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Foreign–native wage gap and tasks: Evidence from the Japanese labor market

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ABSTRACT

This paper provides novel empirical evidence on the foreign–native wage gap in the Japanese labor market, examining the role of tasks. By leveraging government micro-level data and the Japanese version of O*NET, we construct task scores *à la* Acemoglu and Autor (2011) at a detailed occupational level. We then estimate the foreign–native wage gap in the spirit of Mincer (1974). Unconditionally, foreign workers earn 27% less than native workers; 82% of this gap is explained by observable characteristics. Tasks account for roughly one-third of the remaining unexplained gap, suggesting that foreign workers are assigned to lower-wage tasks, typically manual and routine tasks.

1. Introduction

This paper provides novel empirical evidence on the foreign–native wage gap in the Japanese labor market. By utilizing detailed micro-level data from the Japanese Government, we analyze the underlying determinants of the wage disparity in the spirit of the Mincerian wage model (Mincer, 1974). Moreover, by leveraging the Japanese version of O*NET, we employ the task-based approach *à la* Acemoglu and Autor (2011) to show that the task assignment plays the key role in accounting for components of the wage gap unexplained by standard observable characteristics.

Our study is motivated by the significant expansion of foreign employment since the early 2000s. The share of foreign workers in total employment in Japan rose from 0.1% in 1990 to 2.7% in 2022. The increasing acceptance of foreign workers in the national labor market has heightened concerns regarding the earnings gap between native and foreign workers. The Cabinet Office of the Japanese Government documents in the *2024 Annual Report on the Japanese Economy and Public Finance* (Cabinet Office, 2024) that there exists an approximately 28% wage gap between native and foreign workers, and that one-quarter of this difference is unexplained by worker or establishment attributes. We aim to address this disparity by focusing on the distinct patterns of task specialization between native and foreign workers.

This paper contributes to the literature on task and wage disparities, particularly regarding the foreign–native wage gap. Despite tasks becoming central to understanding labor market dynamics, including the gender wage gap,[1] few papers examine their role in the foreign–native wage gap. While Peri and Sparber (2009, 2011) discuss that task specialization is important in understanding immigrant impacts on native wages in the U.S., and Storm (2022) shows it accounts for 10–25 percent of the German foreign–native wage gap, our paper offers new evidence from Japan, demonstrating that task assignment accounts for one-third of the unexplained foreign–native wage gap.

This paper also addresses a data gap that has limited the literature on foreign employment in Japan (e.g., Nakamura et al., 2009; Kambayashi and Hashimoto, 2019). Although Japan has increasingly opened its labor market, empirical research on the wage gap—a central question in immigration and labor economics (e.g., Borjas, 1985; Bartolucci, 2014; Gheasi et al., 2017; Amin and Uyar, 2021; Coulombe et al., 2014)—has been limited by a lack of nationwide micro-level data. We overcome this by utilizing a newly available government dataset covering approximately one million workers, including ten thousand foreign workers, providing the first comprehensive analysis of the foreign–native wage gap in Japan.

The remainder of this paper is structured as follows: Section 2 describes the data and presents descriptive evidence. Section 3 introduces the econometric specification and discusses the results. Section 4 concludes.

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[1] For instance, Autor and Handel (2013), Blau and Kahn (2000), Yamaguchi (2018), Christl and Köppl-Turyna (2020), Ou and Pan (2021), Black and Spitz-Oener (2010) demonstrate that job tasks and skill uses at work explain the gender wage gap in the U.S. and European countries.

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Table 1
Summary statistics.

	(1) All samples				(2) Japanese workers				(3) Foreign workers			
	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max	Mean	Std Dev	Min	Max
Hourly Wage (K JPY)	2.235	1.849	0.347	293.352	2.243	1.851	0.347	293.35	1.685	1.647	0.493	203.7566
Experience	3.310	1.409	1	5	3.327	1.407	1	5	2.071	0.977	1	5
Sex (Female = 1)	0.443	0.497	0	1	0.443	0.497	0	1	0.462	0.499	0	1
Education (College = 1)	0.321	0.467	0	1	0.321	0.467	0	1	0.316	0.465	0	1
Foreign (Foreign = 1)	0.014	0.118	0	1								
Observations	1,077,380				1,066,050				11,330			

Source: Author's calculations from the MHLW Basic Survey of Wage Structure (2022).
Note: Sample weight is applied. Experience is a categorical variable indicating the years of experience in the current occupation;
1: less than a year, 2:1–4 years, 3:5–9 years, 4:10–14 years, and 5:15 years and more.

2. Data and descriptive evidence

2.1. Data source

This study utilizes micro-level data from the Ministry of Health, Labour, and Welfare (2022), *2022 Basic Survey of Wage Structure* (MHLW Wage Survey, henceforth). This establishment-level survey collects data on over a million workers across all sectors, except for primary industries. In 2019, to address increasing policy interest in foreign employment, the MHLW Wage Survey introduced a section requiring sampled foreign workers to report their visa categories. It is currently Japan's only nationwide official labor statistic on foreign workers.

We also leverage the MHLW *jobtag* data, a skill dictionary dataset launched in 2019. Designed similarly to the U.S. O*NET database, *jobtag* allows us to construct task scores for various occupations. We merge the two datasets using the concordance table provided by Komatsu and Mugiyama (2021).

2.2. Construction of task scores

We employ a task-based approach, *à la* Acemoglu and Autor (2011, hereafter AA), to derive task scores for each occupation. AA's framework considers five broad tasks, detailed in Table A.1 in the Appendix, which they measured using the O*NET database. This approach allows us to distinguish jobs based on specific activities that workers perform rather than broad job titles. Using the *jobtag*,[2] we construct task scores for the 134 occupations found in the MHLW Wage Survey data. See AA for a more detailed methodology.

We then reduce AA's five task dimensions into two core scores: non-routine and manual. Then, occupations are categorized as "manual" or "non-manual" based on whether their manual score is above or below its average. Similarly, we categorize them as "routine" or "non-routine". This yields four task categories, which serve as our task index. More details are in the Appendix.

2.3. Summary statistics and descriptive evidence

Table 1 provides the summary statistics for the main variables in the Wage Survey data. After removing observations with incomplete information, our sample includes 1,077,380 workers, with 1.4% (11,330) being foreign. Skill level is a binary variable (1 for a 4-year college degree or higher, 0 otherwise), and work experience is a categorical variable based on years in the current occupation. High-skilled workers are slightly more prevalent among natives (32.1%) than foreign workers (31.6%), and foreign workers generally have less experience. Native workers also show a slightly higher male gender composition.

Given the significant variation in individual work hours, we calculate hourly wages. This involves summing monthly wages and the monthly equivalent of annual bonuses (annual bonus divided by 12), then dividing by monthly work hours. The unconditional mean hourly wage for native workers is 2.24 thousand JPY (approx. 14.23 USD[3]), 34% higher than for foreign workers. Among low-skilled workers, this gap widens further (native: 1.93K JPY; foreign: 1.25K JPY). For high-skilled workers, the native mean wage of 2.97K JPY is 7% higher than the foreign mean of 2.78K JPY.

It is worth noting that foreign workers' wages show less dispersion for the low-skilled (standard deviation of 0.83) than for the high-skilled (1.47). This is largely because over half of them are under the Technical Intern Training Program (TITP) or Student visas (see Table A.2 in the Appendix for details). TITP is a government internship program designed for skill transfer, leading to standardized wages for participants. Student visa holders, often hourly-paid, also tend to have less wage dispersion.

Native and foreign workers also exhibit different industrial sorting patterns. For foreign workers, staffing services (11%) and food products manufacturing (10%) are the top two industries, while for domestic workers, these only account for 2%. The detailed sectoral distributions of native and foreign workers are presented in Table A.3 in the Appendix.

Table 2 compares the distribution of workers across the four task categories defined above. First, low-skilled workers are more likely to hold manual jobs, while high-skilled workers predominantly hold non-manual jobs. This trend is especially pronounced among foreign workers, with 70.1% of foreign low-skilled workers in manual jobs compared to 44.34% of native low-skilled workers. Second, foreign workers are more concentrated in routine jobs than natives, with 74.51% (21.1%) of foreign low(high)-skilled workers in routine jobs compared to 50.21% (18.04%) of native low(high)-skilled workers. This heterogeneous task distribution between native and foreign is consistent with the findings of Peri and Sparber (2009, 2011) for the U.S. and Storm (2022) for the German labor market.

3. Foreign–native wage gap and tasks

This section estimates the foreign–native wage gap by extending the Mincerian wage model:

$$w_{ir}^{jk} = \beta F_i + \mathbf{X}_{ir}^{jk\prime} \boldsymbol{\gamma} + \delta_r + \delta^j + +\delta^k + \epsilon_{ir}^{jk} \tag{1}$$

Here, the dependent variable, w_{ir}^{jk}, represents the log hourly wage of worker i in prefecture r, industry j, and task k. The independent variables include a foreign dummy, F_i (equal to one if worker i is foreign,

[2] https://shigoto.mhlw.go.jp/User/

[3] Using the exchange rate of 157.38 JPY/USD as of 12/25/2024.

Table 2
Distribution of native and foreign workers across tasks.

	Japanese		Foreign	
	Low Educ	High Educ	Low Educ	High Educ
Non-Routine Non-Manual	33.15%	68.97%	9.3%	71.79%
Routine Non-Manual	22.51%	14.58%	20.57%	10.69%
Non-Routine Manual	16.64%	8.82%	16.16%	7.11%
Routine Manual	27.7%	7.63%	53.94%	10.41%

Source: Author's Calculation from MHLW Wage Survey 2022 and *jobtag*.
Note: Sample weight is applied.

Table 3
Regression results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Foreign	−0.272***	−0.138***	−0.144***	−0.0403**	−0.0485***	−0.0329**	−0.0473***	−0.0303*	−0.0415*	−0.0311
	(0.0233)	(0.0213)	(0.0202)	(0.0191)	(0.0160)	(0.0162)	(0.0158)	(0.0158)	(0.0228)	(0.0239)
Female			−0.198***	−0.156***	−0.187***	−0.195***	−0.186***	−0.185***	−0.188***	−0.196***
			(0.00783)	(0.00610)	(0.00662)	(0.00642)	(0.00617)	(0.00617)	(0.00664)	(0.00644)
College and more				0.303***	0.193***	0.161***	0.161***	0.161***	0.193***	0.161***
				(0.0126)	(0.00752)	(0.00724)	(0.00791)	(0.00790)	(0.00752)	(0.00723)
Experience										
1–4 yrs				0.111***	0.104***	0.104***	0.104***	0.105***	0.106***	0.105***
				(0.00588)	(0.00523)	(0.00519)	(0.00504)	(0.00504)	(0.00522)	(0.00519)
5–9 yrs				0.194***	0.186***	0.185***	0.186***	0.186***	0.187***	0.186***
				(0.00774)	(0.00670)	(0.00656)	(0.00647)	(0.00648)	(0.00672)	(0.00659)
10–14 yrs				0.276***	0.264***	0.262***	0.260***	0.261***	0.264***	0.263***
				(0.00939)	(0.00810)	(0.00802)	(0.00786)	(0.00787)	(0.00810)	(0.00803)
15 yrs +				0.432***	0.404***	0.398***	0.393***	0.393***	0.405***	0.399***
				(0.0114)	(0.00898)	(0.00882)	(0.00859)	(0.00859)	(0.00902)	(0.00886)
Manual							−0.0155***	−0.0150***		
							(0.00364)	(0.00369)		
Routine							−0.106***	−0.107***		
							(0.00368)	(0.00367)		
Foreign × Manual								−0.0413***		
								(0.0138)		
Foreign × Routine								0.0609***		
								(0.0157)		
Employment Type F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Prefecture F.E.					Yes	Yes	Yes	Yes	Yes	Yes
Industry F.E.					Yes	Yes	Yes	Yes	Yes	Yes
Task F.E.						Yes				Yes
Exclude TITP/Student									Yes	Yes
N	1 077 380	1 077 380	1 077 380	1 077 380	1 077 380	1 077 380	1 077 380	1 077 380	1 072 303	1 072 303
r2	0.00374	0.285	0.317	0.453	0.549	0.563	0.573	0.573	0.547	0.562

Notes: Standard errors are clustered at the prefecture-industry level. Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

zero otherwise), a vector of worker attributes, $\mathbf{X}_{ir}^{j}$, prefecture fixed effects, δ_r, industry fixed effects, δ^j, and task fixed effects, δ^k. The error term is ϵ_{ir}^{j}. The control variables in $\mathbf{X}_{ir}^{j}$, include sex, work experience, education level, and employment type (distinguishing four types based on full-time/part-time and with/without a contract term). Industry fixed effects (at the two-digit level) account for sectoral sorting, while prefecture fixed effects (covering 47 prefectures) control for inter-regional price level differences. Table 3 summarizes the estimation results.

The unconditional foreign–native wage gap is −.272 and statistically significant in Column 1, indicating foreign workers earn approximately 27% less than native workers. In the subsequent columns, we progressively introduce various worker characteristics as controls. Column 2 shows that the employment type explains roughly half of the unconditional foreign–native wage gap, reducing the gap to 14% (coefficient of −.138). This result is consistent with Japan's wider full-time/part-time wage disparities compared to other advanced economies (Nishimura, 2020). By Column 4, after controlling for gender, education, and experience, the gap further drops to 4% (coefficient of −.040). A comparison of the coefficients on the female dummy (−.156) and high-skilled dummy (.303) reveals that the native wage premium is smaller in magnitude. Including prefecture and industry fixed effects increases the foreign dummy coefficient in magnitude from −.040 to −.049, suggesting foreign workers sort into higher-wage regions and sectors, aligning with policies targeting markets with tight labor supply. In summary, 18% of the unconditional wage gap remains unexplained by worker attributes, regional, and industry compositions.

Column 6 controls for tasks, which reduces the estimated foreign–native wage gap to −.033. This suggests that task assignment accounts for one-third of the previously unexplained portion of the foreign–native wage gap, implying foreign workers are more likely to be assigned to low-paying tasks. To explore this more clearly, Column 7 adds the scores for manual and routine tasks (continuous variables), which foreign workers are more likely to perform (see Table 2). The results confirm that these task scores are significantly negatively associated with wages. In Column 8, we include interaction terms between the foreign dummy and these task scores, which allows us to examine whether the returns to performing manual or routine tasks differ between foreign and native workers. The results are mixed: foreign workers performing manual jobs are paid disproportionately lower wages than natives, while those performing routine jobs are paid higher wages than natives.

Finally, removing workers under the TITP and Student visas from the sample in the last two columns (as their wages may reflect trainee status rather than market determination) yields stable coefficient estimates (−.042 without task fixed effects and −.031 with). Most importantly, with task fixed effects, the foreign–native wage gap becomes statistically insignificant. This muted gap strongly suggests that differing tasks performed by foreign and native workers are a critical factor in explaining observed earning disparities.

4. Conclusion

This paper explores the foreign–native wage gap in the Japanese labor market. Our results confirm that, unconditionally, foreign workers are paid 27% less than native workers, and 82% of this gap is explained by workers' observable attributes. Most notably, task assignment explains one-third of the previously unexplained wage gap. This finding strongly suggests that foreign workers are disproportionately assigned to tasks with lower wages, typically routine and manual tasks. Critically, when we limit the sample to workers on dedicated work visas, the foreign–native wage gap becomes statistically insignificant. We also found that the foreign–native wage gap is less pronounced compared to the gender wage gap, suggesting that concerns about systemic discrimination against foreign workers may be less pressing in comparison to gender-based wage inequities.

Our results align with previous empirical works, such as Storm (2022) and Autor and Handel (2013), which suggest that task assignment is a key driver of earning gaps between native and foreign workers, as well as across genders. The distinct task assignments between native and foreign workers also imply imperfect substitution between these groups, suggesting that the inflow of immigrant workers does not immediately lead to negative impacts on native workers, as argued by Peri and Sparber (2009, 2011). Our findings also raise a key question: whether this heterogeneous task distribution stems from workers' ability or expertise (e.g., language proficiency), or if it reflects the (un)intended consequences of firms' human resource strategies as documented by Doi (2011a,b).[4] Future research should investigate the role of foreign workers within Japanese firms, with a particular focus on the dynamics of task assignment and skill utilization.

[4] Lessem and Sanders (2020) also argues that immigrants to the United States often take jobs below their skill qualifications bdue to the barriers to entering occupations.

Data statement

This work is approved to use the Japanese Government Micro-Level Data: the Basic Survey of Wage Structure (Ministry of Health, Labour, and Welfare). All moments presented in the paper are computed by the authors unless otherwise specified, and those do not always coincide with the numbers published by the government. Due to confidentiality, the raw data would not be shared.

Statement on the usage of generative AI tools

During the preparation of this work, the authors used ChatGPT and Google Gemini in order to proofread the manuscript for grammatical errors. After using these services, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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Appendix. Additional tables and figures

A.1. Construction of task scores

Table A.1 displays the correlation of five task scores that Acemoglu and Autor (2011) propose. See AA for the details of the construction. The table confirms that the scores for 1: Non-routine Analytical task and 2: Non-routine Interactive task are highly positively correlated (0.768). Similarly, the scores for 4: Routine Manual task and 5: Non-Routine Manual task are highly positively correlated (0.751). By aggregating these two sets of task scores, we constructed composite scores for non-routine and manual tasks.

Fig. A.1 plots the occupation-level task scores in a two-dimensional space defined by manual and non-routine tasks. The scores are normalized such that the mean is zero and the standard deviation is unity. We categorize the occupations whose manual score is above its average (zero) as “manual” and below its average as “zero”. Similarly, occupations whose non-routine score is below its average are categorized as “non-routine” and above its average as “routine”.

A.2. Distribution of foreign workers across visas and industries

Table A.2 shows the distribution of foreign workers across visa categories (status of residence). The table compares the heterogeneous distributions between low-education (fourth column) and high-education (fifth column) workers.

Table A.3 shows the distribution of native and foreign workers across sectors. Industries are classified according to the 2-digit Japan Standard Industrial Classification. The table lists 23 industries (out of a total of 91) where foreign workers account for at least 1% of the share.

Table A.1
Correlation across AA’s five task scores.

1: Non-routine Analytical				
0.768	2: Non-routine Interactive			
0.435	0.456	3: Routine Cognitive		
-0.206	0.005	0.266	4: Routine Manual	
-0.366	-0.139	-0.042	0.751	5: Non-Routine Manual

Source: Author’s calculation from MHLW Wage Survey 2022 and *jobtag*.

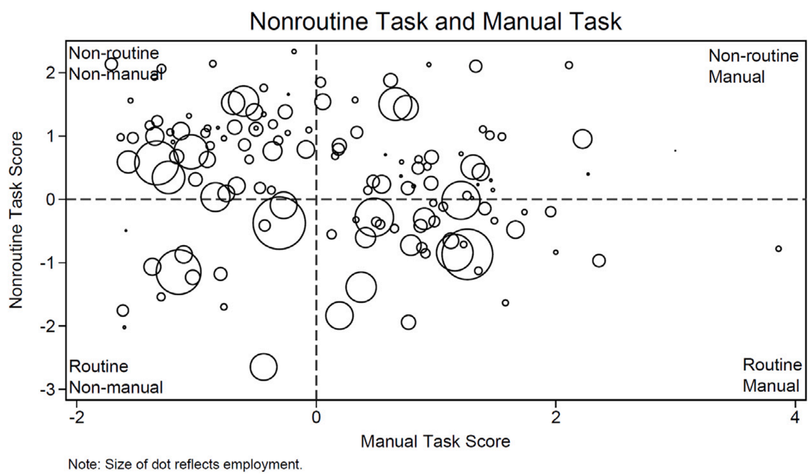

Fig. A.1. Task scores of occupations.

Table A.2
Distribution of foreign workers across visa categories.

		All	Low Educ	High Educ
1	Artist	0.00%	0.10%	0.00%
2	Professor	1.00%	0.00%	3.00%
3	Religious Activities	0.10%	0.00%	0.20%
4	Journalist	0.00%	0.00%	0.00%
5	Highly Skilled Professional	1.00%	0.00%	2.90%
6	Business Manager	0.00%	0.00%	0.10%
7	Legal/Accounting Services	0.00%	0.00%	0.10%
8	Medical Services	0.10%	0.00%	0.20%
9	Researcher	0.20%	0.00%	0.50%
10	Instructor	1.00%	0.10%	2.80%
11	Engineer, Specialist in Humanities, Int’l Service	21.00%	6.60%	49.20%
12	Intra-company Transferee	0.70%	0.20%	1.70%
13	Nursing Care	0.60%	0.70%	0.40%
14	Skilled Labor	1.00%	1.40%	0.20%
15	Specified Skilled Worker (i)	5.20%	7.20%	1.40%
16	Technical Intern Training	25.30%	36.30%	3.90%
17	Cultural Activities	0.00%	0.00%	0.00%
18	Student	13.10%	17.60%	4.30%
19	Dependent	1.90%	2.20%	1.20%
20	Designated Activities	3.60%	5.10%	0.60%
21	Permanent Resident	15.20%	13.50%	18.50%
22	Spouse or Child of Japanese	3.70%	3.30%	4.50%
23	Spouse or Child of Permanent Resident	0.60%	0.70%	0.40%
24	Long-Term Resident	4.60%	5.00%	3.90%
	Total	100%	100%	100%

Source: Author’s calculation from MHLW Wage Survey 2022.
Note: Sample weight is applied.

Table A.3
Distribution of native and foreign workers across industries.

	Japanese	Foreign
Staffing service	2.4%	10.7%
Food products	2.3%	10.0%
Restaurant	5.1%	7.8%
Food and drinks retail	4.6%	6.8%
Special construction	1.0%	6.0%
Transportation machinery	2.1%	5.2%
School education	2.4%	4.0%
Social welfare service	8.5%	3.8%
Textile	0.6%	3.2%
Metal products	1.6%	3.2%
Other business service	4.7%	2.3%
Special service	1.0%	2.3%
General construction	3.2%	2.1%
Plastic products	0.9%	2.0%
Information service	2.6%	1.9%
Retail without stores	0.5%	1.8%
Food and beverages wholesale	1.3%	1.7%
Other education	1.2%	1.6%
Machine and equipment wholesale	2.4%	1.5%
Accommodation	1.1%	1.4%
Production machinery	1.5%	1.3%
Installation construction	1.9%	1.1%
General Machinery	0.8%	1.0%

Source: Author's calculation from MHLW Wage Survey 2022.
Note: Sample weight is applied.

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