Training, Productivity and Wages: Direct Evidence from a Temporary Help Agency[1]

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Abstract

Firms frequently provide general skill training to workers at the firm's cost. Theories proposed that labor market frictions entail *wage compression*, larger productivity gain than wage growth to skill acquisition, and motivates a firm to offer general skill training, but few studies directly test them. We use unusually rich data from a temporary help service firm that records both workers' wages and their productivity as measured by the fees charged to client firms. We find evidence that skill acquired through training and learning-by-doing increases productivity more than wages, which is consistent with wage compression.

JEL classification codes: J24, J42
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1 Introduction

Employers frequently provide free training upfront for their workers to acquire apparently general skill. This observation poses a long-standing puzzle in labor economics because, in a perfectly competitive labor market, the wage offer for general skill is bid up to the value of the marginal revenue product of labor (MRP), and the return to human capital fully accrues to the workers. Thus, employers have an incentive to invest in general skill only when they can shift the cost of training to the workers by paying them lower wages than their productivity (Becker, 1964).

However, in reality, employers provide training opportunities that endow general skill to the trainees whose productivity is apparently not high enough to cover the training cost. Examples include the German apprenticeship system, long-term training offered by large Japanese firms, and general skill training offered by temporary help service firms before assignment to clients (Acemoglu and Pischke, 1998; Holzhausen, 2000; Krueger, 1993). Previous studies have attempted to resolve the puzzle by arguing that the labor market frictions enable firms to reap higher productivity than wage returns to general skill investment, creating *wage compression*, which motivates employers to invest in general skill training of workers (Acemoglu and Pischke, 1998, 1999a,b).[1] However, to our knowledge, no study has directly observed wage compression because measuring productivity growth due to human capital investment is fundamentally difficult.

We use unique worker level data from a temporary help service (THS) firm in Japan to directly observe the MRP of individual workers along with their wages. The business of the THS firm is to procure labor services from workers in the labor market and sell these services to client firms. In each transaction,

[1] Monopsony power that enables the firm to set wages below MRP alone does not necessarily motivate the firm to invest in general skill. Instead, a growing gap between MRP and wages with respect to skill accumulation, which is wage compression, motivates the firm to invest in workers' skills.

we observe both the wage paid to a worker and the fee charged to a client, which represents the MRP of the worker to the THS firm.[2] If the markup of the fee over the wage increases with skill formation through formal training or learning-by-doing, the THS firm has an incentive to offer formal training or assign a worker to a client with the opportunity of learning-by-doing even if the skill is technically transferable across firms. We directly test whether the gap between the fee and the wage increases with respect to formal training or learning-by-doing.

This firm's main service is to assign information communication technology (ICT) engineers to the client firms. The firm employs workers on permanent contracts and pays each worker a monthly salary regardless of whether or not they are assigned to a client. This in contrast to the standard practice of THS firms that hire workers only during the periods they are assigned to their clients. At the start of employment, the firm provides workers training opportunities to acquire or update their ICT skills. The data set covers the period between 2015 and 2020 for around 2,000 employees. Our analysis sample contains information on the monthly fees, wages, billable hours recorded for each worker, and the client the worker is assigned to. It also contains workers' background information such as gender, educational attainment, age, date (year-month) of the entry to the firm, and the branch location the worker is registered with. We infer a worker's training period from the initial non-placement period between being hired and first placed with a client. From this data, we are able to track the dynamic paths of the fee, wage, and billable hours of each worker.

[2] The fee provides a lower bound for the MRP of a worker at the client firm because the client firm will not hire a worker if the fee is higher than MRP. More specifically, if the product market (i.e. the THS service market) is perfectly competitive, the client firm will hire workers until the MRP is equal to the fee. In this case, the fee corresponds to the MRP of the marginal worker, while the MRP is greater than the fee among non-marginal workers. Alternatively, if the client firm has market power over the THS firm, they reduce the service purchase to suppress the fee; while if the THS firm has the market power over the client firm, the THS firm will reduce the service supply to increase the fee. In either case, the MRP at the client firm exceeds the fee.

The data from this THS firm has three attractive features for testing the hypothesis on the general skill training done at the cost of the employers. First, we can infer the length of the initial training period from the time between the start of a worker's employment with the firm and their assignment to a client. During this training period, workers are paid their full monthly salary and are not involved in the production activity. Thus the workers do not pay the training cost in the form of receiving lower wages than productivity. Second, the IT related skills acquired through the training is transferable across employers because workers are assigned to various clients.[3] Third, and most importantly, we directly observe the fee charged to the clients, that is the each worker's MRP, together with their wage. These features suggest that data provide an ideal opportunity to test the wage compression hypothesis.

We first document the career paths of workers in the firm by analyzing the length of their initial training period and tenure at the firm. This confirms that the THS firm typically provides training prior to the initial assignment to a client: the average training period is 2.2 months and varies across employees. Using survival analysis incorporating the right censoring of tenure length we find that workers with longer training periods have, on average, lower hazard rates and longer tenure with the firm. We also show that workers with high service fees charged to clients at initial assignments have substantially higher hazard rates, and that university graduates have lower hazard rates than non-university graduates. These results imply that the composition of workers changes with length of tenure at the firm; thus controlling for such changes is important when estimating tenure-fee and wage profiles, as emphasized in the returns to tenure literature (e.g. Altonji and Shakotko, 1987; Abraham and Farber, 1987; Topel, 1991).

[3] As evidence, during the training period the workers typically obtain network engineer certificates issued by CISCO that is widely recognized in the industry.

Next we examine the initial hourly fees charged to clients and wages paid to workers. Once a worker is assigned to a client, the initial fee is about 38% higher than their initial wage on average. The THS firm charges higher initial fees for workers who receive longer training but does not pay correspondingly higher wages, thus the initial markup rate is higher for those with more training. Although the algorithm determining the length of training is complicated and likely endogenous, this result is consistent with the wage compression hypothesis, and suggests the firm partially recovers the cost of longer training by increasing the gap between the fee and the wage.

We then track the evolution of fees and wages over the course of workers' tenure with the THS firm, to compare the MRP and wage returns to skill acquired through learning-by-doing on assignments to client firms. Controlling for observed worker characteristics and worker fixed effects, workers' wages are essentially constant over the first 15 months of tenure, while the fees charged to clients increase linearly at an annual rate of about 6%, so the markup increases similarly. After 15 months, fees increase at nearly 8% annually while wages increase at about 5.3%, resulting in a continuing annual increase in the firm's markup of about 2.5%. Controlling also for client fixed effects reduces the estimated annual fee growth by about 1% over the first 15 months and 2% after that, but has almost no effect on the estimated wage growth. This implies the firm is able to increase the fee charged by assigning the workers to clients with higher skill requirement, and workers do not share any of these gains in terms of higher wages. The difference between fee and wage growth associated with client switches suggests a further source of labor market friction. The finding that the firm appropriates the quasi-rent associated with client change and workers receive no benefit is consistent with the low prevalence of rent sharing found in the literature (Card et al., 2018).

Finally, we consider the value to the THS firm of hiring and training workers. We do this by estimating the internal rate of return (IRR) associated with the skill investment to the firm. This requires knowledge of the time horizon, and the indirect costs associated with hiring an additional worker, which include recruitment costs, administrative costs of dispatching the employees to the clients and the employer's contribution to the social security insurance. As a baseline scenario, we adopt a 5-year horizon which is approximately the estimated mean completed tenure, assume the costs of hiring a worker and other indirect costs. We then infer the cost of training from the training period length and initial monthly salary, and use the analysis of the training period, tenure length and the evolution of the markup, to calculate the expected return as the product of the expected probability of staying with the THS firm and the expected markup. From this, we estimate the IRR across all workers is 18.9%.[4] This high IRR suggests that the firm can recoup the initial training cost by appropriating the wedge between the fee charged on clients and the wage paid to workers.

It is worth noting that temporary work in the ICT sector differs considerably from that in other areas, for at least two reasons. First, temporary IT sector placements are typically relatively long.[5] This is partly driven by the placements being for substantial IT infrastructure projects which, together with the continually evolving nature of IT infrastructure, contributes to client firms' decisions to outsource such work to THS agencies rather than maintaining suitably qualified permanent workers.[6] Second, IT temporary workers are typically more

[4]The estimated IRR varies from 5% to 23% across a range of parameters that include varying the horizon over 4–6 years, the fixed costs of hiring over 100,000–300,000 JPY, and allowing up to 25% of operational costs as a component of the indirect labor costs.

[5]The average duration of client placements in our sample is 14 months (average completed duration is 12 months). In contrast, Autor (2001) reports annual turnover rates of more than 350% for THS workers in the US, and Segal et al. (1997) reports 53% of temporary workers exit within one quarter and 83% within two quarters.

[6]For example, Market-Research-Telecast (2021) reports that, in Germany, the maximum placement assignment for temporary workers is 18 months and that, for IT assignments, such a maximum duration is not practical because projects often take longer.

highly skilled than temporary workers in other sectors.[7] Although this suggests that temporary workers in the IT sector are atypical of broader THS workers, observing both the provision of training and the evolution of wages and productivity over workers' tenure facilitates analysis of the worker-firm relationship.

Our study contributes to the literature by directly testing the wage compression hypothesis first proposed by Stevens (1994) and further developed by Acemoglu and Pischke (1998, 1999a,b). Some of these studies provide evidence that is consistent with the theoretical prediction, but do not directly show the productivity return to skill investment is larger than the wage return at individual worker level. Using firm level data, research generally finds positive effects of training on productivity, that are often larger than the effects on wages, which implies that firms earn some of the returns to training and so have incentives to pay for it. For example, Dearden et al. (2006) estimated that a 1 percentage point (pp) increase in the fraction of workers receiving training increased value-added per worker by about 0.6% and average wages by 0.3% for firms in the UK, and Konings and Vanormelingen (2015) estimated a 1pp increase in the fraction of workers trained increased productivity by 0.17–0.32%, and average wages by 0.1–0.17% for Belgium firms. In contrast, recent evidence by Morikawa (2021) for Japan finds training has low but similar effects on both productivity and wages, with elasticities of about 0.02. Our study adds to the literature by showing the gap between MRP and wages based on worker level data.

The paper also contributes to the understanding of the operation of THS firms. In the context of upfront training provided by the firm, Krueger (1993) reports that about 60 percent of THS firms that provide secretarial services

[7] Purcell et al. (2004) compare case studies of temporary workers with ICT expertise in computing services, and routine peripheral temporary workers providing customer services to clients in various industries. Segal and Sullivan (1997) report only 20% of temporary workers in the US are college graduates (compared to 24% of permanent workers). In contrast, nearly two-thirds (63%) of workers in our sample have at least a college degree, which is comparable to the fraction among all ICT workers according to 2020 Census.

to the client firms offer computer training to its workers before assigning them to the clients and almost all the firms do so at the cost of the THS firms. Autor (2001) develops a specific model of THS firms to explain the upfront training offered to the workers. Consistent with the theoretical prediction, Autor demonstrated that THS workers who received training from firms earned lower wages. However, as his worker data does not contain the information on the fees charged to clients, a complete test of the theory was not possible. The present study fills this gap in the literature.

The rest of the paper is organized as follows. In the next section we begin by describing the data used in the analysis. In section 3 we provide background discussion of THS firms, and present a simple model of wage compression, based on Acemoglu and Pischke (1999b), to help motivate our analysis. We then document the patterns of the initial training provided to workers, and their subsequent tenure in section 4. In section 5 we present and discuss the main results of our analysis of the dynamics of workers' fees and wages, and the implications for the rate of return to training provision in section 6. The paper then concludes with a summary discussion.

2 The THS firm and their data

The main data used in this study is obtained from a THS firm, focusing on the Information Communication Technology (ICT) industries. The firm is based in the Kantō region, and has several branches located across Japan. The firm employs workers to provide a variety of temporary placements with clients to perform ICT-related tasks for varying period lengths. Throughout our discussion, we will refer to the temporary-help firm as the *firm*, the workers it employs as *workers*, and the client firms they are placed in as *clients*.

The THS firm hires its workers on permanent contracts including the periods the workers are not assigned to clients are used for training. This is in sharp contrast to the typical THS firms that hire workers on a contingent temporary contract basis to cover the service period provided to the client firms. The THS firm employs both non-college and college graduates, as well as workers with and without prior ICT-industry experience. The firm gives intensive training to its new employees before placing them with clients.[8] As we analyze in detail below, the new employees receive intensive training in training rooms in the corporate head quarters (see Panel A of Figure 1). The training program follows a standard curriculum originally developed by the HR section of the firm and emphasizes hands-on instruction, and trainees are assigned problems and solve the problems as a team (Panel B of Figure 1). The training curriculum includes server recovery for example: the instructor intentionally sets problems on the server and the trainees are supposed to diagnose and fix the problems (Panel C of Figure 1). At the end of the training period, the trainees are encouraged to obtain Cisco's CCNA certificate, which is the entry level certificate for network and program engineers.

Workers who complete the initial training program are then assigned to client firms. The clients are typically large firms that hire additional IT engineers to meet a temporary demand increase or outsources a part of IT tasks to the firm. The workers who are assigned to clients onsite are involved in network and server maintenance or software development. While client firms may poach workers to avoid paying the fee-wage margin, from discussions with the management, this appears to occur infrequently for two reasons. First, the large client firms tend to have high skill requirements corresponding to their high wage scale, and many workers cannot clear the bar.[9] Second, the THS and client firms

[8] In addition, workers may receive additional training between placement assignments. However, we ignore this as only 7.7% of workers have idle spells that last at least a month between clients.

[9] Japanese employment practices applied to permanent workers explains why client firms set a high bar to recruit their permanent workers. See Appendix A for the discussion.

generally have an ongoing relationship, and the THS firm has some bargaining power over client firms by assigning a group of workers: if a client poaches workers, the THS firm can abruptly stop assigning workers to retaliate. In addition, because of stringent employment protection laws in Japan, large firms tend to commit to long-term employment and use THS workers for short-term assignments and to accommodate evolving skill requirements.[10] Although being poached by client firms is not common, workers may quit the firm presumably because they accumulate the skill through the initial training and clients' onsite learning-by-doing and receive better wage offers from outside firms.[11]

The main dataset consists of a single pay record of each worker-client pair in each month, covering the period April 2015 to February 2020.[12] Each record includes the worker and client identifiers, the worker's monthly wage, the monthly fee charged to the client and the hours worked for (i.e. charged to) the client in the month.[13] In addition, workers' background characteristics, such as gender, age, education level, the month of entering the temporary help firm, and the

[10]Appendix A provides brief description of legal employment protection applied to workers on permanent contracts.

[11] The fraction of workers who are recruited but never assigned to a client is 16.0 percent in our data set. This high fraction does not necessarily mean many workers leave the firm because non-negligible fraction of workers are assigned to the internal development section of the firm. The firm operates a business section that develops their own products such as health care management system or automation system of the agricultural production.

[12]There are a small number of cases with multiple records in a month for a worker-client pair. According to a manager of the firm, this may occur due to billing additional charges, correcting for mistakes, or duplication of a record. For the first two cases, we need to sum multiple records to obtain the monthly amount. For the last case, the duplicated record should be dropped. To address these cases, we keep one record with an imputed fee and wage. To do this, we calculate both the sum of monthly fee (wage and hours worked), and the average of each across records for a worker-client pair in a month. Imputation is then made by choosing either the sum or the average that is closest to the client mean level, calculated over all worker-months. The hourly fee and hourly wage are then calculated based on the imputed data. About 2.7% of records are dropped in this adjustment.

[13]For a few records (1.6% of the main sample), the actual hours worked in the month are not observed in the data; instead we observe upper and lower bounds ($hoursmax$ and $hoursmin$) of "regular working hours" of a worker-client pair and some adjustment factors (e.g. overtime hours, deductible hours, etc.). In such cases, we impute the hours using the worker's "regular hours" at the client as follows: (1) using other observable records of the worker-client pair, we calculate the location of regular hours within the range as a fraction: $frac = \frac{\text{actual hours worked} - hoursmin + \text{adjustment factors}}{hoursmax - hoursmin}$; (2) calculate the average location of the worker-client pair $\overline{frac}$; and (3) impute the missing hours with $hoursmin + \overline{frac} \cdot (hoursmax - hoursmin) + \text{adjustment factors}$.

branch location the worker is registered at, are collected and merged to the main dataset. The resulting data set is a worker-month panel data.

We first restrict the sample to observations on workers who joined the temporary-help firm in or after April 2015, when the earliest pay record is available. As workers only appear in the data once they are assigned to clients, new employees being observed implies that they start working at the clients right after joining the firm. Shorter than average training periods are possibly associated with higher skill or longer prior experience, leading to a positive selection concern. For this reason, workers entering after November 2019 are also excluded from the sample to ensure a minimum of three-month-stay at the firm over the observation period that ends in February 2020. Observations on workers at one branch are excluded due to the small numbers. Because the wage-tenure relationship appears to become relatively unstable over long tenure range, we also drop observations with tenure greater than 48 months (the 99th percentile). The process above results in a full sample of 35,414 monthly observations on 1,908 workers and 412 clients.

We calculate the hourly fee and wage by dividing the monthly fee and wage by the hours worked, and calculate the relative markup by dividing the fee by wage. The worker's tenure with the THS firm is measured as the number of months from entering the firm to the current month of record. We define the initial training period (discussed in detail later) as the number of calendar months from when a worker joins the firm until they are assigned to their first client. For example, if a worker enters the firm in April and is assigned to a client in May, the training period is defined as one month. We estimate the worker's potential work experience in years as *(age - years of education - 6)*.

Because workers commonly start or end a placement *during* a month, the fee charged for the first and last placement months is typically lower than the intervening months reflecting the shorter actual service hours. In contrast, the worker is paid their full-month wage regardless of the shorter hours worked at the client. Thus, calculating the hourly wage for these months by dividing the monthly salary by the service hours provided to the client is misleading because the calculated hourly wage does not accurately correspond to the compensation for the labor service provided to the client. For this reason, we replace the hourly wage in the first and last month of each worker working at each client with the second and second-to-last month wage respectively. A consequence of this is that we require worker-client spells to last at least three months, and placements of less than 3 months are excluded, since the 'regular' monthly hours worked and thus wage rate are not available. This restriction results in the exclusion of about 2% of monthly observations: our main analysis sample consists of 34,729 observations from 1,784 workers and 376 clients.

Table 1 provides summary statistics of the full sample and the analysis sample. The comparison of the means for the full sample reported in column 1 and the analysis sample in column 2 indicate how dropping the worker-client pair that lasts less than three months affects the sample characteristics. Except for hourly wage, the average characteristics of the two samples are almost identical. As for hourly wage, the mean wage of the analysis sample is about 10 percent lower than the mean wage of the original sample. This lower average wage is largely due to the hourly wage adjustment in the first and last month for each worker-client pair.

Focusing on the analysis sample reported in column 2, female workers make up about one-third of the sample. The firm employs mainly younger workers, with their average age being 27 years, and average (post-education) experience of 6 years. About two-thirds of workers hold at least a bachelor's degree. Workers' average initial training period is 2.2 months, and their average tenure is 16 months.[14] The average hourly fee charged to the clients is 2,885 yen, while the average hourly wage is 2,043 yen, and the average fee/wage ratio is 1.43. The average hourly wage is slightly lower than the national average of 2,300 yen and substantially lower than the internet related service industry average of 2,860 yen.[15] On the other hand, the average fee/wage ratio is slightly lower than the national average of 1.53, and is near the bottom of the 35–65% range for THS work in the US reported by Autor (2001).[16] The average monthly billable hours worked is 156 hours, which is about the hours worked by a full-time workers (8 hours per day for 20 days). The initial hourly fee is slightly lower than the average hourly fee, consistent with there being fee growth. In contrast, the initial hourly wage is slightly higher than the average hourly wage: as we discuss in detail below, this reflects negative selection of workers over tenure; and the initial fee/wage ratio of 1.38 is also lower than the average fee/wage ratio, implying the markup grows with tenure.

The gender differences in the analysis sample, shown in columns 3 and 4, are rather minor. Males are about 1 year older than females, with correspondingly more potential experience when they join the firm. Males are less educated than female: 61 percent of males have a University qualification compared to 67 percent of females. Males also receive on average 0.2 months less initial training, and have about 1 month longer tenure, than females. Average male and female

[14]Note that all averages reported in Table 1 are measured across monthly observations including right censoring observations. The average maximum tenure across all workers is 22.3 months, the average completed tenure across workers with completed spells (30.7% of all workers) is 20 months, and workers' average completed tenure estimated using the log-normal model below is 58.7 months. Right censoring will be discussed further in section 4.2.

[15]According to the Basic Survey of Wage Structure of 2017, the average monthly regular cash compensation was 333,800, the average bonus compensation in the previous year was 905,900, the average scheduled monthly hours was 165 and the average overtime was 13 hours. The average hourly wage is calculated as (333,800+905,900/12)/(165+13) = 2,300. The average hourly wage among employees in internet related service industry was 2,860 yen based on the same method.

[16]The mean hourly fee of THS firms was 2,644 yen and hourly wage was 1,729 yen in 2017 according to Annual Report of THS Service by Ministry of Health, Labor and Welfare. Implied relative mark up is 1.53.

fees and wages are quite similar. The relatively minor gender differences in fees and wages suggest that we can pool both male and female in the analysis.

3 Theoretical Background

This section provides two theoretical discussion to understand the operation of THS in the labor market and their behavior on workers' skill investment in the framework of Acemoglu and Pischke (1999b) to set the ground for the empirical analysis.

3.1 The function of THS in the labor market

In this subsection we discuss the functions that THS firms play in the labor market and how they potentially earn quasi-rent. THS firms exist in the labor market because of the presence of labor market frictions. Client firms experience labor demand fluctuations in response to idiosyncratic shocks and over the business cycle, while workers experience supply fluctuations, for example associated with health shocks or unexpected changes in family responsibilities.

In a perfectly competitive labor market, there is no need for THS because with complete information, competitive markets determine wages such that job vacancies and job seekers are matched immediately. However, in reality, information is not complete in the labor market: information on job vacancies and job seekers is sporadic, and the quality of job candidates is not perfectly known to the employer. Autor (2009) remarks that THS firms cover the sunk cost of job search by identifying, screening and hiring workers. THS firms recoup the sunk cost from the gap between the fee charged to clients and wages paid to workers. Indeed, Smith and Neuwirth (2009) describe the operation of THS firms, and highlight how they select good employees and retain them at relatively low cost.[17] Purcell et al. (2004) report the case of a THS firm that assigns Information and Communication Technology (ICT) engineers to client firms to fill the growing demand for the engineers in the client firms. This case emphasises that the THS firm has a comparative advantage in hiring and training ICT engineers compared with the client firms.

Client firms use THS providers to save on the search costs of hiring workers or the costs of laying off workers associated with labor demand fluctuations over time. On the other hand, THS firms absorb the risks of demand fluctuations of individual client firms by pooling clients to smooth out the idiosyncratic shocks of labor demand. In this framework, THS firms act as insurance providers, exploiting the benefits from the law of large numbers by pooling idiosyncratic shocks to clients. Similarly, THS firms smooth the idiosyncratic labor supply shocks by pooling workers. Any insurance premiums to clients and workers will contribute to the gap between fees charged and wages paid by the THS firm.

THS firms also benefit from information rent. Through its operation, a THS firm accumulates information on workers as well as clients that is costly to acquire. Through the screening and training process, the firm accumulates private information on workers' quality and their comparative advantage. Similarly, through assigning workers to clients, the firm can accumulate knowledge on the tasks implemented on jobs, the skill requirements, and the work place environment of client firms that is costly to acquire. A THS firm can utilize its accumulated information on workers and clients to improve worker-client matches and earn the information rent in the form of the gap between the fee and the wages.

The functions that THS firms play in the labor market discussed here explains why there is a gap between fees and wages. Thus, labor market frictions

[17] In a general equilibrium search model, Neugart and Storrie (2006) incorporate THS as an agent with high matching efficiency.

explain the static markup between wages and fees. In addition, Japan's less flexible labor market (see Appendix A) and thinness of ICT engineer market (Purcell et al., 2004) may increase the value of THS firms. However, this discussion does not explain how the skill investment in workers affects the subsequent markup. To explain the provision of general training upfront by THS firms, in the next subsection we present a simplified version of a wage compression model (Acemoglu and Pischke, 1999b), that clarifies under what conditions THS firms invest in workers' general skill upfront.

3.2 Wage compression and general human capital investment

This subsection presents a simple two period model for the firm's decisions regarding training, wage and fee settings. Our model captures the essence of Acemoglu and Pischke (1999b), and aims to motivate our empirical analysis.[18] We assume constant returns to scale in order to abstract from the determination of the number of workers employed.

In the first period, the firm hires a worker at wage w_1 and trains her with the intensity τ with the cost of training $c(\tau)$. Note that the opportunities for skill formation τ is provided through either formal training or assignment to client firms that enables on-job learning-by-doing in our context. The cost function is a strictly convex function and satisfies the Inada conditions $c' \geq 0$, $c'' > 0$, $c'(0) = 0$ and $c'(\infty) = \infty$. No production takes place in the first period. The training amount τ is public information and outside firms observe it. We assume that a fraction $(p : 0 < p < 1)$ of workers quit between the first and the second

[18] Although Autor (2001) explicitly models the operation of THS, we do not adopt his modelling because the source of the labor market friction is the information asymmetry between incumbent THS and outside firms. Modelling information asymmetry as a source of labor market imperfection is similar to Acemoglu and Pischke (1998). These models predict a positive selection of workers over workers' tenure because incumbent firms terminate the contracts with low ability workers, but our empirical results show the opposite. Thus, we do not employ these models.

periods for exogenous reasons.

In the second period, the THS firm produces a service flow by assigning the worker to a client firm, which is represented by the fee charged to the client, $f(\tau)$. Note that the fee $f(\tau)$ is MRP from the view point of the THS firm, while it is not necessarily so from the view point of the client firm. Given the outside option of the worker $v(\tau)$, the firm pays a wage w_2: $w_2 = v(\tau) + \beta(f(\tau) - v(\tau))$, where β $(0 < \beta < 1)$ is the Nash bargaining power of the worker.

The firm's problem is to maximize the following profit expression:

$$\pi(\tau) = (1-p)(1-\beta)(f(\tau) - v(\tau)) - (c(\tau) + w_1), \tag{1}$$

assuming a zero discount rate, by choosing the intensity of training, τ. The first order condition is

$$(1-p)(1-\beta)(f'(\tau^*) - v'(\tau^*)) = c'(\tau^*), \tag{2}$$

where τ^* is the optimal intensity of training. With the above assumptions on the cost function, β and p, $\tau^* > 0$ if and only if $f'(0) - v'(0) > 0$. This condition requires that the marginal return to training in terms of the service fee must be higher than that in terms of the wage for the training investment takes place. This condition is known to be *wage compression* in the literature and we test if this condition holds in terms of skills acquired through upfront training and learning by doing.

4 Upfront training and workers' tenure

Theories of firm provided general training argue that the employer provides the general training upfront and recoups the investment cost over time from the retained workers. In this section, we examine how much training the THS firm provides, and how the firm succeeds in retaining its workers.

4.1 Length of training period

The THS firm provides IT skill training upfront. How intensive is the training? While we do not have direct record of training participation, all the workers including trainees are employed on a full time basis, thus we can infer the training period from their date of the entry to the firm and the first month placed with a client.

To describe the training period inferred from the dataset, Figure 2 presents the distribution of the length of the initial training period, measured as the number of months between when a worker is hired by the firm and first assigned to a client. This figure implies that the training period typically lasts for 1-3 months for most of the workers. That is, about 3% of workers are placed with a client in their first month of employment, while about three quarters (74%) of workers have 1-2 months of training before placement, 13% have 3 months, and the remaining 10% have 4 or more months of training before being placed. The median and modal training period is 2 months, and the average is about two and a quarter (2.3) months.[19]

The length of training varies across workers for several reasons. In theory, both positive and negative self-selection occurs. If a worker who is identified as eligible receives extended training so that the firm can assign them to a client project with high skill requirement, then the ability of the worker and the length of training is positively associated. On the other hand, the firm may extend the training period for slow learners, in which case the ability of a worker and the length of training is negatively associated. A corporate executive claims that

[19]The mean length differs slightly from that reported in Table 1 (2.2 months), because Table 1 reports the descriptive statistics calculated over worker $\times$ month observations whereas the descriptive statistics reported here is calculated based on worker observations.

both cases occur, but the positive self-selection is more probable because the firm often trains eligible workers for a longer period to assign them to projects with high skill requirements.

To examine whether there is significant heterogeneity in the training period across workers' demographic characteristics, we regress the number of months of training on workers' observed characteristics, and present results in Table 2. In column 1, we tabulate the OLS estimates without controlling for the entry cohort fixed effect. These results confirm there are statistically significant gender and education differences in training, with women and workers with university education receiving about one-quarter of a month (1 week) more training than men and those with less education on average. But differences across other dimensions are not statistically significant. The finding that university graduates receive longer training is consistent with the finding in the literature that educated workers are more likely to participate in training programs (Brunello, 2004; Ikenaga and Kawaguchi, 2013). Since the data set covers various entry cohorts, we estimate the same model with cohort fixed effects. The results reported in column 2 are not substantially different from those in column 1.

4.2 Job tenure with the THS firm

The THS firm potentially recoups the cost of training from retained workers, through the surplus (markup) between the fee charged to clients and the wage paid to workers. Thus the length of tenure of its workers critically determine the return from the upfront general skill investment.

One feature of the tenure length variable is right censoring associated with ongoing tenure at the end of the sample period. In particular, 69.3% of workers in our analysis sample have right-censored employment spells (i.e. are still employed at the sample end). Figure 3 draws the Kaplan-Meier survival estimate that indicates the probability of staying with the THS firm by the month of tenure, addressing the right-censoring issue. The figure shows there is little separation during the first six months of tenure and separation then occurs at a fairly constant rate after that. The estimated annual separation rate is 9.2%, comparable to the average level in the information industry,[20] and slightly fewer than one half of workers stay with the THS firm more than 48 months.[21]

Our goal is to estimate the growth rates of fees and wages, but workers' composition changes over tenure if the workers' complete tenure are different across workers' observed and unobserved characteristics. As the literature on the return to tenure shows, the systematic change of the workers composition poses a challenge in the estimation of the growth rates of fees and wages along with tenure.[22]

To illustrate the selection over tenure, Figure 4 shows the means of initial hourly fees and wages by the length of tenure. Both initial fees and wages are individual specific and if the attrition occurs at random, the means of these variables should be constant over tenure. In contrast, the mean of the initial fee decreases over tenure length, suggesting that the employees with high initial fees are more likely to quit. On the other hand, we do not observe a systematic change in mean wages by employees' tenure. The high initial fee arguably captures the high skill of the employees and thus decreasing mean initial fees over tenure implies that the employees are negatively selected over tenure.

Some workers leave the THS firm early and others have long tenures. To examine the determinants of workers' tenure length, we estimate duration models, allowing for right censoring of the tenure variable. Among the parametric du-

[20]According to the survey of employment dynamics, the annual separation rate in the information industry was 9.6 percent in 2019.

[21]Furthermore, among workers who started with the firm in 2015 (the first year of observation), 56% have right-censored spells, the average maximum tenure of workers is 39 months, and the average completed tenure (i.e. among those who are not right-censored) is 32 months.

[22]Altonji and Shakotko (1987), Abraham and Farber (1987), and Topel (1991) are the representative works in the field.

ration models, we choose the log-normal as the baseline hazard function among alternative baselines, such as Exponential, Log-logistic, Weibull and Generalized Gamma, using the Akaike information criterion.[23] Figure 3 shows that the survival rate predicted with log-normal model is similar to the Kaplan-Meier estimates.

We also attempt to characterize the composition changes of workers' quality over tenure. We control for a quadratic in potential years of labor market experience, and indicator variables for female, 4-year university graduates, and the firm's branch location. In addition, we include the initial fee charged to the client, the initial wage paid to the worker and the initial markup as explanatory variables to proxy for unobserved worker quality effects.

Table 3 reports the estimates of the log-normal hazard model. The estimated coefficients show the effects on the hazard relative to the baseline hazard rate: a coefficient larger than 1 implies higher hazard rate than baseline, and smaller than 1 implies lower hazard rate than baseline. Since the initial fee, wage and markup are highly co-linear, we include each variable separately in turn.[24] We consider alternative specifications to handle the heterogeneity using either monthly fees (wages or markup rates) and hours worked, or *hourly* measures of fees, wages and markup rates.

The first three columns of Table 3 report the regression estimates of the specification using the initial *monthly* fees, wages and the markup, along with the hours worked as the explanatory variables. We find that the length of a worker's initial training period is (positively) associated with lower hazard rates, hence longer tenures with the firm.[25] For example, the estimates imply

[23] The estimates based on Cox proportional hazard model, where the shape of the base line hazard function is not specified, provide almost identical estimates.

[24] We have also estimated specifications that include both the initial fee and wage. This results in the respective estimated coefficients becoming extenuated relative to those presented in Table 3, but otherwise the results are largely consistent.

[25] This is consistent with Royalty (1996), who finds that training is associated with lower turnover. The effects are statistically significant in the specification including either the

that an extra month of training is predicted to lower the hazard rate by about 2.5 percent. Interpreting this effect is complicated by possible endogeneity of the training offered by the firm. For instance, the firm may provide more intensive training for the workers that are expected to have longer tenures. For this reason, we do not interpret it causally; nonetheless, it does suggest training may have positive effects on workers' tenure at the firm.

Column 1 of Table 3 shows that workers with high initial monthly fees are (statistically significantly) more likely to separate: a 10 percent higher fee is predicted to increase the hazard rate by about 4.9 percent ((1.486-1) $\times$ 0.1). This large coefficient implies workers are dynamically *negatively* selected over tenure. While workers with the high initial fee are attractive to the THS firm, this result suggests the firm struggles to retain them under the current wage scheme. Column 2 shows the opposite that workers with high initial monthly wages have statistically significantly lower hazard rates. Consistent with these results for fees and wages, the results in column 3 show that a high initial fee-wage margin significantly increases the hazard rate. Initial hours worked do not appear to be systematically related on the hazard rate.

The final three columns of Table 3 replicate the results using the initial *hourly* fees, wages and the markup. The estimates are broadly similar to those in the previous columns, although with more muted effects: workers with higher initial hourly fees or markups are more likely to separate, while those with higher wages are less likely to (but not statistically significantly so). Consequently, the workers with low outside options stay with the firm and as such workers will be negatively selected over tenure.

In addition, the results in Table 3 imply there are important composition change of workers in terms of observed characteristics. Across the specifications,

initial fee or markup, but not with initial wage (columns 2 and 5); however, the coefficients are similarly sized across the specifications.

we robustly find that university graduates are about 9-13 percent less likely to separate at any moment of the tenure. In this regard, workers are *positively* selected over tenure. Furthermore, the gender differences in the hazard rate suggest female workers are 8-10 percent more likely to separate than the male workers, though they are not statistically significant.

To summarize the findings from the survival analysis of the tenure length, we find that the workers with longer training periods are less likely to separate, while those with high initial fees are more likely to separate. Thus, the average initial fee decreases as the tenure increases because of the composition change of workers. On the other hand, university graduates are systematically less likely to separate, thus the fraction of workers with university degrees increases as tenure deepens. In the end, the workers' selection over tenure is nuanced and complicated. Thus, the estimation of fee, wage and markup growth without correcting for composition changes may suffer from either the upward or downward biases. A main take away for the fee and wage growth analysis is the importance of controlling for the composition change of workers both in terms of unobserved and observed characteristics.

A few comments on the relevance of the survival analysis results and the theoretical predictions. According to the models that generate wage compression because of the information asymmetry in the labor market (Acemoglu and Pischke, 1998; Autor, 2001), the gap between MRP and wages originates from the information rent. That is, the firm selects only high ability workers based on their private information, resulting in dynamic positive selection of workers. In contrast, we find evidence of dynamic negative selection of workers over tenure, likely because high skilled workers receive better outside offers. Thus, our empirical findings are not consistent with the prediction of wage compression due to the information asymmetry. That the wage compression occurs for reasons other than information asymmetry, such as labor market friction, indicates our findings on the selection do not contradict the wage compression hypothesis in general.

5 Fees and wages

The THS firm presumably attempts to recoup the upfront cost of general skill investment from the gap between the fees charged to clients and wages paid to retained workers. In this section, we analyze first how the initial fees and wages are determined, and then how these variables evolve over workers' tenure with the firm.

5.1 Initial fees, wages and markup

After the initial general skill training period, each worker is assigned to a client firm. We next consider how fees and wages are determined in this first assignment. In particular, we examine how the initial fees, wages and consequent markup are related to workers' characteristics and, importantly, the length of their initial training.

First, in Figure 5, we plot the average initial assignment fee and wage by the length of training period in month. The left panel shows that the length of training and the average initial fee are positively correlated, with the average fee increasing almost monotonically with length of training. While the average fee among workers who receive at least 6 months of training is relatively high, as shown in Figure 2 few workers receive this amount of training. In contrast, the right panel shows no obvious relationship between the length of training and the average initial assignment wage. These figures suggest that MRP increases with the length of training but wages do not.

Next, we examine the relationship between the length of training and the fee and wages, conditional on observed characteristics of workers. Table 4 reports regression results of the first month initial fees, wages and markups on the workers' characteristics and the length of their training period. The explanatory variables include a quadratic in potential years of labor market experience, and indicator variables for female, university graduate, as well as controls for the firm's branch location, and the month-year of entry to the firm. First, consistent with Figure 5, we find that workers' length of training is positively correlated with the initial fees charged to clients (each month of training is associated with 1.8% higher fee), but is uncorrelated with the wages paid, and so is also positively associated with the initial markup.

We also find statistically significant effects of potential experience on fees, wages and markups. Not surprisingly, we find that more experienced workers are paid higher wages and generate higher fees: we estimate a (weakly) convex relationship between the initial fee and years of potential experience (column 1) (i.e. a weakly positive second derivative), and also between initial wages and potential experience (column 2). These two convex relationships generate a weakly concave relationship between the initial markup rate and potential experience (column 3): the log(markup rate) increases in potential labor market experience up to 23.7 years of experience (i.e. $23.7 = 0.009/(2 \times 0.00019)$). Given the average potential experience in the analysis sample is 6.4 years, this implies the THS firm gains a higher margin by hiring more experienced workers. These results again suggest that worker skill, in terms of potential experience, is more strongly associated with the fee than with the wage. While the years of potential experience is public information equally observed by the incumbent firm and outside firms, the THS firm appears to capture the rent from the labor market friction. Finally, we estimate that initial fees, wages and markups are only weakly related to gender and education level.

The patterns of the relationship between training and fees and wages are consistent with the theoretical prediction that a worker's skill increases their productivity at the firm, but does not increase their outside option. However, establishing that these reflect causal impacts of training is difficult because the length of training is a choice variable of the firm. There are two possible sources of endogeneity. First, training may be endogenous to the initial client placement, in that the firm must ensure the worker has the required skills before starting a placement.[26] That is, more complex placements that require higher levels of skills will typically require more training, and such placements are expected to pay higher fees. In this case, the placement endogneity explains the amount of training received by the worker, but does not threaten the causal interpretation of the relationship between training and fees, if the firm's assignment of workers to the complex placements is orthogonal to the workers' ability.

Second, training may be positively or negatively selected on workers' ability, which will bias up or down the true (causal) effects of training on productivity and wages. For instance, the firm may prolong the training period of those workers who exhibit high ability during the training period and dispatch such workers to the clients charging high fees. Alternatively, more training may be required for less able workers. However, given that initial wages are uncorrelated with the training suggests that any positive selection bias in the estimated productivity effect of training is orthogonal to skills rewarded in wages.

Disentangling these two possible selection effects to identify the causal effects of training is beyond what is possible with the current data due to the lack of credible exogenous variation in training length. However, given the provision of training is costly, the firm provides longer training to workers because they expect the workers will acquire skills necessary to fulfill the requirements

[26]This does not imply the training provided is 'client-specific' training, although it is likely to involve alternative task-specific modules.

of clients. Therefore, we argue that longer training periods increase the productivity of workers, admitting possible overestimation of the impact. Also, these patterns suggest that the firm is able to recoup the cost of training investment due to the rent created by the friction in the labor market (Acemoglu and Pischke, 1999b).

5.2 Growth rates of fees, wages and markups

Thus far we have analyzed the effect of the initial training on the initial assignment fees and wages to analyze the returns to skill accumulation through formal training. Worker skills are also formed through their experience at client sites via learning-by-doing or on-the-job-training.[27] We now examine how such skill acquired on the job affects fees and wages. For this purpose, we analyze the growth rates of fees, wages and markups with tenure to shed light on the division of the return of skill upgrading between the firm and the workers.

Our analysis begins with a linear returns to tenure model, which captures the main results. But, based on the empirical pattern of wage growth, we then extend this baseline model to consider a linear spline model.

5.2.1 Baseline linear model

For our baseline analysis, we estimate alternative specifications of the linear tenure model:

$$\ln(Y_{ijt}) = \beta_1 Ten_{it} + \beta_2 Train_i + X_{it}\gamma + c_i + d_j + u_{ijt}, \tag{3}$$

where Y_{ijt} is either the hourly fee, wage or markup of worker-i at the client firm-j in month-t; Ten_{it} is the worker's current tenure in months (measured

[27] The distinction between learning-by-doing and on-the-job-training is conceptually clear as articulated by Heckman et al. (2002), but empirical distinction is difficult with our data.

in years); $Train_i$ is the length of training period; X_{it} is a vector of control variables; c_i and d_j are worker and client fixed effects respectively; and u_{ijt} is an idiosyncratic error term. We estimate the model weighted by monthly service hours, and cluster the standard errors at the worker level. In contrast to the literature (e.g. Abraham and Farber, 1987; Altonji and Shakotko, 1987) that emphasizes the importance of job matching in estimating the returns to tenure in wages, we do not require controls for the worker-firm match effects, because our data comes from a single firm and the worker fixed effects fully captures the worker-firm match effects. In specifications with worker fixed effects, the training period is absorbed in the worker fixed effects. Furthermore, we are able to control for client fixed effects to examine the contribution of changing clients on the evolution of the firm's fees and a worker's wages.[28]

Due to the standard identification problem associated with co-linearity of cohort, age, and time effects, we cannot include both year-month and individual fixed effects along with the tenure length. That is, conditioning on individual worker fixes the starting date and thus adding the tenure length exactly matches a specific year and month as pointed out by Card et al. (2018) in general context of employer-employee matched data. Instead, we control for regional time varying labor market effects using the quarterly unemployment rate measured for nine regions, and regional inflation using the consumer price index (CPI).[29] We also control for the length of the worker's initial training period, gender, education, a quadratic in initial potential experience, and the firm-branch.

As expressed, equation (3) assumes that the natural logarithm of hourly fees, wages and the markup depend linearly on tenure length. In order to check

[28]The client effects will capture both the average complexity across placements within a client, as well as the client premium conditional on the complexity of a placement. We are not able to distinguish these factors in the data.

[29]The unemployment rate is based on monthly Labor Force Survey. The finest unemployment rate published is at nine regions and quarterly periods to assure the precision of the estimates. The 2015-base monthly CPI for ten metropolitan areas is published by the Statistics Bureau of Japan.

this, we have estimated non-parametric tenure profiles using separate dummy variables for each tenure month. More specifically, we estimated the model:

$$ln(Y_{ijt}) = \sum_{s=1, s\neq 4}^{48} \beta_s \mathbb{1}[Ten_{it} = s] + X_{it}\gamma + c_i + u_{ijt}. \tag{4}$$

The model includes the individual fixed effects because the previous analysis points to the importance of the selection.

In Figure 6 we plot each of the estimated hourly fee, wage and markup tenure profiles (together with their 95 percent confidence intervals) from equation (4) with the same observable controls discussed above.[30] The pattern of fee growth appears remarkably linear, with fees increasing at about 5% annually. In contrast, wages appear roughly flat over the first 18 months or so, before rising approximately linearly and in parallel to fees after that. These patterns imply the markup increases at approximately the same rate as fees over the first 18 months, and then much slower after that as wages increase. Given these patterns, we will estimate both simple linear specifications for each of the (fee, wage and markup) outcomes, as well as linear-spline versions allowing for a break in trend after a certain threshold.

We begin by summarizing the results from models with linear tenure profiles. Table 5 tabulates the tenure coefficients from five alternative regression specifications for equation (3) for hourly fee in column 1, hourly wage in column 2, and hourly markup in column 3. In the first model, we include only the vector of control variables in addition to tenure, and estimate statistically significant positive effects of tenure on each outcome, of 1.0% per year for the

[30] The figures do not show coefficients for the first three months as these estimates are noisy because many workers are in their training period. We have also estimated specifications controlling only for observable characteristics, and also including client or worker-client fixed effects (analogous to models 1–5 described below). The profiles are similar in terms of the linearity of fee growth, and non-linearity in wage growth to those in Figure 6 when client fixed effects are included, and steeper than when worker and client fixed effects are excluded. A similar exercise for monthly hours worked shows average hours decline somewhat with tenure.

hourly fee charged, 0.4% for the hourly wage, and the difference between these (0.6%) for the hourly markup. When we include worker fixed effects (model 2), the estimated tenure effects are substantially higher than those for model 1: we estimate that fees increase 7.2% annually, wages increase 3.4%, and the markup wedge increases 3.7%. The substantial downward bias of the tenure profiles of the OLS estimates reflects the negative selection of employees over tenure. Thus, we treat the model estimates with employee fixed effects as preferred estimates.

In the subsequent models presented in Table 5, we also control for the clients that workers are assigned to, using either client fixed effects (model 3), additional controls for the client order (model 4), or worker-client fixed effects (model 5). The estimated tenure effects are comparatively stable across these three models. The annual growth in workers' hourly wages in these models (3.2-3.4%) is very similar to that in model 2, implying wages paid by the firm are independent of client effects. In contrast, the estimated growth in the hourly fee charged by the firm for workers is substantially lower in model 3 (5.5%) than that estimated in model 2 (7.2%); and as a result there is also variation in the estimated effect on the hourly markup across these models.[31] Adding client order (model 4) or worker $\times$ client fixed effects (model 5) has little effect on the estimated growth rate (5.0%), implying that the worker-client match does not play important role. The linearly additive worker and client fixed effects imply that the unobserved skill possessed by a worker is transferable across clients and thus general skill.

Comparing the estimates of fee growth from models 2 and 3 implies nearly one quarter (1.7%) of the 7.2% growth in model 2 is associated with the firm improving the assignment of workers to clients paying high fees. However, the

[31] To estimate the client fixed effects on top of the worker fixed effects, we need to have client changes within an individual worker. In the analysis sample, 40% of workers have 2 or more client placements, and workers are assigned to 1.6 clients on average, with an average assignment length of 14 months. These client changes are sufficient to identify the client fixed effects.

wage growth estimates imply none of this improved client quality effect is passed on to the workers in terms of higher wages.[32] The finding that THS firm assigns its experienced employees to high-fee clients over time but does not increase their wages at the timing of client change is consistent with the presence of the labor market friction. Thus the THS firm fully captures the rent due to the accumulated skill through learning-by-doing. The finding that the quasi-rents associated with client change all accrue to the firm and not to workers is consistent with the low incidence of rent sharing found in the literature (Card et al., 2018). That temporary help workers do not engage in rent-sharing is perhaps not surprising given their relatively short tenures with the firm. How much workers on alternative labor contracts benefit from rent-sharing is an interesting future research direction.

5.2.2 Linear-spline model

Close examination of Figure 6 suggests that the hourly wages are essentially constant until around month 18 and then grow linearly. Given this, we now relax the linearity assumption on the relationship between tenure in month and natural logarithm of fees and wages. We capture this kink in the wage profile by adopting a linear spline function with a single knot.

The linear spline model extends equation (3) as:

$$\ln(Y_{ijt}) = \beta_{11}Ten_{it} + \beta_{12}Ten_{it}\mathbb{1}[T_{it} \geq \bar{T}] + \beta_2 Train_i + X_{it}\gamma + c_i + d_j + u_{ijt}, \quad (5)$$

where the threshold $\bar{T}$ is the knot that determines the kink point of the linear functions. We have estimated the model for wages with $\bar{T} = \{12, ..., 24\}$ and

[32] To understand the client effects on fees and wages, for workers who are assigned to at least two clients, we have also conducted an event study for fees and wages around the start date with the second client. From this, we observe steady growth in fees of about 5% annually, both before and after the client change, and a discrete jump in fees of about 10% at the time of client change. In contrast, wages show much weaker growth and no jump associated with the change in client. These patterns are consistent with the results in Table 5.

calculated the R^2 for each model. We find the R^2 for the wage equation is maximized with $\bar{T} = 15$, and choose this as the knot point. We apply the same knot point for the fee and the margin equations.

Table 6 summarizes results from the linear-spline tenure profiles with the knot point at 15. The estimated tenure effects for the fee models (columns (1) and (2)) are generally similar to those in Table 5, with small and statistically insignificant changes after 15 months, except for model 2 with worker fixed effects. In contrast, the estimates for the wage models 2–5 confirm there is essentially no wage growth over the first 15 months after controlling for worker fixed effects; and after 15 months wages grow relatively strongly by 5.1–5.3%. As a result of the roughly linear fee growth and linear-spline wage growth, we estimate stronger growth in markup over the first 15 months followed by much weaker growth, than in the linear models in Table 5. For example, the estimated markup growth is 6.7% over the first 15 months and 2.6% growth after that in model 2; and 5.8% and 0.6% respectively for model 3.

The difference in the estimated fee growth in the models with and without client effects in Table 6 are broadly consistent with those in Table 5. The results imply that client quality effects become more important with tenure, accounting for 0.9% of the 6.2% annual growth over the first 15 months, and 2.1% of the 7.9% growth after that. Again, we find that workers' wage growth is independent of such client quality improvement, implying the firm does not pass on any of these benefits to the workers in terms of higher wages.

Based on the results in Tables 5 and 6, and consistent with the non-parametric profiles in Figure 6, we conclude that the hourly fee-tenure profile is adequately characterized by a simple linear specification, while the wage and markup profiles are better characterized by linear-spline profiles. However, for consistency in specifications across the outcomes, we will continue to report both linear and linear-spline model results for each outcome.

5.2.3 Heterogeneous returns to tenure across employees

The estimates of the fee-tenure and wage-tenure profiles suggest that the THS firm has monopsony power among the retained workers because of the labor market friction. The degree of labor market friction can well be different across workers depending on their background characteristics. For example, the literature points to the difference in the labor supply elasticities between male and female explains the gender wage gap (Manning, 2013; Barth and Dale-Olsen, 2009; Webber, 2016). Motivated by this prediction, we next consider whether the tenure effects are constant across workers, or whether these vary systematically across some identifiable dimensions. To do this, we extend the linear and linear-spline models (equations (3) and (5)) to include interactions of the tenure profile with workers' observed characteristics, including quadratic in initial experience, and dummy variables for female, 4-year university graduate and the branch fixed effects.

Table 7 summarizes the linear-tenure specification results for the hourly fee, wage and markup outcomes, based on three model specifications with various combination of fixed effects: extensions to models 2, 3 and 5 in Table 5. The estimated main tenure effects for fees are relatively similar to those in Table 5, while the main effects are lower for wages and consequently higher for markup. The estimated interaction effects are relatively consistent across the three models. Despite the length of initial training being positively correlated with the initial fee, we find no evidence that training differentially affects either the fee, wage or markup growth over tenure. However, we do find annual wage growth for females is about 1% stronger than for males, and annual fee growth is 1-1.5% stronger for University graduates than non-graduates (fee growth also appears to be 0.5-1% stronger for females than males). F-tests for the joint hypothesis of no tenure-interactions is rejected for all models except model 5 markup.

The estimates for the linear-spline specifications of models 2 and 3 are presented in Table 8. The main tenure coefficients imply strong and essentially linear annual fee growth (about 6% in model 3), small and insignificant wage growth over the first 15 months followed by strong growth thereafter (about 4.0%), and strong markup growth over the first 15 months (about 8% in model 3) and weakly positive growth after that point. Although the tenure interaction effects are more complicated than in the linear models, the estimates again suggest that females have 0.5-1% faster wage growth than males, and that University graduates have faster fee (1.5-2.5%) and wage (1-1.5%) growth than non-graduates, particularly over the first 15 months. When controlling for client effects, we also find some evidence that longer training periods is associated with slower fee growth over the first 15 months.

The results in this subsection indicate there is some statistically significant heterogeneity across gender and educational backgrounds, but these are not substantial, implying the heterogeneity in the fee-tenure and wage-tenure profiles are not important. As far as growth rates are concerned, we do not find evidence for the heterogeneous labor market frictions across types of workers.

6 Internal rate of return

Thus far we have documented the wedge between fees and wages, and show that this wedge grows with the worker's tenure. This finding suggests that the THS firm potentially has an incentive to provide training opportunities to acquire general skill upfront at the cost of the THS firm. On the other hand, the survival analysis in Figure 3 showed that less than half of employees stay with the THS firm for 48 months. Considering the attrition of workers, does it pay for the THS firm to invest in the workers on average?

To address this issue, we assess the internal rate of return to the firm from employing and training workers. To do this, we need to identify the costs associated with hiring and training workers, the subsequent expected returns from those investments, and the relevant time horizon over which the discounted value of the returns will accrue. In what follows, we provide estimates based on a baseline scenario, and then consider the robustness of the estimates to varying the adopted parameter values in this scenario.

First, we discuss the costs of hiring and training to the THS firm. Based on discussions with the firm's management, we assume the hiring cost is approximately 200,000 Japanese Yen (JPY) per worker. From the available firm data, we only observe the direct labor costs the firm pays workers during the training periods, and not other fixed operational costs or training-related costs that the firm may incur. However, from information provided by the Japan Staffing Services Association (JASSA) we assume that the firm's fixed costs of operation account for about 21.6% of its total wage costs.[33] We use this to estimate the cost of training a worker as the worker's initial monthly wages (W_{i0}) multiplied by the estimated duration their initial training period (T_{i0}), and scale this up by 21.6%. Then, the firm's total cost of hiring and training a worker is:

$$Cost_i = T_{i0} \times 1.216 \times W_{i0} + 200,000.$$

Next, we calculate the firm's monthly flow return to the training provided to the worker as the surplus of the monthly fee the firm receives from a client (F_{it}) over the adjusted monthly cost – i.e. the scaled-up wage paid to the worker

[33]The JASSA is the industry organization of government-approved temporary work agencies. According to JASSA data, on average the fee charged to clients consists of the direct wages paid to workers (70.0%), the employer's contribution to the social security account (10.9%), reserve for leave payments (4.2%), the operation cost (13.7%), and operating profit (1.2%) (`https://www.jassa.or.jp/keywords/index3.html`, viewed on September 8, 2022.). Among these items, we treat the social security contribution and the reserve for leave payment as the indirect cost. This assumption entails the ratio of operational costs to wage payments to be $(4.2 + 10.9)/70 \approx 0.216$.

$(1.216 * W_{it})$. The expected value of the return to the training is defined as:

$$E(Return_i t) = \hat{P}_{it}(\hat{F}_{it} - 1.216 * \hat{W}_{it}),$$

where $\hat{P}_{it}$ is the estimated survival rate for worker-i in month-t, estimated using the model in column 6 of Table 3; and $(\hat{F}_{it} - 1.216 * \hat{W}_{it})$ is the estimated (absolute) markup for worker-i in month-t, based on the worker fixed effect linear spline model (Model 2 in Table 6), allowing for a constant fixed cost component of 21.6% of wages.[34]

We then define the internal rate of return as the discount rate which equates the average expected discounted value of the return across workers in the main sample over a 5-year period to the average cost of hiring and training a worker. This choice of investment horizon is based on the finding that the average completed tenure is about 5 years (58.6 months).

Given this set of baseline parameters, the monthly internal rate of return (MIRR) to the firm is calculated as:

$$E(Cost_i) = E(\sum_{t=T_{i0}+1}^{60} (\frac{1}{1+MIRR})^{t-1} E(Return_{it}));$$

and the annual internal rate of return (IRR) is defined as:[35]

$$IRR = 1 - (1 - MIRR)^{12}.$$

Table 9 summarizes the estimated internal rates of return for this baseline scenario in row 1. We find that the average expected internal rate of return is 18.9% across all workers.

[34]To do this, we first estimate $l\hat{og(F_{it})}$ and $l\hat{og(W_{it})}$ from their respective regressions, then exponentiate each to levels and form $(\hat{F}_{it} - 1.216 * \hat{W}_{it})$.

[35]This calculation is based on the fact that $\frac{1}{1+IRR} = \frac{1}{(1+MIRR)^{12}}$. Thus by approximation, $1 - IRR = (1 - MIRR)^{12}$.

We examine the heterogeneity of the internal rate of returns by demographic characteristics. The expected internal rate of returns are higher for females (20.8%) than for males (17.5%) workers. As for educational attainment, the estimated internal rate of return is substantially higher for university graduates (22.9%) than workers without University degrees (9.9%). This finding is consistent with the firm's change in the policy to hire more college graduates according to the firm's management. As for previous potential labor market experience, the internal rate of return is 17.6% for workers with 0-5 years and 21.9% for workers with 6+ years of experience, thus the internal rates of return are slightly higher among workers with more labor market experience.

As there is a degree of uncertainty in each of the assumed time horizon, recruitment cost and ratio of operational costs to wages, we vary each of these to assess the sensitivity of estimated IRR. First, we change the investment horizon by adding and subtracting one year (Figure 3 shows 4- and 6-years correspond roughly to the median and 75th percentiles of completed tenure respectively). Adopting a longer (6-year) horizon in row 2, increases the IRR to 21.8% from the 18.9% baseline estimate. Conversely, in row 3, the shorter (4-year) horizon results in a lower IRR of 13.2%. These results indicate that the IRR is sensitive to the choice of investment horizon. We argue that the five years horizon is a reasonable baseline given the average completed tenure.

We next examine the sensitivity to changes in the baseline recruitment cost. Assuming a higher recruitment cost of 300,000 JPY, row 4 of Table 9 reports the estimated IRR is 14.8% (4.1 percentage points lower than the baseline). Conversely, using a lower recruitment cost of 100,000 JPY, the estimated IRR in the third row is 23.4% as reported in row 5. From this we infer the estimated IRR is also sensitive to changes in the recruitment cost parameter, reflecting that the recruitment cost is not negligible in the five years planning horizon.

Finally, we assess the sensitivity of the estimated IRR to the ratio of operational costs to wage payments. As explained before, the firm pays 21.6% more in addition to the wage payments to cover the employer's contribution to the social security account and a worker's leave payments. Since the Japanese government regulates the social security tax and the mandatory length of the paid leave, assuming a markup of 21.6% is arguably a lower bound to the additional labor costs. Thus we examine the robustness of the calculation results by adding a quarter of the operation cost that consists 13.7% of the fee charged on clients according to JASSA, which has the effect of raising the multiplier to 1.265 from 1.216.[36] To avoid double counting of the recruitment cost, in this case we exclude the 200,000 JPY recruitment cost. The estimated IRR, reported in row 6, is 5.3%, compared to 18.9% in the baseline model. This result shows that the changing the assumption on the operation cost proportional to wage cost substantially affects IRR estimate.

Overall, the IRR calculations in this section suggest that the firm's business model of hiring and training workers is profitable. However, we emphasize the caveats that the IRR estimates are sensitive to the choice of the investment horizon as well as the choice of the estimates for the recruitment and operation costs. Due to the lack of knowledge on other operation costs, such as pecuniary costs of training, costs related to managing workers dispatched to clients, sales cost, we believe the estimates should be interpreted as indicative, and the actual internal rate of return could be different from the ones reported here. However, these ball park numbers arguably assure that the THS firm has sufficient room to collect the upfront investment cost.

This suggests that the firm's average rate of return associated with providing initial training to workers is moderate to substantial. Among the existing stud-

[36] In particular, we modify the multiplier introduced in footnote 33 to $(4.2 + 10.9 + 13.7/4)/70 \approx 0.265$.

ies on the internal rate of return to human capital investment, Altonji (1993) for instance estimates the internal rate of return to the first year college attendance when the return to education is uncertain. He reports that the internal rate of return ranges from five to ten percent based on US data. In a different context, Algan et al. (2022) examine the impact of early childhood intervention to improve social skills and self-control on employment income and social transfer based on the data set from Montreal, Canada. The estimated IRR of the study is 17%. Although our baseline estimated return to training here is greater than these estimates, the range of estimates across the scenarios is broadly consistent with the existing estimates.

7 Conclusion

We use unusually rich data from a temporary help services firm to test whether skill investment leads to so called *wage compression*, with higher returns to productivity than wages. Our data on the wages paid to workers and the fees charged to clients for their services allows us to directly test the hypothesis because the fees represent workers' productivity. Drawing on this unique data set, we find three pieces of evidence that are consistent with wage compression.

First, we document that the firm provides general skill training to workers at the start of their employment spell for about 2.2 months on average. Importantly, the length of a worker's training period is positively correlated with the initial fee charged on their first client placement, but is uncorrelated with their initial wage. This is consistent with training increasing workers' productivity, as reflected by the fee charged to clients, but the higher productivity is fully captured by the firm.

Second, we find that skill acquired through learning-by-doing induces higher fee growth than wage growth over a worker's tenure. We estimate that the hourly fee charged by the firm increases roughly linearly with tenure at 6-8% annually, while wages are essentially constant over the first 15 months before increasing at about 5.3%. Thus, the relative markup between wages and fees increases strongly over the first 15 months and continues to increase at about 2.5% after that.

Third, we document the importance of client upgrading as a source of productivity growth. By comparing the returns to tenure from models with and without client fixed effects, we estimate that about one-quarter of the annual growth in the firm's fee charged to clients is associated with client quality upgrading. In contrast, workers' wages are independent of the clients that they are placed with, implying they do not share any of the productivity benefits associated with client quality upgrading.

Each of these results is consistent with the wage compression hypothesis that skill accumulation, either through formal training or learning-by-doing, increases productivity more than wages. Our empirical findings corroborate the theory that explains the investment in general human capital at the firm's cost by Stevens (1994), Acemoglu and Pischke (1998), and Autor (2001). While our analysis is from a single temporary help agency operating in Japan, the findings provide clear and consistent evidence of wage compression.

Finally, our findings also shed light on the function of THS agents in the labor market. As pointed out by previous studies (Krueger, 1993; Autor, 2001), THS firms provide training opportunities to workers and place trained workers with clients. Thus, THS agencies function as the combination of a school and an employment agency, and have direct incentives to design the curriculum in response to the skills demanded by clients. For this reason, THS providers arguably have advantages in training provision over schools in response to fluctuating demand for skills. Although policy makers may criticize THS agents for exploiting their workers via an apparently high margin of the service fee over the wages, they should also pay attention to the function of such agents as promoters of skill accumulation when they design the regulation of the industry.

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Table 1: Summary statistics

Mean (SD)	(1) Full sample	(2) Main sample	(3) Main sample: Males	(4) Main sample: Females
Female	0.32	0.33	—	—
Age	27.3	27.3	27.6	26.7
(years)	(3.9)	(3.9)	(4.2)	(3.1)
Education: University+	0.63	0.63	0.61	0.67
Potential work experience	6.4	6.4	6.7	5.6
(years)	(4.1)	(4.1)	(4.4)	(3.4)
Training period	2.2	2.2	2.1	2.3
(months)	(2.2)	(2.2)	(2.0)	(2.4)
Tenure	16.3	16.4	16.8	15.7
(months)	(10.6)	(10.6)	(10.8)	(10.2)
Hourly fee	2,889	2,885	2,866	2,924
	(785)	(784)	(829)	(679)
Hourly wage	2,228	2,043	2,040	2,050
	(2,561)	(551)	(590)	(459)
Relative markup	1.39	1.43	1.42	1.44
(fee/wage)	(0.28)	(0.35)	(0.38)	(0.28)
Hours worked	155.2	155.7	156.6	154.0
(monthly)	(27.7)	(26.8)	(26.4)	(27.7)
Initial hourly fee	—	2,763	2,763	2,763
		(995)	(995)	(997)
Initial hourly wage	—	2,058	2,056	2,063
		(529)	(501)	(585)
Initial relative markup	—	1.38	1.38	1.39
		(0.53)	(0.54)	(0.53)
No. observations	35,414	34,729	23,453	11,276
No. Workers	1,908	1,784	1,164	620
No. Clients	412	376	288	240

Notes: Column 1 represents all the observations. The main sample used in the analysis is shown in Column 2, with hourly wage adjusted and worker-client pair lasting shorter than 3 months excluded. By this restriction, 124 workers together with 36 clients are dropped. This attrition potentially results from the workers who have only been working for clients temporarily, and the clients which have never set up long-term relationship with any workers. The mean of unadjusted hourly wage in the main sample in Column 2 is 2,187 (SD=2,256), which is close to that in the full sample in Column 1, implying that the gap in hourly wage comes systematically from the downward adjustment, not sample selection.

Table 2: Determinants of initial training period measured in month

	(1)	(2)
Potential experience at entry	0.002	0.011
	(0.040)	(0.048)
Potential experience^2/100	0.213	0.116
	(0.222)	(0.253)
Female	0.233*	0.304**
	(0.123)	(0.121)
University+	0.269*	0.280**
	(0.139)	(0.141)
Entry cohort FE	No	Yes
No. observations	1,784	1,784
R^2	0.012	0.101
Sample mean	2.271	2.271

Notes: Standard errors are reported in parentheses. Entry cohort is defined by the fiscal year-month of entry. Each model includes branch office fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Survival estimate based on Log-normal model: Tenure

	(1)	(2)	(3)	(4)	(5)	(6)
Training period	0.974**	0.979*	0.973**	0.975**	0.978**	0.973**
(months)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Initial monthly fee	1.486***					
(in log)	(0.212)					
Initial monthly wage		0.490*				
(in log)		(0.180)				
Initial monthly markup			1.794***			
(in log)			(0.276)			
Initial hours worked	0.777*	0.943	0.762*			
(in log)	(0.118)	(0.144)	(0.114)			
Initial hourly fee				1.392***		
(in log)				(0.165)		
Initial hourly wage					1.015	
(in log)					(0.154)	
Initial markup						1.647***
(in log)						(0.249)
Potential experience	1.015	1.024	1.014	1.016	1.022	1.015
at entry (years)	(0.017)	(0.017)	(0.016)	(0.016)	(0.017)	(0.017)
Potential experience^2/100	0.932	0.970	0.964	0.933	0.928	0.956
	(0.076)	(0.083)	(0.079)	(0.076)	(0.077)	(0.079)
Female	1.088	1.096	1.076	1.089	1.103*	1.081
	(0.061)	(0.062)	(0.060)	(0.061)	(0.062)	(0.061)
University+	0.871**	0.909	0.881**	0.876**	0.884**	0.876**
	(0.052)	(0.055)	(0.052)	(0.051)	(0.053)	(0.052)
Log lik.	-1,197.75	-1,199.69	-1,194.34	-1,198.09	-1,201.88	-1,196.42
Chi-squared	31.568	27.679	38.372	30.873	23.296	34.217
No. observations	1,784	1,784	1,784	1,784	1,784	1,784

Notes: Exponentiated coefficients are reported. Standard errors calculated as $SE(coef.) \times \exp(coef.)$ are reported in parentheses. The asterisks indicate the p-value for the null hypothesis that the coefficient is 1. Test of hypothesis is in terms of original metric. For example, for the initial monthly fee in Column 1, $t{-}stat = (\log(1.486))/(0.212/1.486) \approx 2.78$. The initial fee, wage and hours are measured in each worker's second month of placement; the fee, wage, markup, and hours worked variables are in logarithms. Each model also includes branch office controls but the estimated coefficients are not reported. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Determinants of hourly fee, wage and markup at the first pay

	(1) log(fee)	(2) log(wage)	(3) log(markup)
Training period	0.018***	0.002	0.016***
	(0.003)	(0.002)	(0.003)
Potential experience at entry	0.009*	0.000	0.009*
	(0.005)	(0.003)	(0.005)
Potential experience^2/100	0.042**	0.061***	-0.019
	(0.021)	(0.013)	(0.022)
Female	0.005	-0.001	0.006
	(0.017)	(0.009)	(0.020)
University+	0.016	0.009	0.007
	(0.016)	(0.010)	(0.018)
No. observations	1,784	1,784	1,784
R^2	0.127	0.114	0.077

Note: Standard errors are reported in parentheses. Each model includes entry month-year and branch fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Annual growth rates – Homogeneous linear models

	(1) Fee	(2) Wage	(3) Markup
Model 1	0.010***	0.004	0.006*
(Controls only)	(0.004)	(0.003)	(0.003)
	[0.137]	[0.159]	[0.037]
Model 2	0.072***	0.034***	0.037***
(Worker FE)	(0.004)	(0.003)	(0.004)
	[0.452]	[0.485]	[0.348]
Model 3	0.055***	0.032***	0.023***
(Worker & Client FE)	(0.003)	(0.003)	(0.004)
	[0.501]	[0.522]	[0.396]
Model 4	0.050***	0.032***	0.017***
(+ Client order)	(0.003)	(0.003)	(0.004)
	[0.504]	[0.522]	[0.399]
Model 5	0.050***	0.032***	0.018***
(Worker × Client FE)	(0.003)	(0.003)	(0.004)
	[0.536]	[0.551]	[0.437]
No. observations	34,729	34,729	34,729
Workers	1,784	1,784	1,784
Clients	376	376	376

Notes: Standard errors are in parentheses (clustered at the worker level), R^2 are reported in brackets. Observations are weighted by the hours worked of each month and each worker. All models, control variables also include gender, education level, a quadratic in initial potential experience at entry, branch, and regional CPI unemployment rate and CPI. Model 1 includes no fixed effects; Model 2 includes worker fixed effects; Model 3 includes worker and client fixed effects; Model 4 includes worker and client fixed effects, and the order of client; and Model 5 includes worker × client fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Annual growth rates – homogeneous linear spline models

	Fee		Wage		Markup	
	(1) Tenure	(2) Tenure ×After 15m.	(3) Tenure	(4) Tenure ×After 15m.	(5) Tenure	(6) Tenure ×After 15m.
Model 1	0.014**	-0.001	-0.037***	0.061***	0.051***	-0.062***
(Controls only)	(0.007)	(0.009)	(0.004)	(0.006)	(0.007)	(0.008)
	[0.137]		[0.167]		[0.040]	
Model 2	0.062***	0.017**	-0.005	0.058***	0.067***	-0.041***
(Worker FE)	(0.007)	(0.008)	(0.005)	(0.005)	(0.008)	(0.008)
	[0.453]		[0.491]		[0.349]	
Model 3	0.053***	0.005	-0.006	0.057***	0.058***	-0.052***
(Worker & Client FE)	(0.007)	(0.007)	(0.005)	(0.005)	(0.007)	(0.008)
	[0.501]		[0.527]		[0.398]	
Model 4	0.045***	0.008	-0.006	0.057***	0.051***	-0.049***
(+ Client order)	(0.007)	(0.007)	(0.005)	(0.005)	(0.007)	(0.008)
	[0.504]		[0.528]		[0.401]	
Model 5	0.050***	0.002	-0.004	0.056***	0.054***	-0.054***
(Worker × Client FE)	(0.007)	(0.008)	(0.005)	(0.006)	(0.007)	(0.008)
	[0.536]		[0.555]		[0.439]	

Notes: Standard errors in parentheses (clustered at individual level). Estimation is weighted by hours worked. See notes to Table 5 for details of the model specifications. All models are based on 34,729 observations on 1,784 workers and 376 firms. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Annual growth rates – heterogeneous linear models

	Model 2: Worker FE			Model 3: Worker FE + client FE			Model 5: Worker × client FE		
	(1) Fee	(2) Wage	(3) Markup	(4) Fee	(5) Wage	(6) Markup	(7) Fee	(8) Wage	(9) Markup
Tenure	0.078***	0.018***	0.060***	0.053***	0.016***	0.037***	0.043***	0.015***	0.027***
(years)	(0.009)	(0.006)	(0.009)	(0.008)	(0.006)	(0.009)	(0.009)	(0.006)	(0.010)
×Potential experience	-0.001	0.001	-0.002	0.001	0.001	-0.000	0.001	0.002	-0.000
at entry (years)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
×Potential $\exp^2/100$	-0.003	-0.004	0.002	-0.008*	-0.004	-0.004	-0.008	-0.005	-0.003
	(0.006)	(0.004)	(0.006)	(0.004)	(0.004)	(0.006)	(0.005)	(0.004)	(0.007)
×Training period	-0.000	0.001	-0.001	-0.001	-0.000	-0.001	-0.001	-0.000	-0.000
(months)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
×Female	0.003	0.011***	-0.007	0.005	0.011***	-0.006	0.010	0.008**	0.002
	(0.006)	(0.004)	(0.006)	(0.006)	(0.004)	(0.005)	(0.006)	(0.004)	(0.006)
×University+	0.011*	0.006	0.006	0.015***	0.007*	0.008	0.015**	0.009**	0.007
	(0.006)	(0.004)	(0.006)	(0.006)	(0.004)	(0.006)	(0.007)	(0.004)	(0.007)
No. observations	34,729	34,729	34,729	34,729	34,729	34,729	34,729	34,729	34,729
Workers	1,784	1,784	1,784	1,784	1,784	1,784	1,784	1,784	1,784
Clients	376	376	376	376	376	376	376	376	376
R^2	0.454	0.486	0.351	0.502	0.523	0.398	0.537	0.552	0.438
F-statistics	2.15*	3.16***	2.52**	4.90***	3.03***	2.10*	4.30***	2.20*	1.16

Notes: Standard errors in parentheses (clustered at individual level). Estimation is weighted by hours worked. F-statistics are for the joint hypothesis: 5 tenure interaction terms (potential experience, potential experience^2, training period, female, university+) are equal to 0. See notes to Table 5 for details of the model specifications. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Annual growth rates – heterogeneous linear-spline models

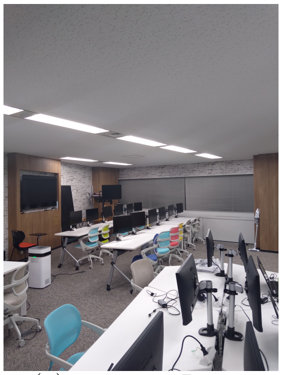
	Model 2: Worker FE			Model 3: Worker & client FE		
	(1) Fee	(2) Wage	(3) Markup	(4) Fee	(5) Wage	(6) Markup
Tenure	0.078***	-0.019	0.097***	0.059***	-0.023**	0.082***
	(0.016)	(0.012)	(0.015)	(0.015)	(0.011)	(0.016)
×After 15m.	0.012	0.061***	-0.049***	-0.000	0.063***	-0.063***
	(0.012)	(0.009)	(0.012)	(0.011)	(0.008)	(0.011)
×Pot-Exp at entry	-0.004	-0.000	-0.004	0.000	0.001	-0.001
	(0.003)	(0.002)	(0.003)	(0.003)	(0.002)	(0.003)
×Pot-Exp×After 15m.	0.002	0.001	0.001	0.001	0.000	0.000
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
×Pot-Exp^2/100	0.009	-0.001	0.010	-0.006	-0.007	0.000
	(0.016)	(0.011)	(0.012)	(0.012)	(0.010)	(0.011)
×Pot-Exp^2/100×After 15m.	-0.009	-0.003	-0.006	-0.001	0.002	-0.003
	(0.013)	(0.007)	(0.010)	(0.010)	(0.006)	(0.008)
×Training period	-0.003	0.000	-0.003	-0.005**	0.000	-0.005**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)
×Training×After 15m.	0.001	-0.001	0.003	0.003*	-0.002*	0.005***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.002)
×Female	0.014	0.011	0.004	0.008	0.006	0.002
	(0.011)	(0.007)	(0.011)	(0.010)	(0.007)	(0.010)
×Female×After 15m.	-0.008	0.001	-0.010	-0.002	0.005	-0.007
	(0.008)	(0.005)	(0.008)	(0.007)	(0.005)	(0.007)
×University+	0.021**	0.015**	0.006	0.024**	0.016**	0.008
	(0.010)	(0.007)	(0.010)	(0.010)	(0.007)	(0.010)
×University+×After 15m.	-0.008	-0.007	-0.000	-0.007	-0.007	0.000
	(0.007)	(0.005)	(0.007)	(0.006)	(0.005)	(0.006)
After 15m.	Yes	Yes	Yes	Yes	Yes	Yes
Tenure×Branch	Yes	Yes	Yes	Yes	Yes	Yes
Regional CPI/Unemployment	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.455	0.492	0.352	0.502	0.529	0.401
F-statistics	1.83**	2.41***	1.52	3.12***	3.30***	1.60

Notes: Standard errors in parentheses (clustered at individual level). Estimation is weighted by hours worked. F-statistics are for the joint hypothesis: 10 tenure interaction terms (potential experience, potential experience^2, training period, female, university+) are equal to 0. See notes to Table 5 for details of the model specifications. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

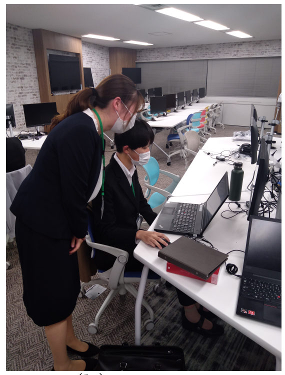
Table 9: Estimated annual internal rate of return

		Gender		Education		Experience at entry	
	(1) Full sample	(2) Males	(3) Females	(4) Non-university	(5) University	(6) 0-5 years	(7) 6+ years
1. Baseline	0.189	0.175	0.208	0.099	0.229	0.176	0.219
2. 6-year Horizon	0.218	0.207	0.233	0.133	0.256	0.211	0.241
3. 4-year Horizon	0.132	0.112	0.159	0.037	0.175	0.110	0.176
4. FC=300,000 JPY	0.148	0.134	0.168	0.051	0.192	0.137	0.177
5. FC=100,000 JPY	0.234	0.220	0.252	0.153	0.270	0.220	0.266
6. Multiplier=1.265, FC=0	0.053	0.024	0.092	-0.132	0.121	0.043	0.087
N	1,784	1,164	620	668	1,116	1,133	651

Notes: The IRR estimates are based on the estimated survival rates based on Table 3, and wage and fee growth from model 2 in Table 6. The baseline scenario in row 1 assumes a 5-year (60 month) horizon, the fixed cost (FC) of hiring is 200,000 JPY, and the indirect labor costs is 21.6% of wages (multiplier=1.216). In rows 2-6, we adjust these parameters as indicated. See text discussion for details.



(a) Training Room



(b) Trainees

(c) Server

Figure 1: Training Program of the THS firm

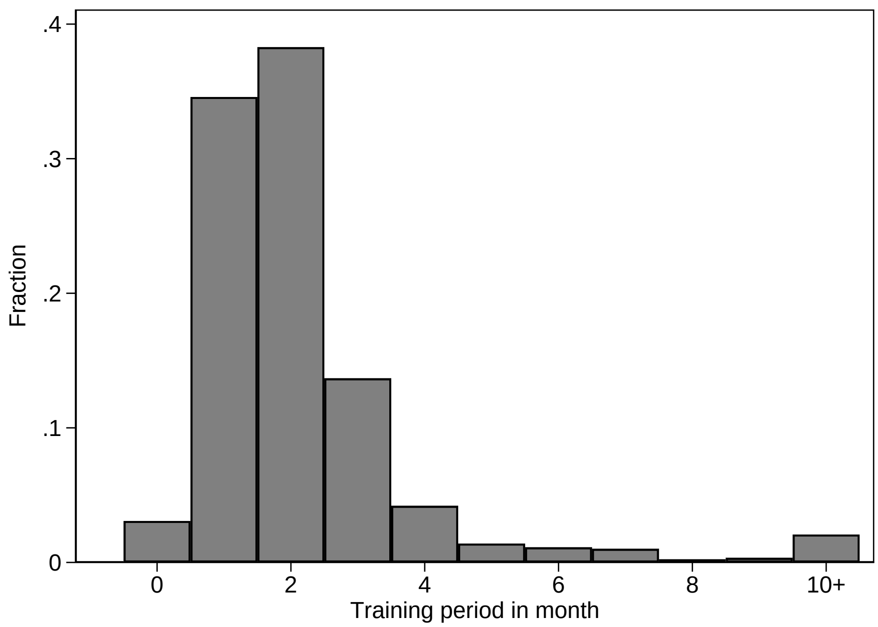


Figure 2: Histogram of pre-placement training period

Notes: The training period is defined as the number of months from a worker's entry to the firm until they are first placed with a client; 76% of workers have training period of 0–2 months.

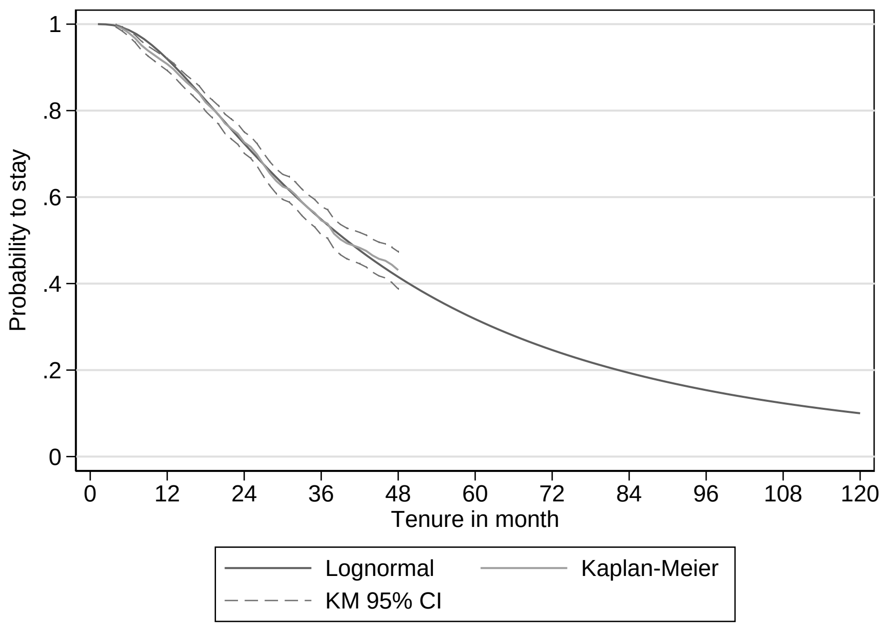


Figure 3: Estimated survival probability: Log-normal model and Kaplan-Meier estimator

Notes: The observations with 3 months and less are excluded from the sample. Therefore, the flat survival rate of the first three months is 1. The dark line indicates the predicted probability to stay based on the log-normal model. The gray line shows the non-parametric Kaplan-Meier estimate. The dashed lines indicate the 95% confidence interval of the Kaplan-Meier estimate.

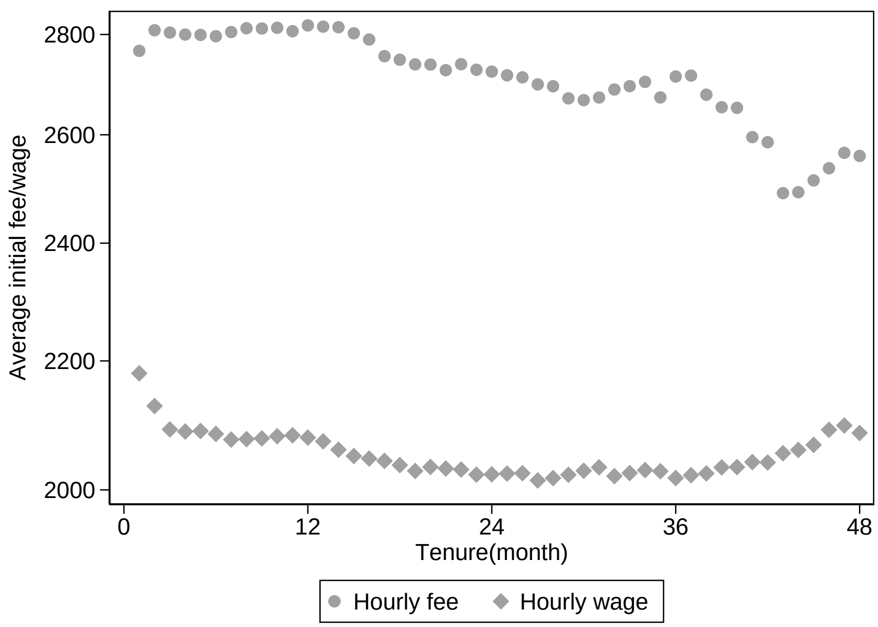


Figure 4: Average initial fee & wage by tenure

Notes: Each point indicates the average hourly fee and wages at the initial assignment.

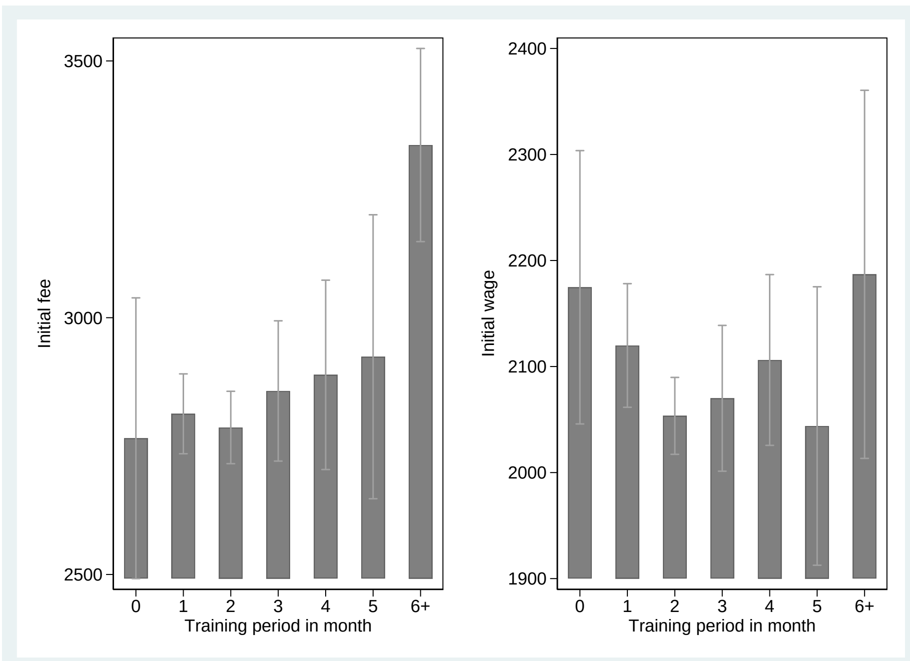


Figure 5: Average initial fees and wages by training length in month

Notes: Each bar height shows the average fee or wages at the initial assignment by the months of training period.

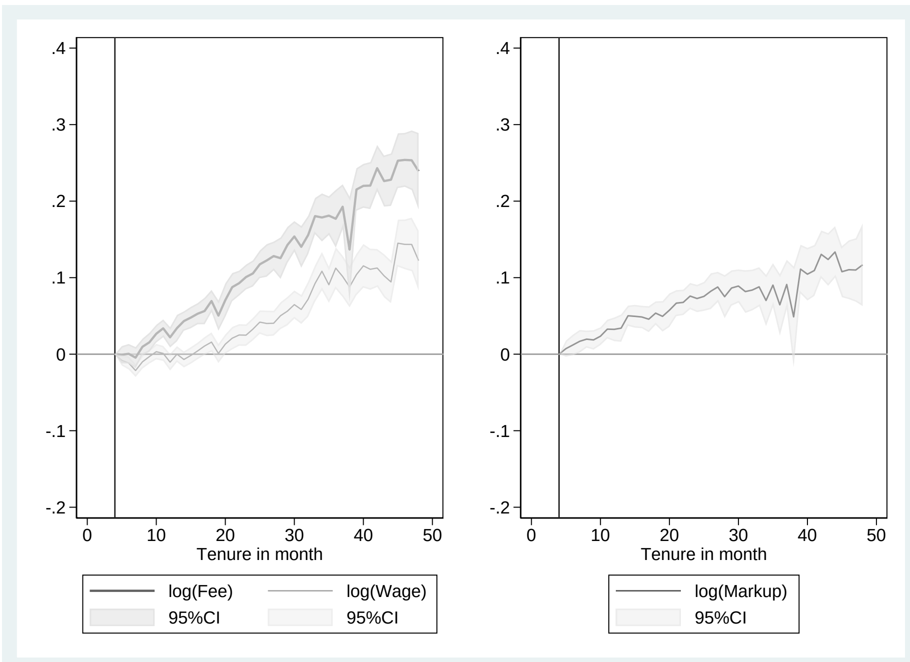


Figure 6: Non-parametric tenure profiles for hourly fee, wage and markup

Notes: Hourly fee, wage and markup (in logs) are regressed on monthly tenure dummies, controlling for worker fixed effects, regional CPI and unemployment rate (i.e the non-parametric version of Model 2). The estimated coefficients for 0-3 months are suppressed. The vertical line is at tenure = 4, which is used as the base. The estimation is based on 34,729 observations from 1,784 workers and 376 clients.

Appendix

A Inflexibility of Japanese labor market

This appendix discusses features of Japanese labor market to understand the empirical results in this paper, particularly the low turnover rate of THS workers and high internal rate of return of the THS firm.

The literature on the comparison between the US and Japanese labor market focuses on the difference of labor market fluidity in two economies. Early studies argue that the larger fraction of bonuses in annual compensation (Hashimoto, 1979), lower job turnover rate, and steeper tenure-wage profile (Hashimoto and Raisian, 1985) in Japan than in the US is consistent with the notion that firm-specific human capital plays a more important role in Japan than in the US. More recently, using data until the mid 2000s, Kambayashi and Kato (2017) demonstrate that prime-age male workers with at least five years of tenure in Japan continued to enjoy much higher job stability than did their U.S. counterparts, suggesting that the labor markets of Japan and the US remain substantially different. Kawaguchi and Ueno (2013) also demonstrate that the mean tenure at age of 40 was about 10 years in Japan compared to about 7 years in the US in the mid 2000s.

While prime-age male workers continue to enjoy job stability as permanent workers, from the mid 1980s, both female and young workers are increasingly likely to be on fixed-term employment contracts (Asano et al., 2013). The increase in workers on fixed-term contract suggests a two-tier labor market characterized by permanent versus fixed-term contracts. Workers on fixed-term contracts, including those dispatched through THS firms, provide both employment and wage flexibility to firms', independent of their relationships with permanent workers. In the US context, Houseman et al. (2003) shows that firms hire additional temporary workers by paying higher fees than permanent workers in upswings because paying higher fees to such workers does not propagate through to the wage setting of permanent workers. Kalleberg (2003) argue that many US firms secure the benefits of having internal labor markets and employment flexibility by mixing permanent and fixed-term contract workers. Indeed, in Japanese context, Yokoyama et al. (2021) report that firms adjusted the employment of THS workers in response to the Global Financial Crisis while maintaining the employment of permanent workers. This result suggests the presence of dual structure within a firm.

Because permanent workers enjoy employment protection and steep tenure-wage profiles, high ability workers are less likely to quit, leading to severe adverse selection in the mid-career labor market (Abe, 1994). Consequently, Japanese employers tend to hire fresh graduates in preference to mid-career job seekers, implying the transition from fixed-term to permanent contracts is difficult. Kondo (2007) shows that workers who start their career on fixed-term contracts due to the adverse economic condition at the time of school graduation remain in this employment status for a long time. Genda et al. (2010) further demonstrates that the effects of labor market conditions at the time of graduation are more persistent in Japan than the US in terms of employment status and earnings.

Theoretical research addresses the difference in labor market fluidity between Japan and the US. Abe (1994) sets out a model of adverse selection in the labor market where unobserved ability creates a Lemon's problem. Her model extends the Greenwald (1986)'s adverse selection model by incorporating firm-specific skill accumulation that can improve the match quality between an employee and an employer. In this setting, two equilibria emerge. In one equilibrium, a bad match resolves and results in both high and low ability workers joining the second hand labor market. In the other equilibrium, a bad match between an employee and an employer is overcome by firm-specific human capital accumulation among high ability workers, so that only low ability workers join the second hand labor market, creating the Lemon's problem. Abe argues the former equilibrium corresponds to the US labor market, and the latter equilibrium to the Japanese labor market. Moriguchi (2003) argues that the bifurcation of employment practices in the two economies originates from the Great Depression in the 1930s.

Theorists also propose various other mechanisms to explain the difference between Japanese and US labor markets. Morita (2001) argues that the active continuous improvement of production processes by Japanese firms makes firm-specific human capital more important in Japan. On the other hand, Owan (2004) argues that differences in the promotion policies between Japanese and US firms is a key to the differences in labor market features between Japan and the US. He also argues that the consequent late promotion policy of Japanese firms result in the wage compression pointed out by Acemoglu and Pischke (1999b).

Furthermore, the legal setting reinforces Japanese employment practices by giving practically asymmetric employment protections between permanent and fixed-term contract workers. Reflecting Japanese employment practices assuring job stability among permanent workers, court decisions have supported permanent workers having *de facto* legal employment protection (Hatta and Ouchi, 2018). For example, Japanese employment contract law requires firms to prove 1) the need for termination of the employment contract, 2) the possibility of reallocation of the worker within a firm is exhausted, 3) the selection of the terminated worker is fair, and 4) the procedure for the termination is according to formal procedure. If the firm fails to prove these conditions are satisfied, the dismissal is judged as unjust and the judges request the reinstatement of the worker. The range of tasks that permanent and fixed-term contract workers can implement is assumed to be different, thus the degree of employment protection is virtually different between workers on such contracts. This legal setting makes the firing cost of permanent workers high.

In summary, the features of Japanese labor market provide incentives for client firms to use THS workers to avoid long-term employment commitments. Also high barriers to obtaining permanent contract jobs in the mid career market makes it difficult for THS workers to transit into the permanent jobs of non-THS firms, thus extending their tenure with the THS firm. This strengthens the degree of the wage compression.