\Delta h(k,l)) - rk - \kappa\frac{l^{1+\gamma}}{(1+\gamma)} - cv$ subject to $\Delta h(k,l) = Ak^{\alpha}l^{(1-\alpha)}$ and $p = \xi(v/s)^{\phi}$. The market equilibrium is socially inefficient and does not coincide with the social planner's optimal choices because the workers and new firms do not internalize the cost of the incumbent firms' investment in the first period.

[11] While in our setting, the investments from firms and workers tend to co-move and there is always some extent of co-investment in human capital, this is not necessary to always be the case. For example, we show in Figure A4 that if we modify the joint human capital production function to $\Delta h = Ak^{\alpha}(l+l_0)^{(1-\alpha)}$, i.e. there is a lower bound of the workers' investment due to say learning by doing during the production, then the workers' additional investment can be very close to 0, and the firms' investment could become non-increasing along with the increase in p.

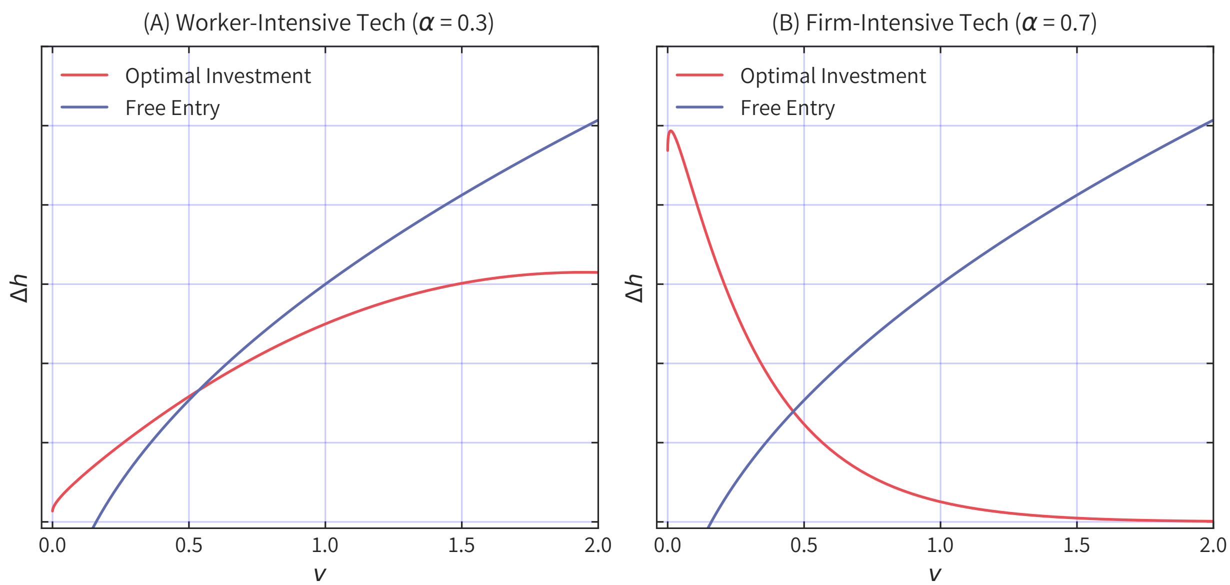
Figure 7: Optimal Investment/Training Under Different Technologies



Notes. This figure illustrates the different optimal human capital investments in the equilibrium, l^*, k^*, and Δh^*, for two scenarios of different human production function technologies: worker-intensive ($\alpha = 0.3$), and firm-intensive ($\alpha = 0.7$).

v, we consider v, much like p, as an indicator of labor market liquidity. For the two cases of different human capital investment technologies, the optimal investment mirrors the curves in Figure 7, yielding distinct curves in these two scenarios due to the difference in the relative importance of workers' input and firms' input. In contrast, the curve of free entry condition remains the same in both cases. What is interesting about the results is that, while these two equilibriums generate similar equilibrium human capital growth Δh^* and vacancy intensity v^* in our simple illustrating examples, they yield distinct interpretations in these two economies. In the worker-intensive case shown in Panel A, the market liquidity is too low, resulting in social suboptimal human capital investment. This is because the market liquidity isn't high enough to generate adequate incentives for the worker side to invest in their human capital. In contrast, in the firm-intensive case in Panel B, the human capital investment level is also socially suboptimal, but here the issue is that market liquidity is too high. The level v^* now significantly impedes the firms' incentives as, in the firm-intensive human capital investment function, firms have a considerably larger factor share and require lower market mobility to stimulate their investment. Thus, our simple model generates the results that, with different types of technologies in the human capital investment functions, the most appropriate labor market mobility for including optimal human capital investments and labor productivity can vary significantly. Consequently, if firms in a labor market have the ability to influence labor market mobility through establishing various labor market institutions, then under different technologies, different labor markets would have significantly diverse incentives to evolve, leading to very different labor market mobilities and wage structures.

Figure 8: Equilibrium and Inefficiency



Notes. This figure characterizes the equilibrium as intersection of the optimal investment equation and the free entry equation. Similarly to Figure 7, we do this for two scenarios of different human production function technologies: worker-intensive ($\alpha = 0.3$), and firm-intensive ($\alpha = 0.7$).

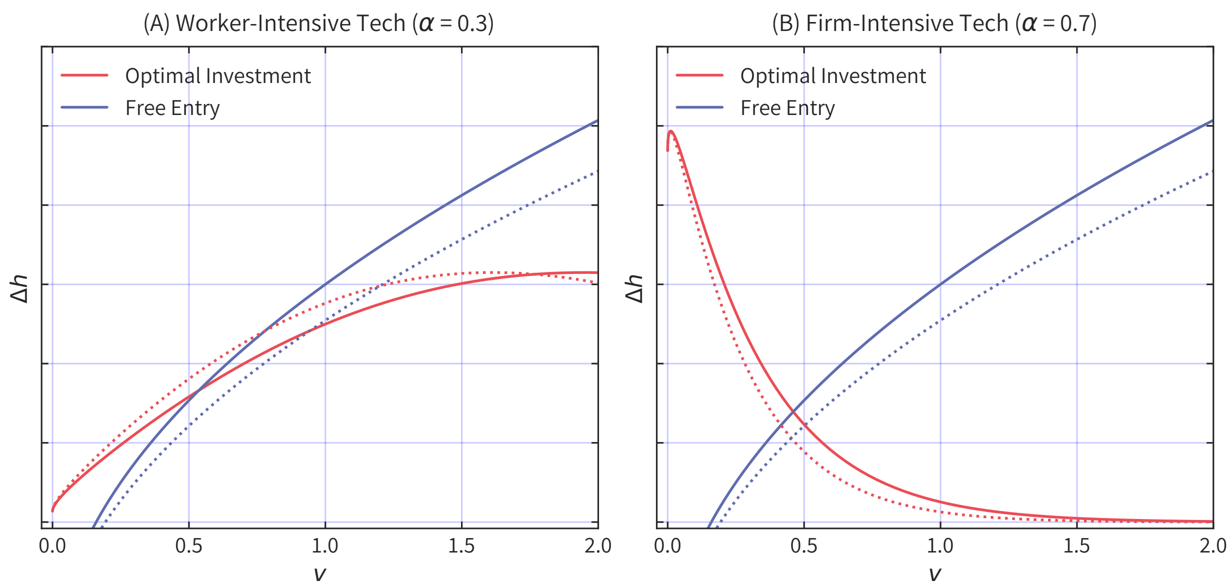
4 Discussion

In this section, we leverage our learning-vs-training model developed earlier to shed light on the distinct empirical findings pertaining to IT jobs in Japan and China, and elucidate the possible mechanisms driving the different equilibrium outcomes in these two countries. Although our reasonings are largely conjectural and do not preclude other potential explanations, we demonstrate that our theoretical framework can coherently account for not only the currently disparate features of labor markets and technological advancement in Japan and China but also the long-term historical trajectories through which they achieved fast development and evolved their current market institutions. In fact, our model's insights extend beyond the specific cases of Japan and China, and the modern IT industry, generally applying to broader contexts and aiding in elucidating the overall picture of labor market structures, technological adoption, and progress across various nations in different development stages.

We begin with our explanations on the differences between Japan and China in terms of jobs and technologies within the IT industry. First, acknowledging the marked difference in labor market fluidity between the two countries, especially considering the stagnant labor market turnover in Japan due to lifetime employment norms, it is then straightforward to use our model to account for the diverse labor market features observed in our vacancy data. Key to understanding this is, again, the realization that within the IT industry, workers can easily enhance their human capital through formal education in computer science or off-the-job training, gaining access to the latest technologies like machine learning via abundant internet resources. In comparison, IT firms may not necessarily hold significant advantages in training workers, especially in terms of cutting-edge technologies, as rapid advancements could lead to inconsistencies within existing firm systems. Consequently, the human capital investment function in the IT industry is likely skewed towards being worker-intensive, with firms relying on workers to put more effort into human capital investment and newest technologies adoption. In this scenario, the notably illiquid labor market in Japan stymies workers' incentives to invest in novel technologies and advanced IT skills, such as machine learning or artificial intelligence. Instead, it encourages firms to take on the responsibility of human capital investment by systemically training their workers, despite such training potentially being largely inefficient. As a result, workers lack the motivation to invest independently and engage in on-the-job search, and firms, on the other hand, do not care about their potential workers' education and experience and are reluctant to offer substantial wage premiums, as they do not anticipate encountering workers with high human capital levels in the labor market. Contrastingly, the situation is reversed in the Chinese labor market. Characterized by minimal labor protection, the Chinese labor market operates with minimum frictions, making it ideally suited for the IT industry by maximizing incentives for workers to invest in human capital independently and actively seek out wage-enhancing opportunities through on-the-job search. As a consequence, Chinese firms tend not to provide training but rely on workers to learn and adopt the latest and most productive technologies, and offer significant wage premiums for highly skilled talent, continuously poaching competent workers from competing firms. In essence, the rigid Japanese labor market stifles the human capital investment of Japanese IT workers, their wage potential, and the development of the industry amidst rapid technological progress. Conversely, the unrestricted Chinese labor market fosters continual technology learning and adoption by workers, with Chinese IT firms flourishing by poaching and generously compensating these industrious workers.

The natural question that arises subsequantly is: why has the Japanese labor market evolved in such a way that it stifles labor market turnover? We propose that the emergence of Japan's labor market system, characterized by lifetime employment, firm-sponsored training, and strict tenure-based job ladders, can be also readily reconciled through our framework. The key to understanding this lies in acknowledging that the typical Japanese labor market institutions took shape during the rapid economic growth period of the early post-war era in the 1950s and 1960s. At that time, the dominant industries in the Japanese economy were heavy manufacturing, such as steel and iron, automobile and shipbuilding, chemistry, and electronic appliances. It was virtually impossible for workers in these industries to train themselves, as this would require large facilities and significant capital expenditures. Furthermore, without the easy flow of knowledge characteristic of the IT era, most human capital could only be acquired through practical experience or expert guidance and was challenging to transmit across geographical distances. Consequently, the labor factor share in the human capital investment function, $1 - \alpha$, was close to 0. While firms could bear the costs of capital and equipment procurement or hiring experienced trainers, thereby making human capital investment through training viable, they concurrently faced a hold-up problem since the human capital acquired from training, embedded in the workers, was susceptible to free-riding by other firms who could poach workers with higher wages. Consequently, manufacturing firms in the Japanese post-war industrialization era desired a labor market with extremely low worker turnover to ensure a return on their investment in workers. Arguably, during this period, Japanese society innovated its renown institutional structures in its labor market, establishing lifetime employment and strict tenure-wage ladders, all of which helped reduce the risk of worker exit or job hopping and facilitated intensive firm-sponsored training. However, these labor market institutions, emerged from historical contingency, have persisted in the face of technological advancement and structural changes in recent decades, perhaps due to established social norms and customs with inherently rigid nature, resisting changes. These historical institutions have thus become inconsistent with the distinct nature of human capital investment and technology adoption in the contemporary IT industry, inhibiting the development of Japan's IT industry and the productivity and wage levels of its IT workers. These potential resistances to change can also be visualized through our model by positing an increase in search efficiency, ζ, or an augmentation in the technology gap, z_2. As shown in Figure 9 and Figure 10, while these two advancements yield substantial increases in human capital investment and labor market vacancy postings under worker-intensive technology, their impact under the firm-intensive technology conversely results in decreased human capital investment and prompts only moderate changes in vacancy openings. Consequently, firms that evolved within a worker-intensive technology environment lack the incentive to disrupt the status quo. A significant transformation may only occur when these incumbent firms are entirely supplanted by new enterprises employing innovative technologies.

Figure 9: Increase in Search Efficiency ξ

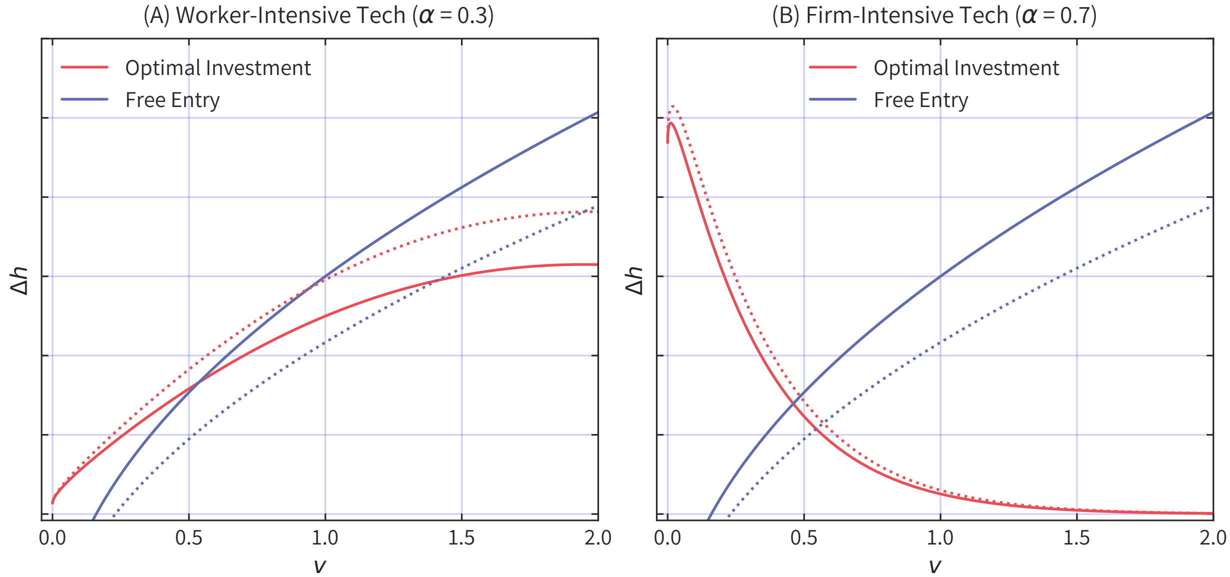


Notes. This figure illustrates the shift in the equilibrium outcomes by increasing the search efficiency parameter ξ in the firm-worker matching function.

The obvious question then is why China, which has also undergone a rigorous process of industrialization, technological catch-up, and economic growth between the 1980s and 2020s, has managed to maintain a highly fluid labor market ready for new IT technologies. Our conjectural response is that while China has also made significant strides in manufacturing development and technology adoption, it has done so in a manner starkly different from Japan. In China, low labor turnover is primarily observed in the large state-owned sector (Feng and Guo, 2021), and these state-owned firms have undertaken substantial capital investment in manufacturing and building infrastructure (Song, Storesletten, and Zilibotti, 2011). In other words, the hold-up problem has been addressed through rigid labor market institutions in the state-owned sector, leaving the private sector's labor market completely intact and fluid.[12] With structural transformation and ICT-based technological progress, the

[12] While a state-owned sector with low labor turnover might seem less efficient than the Japanese model at

Figure 10: Increase in Technology Gap z_2



Notes. This figure illustrates the shift in the equilibrium outcomes by increasing the productivity of new entrants in the second period z_2 due to technological progress, thus generating an enlarged productivity gap between the incumbent firms and new firms.

government sectors gradually diminished or reformed (Hsieh and Song, 2015), and the burgeoning Chinese IT industry grew almost entirely from the fluid labor market in the private sector. Through this segregation of two labor markets, the Chinese economy avoided the trap of a sluggish and illiquid labor market necessary for manufacturing development, as seen in Japan's case, and preserved the ability to foster new industries that best fit entirely different labor market institutions.

Lastly, we extend the implications of our model to a more general context, suggesting diverse roles for labor market structures on technological adoption and economic development across different stages of national development. When a country is positioned at the lower end of the income and technological spectrum, a firm-intensive approach to capital investment and training, aimed at developing a robust manufacturing foundation, might be paramount. In this scenario, labor market institutions that curb excessive labor turnover are vital to resolving the firm hold-up problem, whether through social norms and customs as seen in Japan, or through a heavily regulated state-owned sector as seen in China. This might explain why, as noted in Donovan et al. (2022), labor market fluidity is negatively

solving the worker hold-up problem because workers can still flow out to the private sector, we propose that such a solution is viable because state-owned firms often enjoy other policy benefits like low interest rates or low taxes, making the private sector unable to compete in cases of large capital and equipment investment.

correlated with development in a global comparison, with workers in less developed countries often experiencing excessive turnover, moving back and forth on the lower rungs of the job ladder. Similarly, Ma et al. (2021) demonstrates that levels of firm-provided training are positively correlated with development, suggesting a hold-up problem in firm training in less developed countries, where a large portion of the workforce is self-employed and lack opportunities of working in formal sectors. However, when a country has climbed to the upper-end or frontier of the income and technology spectrum, the structural transformation and IT technological progress it has undergone lessen the importance of firm-based capital investment and reduce the cost of worker-based investment and technology adoption. At this point, the country needs to transition to a more competitive and frictionless labor market that addresses the worker hold-up problem and promotes worker-initiated human capital investment and on-the-job search for improved compensation. Perhaps this is why, as suggested by Engbom (2022), when we narrow our focus to affluent countries like those in Europe, we observe a positive relationship between labor market fluidity and lifecycle wage growth. Consequently, our model predicts a U-shaped relationship between development and labor market dynamics across nations in the full spectrum of development. In essence, our theory posits that the nature of technologies is crucial for determining which labor market actors should bear the responsibility for human capital investment and technology adoption, and that once efficient labor market institutions, developed based on earlier technology regimes, could become legacy ones that no longer align with current technological circumstances.

5 Conclusion

In this paper, we present a comparative study of the Information Technology (IT) industry in Japan and China, analyzed through the lens of online job postings. Our findings show that, compared to their Chinese counterparts, Japanese IT firms have fewer requirements for formal education, working experience, and knowledge of the latest technologies, but they tend to provide more in-house training on relatively out-of-date IT technologies. In addition, Japanese IT firms offer significantly smaller wage premiums, while their workers enjoy noticeably longer tenures. We propose an explanation for the inability of Japanese IT firms to adopt new technologies and pay skill premiums by constructing a learning-vs-training model, where the inputs of firms and workers to the joint human capital investment are not perfect substitutes. Low turnover in the Japanese labor market, due to its institutions of life-cycle employment and tenure-wage ladder, inhibits workers' incentives for independent learning and on-the-job searching, as the chance of matching with high productivity firms are low. Instead, it encourages firms to dominate the investment in human capital production, even if this is technologically inefficient. In contrast, the fluid labor market in China's private sector compels Chinese firms to rely on their workers for human capital investment and the adoption of the newest technologies, who are incentivized through active poaching and high wages, leading to substantial creative destruction in the Chinese market. A nice feature of our model is that it can also account for the establishment of Japan's distinctive labor market institutions within the same theoretical framework by putting it into a different technological regime. During the rapid post-war growth of Japan's manufacturing industry, a solution was needed for the hold-up problem faced by firms, and the Japanese labor market system was thus designed to discourage labor market turnover and facilitate firm-sponsored training. However, these historically contingent institutions have not adapted well to the modern IT industry, which relies less heavily on firm investment, leading to the technological backwardness in Japan's IT industry. In conclusion, our results underline the importance of considering the distinct roles of firms and workers in human capital investment across different technological environments, as well as the need to address the two-sided hold-up problem in such investments arisen from labor market frictions.

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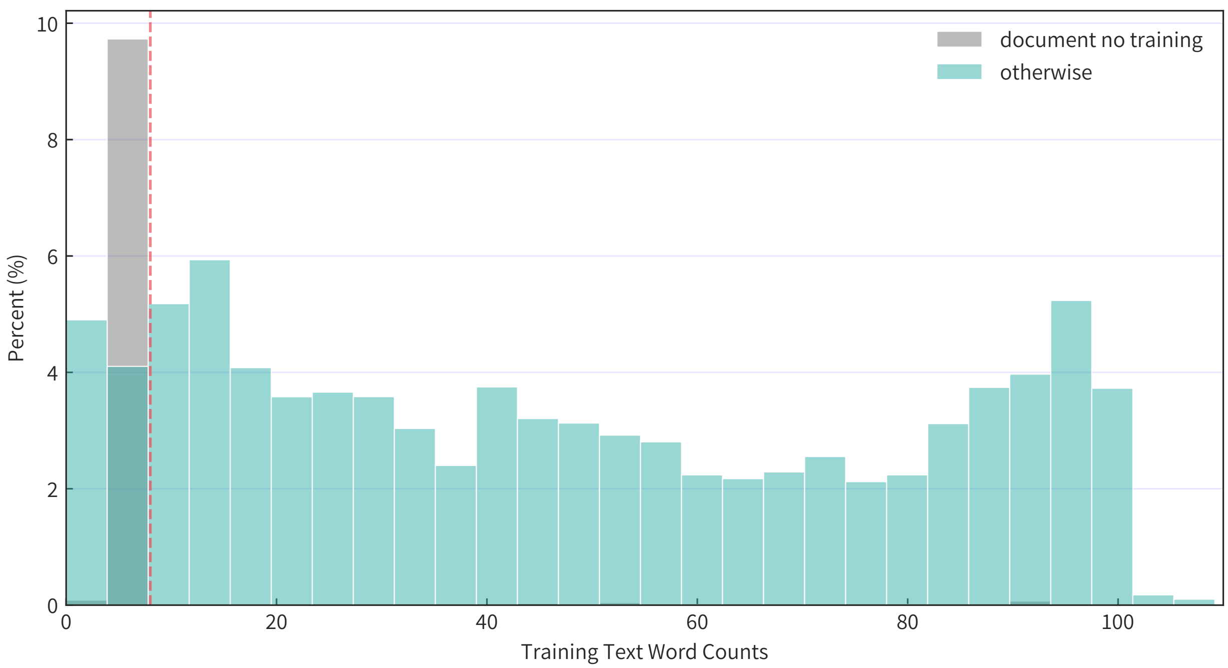
Appendices

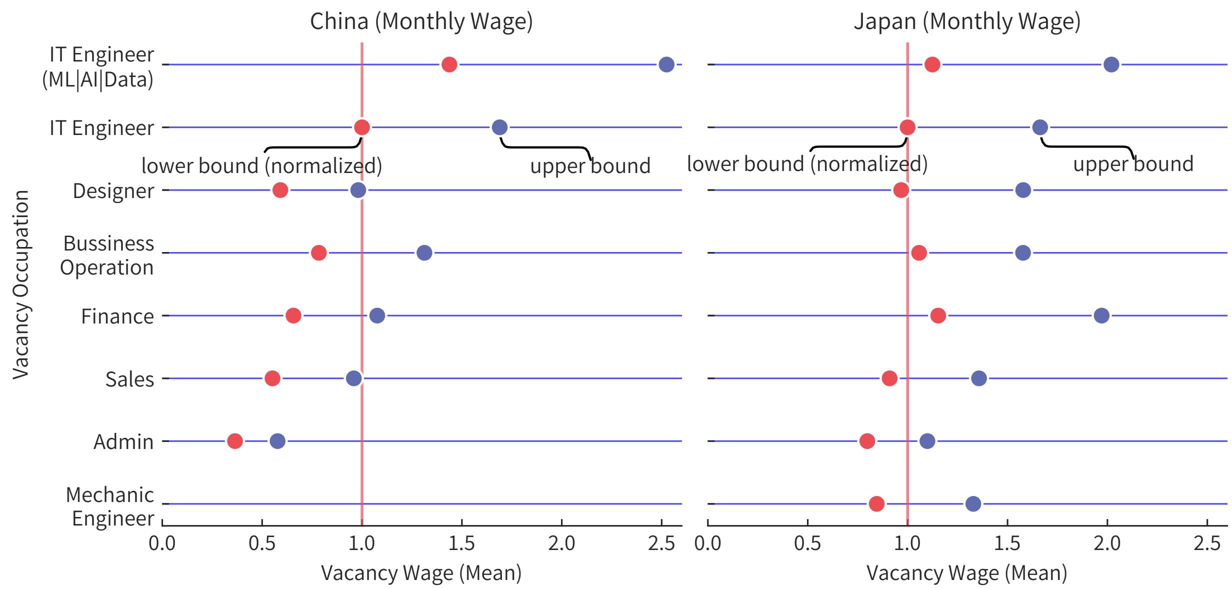
A Additional Tables and Figures

Figure A1: Training Texts in Japanese IT Job Vacancies



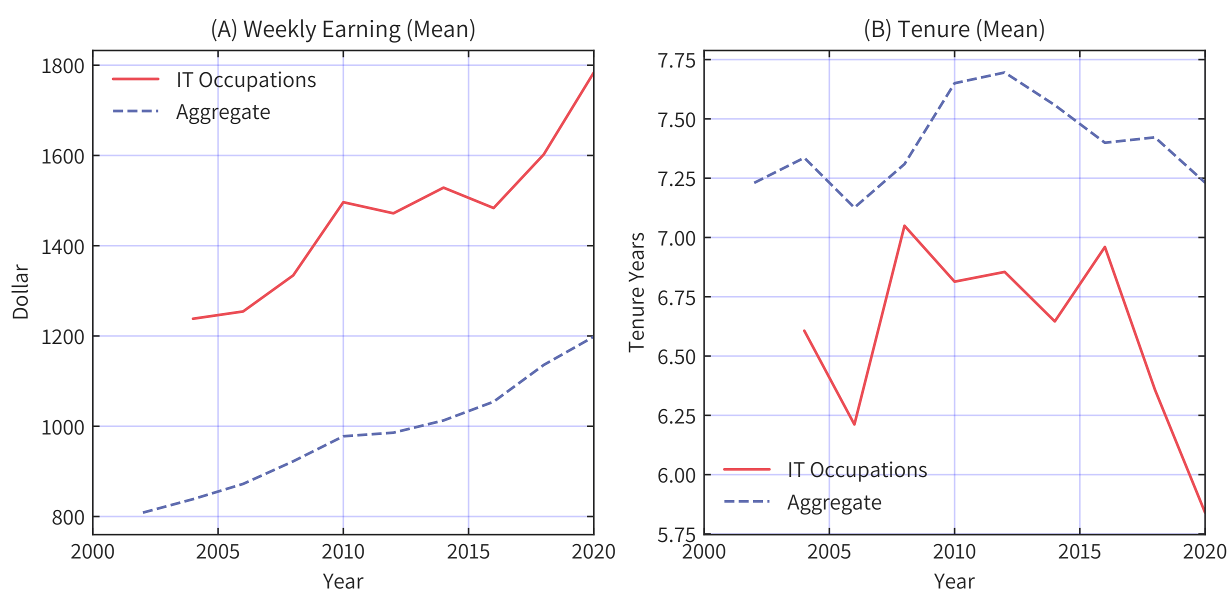
Notes. This figure represents the distribution of text length related to training information in the Japanese job postings. Job postings in Japan feature a specific column for employers to detail the training provisions. We define a job as offering training if the content in this column exceeds ten words. This threshold helps classify postings with no or very brief training descriptions as jobs without training, and can be raised to higher values.

Figure A2: Mean Posted Wage (Monthly)



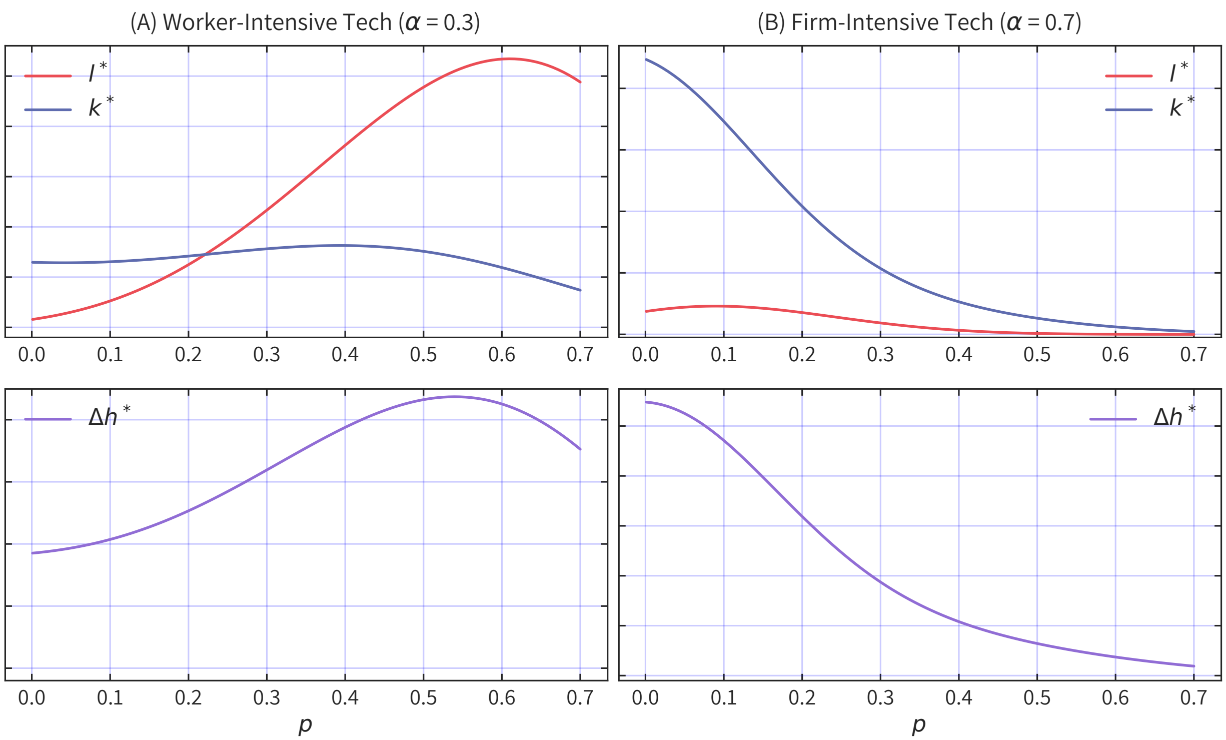
Notes. See the note in Figure 5, with the only difference being that here we replace yearly wage with monthly wage data for the Japanese dataset.

Figure A3: Mean Salary and Mean Tenure from US Census Data (CPS)



Notes. This figure illustrates the trends in average weekly earnings and tenure for IT occupations compared to the national average in the U.S., using data from the U.S. Current Population Survey (CPS). The IT occupations correspond to the SOC computer occupations.

Figure A4: Investment/Training Under Different Technologies



Notes. See the note in Figure 7. The only difference is that now we assume the human capital production function to be $\Delta h = Ak^{\alpha}(l + l_0)^{(1-\alpha)}$.