TCER Working Paper Series

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July 2015

Working Paper E-95
http://tcer.or.jp/wp/pdf/e95.pdf

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Abstract

This paper investigates factors preventing inter-industry labor reallocation by estimating the determinants of inter-industry worker flow and earnings change after a job change. We find that the difference in required tasks is an important reason for earnings reduction after an inter-industry job change, and thus, workers may hesitate to move to industries requiring a different set of tasks for fear of losing the wage premium acquired by task-specific human capital. In addition, more workers switch to industries with which their previous industry had larger transactions, although it affects earnings changes only marginally. On the other hand, industry performance does not affect labor inflow or wage changes significantly for inter-industry job changes. Young men, less educated women, and those quitting previous jobs for family or health reasons are more likely to move to industries requiring a different set of tasks, and young individuals who lost their jobs involuntarily are less likely to do so. Individuals more likely to move are not necessarily those whose earnings loss associated with the move is small: earning losses associated with task distance are relatively small among younger and less educated workers and are uncorrelated with the reasons for quitting the previous job.

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June 7, 2015

Abstract

This paper investigates factors preventing inter-industry labor reallocation by estimating the determinants of inter-industry worker flow and earnings change after a job change. We find that the difference in required tasks is an important reason for earnings reduction after an inter-industry job change, and thus, workers may hesitate to move to industries requiring a different set of tasks for fear of losing the wage premium acquired by task-specific human capital. In addition, more workers switch to industries with which their previous industry had larger transactions, although it affects earnings changes only marginally. On the other hand, industry performance does not affect labor inflow or wage changes significantly for inter-industry job changes. Young men, less educated women, and those quitting previous jobs for family or health reasons are more likely to move to industries requiring a different set of tasks, and young individuals who lost their jobs involuntarily are less likely to do so. Individuals more likely to move are not necessarily those whose earnings loss associated with the move is small: earning losses associated with task distance are relatively small among younger and less educated workers and are uncorrelated with the reasons for quitting the previous job.

*This research is supported by JSPS KAKENHI Grant Number 23730235 (PI: Ayako Kondo). We are grateful to the anonymous reviewer, Kosuke Aoki, Naoko Hara, Ryo Horii, Munechika Katayama, Ryo Kato, Yasusada Murata, Kentaro Nakajima, Soichi Ohta, Shintaro Yamaguchi, and seminar participants at Kyoto Summer Workshop, Bank of Japan, Tohoku University, Policy Modeling Conference 2014, JEA spring meeting 2014, Keio University, Kansai Labor Workshop, and GRIPS for helpful discussions and suggestions. The data for this secondary analysis, "Working Person Survey, Recruit Works Institute," was provided by the Social Science Japan Data Archive, Center for Social Research and Data Archives, Institute of Social Science, The University of Tokyo. Views expressed are those of authors and do not necessarily reflect those of the Bank of Japan.

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1 Introduction

The Japanese economy has experienced substantial changes in its industry structure. Given the increasing trend in unemployment in the recent few decades and the shrinking working-age population, facilitating the reallocation of labor from declining sectors to growing sectors is an important policy goal.[1] However, in reality, there are persistent discrepancies in employment growth, wage growth, and vacancy rates across industries. This paper aims to uncover the factors hindering inter-industry labor reallocation in Japan.

Specifically, we focus on the differences in required tasks as one of the important determinants of inter-industry worker flow and compare their impact with the impacts of other factors such as a proxy for the chances of communication among workers and the productivity of source and destination industries. Then, we examine whether the factors that affect inter-industry worker flow are also relevant to earnings changes associated with inter-industry job changes. The idea behind this is that if some factors specific to a particular industry pair aggravate the earnings losses associated with moves between the two industries, these factors should also decrease the number of workers moving between these industries.

Our analysis relates to the literature on earnings losses associated with job changes and industry-specific human capital. It is widely known that job changers tend to experience earnings losses when they are forced to move to a different industry, as shown by Abe (2005) and Yugami (2005) for Japanese workers and Jacobson, Lalonde and Sullivan (1993) for displaced workers in the United States. Neal (1995) and Parents (2000) argued that such losses are caused by the loss of industry-specific human capital.[2] Furthermore, Poletaev and Robinson (2008) showed that the differences in task portfolios between the previous and current jobs are the major source of earnings losses associated with such inter-industry job changes.[3] We aim to build on these studies by determining the extent to which differences in the required tasks hinder inter-industry labor

[1] Note that "growing" sectors are not necessarily sectors with high labor productivity. As Baumol (1967) pointed out, employment growth in sectors with high labor productivity is often slower than that in less productive sectors, because improved labor productivity is absorbed by a fall in the relative prices of products of the former sectors.

[2] In the same vein, the loss of occupation-specific human capital leads to a substantial earnings loss after a job change to a different occupation (Shaw, 1984; Kambourov and Manovskii 2009). According to Sullivan (2010), both industry-specific and occupation-specific human capital are the key determinants of wages.

[3] Gathmann and Schönberg (2010) and Yamaguchi (2012) also argued that task-specific human capital is an important determinant of wages and earnings.

reallocation.

A methodological innovation of this study is our application of the gravity model, which is widely used in the literature on international trade, to quantify the effects of factors specific to each industry pair and to identify factors that affect flows between one industry and all the other industries in a single framework.[4] With this idea, we begin analyzing the aggregate-level worker flow data sourced from the Labour Force Survey. We find that differences in required tasks are much more important in determining worker flow than the performance of either the source or the destination industry.

Given this finding, we further analyze earnings changes using individual level data from the Working Person Survey. We find that large earnings losses are indeed associated with inter-industry moves that involve large changes in required tasks. These results may seem to imply that workers are afraid that task-specific human capital they had accumulated in the previous job may become useless if they move to a job in a different industry, and thus, they tend to avoid moving to a different industry.

However, we also find that the size of the earnings loss is not always systematically related to the characteristics determining the likelihood of moving to a distant industry. That is, those who tend to move to a more distant industry do not necessarily lose less by moving to a distant industry. Specifically, we analyzed age, education, and reasons for quitting as factors that may affect the cost of moving to a distant industry and thus the likelihood of moving to a distant industry. We find that for education alone, those who would lose less by moving tend to move more.

Furthermore, industry performance has little impact on earnings after a job change. Our estimates cannot be interpreted as a causal effect, because we observe earnings changes only for workers who actually switched jobs. Nonetheless, the lack of correlation between industry performance and earnings changes may imply that industries with higher productivity or stronger labor demand do not necessarily offer better employment opportunities for job changers.

The rest of the paper is organized as follows. The next section describes the empirical model

[4]Cortes and Gallipoli (2014) took a similar approach to analyze mobility across occupations in the United States. We are not aware of any other applications of the gravity model to worker mobility.

and data. Sections 3 and 4 present the results on worker flow and earnings after job changes. Section 5 explores what types of workers tend to move to a distant industry in terms of required tasks. Section 6 concludes.

2 Data and methodology

We begin with the analysis of inter-industry worker flow using data from the Labour Force Survey. Specifically, we estimate a gravity model of inter-industry worker flow. Section 2.1 explains the functional form and the construction of the proxies of mobility cost and industry performance, and it also provides a detailed description about the data from the Labour Force Survey.

Next, we investigate earnings changes and characteristics of inter-industry movers using data from the Working Person Survey. First, we estimate the effects of factors that affect worker flow on earnings changes. It turns out that the distance between required tasks is a very important determinant of worker flows and earnings changes; thus, following the analyses of earnings, we further explore the characteristics of workers who move to industries requiring a different set of tasks. Section 2.2 describes the equations to be estimated using the Working Person Survey.

2.1 Analysis of worker-flow using the Labour Force Survey

2.1.1 Gravity model of inter-industry worker flow

We borrow the functional form of the gravity equation with country specific components, proposed by Anderson and van Wincoop (2003). Although the theoretical model of international trade on which the gravity model based on is irrelevant to inter-industry worker flow within a country,[5] the functional form of the Anderson–van Wincoop Gravity Equation can capture the following features of inter-industry worker flow: (1) The sizes of inflow to and outflow from each industry are proportional to the size of total employment for the industry, (2) factors specific to a pair of

[5] The original gravity model of international trade assumes that the volume of trade between two countries is proportional to the sizes of the countries' economies (often measured by GDP), and it decreases with the distance between the two countries, which is a proxy for the trade cost. Anderson and van Wincoop (2003) added multilateral resistance, a factor that increases the trade cost of country with any other countries. Note that the multilateral resistance terms in Anderson and van Wincoop (2003) are derived from a general equilibrium framework and are subject to some parameter restrictions, whereas the industry-specific factors in our model are not.

industries affect the mobility cost between the two industries, and (3) some other factors affect outflow from or inflow to a specific industry.[6]

Specifically, the number of workers who moved from industry j to industry k in year t, W_{jkt}, can be modeled as follows:

$$W_{jkt} = \alpha_0 E_{jt}^{\alpha_1} E_{kt}^{\alpha_2} D_{jk}^{\alpha_3} e^{(\theta_{jt}+\eta_{kt}+\lambda_t)} + \varepsilon_{jkt} \tag{1}$$

where E_{jt} is the number of workers employed in industry j, D_{jk} is the mobility cost between industries j and k, and θ_{jt} and η_{kt} represent factors affecting outflow from industry j and inflow to industry k, respectively. λ_t represents macroeconomic factors that affect the total worker flow in year t for all industries. ε_{jkt}, the error term, is assumed to be random and independent from any variables in the model. α_0 is expected to be positive, while α_1 and α_2 are expected to be close to 1, and α_3 is expected to be negative.

Furthermore, D_{jk}, the mobility cost between industries j and k, is decomposed into S_{jk}, the difference in the required tasks for industries j and k, and T_{jk}, the chance for industry j's workers to communicate with industry k's workers. Our definitions for these variables appear in the next subsection. D_{jk} can be written as follows:

$$D_{jk} = S_{jk}^{\beta_1} T_{jk}^{\beta_2} \tag{2}$$

β_1 is expected to be positive, and β_2 is expected to be negative.

The factors affecting outflow from industry j in year t are written as the sum of an industry-fixed factor, γ_{0j}, and a factor proportional to the industry performance, p_{jt}.

$$\theta_{jt} = \gamma_{0j} + \gamma_1 p_{jt} \tag{3}$$

Likewise, factors affecting inflow to industry k in year t are written as

[6] The factors that affect mobility cost can be translated into the "distance" term in the gravity model, while those affecting inflows to and outflows from a specific industry can be modeled just like the multilateral resistance term in the Anderson–van Wincoop model.

$$\eta_{kt} = \delta_{0k} + \delta_1 p_{kt} \tag{4}$$

By substituting (2), (3), and (4) into (1), we get

$$\begin{aligned} W_{jkt} = \exp(&\log \alpha_0 + \alpha_1 \log E_{jt} + \alpha_2 \log E_{kt} + \alpha_3 \beta_1 \log S_{jk} \\ &+ \alpha_3 \beta_2 \log T_{jk} + \gamma_{0j} + \gamma_1 p_{jt} + \delta_{0k} + \delta_1 p_{kt} + \lambda_t) + \varepsilon_{jkt} \end{aligned} \tag{5}$$

We follow Silva and Tenreyro (2006) and estimate (5) using the maximum likelihood method, which is mathematically identical to estimating a Poisson regression of W_{jkt} with $\log E_{jt}$, $\log E_{kt}$, $\log S_{jk}$, $\log T_{jk}$, p_{jt}, p_{kt}, and the dummies for the source and destination industries.

2.1.2 Proxies of mobility cost and industry performance

As mentioned above, we model the mobility cost between industries as a compound of the differences in required tasks and chances for communication between each industry's workers.

To measure the differences in required tasks, we quantify each task component required by each industry by taking the weighted average of the occupation-based task indices defined by Matsumoto et al. (2012). Here, we define task as a component required in a job. Industry refers to a kind of aggregation of jobs, and occupation is another kind of aggregation of jobs. Since the indices devised by Matsumoto et al. (2012) are available at the occupation level only, we use the employment share of each occupation in the total employment of the industry as the weight.

Specifically, Matsumoto et al. (2012) provide a score that is standardized to a mean of 0.0 and a standard deviation of 1.0 for each cell of a matrix of 601 occupations and 30 job components.[7] Each cell represents to what extent job component m is required in occupation o, based on a web survey of 21,033 Japanese workers conducted by the Japan Institute for Labour Policy and

[7] This is the Japanese version of O*NET or the Dictionary of Occupational Titles. Applying the same method as Autor, Levy, and Murnane (2003), Ikenaga and Kambayashi (2010) used this matrix to examine the degree of polarization of the Japanese labor market. The Dictionary of Occupational Titles has been used to measure distances in required tasks between jobs and occupations in the U.S. by many researchers, including Poltarev and Robinson (2008) and Yamaguchi (2012).

Training (JILPT) from 2003-2006. Among the 30 job components, we use 13 components related to the tasks requirement. More detailed information is provided in Appendix A.1.

We calculate the index of task component m for industry j, $\hat{s}_{mj}$, by taking the average of the index of task component m for each occupation weighted by the employment share of each occupation in the total employment of industry j. In order to match it with the matrix of the number of employees in each industry-occupation cell taken from the Employment Status Survey[8] 2007, the original table of 601 occupations is aggregated to a table of 55 occupations by taking simple averages of the index across occupations.

Let s_{mo} denote the index for occupation o and task component m, and let E_{oj} be the number of employees in occupation o and industry j. Then, we calculate the index of task component m for industry j, $\hat{s}_{mj}$, as follows:

$$\hat{s}_{mj} = \sum_{o=1}^{55} \frac{E_{oj}}{\sum_{o=1}^{55} E_{oj}} s_{mo} \tag{6}$$

The difference in the required tasks between industries j and k is measured as the Euclid distance:

$$S_{jk} = \sqrt{\sum_{m=1}^{13} (\hat{s}_{mj} - \hat{s}_{mk})^2} \tag{7}$$

Hereafter we call S_{jk} "task distance."

The ratio of the total output of industry j sold to industry k is calculated from the Input-Output Table for Japan for 2005.[9] This variable is a proxy of the chances for communication between workers in the two industries. The idea is that, if a worker in industry j has many chances to communicate with workers in industry k, it will help him/her find a job in industry k. Since the communication should be in both directions, we sum up the ratio of the output of the source industry sold to the destination industry and the ratio of the output of the destination

[8]The Employment Status Survey is a quinquennial, large-scale cross section survey conducted by the Statistics Bureau.

[9]We used the table with 108 industries. We recoded these 108 industries to consistent coding with each of the Labour Force Survey's 51 industries and the Working Person Survey's 34 industries.

industry sold to the source industry. Hereafter, we call this sum, T_{jk}, the "transaction index."

As the proxies of industry performance, p_{jt} and p_{kt}, we test the following four variables: the annual growth rate of total factor productivity (TFP), the industry's average return on assets (ROA), average monthly earnings, and unfilled vacancy rate. We use all four variables rather than choosing any one, because each variable represents a slightly different aspect of the industry's performance. The TFP growth rate reflects the industry's medium-term growth, whereas the ROA captures a shorter term fluctuation. The monthly earnings reflect the attractiveness of the industry from the viewpoint of workers, and the unfilled vacancy rate represents the excess labor demand, that is, the ease of getting a job in the industry. Table A1 in the Appendix describes the data sources and the detailed definitions of these variables.

Note that we run a separate regression for each variable instead of including all of them in one regression for two reasons. First, although these variables reflect different aspects of the industry's performance, they are highly correlated. Thus, including more than one performance variable may lead to a severe multicollinearity problem. Second, practically, the set of industries for which all four variables are available is quite limited.

2.1.3 Worker flow data from the Labour Force Survey

Worker flow data are taken from the Labour Force Survey, which is conducted by the Statistics Bureau of the Ministry of Internal Affairs and Communications. The survey covers all households in Japan. The information on job change is available from the special questionnaire, which is distributed to about 21 thousand people older than 15 every month.

Specifically, we define W_{jkt} as the number of workers employed in industry k in year t who left industry j within a year before the survey. We use 2-digit industry codes (*chubunrui*) with some modifications described in the Appendix.[10] The number of industries in the final dataset is 51, and we calculate W_{jkt} for males and females separately. In order to maintain the exact same industry codes throughout the data period, we limit our data to the years 2003-2008, during which the 11th revision of the Japan Standard Industrial Classification was applied. Thus, the total number of

[10]The worker flow data classified by the 2-digit industry code are not publicly available, and thus, we estimated them using microdata after securing the approval of the Statistics Bureau.

observations is $51 \times 51 \times 2 \times 6 = 31,212$. E_{jt} and E_{kt} are defined as the numbers of workers in the source industry and the destination industry, respectively. Although the Labour Force Survey is conducted monthly, we convert W_{jkt}, E_{jt}, and E_{kt} to annual data by taking the average over 12 months. Then the industry-level variables defined in the previous subsection are merged using the industry and year.

Table 1 shows the summary statistics of worker flow data. Note that 75 percentile of W_{jkt} is 0. That is, more than three in four pairs of industries have no job changers between them in the data. The distribution of the transaction index is also skewed and has a very long tail.

2.2 Analysis of earnings changes and likelihood of move to a distant industry using data from the Working Person Survey

2.2.1 Earnings changes

After examining the determinants of worker flow, we examine the effect of variables on earnings changes that are associated with inter-industry job changes. If a factor that decreases worker flow between two industries actually lowers earnings after the job change, the anticipated earnings loss associated with the move may be the main obstacle to worker reallocation. Specifically, we estimate the following equation using the sample of job changers:

$$\log I_{ijkt} = \beta_0 + \beta_1 X_{ijkt} + \beta_2 S_{jk} + \beta_3 T_{jk} + \beta_4 p_{jt} + \beta_5 p_{kt} + \xi_j + \zeta_k + \lambda_t + \varepsilon_{ijkt} \tag{8}$$

where I_{ijkt} is individual i's annual earnings after moving from industry j to industry k in year t. X_{ijkt} refers to control variables such as age and its square, education, indicators of regular/non-regular status of current and previous jobs (hereafter "employment status dummies"), and log annual earnings before the move. S_{jk}, T_{jk}, p_{jt}, and p_{kt} are the same as defined in the previous subsections, and ξ_j and ζ_k are the source and destination industry fixed effects, respectively. λ_t is a year effect, and ε_{ijkt} is a random error term.

Note that earnings changes after a job change are observable only for those who actually moved. People tend to avoid moving when the earnings loss associated with the job change is large. Our earnings regression (8) does not account for this endogenous selection of job changers. If there were a good instrumental variable, we could use Heckman's (1979) selection model to solve this endogenous sample selection; however, practically it is very difficult to find an instrumental variable that affects the probability of job change but does not have any direct effect on earnings and is uncorrelated with any unobservable individual characteristics that could affect earnings.

Therefore, β_2 and β_3 cannot be interpreted as the causal effect for the population including those who choose not to move. Nevertheless, if β_2 is significantly negative, it means that people who actually moved to a distant industry experienced, on average, a larger earnings loss. This observed negative correlation itself may impede labor reallocation between distant industries by generating the expectation for earnings loss.

Using the sample of all job changers including those who moved within an industry, we further explore how much of the earnings loss associated with inter-industry job changes is attributable to the differences in the required tasks. Specifically, we estimate the following equation:

$$\log I_{ijkt} = \beta_0 + \beta_1 1(j \neq k) + \beta_2 \tilde{S}_{it} + \beta_3 T_{jk} + \beta_4 X_{ijkt} + \xi_j + \zeta_k + \lambda_t + \varepsilon_{ijkt} \tag{9}$$

$1(j \neq k)$ is a dummy for the inter-industry move. We explore how the coefficient of this dummy, β_1, changes when we change the controls for task changes, $\tilde{S}_{it}$. We try the following four specifications (1) no control for task distance, (2) control for task distance between the source and destination industries (S_{jk} in equation (8), which is 0 for intra-industry changes), (3) control for task distance between current and previous jobs calculated based on the actual occupation[11] rather than industry, and (4) including both task distance between industries and task distance between the actual occupations. Other explanatory variables are the same as equation (8), except that we omit time-variant industry performance p_{jt}, and p_{kt} to avoid running the same regression four times.[12]

[11]Since the original job component indices by Matsumoto et al. (2012) refer to the occupation level, the distance between occupations should be a more precise measure of the distance between current and previous jobs.

[12]We confirmed that inclusion of industry performance variables does not change the results qualitatively. In addition, as shown in Table 4, none of the industry performance variables has a statistically significant effect on earnings after a job change.

2.2.2 Individual characteristics and cost of inter-industry job changes

Next, we explore the types of workers who tend to move to an industry requiring tasks quite different from those required in the previous job's industry. We focus on the following three factors: (1) age, (2) educational background, and (3) reason for the job change. In addition, we explore how the earnings loss by moving to a distant industry varies with these factors. The idea is that, if a worker loses relatively less by moving to a distant industry, they may be more willing to move to such an industry. To examine this idea, for each of the three factors, we estimate the following system of equations:

$$S_{jk} = \beta_0 + \beta_1 X_{ijkt}^S + \sum_{f=1}^{F} \gamma_f 1(a_{it} = A_f) + \varepsilon_{it} \tag{10}$$

$$\log I_{ijkt} = \delta_0 + \delta_1 X_{ijkt}^I + \sum_{f=1}^{F} \theta_f 1(a_{it} = A_f) + \lambda_0 S_{jk} + \sum_{f=1}^{F} \lambda_f 1(a_{it} = A_f) S_{jk} + \eta_{it} \tag{11}$$

where a_{it} is a categorical variable indicating the factor of interest: (1) age at the time of job change (25 or younger, 25-34, 35-44, 45-54, 55-59), (2) education (high school or less, vocational school/junior college/technical college, college or higher), or (3) reason for the job change (involuntary termination, family or health reasons, discontent with the previous job, for a better career).[13] Control variables X_{ijkt}^S include employment status dummies, and X_{ijkt}^I include employment status dummies and log earnings of previous jobs. We allow correlation between ε_{it} and η_{it} and estimate a seemingly unrelated regressions (SUR) model.

γ_f represents the effect of a_{it} itself on the task distance, and λ_f represents how the effect of task distance on the earnings changes with a_{it}. If workers who are relatively more likely to move to an industry requiring tasks different from the current job are indeed experiencing smaller earnings losses associated with task distance, the signs of γ_f in equation (10) and λ_f in equation (11) should be the same.

There are two reasons why some workers may experience smaller earnings losses than others when they move to a distant industry. The first potential reason is that they may be able to find a job requiring similar tasks even though they move to a distant industry. In other words, task

[13] Detailed definitions for "reasons for job change" are provided in Appendix A.3.

distance between the current and previous jobs based on actual occupations is smaller for them after controlling for task distance between industries. To examine this, we estimate the following equation:

$$\bar{S}_{ijkt} = \beta_0 + \beta_1 X^S_{ijkt} + \sum_{f=1}^{F} \gamma_f 1(a_{it} = A_f) + \delta S_{jk} + \varepsilon_{it} \tag{12}$$

$\bar{S}_{ijkt}$ is task distance between the current and previous jobs based on actual occupations for worker i who moved from industry j to k in year t. If the workers who experience smaller earnings losses are more likely to find a similar job in a given industry, the signs of λ_f in equation (11) and γ_f in equation (12) should be opposite.

The second potential reason is that the cost of moving to a job requiring different tasks is smaller for these workers. For example, such a cost may be smaller for younger workers because they have not yet accumulated adequate skills specific to each task, and thus, they do not lose much. To examine this possibility, we estimate the following equation:

$$\begin{aligned}\log I_{ijkt} = \delta_0 + \delta_1 X^I_{ijkt} + \sum_{f=1}^{F} \theta_f 1(a_{it} = A_f) \\ + \bar{\lambda}_0 \bar{S}_{ijkt} + \sum_{f=1}^{F} \bar{\lambda}_f 1(a_{it} = A_f)\bar{S}_{ijkt} + \lambda_0 S_{jk} + \sum_{f=1}^{F} \lambda_f 1(a_{it} = A_f) S_{jk} + \eta_{it}\end{aligned} \tag{13}$$

This equation is basically the same as equation (11) except that the measure of task distance is based on the actual occupations. We also add controls for task distance between industries and interactions with worker's characteristics to see whether the task distance of actual occupations has a stronger effect than the distance between industries. If the cost of moving to a job requiring different tasks is indeed smaller for those who tend to move to a distant industry, the signs of $\bar{\lambda}_f$ should be the same as γ_f in equation (10).

2.2.3 Working Person Survey

Data for earnings and individual characteristics of job changers are taken from the Working Person Surveys for 2006, 2008, and 2010, conducted by the Recruit Works Institute. The universe comprises employed people aged 18-59, living in 5 prefectures (4 for the 2010 survey)[14] located in the greater Tokyo metropolitan area. The advantage of using data from the Working Person Survey is that it provides detailed information about current and previous jobs as well as earnings and industry.

However, an important drawback is that the year when a worker left the previous employer is not available. Thus, we cannot exclude workers who were out of the labor force for some time before starting their current jobs. This is a problem particularly for women, because many married women withdraw from the labor force when their children are young.

For the analysis of earnings changes and task distance associated with a job change, we limit our sample to those who started to work at the current employer between 2000 and 2010. Table 2 shows the summary statistics.

Since the effects of age and education might be different for males and females, all the analyses are done for the pooled sample of men and women, men only, and women only.

3 Results on worker flow

Table 3 shows the estimated coefficients in equation (5), the gravity model of inter-industry worker flow:

$$\begin{aligned} W_{jkt} = \exp(&\log \alpha_0 + \alpha_1 \log E_{jt} + \alpha_2 \log E_{kt} + \alpha_3\beta_1 \log S_{jk} \\ &+ \alpha_3\beta_2 \log T_{jk} + \gamma_{0j} + \gamma_1 p_{jt} + \delta_{0k} + \delta_1 p_{kt} + \lambda_t) + \varepsilon_{jkt} \end{aligned}$$

Panels A and B show the results for men and women, respectively. Each column includes different variables for p_{jt} and p_{kt}, which capture industry performance. As expected, the coefficients of the sizes of the total employment of the destination and source industries are close to 1 in all specifications. Further, log task distance, the measure for the differences in required tasks between the two industries, has a significantly negative impact on worker flow. In contrast, the transaction

[14] The 2006 and 2008 surveys covered Tokyo, Kanagawa, Chiba, Saitama, and Ibaraki. The 2010 survey did not cover Ibaraki.

index has a significantly positive impact on the worker flow between the two industries.

Marginal effects of a one standard deviation increase in log task distance and log transaction index are presented at the bottom of Table 3. The marginal effect in each column is evaluated at the mean of the sample used for each regression. The marginal effect of a standard deviation increase in the log task distance ranges from -0.02 to -0.07. This means that a one standard deviation increase in task distance leads to about 30-100 fewer inter-industry movers per year (note that W_{jkt} is measured in 1000 persons). Given that the 90th percentile of W_{jkt} is 0.69, this is not a trivial impact. Likewise, a standard deviation increase in the log transaction index leads to 10-60 more inter-industry moves per year. These marginal effects are slightly larger for men.

In contrast, the coefficients on the variables for industry performance are statistically insignificant. Among them, the TFP and ROA of the destination industry possess a negative sign, contrary to the expectation, for men. For women, although the sign of TFP of the destination industry is positive, that of TFP of the source industry is also positive. Therefore, it is not likely that workers changing industries experience improved productivity? The other two variables are related to the labor market, and they seem to be slightly more relevant. For both men and women, the average log earnings of the source industry have a negative effect, and the unfilled vacancy rate of the destination industry has a positive effect, although it is not statistically significant. This probably implies that workers are hesitant to resign from industries that pay better, and it is easier for them to find a job where excess labor demand is high.

4 Results on earnings after an inter-industry job change

Table 4 shows the estimated coefficients in equation (8), the regression of earnings after a job change:

$$\log I_{ijkt} = \beta_0 + \beta_1 X_{ijkt} + \beta_2 S_{jk} + \beta_3 T_{jk} + \beta_4 p_{jt} + \beta_5 p_{kt} + \xi_j + \zeta_k + \lambda_t + \varepsilon_{ijkt}$$

Panels A and B show the results for men and women, respectively. Each column includes different variables for p_{jt} and p_{kt}.

Log task distance has a statistically significant negative effect on earnings in all specifications. That is, a worker faces loss of earnings when he/she moves to an industry requiring tasks different from those required in the previous job. Thus, it might be the case that an anticipated loss of earnings prevents workers from making job changes. Since one standard deviation of the task distance is 0.60 for inter-industry movers, the effect of a one standard deviation increase in the task distance decreases earnings by about 1.6-2.6%. To put it differently, given that the average task distance is 1.55 for inter-industry movers, an average inter-industry mover experiences earnings changes of about 4-7% due to the change in required tasks.[15]

Although the transaction index has a positive effect on earnings after a job change, the coefficients are statistically insignificant, except for Column (4) of Panel B. Moreover, the size of the effect is small. Since one standard deviation of the transaction index is 9.3% (i.e., 0.093) for inter-industry movers, the effect of a one standard deviation increase in the transaction index increases earnings by at most 0.7% only. Furthermore, none of the variables for industry performance has statistically significant effects on earnings after a job change. This implies that growing industries do not necessarily offer better salaries.

Table 4 also reports the coefficients of employment status dummies. Not surprisingly, a move from regular to non-regular employment is associated with a large earnings loss. The earnings gain from moving from non-regular to regular employment is much smaller, probably because regular jobs available for job seekers previously hired as non-regular workers are limited and in worse conditions . In any case, even after controlling for the changes in employment status, the distance in required tasks is an important determinant of earnings change after a job change.

Table 5 presents the estimated coefficients of a dummy for inter-industry move and task distance measures in equation (9):

$$\log I_{ijkt} = \beta_0 + \beta_1 1(j \neq k) + \beta_2 \tilde{S}_{it} + \beta_3 T_{jk} + \beta_4 X_{ijkt} + \xi_j + \zeta_k + \lambda_t + \varepsilon_{ijkt}$$

First, columns (1) and (5) show that without controlling for task distance, inter-industry movers

[15] In Appendix B.2, we estimate the same model using the subsample of inter-industry movers only. Although the estimated effect of the task distance becomes statistically insignificant, the size of the coefficient remains the same at least for men, and if both men and women are pooled, it becomes statistically significant again.

experience, on average, a 5-percentage point larger earnings loss than intra-industry movers. However, columns (2) and (6) show that this negative effect becomes insignificant after controlling for task distance between source and destination industries. Although the coefficients of such task distance are not statistically significant, the point estimates are roughly comparable to those in Table 3. The insignificance is due to the boosted standard errors, probably because of the multicollinearity between the inter-industry move dummy and task distance. For men, however, some factors other than inter-industry move seem to have an impact, because the absolute value of the coefficient of inter-industry move dummy in column (2) remains about half as large as that in column (1), and the absolute value of the coefficient of task-distance between industries in column (2) is only about two thirds of those in Table 3.

In columns (3) and (7), we control for task distance between current and previous jobs measured using actual occupations instead of task distance between industries. The coefficient of inter-industry move remains insignificant. Furthermore, columns (4) and (8) show that, when both task distances between industries and between actual occupations are included, only the distance between actual occupations has a statistically significant negative effect. This implies that what actually matter is a change in tasks required by the job itself.

5 Worker types prone to move to industries requiring different task sets

So far, we have shown that differences in required tasks are one of the major determinants of inter-industry worker flows and that an inter-industry job change associated with a larger change in required tasks leads to a larger decline in earnings after the job change. Combining these two facts suggests that the anticipated earnings loss may deter workers from making inter-industry job changes and hinders smooth reallocation of the labor force from the declining industry to the emerging industry. If so, workers with relatively small earnings losses associated with changes in required tasks may be more willing to move to distant industries. This section investigates this possibility.

Before exploring who is more likely to move to an industry requiring tasks different from the previous job, it is informative to learn who is more likely to change jobs and move across industries. In Appendix B.1, we examine how the likelihood of a job change and inter-industry move are affected by individual characteristics (age and education) and industry performance. To summarize, we find that women are more likely to change jobs and move across industries than men, and the effect of age is quite different across genders. For men, the probabilities of a job change and an inter-industry move increase with age until they reach 40 and become flat after 40. In contrast, women who were 30-39 years old as of 2000 are the most likely to change jobs and move across industries. On the other hand, the effect of education is similar across genders: more educated workers tend to move less across industries. Lastly, none of the industry performance measures has a statistically significant effect.

To explore which workers tend to move to an industry requiring tasks different from their current jobs and whether they are indeed experiencing smaller earnings losses, Tables 6a-6c present the estimated coefficients of equations (10) and (11):

$$S_{jk} = \beta_0 + \beta_1 X^S_{ijkt} + \sum_{f=1}^{F} \gamma_f 1(a_{it} = A_f) + \varepsilon_{it}$$

$$\log I_{ijkt} = \delta_0 + \delta_1 X^I_{ijkt} + \sum_{f=1}^{F} \theta_f 1(a_{it} = A_f) + \lambda_0 S_{jk} + \sum_{f=1}^{F} \lambda_f 1(a_{it} = A_f) S_{jk} + \eta_{it}$$

If γ_f, the coefficients of factor dummies (e.g. age category) in the upper panel of the table, have the same signs as λ_f, the coefficients of the interaction terms between task distance and these factor dummies in the lower panel, it implies that workers who tend to move experience smaller earnings losses after a job change. Each table corresponds to the following three factors: a) age, b) educational background, and c) reason for the job change. All the analyses are conducted separately for men and women.

Table 6a shows the results for age at the time of the job change. The reference group is 35-44 years old. The upper panel shows the effect of age on task distance differs across men and women. While young men are more likely to move to an industry requiring different tasks than prime-aged men, young women are less likely to do so. Interestingly, the effect of age on the task distance among job changers is similar to the effects of age on the likelihood of job changes and inter-industry moves among all workers, which is described in Appendix B.1. This implies that people who move more often tend to move to relatively distant industries.

In contrast, the effect of task distance on earnings, shown in the lower panel, does not fit the same pattern. For both men and women, young workers tend to lose less by moving to a distant industry. This is not surprising because young workers have not invested much on industry- or task-specific human capital and thus do not have much to lose. Nonetheless, young women are less likely to move across industries, and even if they move, they tend to move to industries requiring a similar set of tasks. Furthermore, old men lose more by moving to a distant industry, but they are rather slightly more likely to move. These patterns might reflect the differences in labor demand for each age group; that is, the lack of employment opportunities in industries requiring similar tasks forces old men to move to a distant industry.

Next, Table 6b shows the results for educational background. The reference group is vocational school/junior college/technical college, that is, those with a few years of post-secondary education. For men, there is little difference between "high school or less educated" and "college or more educated," and both groups are more likely to move to distant industries than the reference group. The cost of moving to a distant industry is smaller for them as well. For women, workers with high school education or less are more likely to move to a distant industry, and high school graduates tend to lose less than college graduates by moving to a distant industry. These results imply that in terms of education, those who lose less by moving to distant industry tend to move to a more distant industry.

Lastly, Table 6c shows the results regarding the reason for the job change. The reference group is "discontented with the previous job" and includes people who did not like something about the previous job, such as wages, relationship with colleagues, etc. Male workers who are involuntarily forced to leave the previous job are less likely to move. However, for men, the effect of task distance on earnings after a job change is not significantly correlated with the reason for quitting. Rather, involuntary termination for women is associated with larger earnings loss.

In addition, workers who quit for family or health reasons tend to move to a distant industry, though the result is not statistically significant for men. However, the earnings loss by moving to a distant industry is not smaller for them. Workers who left for family or health reasons may tend to be less concerned about the disadvantage associated with a job change, perhaps because private reasons would have pressed them to change other working conditions such as hours of work. In addition, we have to keep in mind that we do not have access to data regarding the time the respondent left the previous employer. Therefore, we cannot exclude people who left their previous jobs a long time ago. This is particularly relevant for workers who quit for family or health reasons, because many of them withdraw from the labor force for several years.[16]

Tables 7a-7c present the estimated coefficients in equation (12):

$$\bar{S}_{ijkt} = \beta_0 + \beta_1 X^S_{ijkt} + \sum_{f=1}^{F} \gamma_f 1(a_{it} = A_f) + \delta S_{jk} + \varepsilon_{it}$$

Recall that, if the workers who experience smaller earnings losses are more likely to find a similar job in a given industry, the signs of λ_f in equation (11) and γ_f in equation (12), which are reported in Table 6a-c, should be opposite.

In Table 7a, the coefficients of age on task distance between current and previous jobs have the same signs as those reported in Table 6a. In contrast, Table 7b shows that male college graduates are much less likely to move to distant jobs once the task distance between industries is controlled, whereas Table 6b shows that male college graduates are more likely to move to a distant industry than vocational/junior college graduates. Table 7c shows no statistically significant differences across reasons for quitting, except that men who quit for a better career tend to move to closer jobs.

Therefore, only in Table 7b , the estimated γ_f possess opposite signs to the estimated λ_f in Table 6b, which means that male workers experiencing smaller earnings losses associated with a move to a distant industry will find a job requiring similar tasks. For age and reasons for quitting, however, this logic does not explain the observed pattern in Table 6.

[16] Also, it is worth mentioning that the level of earnings itself varies with the reason for quitting, even with controls for the previous job's earnings. Workers who quit for family or health reasons experience the largest decline in earnings. They earn much less even compared to involuntary job changers who were forced to quit due to dismissal or bankruptcy.

Then, is the cost of moving to a job requiring different tasks smaller for workers who experience smaller earnings losses associated with moving to a distant industry? Tables 8a-8c present the estimated coefficients in equation (13):

$$\log I_{ijkt} = \delta_0 + \delta_1 X^I_{ijkt} + \sum_{f=1}^{F} \theta_f 1(a_{it} = A_f)$$
$$+ \bar{\lambda}_0 \bar{S}_{ijkt} + \sum_{f=1}^{F} \bar{\lambda}_f 1(a_{it} = A_f) \bar{S}_{ijkt} + \lambda_0 S_{jk} + \sum_{f=1}^{F} \lambda_f 1(a_{it} = A_f) S_{jk} + \eta_{it}$$

Recall that, if the cost of moving to a job requiring different tasks is indeed smaller for those who tend to move to a distant industry, the signs of $\bar{\lambda}_f$ should be the same as γ_f in equation (10) (reported in the upper panel of Tables 6a-c).

Table 8a shows that the coefficients of the interaction terms between task distance of the actual job and dummies for age follow the same pattern as those presented in Table 6a. Therefore, for age, the cost of moving to a job requiring different tasks is actually lesser for workers who experience smaller earnings losses associated with a move to a distant industry.

As shown in Table 8b, however, the coefficients of the interaction terms between task distance and dummies for education are quite different from those in Table 6b. Therefore, regarding educational background, the first explanation is more relevant than the second explanation.

To summarize, we find that young men are more likely to move to an industry requiring different tasks than prime-aged men, whereas young women are less likely to do. Yet, as shown in Table 6a, those who tend to move do not necessarily lose less, although a comparison between Tables 6a and 8a implies that earnings loss by moving to distant industry is smaller for young workers because the cost of moving to a different job itself is smaller for them. Likewise, female workers who quit for family or health reasons tend to move more, and male workers who quit for involuntary termination tend to move less, but this pattern is not caused by the differences in the cost of moving to different jobs. Only for education, workers who lose less by moving tend to move more, and at least for men, more educated workers lose less by moving to a distant industry because they can find a similar job within that industry.

6 Concluding remarks

This paper has examined the determinants of worker flow by applying the gravity model, using the differences in required tasks and the volume of transaction between two industries as proxies for distance. The results show that workers tend to move to industries with close relationships in terms of chances for transactions and industries that are similar in terms of required tasks. Industry performance does not play an important role. Further, we found that large earnings losses are associated with inter-industry moves involving large changes in required tasks. However, the size of this loss is not always systematically related to the likelihood of moving to an industry requiring a different set of tasks than the previous job. Again, industry performance has little impact on earnings after a job change.

Encouraging reallocation of labor from declining sectors to growing sectors is an important issue in designing macroeconomic policies. Our findings on the negligible impact of industry performance imply the lack of spontaneous labor reallocation. Further, the negative effect of task distance on earnings after a job change implies that workers may hesitate to move to industries requiring a different set of tasks for fear of losing the wage premium acquired by task-specific human capital. To foster smoother inter-industry labor reallocation, it is necessary to provide opportunities to acquire skills and knowledge required to perform tasks in industries with growing labor demand. Since it is unlikely that firms would voluntarily provide such training , it should be provided by public training programs .

A remaining puzzle is the lack of a systematic relationship between the likelihood of moving to distant industries and the size of earnings loss associated with task distance between current and previous industries. We hypothesized that anticipated earnings loss prevents inter-industry move, and thus, individuals more likely to move should lose relatively less by moving to distant industries. However, the results presented in Section 5 do not support this hypothesis. It may be because different groups face different labor demand conditions, and this makes the selection of job changers different across those groups. As we explained in Section 2.2.1, it is very difficult to fully account for the endogenous selection of job changers with our dataset. This is an important limitation of the current paper, and solving it is left for future research.

A Data Appendix

A.1 Task indices provided by Matsumoto et al (2012)

The Japan Institute of Labor Policy and Training (JILPT) conducted a web survey of 21,033 Japanese workers from 2003-2006. The survey asked about (1) the respondent's current occupation in his/her job, and (2) to what extent each of the 94 job components is required in or applicable to his or her job (measured as a value between 1 and 5). Matsumoto et al. (2012) used data from this survey to calculate the Z-scores of the following 30 job components for each of 601 occupations.

- Interests (RIASEC; same as O*NET)
  - Realistic
  - Investigative
  - Artistic
  - Social
  - Enterprising
  - Conventional
- Work values (same as O*NET except that "support" and "working conditions" are replaced by Growth)
  - Achievement
  - Growth (Self-development)
  - Recognition
  - Relationships
  - Independence
- Work conditions (14 questions are aggregated to 5 factors by factor analysis)
  - Desk work

  - Communication with others
  - Outdoor
  - Influential / high responsibility
  - Line operation
- Skills (35 questions are aggregated to 6 factors by factor analysis)
  - Basic
  - Mathematical
  - Technical
  - Human
  - Computing
  - Management
- Knowledge (33 questions are aggregated to 7 factors by factor analysis)
  - Science and technology
  - Arts and humanity
  - Medical
  - Business
  - Language
  - Civil engineering and security
  - Chemistry and biology

We use the 13 components from the sections titled "Skills" and "Knowledge" to calculate the task distance. In an earlier version of this paper, we used all 30 components. The results do not change qualitatively.

In the main specification, we assume that the changes in required tasks for moves from industry j to k and vice versa are the same. Since a move from an industry that requires more of the task component to one that requires less of it may be easier than the reverse, we tried an alternative measure of task distance to count upward and downward moves separately: $\tilde{S}^1_{jk} = \sqrt{\sum_{m=1}^{13}(\hat{s}_{mj} - \hat{s}_{mk})^2 * 1(\hat{s}_{mj} > \hat{s}_{mk})}$, and $\tilde{S}^2_{jk} = \sqrt{\sum_{m=1}^{13}(\hat{s}_{mj} - \hat{s}_{mk})^2 * 1(\hat{s}_{mj} < \hat{s}_{mk})}$, respectively. However, both $\tilde{S}^1_{jk}$ and $\tilde{S}^2_{jk}$ tend to have significantly negative effects on worker flow when one of them is included, and multicollinearity from the strong correlation between $\tilde{S}^1_{jk}$ and $\tilde{S}^2_{jk}$ ($corr(\tilde{S}^1_{jk}, \tilde{S}^2_{jk}) = 0.55$) makes the estimated coefficients unstable and imprecise when both measures are included simultaneously. Thus, we do not use this separate measure.

In the same vein, the strong correlations between the distances in each of the 13 components make it difficult to estimate the effect of distance in each component separately.

A.2 Industry and Occupation Coding

The Labour Force Survey for 2003-2008 used the 11th revision of the Japan Standard Industrial Classification. The original 2-digit classification includes 96 industries. We make the following modifications in order to merge the variables taken from other data sources.

1. The following variables are deleted because they are not covered in the other data sources: Agriculture; Forestry; Fishery; Aquaculture; Postal services (except otherwise classified); Cooperative associations (not elsewhere classified); Professional services (not elsewhere classified), Political, business and cultural organizations; Religion; Miscellaneous services; Foreign governments and international agencies in Japan; National government services; and Local government services.

2. Manufacture of textile mill products, except apparel and other finished products made from fabrics and similar materials and Manufacture of apparel and other finished products made from fabrics and similar materials are combined into Manufacture of textile including apparel.

3. Manufacture of general machinery and Manufacture of precision instruments and machinery are combined into Manufacture of general machinery.

4. Road passenger transport and Road freight transport are combined into Road transport.

5. Five separate categories of retail trade are combined into a single category Retail trade.

6. General eating and drinking places and Spree eating and drinking places are combined into Eating and drinking place.

7. Medical and other health services and Public health and hygiene are combined into Medical and health care.

8. School education and Miscellaneous education, learning support are combined into Education.

9. Automobile maintenance services and Machine, etc. repair services (except otherwise classified) are combined into Maintenance and repair services.

These modifications reduce the number of remaining industries from 96 to 51.

Industry coding in the Working Person Survey is different from that in the Japan Standard Industrial Classification. There are 66 industries in the original data, but in order to make the coding consistent with the other data taken from government surveys, we need to merge some industries into a larger category. Consequently, the analysis sample includes 34 industries.

We also make modifications to the industry coding of data sources for the explanatory variables. In addition, the occupation coding of the Employment Status Survey is also modified so that it can be merged with the task data taken from Matsumoto et al (2012). A cross-walk table of industry and occupation codes (in Japanese) is available upon request.

A.3 Reasons for job change

The original questionnaire asked the respondent to pick the most important reason for a job change from 22 options including "Others." We dropped job changers who answered "Others" and divided the remaining 21 options into 4 categories as follows:

"Involuntary termination": (1) mandatory retirement, (2) expiration of employment contract, (3) bankruptcy or dismissal for downsizing.

"Family or health reason": (4) marriage, (5) childbirth, (6) to focus on childcare, (7) family caregiving, (8) injury or disease.

“Discontent with the previous job”: (9) not satisfied with wages, (10) not satisfied with evaluation, (11) bad working conditions (hours and days of work, location, etc.), (12) too physically demanding, (13) too mentally demanding, (14) can't utilize ability and expertise, (15) do not feel I am “growing” in my job , (17) anxiety for the company's future, (18) discontent with recent job transfer (including both intra-firm relocation and transfer to affiliated companies), (19) frustrated by colleagues.

”For a better career”: (16) got an offer of a better job, (20) to study for further education or to acquire a license, (21) to start one's own business.

B Background analyses and robustness checks

B.1 Determinants of job changes

First, we investigate individual characteristics that affect the probability of inter-industry job changes. Since the Working Person Survey is not panel data, it merely conveys whether each worker has experienced a job change or an inter-industry job change during a specific period of time, namely 2000-2010. We investigate how the probability of an inter-industry job change is affected by individual characteristics such as age and education. Specifically, we estimate the following regression:

$$Y_{ij} = \beta_0(+\beta_1 female_i) + \sum_a \gamma_a 1(age2000_i \in agecateg_a) + \sum_e \delta_e 1(educ_i \in educcateg_e) + \xi_j \quad (14)$$

where Y_{ij} takes 1 if individual i has experienced an inter-industry job changes since 2000. $age2000_i$ is the individual i's age as of 2000, and age categories are 5-year intervals beginning from those younger than 15 and counting up to those aged 54-55. We also include dummy variables for education. The subscript j indicates individual i's industry at the beginning of the period (previous industry if i has changed his/her job since 2000, and current industry otherwise) and ξ_j represents industry fixed effects.

For this analysis, the sample includes all individuals who started work prior to 2000. The dependent variables are defined as follows. The indicator for job change takes 1 if the worker started the current job between 2000-2010 and has resigned from a job at least once (i.e., the current job is not the first job) and 0 otherwise. The indicator for inter-industry job change takes 1 if the indicator for job change takes 1 and if the industries of the current and previous jobs are different. The industry at the beginning of the period is defined as the industry of the previous job for those who have changed their jobs since 2000 and that of the current job for the others. Table B1 shows the summary statistics.

Table B2 shows estimated coefficients on the female dummy, dummies for age categories as of 2000, and education dummies in equation (14). The dependent variables are a dummy for having changed a job between 2000 and the survey year ("Job change") and a dummy for having moved across industries between 2000 and the survey year ("Inter-ind. move"). All the regressions include dummies for the industry at the beginning of the period, namely the industry of the previous job for those who have changed their jobs since 2000 and that of the current job for the others.

There are substantial differences between men and women. First, women are more likely to change jobs and move across industries than men. Also, the effect of age is quite different. Younger men (less than 40) are more likely to change jobs and move across industries, except for the youngest group, many of whom were still in school in 2000 and thus had spent shorter time periods in the labor force at the time of the survey. For men older than 40 as of 2000, the probabilities of job change and inter-industry move are mostly the same as those for the reference group, except for the positive coefficients on ages 45-49. These positive coefficients may reflect involuntary resignations due to downsizing, but the size of the coefficients is not very large. In contrast, women who were 30-39 years old as of 2000 are the most likely to change jobs and move across industries. This is probably because many women resign from full-time jobs after the birth of the first child and return to the labor force after their child starts kindergarten or elementary school. Note that the Working Person Survey does not provide information on when the worker quit the previous job; thus, the timing of the "job change" in our data is actually the timing when the worker started her current job.

The effect of education is similar across genders. College graduates are much less likely to change jobs and move across industries than high school graduates, the reference group. Those who went to vocational school after finishing high school also tend to stay in the same job, probably because they are more likely to have a specialist job. The effect of junior college is significantly negative only for women, but this insignificance for men is likely to be due to the small number of men who go to junior college.

In addition, Table B3a and B3b show the effects of industry performance and age categories on separation and hiring rates using data taken from the publicly available tables of the Employment Trend Survey. Basically, industry performance does not affect separation or hiring rates much. This is consistent with the insignificant effect of industry performance on worker flow presented in Table 3. Note that the effects of age do not look similar to those presented in Table B2 because of the differences in the definitions of the dependent variables. "Separation" in the Employment Trend Survey includes those who permanently withdraw from the labor force, and "hiring" includes those who got a job for the first time. However, the job changers in the Working Person Survey include only those who resigned from a job and started a new job sometime between 2000 and 2010.

B.2 Earnings changes among inter-industry movers only

The earnings loss associated with a job change is smaller for intra-industry job changers than inter-industry job changers, and the task distance is, by definition, zero for intra-industry movers. Thus, to check the robustness of the significant effects of task distance, we estimate the same model as equation (8), or Table 4, using the subsample of inter-industry movers only. The results are shown in Table B4 Panels A-C. Although the estimated effect of the task distance becomes statistically insignificant due to the boosted standard errors, the size of the coefficient remains the same for men at least. Furthermore, if both men and women are pooled, it becomes statistically significant again.

B.3 Robustness checks excluding the medical and caring industry

Japan's medical industry grew exponentially in the 2000s, recording the highest growth among all industries. However, worker compensation in this industry is highly controlled by the public health and caring insurance systems, and thus, earnings for workers in this industry are determined differently from those in other industries. Since a large proportion of job changers, especially females, move to this industry, there is the concern that data from this particular industry might bias our estimates.[17]

Therefore, we check the robustness of our results by excluding the data of the medical and caring industry from our sample. Table B5 shows the estimated effects on the volume of inter-industry worker flow. Specifically, we drop flows from and to the medical and caring industry from our sample and estimate equation (5). The coefficients of log task distance and log transaction index are almost the same as those in Table 3.

Using the same specification as that in Table 4, Table B6 shows the effects on the earnings change. We exclude workers who moved to or from the medical and caring industry from the sample. The estimated coefficients are hardly affected by the exclusion of these workers.

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Table 1. Summary statistics of Worker-flow data

	mean	sd	p50	p75	p90	N
Worker flow (1000 persons)	0.43	3.55	0.00	0.00	0.69	31,212
Total employment of destination industry	459.2	774.2	179.9	436.4	1128.6	31,212
Total employment of source industry	459.2	774.2	179.9	436.4	1128.6	31,212
Task distance	1.45	0.71	1.54	1.95	2.26	31,212
Transaction index	3.8%	10.2%	1.0%	2.9%	8.8%	31,212
TFP growth rate of destination industry	0.43%	3.47%	0.35%	1.86%	4.63%	28,764
TFP growth rate of source industry	0.43%	3.47%	0.35%	1.86%	4.63%	28,764
ROA of destination industry	4.30	2.74	3.98	5.59	6.79	27,930
ROA of source industry	4.30	2.74	3.98	5.59	6.79	27,930
log average monthly earnings of destination industry	341.6	61.5	335.8	375.2	426.6	27,744
log average monthly earnings of source industry	341.6	61.5	335.8	375.2	426.6	27,744
Unfilled vacancy rate of destination industry	1.1%	1.1%	0.8%	1.3%	1.9%	22,440
Unfilled vacancy rate of source industry	1.1%	1.1%	0.8%	1.3%	1.9%	22,440

Note: Unit of the observation is a cell by source industry, destination industry, sex, and year (2003-2008). Thus, N should be equal to (number of industries for which the variable is available)$^2 \times 2 \times 6$.

Table 2. Summary statistics of Working Person Survey

	All job changers			Inter-industry movers only		
	All	Male	Female	All	Male	Female
Sample size	7,667	3,681	3,986	4,505	1,976	2,529
Annual earnings after job change (10,000 yen)	291.94	405.46	187.11	261.31	368.92	167.08
log of annual earnings after job change	5.36	5.81	4.93	5.26	5.74	4.83
Annual earnings before job change (10,000 yen)	335.05	442.55	235.78	304.61	399.55	220.96
log of annual earnings before job change	5.54	5.89	5.21	5.45	5.79	5.15
Education						
Jr. High School	3.3%	4.6%	2.1%	4.0%	5.4%	2.8%
High school	32.0%	29.3%	34.4%	37.6%	34.3%	40.5%
Vocational college (1-3yr)	17.3%	15.7%	18.7%	14.6%	13.0%	16.0%
Junior college (2yr; AA equivalent)	11.1%	1.3%	20.2%	11.4%	1.4%	20.0%
Kosen (Tech college; AA equivalent)	1.5%	2.7%	0.4%	1.4%	2.8%	0.3%
College (4year)	32.0%	41.8%	22.8%	29.2%	40.3%	19.7%
Graduate school	2.8%	4.6%	1.3%	1.8%	2.9%	0.9%
Year of job change	2005.5	2005.4	2005.6	2002.0	2000.7	2003.2
Age at the time of job change	35.48	34.62	36.27	34.19	31.99	36.09
Reason of quit						
Involuntary termination	15.8%	18.4%	13.3%	12.3%	14.4%	10.5%
Family or health reason	19.5%	3.3%	34.5%	24.7%	4.0%	42.8%
Discontent with the previous job	51.9%	61.8%	42.6%	49.9%	63.9%	37.7%
For a better career	12.9%	16.4%	9.6%	13.1%	17.7%	9.1%
Employment status before and after job change						
Currently regular, previously regular	43.3%	64.5%	23.7%	41.8%	64.9%	21.8%

Currently regular, previously non-regular	12.1%	11.2%	12.8%	13.4%	13.1%	13.7%
Currently non-regular, previously regular	18.5%	11.5%	25.0%	20.8%	11.2%	29.2%
Currently non-regular, previously non-regular	26.2%	12.8%	38.5%	24.0%	10.9%	35.4%
Task distance between the destination and source industries	0.88	0.78	0.98	1.55	1.49	1.60
Transaction index	28.5%	25.0%	31.8%	9.5%	9.6%	9.4%
TFP growth rate of destination industry	0.06%	0.03%	0.08%	0.06%	0.07%	0.05%
TFP growth rate of source industry	0.04%	0.02%	0.06%	0.08%	0.10%	0.07%
ROA of destination industry	3.67%	3.69%	3.66%	3.53%	3.59%	3.48%
ROA of source industry	3.74%	3.67%	3.81%	3.60%	3.47%	3.69%
Log average monthly earnings of destination industry	5.78	5.81	5.76	5.77	5.79	5.75
Log average monthly earnings of source industry	5.79	5.81	5.77	5.77	5.78	5.77
Unfilled vacancy rate of destination industry	0.91%	0.90%	0.91%	1.00%	0.95%	1.04%
Unfilled vacancy rate of source industry	0.91%	0.91%	0.90%	1.00%	0.99%	1.01%
Task distance between current and previous jobs (measured based on occupation)	1.82	1.74	1.91	2.60	2.77	2.47

Table 3 Determinants of inter-industry worker flow

A. Men

	(1)	(2)	(3)	(4)
log total employment	1.103***	0.960***	0.993***	0.904***
of destination industry	[0.220]	[0.328]	[0.295]	[0.274]
log total employment	0.730***	1.398***	1.215***	0.875***
of source industry	[0.258]	[0.335]	[0.255]	[0.314]
log task distance	-0.428***	-0.475***	-0.418***	-0.441***
	[0.029]	[0.043]	[0.030]	[0.033]
log transaction index	0.129***	0.086***	0.091***	0.124***
	[0.016]	[0.019]	[0.015]	[0.017]
TFP growth rate	-1.047			
of destination industry	[0.675]			
TFP growth rate	0.491			
of source industry	[0.658]			
ROA		-0.072		
of destination industry *100		[0.068]		
ROA		-0.024		
of source industry *100		[0.027]		
log average earnings			0.926	
of destination industry			[0.651]	
log average earnings			-1.047	
of source industry			[0.729]	
Unfilled vacancy rate				4.843
of destination industry				[2.973]
Unfilled vacancy rate				-0.906
of source industry				[3.398]
Observations	12,876	10,260	11,964	9,370
Marginal effects of				
a SD change of:				
Log task distance	-0.045	-0.063	-0.068	-0.054
Log transaction index	0.052	0.043	0.058	0.056

Note: Coefficients of Poisson regressions. See the text for details. The number of observation is smaller than that in Table 1 because observations with 0 or negative values for the transaction index or task distance are dropped in order to take log of them. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 3 Determinants of inter-industry worker flow

B. Women

	(1)	(2)	(3)	(4)
log total employment	1.245***	0.916***	0.972***	1.053***
of destination industry	[0.255]	[0.250]	[0.225]	[0.315]
log total employment	0.608**	0.843***	0.848***	0.135
of source industry	[0.278]	[0.314]	[0.207]	[0.335]
log task distance	-0.315***	-0.443***	-0.320***	-0.387***
	[0.035]	[0.042]	[0.034]	[0.040]
log transaction index	0.080***	0.037**	0.063***	0.089***
	[0.019]	[0.015]	[0.014]	[0.021]
TFP growth rate	0.937			
of destination industry	[0.773]			
TFP growth rate	0.900			
of source industry	[0.759]			
ROA		0.010		
of destination industry *100		[0.027]		
ROA		-0.013		
of source industry *100		[0.022]		
log average earnings			0.019	
of destination industry			[0.643]	
log average earnings			-0.748	
of source industry			[0.681]	
Unfilled vacancy rate				3.509
of destination industry				[3.280]
Unfilled vacancy rate				0.627
of source industry				[3.368]
Observations	12,336	9,820	11,444	8,950
Marginal effects of				
a SD change of:				
Log task distance	-0.024	-0.061	-0.050	-0.039
Log transaction index	0.022	0.017	0.035	0.031

Note: Coefficients of Poisson regressions. See the text for details. The number of observation is smaller than that in Table 1 because observations with 0 or negative values for the transaction index or task distance are dropped in order to take log of them. Also, all industry pairs with mining are dropped because so few women leave or enter the mining industry that poisson regression including mining does not converge on STATA. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 4 Changes in earnings after inter-industry job change

A. Men, all job changers

	(1)	(2)	(3)	(4)
Task distance between the	-0.031***	-0.034***	-0.040***	-0.036***
source & destination industries	[0.010]	[0.010]	[0.012]	[0.011]
Transaction index between the	0.048	0.032	0.033	0.023
source & destination industries	[0.032]	[0.032]	[0.036]	[0.032]
TFP growth rate	0.065			
of destination industry	[0.293]			
TFP growth rate	-0.351			
of source industry	[0.323]			
ROA		-0.007		
of destination industry *100		[0.007]		
ROA		0.006		
of source industry *100		[0.005]		
log average earnings			0.178	
of destination industry			[0.367]	
log average earnings			0.005	
of source industry			[0.353]	
Unfilled vacancy rate				-0.013
of destination industry *100				[0.012]
Unfilled vacancy rate				0.013
of source industry *100				[0.012]
Employment status:	-0.388***	-0.390***	-0.402***	-0.383***
from regular to non-regular	[0.034]	[0.032]	[0.033]	[0.032]
Employment status:	0.023	0.024	0.032	0.028
from non-regular to regular	[0.022]	[0.022]	[0.024]	[0.022]
Employment status:	-0.149***	-0.149***	-0.152***	-0.146***
from non-regular to non-regular	[0.031]	[0.029]	[0.031]	[0.030]
Observations	3,330	3,669	3,203	3,540
R-squared	0.674	0.691	0.689	0.694

Note: Linear regression of log annual earnings after job change. Control variables omitted from the table include age and squared age, log earnings of the previous job, dummy variables for year of obtaining the current job, year of the survey, industry of current and previous jobs, and education. Reference group of employment status is “from regular to regular.” *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 4 Changes in earnings after inter-industry job change

B. Women, all job changers

	(1)	(2)	(3)	(4)
Task distance between the	-0.036**	-0.037**	-0.044**	-0.026
source & destination industries	[0.016]	[0.016]	[0.017]	[0.018]
Transaction index between the	0.07	0.062	0.045	0.074*
source & destination industries	[0.043]	[0.042]	[0.045]	[0.045]
TFP growth rate	0.014			
of destination industry	[0.380]			
TFP growth rate	0.15			
of source industry	[0.389]			
ROA		0.004		
of destination industry *100		[0.005]		
ROA		-0.002		
of source industry *100		[0.005]		
log average earnings			0.716	
of destination industry			[0.472]	
log average earnings			0.496	
of source industry			[0.490]	
Unfilled vacancy rate				0.029
of destination industry *100				[0.018]
Unfilled vacancy rate				-0.012
of source industry *100				[0.020]
Employment status:	-0.805***	-0.790***	-0.793***	-0.796***
from regular to non-regular	[0.030]	[0.028]	[0.030]	[0.029]
Employment status:	0.182***	0.185***	0.166***	0.196***
from non-regular to regular	[0.028]	[0.027]	[0.028]	[0.028]
Employment status:	-0.301***	-0.301***	-0.316***	-0.283***
from non-regular to non-regular	[0.031]	[0.029]	[0.030]	[0.030]
Observations	3,532	3,949	3,589	3,646
R-squared	0.586	0.577	0.577	0.584

Note: Linear regression of log annual earnings after job change. Control variables omitted from the table include age and squared age, log earnings of the previous job, dummy variables for year of obtaining the current job, year of the survey, industry of current and previous jobs, and education. Reference group of employment status is “from regular to regular.” *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 5 Changes in earnings after job changes, including intra-industry moves, and differences in required tasks before and after the job change

	Men			
	(1)	(2)	(3)	(4)
Inter-industry move (dummy)	-0.055***	-0.024	-0.015	-0.018
	[0.017]	[0.032]	[0.023]	[0.036]
Task distance between the		-0.022		0.002
source & destination industries		[0.019]		[0.020]
Task distance between current and			-0.019***	-0.019***
previous jobs (based on occupations)			[0.004]	[0.005]
Transaction index between the	0.037	0.03	0.045	0.046
source & destination industries	[0.033]	[0.033]	[0.037]	[0.036]
Observations	3,681	3,681	2,729	2,729
R-squared	0.693	0.693	0.72	0.72
	Women			
	(5)	(6)	(7)	(8)
Inter-industry move (dummy)	-0.043*	0.010	0.008	-0.027
	[0.023]	[0.044]	[0.025]	[0.047]
Task distance between the		-0.041		0.029
source & destination industries		[0.030]		[0.033]
Task distance between current and			-0.023***	-0.023***
previous jobs (based on occupations)			[0.006]	[0.006]
Transaction index between the	0.090**	0.06	0.105***	0.128***
source & destination industries	[0.036]	[0.043]	[0.040]	[0.049]
Observations	3,986	3,986	3,242	3,242
R-squared	0.578	0.578	0.59	0.59

Note: Linear regression of log annual earnings after job change. Control variables omitted from the table include age and squared age, log earnings of the previous job, dummy variables for year of obtaining the current job, year of the survey, industry of current and previous jobs, education, and dummy indicators of employment status before and after job change. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. The sample sizes of columns (3), (4), (7) and, (8) are smaller than the other columns because some of the occupation codes in the Working Person Survey do not fit to any occupation in Matsumoto et al (2012) and thus we were unable to calculate task distance based on actual occupations for them.

Table 6a Task distance between the source and destination industries and earnings change; by age at the time of getting the current job (reference: 35-44 years old)

	Men	Women
Eq(10): Y=task distance between industries		
Age: 25 or younger	0.169***	-0.104**
	[0.046]	[0.044]
Age: 25-34	0.080**	-0.108***
	[0.035]	[0.033]
Age: 45-54	-0.067	-0.017
	[0.046]	[0.039]
Age 55-59	0.073	0.003
	[0.071]	[0.080]
Eq(11): Y=log(earnings)		
Task distance*	0.053**	0.140***
Age: 25 or younger	[0.025]	[0.031]
Task distance*	0.004	0.037
Age: 25-34	[0.020]	[0.024]
Task distance*	-0.067**	0.045
Age: 45-54	[0.026]	[0.028]
Task distance*	-0.080**	-0.054
Age 55-59	[0.040]	[0.057]
Observations	4,017	4,546

Note: Seemingly unrelated regression of equations (10) and (11). Variables omitted from the table are employment status dummies in the task distance regressions, age category dummies, task distance, employment status dummies and log earnings of the previous jobs in earnings regressions. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 6b Task distance between the source and destination industries and earnings change; by education (reference: vocational school, jr college and technical college)

	Men	Women
Eq(10): Y=task distance between industries		
High School or less	0.063*	0.117***
	[0.038]	[0.030]
College (4year) or more	0.072**	0.024
	[0.037]	[0.035]
Eq(11): Y=log(earnings)		
Task distance*	-0.040*	0.028
High School or less	[0.021]	[0.022]
Task distance*	-0.057***	-0.042*
College (4year) or more	[0.021]	[0.025]
Observations	4,017	4,546

Note: Seemingly unrelated regression of equations (10) and (11). Variables omitted from the table are employment status dummies in the task distance regressions, education category dummies, task distance, employment status dummies, and log earnings of the previous jobs in earnings regressions. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 6c Task distance between the source and destination industries and earnings change; by the reasons why the respondent quit the previous job (reference: discontent with the previous job)

	Men	Women
Eq(10): Y=task distance between industries		
Involuntary termination	-0.131***	-0.038
	[0.037]	[0.044]
Family or health reason	0.082	0.171***
	[0.076]	[0.032]
For a better career	-0.046	-0.053
	[0.038]	[0.049]
Eq(11): Y=log(earnings)		
Task distance*	-0.034	-0.039***
Involuntary termination	[0.021]	[0.015]
Task distance*	-0.036	-0.031
Family or health reason	[0.040]	[0.031]
Task distance*	-0.02	-0.024
For a better career	[0.021]	[0.022]
Observations	3,835	4,312

Note: Seemingly unrelated regression of equations (10) and (11). Variables omitted from the table are employment status dummies in the task distance regressions, dummies for the reason of job change, task distance, employment status dummies, and log earnings of the previous jobs in earnings regressions. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 7a Determinants of task distance between current and previous jobs (based on occupation); by age at the time of getting the current job (reference: 35-44 years old)

Y=task distance between current and previous jobs

	Male	Female
Age: 25 or younger	0.328***	-0.128
	[0.107]	[0.089]
Age: 25-34	0.08	-0.105
	[0.082]	[0.070]
Age: 45-54	0.188	-0.078
	[0.114]	[0.083]
Age 55-59	0.149	-0.297*
	[0.190]	[0.165]
Task distance between the source & destination industries	1.165***	0.938***
	[0.038]	[0.031]
Observations	3,198	4,078
R-squared	0.267	0.198

Note: *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Variable omitted from the table are employment status dummies.

Table 7b Determinants of task distance between current and previous jobs (based on occupation); by education (reference: vocational school, jr college and technical college)

Y=task distance between current and previous jobs

	Male	Female
High School or less	-0.022	0.039
	[0.086]	[0.063]
College (4year)	-0.214**	0.088
or more	[0.084]	[0.078]
Task distance between the	1.171***	0.940***
source & destination industries	[0.037]	[0.031]
Observations	3,198	4,078
R-squared	0.266	0.198

Note: *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Variable omitted from the table are employment status dummies.

Table 7c Determinants of task distance between current and previous jobs (based on occupation); by the reasons why the respondent quit the previous job (reference: discontent with the previous job)

Y=task distance between current and previous jobs

	Male	Female
Involuntary termination	-0.015	-0.151
	[0.092]	[0.095]
Family or health reason	0.242	0.051
	[0.183]	[0.068]
For a better career	-0.180**	-0.02
	[0.086]	[0.105]
Task distance between the	1.160***	0.944***
source & destination industries	[0.039]	[0.031]
Observations	3,057	3,869
R-squared	0.262	0.201

Note: *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Variable omitted from the table are employment status dummies.

Table 8a Earnings change due to differences in required tasks between current and previous jobs; by age at the time of getting the current job (reference: 35-44 years old)

	Male	Female
Task distance between current and	-0.012	-0.032***
previous jobs (based on occupations)	[0.009]	[0.010]
Task distance bet jobs *	0.01	0.025
Age: 25 or younger	[0.015]	[0.017]
Task distance bet jobs *	-0.01	0.015
Age: 25-34	[0.011]	[0.014]
Task distance bet jobs *	-0.029**	-0.007
Age: 45-54	[0.014]	[0.015]
Task distance bet jobs *	-0.055*	0.052
Age 55-59	[0.029]	[0.033]
Task distance between the	-0.042*	-0.068***
source & destination industries	[0.022]	[0.022]
Task distance bet. industries*	0.066*	0.122***
Age: 25 or younger	[0.040]	[0.034]
Task distance bet. industries *	0.033	0.018
Age: 25-34	[0.026]	[0.029]
Task distance bet. industries *	-0.021	0.053
Age: 45-54	[0.035]	[0.033]
Task distance bet. industries *	-0.008	-0.047
Age 55-59	[0.082]	[0.067]
Observations	2,991	3,731
R-squared	0.696	0.558

Note: Variables omitted from the table: employment status dummies, log earnings of the previous jobs and dummies for age categories. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 8b Earnings change due to differences in required tasks between current and previous jobs; by education (reference: vocational school, jr college and technical college)

	Male	Female
Task distance between current and	-0.021**	-0.039***
previous jobs (based on occupations)	[0.009]	[0.009]
Task distance bet jobs *	0.009	0.029**
High School or less	[0.012]	[0.012]
Task distance bet jobs *	-0.01	0.018
College (4year) or more	[0.011]	[0.014]
Task distance between the	0.023	-0.024
source & destination industries	[0.023]	[0.020]
Task distance bet. industries *	-0.049	-0.008
High School or less	[0.032]	[0.026]
Task distance bet. industries *	-0.054**	-0.04
College (4year) or more	[0.027]	[0.031]
Observations	2,991	3,731
R-squared	0.688	0.549

Note: Variables omitted from the table: employment status dummies, log earnings of the previous jobs, dummies for high school and college education. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Table 8c Earnings change due to differences in required tasks between current and previous jobs; by the reasons why the respondent quit the previous job (reference: discontent with the previous job)

	Male	Female
Task distance between current and	-0.018***	-0.023***
previous jobs (based on occupations)	[0.005]	[0.008]
Task distance bet jobs *	-0.007	0.016
Involuntary termination	[0.011]	[0.016]
Task distance bet jobs *	-0.073**	-0.006
Family or health reason	[0.031]	[0.013]
Task distance bet jobs *	0.001	0.015
For a better career	[0.013]	[0.015]
Task distance between the	-0.01	-0.016
source & destination industries	[0.014]	[0.016]
Task distance bet. industries*	-0.017	-0.05
Involuntary termination	[0.031]	[0.032]
Task distance bet. industries *	0.075	-0.006
Family or health reason	[0.087]	[0.027]
Task distance bet. industries *	-0.018	-0.014
For a better career	[0.028]	[0.030]
Observations	2,857	3,538
R-squared	0.686	0.588

Note: Variables omitted from the table: employment status dummies, log earnings of the previous jobs, dummies for reasons of quits. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Appendix Table A1 Sources and definitions of variables for industry performance

Variable	Definition	Data source	Method of aggregation across industries
TFP growth rate	Annual growth rate of the industry's TFP.	JIP database, RIETI. http://www.rieti.go.jp/en/database/JIP2012/index.html. 4 growth accounting > 19 TFP growth rate by sector.	Simple average.
ROA	Current profit divided by total asset.	Financial Statements Statistics of Corporations by Industry (hojinkigyotokei), Ministry of Finance.	Sum of profits divided by sum of asset.
Average monthly earnings	Average monthly earnings of the industry, including overtime pay but excluding bonus.	Basic Survey of Wage Structure, Ministry of Welfare, Labor, and Health.	Average weighted by the number of employees of each industry.
Unfilled vacancy rate	The number of "Unfilled vacancies (mijusoku kyujin)" divided by the number of employees.	Survey of Employment Trend, Ministry of Welfare, Labor, and Health.	Sum of unfilled vacancy divided by sum of employees.

Appendix Table B1 Summary statistics of Sample from Working Person Survey used in Table A3 (including those who did not change jobs)

	All			Job changers only		
	All	Male	Female	All	Male	Female
Sample size	21,639	12,668	8,971	7,667	3,681	3,986
Earnings as of survey	429.6	559.3	242.7	333.1	463.2	210.7
Age in 2000	30.4	30.7	30.0	30.0	29.2	30.6
Education						
Jr. High School	3.26%	3.72%	2.61%	3.3%	4.59%	2.11%
High school	30.32%	27.8%	33.86%	31.98%	29.34%	34.42%
Vocational college (1-3yr)	14.15%	12.09%	17.05%	17.26%	15.65%	18.74%
Junior college (2yr; AA equivalent)	8.26%	1.02%	18.48%	11.13%	1.28%	20.22%
Kosen (Tech college; AA equivalent)	1.55%	2.41%	0.33%	1.54%	2.74%	0.43%
College (4year)	38.44%	47.27%	25.97%	31.96%	41.84%	22.83%
Graduate school	4.03%	5.7%	1.68%	2.84%	4.56%	1.25%
Job changers	35.4%	29.1%	44.4%	-	-	-

Appendix Table B2 Determinants of job changes and inter-industry move

	All		Male		Female	
Dept. var	Job change	Inter-ind. Move	Job change	Inter-ind. move	Job change	Inter-ind. move
Female	0.184***	0.190***				
	[0.007]	[0.007]				
ageU15	-0.239***	-0.139***	-0.078***	0.005	-0.429***	-0.307***
(as of 2000)	[0.015]	[0.014]	[0.019]	[0.017]	[0.022]	[0.022]
age15_19	-0.014	0.001	0.126***	0.116***	-0.195***	-0.152***
(as of 2000)	[0.013]	[0.012]	[0.016]	[0.014]	[0.019]	[0.020]
age20_24	0.122***	0.071***	0.219***	0.155***	-0.019	-0.052**
(as of 2000)	[0.012]	[0.012]	[0.016]	[0.014]	[0.019]	[0.020]
age25_29	0.089***	0.046***	0.169***	0.101***	-0.027	-0.034*
(as of 2000)	[0.012]	[0.011]	[0.015]	[0.013]	[0.019]	[0.020]
age30_34	0.048***	0.024**	0.073***	0.032***	0.019	0.022
(as of 2000)	[0.012]	[0.011]	[0.015]	[0.012]	[0.019]	[0.021]
age40_44	-0.033**	-0.022*	-0.002	-0.007	-0.087***	-0.051**
(as of 2000)	[0.013]	[0.012]	[0.016]	[0.013]	[0.021]	[0.022]
age45_49	-0.041***	-0.035***	0.058***	0.039***	-0.185***	-0.142***
(as of 2000)	[0.013]	[0.012]	[0.016]	[0.013]	[0.021]	[0.021]
age50_54	-0.110***	-0.089***	0.027	0.016	-0.311***	-0.243***
(as of 2000)	[0.019]	[0.016]	[0.023]	[0.019]	[0.031]	[0.029]
Junior HS	0.073***	0.005	0.090***	0.028	0.052*	-0.013
	[0.019]	[0.018]	[0.024]	[0.022]	[0.030]	[0.033]
Vocational	-0.018*	-0.041***	-0.001	-0.026**	-0.031**	-0.052***
(after HS)	[0.011]	[0.010]	[0.015]	[0.013]	[0.015]	[0.016]
Jr college	-0.016	0.003	0.02	0.027	-0.043***	-0.028*
	[0.013]	[0.013]	[0.041]	[0.038]	[0.014]	[0.015]
Tech college	-0.022	-0.031	-0.003	0.007	0.036	-0.091
	[0.027]	[0.024]	[0.029]	[0.025]	[0.083]	[0.084]
College	-0.158***	-0.109***	-0.124***	-0.070***	-0.177***	-0.145***
	[0.008]	[0.008]	[0.010]	[0.009]	[0.014]	[0.014]
Grad school	-0.209***	-0.162***	-0.175***	-0.128***	-0.259***	-0.201***
	[0.017]	[0.014]	[0.019]	[0.015]	[0.041]	[0.038]
Observations	21,639	21,639	12,668	12,668	8,971	8,971
R-squared	0.158	0.109	0.111	0.067	0.135	0.102

Note: Linear regressions with controls for initial industry dummies. Standard errors are in brackets. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Reference group for education is high school.

Appendix Table B3a Determinants of separation and hiring rates (Male)

	Separation rate				Hiring rate			
Age 15-19	14.515***	14.114***	15.099***	15.631***	68.820***	68.517***	74.049***	73.311***
	[1.283]	[1.275]	[1.222]	[1.156]	[1.364]	[1.352]	[1.708]	[1.641]
Age 20-24	11.301***	11.223***	11.296***	11.332***	28.234***	28.910***	29.743***	29.731***
	[1.277]	[1.269]	[1.216]	[1.151]	[1.357]	[1.345]	[1.700]	[1.634]
Age 25-29	6.255***	6.488***	6.390***	6.325***	8.070***	8.583***	8.938***	8.541***
	[1.277]	[1.269]	[1.216]	[1.151]	[1.357]	[1.345]	[1.700]	[1.634]
Age 30-34	2.709**	2.841**	2.823**	2.482**	2.708**	2.788**	2.814*	2.815*
	[1.277]	[1.269]	[1.216]	[1.151]	[1.357]	[1.345]	[1.700]	[1.634]
Age 40-44	-0.72	-0.872	-0.838	-1.043	-1.142	-1.386	-1.35	-1.355
	[1.277]	[1.269]	[1.216]	[1.151]	[1.357]	[1.345]	[1.700]	[1.634]
Age 45-49	-0.523	-0.719	-0.791	-0.947	-1.606	-1.791	-1.803	-1.77
	[1.277]	[1.269]	[1.216]	[1.151]	[1.357]	[1.345]	[1.700]	[1.634]
Age 50-54	-0.143	-0.374	-0.534	-0.568	-2.491*	-2.782**	-2.494	-2.452
	[1.277]	[1.269]	[1.216]	[1.151]	[1.357]	[1.345]	[1.700]	[1.634]
Age 55-59	0.944	0.667	0.692	0.899	-2.125	-2.315*	-2.131	-1.827
	[1.277]	[1.269]	[1.216]	[1.151]	[1.357]	[1.345]	[1.700]	[1.634]
TFP	4.922				16.124			
	[13.203]				[14.037]			
ROA		-0.339				0.536*		
		[0.283]				[0.300]		
Log average earnings			25.440*				22.099	
			[15.424]				[21.549]	
Unfilled vacancy rate				0.123				1.15
				[0.572]				[0.812]
Observations	1,482	1,482	1,527	1,743	1,482	1,482	1,527	1,743
R-squared	0.29	0.292	0.309	0.325	0.778	0.782	0.714	0.701

Note: Data for separation and hiring rates are taken from Employment Trend Surveys 2004-2008. Linear regressions with controls for industry dummies and year dummies. Standard errors are in brackets. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Appendix Table B3b Determinants of separation and hiring rates (Female)

	Separation rate				Hiring rate			
Age 15-19	7.107***	7.439***	7.575***	7.822***	66.429***	63.559***	63.437***	65.444***
	[1.325]	[1.308]	[1.200]	[1.198]	[1.815]	[1.513]	[1.443]	[1.626]
Age 20-24	8.817***	9.166***	8.919***	8.945***	17.224***	17.350***	17.492***	18.149***
	[1.302]	[1.288]	[1.190]	[1.180]	[1.784]	[1.490]	[1.431]	[1.602]
Age 25-29	9.095***	9.211***	9.247***	9.253***	3.439*	3.350**	3.526**	3.806**
	[1.302]	[1.288]	[1.190]	[1.180]	[1.784]	[1.490]	[1.431]	[1.602]
Age 30-34	2.589**	2.606**	2.720**	2.945**	0.369	0.618	0.991	0.473
	[1.302]	[1.288]	[1.190]	[1.180]	[1.784]	[1.490]	[1.431]	[1.602]
Age 40-44	-3.170**	-3.168**	-2.845**	-2.918**	-3.883**	-3.899***	-4.104***	-3.381**
	[1.302]	[1.288]	[1.190]	[1.180]	[1.784]	[1.490]	[1.431]	[1.602]
Age 45-49	-3.881***	-3.839***	-4.538***	-4.049***	-7.339***	-7.185***	-6.737***	-7.044***
	[1.302]	[1.288]	[1.190]	[1.180]	[1.784]	[1.490]	[1.431]	[1.602]
Age 50-54	-5.252***	-5.120***	-4.774***	-5.017***	-10.860***	-10.661***	-10.033***	-10.150***
	[1.302]	[1.288]	[1.190]	[1.180]	[1.784]	[1.490]	[1.431]	[1.602]
Age 55-59	-5.263***	-5.065***	-4.816***	-4.897***	-12.436***	-12.151***	-11.667***	-11.479***
	[1.302]	[1.288]	[1.190]	[1.180]	[1.784]	[1.490]	[1.431]	[1.602]
TFP	9.954				-3.781			
	[13.514]				[18.512]			
ROA		-0.152				-0.101		
		[0.289]				[0.335]		
Log average earnings			-15.743				-14.235	
			[15.093]				[18.147]	
Unfilled vacancy rate				-0.316				-0.855
				[0.584]				[0.793]
Observations	1,475	1,476	1,525	1,736	1,475	1,476	1,525	1,736
R-squared	0.307	0.314	0.333	0.339	0.677	0.737	0.747	0.686

Note: Data for separation and hiring rates are taken from Employment Trend Surveys 2004-2008. Linear regressions with controls for industry dummies and year dummies. Standard errors are in brackets. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Appendix Table B4 Determinants of earnings after inter-industry job change (same specification as Table 4 with different sample)

A. Men, inter-industry movers only

	(1)	(2)	(3)	(4)
Task distance between the	-0.033	-0.033	-0.036	-0.035
source & destination industries	[0.027]	[0.027]	[0.029]	[0.028]
IO index	-0.016	0.029	0.031	0.113
	[0.131]	[0.124]	[0.136]	[0.122]
TFP growth rate	-0.03			
of destination industry	[0.352]			
TFP growth rate	-0.611			
of source industry	[0.403]			
ROA		-0.006		
of destination industry *100		[0.011]		
ROA		0.005		
of source industry *100		[0.005]		
log average earnings			0.415	
of destination industry			[0.512]	
log average earnings			0.171	
of source industry			[0.446]	
Unfilled vacancy rate				-0.009
of destination industry *100				[0.018]
Unfilled vacancy rate				0.012
of source industry *100				[0.017]
Employment status:	-0.426***	-0.444***	-0.452***	-0.442***
from regular to non-regular	[0.042]	[0.040]	[0.042]	[0.041]
Employment status:	0.02	0.016	0.015	0.018
from non-regular to regular	[0.029]	[0.028]	[0.032]	[0.029]
Employment status:	-0.202***	-0.202***	-0.209***	-0.200***
from non-regular to non-regular	[0.048]	[0.044]	[0.047]	[0.045]
Observations	1,773	1,967	1,722	1,875
R-squared	0.614	0.646	0.644	0.653

Note: Linear regression of log annual earnings after job change. Control variables omitted from the table include age and squared age, log earnings of the previous job, dummy variables for year of obtaining the current job, year of the survey, industry of current and previous jobs, and education. Reference group of employment status is “from regular to regular.” *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Appendix Table B4 Determinants of earnings after inter-industry job change (same specification as Table 4 with different sample)

B. Women, inter-industry movers only

	(1)	(2)	(3)	(4)
Task distance between the	-0.015	-0.020	-0.034	0.003
source & destination industries	[0.036]	[0.037]	[0.040]	[0.039]
IO index	-0.028	-0.039	-0.071	-0.005
	[0.173]	[0.190]	[0.211]	[0.226]
TFP growth rate	0.024			
of destination industry	[0.465]			
TFP growth rate	0.109			
of source industry	[0.477]			
ROA		0		
of destination industry *100		[0.007]		
ROA		-0.006		
of source industry *100		[0.006]		
log average earnings			0.674	
of destination industry			[0.571]	
log average earnings			0.45	
of source industry			[0.578]	
Unfilled vacancy rate				0.014
of destination industry *100				[0.023]
Unfilled vacancy rate				-0.029
of source industry *100				[0.026]
Employment status:	-0.791***	-0.775***	-0.777***	-0.775***
from regular to non-regular	[0.038]	[0.036]	[0.037]	[0.037]
Employment status:	0.177***	0.174***	0.159***	0.185***
from non-regular to regular	[0.037]	[0.036]	[0.038]	[0.037]
Employment status:	-0.372***	-0.379***	-0.397***	-0.358***
from non-regular to non-regular	[0.042]	[0.039]	[0.042]	[0.040]
Observations	2,256	2,498	2,266	2,255
R-squared	0.541	0.532	0.528	0.543

Note: Linear regression of log annual earnings after job change. Control variables omitted from the table include age and squared age, log earnings of the previous job, dummy variables for year of obtaining the current job, year of the survey, industry of current and previous jobs, and education. Reference group of employment status is “from regular to regular.” *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Appendix Table B4 Determinants of earnings after inter-industry job change (same specification as Table 4 with different sample)

C. Men and women pooled, inter-industry job changers only

	(1)	(2)	(3)	(4)
Task distance between the	-0.038*	-0.040*	-0.050**	-0.029
source & destination industries	[0.022]	[0.023]	[0.024]	[0.023]
IO index	-0.009	0.002	-0.013	0.06
	[0.109]	[0.114]	[0.125]	[0.122]
TFP growth rate	0.112			
of destination industry	[0.305]			
TFP growth rate	-0.083			
of source industry	[0.324]			
ROA		-0.001		
of destination industry *100		[0.006]		
ROA		-0.003		
of source industry *100		[0.004]		
log average earnings			0.547	
of destination industry			[0.402]	
log average earnings			0.343	
of source industry			[0.377]	
Unfilled vacancy rate				0.005
of destination industry *100				[0.015]
Unfilled vacancy rate				-0.012
of source industry *100				[0.016]
Employment status:	-0.698***	-0.687***	-0.683***	-0.679***
from regular to non-regular	[0.028]	[0.027]	[0.028]	[0.028]
Employment status:	0.112***	0.105***	0.102***	0.113***
from non-regular to regular	[0.024]	[0.023]	[0.025]	[0.023]
Employment status:	-0.303***	-0.308***	-0.318***	-0.291***
from non-regular to non-regular	[0.031]	[0.029]	[0.031]	[0.030]
Observations	4,029	4,465	3,988	4,130
R-squared	0.65	0.647	0.638	0.652

Note: Linear regression of log annual earnings after job change. Control variables omitted from the table include female dummy, age and squared age, log earnings of the previous job, dummy variables for year of obtaining the current job, year of the survey, industry of current and previous jobs, and education. Reference group of employment status is “from regular to regular.” *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Appendix Table B5 Determinants of inter-industry worker flow, excluding medical and caring industry (same specification as Table 3)

A. Men

	(1)	(2)	(3)	(4)
log total employment	1.103***	0.964***	1.033***	0.911***
of destination industry	[0.220]	[0.323]	[0.298]	[0.275]
log total employment	0.730***	1.418***	1.222***	0.863***
of source industry	[0.258]	[0.336]	[0.257]	[0.316]
log task distance	-0.428***	-0.458***	-0.405***	-0.429***
	[0.029]	[0.044]	[0.030]	[0.033]
log transaction index	0.129***	0.087***	0.091***	0.122***
	[0.016]	[0.020]	[0.016]	[0.018]
TFP growth rate	-1.047			
of destination industry	[0.675]			
TFP growth rate	0.491			
of source industry	[0.658]			
ROA		-0.086		
of destination industry *100		[0.070]		
ROA		-0.019		
of source industry *100		[0.028]		
log average earnings			1.001	
of destination industry			[0.657]	
log average earnings			-1.037	
of source industry			[0.734]	
Unfilled vacancy rate				5.394*
of destination industry				[2.991]
Unfilled vacancy rate				-0.952
of source industry				[3.444]
Observations	12,876	9,820	11,444	8,950

Note: Coefficients of Poisson regressions. See the text for details. The number of observation is smaller than that in Table 1 because observations with 0 or negative values for the transaction index or task distance are dropped in order to take log of them. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Column (1) is the same as in Table 3A, because column (1) of Table 3A does not include medical and caring industry due to unavailability of TFP growth rate.

Appendix Table B5 Determinants of inter-industry worker flow, excluding medical and caring industry (same specification as Table 3)

B. Women

	(1)	(2)	(3)	(4)
log total employment	1.245***	0.882***	0.932***	0.999***
of destination industry	[0.255]	[0.253]	[0.228]	[0.322]
log total employment	0.608**	0.927***	0.904***	0.436
of source industry	[0.278]	[0.318]	[0.211]	[0.339]
log task distance	-0.315***	-0.407***	-0.283***	-0.347***
	[0.035]	[0.045]	[0.035]	[0.041]
log transaction index	0.080***	0.033*	0.063***	0.081***
	[0.019]	[0.019]	[0.017]	[0.023]
TFP growth rate	0.937			
of destination industry	[0.773]			
TFP growth rate	0.900			
of source industry	[0.759]			
ROA		0.019		
of destination industry *100		[0.031]		
ROA		-0.002		
of source industry *100		[0.026]		
log average earnings			-0.066	
of destination industry			[0.680]	
log average earnings			-0.743	
of source industry			[0.707]	
Unfilled vacancy rate				2.059
of destination industry				[3.503]
Unfilled vacancy rate				1.413
of source industry				[3.473]
Observations	12,336	9,390	10,936	8,540

Note: Coefficients of Poisson regressions. See the text for details. The number of observation is smaller than that in Table 1 because observations with 0 or negative values for the transaction index or task distance are dropped in order to take log of them. Also, all industry pairs with mining are dropped because so few women leave or enter the mining industry that poisson regression including mining does not converge on STATA. *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Column (1) is the same as in Table 3B, because column (1) of Table 3B does not include medical and caring industry due to unavailability of TFP growth rate.

Appendix Table B6 Changes in earnings after inter-industry job change, excluding medical and caring industry (same specification as Table 4)

A. Men, all job changers

	(1)	(2)	(3)	(4)
Task distance between the	-0.029***	-0.032***	-0.037***	-0.033***
source & destination industries	[0.010]	[0.010]	[0.012]	[0.011]
IO index	0.018	0.012	0.003	0.009
	[0.031]	[0.031]	[0.036]	[0.031]
TFP growth rate	0.18			
of destination industry	[0.283]			
TFP growth rate	-0.4			
of source industry	[0.306]			
ROA		-0.002		
of destination industry *100		[0.007]		
ROA		0.002		
of source industry *100		[0.005]		
log average earnings			0.271	
of destination industry			[0.374]	
log average earnings			-0.136	
of source industry			[0.361]	
Unfilled vacancy rate				-0.015
of destination industry *100				[0.012]
Unfilled vacancy rate				0.013
of source industry *100				[0.012]
Employment status:	-0.386***	-0.386***	-0.400***	-0.378***
from regular to non-regular	[0.033]	[0.032]	[0.033]	[0.032]
Employment status:	0.014	0.014	0.017	0.019
from non-regular to regular	[0.022]	[0.021]	[0.024]	[0.022]
Employment status:	-0.156***	-0.154***	-0.154***	-0.149***
from non-regular to non-regular	[0.032]	[0.030]	[0.032]	[0.031]
Observations	3,133	3,442	2,991	3,317
R-squared	0.677	0.693	0.692	0.695

Note: Linear regression of log annual earnings after job change. Control variables omitted from the table include age and squared age, log earnings of the previous job, dummy variables for year of obtaining the current job, year of the survey, industry of current and previous jobs, and education. Reference group of employment status is "from regular to regular." *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.

Appendix Table B6 Changes in earnings after inter-industry job change, excluding medical and caring industry (same specification as Table 4)

B. Women, all job changers

	(1)	(2)	(3)	(4)
Task distance between the	-0.035**	-0.037**	-0.045**	-0.029
source & destination industries	[0.017]	[0.017]	[0.018]	[0.018]
IO index	0.103	0.098	0.05	0.079
	[0.076]	[0.079]	[0.083]	[0.080]
TFP growth rate	-0.158			
of destination industry	[0.425]			
TFP growth rate	-0.103			
of source industry	[0.438]			
ROA		0.005		
of destination industry *100		[0.007]		
ROA		-0.005		
of source industry *100		[0.006]		
log average earnings			0.811	
of destination industry			[0.506]	
log average earnings			0.493	
of source industry			[0.527]	
Unfilled vacancy rate				0.023
of destination industry *100				[0.019]
Unfilled vacancy rate				-0.021
of source industry *100				[0.022]
Employment status:	-0.770***	-0.750***	-0.749***	-0.759***
from regular to non-regular	[0.034]	[0.033]	[0.034]	[0.034]
Employment status:	0.151***	0.161***	0.140***	0.174***
from non-regular to regular	[0.032]	[0.031]	[0.033]	[0.033]
Employment status:	-0.291***	-0.297***	-0.310***	-0.275***
from non-regular to non-regular	[0.035]	[0.032]	[0.034]	[0.034]
Observations	2,725	3,048	2,764	2,775
R-squared	0.582	0.57	0.57	0.575

Note: Linear regression of log annual earnings after job change. Control variables omitted from the table include age and squared age, log earnings of the previous job, dummy variables for year of obtaining the current job, year of the survey, industry of current and previous jobs, and education. Reference group of employment status is “from regular to regular.” *, **, and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively.